Incentive-Based D2D Relaying in Cellular Networks

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***Abstract*— Device-to-device (D2D) relaying is a concept, where some users relay data of cell-edge users (CUEs) experiencing a bad channel quality to a base station. While this research topic has received plenty of attention, a critical aspect of the D2D relaying remains a selfish nature of the users and their limited willingness to relay data for others. Thus, we propose a scheme to identify potential candidates for the relaying and provide a sound incentive to these relaying users (RUEs) to motivate them helping other users. First, we provide a detailed theoretical analysis showing when and if the relaying is beneficial for the CUE(s) and related RUE. Second, to choose among all possible incentive-compliant relaying options, we formulate the optimal CUE-to-RUE matching problem maximizing a network-wide performance. Since the optimal solution is hard to obtain for a high number of users, we propose a low-complexity greedy algorithm and prove its constant worst-case approximation guarantees to the optimum. Finally, we derive a closed-form expression for a fair allocation of the resources among the CUEs and the RUEs. The proposed framework more than doubles the users' capacity and/or reduces the energy consumption by up to 87% comparing to existing incentive-based relaying schemes.**

***Index Terms*— Device-to-device, relaying, incentives, relay selection, submodularity, worst-case guarantees.**

I. Introduction

DEVICE-TO-DEVICE (D2D) communication is seen as a way to increase the capacity and energy efficiency of contemporary mobile networks by allowing a direct communication of two devices in proximity [1], [2]. The D2D communication can be exploited also for various relaying purposes [3], [4], such as: (i) relaying of data between two D2D users (see, e.g., in [5]–[9]), (ii) extending a cell coverage so that the user equipment (UE) out of coverage can communicate with a base station (BS) via a relay UE (RUE) [10]), or (iii) enhancing the capacity of the UEs with a low channel quality to the BS if the UE is shadowed by an obstacle or located at the cell edge.

A number of works targeting scenario with the relaying of data from cell-edge UEs (CUEs) to the BS consider only the relaying via the RUEs that are not transmitting/receiving their own data at that moment. For example, the objective in [11]–[14] is to enhance the capacity of the CUEs and the authors in [15] minimize the energy consumption of the CUEs. All schemes considering inactive RUEs, however, pose an important disadvantage to the RUEs, whose energy consumption is increased in the process. Thus, *the RUE has no motivation to act as the relay* due to the selfish nature of most of the users. This observation gets even more aggravated if the energy spent for a reception of data by the RUE from the CUEs, neglected in the above works, is also considered. The use of the active RUEs instead of the inactive ones is assumed in [16], where the authors aim to minimize the transmission energy of the RUEs and the CUEs via the Hungarian algorithm. However, similar to [15], the reception energy for relaying is not considered, hence, even this solution may increase the overall energy consumption of the RUEs.

Although [11]–[16] show very promising gains introduced by the D2D relaying, none of them targets a problem of motivating the UEs to act as the RUEs and spend their own energy for the relaying of data form other UEs. One way to motivate the UEs to perform the relaying is considered in [17], [18], where a *token-based incentive* mechanism is proposed. In this concept, the UE that receives a help from any idle RUE pays with a token to that RUE. The token can be used by the RUE in the future when the RUE asks for the help itself. A similar approach to the one with tokens is considered also in [19]–[21], where the authors suggest a *virtual currency-based incentive* mechanism. The RUEs are rewarded with a virtual currency (or a credit) whenever they act as the relays. The received currency is then used by the UEs to pay to other UEs for the relaying services in the future. Other works motivate the users to act as the relays by means of *social-aware incentives*. In [22], the authors explore a social relationship among the users and assume that close friends are more likely to relay the data for each other. Along similar lines, in [23], the authors propose *contract theory-based incentives*, where the users prefer to help their friends rather than strangers. An incentive mechanism for the relaying considering also an energy efficiency is proposed in [24], where the relays are rewarded with a longer transmission time, thus, reducing their energy consumption.

A. Drawbacks of Existing Incentives Schemes

Although all incentive-based works significantly contributes to the problem of the UEs' motivation acting as the relay, they still have following drawbacks. The token/currency-based approaches [17]–[21] are plagued by two key shortcomings: (i) it is hard to estimate if the potential future gain (from earning a token or some currency) outweighs the immediate energy cost of the relaying; (ii) unless radio channel characteristics and traffic demands are uniformly distributed among all UEs

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over time, the token-based mechanisms can lead to deadlocks. The main drawback of the social-aware incentive approaches [22], [23] is: (i) there may not be any available friends in vicinity or (ii) the exploitation of only the friends for relaying is usually far from the optimal in terms of the communication capacity.

Moreover, none of the above-mentioned incentive-based approaches addresses the problem of an increased energy consumption of the RUEs. Although [24] tackles the energy consumption, it neglects the additional energy required for the data reception at the relay. However, the reception energy eventually increases the overall energy consumption. Besides, the works trying to incentivize the RUEs *restricts the number of CUEs exploiting each RUE to one*, thus, fairly limits a potential of the whole D2D relaying concept. On top of that, these works either do not address a critical problem of the relay selection ([19], [21]) or *no performance guarantees are given* for the proposed relay selection schemes ([17], [18], [20], [22]–[24]).

B. Contributions

Motivated by the drawbacks of the above-mentioned papers, we propose a flexible incentive-based relaying framework that guarantees *immediate* rewards for the RUE as well as for *all* CUEs exploiting the RUE. The contributions can be summarized as follows:

- We provide a detailed theoretical analysis showing when and if the matching of one or more CUEs with the RUE is beneficial in terms of the capacity, energy, or both. While the CUEs benefit due to a superior relaying channel quality, the RUE profits, as it can exploit a part of the CUE(s) resources for its own transmission.
- We formulate an optimal CUE-to-RUE matching problem to determine the relaying groups maximizing the network-wide performance. As the optimal solution is hard to obtain for a high number of UEs, we also propose a low-complexity greedy algorithm and we prove that the proposed greedy approach has a constant worst-case approximation guarantees to the optimum.
- We find a closed-form expression for the allocation of resources among the UEs in the relaying group to ensure a fairness among the CUEs and the RUE in terms of absolute or relative gains.

This work is an extended version of our prior paper [25], where we outline the general idea and indicate a performance for the case with just one CUE relaying via single RUE.

The rest of the paper is structured as follows. The next section describes the system model. Section III outlines the proposed incentive framework. A theoretical analysis on a capacity gain and potential energy savings is given in Section IV. Section V formulates an optimal CUE-to-RUE matching problem, describes a low-complexity greedy algorithm and discusses its submodularity properties. Section VI gives closed-form expression for fair resource allocations of all users within D2D relaying group. Section VII analyzes the effectiveness of the proposed incentive framework. The last section gives our conclusions.

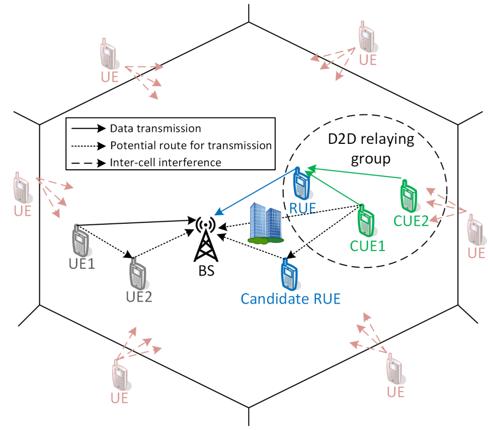


Fig. 1. Example of system model for Urban scenario where: (i) UE1 transmits data directly as a matching of UE1 with UE2 is not beneficial and (ii) CUE1 and CUE2 selects to relay data via the RUE, thus creating D2D relaying group.

II. System Model

We consider an urban scenario with multiple cells and multiple UEs, as shown in Fig. 1. Every UE is already associated with a BS, and CUEs in the cell can only be paired with the RUEs in the same cell.[1] Hence, we can focus the description of our scheme on a single cell, where interference from nearby cells is included in the physical layer model, as is common in other related works (see, e.g., [26]–[28]). We focus on the uplink, where the energy consumption of the UEs is critical. Although the proposed idea can be applied also to downlink, it would require notable changes to the overall concept and a novel solution that goes beyond the scope of this paper. The BS serves N active UEs that are randomly distributed in the cell. The UEs with favorable channels to the BS can relay data of the CUEs. The CUE is defined as the UE with a bad channel quality to the BS due to either its far distance to the BS or an obstacle in the communication path. Each CUE and its serving RUE, thus, create a D2D pair where the CUE plays the role of a transmitter while the RUE act as a receiver.

A. Physical Layer Model

The BS has a bandwidth B at its disposal. The bandwidth is split into N orthogonal uplink channels so that each UE is assigned with one channel of a bandwidth B_n. The signal to interference plus noise ratio (SINR) between any transmitter (i.e., UE, CUE, or RUE) and any receiver (RUE or BS) is expressed as:

$$\gamma_{t,r} = \frac{p_t g_{t,r}}{B_n(\sigma_0 + I_{s,r})}, \tag{1}$$

where p_t is the transmission power of the transmitter, $g_{t,r}$ represents the channel gain between the transmitter and the receiver, σ_0 is the noise spectrum density per Hz, and $I_{s,r}$ is the sum interference from the adjacent cells at the receiver.

