Abstract—Wireless nodes in future communication systems are expected to overcome three barriers when compared to their transitional counterparts, namely to support significantly higher data rates, have long-lasting energy supplies and remain fully operational in interference-limited heterogeneous networks. This could be achieved by providing three promising features, which are radio frequency (RF) energy harvesting, improper Gaussian signaling and operating in full-duplex communication mode, i.e., transmit and receive at the same time within the same frequency band. In this paper, we consider these aspects jointly in a multi-antenna heterogeneous two-tier-network. Thus, the users in the femto-cell are sharing the scarce resources with the cellular users in the macro-cell and have to cope with the interference from the macro-cell base station as well as the transmitter noise and residual self-interference (RSI) due to imperfect full-duplex operation. Interestingly enough, while these impairments are detrimental from the achievable rate perspective, they are beneficial from the energy harvesting aspect as they carry RF energy. In this paper, we consider this natural trade-off jointly and propose appropriate optimization problems for beamforming and optimal resource allocation. Various receiver structures are employed for both information detection (ID) and energy harvesting (EH) capabilities. The paper aims at characterizing the trade-off between the achievable rates and harvested energies. Rate and energy maximization problems are thoroughly investigated. Finally, the numerical illustrations demonstrate the impact of the energy harvesting on the achievable rate performance.

Index Terms—Heterogeneous networks, full-duplex communication, self-interference, energy harvesting, improper Gaussian signaling, Pareto boundary, augmented covariance matrix.

I. INTRODUCTION

Wireless communication systems are facing difficulties in fulfilling the ever increasing demands of the customers operating in various communication standards. In order to fulfill the rate demands of the users, the achievable rate region of the users need to be improved. Enhancing the achievable rates of the users with limited transmission power requires smart transceiver algorithms and techniques. Simultaneous transmission and reception within the same frequency band and time slot, i.e., full-duplex communications is an outstanding alternative for future communications, as it enables to almost doubling the spectral efficiency when compared to half-duplex operation. However, this comes not for free and additional hardware and processing is required to cancel the resulting self-interference due to the full-duplex operation [1]. Self-interference can be partially suppressed passively by means of transmitter and receive isolation [2], [3], or it might be actively cancelled in analog and digital domain by signal processing methods [4]–[6]. Thus, an residual self-interference (RSI), which is assumed to be fully cancelled in most theoretical works, still remains in practice. Moreover, transmitter noise due to the non-linear behaviour of the power amplifiers and limited dynamic range of the elements [7], [8] can not be ignored as well for such applications.

Accomplishing higher data rates with corresponding signal processing tasks requires longer lasting energy supplies both for transmitters and receivers. Senders need to transmit with limited power due to hardware constraint (battery life-time) while the receivers are required to decode and process large amount of data under similar conditions. Hence, the users with infeasible plug-in recharging, demand energy which needs to be provided in a wireless fashion. For this purpose, energy harvesting-capable (EHC) receivers could be deployed which harvest the energy in the environment, e.g., solar or RF energy. Thus, the life-time of the system can be improved from the energy in the air. The required energy is sometimes available at a user’s surroundings and needs to be harvested, however, sometimes the required energy is not at its disposal and needs to be provided by the network. Thus, the study of power transmission and energy harvesting has become the focus of research community recently. For instance, the authors in [9] study delay-limited communication with EHC nodes. In [10], the authors develop an outer bound for the rate-energy region considering energy harvesting constraints. Furthermore, the authors in [11] focus on the sum rate optimization of an energy harvesting MISO communication system with feedback. The authors in [12] study the performance limits of MIMO broadcast channel, in which the base station (BS) is responsible for both information and power transmission.

