A Socio-Technical Approach to Capacity Maximization for Device-to-Device Relay Selection

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Abstract— **Device-to-Device (D2D) relaying is considered a promising technology to increase the data rates in next generation networks. We consider the D2D relay selection problem in which cell-edge mobile devices (CMDs), having bad channel conditions to the access point (AP), may forward their data to the AP via relaying mobile devices (RMDs) with better channel conditions. For this purpose, the RMDs sacrifice a fraction of their communication bandwidth and energy to relay the data of the CMDs. A key challenge in D2D relaying is to increase the willingness of RMDs to act as relays to CMDs. To overcome this challenge, considering the technical perspective of bandwidth allocation and transmit power optimization is not enough. In addition, the social perspective is important with the users' different individual motivations to participate, such as strong social relationships between CMDs and RMDs and an altruistic motivation to help CMDs. In this paper, we address the D2D relay selection problem with a socio-technical approach, i.e., we consider the RMDs as individual decision makers whose participation decision is influenced by its preferences regarding technical and social motivations. Furthermore, we formulate a relay selection problem to maximize the expected capacity under the a priori unknown decisions of the RMDs regarding their participation. To solve this problem, we propose a novel decentralized, preference-aware D2D relay selection algorithm, termed DPA-D2D, which is based on game theory. We show that the CMDs' capacity gain is more than $40\,\%$ higher compared to state-of-the-art D2D relay selection algorithms.**

I. Introduction

The ever-increasing demand for high-speed mobile connectivity poses a major challenge for existing mobile networks. To overcome this challenge, device-to-device (D2D) relaying is a promising way to increase the capacity of the mobile network by leveraging the direct communication links between mobile devices (MDs) [1]. Additionally, novel machine learning paradigms, such as federated learning, can benefit from D2D relaying [2]. D2D relaying enables cell-edge mobile devices (CMDs) that suffer from a bad channel quality to relay data to the access point (AP) via relaying mobile devices (RMDs). Using D2D relaying, the coverage, capacity and energy efficiency of mobile networks can be improved [1]. In D2D relaying, a crucial challenge lies in the relay selection problem, i.e., determining which MDs serve as RMDs for specific CMDs. The main challenges that D2D relaying poses from the socio-technical perspective are:

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1) Achieving a high participation rate: The success of D2D communication depends on the MDs' decisions to participate. For this, the users' different individual social, technical and altruistic motivations play an important role. There are factors that increase the motivation to participate such as close social relationships and factors that reduce the motivation to participate such as additional energy consumption or lower data rates. To study the decision making, these motivations have to be analyzed and combined into a realistic decision-making model [3].
2) Efficient allocation of bandwidth and power: The constrained communication bandwidth provided by the AP requires to find an efficient resource allocation such that the available bandwidth is shared efficiently between the different MDs [4]. Furthermore, the limited batteries of the MDs require the optimization of the transmit power.

To overcome these challenges, existing works [4]–[9] have proposed *social-aware* D2D communication to leverage social relationships between the MDs to jointly consider the physical and the social layer. The social layer contains all the relevant information about the users' relationships towards each other. In [4], a centralized D2D relaying algorithm is proposed that considers the social relationships between the users to motivate the users to participate. The authors of [5] analyze users' check-in behaviors, interests, and social relationships to choose an appropriate relay node. In [6], a two-hop social relationship model is presented. In [7] and [8], socially stable matching models are introduced to balance physical layer security and throughput of the wireless network. However, these works [4]–[8], primarily focus on social relationships between users and neglect other factors of the RMDs' decision making process, such as energy consumption, data rates or the human decision making process. In [9], a dynamic socially-motivated D2D relay selection mechanism is presented, utilizing a generalized satisfaction index to design a unified quality of experience (QoE) criterion, thereby facilitating the trade-off between QoE and resource efficiency. In [10] and [11], the authors conducted user studies to understand the preferences and decision making behavior of potential RMDs. Although the authors of [11] analyzed the decision making of RMDs by conducting user studies, no relay selection algorithm has been proposed. Clearly, the related literature [4]–[11] is lacking a complete socio-technical approach, where the social layer and the physical layer of the network, the users' different motivations and the decision-making are jointly considered.

D2D relay selection approaches that rely on incentives, such as payments in tokens or currency, face a major challenge: potential RMDs cannot determine if the future monetary gains will justify the immediate costs of relaying [12].

In this paper, our contributions are as follows.

- Unlike related works [4]–[11], we provide a socio-technical formulation of the D2D relay selection problem, integrating a realistic model of human decision-making, social relationships, and the bandwidth and power allocation.
- Our approach considers the users' individual preferences and we analyze their altruistic motivation to participate, rather than relying on incentives.
- We propose a novel decentralized, preference-aware D2D relay selection algorithm, termed DPA-D2D, to maximize the expected capacity of the D2D network. The proposed algorithm adapts the D2D relay selection, including the allocation of bandwidth and power, to the users' individual preferences, their social relationships and altruistic motivation, thereby increasing the participation probability.