B. Energy Consumption Model

A part of the proposed incentive mechanism is the energy reduction at the side of the RUEs (and potentially at the CUEs as well). The energy consumed by the UE due to

[1]We defer the problem of the user association to future work.

the transmission/reception of data is derived according to a well-established empirical model defined in [29]. In both uplink (transmission) and downlink (reception), the power consumption consists of the signal processing parts P_T^{bb} and P_R^{bb}, the radio communication parts P_T^{rf} and P_R^{rf}, and a consumption of the communication circuitry P_T^{on} and P_R^{on}. The powers consumed by the transmission (P_T) and the reception (P_R) are, then, defined as:

$$P_T = P_T^{bb} + P_T^{rf} + P_T^{on}, \tag{2}$$

$$P_R = P_R^{bb} + P_R^{rf} + P_R^{on}, \tag{3}$$

where the exact values and the calculation of individual parameters is in line with [29]. The total energy consumption of the UE by the transmission/reception (in J) is then a sum of both components weighed by the transmission time t_T and the reception time t_R:

$$E = P_T t_T + P_R t_R. \tag{4}$$

C. Assumptions

We adopt several assumptions and key distinctions of the proposed scheme: (i) the RUEs are assumed to be *active* and, thus, are expected to transmit their own data, in addition to the CUE data to be relayed; this is not the case in most of the related works, where only idle RUEs are considered, (ii) our scheme allows for multiple CUEs to be attached to the same RUE, provided that all CUEs and the RUEs can benefit from the relaying (this is contrary to, e.g., [11]–[23]), (iii) the CUE can use only one RUE at a time, although there might exist cases, where using more than one RUE by some CUEs might offer further benefits, this would come at a significant protocol complexity and our preliminary analysis suggests the benefits to be minimal, and (iv) we assume full knowledge of channel state information (CSI) similarly as in number of the recent studies (see, e.g., [30], [31]). Note that, there is no need to exchange CSI among all transmitters to select an appropriate relay for the CUEs in our proposal, as the potential RUEs should be in a relative proximity to the CUEs. Thus, only a relatively small subset of nearby UEs of the CUE should be considered as a set of the potential relays for which CSI should be known. Also, [32] shows that deep neural networks are able to predict the channel between any two D2D users with a high accuracy only from the users' cellular channels (i.e., channels from the user to the base station(s)). Such solution works even for none line of sight communication and in a scenario with dynamic objects (vehicles, etc.). Thus, the signaling cost is significantly reduced down to a negligible level. Note that the impact of an inaccurate CSI prediction can result in a suboptimal selection of the relays for some of the CUEs and to a subsequent degradation in the performance. Thus, we analyze the impact of the inaccurate CSI in Section VII.

III. High Level Overview of Proposed Incentive Framework for D2D Relaying

A motivation of the users relay data for others is a crucial aspect of the D2D relaying concept. In our proposed framework, any active UE that becomes the RUE can enjoy immediate benefit in terms of: (i) an increase in the capacity,

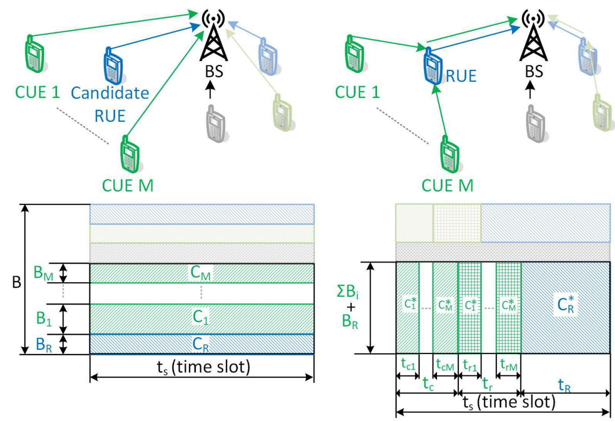


Fig. 2. Example of channel allocation in case without relaying (left) and with relaying (right). Figure highlights one reference D2D relaying group with one RUE and M CUEs.

(ii) a decrease in the energy consumption, or (iii) a combination of both. Any of these three options is selected according to the RUE's personal preferences. Of course, the CUEs should benefit from the relaying in the same way as the RUE.

The increased capacity or the decreased energy consumption of the RUE is feasible by rendering a part of the radio resources of the CUE to the RUE. This is illustrated in Fig. 2 for one potential RUE and M CUEs. Without relaying (left part of Fig. 2), all UEs use orthogonal channels within each time slot (t_s). Via these channels, the data is sent directly to the BS. Then, the baseline capacity of the i-th CUE (C_i) and the candidate RUE (C_R) without relaying during each time slot is expressed as:

$$C_i = B_i log_2 \left(1 + \frac{p_i g_{i,b}}{B_i (\sigma_0 + I_{s,r})}\right) t_s, \tag{5}$$

$$C_R = B_R log_2 \left(1 + \frac{p_r g_{r,b}}{B_R (\sigma_0 + I_{s,r})}\right) t_s, \tag{6}$$

where B_i and B_R are the bandwidths allocated initially by the BS to the i-th CUE and the potential RUE, respectively, p_i and p_r represent the transmission powers of the i-th CUE and the RUE, respectively, $g_{i,b}$ stands for the channel gain between the i-th CUE and the BS, and $g_{r,b}$ corresponds to the channel gain between the RUE and the BS.

If the candidate RUE starts to actually relay data for the CUEs, the resources of the CUEs and the RUE are aggregated and accessed in a time division manner as shown in the right part of Fig. 2. Note that if the relaying would be done fully in a frequency division manner, the RUEs should be able to receive and send data simultaneously. This would, however, assume that the RUEs are able to work in full duplex, while we assume only more practical half-duplex devices. Also note that the whole proposed concept is seen rather as OFDMA, where the transmissions of the UEs are separated in both frequency and time (see the right part of Fig. 2, where the D2D relaying groups work in the time division manner while the D2D relaying groups are separated with respect to each other and also to other UEs in the frequency division manner).

For each D2D relaying group, the whole transmission interval t_s (e.g., a time slot) is split into three separated parts.

The CUEs transmit their data to the RUE at the beginning of each time slot, the CUE 1 during the slot t_{c1}, the CUE 2 during the slot t_{c2}, and so forth, one after the other. The total duration of this part is $t_c = \sum_{i=1}^{M} t_{ci}$. In the second part, the RUE transmits (relays) the data of the CUEs. The data of the i-th CUE is relayed during t_{ri} and other CUEs follows again one after the other with the overall time duration equal to $t_r = \sum_{i=1}^{M} t_{ri}$. Finally, in the last part, the RUE transmits its own data during t_R. In the case of relaying, the capacity of the i-th CUE (C_i^*) and the RUE (C_R^*) is defined as:

$$C_i^* = B_s log_2 \left(1 + \frac{p_i g_{i,r}}{B_s(\sigma_0 + I_{s,r})}\right) t_{ci}, \tag{7}$$

$$C_R^* = B_s log_2 \left(1 + \frac{p_r g_{r,b}}{B_s(\sigma_0 + I_{s,r})}\right) \left(t_s - \sum_{i=1}^{M}(t_{ci} + t_{ri})\right), \tag{8}$$

where $B_s = B_R + \sum_{i=1}^{M} B_i$ is the aggregated channel bandwidth of the D2D relaying group, and $g_{i,r}$ corresponds to the channel gain between the i-th CUE and the RUE.

Obviously, the setting of t_{ci}, t_{ri}, and t_R parameters influence the relaying gain experienced by the CUEs and the RUE. To that end, we analyze when and if all involved parties within the relaying group benefit from the relaying in Section IV. Then, in Section V, we formulate the optimal group formation and we propose the greedy approach leading to a close-to-optimal performance. Finally, we derive closed-form expressions for the fair allocation of resources within the formed relaying groups in Section VI.

IV. Analysis of Relaying Gain

This section analyzes first when the relaying is profitable for the RUE and the CUEs in terms of the capacity and, then, it discuss a possible reduction in the energy consumption.

A. Capacity Gain

Taking (5)-(8) into mind, the relative gain of the i-th CUE (α_i) and the RUE (β), resulting from the appointment of the RUE as the relay for the i-th CUE, is defined as:

$$\alpha_i = \frac{C_i^*}{C_i} = \frac{K_i^* t_{ci}}{K_i t_s}, \tag{9}$$

$$\beta = \frac{C_R^*}{C_R} = \frac{K_R^*\left(t_s - \sum_{i=1}^{M}(t_{ci} + t_{ri})\right)}{K_R t_s}. \tag{10}$$

where $K_i = B_i log_2(1 + \frac{p_i g_{i,b}}{B_i(\sigma_0 + I_{s,r})})$ and $K_R = B_R log_2(1 + \frac{p_r g_{r,b}}{B_R(\sigma_0 + I_{s,r})})$ for the i-th CUE and the RUE, respectively. Moreover, the use of K_i^* and K_R^* refer to the case when the relaying is applied, analogously as in (7) and (8).

For $\alpha_i > 1$, the i-th CUE benefits from the relaying. Similarly, for $\beta > 1$, the RUE benefits from the relaying. As a matter of fact, the relaying is of interest if it is mutually beneficial for the CUEs and the RUE, i.e., if both $\alpha_i > 1$ ($\forall i \in \mathcal{M} = \{m_1, m_2, \ldots, m_M\}$ and $\beta > 1$. However, increasing α_i (the relative gain for the i-th CUE) by extending t_{ci} (the duration of D2D transmission) reduces β (the relative gain for the RUE) and vice versa. In this respect, the following lemma defines the condition for which all UEs within the D2D relaying group benefit from the relaying.

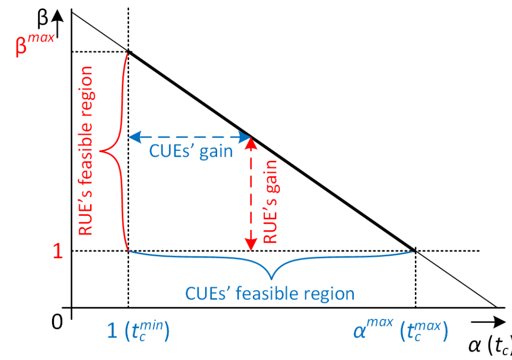


Fig. 3. Illustrative example of the feasible operational regions of RUE and CUEs, where all involved UEs benefits from relaying. Note that β^{max} and α^{max} are achieved for $\alpha = 1$ and $\beta = 1$, respectively.

Lemma 1: All M CUEs and the RUE in any D2D relaying group benefit from the relaying in terms of capacity, if:

$$\sum_{i=1}^{M} \frac{K_i}{K_i^*} t_s < \sum_{i=1}^{M} t_{ci} < \frac{(K_R^* - K_R) t_s}{K_R^*} - \sum_{i=1}^{M} t_{ri}, \tag{11}$$

while $t_{ci} > t_{ci}^{min}$, $\forall i \in \mathcal{M}$, where t_{ci}^{min} is the time allocation interval for which the i-th CUE has the relative gain $\alpha_i = 1$.

Proof: See proof in Appendix A.1. ■

After t_{ci} is obtained for all CUEs according to Lemma 1, t_{ri} and t_R are derived as:

$$t_{ri} = \frac{K_i^*}{K_R^*} t_{ci}, \ \forall i \in \mathcal{M}, \tag{12}$$

$$t_R = t_s - \sum_{i=1}^{M} t_{ci} - \sum_{i=1}^{M} t_{ri}. \tag{13}$$

It turns out that t_c^{min} (and respective allocation of the time resources) also maximizes the total capacity of the given D2D relaying group while assigning t_c^{max} minimizes the total capacity. In this respect, we formulate the following lemma.

Lemma 2: The upper bound on the total capacity is achieved for the case when each i-th CUE attached to the RUE is allocated with t_{ci}^{min}, i.e., if $t_{ci} = t_{ci}^{min}$, $\forall i \in \mathcal{M}$. Contrary, if $t_c = t_c^{max} = \sum_{i=1}^{M} t_{ci}^{max}$, the lower bound on the total capacity improvement is achieved by the relaying.