In this work we consider a heterogeneous two-tier network with a single multiple-antenna macro-cell base station (BS) serving $K$ cellular users. Additionally, in a femto-cell, a pair of multiple-antenna D2D nodes exchanges information in a full-duplex mode. Hence, the full-duplex D2D users suffer from both self-interference and interference from the cellular macro-cell users and vice versa. All users in this heterogeneous network, i.e., both cellular and full-duplex D2D users, are assumed to be equipped with an energy conversion chain that converts the incident RF signal energy to direct current in

Harvesting the (Self-)Interference in Heterogeneous Full-Duplex Networks For Joint Rate-Energy Optimization

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order to load the energy buffer \[13\]. By this capability, the users’ demand go beyond the traditional information transfer perspective as they demand energy as well. Therefore, on one hand self-interference and the interference from the other users is deteriorating the process of decoding the desired message reliably, on the other hand the users could use the energy of the interference for EH purposes. Considering energy and information rate demands of the users, we study the performance limits of the cellular and D2D users in the network. These limits are due to the intrinsic trade-off between the demands. Considering this trade-off, the optimal rate tuples of the cellular users and full-duplex D2D users capable of EH are studied. Moreover, the optimal rate-energy pairs are investigated. Thus, we address two main problems,

- What is the achievable rate region of the cellular users and D2D pair under certain transmit power and received energy constraints?
- What is the optimal rate-energy tuples of the D2D users under cellular users’ QoS and power constraints?

The two questions will be answered in an optimization framework. We will establish appropriate optimization problems for joint information detection (ID) and EH transceiver structures and compare their performance. In this work, different ID and EH receivers are investigated. The users could be equipped with antenna separation (AS) receivers, where the energy and information of RF signals are caught simultaneously over different antennas. Power splitting (PS) and time-sharing (TS) are other alternatives for joint ID and EH purposes \[14\]. By splitting the received signal power, the energy of one portion is converted to direct current in order to load the energy buffer, while the information out of the other portion is decoded. Time-sharing between the energy harvesting and information detection phases allows EH and ID in separate time instants.

In order to improve the achievable rate and energy performance with the specified receiver types, we employ improper Gaussian signaling \[15\] in the transmission phase, which has not been considered so far in two-way full-duplex context (to the best of the authors’ knowledge). Improper Gaussian signaling has been shown to be beneficial in interference channels (IC) and X-channels from the achievable rate perspective \[15, 16, 17, 18\].

By utilizing improper Gaussian signaling, the outermost rate region and rate-energy region is investigated by formulating Chebyshev weighting function \[19\]. Then, the problems are reformulated as positive semi-definite programs (PSD) with non-convex constraints. The non-convex constraints are relaxed by the well-known semi-definite relation (SDR) method \[20\]. Hence the resulting convex optimization problems are solved efficiently. If the optimal solutions are not rank-1, the Gaussian randomization process \[20, 21, 22, 23\] is further utilized to acquire suboptimal rank-1 solutions.

Notation: In this paper, we represent scalars in italics and vectors in boldface lower-case letters, while the matrices are expressed in boldface upper-case. \(\text{Tr}(A), |A|, A^H, A^*, A^T\) represent the trace, determinant, Hermitian, complex conjugate and transpose of matrix \(A\), respectively. We define matrix \(B\) which is composed of the diagonal elements of matrix \(A\) as, \(B = \text{diag}(A)\). Matrix \(A\) is a positive semi-definite matrix if \(A \succeq 0\). The expectation operator is represented by \(E\).

II. SYSTEM MODEL

In this paper, we consider a cellular network as shown in Fig. 1 in which a base-station equipped with \(N\) antennas is serving a set of \(K\) cellular users. This network operates in a half-duplex mode, i.e., the uplink and downlink operation is performed in successive time instances. In order to overcome the limitations of their local battery supplies, the cellular users are equipped with energy-harvesting (EH) receiver chains. Those receiver chains capture the energy of the RF signals in their environment. Further, in this cell two additional D2D users are deployed, which exchange data in an underlay cognitive mode, \[24, 25, 26\]. This exchange is performed in a full-duplex mode, i.e., the D2D users are able to receive and transmit at the time within the same frequency band. Here, we follow the design proposed and utilized in \[27, 28\], in which a full-duplex node is using a subset \(M\) of its antennas for transmission and the remaining ones for reception. Similar to the cellular users, the D2D users are equipped with EH receiver chains.