II. System model

A. Overview

We consider a scenario with focus on the uplink transmission to a single AP of a mobile network, as seen in Fig. 1. We consider M MDs to be located within the considered area. The MDs can be categorized into two types. (i) CMDs, which are experiencing a bad channel quality due to the far distance to the AP or obstructions. (ii) Potential RMDs, which are MDs with a good channel quality and therefore can act as relay for the CMDs. We consider two hop D2D relaying, i.e., each CMD can only use one RMD as relay.

To initiate the D2D relaying, each CMD can send a relaying request to a potential RMD in its vicinity. This relaying request contains information about how much data needs to be forwarded. Based on this request, the RMD can calculate its cost for relaying in terms of the additional transmit power and the transmit time required for the relaying. Additionally, the RMD observes the social relationship to the CMD sending the request. The RMD then decides based on its individual preferences whether to accept the relaying request and forward the data to the AP or not. The RMD's individual preferences balance the social relationship with the CMD against the costs of forwarding, including transmit power and time.

B. Physical layer

The AP has an available bandwidth B^{AP}, which is shared equally between the M MDs. We assume an orthogonal multiple access scheme, such as orthogonal frequency division multiple access (OFDMA) to mitigate interference among the MDs. Therefore, the available channel bandwidth of MD m is given by $B_m = B^{\mathrm{AP}}/M$. The transmit power of MD m is denoted by p_m^{MD} and the channel gain between MD m and

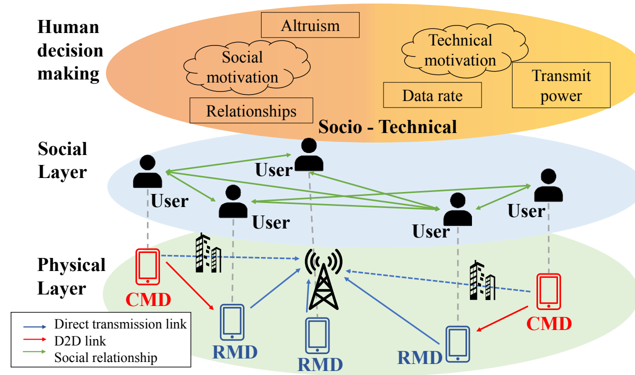

Fig. 1. Overview of the physical and social layer in a D2D uplink scenario.

the AP is denoted by $g_{m,\mathrm{AP}}^{\mathrm{MD}}$. The signal to interference plus noise ratio (SINR) of MD m is therefore given by

$$\mathrm{SINR}_m^{\mathrm{AP}} = \frac{p_m^{\mathrm{MD}} g_{m,\mathrm{AP}}^{\mathrm{MD}}}{B_m(\sigma_0 + I_0)}, \tag{1}$$

where σ_0 denotes the noise power spectral density and I_0 the interference power spectral density. The channel capacity of this respective MD is then given by

$$C_m^{\mathrm{MD,AP}} = B_m \log_2\left(1 + \mathrm{SINR}_m^{\mathrm{AP}}\right). \tag{2}$$

The amount of data an MD can send to the AP during an upload time slot t_s is therefore given by $s_m = C_m^{\mathrm{MD,AP}} t_s$. The energy required to transmit the data of size s_m is given by $E_m = p_m^{\mathrm{MD}} t_s$.

We assume that out of the total M MDs, N are CMDs and $K = M - N$ are potential RMDs. In order to improve its data rate, the CMD n can request a potential RMD to relay its data. This relaying request from CMD n to the potential RMD k is denoted by the indicator variable $x_{n,k} = 1$. If this potential RMD accepts the relaying request, a D2D connection is established between CMD n and RMD k. The participation decision of RMD k to forward data from CMD n is denoted by the indicator variable $y_{n,k} = 1$. To successfully establish a D2D connection, both, the CMD and the RMD have to make a decision: The CMD has to send a relaying request ($x_{n,k} = 1$), and the RMD has to decide to participate ($y_{n,k} = 1$).

When establishing the D2D connection, the CMD disconnects from the AP, therefore the bandwidth which was previously allocated, can be used by other MDs which are still connected to the AP. Given the number L of successfully established D2D pairs, each MD m gets a bandwidth

$$B_m^* = \frac{B^{\mathrm{AP}}}{M - L} \tag{3}$$

which corresponds to an equal sharing of the AP's bandwidth among the remaining $M - L$ MDs that are still connected to the AP. The capacity

$$C_{k,\mathrm{AP}}^{\mathrm{RMD}} = B_k^* \log_2\left(1 + \mathrm{SINR}_k^{\mathrm{AP}}\right) \tag{4}$$

describes the channel between the RMD k and the AP. The capacity of the channel between the CMD n and the RMD k

after establishing the D2D connection is

$$C_{n,k}^{\mathrm{CMD}} = B_k^* \log_2\left(1 + \mathrm{SINR}_{n,k}\right), \tag{5}$$

where $\mathrm{SINR}_{n,k}$ is the SINR between CMD n and RMD k.