Proof: See proof in Appendix A.2. ■

All the values of $\sum_{i=1}^{M} t_{ci}$ in between the boundaries defined by (11) *do improve the total capacity of the D2D relaying group*. This is illustrated in Fig. 3, which shows a feasible operational region (depending on allocation of t_c), where the RUE and the CUEs gain in terms of the capacity.

B. Energy Consumption Reduction

In practice though, we want to properly incentivize the RUEs and the CUEs to form the relaying group as the relaying itself can cost also an additional energy consumed by the RUE. In fact, the energy consumption can be reduced by a decrease in the transmission power. This option can be attractive especially for the users who do not need to increase their capacity (or only marginal increase is needed) while prolonging a battery life-time of the UE is of more interest. This inevitably reduces the capacity gain of the CUE/RUE obtained by the allocation of t_{ci} as described above. Thus, we allow to decrease the transmission power at the cost of a full or a partial reduction in the capacity gain obtained by the relaying. Nonetheless, the capacity should not be decreased below C_i or C_R as the capacity of the UEs still should not drop below their original respective capacities.

On the other hand, if the users do not care much about the energy consumption (e.g., if the device is plugged in the electricity or if the device is fully charged), the transmission power can be optionally increased to further enhance the capacity. This option is feasible since the proposed allocation scheme partly reduces the energy consumption simply by adopting the relaying. Note that this is due to the fact that the transmission time of the UEs is reduced by switching from the frequency division manner to the time division (see Fig. 2). This optional power "boost", however, can be applied only if the following conditions hold: (i) the constraint on the maximal allowed transmission power (P_{max}) is not violated and (ii) the energy consumption of the UE in the case of relaying (E_R^*) is not higher than the energy consumption before the relaying is adopted (E_R). Also note that only the RUEs are allowed to increase their capacity by the power boost, since the power boost of the CUEs capacity inevitably negatively affects the gain of the RUE (i.e., t_{r1} would be increased and, thus, t_R would be decreased). The maximum capacity gain of the RUE due to the boosting of the transmission power, while above-mentioned constrains are fulfilled, is defined by the following lemma.

Lemma 3: The maximum capacity gain of the RUE due to the capacity boost is expressed as:

$$G_B = B_s log_2\left(\frac{B_s\left(\sigma_0 + I_{s,0}\right) + p_r^B g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right) + p_r g_{r,b}}\right)\left(t_s - t_c\right), \quad (14)$$

where p_r^B represents the RUE's boosted transmission power calculated as $p_r^B = min(p_r^*, P_{max})$, and p_r^* is the transmission power for which $E_R = E_R^*$.

Proof: See proof in Appendix A.3. ∎

Now, the feasible energy consumption reduction is directly proportional to the transmission power of the UE and depends on the limits within which the CUEs or the RUE can transmit. Thus, the following lemma defines allowable range of any i-th CUE and the RUE, respectively.

Lemma 4: The allowable range of the transmission power of the i-th CUE and the RUE (considering also possible power boost in case of the RUEs) are expressed as:

$$\kappa_i\left(2^{\frac{K_i t_s}{B_s t_{ci}}} - 1\right) \le p_i \le \kappa_i\left(2^{\frac{\rho G_i + K_i t_s}{B_s t_{ci}}} - 1\right), \quad (15)$$

$$\kappa_R\left(2^{\frac{K_R t_s + \sum_{i=1}^{M} K_i^* t_{ci}}{B_s\left(t_s - \sum_{i=1}^{M} t_{ci}\right)}} - 1\right) p_r \le \kappa_R\left(2^{\frac{\rho(G_R + G_B) + K_R t_s + \sum_{i=1}^{M} K_i^* t_{ci}}{B_s\left(t_s - \sum_{i=1}^{M} t_{ci}\right)}} - 1\right), \quad (16)$$

where $\kappa_i = \frac{B_s(\sigma_0 + I_{s,0})}{g_{i,r}}$ and $\kappa_R = \frac{B_s(\sigma_0 + I_{s,0})}{g_{r,b}}$, $G_i = C_i^* - C_i$ stands for the absolute gain of the i-th CUE, $G_R = C_R^* - C_R$ represents the absolute gain of the RUE, and $\rho = \langle 0, 1\rangle$ represents the parameter indicating a decrease in G_i and G_R, respectively.

Proof: See proof in Appendix A.4. ∎

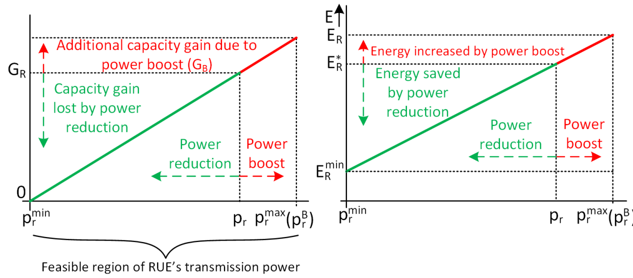


Fig. 4. Illustrative example of the feasible transmission power regions for the RUE and its impact on achieved capacity gain (left figure) and energy consumption (right figure).

An illustrative example of the feasible region of the RUE's transmission power and its impact on the capacity gain and the energy consumption is shown in Fig. 4 (note that the similar figure applies for the CUEs as well, just without the power boost). Fig. 4 shows that there is a trade-off between the capacity gain and the energy consumption. If p_r is decreased, the energy consumption of the RUE is decreased while the capacity gain due to relaying is lowered. If p_r is increased, the relaying capacity gain is increased at the cost of a higher energy consumption.

V. INCENTIVE-ALIGNED RELAYING GROUPS FORMATION

So far, we have analyzed conditions when the UEs in the D2D relaying group benefit from the relaying in terms of the capacity enhancement and/or the reduction in the energy consumption. For example, in the case of the capacity increase, any i-th CUE can get matched with any RUE for which the feasible region of t_{ci}, as defined in (11), is non-empty, since both the RUE and the CUEs benefit. Given multiple RUE options for each CUE and multiple CUEs that potentially prefer the same RUE, an algorithm is needed to efficiently select among the feasible CUE-RUE combinations.

To select an individual CUE-RUE pairs and, thus, create individual D2D relaying groups, we define the matrix $\mathbf{G}^p$ of the potential gains where $G_{i,j}^p \in \mathbf{G}^p$ is the capacity gain introduced if the i-the UE would exploit the j-th UE as the relay is expressed as:

$$G_{i,j}^p = \begin{cases} G_i + G_R + G_B, & \text{if } G_i \ge 0 \text{ and } (G_R + G_B) \ge 0 \\ 0, & \text{if } G_i < 0 \text{ or } (G_R + G_B) < 0 \end{cases} \quad (17)$$

The capacity gain is composed of the absolute gain of the i-th CUE (G_i), the absolute gain of the RUE (G_R), and also of the capacity boost set in line with Lemma 3 (G_B). Note that G_i is calculated as a difference between C_i^* and C_i and G_R is derived as a difference between C_R^* and C_R as explained in Lemma 4. Both G_i and G_R depend on the allocation of the transmission intervals for the CUEs (i.e., t_{ci}) and the RUE (i.e., t_{ri} and t_R). In this regard, t_{ci} is determined first according to the expected gain of the i-th CUE (α_i). For example, in case of the upper bound, α_i is set to 1 and t_{ci} is calculated via (9). If t_{ci} is within the allowable interval guaranteeing benefit to both the CUE and the RUE (as defined by Lemma 1), t_{ri} and t_R are calculated according to (12) and (13), respectively. The $G^p_{i,j}$ is positive if both the CUE and the RUE experience a non-negative capacity gain in case of the relaying. If the CUE and/or RUE would experience a negative capacity gain, $G^p_{i,j}$ is set to 0. The diagonal values of $\mathbf{G}^p$ are also set to 0 as the UE cannot act as its own relay.

Our objective is then to select the CUE-RUE pairs among the feasible combinations of the CUEs and the RUEs, so as to maximize the relaying gain and, consequently, also the sum total capacity of the system. As the solution differs for the case where just single CUE is allowed to be attached to each RUE (i.e., if $M = 1$) and the case where multiple CUEs can exploit the same relay ($M > 1$), we first focus on a single-CUE case. Then, we contemplate necessary modifications to extend the problem to the multi-CUE case.

A. Single-CUE Case

In single-CUE per RUE case, each CUE can use only one RUE and, at the same time, each RUE can relay data only for one CUE. Thus, the objective is formulated as:

$$\begin{aligned} \underset{x_{ij}}{\text{maximize}} \ & \sum_i \sum_j x_{ij} G^p_{i,j} \\ \text{s.t. a)} \ & \sum_j x_{ij} \le 1, \quad \forall i \\ \text{b)} \ & \sum_i x_{ij} \le 1, \quad \forall j \end{aligned} \tag{18}$$

where $x_{ij} \in \{0, 1\}$ is the control variable indicating whether the i-th CUE is matched with j-th RUE ($x_{ij} = 1$) or not ($x_{ij} = 0$), the constraint a) ensures that each CUE attaches to at most one RUE, and the constraint b) guarantees that each RUE serves up to one CUE.

Due to a) and b) constraints, one-to-one matching problem should to be solved. While this is an integer program (so, generally hard) it can, in fact, be optimally solved using the Hungarian algorithm [33]. However, the Hungarian algorithm is characterized by a relatively high complexity ($\mathcal{O}(N^3)$). As a result, we show the performance achieved by Hungarian algorithm as a benchmark and we propose a low-complexity sub-optimal greedy algorithm with the worst-case approximation guarantees to the optimal solution.

The selection of the relays by our greedy algorithm is described in Algorithm 1. At the beginning, $G^p_{i,j} \in \mathbf{G}^p, \forall i, j \in \{1, \ldots, N\}$ is calculated according to (17) as shown in line 1. Based on the $\mathbf{G}^p$, the D2D pair for relaying is established by the i-th CUE and the j-the RUE that yields the highest capacity gain (lines 3, 4). In other words, indexes i and j corresponding to the maximum gain in the whole $\mathbf{G}^p$ (over all rows and all columns) defines the CUE and its selected RUE, respectively. Then, the i-th row and j-th column in $\mathbf{G}^p$ matrix containing the maximum value of the gain is set to zero to ensure the constraints a) and b) in (18) (lines 5, 6). The whole process is repeated (i.e., lines 2-7) until all values in $\mathbf{G}^p$ are zeroed out.