Now, let the set of cellular users be denoted as \(C\). For convenience, we define the set of the two D2D users as \(D\). Then, the channel input-output relationships at each time instant (we skip the time index for simplicity) are given by

\[
y_k = h_{kB}^H(x_B + e_B)
\]

\[
+ \sum_{j=1}^{2} h_{kj}^H(x_j + e_j) + n_k, \quad \forall k \in C \quad \text{(cellular)}
\]

\[
z_j = g_{ij}^H(x_i + e_i) + g_{ijB}^H(x_B + e_B)
\]

\[
+ g_{ij}^H(x_j + e_j) + n_j', \quad \forall j, i \in D, i \neq j \quad \text{(D2D)}
\]

where \(y_k\) and \(z_j\) denote the received signals at the \(k^{th}\) cellular user and at the \(j^{th}\) D2D user, respectively. Furthermore, the transceiver noise is expressed by \(e \in \mathbb{C}^M\times 1\). Transmitter noise appears mainly due to the limited transmitter dynamic range (DR). The entities \(n\) and \(n'\) represent realizations of independent and identically distributed zero-mean proper Gaussian noise with variance \(\sigma^2\), i.e., \(\mathcal{CN}(0, \sigma^2)\). The interference channel vector between the \(k^{th}\) D2D user and the BS is denoted by \(g_{kB} \in \mathbb{C}^{N\times 1}\) and the self-interference channels are represented by \(g_{kk} \in \mathbb{C}^{M\times 1}\). The direct link between the \(k^{th}\) and \(l^{th}\) D2D users is given by \(g_{kl} \in \mathbb{C}^{M\times 1}\). The channel vectors from the BS and the \(i^{th}\) D2D user to the \(j^{th}\) D2D user are represented by \(h_{jB} \in \mathbb{C}^{N\times 1}\) and \(h_{ji} \in \mathbb{C}^{M\times 1}\), respectively.

The transmit signal of the BS is denoted as \(x_B \in \mathbb{C}^{N\times 1}\) which is given by

\[
x_B = \sum_{k=1}^{N} v_{Bk} d_{Bk} = V_B d_B,
\]

where \(d_{Bk}\) and \(v_{Bk}\) are the \(k^{th}\) information signal and beamforming vector intended for the \(k^{th}\) cellular user, respectively. The BS transmit beamforming matrix \(V_B\) and
the transmit information signal vector \( d_B \) are defined as \( V_B = [v_{B_1}, ..., v_{B_K}] \) and \( d_B = [d_{B_1}, ..., d_{B_K}]^T \), respectively. Similarly, the transmit signal of the D2D users is given by

\[
x_j = v_j d_j, \quad \forall j \in D,
\]

where the information signal \( d_j \) is beamformed in the direction of \( v_j \). Note that the information signals \( d_{B_k} \), \( d_j \), \( \forall k \in C \), \( j \in D \) are assumed to be independently identically distributed complex random Gaussian signals with unit variance. If the real and imaginary part of \( d_{B_k} \), \( \forall k \in C \) and \( d_j \), \( \forall j \in D \) have equal power and are uncorrelated, then the signaling type is referred to as proper Gaussian signaling. Otherwise, it is referred to as improper Gaussian signaling [29]. We discuss the differences between the two signaling types in more details in Appendix A.

Moreover, we assume here that the D2D users are equipped with \( M + 1 \) antennas, where \( M \) antennas are utilized for transmission and a single antenna is used for reception.

In this work, we assume perfect and global channel knowledge except for the self-interference channel. This assumption is due to imperfect self-interference cancellation in practical full-duplex systems [30]. In more details, the self-interference due to full-duplex operation is assumed to be cancelled to some significant extent (based on the channel estimate), but not completely (channel estimation error). Thus, the received signals at the D2D users can be rewritten as

\[
z_j = g_j^H (x_i + e_i) + g_{jB}^H (x_B + e_B) + \Delta g_{jj}^H x_j + g_{jj}^H e_j + n_j, \quad \forall j, i \in D, j \neq i,
\]

where the residual self-interference (RSI) channel due to imperfect self-interference channel estimation is represented by \( \Delta g_{jj} \). Assuming improper Gaussian signaling (see Appendix A for details), the transmitter noise \( e_j \) in (5) is modelled as