When relaying, the CMD and the RMD use the same spectrum, employing time division multiple access (TDMA), as proposed in [12] and [13]. The time slot t_s is divided into three time slots $t^{\mathrm{rec}}, t^{\mathrm{relay}}$ and t^{trans} for receiving, relaying and transmitting data. In the first time slot t^{rec}, the RMD receives the data of the size $s_n^{\mathrm{rec}} = C_{n,k}^{\mathrm{CMD}} t^{\mathrm{rec}}$ from the CMD. In t^{relay}, the RMD forwards this data of the CMD's to the AP, i.e., $s_k^{\mathrm{relay}} = s_n^{\mathrm{rec}} = C_{k,\mathrm{AP}}^{\mathrm{RMD}} t^{\mathrm{relay}}$. Finally, in t^{trans} the RMD transmits its own data of the size $s_k^{\mathrm{trans}} = C_{k,\mathrm{AP}}^{\mathrm{RMD}} t^{\mathrm{trans}}$.

The CMD's achievable capacity gain $G_{n,k}^{\mathrm{CMD}}$ when relaying via RMD k is the capacity difference

$$G_{n,k}^{\mathrm{CMD}} = C_{n,k}^{\mathrm{CMD}} t^{\mathrm{rec}} - C_{n,\mathrm{AP}}^{\mathrm{CMD}} t_s = s_n^{\mathrm{rec}} - s_n \tag{6}$$

between the relaying case and the non-relaying case. Compared to the case of no relaying, the RMD has only the time $t^{\mathrm{trans}} < t_s$ to send its own data, which decreases the amount $s_k^{\mathrm{trans}} \leq s_k$ of data transmitted in a time slot. We define the loss in data rate of the RMD as

$$\gamma_k^{\mathrm{data}} = \frac{s_k^{\mathrm{trans}}}{s_k}, \tag{7}$$

the quotient between the data size before and after establishing the D2D connection.

To compensate for the additional data of the CMD, the RMD increases its transmit power by a factor $\gamma_k^{\mathrm{power}}$, i.e.,

$$p_k^{\mathrm{RMD}} = (1 + \gamma_k^{\mathrm{power}}) p_m^{\mathrm{MD}} \tag{8}$$

which results in an additional battery consumption. Therefore, the attributes of the physical layer of the D2D connection are given by $\gamma_k^{\mathrm{power}}$ and γ_k^{data}.

C. Social layer and altruistic motivation

In the social layer, we consider the social relationships between the users of the MDs. Users of MDs are often *socially motivated*, i.e., they prefer to act as a relay for users to whom they have strong social relationships to. To model the relationships, we construct a social graph, as seen in Fig. 1, for our social network. The vertices of the graph are the users, which have social connections between each other, e.g., family, friend or stranger. The edges of the graph are the relationships between the users, and the weights $r_{n,k} \in \mathbb{R}$ denote the strength of the relationship between CMD n and its potential RMD k. We define the matrix $\boldsymbol{R} = (r_{n,k})$ to represent all the relationships between the N CMDs and the K potential RMDs.

In addition to the social motivation to help CMDs with a high $r_{n,k}$, each potential RMD has an RMD-specific *altruistic motivation* $c_k \in \mathbb{R}$ to help CMDs [11]. This altruistic motivation reflects the general willingness to act as RMD even for unknown CMDs. High values of c_k indicate that a user is in general more willing to act as RMD.

D. Preferences and human decision-making model

The users are considered to be individual decision makers, with their own utility functions [11]. The D2D relaying between a CMD and an RMD is defined by the properties of the technical layer, namely the RMD's increase in transmit power given by $\gamma_k^{\mathrm{power}}$ and the RMD's lower data rate given by γ_k^{data}. Additionally, the social and altruistic motivations of the potential RMDs impact the decision of whether the RMD chooses to participate.

The individual preferences of RMD k determine the weighting of these properties and they are represented by the functions $\boldsymbol{\theta}_k^{\mathrm{power}}(\gamma_k^{\mathrm{power}})$,$\boldsymbol{\theta}_k^{\mathrm{data}}(\gamma_k^{\mathrm{data}})$,$\boldsymbol{\theta}_k^{\mathrm{social}}(r_{n,k})$ and the altruistic motivation c_k. The preference function $\boldsymbol{\theta}_k^{\mathrm{power}}(\gamma_k^{\mathrm{power}})$ reflects how sensitive the potential RMD is towards additional energy consumption. The preference function $\boldsymbol{\theta}_k^{\mathrm{data}}(\gamma_k^{\mathrm{data}})$ reflects how sensitive the potential RMD is towards a reduced data rate. The preference function $\boldsymbol{\theta}_k^{\mathrm{social}}(r_{n,k})$ reflects how motivated the potential RMD is to help CMDs with a close relationship.