The complexity of the proposed Algorithm 1 is in the worst case $\mathcal{O}(N^2 \log N)$. The reason is that Algorithm 1 initially checks N^2 entries in $\mathbf{G}^p$, selects the one with the highest value,

Algorithm 1 Incentive-Aligned Relaying Groups Formation

1: Derive $G^p_{i,j} \in \mathbf{G}^p, \forall i, j \in \{1, \ldots, N\}$
2: **while** $\max(G^p_{i,j}) > 0$ **do**
3: $\quad \{i, j\} \leftarrow \max(G^p_{i,j})$
4: $\quad$ Create D2D pair from i-th CUE and j-th RUE
5: $\quad$ Set i-th row in $\mathbf{G}^p$ to 0
6: $\quad$ Set j-th column in $\mathbf{G}^p$ to 0
7: **end while**

and remove one row and one column from $\mathbf{G}^p$. In the next rounds, the algorithm respectively checks $(N-1)^2$, $(N-2)^2$, and so on till 1 entry in $\mathbf{G}^p$. Still, even for relatively small numbers of the UEs (up to 100 UEs), the complexity of the proposed greedy algorithm is significantly lower comparing to the complexity of the Hungarian algorithm. Consequently, Algorithm 1 offers a good trade-off between the complexity and the performance, which is close-to-optimal, as demonstrated, e.g., in [34], [35] and later in the simulations results.

The following theorem states that the greedy algorithm (Algorithm 1) provides a worst-case approximation guarantee to the optimal. Note that, in the simulation results, the greedy algorithm actually performs much closer to the optimal.

Theorem 5: The optimization problem of (18) is monotone submodular in the control variables x_{ij}, subject to an intersection of matroid constraints. As a result, the proposed Algorithm 1 is guaranteed to provide a $\frac{1}{3}$ approximation ratio to the optimal.

Proof: See proof in Appendix B.1. ∎

B. Multi-CUE Case

This subsection discusses the more general case when the constrain b) in (18) is relaxed and multiple CUEs can exploit the same RUE. Then, the problem in (18) is rewritten as:

$$\begin{aligned} \underset{x_{ij}}{\text{maximize}} \ & \sum_i \sum_j x_{ij} G^p_{i,j} \\ \text{s.t. a)} \ & \sum_j x_{ij} \le 1, \quad \forall i \end{aligned} \tag{19}$$

Contrary to (18), (19) cannot be solved optimally by the Hungarian algorithm, since this is a many-to-one matching problem while the Hungarian algorithm is applicable only to one-to-one matching problems. Moreover, the order in which the CUEs are assigned to the RUE matters. The reason is that, by selecting any i-th CUE to use the j-th RUE, the channel bandwidth available for the j-th RUE is increased by adding the channel bandwidth of the i-th CUE to this particular D2D relaying group (see Fig. 2). This implies a need to recalculate the remaining positive gains in the j-th column of $\mathbf{G}^p$. Hence, a different ordering in which the CUEs are added may result in a different grouping and a different performance.

The optimal solution can be derived by the full search, i.e., by trying all possible combinations of the matching of the CUEs with the RUEs. The full search, however, checks $\frac{K!}{(K-L)!}$ possible combinations, where K is the number of positive elements in the initially created $\mathbf{G}^p$ and L is the number of CUEs that can initially be attached to at least one RUE (i.e., the number of CUEs with at least one positive

Algorithm 2 Optimal Algorithm for Multi-CUE case

1: Identify all positive $G^p_{i,j} \in \mathbf{G}^p$ that cannot be selected together
2: Divide $\mathbf{G}^p$ into S sub-matrices
3: Check all combinations in each sub-matrix
4: Select the matching in each sub-matrix maximizing gain
5: Select the matching among all sub-matrices max. gain

entry in $\mathbf{G}^p$). Unfortunately, there is no way to find the optimal solution for higher number of UEs due to excessive number of combinations to be checked. To this end, we outline a way that is able to notably decrease the number of combinations to be checked while still obtaining the optimal matching.

The optimal algorithm reducing the number of combinations is described in the following five subsequent steps (see Algorithm 2). First, all the positive entries in the $\mathbf{G}^p$ matrix that cannot be selected together are identified. More specifically, since the CUEs cannot exploit multiple number of RUEs, at most only one positive entry in each i-th row of $\mathbf{G}^p$ can be selected. Second, the matrix $\mathbf{G}^p$ is divided into S sub-matrices in such a way that each sub-matrix contains only the positive entries, which can be selected together. This way we avoid checking the combinations that are not allowed. Also, if there is only one positive entry in the i-th row, this entry is included in each sub-matrix. In the third step, all matching combinations in each created sub-matrix are checked separately. Due to second step, each CUE can be matched with just one RUE in each sub-matrix. Consequently, the matching can be done separately also for each RUE (i.e., for each row in each sub-matrix), since the matching of the CUEs to the RUE affects only other CUEs that are already attached to (or to be potentially attached) to the same RUE. Then, in the fourth step, the matching combination yielding the highest gain is selected for each sub-matrix. Finally, the matching yielding the highest gain out of these matching combinations is selected. Despite a reduced complexity of Algorithm 2 with respect to the full search, the optimal solution still cannot be obtained for a very high numbers of the UEs. Hence, we show the optimal solution only for up to 24 UEs and propose an alternative greedy low-complexity algorithm solving (19).

The greedy algorithm for the multi-CUE case is based on Algorithm 1 proposed for the single-CUE case. Still, we need to make a modification of line 6. Thus, instead of setting all remaining positive entries in the j-th column in $\mathbf{G}^p$ to 0, these are updated. More specifically, we recalculate potential gain of any CUE with the positive entry in the j-th column. This update is necessary, since the CUEs attached to the j-th RUE (and the j-th RUE itself as well) exploit a wider channel bandwidth containing individual bandwidths of each CUE attached to the same RUE, as explained above. Consequently, by matching any new CUE with this RUE, the potential gain by adding yet another CUE to this particular D2D relaying group is decreased as σ_0 and $I_{s,0}$ is increased with the use of wider channel. Moreover, t_{ci} and t_{ri} of the CUEs already matched with the j-th RUE are updated as well after the new CUE is added to this D2D relaying group, together with the transmission time of this particular RUE (t_R).

The complexity of the modified Algorithm 1 for the multi-CUE case is, in the worst case, $\mathcal{O}(\frac{N^3+N^2}{2})$. The algorithm goes first through N^2 entries, selects the highest one, and deletes the row. Then, the algorithm subsequently searches over $N(N-1)$, $N(N-2)$, till N entries in $\mathbf{G}^p$. Thus, the complexity is derived as $\mathcal{O}(N^2+N(N-1)+\cdots+N) = \mathcal{O}(N^2 + N\sum_{i=1}^{N-1} i) = \mathcal{O}(\frac{N^3+N^2)}{2})$. Note that while the greedy algorithm for the multi-CUE case can be solved in a polynomial time, the optimal solution cannot be solved in the polynomial time.

While the greedy algorithm for the multi-CUE case is similar to the single-CUE one, the approximation guarantee(s) it gives depend on some additional network parameters. In the following results, we consider some important sub-cases.

Lemma 6: Assume that every UE has an equal bandwidth B allocated, and a maximum of M CUEs per RUE is allowed. Assume further that the initial $\mathbf{G}^p$ matrix contains only the candidate CUE-RUE pairs for which $G^p_{i,j} \geq 0$ if the CUE and the RUE bandwidth is B and $M \cdot B$, respectively. Then, the modified greedy algorithm again achieves a $\frac{1}{3}$ approximation.

Proof: See proof in Appendix B.2 ■

Remark 1: We remind the reader that the initial matrix $\mathbf{G}^p$ contains only candidate pairs who can benefit from the relaying in a one-to-one situation (i.e., a positive gain from the relaying can be achieved for both). The additional assumptions in Lemma 6, hence, only refer to such pairs, and not any CUE-RUE pair (whose channel can be arbitrarily bad), and thus are satisfied in most scenarios.

Remark 2: Other approximation algorithms, besides the greedy one, can be used for our optimization problem (e.g., continuous relaxation and pipage rounding [36]). These, however, give worse approximation guarantees for polymatroid constraints, like the ones we have in our optimization problem (i.e., $\frac{0.38}{p}$ approximation for p matroids [37]). Moreover, there exists significant recent literature in the field of accelerated greedy [38] or stochastic greedy schemes [39] that can further improve the running time of basic greedy. We see as an advantage of our analytical contribution that such improvements are applicable. However, the actual investigation of such refinements, we believe, is orthogonal to this work and beyond the scope of the paper.

VI. Derivation of Fair Resource Allocation

In this section, we address a fair allocation of the communication resources *within the same D2D relaying group* (i.e., for all CUEs connected to the same RUE). There is no requirement on the fairness among different RUE groups (and neither should be), which might even implement different fairness policies to be agreed upon by the participants. This fairness is achieved by an appropriate allocation of the resources during the time slot among the CUEs and the RUE (i.e., by the allocation of t_{ci}, t_{ri}, and t_R).

We follow two common fair allocation principles, where the CUEs and the RUE have either: (i) the same relative capacity gain (this can be also interpreted as a proportional fairness) or (ii) the same absolute capacity gain. The following two lemmas give closed-form expressions on the time allocation for the CUEs (i.e., t_{ci}) resulting in the same relative and absolute gains of all M CUEs and RUE within the same relaying group.

Lemma 7: The same relative capacity gain for each member of the D2D relaying group is achieved if:

$$t_{ci} = \frac{K_1^* K_i}{K_1 K_i^*} t_{c1}, \tag{20}$$

where t_{c1} *is derived as:*

$$t_{c1} = \frac{K_1 K_R^* t_s}{K_R K_1^* + K_1(K_1^* + K_R^*) + K_1^* K_R^* \left(\sum_{i=2}^{M} \left(\frac{K_i}{K_i^*} + \frac{K_i}{K_R^*}\right)\right)}. \tag{21}$$

The (21) has a solution always if β *is increased by creating any* i*-th CUE-RUE pair, i.e., if the* i*-th CUE does not degrade the capacity of the RUE for* $\alpha_i = 1$.

Proof: See proof in Appendix C.1. ∎

When t_{ci} is obtained for all CUEs relaying via the same RUE as described above, t_{ri} with t_R are derived according to (12) and (13), respectively.