\[
e_j \sim \mathcal{CN}(0, \tilde{Q}_{e_j}),
\]

\[
\tilde{Q}_{e_j} = \kappa \tilde{C}_{x_j} = \kappa \begin{pmatrix} C_{x_j} & \tilde{C}_{x_j} \\ \tilde{C}_{x_j} & C_{x_j} \end{pmatrix},
\]

which states that the transmitter noise follows an improper Gaussian distribution with zero mean and augmented covariance matrix \( \kappa C_{x_j} \), with \( \kappa \ll 1 \). Further, the transmitter noise is statistically independent from the transmit signal, which is given by (6). The assumption of an improper transmitter noise is due to the generated improper information signal in baseband and imbalance between the in-phase and quadrature (I/Q) components, where the latter is discussed in [31].

The authors in [5] propose a transmitter noise model whose covariance is composed of the diagonals of the transmit signal covariance matrix. By plugging their model in our general
model, (8) is recast as
\[ \tilde{\mathbf{Q}}_{ej} = \kappa \tilde{\mathbf{C}}_{ej} = \kappa \left( \begin{array}{cc} \text{diag}(\mathbf{C}_{ej}) & \mathbf{C}_{ej} \\ \mathbf{C}_{ej} & \text{diag}(\mathbf{C}_{ej}) \end{array} \right). \] (9)

The transmitter noise undergoes self-interference channel and can not be cancelled at the receiver. This is due to the absence of transmitter noise knowledge at the receivers. However, except for the D2D users the contribution of the transmitter noise can be ignored at all receivers. This assumption is valid due to the low power of transmitter noise and relative strength of self-interference channel compared to other channels. Hence, the system model is simplified to
\[ y_k = h_{kB}^H x_B + \sum_{j=1}^{2} h_{kj}^H x_j + n_k, \quad \forall k \in \mathcal{C}, \quad (10) \]
\[ z_j = g_{ji}^H x_i + g_{kj}^H x_B + \Delta g_{jj}^H x_j + g_{ji}^H e_j + n_j, \quad \forall i, j \in \mathcal{D}, i \neq j. \] (11)

By plugging (3) and (4) into (10) and (11), the received signal is recast as
\[ y_k = \frac{1}{M} \sum_{m=1}^{M} \mathbf{v}_m \mathbf{x}_m + \sum_{j=1}^{2} h_{kj}^H \mathbf{v}_j \mathbf{d}_j \]
\[ + \frac{1}{M} \sum_{m=1}^{M} \mathbf{v}_m \mathbf{d}_m + n_k, \quad \forall k \in \mathcal{C}, \quad (12) \]
\[ z_j = g_{ji}^H \mathbf{v}_i \mathbf{x}_i + \Delta g_{jj}^H \mathbf{v}_j \mathbf{d}_j + g_{ji}^H \mathbf{e}_j + n_j, \quad \forall i, j \in \mathcal{D}, i \neq j. \] (13)

Here, we observe the dilemma we are facing in harvesting energy in this network. While the interference terms in expressions (12) and (13) are detrimental to the rate performance as they represent harmful interference, they are beneficial for energy harvesting as they possess energy. In this work, we investigate various types of ID and EH chains at the receiver that will be discussed in the following. We utilize the models introduced in (14) for simultaneous wireless information and energy reception. For the purpose of ID, both cellular and full-duplex users deploy single receive antenna. For the purpose of EH, different structures are utilized,

- **Antenna separation (AS):** The users could be equipped with an extra receive antenna for EH purpose. We assume that the signals arriving at both antennas (one for ID and one for EH) are experiencing fully-correlated channels. Due to the small-size hand-held mobile stations, the physical distance between the antenna elements in an array antenna is small. Thus the received signals are highly correlated.

- **Power splitting (PS):** The users could split received signal power for joint ID and EH in one channel use. This could be achieved by utilizing a power splitter at the receivers.

- **Time sharing (TS):** The users have the option to change the receive strategy and by time-sharing between ID and EH phases, (ID and EH in different channel uses).