The utility of the RMD k relaying the data from CMD n is denoted by $U_{n,k}^{\mathrm{RMD}}$ and depends on the aforementioned preference functions. The utility function

$$U_{n,k}^{\mathrm{RMD}} = \boldsymbol{\theta}_k^{\mathrm{power}}(\gamma_k^{\mathrm{power}}) + \boldsymbol{\theta}_k^{\mathrm{data}}(\gamma_k^{\mathrm{data}}) + \boldsymbol{\theta}_k^{\mathrm{social}}(r_{n,k}) + c_k, \tag{9}$$

is the sum of the terms for the additional transmit power $\boldsymbol{\theta}_k^{\mathrm{power}}(\gamma_k^{\mathrm{power}})$, reduced data rate $\boldsymbol{\theta}_k^{\mathrm{data}}(\gamma_k^{\mathrm{data}})$, social motivation $\boldsymbol{\theta}_k^{\mathrm{social}}(r_{n,k})$ and altruistic motivation c_k. Whether or not an RMD is willing to participate in the D2D-connection depends on its utility. If $U_{n,k}^{\mathrm{RMD}}$ takes a positive value the RMD will be more likely to act as a relay, however, when it is negative the RMD will probably reject the relaying request.

To reflect a realistic decision making process, we model the decision making process using a bounded rationality model [3]. In this model, it is assumed that some users will reject a relaying request ($y_{n,k} = 0$) although their utility is positive. This is due to the fact that some users make mistakes or do not have full information about the technology [3]. The probability, that RMD k accepts the relaying request ($y_{n,k} = 1$) from CMD n is given by [3]

$$P(U_{n,k}^{\mathrm{RMD}}) = \frac{e^{\lambda U_{n,k}^{\mathrm{RMD}}}}{1 + e^{\lambda U_{n,k}^{\mathrm{RMD}}}} \tag{10}$$

where λ is the precision parameter and reflects the rationality of the user [3]. If λ gets close to zero, the RMD acts irrational, i.e., the probability of accepting a relaying request approaches $P(U_{n,k}^{\mathrm{RMD}}) = 1/2$, independent of the utility. If λ increases, the rationality of the MD increases, i.e., the utility has a stronger influence on the probability of participation.

E. Problem Formulation: Preference-Aware Relay Selection

In contrast to [8], we model the relay selection problem incorporating the physical layer, the social layer and a realistic model for the decision making process. As the participation decisions of the RMDs are stochastic and their decisions are not known in advance, we argue that the aim is to

Algorithm 1 Decentralized preference-aware D2D relay selection algorithm (DPA-D2D)

1: CMDs send broadcast message to potential RMDs in proximity
2: Potential RMDs broadcast their channel quality and their preferences
3: CMDs solve (13) and rank RMDs in the list PL_n^{CMD}
4: **while** CMDs unmatched with non-empty PL_n^{CMD} **do**
5: **for** CMD $n \in \mathcal{N}$ **do**
6: Propose to RMD k^* on top of their preference list PL_n^{CMD}.
7: Remove k^* from it's preference list PL_n^{CMD}.
8: **end for**
9: **for** RMD $k \in \mathcal{K}$ **do**
10: Receive requests from proposing CMDs and construct own preference list PL_k^{RMD}
11: Select best CMD n^* from proposing CMDs
12: Transmit acceptance to n^*, reject all others.
13: **end for**
14: **end while**
15: Accepted CMDs send relaying requests $x_{k,n}$.
16: RMDs decide whether to participate ($y_{k,n} = 1$) or not ($y_{k,n} = 0$).

maximize the *expected* capacity gain of the whole network. This is challenging as the relay selection has to consider the achievable capacity gain as well as the RMDs' preferences and decision making.

For CMD n and the potential RMD k, the expected capacity gain

$$\mathbb{E}(G_{n,k}^{\text{CMD}}) = P(U_{n,k}^{\text{RMD}})G_{n,k}^{\text{CMD}}. \tag{11}$$

is the product of the participation probability $P(U_{n,k}^{\text{RMD}})$ of (10) and the achievable capacity gain of $G_{n,k}^{\text{CMD}}$ of (6). In order to maximize the network's capacity, we want to select pairs of CMDs and RMDs such that the sum of the expected capacity gain is maximized. This problem can be expressed as an optimization problem

$$\underset{x_{n,k},\gamma_k^{\text{power}},\gamma_k^{\text{data}}}{\arg\max} \quad \sum_{n=0}^{N}\sum_{k=0}^{K} x_{n,k}\mathbb{E}(G_{n,k}^{\text{CMD}}) \tag{12}$$

$$\text{s.t.} \quad \sum_{n=0}^{N} x_{n,k} \leq 1, \ \forall k \tag{12a}$$

$$\sum_{k=0}^{K} x_{n,k} \leq 1, \ \forall n \tag{12b}$$

where $x_{n,k}$ is the indicator variable whether CMD n sends a relaying request to RMD k. Constraint (12a) ensures that each RMD only acts as relay for one CMD and constraint (12b) ensures that each CMD only forwards its data via one RMD.

III. Preference-Aware Relay Selection Algorithms

In this section, we discuss two different preference-aware relay selection algorithms. Firstly, we propose a novel decentralized, preference-aware relay selection algorithm based on game theory. Secondly, we briefly describe a centralized solution to the optimization problem (12) using a central optimizer to use as a benchmark for our proposed algorithm.