Lemma 8: The same absolute capacity gain for each member of the D2D relaying group is achieved if:

$$t_{ci} = \frac{K_1^* t_{c1} - K_1 t_s + K_i t_s}{K_i^*}. \tag{22}$$

where t_{c1} *is calculated as:*

$$t_{c1} = \frac{\left(M K_1 - K_R + K_R^* + K_R^* \sum_{i=2}^{M} \left(\frac{K_1 - K_i}{K_i^*} - \frac{K_i}{K_R^*}\right)\right) t_s}{(M+1) K_1^* + K_R^* + K_1^* K_R^* \sum_{i=2}^{M} \frac{1}{K_i^*}}. \tag{23}$$

The (23) has a solution always if $G_R > 0$ *for the case when* $G_i = 0,\ \forall i \in \mathcal{M}$.

Proof: See proof in Appendix C.2. ∎

When t_{ci} is obtained for all CUEs relaying via the same RUE, t_{ri} and t_R are again derived according to (12) and (13), respectively.

VII. Simulations

This section first describes a simulation setup for an evaluation of the proposed incentive framework. Also existing competitive incentive schemes related to our work are introduced. Then, we present the simulation results and discuss the gains with respect to the existing schemes.

A. Simulation Setup

The simulations, performed in MATLAB, are run for 1000 random drops. Within each drop, up to 100 UEs are uniformly distributed in the simulation area with the size of 500×500 m. The results are then averaged out over all drops. Without lose of generality, we consider that the BS splits the available bandwidth among the UEs equally in the simulations. The channel models between the UEs and the BS and among the individual UEs are in line with 3GPP considering the outdoor-to-outdoor environment [40]. The simulations are performed for an urban scenario, where possible obstacles between any transmitter and any receiver can turn a line of sight (LoS) communication into a non line of sight (NLoS). The probability of LoS is determined according to 3GPP for Urban Macrocell scenario, where the probability of LoS decreases with the distance between the transmitter and the receiver [41]. If there is the NLoS communication between any two nodes, 20 dB is added to the link attenuation representing an obstacle. As we consider a multicell environment, we model the inter-cell interference at any receiver randomly according to Gamma distribution (see [42]). The simulation parameters are summarized in Table I.

TABLE I

Parameters and Settings for Simulations

Parameter	Value
Carrier frequency	2 GHz
Simulation area	500x500 m
Number of UEs (N)	10-100
Bandwidth available at BS in uplink (B)	20 MHz
Max. transmission power of UE, CUE, RUE	23 dBm
Noise spectral density (σ_0)	-173 dBm/Hz
Mean interference from adjacent cells ($I_{s,0}$)	-140 dBm/Hz
Height of BS/UE antenna	30/1 m
Number of simulation drops	1000

The performance of the proposed framework is demonstrated for several proposed relaying groups formation schemes: (i) greedy selection following Algorithm 1, where only one CUE can exploit single RUE (denoted as "*Greedy: M=1*"), (ii) greedy selection where multiple CUEs can exploit the same RUE ("*Greedy: M>1*"), (iii) Hungarian algorithm that is able to find the optimal relaying groups for the single CUE per RUE case ("*Optimal: M=1*"), and (iv) optimal scheme defined in Algorithm 2 for the multi-CUE case ("*Optimal: M>1*"). Note that the optimal scheme for the multi-CUE case is shown only for up to 24 UEs due to its huge complexity.

The proposed incentive framework is confronted with other two existing types of the incentive-based schemes for the D2D relaying. The first type is based on the token/virtual currency incentives, where the CUEs enhance their capacity while the RUEs receive tokens or some virtual credits to perform the relaying as proposed in [19]–[21] (see Introduction section for more details). We label this type of schemes as "*T/VC incentives*". The second type is based on the social-aware incentives, where the relaying is done only by friends as other UEs are not willing to perform the relaying due to selfish nature of the users, see, e.g., [22], [23]. We label this type as "*SA incentives*". We also show a baseline scheme without relaying ("*No relaying*") demonstrating the relaying gain introduced by our proposal and by competitive schemes.

B. Simulation Results

The simulation results are divided into three parts: i) showing the potential maximum capacity gain achieved by the proposal, ii) analyzing a trade-off between the capacity gain and the energy consumption reduction, and iii) investigating the performance of our proposal if the gain is shared fairly among the UEs within the same D2D relaying group, as derived in Section VI.

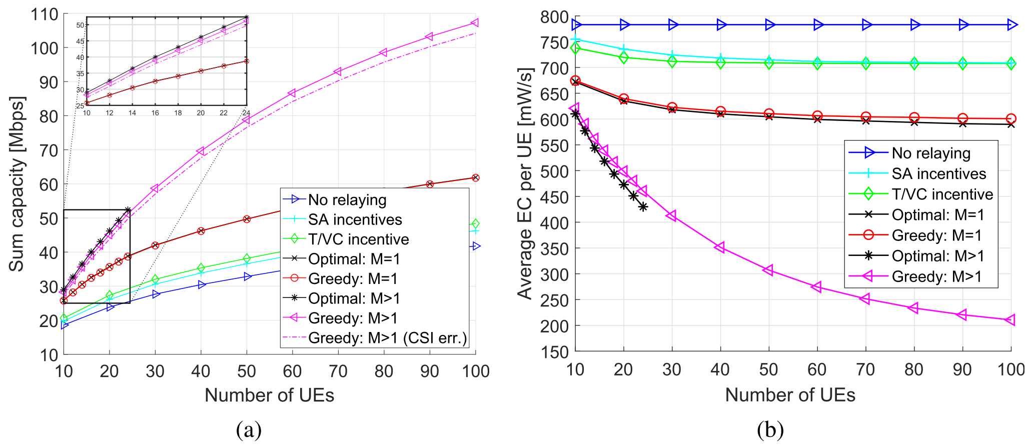


Fig. 5. Performance of the proposal depending on the number of UEs in terms of sum capacity (a) and average energy consumption per UE (b) ($\rho = 1$).

1) Evaluation of Potential Maximum Capacity Gain: Fig. 5a illustrates that the sum capacity increases with the number of UEs as the probability of finding a suitable RUE for each CUE is generally higher with the more deployed UEs. The highest sum capacity is always reached by the proposed greedy algorithm, which allows multiple CUEs to connect to single RUE (*Greedy: M>1*). The proposed *Greedy: M>1* improves the sum capacity by up to 156.8%, 132%, and 121.9% comparing to *No relaying*, *SA incentives*, and *T/VC incentives*, respectively. The gain of *Greedy: M>1* over *SA incentives* is due to the fact that more relaying options are available in the case of the proposed *Greedy: M>1*. Similarly, the gain with respect to *T/VC incentives* is achieved thanks to the proposed flexible incentive mechanism, where the RUEs give a consent to the relaying only if the RUEs have an immediate profit (i.e., reach a higher capacity in this case). The gain of the proposal is more significant if the RUE is exploited by multiple CUEs. However, even the case permitting only one CUE per RUE (*Greedy: M=1*) outperforms *No relaying*, *SA incentives*, and *T/VC incentives* by 47.9%, 33.6%, by 27.8% for 100 UEs.

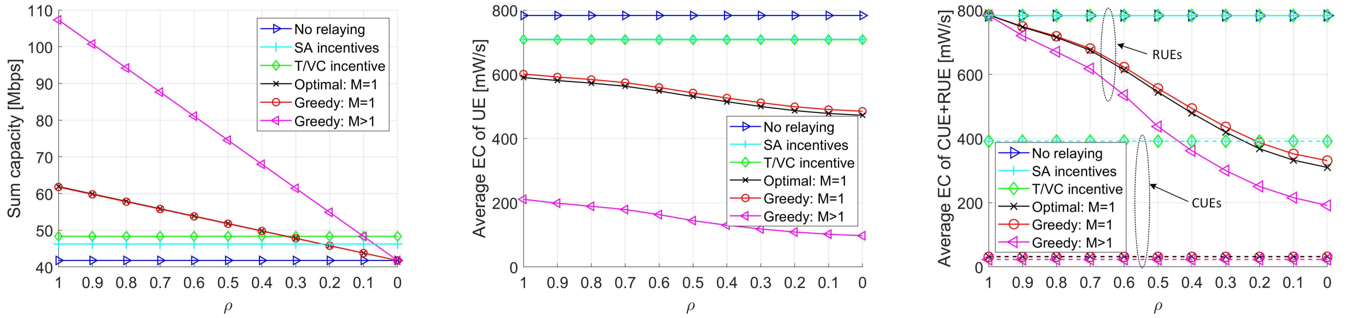
Fig. 5a also demonstrates that the proposed Greedy algorithm reaches a close-to-optimal performance for both single- and multi- CUE per RUE cases. The performance gap between the Optimal and Greedy selection of relays for the single-CUE case is less than 0.5% (the curves for optimal and greedy algorithms overlap). Although the performance gap between the Optimal and Greedy algorithms for the multi-CUE case increases, this gap is still below 2.4%. These encouraging results confirm the fact that the greedy algorithms are known to give a close-to-optimal performance in practical scenarios.

Last, Fig. 5a also investigates the impact of the inaccurate CSI estimation on the performance of *Greedy: M>1* (labeled as *Greedy: M>1 (CSI err.)*). Note that the channel gain estimation error is selected randomly and varies between -10% and 10% with respect to a real channel gain. Despite this rather high channel estimation error, the decrease in the sum capacity is only up to 2.9%. This confirms a robustness of the proposed scheme against the channel estimation errors and it validates its suitability even for the practical applications.

Fig. 5b shows the average energy consumption per UE. The energy consumption decreases with the number of UEs, as more number of the CUEs exploit the RUEs. The most significant energy consumption reduction is attained by the proposed *Greedy: M>1* scheme, which enables the energy consumption reduction by up to 73.1%, 70.3%, and 70.2% comparing to *No relaying*, *SA incentives*, *T/VC incentives*, respectively. The reason for such a notable reduction in the energy consumption is that multiple CUEs can be attached to the same RUE and, thus, the transmission intervals of the CUEs are significantly reduced with respect to the other schemes. Note that the more CUEs are attached to the RUE the shorter transmission intervals of the CUEs are as a wider channel bandwidth is utilized by the CUEs and the RUE, especially for a higher number of the UEs in the cell as the number of CUEs relaying data via the same RUE increases. Still, even the simplified proposed scheme *Greedy: M=1* reduces the energy consumption by up to 23.3% comparing to *No relaying*, up to 15.3% comparing to *SA incentives*, and up to 15.1% comparing to *T/VC incentives*. Note that the gap between the proposed Optimal and Greedy schemes is small and the proposed Greedy scheme reduces the energy consumption by up to 1% (for the single-CUE case) and up to 6.4% (for the multi-CUE case) less then the optimum.