A. Decentralized preference-aware relay selection algorithm

We propose to use a game-theoretic approach based on the concept of *stable matching* [14] to locally maximize the expected capacity gain and to achieve stability, i.e., neither a CMD nor a RMD has an incentive to change the relay selection. For existing works on stable matching and D2D relay selection, e.g., as in [8], the Gale Shapley (also called deferred-acceptance) algorithm [15] is used. However, this algorithm is not directly applicable as the CMDs' expected capacity gains $\mathbb{E}(G_{n,k}^{\text{CMD}})$ depends on the RMDs' preferences as seen in (11). Additionally, in contrast to [8], the resource allocation has to be optimized, namely the transmit power increase γ_k^{power} of the RMD and the data rate factor γ_k^{data} of the RMD.

Algorithm 1 shows our proposed decentralized preference-aware relay selection (DPA-D2D) algorithm. Initially, all CMDs broadcast messages to identify potential RMDs in their vicinity (line 1). Potential RMDs receiving these messages then respond by sending their channel quality $g_{k,\text{AP}}^{\text{RMD}}$ as well as their preferences to *trusted* CMDs in the broadcasting range d_k^{BC} (line 2). An RMD trusts a CMD if the social relationship exceeds a threshold, i.e., $r_{n,k} > r^{\text{threshold}}$. Since all RMDs always have the chance to reject the relaying request from a CMD, they have no benefit from misrepresenting their preferences, thus, we assume fully truthfulness. The CMDs receive the information and determine the maximum expected capacity gain $\mathbb{E}(G_{n,k}^{\text{CMD}})^*$ for each potential RMD by solving

$$\mathbb{E}(G_{n,k}^{\text{CMD}})^* = \underset{\gamma_k^{\text{power}},\gamma_k^{\text{data}}}{\arg\max} \ P(U_{n,k}^{\text{RMD}})G_{n,k}^{\text{CMD}}, \tag{13}$$

where $P(U_{n,k}^{\text{RMD}})$ is given by (10) and $G_{n,k}^{\text{CMD}}$ is given by (6). Based on $\mathbb{E}(G_{n,k}^{\text{CMD}})^*$, the CMD can derive a ranking PL_n^{CMD} of potential RMDs (line 3). The CMD proposes to the RMD k^* which is on top of PL_n^{CMD} with a request containing the optimal values of γ_k^{power} and γ_k^{data} from (13). Afterwards, it removes k^* from its list PL_n^{CMD} (lines 6 and 7). The RMDs receive the proposals from the CMDs and construct also a ranking PL_k^{RMD} of CMDs based on (9). The RMD selects the CMD with the highest utility from PL_k^{RMD} and transmit an acceptance message to it, all other proposing CMDs receive a rejection message (lines 10,11 and 12). The rejected CMDs propose to the next best RMD from PL_n^{CMD} and the procedure repeats until all CMDs either selected a potential RMD or have an empty ranking PL_n^{CMD}. After this procedure is finished, the accepted CMDs send their relaying requests to their RMDs (line 15). The RMDs decide then, based on γ_k^{data}, γ_k^{power} and $r_{n,k}$, if they want to participate or not (line 16).

In the proposed DPA-D2D algorithms, we leverage the local computing capabilities of the CMDs to optimize the resource allocation (13). Additionally, the RMDs report their preferences only to trusted CMDs to increase privacy. Furthermore, the algorithm converges to a stable matching, i.e., it is not possible that a CMD can improve its expected capacity $\mathbb{E}(G_{n,k}^{\text{CMD}})$ by changing the RMD and simultaneously the RMD can not improve its utility $U_{n,k}^{\text{RMD}}$ by changing the CMD. The proof is only outlined here, a more detailed and formalized version can be found in [15]. The proof works by contradiction, i.e., suppose there is one CMD n' and one RMD k' that are currently not forming a D2D pair, but could improve by leaving their current D2D pairs (n', k) and (n, k') and form a D2D pair (n', k') together. In the following, the

CMD n' and the RMD k' are said to form a *blocking pair*. Algorithm 1 continually removes the blocking pairs, as n' has to send a proposal to k' before k if the expected capacity is higher. Additionally, k' will accept n' before n, as the utility is higher. This leads to the fact that the blocking pair will be resolved and the D2D pair (n', k') will be formed. Therefore, after Algorithm 1 is completed, no blocking pair can exist and the resulting relay selection is a stable matching.

B. Centralized optimal relay selection

We briefly describe an approach to directly solve the optimization problem (12) using a central optimizer (CO). In the first step, all MDs transmit their channel quality, location and preferences to the CO. The CO leverages this information to evaluate the relationships between MDs, potentially based on their contact history or social networks. Knowing the social relationships and the user preferences, the CO can solve the relay selection and resource allocation such that the expected capacity gain is maximized. Then, the maximum expected capacity $\mathbb{E}(G_{n,k}^{\mathrm{CMD}})^*$ is derived according to (13) for all possible combinations of CMDs and RMDs. The algorithm employs the so-called Hungarian Algorithm [13] for solving the optimization problem (12). After finding the optimal D2D pairs, the CO sends relaying request $x_{n,k}$ to the RMDs, asking if they are willing to participate in a D2D relaying with γ_k^{data} and $\gamma_k^{\mathrm{power}}$, that the CO has selected. The RMD then makes its decision $y_{n,k} \in \{0, 1\}$ whether to participate or not.

Note that the centralized optimal relay selection is only a benchmark for our proposed DPA-D2D approach as it is not applicable in realistic scenarios. This centralized optimal relay selection is not suitable for large networks due to the large communication overhead to the CO and due to the fact that all CMDs and RMDs have to report their locations and social relationships. Additionally, the computational overhead is large, as the expected capacity gains have to be evaluated for all possible combinations of CMDs and RMDs.

IV. Numerical Evaluation

A. Simulation Setup

For the simulations, up to 100 MDs are placed uniformly distributed within an area of $500\,\mathrm{m} \times 500\,\mathrm{m}$ around the AP. The channel gain of a MD m with the distance d_m to the AP is given by $g_{m,\mathrm{AP}}^{\mathrm{MD}} = (d_m/d_0)^{-\alpha}$, where $\alpha = 4$ is the fading coefficient and $d_0 = 1\,\mathrm{m}$ is the reference distance. Similar to [13], we set the noise power spectral density $\sigma_0 = -173\,\mathrm{dBm/Hz}$ and the mean interference from adjacent cells $I_0 = -140\,\mathrm{dBm/Hz}$. The precision parameter λ reflecting the user's rationality is set to 0.5. The bandwidth $B^{\mathrm{AP}} = 20\,\mathrm{MHz}$ of the AP is shared equally between the MDs and 20% of the MDs are CMDs, located at the cell edge, i.e., $d_n \geq 200\,\mathrm{m}$ and have a None-line-of-sight (NLOS) connection to the AP which introduces an additional attenuation of $20\,\mathrm{dB}$.

To derive our social graph, we used the tracing data set from [16]. In this data set, the social strength between nine MDs based on Bluetooth contact duration is measured over 12 days. We extrapolated this social graph to $M = 100$ MDs, using the assumption that the distribution of relationship strength $r_{k,n}$ remains the same. The user preferences are presented in Table I, where $\mathcal{N}(x, y)$ refers to a normal distribution with mean value x and variance y. We simulated 2000 Monte-Carlo iterations and averaged over the outcomes.

TABLE I
User preferences from studies conducted in [11]

Type	Value	Preference function value
Altruism		$c_k \sim \mathcal{N}(1.75, 4.90)$
Social	$r_{n,k} = 4$ (*Family*)	$\boldsymbol{\theta}_k^{\mathrm{social}}(4) \sim \mathcal{N}(3.48, 2.34)$
	$r_{n,k} = 3$ (*Friend*)	$\boldsymbol{\theta}_k^{\mathrm{social}}(3) \sim \mathcal{N}(1.07, 0.81)$
	$r_{n,k} = 2$ (*Acquaintance*)	$\boldsymbol{\theta}_k^{\mathrm{social}}(2) \sim \mathcal{N}(-1.60, 1.16)$
	$r_{n,k} = 1$ (*Stranger*)	$\boldsymbol{\theta}_k^{\mathrm{social}}(1) \sim \mathcal{N}(-2.95, 1.67)$
Power	$\gamma_k^{\mathrm{power}} = 5\,\%$	$\boldsymbol{\theta}_k^{\mathrm{power}}(0.05) \sim \mathcal{N}(0.08, 0.55)$
	$\gamma_k^{\mathrm{power}} = 10\,\%$	$\boldsymbol{\theta}_k^{\mathrm{power}}(0.1) \sim \mathcal{N}(0.18, 0.36)$
	$\gamma_k^{\mathrm{power}} = 15\,\%$	$\boldsymbol{\theta}_k^{\mathrm{power}}(0.15) \sim \mathcal{N}(-0.26, 0.64)$
Data	$\gamma_k^{\mathrm{data}} = 50\,\%$	$\boldsymbol{\theta}_k^{\mathrm{data}}(0.5) \sim \mathcal{N}(0.40, 0.58)$
	$\gamma_k^{\mathrm{data}} = 25\,\%$	$\boldsymbol{\theta}_k^{\mathrm{data}}(0.25) \sim \mathcal{N}(-0.40, 0.58)$

For the evaluation of our proposed DPA-D2D approach, we compare our results with three benchmarks. Firstly, the "RSMA" algorithm [8], which is a state-of-the-art decentralized algorithm that considers the social layer as well as the physical layer in the relay selection. It is based on a stable matching of D2D pairs where the RMDs' utilities are weighted sums of the achievable capacity gain and the strength of the social relationship between the users. Secondly, the "Hungarian" relay selection, which uses the Hungarian Algorithm as described in [4] and [17] to maximize the sum of the achievable capacity (6). Thirdly, the "Centralized" approach, which is described in Section III-B. Additionally, we compare our algorithm to the case of "No Relaying", when there is no D2D communication and every MD is connected to the AP.