2) Trade-Off Between Relaying Capacity Gain and Energy Consumption Reduction: This subsection a sheds light on the performance of the proposal if a part of the capacity gain introduced by the proposed relaying is sacrificed in order to reduce the energy consumption of the UEs via the power reduction described in Section IV. Note that the results are for 100 UEs in the system, thus, the performance of *Optimal: M>1* cannot be shown due to its complexity. As expected, if ρ decreases the sum capacity of the proposal decreases as well, since more capacity gain is transformed to the reduction in the energy consumption (see Fig. 6a). Hence, for $\rho = 0$, the proposal performs as if there would be no relaying and the whole capacity gain is translated to the energy savings.

Fig. 6b illustrates the impact of varying ρ on the average energy consumption of the UEs. The proposal (both for single- and multi- CUE case) reduces the energy consumption more significantly for a lower ρ. Hence, when compared to Fig. 5b, the proposed *Greedy M>1* algorithm further reduces the energy consumption from 73.1% to 87.6%, from 70.3% to 86.3%, and from 70.2% to 86.2% with respect to *No relaying*, *SA incentives*, and *T/VC incentives*, respectively, for $\rho = 0$.



(a) (b) (c)

Fig. 6. Impact of transmission power reduction on sum capacity (a) and average energy consumption of all UEs (b) and energy consumption of CUEs and RUEs (c) (100 UEs).

Even if *Greedy M=1* algorithm is not able to offer such notable energy savings as *Greedy M>1*, it still significantly outperforms *No relaying*, *SA incentives*, and *T/VC incentives* up to 38.1%, 31.6%, and 31.5%, respectively.

Fig. 6c analyzes the energy savings experienced by the CUEs and the RUEs separately. The RUEs benefit notably in terms of the energy consumption reduction if ρ is decreased. More specifically, *Greedy: M>1* and *Greedy: M=1* reduce the energy consumption roughly by up to 75.6% and 57.7%, respectively, comparing to both competitive incentive schemes. On the contrary, there is no further reduction in the energy consumption of the CUEs resulting from a decreasing ρ. This is due to the fact that Fig. 6c depicts the case for $\alpha_i = 1$, $\forall i$, i.e., the CUEs experience no gain in terms of the capacity. Thus, there is no relaying capacity gain to be sacrificed by the CUEs as in the case of the RUEs. Still, we observe that the CUEs significantly lower the energy consumption by 97.1% with respect to *No relaying* and by 94.1% with respect to both *SA incentives* and *T/VC incentives*. The reason for such a huge energy consumption reduction is that the CUEs notably minimize their transmission intervals if the proposed relaying is applied.

Now, we demonstrate the energy savings introduced by the proposed *Greedy: M>1* algorithm with respect to all competitive schemes in Fig. 7. In this figure, we illustrate the energy savings achieved by the proposed relaying for the case when the proposed *Greedy: M>1* reaches the same capacity as individual competitive schemes. The proposed *Greedy: M>1* performs the same in terms of the capacity as *No relaying*, *SA incentives*, and *T/VC incentives* for $\rho = 0$, $\rho = 0.07$, and $\rho = 0.1$, respectively, see Fig. 6a. For these values of ρ, *Greedy: M>1* algorithm reduces the energy consumption of the UEs by 87.6%, 85.9%, and 85.6% comparing to *No relaying*, *SA incentives*, and *T/VC incentives*, respectively. The energy saving of only CUEs is 97.1% comparing to *No relaying* and 94.1% comparing to both incentive schemes. Finally, the energy savings of the RUEs is 75.6%, 73.7%, and 72.5% in comparison to *No relaying*, *SA incentives*, and *T/VC incentives*, respectively. The results above demonstrate that our proposal is able to significantly decrease the energy consumption while offering the same capacity as the competitive schemes.

3) Fair Resource Allocation: This subsection studies the impact of the proposed fair allocation derived in Section VI.

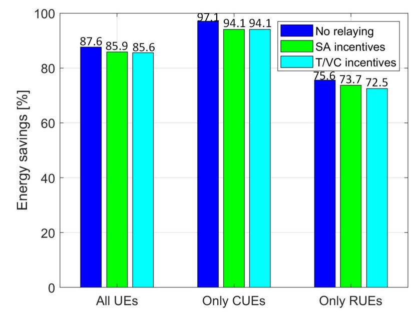
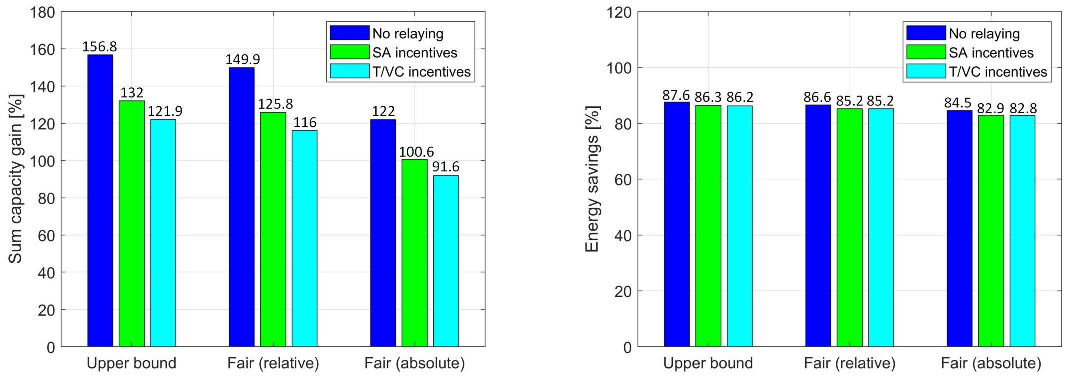


Fig. 7. Energy consumption savings reached by proposed algorithm *Greedy:M>1* with respect to competitive schemes if ρ is set so that individual competitive schemes reach the same sum capacity as the proposal (see Fig. 6a).

We analyze the performance for three allocation cases: (i) upper bound performance in terms of the sum capacity (achieved if $\alpha_i = 1$, $\forall i$); (ii) fair allocation ensuring the same relative gain for the UEs within the same D2D relaying group, i.e., $\alpha_i = \beta$, $\forall i$, labeled as *Fair (relative)*, and (iii): fair allocation guaranteeing the same absolute gain, i.e., $G_{Ci} = G_R$, $\forall i$, labeled as *Fair (absolute)*.

Fig. 8 shows that even the fair allocation introduces a significant improvement with respect to the existing works. If the goal is to guarantee the same relative gains for all CUEs and the RUE within one relaying group, the sum capacity gain with respect to *No relaying*, *SA incentives*, and *T/VC incentives* is 149.9%, 125.8%, and 116%, respectively (Fig. 8a). Even if the same absolute gain is ensured for all UEs within the relaying group, the proposed scheme is still superior to the competitive ones and its gain is at least 91.6% (see Fig. 8a).

From the energy savings perspectives, both fair resource allocations within the relaying group offer a similar energy savings as the *Upper bound*. More specifically, the fair allocation results in the energy savings equal to 85.2% (if the same relative gains are ensured) and 82.8% (if the absolute gains are guaranteed) with respect to *T/VC incentives*, which is the best performing competitive scheme. Note that slightly lower energy savings achieved by the *Fair (absolute)* comparing to the *Upper bound* and the *Fair (relative)* is a result of the fact that improving the performance of the poorly performing UEs by the *Fair (absolute)* allocation costs too many resources, which cannot be exploited by the UEs that can use these resources more efficiently.



(a) The sum capacity gain ($\rho = 1$).

(b) Energy savings ($\rho = 0$).

Fig. 8. Analyzes of fair resource allocation of proposed *Greedy: M>1* over competitive schemes (100 UEs).

TABLE II
SUMMARY OF KEY NOTATIONS

Notation	Description
N	Number of UEs and channels
M	Number of CUEs attached to the RUE
$\gamma_{t,r}$	SINR between any transmitter (TX) and receiver (RX)
P_{max}	Maximum transmission power of UE
$g_{t,r}$	Channel gain between any TX and RX
p_t, p_i, p_r	Transmission power of any TR, i-th CUE, and RUE
p_r^B	Boosted transmission power of RUE
p_r^*	Transmission power of RUE for which $E_R = E_R^*$
σ_0	Noise spectral density
$I_{s,r}$	Mean sum interference from adjacent cells at RX
p_T^{bb}, p_R^{bb}	Power consumption of processing parts at TX and RX
p_T^{rf}, p_R^{rf}	Power consumption of comm. parts at TX and RX
p_T^{on}, p_R^{on}	Power consumption of comm. circuitry at TX and RX
P_T, P_R	Power consumption of TX and RX
E	Total energy consumption of the UE
E_R, E_R^*	Energy consumption of the RUE w/o and with relaying
t_T, t_R	Transmission and reception time
t_s	Duration of a time slot
t_{ci}, t_{ri}, t_R	Transmission time of i-th CUE, of RUE on behalf of i-th CUE, and RUE
B	Bandwidth (BW) available at the BS
B_i, B_R, B_s	Channel BW of i-th CUE, RUE, and aggregated BW
C_i, C_R	Capacity of i-th CUE and RUE w/o relaying
C_i^*, C_R^*	Capacity of i-th CUE and RUE with relaying
K_i, K_R	Normalized capacity of i-th CUE and RUE w/o relaying
K_i^*, K_R^*	Normalized capacity of i-th CUE and RUE with relaying
α_i, β	Relative relying gain of i-th CUE and RUE
G_i, G_R	Absolute relaying gain of i-th CUE and RUE
G_B	The maximum gain of the RUE by capacity boost
$\mathbf{G}^p$	Matrix with potential relaying gains
$G_{i,j}^p$	Relaying gain if i-th CUE is attached to j-th RUE
$x_{i,j}$	Control variable indicating if i-th CUE uses j-th RUE

VIII. CONCLUSION

In this paper, we have proposed a novel incentive framework for the D2D relaying to motivate the UEs to relay the data of the cell edge UEs. The UEs are motivated to perform the relaying via a natural increase in their own capacity and/or a decrease in the energy spent for communication. We have proven that the proposed low-complexity greedy algorithm handling the relay selection for the CUEs is of a submodular nature giving the worst-case approximation guarantees to the optimal performance. Furthermore, we have derived a closed-form expression for the fair allocation of the resources among the RUE and the CUEs exploiting this RUE. We have demonstrated that the proposed scheme reaches a close-to-optimal performance and is able to more than double the capacity and/or reduce the energy consumption by roughly up to 87% when compared to the existing incentive-based relaying schemes.