B. Simulation Results

We analyze the sum of the CMDs' capacities of the proposed DPA-D2D algorithm and the baseline algorithms in Fig. 2. The "Centralized" approach yields the highest sum of the CMDs' capacities of $14.8\,\mathrm{Mbit/s}$ for $M = 100$, as it can achieve the optimum due to complete information at the CO. Our proposed decentralized privacy-preserving approach is within $98\,\%$ of the "Centralized" approach. The "RSMA" ("Hungarian") approach achieves around $9.53\,\mathrm{Mbit/s}$ ($8.37\,\mathrm{Mbit/s}$), which is $65.4\,\%$ ($57.5\,\%$) of the proposed DPA-D2D algorithm. This is due to the fact that many RMDs reject the relaying requests, as their preferences are not considered. Using "No relaying", all CMDs have a low capacity and therefore can only send with a low data rate to the AP.

Fig. 3 shows the number of D2D pairs for the different relay selection algorithms. It can be seen that the preference-aware algorithms DPA-D2D and "Centralized" achieve a high participation rate, as $N = 19$ CMDs are part of a D2D pair. This means that $K = 19$ RMDs were willing to participate in the D2D communication. The "RSMA" algorithm achieves in average $N = 11.6$ as it does not include the preferences of the

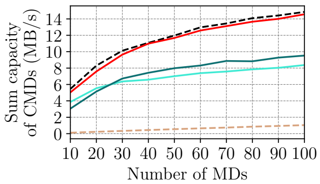

Fig. 2. Sum of CMDs' capacities as a function of the number M of MDs.

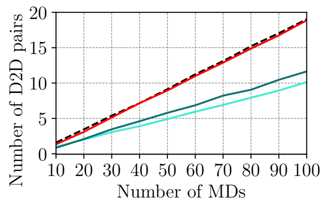

Fig. 3. Average number of D2D pairs as a function of M.

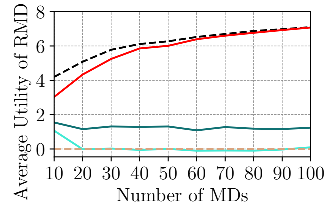

Fig. 4. Average utility $U_{n,k}^{\mathrm{RMD}}$ of the RMDs as a function of M.

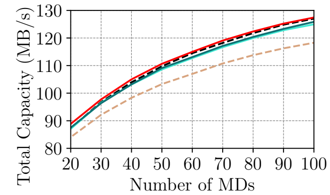

Fig. 5. Sum of the capacity of all MDs as a function of M.

RMDs, although it considers the social relationships between the users. For the "Hungarian" algorithm, only $N = 10.1$ CMDs find a RMD willing to act as relay. Therefore, both algorithms have a lower participation rate of RMDs compared to the DPA-D2D and "Centralized" algorithm. The "RSMA" algorithm achieves a higher participation rate than the "Hungarian" approach, as it considers the social relationships.

The average RMD's utility $U_{n,k}^{\mathrm{RMD}}$ from (9) can be seen in Fig. 4. The preference-aware algorithms DPA-D2D and "Centralized" achieve a higher utility of the RMDs as they include the different preferences of the RMDs. Specifically, the transmit power $\gamma_k^{\mathrm{power}}$ and the data rate γ_k^{data} is adapted to the RMDs' preferences $\boldsymbol{\theta}_k^{\mathrm{power}}$,$\boldsymbol{\theta}_k^{\mathrm{data}}$, $\boldsymbol{\theta}_k^{\mathrm{social}}$ and the weights $r_{n,k}$. The "RSMA" and "Hungarian" approach are designed to maximize the achievable capacity, i.e., the transmit power increase $\gamma_k^{\mathrm{power}}$ and the data rate reduction γ_k^{data} of the RMD might be higher than preferred by the RMD, thus leading to a lower utility. As the "RSMA" approach considers the social relationships of the users, it provides a higher utility for the RMDs than the "Hungarian" approach.

Fig. 5 shows the system capacity, i.e., the sum of all MDs' capacity, including the capacity of the CMDs and RMDs. It can be seen that the "Centralized" and the DPA-D2D algorithm achieve a $2.5\,\mathrm{Mbit/s}$ higher system capacity than the "RSMA" and "Hungarian" algorithm. The proposed DPA-D2D algorithm can achieve a total improvement of $7\,\%$ over the "No relaying" case. Therefore, an overall system capacity improvement is achieved, not only for the CMDs, although the RMDs sacrifice some of their own capacity for the D2D relaying. We also analyzed the impact of the broadcast range d_k^{BC} on the CMDs' sum capacity, which showed that for a broadcast range of $d_k^{\mathrm{BC}} = 150\,\mathrm{m}$ $(100\,\mathrm{m})$ still $93.3\,\%$ $(73\,\%)$ of the sum capacity of the "Centralized" approach are achieved.