APPENDIX A

1. Proof of Lemma 1

The minimum allowable value for t_c (denoted as t_c^{min}), is that for which the capacity of every CUEs relaying through the same RUE is exactly the same as its original capacity without the relaying, i.e., $\alpha_i = 1$, $\forall i \in \mathcal{M}$. Thus, using (9) and considering $\alpha_i = 1$, we obtain:

$$t_c^{min} = \sum_{i=1}^{M} t_{ci}^{min} = \frac{K_1}{K_1^*} t_s + \cdots + \frac{K_M}{K_M^*} t_s = \sum_{i=1}^{M} \frac{K_i}{K_i^*} t_s, \quad (24)$$

The maximum value of t_c (denoted as t_c^{max}) is given when $\beta = 1$, i.e., the CUEs gains an additional capacity while the RUE is as good as without relaying (i.e., loses no capacity). The t_c^{max} is derived from (10) considering $\beta = 1$ as:

$$t_c^{max} = \sum_{i=1}^{M} t_{ci} = \frac{(K_R^* - K_R) t_s}{K_R^*} - \sum_{i=1}^{M} t_{ri}, \quad (25)$$

From (24) and (25), we derive the operational region of t_c as:

$$\sum_{i=1}^{M} \frac{K_i}{K_i^*} t_s < \sum_{i=1}^{M} t_{ci} < \frac{(K_R^* - K_R) t_s}{K_R^*} - \sum_{i=1}^{M} t_{ri}, \quad (26)$$

2. Proof of Lemma 2

Let's assume that any t_{ci}^{min} is increased by Δt_{ci} so that $t_{ci} = t_{ci}^{min} + \Delta t_{ci}$. Then, the i-th CUE capacity in (7) is increased by $\Delta C_i^* = K_i^* \Delta t_{ci}$. Simultaneously, the RUE capacity in (8) is decreased by $\Delta C_R^* = -K_R^* \Delta t_{ci} - K_R^* \Delta t_{ri} = -K_R^* \Delta t_{ci} - K_i^* \Delta t_{ci}$. We can substitute $K_R^* \Delta t_{ri}$ for $K_i^* \Delta t_{ci}$ as the amount of data relayed by the RUE on behalf of the i-th CUE is the same as the data send by the CUE during t_{ci}. Thus, any increase in t_{ci}^{min} by Δt_{ci} leads to an overall decrease in the capacity equal to $\Delta C_i^* + \Delta C_R^* = -K_R^* \Delta t_{ci}$. As a result, t_c^{min} corresponds to the upper bound capacity.

It is easy to see, following the same reasoning as above, that for any decrease in t_c^{max} by Δt_{ci}, the total capacity is always increased by $K_R^* \Delta t_{ci}$. Consequently, allocating t_c^{max} to the CUEs corresponds to the lower bound capacity.

3. Proof of Lemma 3

The maximum gain by the power boost can be calculated as a ratio of the RUE's capacity if transmitting with p_r^B (i.e., transmission power if the power boost is applied) to the case when only p_r is utilized (i.e., no power boost). Consequently, taking (8) into account and assuming that the RUE transmits over $t_s - \sum_{i=1}^{M} t_{ci}$ time interval, we can calculate G_B in the following way:

$$\begin{aligned} G_B &= B_s log_2 \left(1 + \frac{p_r^B g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right)(t_s - t_c) \\ &\quad - B_s log_2 \left(1 + \frac{p_r g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right)(t_s - t_c) \\ &= B_s log_2 \left(\frac{B_s\left(\sigma_0 + I_{s,0}\right) + p_r^B g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right)(t_s - t_c) \\ &\quad - B_s log_2 \left(\frac{B_s\left(\sigma_0 + I_{s,0}\right) + p_r g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right)(t_s - t_c) \\ &= B_s log_2 \left(\frac{B_s\left(\sigma_0 + I_{s,0}\right) + p_r^B g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right) + p_r g_{r,b}}\right)(t_s - t_c). \end{aligned} \tag{27}$$

4. Proof of Lemma 4

To determine an allowable range of the transmission power, we first derive an absolute gain of each particular UE. Specifically, the absolute gain of the i-th CUE is determined from (5) and (7) as:

$$G_i = C_i^* - C_i = B_s log_2 \left(1 + \frac{p_i g_{i,r}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right) t_{ci} - K_i t_s, \tag{28}$$

and, similarly, the absolute gain of the RUE is obtained from (6) and (8) as:

$$\begin{aligned} G_R + G_B &= C_R^* - C_R + G_B \\ &= B_s log_2 \left(1 + \frac{p_r g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right)(t_s - \sum_{i=1}^{M} t_{ci}) \\ &\quad - \sum_{i=1}^{M} K_i^* t_{ci} - K_R t_s, \end{aligned} \tag{29}$$

Then, (28) and (29) is rearranged in the following way:

$$\frac{\rho G_i + K_i t_s}{B_s t_{ci}} = log_2 \left(1 + \frac{p_i g_{i,r}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right), \tag{30}$$

$$\begin{aligned} &\frac{\rho(G_R + G_B) + \sum_{i=1}^{M} K_i^* t_{ci} + K_R t_s}{B_s(t_s - \sum_{i=1}^{M} t_{ci})} \\ &\quad = log_2 \left(1 + \frac{p_r g_{r,b}}{B_s\left(\sigma_0 + I_{s,0}\right)}\right), \end{aligned} \tag{31}$$

Finally, from (30) and (31), we express p_i and p_r as:

$$p_i = \kappa_i (2^{\frac{\rho G_i + K_i t_s}{B_s t_{ci}}} - 1), \tag{32}$$

$$p_r = \kappa_R (2^{\frac{\rho(G_R + G_B) + K_R \cdot t_s + \sum_{i=1}^{M} K_i^* t_{ci}}{B_s(t_s - \sum_{i=1}^{M} t_{ci})}} - 1), \tag{33}$$

From (32) and (33), we see that if $\rho = 0$, the CUE/RUE sacrifice the whole capacity gain in order to reduce the energy consumption and the CUE and the RUE transmit with the minimal transmission power. Contrary, if $\rho = 1$, no energy reduction is achieved and the CUE/RUE does not reduce its transmission power at all. Thus, the maximal transmission power is used.

Appendix B

1. Proof of Theorem 5

The elements $G_{i,j}^p$ are independent of each other, since the D2D pairs have orthogonal resources. Hence, every time a new pair is added, the gain increases. Furthermore, assume that the subset of the selected pairs is A and we add the next pair $\{i, j\}$. Assume further another set of the selected D2D pairs $A \subset B$. Then $\{i, j\}$ either have the same $G_{i,j}^p$ value, or is 0, if that i or j have already been assigned in B. This satisfies the submodularity requirement [43]. Finally, it is easy to see that the first set of constraints defines a matroid (max of one item per row) and the second set is another matroid (max of one item per column). It is known that a greedy algorithm yields an approximation ratio of $\frac{1}{(p+1)}$, when the constraints are the intersection of p matroids (or in general, a p-system independent constraint) [44]. Hence, given that we have 2 matroids for our problem this gives a $\frac{1}{3}$ approximation for the greedy algorithm.

2. Proof of Lemma 6

The objective is submodular using the similar arguments as in Theorem 5. As more and more pairs are selected, each gain $G_{i,j}^p$ either becomes 0 (the i-th CUE has already been assigned to an RUE) or is decreased (the j-th RUE has already been assigned some other CUEs, so the gain for the i being associated to the j is smaller. The additional condition, that of $G_{i,j}^p \geq 0$ if the CUE bandwidth, where B and the RUE $M \cdot B$, ensures the objective's monotonicity, even if the RUE ends up serving the maximum number (M) of the CUEs. Finally, the constraint set is again an intersection of the matroids, leading to the same approximation ratio as in Theorem 5, the difference being that the optimal value now cannot be obtained in polynomial time.

Appendix C

1. Proof of Lemma 7

The same relative gain of the CUEs and the RUE is guaranteed if $\alpha_1 = \alpha_2 = \cdots = \alpha_M = \beta$. Thus, using (9), we can write:

$$\frac{K_1^* t_{c1}}{K_1 t_s} = \frac{K_2^* t_{c2}}{K_2 t_s} = \cdots = \frac{K_M^* t_{cM}}{K_M t_s} = \beta. \tag{34}$$

Hence, (20) is easily derived from (34). Then, we determine t_{c1}. Considering that $\alpha_1 = \beta$, the following is derived from (9) and (10) by applying several simple math operation:

$$\frac{K_1^* K_R}{K_1} t_{c1} = K_R^* t_s - K_R^* \sum_{i=1}^{M} t_{ci} - K_R^* \sum_{i=1}^{M} t_{ri}. \tag{35}$$

Taking into account that $K_R^* \sum_{i=1}^{M} t_{ri} = \sum_{i=1}^{M} K_i^* t_{ci}$ (i.e., the RUE retransmits the same amount of the CUEs' data as the amount of data transmitted by the CUEs to the RUE) and substituting all t_{ci} in (35) using (20), we can write:

$$\begin{aligned} \frac{K_1^* K_R}{K_1} t_{c1} &= K_R^* t_s - K_R^* t_{c1} - \frac{K_1^* K_R^*}{K_1} \sum_{i=2}^{M} \frac{K_i}{K_i^*} t_{c1} \\ &\quad - K_1^* t_{c1} - \sum_{i=2}^{M} \frac{K_1^* K_i}{K_1} t_{c1}. \end{aligned} \tag{36}$$

Finally, t_{c1} is derived according to (21). The rest of t_{ci} is calculated from (20) via inserting t_{c1} obtained in (21).

2. Proof of Lemma 8

The same absolute gain for all UEs is guaranteed when $G_1 = \cdots = G_M = G_R$, that is, if:

$$K_1^* t_{c1} - K_1 t_s = K_M^* t_{cM} - K_M t_s = G_R \tag{37}$$

Equation (22) is again derived from (37). Then, analogously to the case with the same relative gains, we first determine t_{c1} and the rest of t_{ci} is calculated by (22) afterwards. Thus, we need to fulfill the following:

$$K_1^* t_{c1} - K_1 t_s = K_R^* \left(t_s - \sum_{i=1}^{M} (t_{ci} + t_{ri}) \right) - K_R t_s. \tag{38}$$

Equation (38) is rewritten exploiting (22) and considering that $K_R^* \sum_{i=1}^{M} t_{ri} = \sum_{i=1}^{M} K_i^* t_{ci}$ as:

$$\begin{aligned} K_1^* t_{c1} - K_1 t_s & \\ = K_R^* & \left(t_s - t_{c1} - \sum_{i=2}^{M} \frac{K_1^* t_{c1} - K_1 t_s + K_i \cdot t_s}{K_i^*} \right) \\ & - K_1^* t_{c1} - \sum_{i=2}^{M} (K_1^* t_{c1} - K_1 t_s + K_i t_s) - K_R t_s. \end{aligned} \tag{39}$$

From (39), we finally express t_{c1} as presented in (23). Subsequently, any t_{ci} is calculated according to (22).

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References

[1] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 4, pp. 1801–1819, 4th Quart., 2014.

[2] D. Wen, G. Yu, and L. Xu, "Energy-efficient mode selection and power control for device-to-device communications," in *Proc. IEEE Wireless Commun. Netw. Conf.*, Doha, Qatar, Apr. 2016, pp. 1–7.

[3] P. Mach, Z. Becvar, and T. Vanek, "In-band device-to-device communication in OFDMA cellular networks: A survey and challenges," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 1885–1922, 4th Quart., 2015.

[4] O. A. Amodu, M. Othman, N. K. Noordin, and I. Ahmad, "Relay-assisted D2D underlay cellular network analysis using stochastic geometry: Overview and future directions," *IEEE Access*, vol. 7, pp. 115023–115051, 2019.

[5] S. Dang, G. Chen, and J. P. Coon, "Outage performance analysis of full-duplex relay-assisted device-to-device systems in uplink cellular networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 5, pp. 4506–4510, May 2017.

[6] T. Liu, J. C. S. Lui, X. Ma, and H. Jiang, "Enabling relay-assisted D2D communication for cellular networks: Algorithm and protocols," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 3136–3150, Aug. 2018.

[7] S. Dang, G. Chen, and J. P. Coon, "Multicarrier relay selection for full-duplex relay-assisted OFDM D2D systems," *IEEE Trans. Veh. Technol.*, vol. 67, no. 8, pp. 7204–7218, Aug. 2018.

[8] J. Sun, Z. Zhang, C. Xing, and H. Xiao, "Uplink resource allocation for relay-aided device-to-device communication," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 12, pp. 3883–3892, Dec. 2018.

[9] B. Klaiqi, X. Chu, and J. Zhang, "Energy- and spectral-efficient adaptive forwarding strategy for multi-hop device-to-device communications overlaying cellular networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 9, pp. 5684–5699, Sep. 2018.

[10] L. Wang, T. Peng, Y. Yang, and W. Wang, "Interference constrained relay selection of D2D communication for relay purpose underlaying cellular networks," in *Proc. 8th Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Shanghai, China, Sep. 2012, pp. 1–5.

[11] J. Deng, A. A. Dowhuszko, R. Freij, and O. Tirkkonen, "Relay selection and resource allocation for D2D-relaying under uplink cellular power control," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, San Diego, CA, USA, Dec. 2015, pp. 1–6.

[12] J. Zhao, K. K. Chai, Y. Chen, J. Schormans, and J. Alonso-Zarate, "Two-level game for relay-based throughput enhancement via D2D communications in LTE networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.

[13] J. Gui and J. Deng, "Multi-hop relay-aided underlay D2D communications for improving cellular coverage quality," *IEEE Access*, vol. 6, pp. 14318–14338, 2018.

[14] X. Xu, J. Wang, and X. Tao, "Analytical modeling for caching enabled UE-to-network relay in cellular networks," *IEEE Access*, vol. 6, pp. 51061–51068, 2018.

[15] J. Wang, X. Xu, X. Tang, S. Zhang, and X. Tao, "Analytical modeling of mode selection for UE-to-network relay enabled cellular networks with power control," in *Proc. IEEE Int. Conf. Commun. Workshops (ICC Workshops)*, Kansas City, MO, USA, May 2018, pp. 1–6.

[16] S. Zhang, X. Xu, M. Sun, X. Tang, and X. Tao, "Energy efficient uplink transmission for UE-to-network relay in heterogeneous networks," in *Proc. IEEE PIMRC*, Montreal, QC, Canada, Oct. 2017, pp. 1–7.

[17] N. Mastronarde, V. Patel, J. Xu, and M. van der Schaar, "Learning relaying strategies in cellular D2D networks with token-based incentives," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Atlanta, GA, USA, Dec. 2013, pp. 1–7.

[18] N. Mastronarde, V. Patel, and L. Liu, "Device-to-device relay assisted cellular networks with token-based incentives," in *Proc. IEEE Int. Conf. Commun. Workshop (ICCW)*, London, U.K., Jun. 2015, p. 698.

[19] Z. Zhu, S. Jin, Y. Yang, H. Hu, and X. Luo, "Time reusing in D2D-enabled cooperative networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 5, pp. 3185–3200, May 2018.

[20] Q. Xu, Z. Su, and S. Guo, "A game theoretical incentive scheme for relay selection services in mobile social networks," *IEEE Trans. Veh. Technol.*, vol. 65, no. 8, pp. 6692–6702, Aug. 2016.

[21] Q. Shen, W. Shao, and X. Fu, "D2D relay incenting and charging modes that are commercially compatible with B2D services," *IEEE Access*, vol. 7, pp. 36446–36458, 2019.

[22] Y. Li, Z. Zhang, H. Wang, and Q. Yang, "SERS: Social-aware energy-efficient relay selection in D2D communications," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 5331–5345, Jun. 2018.

[23] P. Yang, Z. Zhang, J. Yang, and X. Wang, "Incorporating user willingness in contract-based incentive mechanism for D2D cooperative data forwarding," *IEEE Access*, vol. 6, pp. 54927–54937, 2018.

[24] Q. Sun, L. Tian, Y. Zhou, J. Shi, and X. Wang, "Energy efficient incentive resource allocation in D2D cooperative communications," in *Proc. IEEE Int. Conf. Commun.*, London, U.K., Jun. 2015, pp. 1–6.

[25] P. Mach, Z. Becvar, and T. Spyropoulos, "Incentive mechanism and relay selection for D2D relaying in cellular networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Waikoloa, HI, USA, Dec. 2019, pp. 1–7.

[26] A. Ramezani-Kebrya, M. Dong, B. Liang, G. Boudreau, and S. H. Seyedmehdi, "Robust power optimization for device-to-device communication in a multi-cell network under partial CSI," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Paris, France, May 2017, pp. 1–6.

[27] B. V. R. Gorantla and N. B. Mehta, "Allocating multiple D2D users to subchannels with partial CSI in multi-cell scenarios," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Shanghai, China, May 2019, pp. 1–6.

[28] B. V. R. Gorantla and N. B. Mehta, "Resource and computationally efficient subchannel allocation for D2D in multi-cell scenarios with partial and asymmetric CSI," *IEEE Trans. Wireless Commun.*, vol. 18, no. 12, pp. 5806–5817, Dec. 2019.

[29] M. Lauridsen, L. Noël, T. B. Sørensen, and P. Mogensen, "An empirical LTE smartphone power model with a view to energy efficiency evolution," *Intel Technol. J.*, vol. 18, no. 1, pp. 172–193, Mar. 2014.

[30] M. R. Mili, A. Khalili, N. Mokari, S. Wittevrongel, D. W. K. Ng, and H. Steendam, "Tradeoff between ergodic energy efficiency and spectral efficiency in D2D communications under rician fading channel," *IEEE Trans. Veh. Technol.*, vol. 69, no. 9, pp. 9750–9766, Sep. 2020.

[31] O. Yazdani, M. Monemi, and G. Mirjalily, "Fast globally optimal transmit antenna selection and resource allocation scheme in mmWave D2D networks," *IEEE Trans. Mobile Comput.*, early access, Jul. 14, 2020, doi: 10.1109/TMC.2020.3009183.

[32] M. Najla, Z. Becvar, P. Mach, and D. Gesbert, "Predicting device-to-device channels from cellular channel measurements: A learning approach," *IEEE Trans. Wireless Commun.*, vol. 19, no. 11, pp. 7124–7138, Nov. 2020.

[33] H. Kuhn, "The hungarian method for the assignment problem," *Nav. Res. Logistics Quart.*, vol. 2, no. 1, pp. 83–97, Mar. 1955.

[34] A. Krause, A. Singh, and C. Guestrin, "Near-optimal sensor placements in Gaussian processes: Theory, efficient algorithms and empirical studies," *J. Mach. Learn. Res.*, vol. 9, no. 2, pp. 235–284, 2008.

[35] D. Tsigkari and T. Spyropoulos, "An approximation algorithm for joint caching and recommendations in cache networks," 2020, *arXiv:2006.08421*. [Online]. Available: http://arxiv.org/abs/2006.08421

[36] A. A. Ageev and M. I. Sviridenko, "Pipage rounding: A new method of constructing algorithms with proven performance guarantee," *J. Combinat. Optim.*, vol. 8, no. 3, pp. 307–328, Sep. 2004.

[37] C. Chekuri, J. Vondrak, and R. Zenklusen, "Submodular function maximization via the multilinear relaxation and contention resolution schemes," in *Proc. 43rd ACM Symp. Theory Comput. (STOC)*, San Jose, CA, USA, Jun. 2011, pp. 783–792.

[38] M. Minoux, "Accelerated greedy algorithms for maximizing submodular set functions," in *Optimization Techniques*, in Lecture Notes in Control and Information Sciences, vol. 7, J. Stoer, Eds. Berlin, Germany: Springer, 1978, pp. 234–243.

[39] B. Mirzasoleiman, A. Badanidiyuru, A. Karbasi, J. Vondrak, and A. Krause, "Lazier than lazy greedy," in *Proc. Artif. Intell. Conf.*, Austin, TX, USA, 2015, pp. 1812–1818.

[40] *Study on LTE Device to Device Proximity Services*, document TR 36.843, 3GPP, 2014.

[41] *Evolved Universal Terrestrial Radio Access (E-UTRA), Further Advancements for E-UTRA Physical Layer Aspects*, document TR 36.814, 3GPP, 2017.

[42] I. Viering, A. Klein, M. Ivrlac, M. Castaneda, and J. A. Nossek, "On uplink intercell interference in a cellular system," in *Proc. IEEE Int. Conf. Commun.*, Istanbul, Turkey, Jun. 2006, pp. 2095–2100.

[43] A. Krause and D. Golovin, "Submodular function maximization," in *Tractability: Practical Approaches to Hard Problems*. Cambridge, U.K.: Cambridge Univ. Press., Feb. 2011, pp. 71–104.

[44] G. Calinescu, C. Chekuri, M. Pál, and J. Vondrák, "Maximizing a monotone submodular function subject to a matroid constraint," *SIAM J. Comput.*, vol. 40, no. 6, pp. 1740–1766, Jan. 2011.

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