V. Conclusion

In this paper, we have studied the D2D relay selection problem from the socio-technical perspective. We have analyzed the social layer, physical layer, user preferences and the decision-making process of the RMDs. From this, we have derived a stochastic participation model of the RMDs based on their preferences regarding transmit power, data rate, social motivation and altruistic motivation. Based on this model, we formulated an optimization problem to maximize the expected capacity gain by using D2D communication considering the unknown participation decisions of the RMDs. We proposed a novel game-theoretic algorithm based on stable matching, termed DPA-D2D, to find a stable solution, which ensures that neither an RMD nor a CMD can improve by changing the relay selection. In a comparison with state-of-the-art benchmark algorithms, we have shown that the sum capacity of the CMDs can be increased by $52.9\,\%$ due to an increase of the participation rate of RMDs by $72.7\,\%$.

References

[1] P. Mach and Z. Becvar, "Device-to-Device Relaying: Optimization, Performance Perspectives, and Open Challenges towards 6G Networks," *IEEE Commun. Surveys & Tutorials*, pp. 1–1, 2022.

[2] S. Hosseinalipour, S. S. Azam, C. G. Brinton, N. Michelusi, V. Aggarwal, D. J. Love, and H. Dai, "Multi-Stage Hybrid Federated Learning Over Large-Scale D2D-Enabled Fog Networks," *IEEE/ACM Transactions on Networking*, vol. 30, no. 4, pp. 1569–1584, 2022.

[3] S. Maghsudi and M. Davy, "Computational Models of Human Decision-Making with Application to the Internet of Everything," *IEEE Wireless Commun.*, vol. 28, no. 1, pp. 152–159, 2021.

[4] P. Mach, Z. Becvar, and T. Spyropoulos, "Coping with Spatial Unfairness and Overloading Problem in Mobile Networks via D2D Relaying," *IEEE Wireless Communications*, vol. 31, no. 1, pp. 78–84, 2024.

[5] M. Hu, B. Liu, H. Huang, W. Xiang, and Y. Tao, "Social-Aware Relay Selection Scheme for Relay-Based D2D Communications," *IEEE Access*, vol. 6, pp. 73 293–73 304, 2018.

[6] J. Wang, J. Ma, Y. Li, and X. Liu, "D2D Communication Relay Selection Strategy Based on Two-hop Social Relationship," in *IEEE Int. Conf. on Electronic Information and Commun. Technology (ICEICT)*, 2021, pp. 592–595.

[7] B. Wang, Y. Sun, H. M. Nguyen, and T. Q. Duong, "A Novel Socially Stable Matching Model for Secure Relay Selection in D2D Communications," *IEEE Wireless Commun. Letters*, vol. 9, no. 2, pp. 162–165, 2020.

[8] X. Zhou, D. Pan, H. Song, and X. Huang, "Socially-Aware D2D Pair Strategy: A Stable Matching Approach," in *IEEE 39th International Performance Comp. and Commun. Conf. (IPCCC)*, 2020, pp. 1–4.

[9] M. Wu, Y. Xiao, Y. Gao, and M. Xiao, "Dynamic Socially-Motivated D2D Relay Selection With Uniform QoE Criterion for Multi-Demands," *IEEE Trans. on Commun.*, vol. 68, no. 6, pp. 3355–3368, 2020.

[10] H. Al-Shatri, K. Keller, F. Jacobfeuerborn, O. Hinz, and A. Klein, "Eliciting and Considering Underlay User Preferences for Data-Forwarding in Multihop Wireless Networks," *IEEE Access*, vol. 7, pp. 40 052–40 067, 2019.

[11] K. Keller, M. Ott, O. Hinz, and A. Klein, "Influence of Social Relationships on Decisions in Device-to-Device Communication," *IEEE Access*, vol. 9, pp. 106 459–106 475, 2021.

[12] P. Mach, Z. Becvar, and T. Spyropoulos, "Incentive Mechanism and Relay Selection for D2D Relaying in Cellular Networks," in *Proc. of IEEE Global Commun. Conf. (GLOBECOM)*, 2019, pp. 1–7.

[13] P. Mach, T. Spyropoulos, and Z. Becvar, "Incentive-Based D2D Relaying in Cellular Networks," *IEEE Transactions on Communications*, vol. 69, no. 3, pp. 1775–1788, 2021.

[14] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: fundamentals and applications," *IEEE Communications Magazine*, vol. 53, no. 5, pp. 52–59, 2015.

[15] A. E. Roth, "Deferred Acceptance Algorithms: History, Theory, Practice, and Open Questions," *Int. Journal of Game Theory*, vol. 36, no. 3, pp. 537–569, Jan. 2008.

[16] S. Firdose, L. Lopes, W. Moreira, R. Sofia, and P. Mendes, "Crawdad copelabs/usense," 2022. [Online]. Available: https://dx.doi.org/10.15783/C7D885

[17] F. Nizam, M. bin Roslee, Z. Yusoff, K. Anuar, K. H. Alzoubi, M. A. A. Elgamati, and M. J. Billah, "Resource Allocation Algorithm for D2D Communication in Cellular Networks Based on Hungarian Algorithm," in *Proc. of the IEEE Malaysia Int. Conf. on Commun. (MICC)*, 2019, pp. 106–111.