For simplicity in presenting the optimization problems, we distribute the aforementioned joint ID and EH techniques among the users. As in Fig. 2 we allow cellular users to harvest the energy of the incident RF signal by AS structure, while full-duplex D2D users employ either PS or TS for energy harvesting purpose. With the proposed structures for the users in the network, we will formulate the achievable rates and energies in the next section.

### III. Achievable Rates and Energies

In this section, we formulate the achievable rates of the users assuming Gaussian codebook at the transmitters. In order to decode the desired signals, the users ignore interference, i.e., treat interference as noise. The users’ achievable rates are bounded by (refer to Appendix A for the entropy expression of Gaussian signals)

\[ r_k \leq I(y_k; x_B, h_{kj}, h_{kB}) \]
\[ = h(y_k|x_{kj}, h_{kB}) - h(y_k|x_B, h_{kj}, h_{kB}) \]
\[ = 1 \log \left( \frac{|C_{yk}|}{|C_{wk}|} \right), \quad \forall k \in \mathcal{C}, \quad (14) \]
\[ r_j' \leq I(z_j; x_i, g_{ji}, g_{jB}) \]
\[ = h(z_j|x_i, g_{ji}, g_{jB}) - h(z_j|x_B, x_i, g_{ji}, g_{jB}) \]
\[ = 1 \log \left( \frac{|C_{zj}|}{|C_{qj}|} \right), \quad \forall j, i \in \mathcal{D}, i \neq j, \quad (15) \]

where \( C_{yk} \) and \( C_{zj} \) represent the augmented covariance matrices of the received signal at the cellular and D2D users, respectively. The received interference-plus-noise at the \( k \)th cellular user and \( j \)th D2D users are denoted by \( C_{wk} \) and \( C_{qj} \), respectively. The augmented covariance matrices in (14) and (15) are composed of the variance and pseudo-variance. According to the definitions of variance and pseudo-variance in Appendix A and the transmit noise model in (8), we write the variance of the received signals in (12) and (13) as

\[ C_{yk} = h_{kB}^H \mathbf{C}_{xB} h_{kB} + \sum_{j=1}^{2} h_{kj}^H \mathbf{C}_{sj} h_{kj} + \sigma_n^2, \quad \forall k \in \mathcal{C}, \quad (16) \]
\[ C_{zj} = g_{ji}^H \mathbf{C}_{x_i} g_{ji} + g_{kj}^H \mathbf{C}_{xB} g_{kj} + \Delta g_{jj}^H \mathbf{C}_{x_j} \Delta g_{jj} + \kappa g_{ji}^H \text{diag}(\mathbf{C}_{x_i}) g_{ji} + \sigma_n^2, \quad \forall j, i \in \mathcal{D}, i \neq j, \quad (17) \]

where, \( \mathbf{C}_B = \mathbf{V}_B \mathbf{E} \{ \mathbf{d}_B \mathbf{d}_B^H \} \mathbf{V}_B^H \) and \( \mathbf{C}_x = \mathbf{V}_j \mathbf{E} \{ \mathbf{d}_j \mathbf{d}_j^H \} \mathbf{V}_j^H \) are the BS and D2D transmit covariance matrices, respectively. Moreover, we formulate the interference-plus-noise variance as:

\[ C_{wk} = C_{yk} - h_{kB}^H \mathbf{C}_{xB} h_{kB}, \quad \forall k \in \mathcal{C}, \quad (18) \]
\[ C_{qj} = C_{zj} - g_{ji}^H \mathbf{C}_{xB} g_{ji}, \quad \forall j, i \in \mathcal{D}, i \neq j, \quad (19) \]

where \( \mathbf{C}_{xB} = \mathbf{V}_B \mathbf{E} \{ \mathbf{d}_B \mathbf{d}_B^H \} \mathbf{V}_B^H \) is the \( k \)th cellular user’s desired stream covariance matrix. In addition to the variances,
the pseudo-variances of the received signals and interference-plus-noise are required in order to obtain the augmented covariance matrices required in the rate expressions in (14) and (15). Based on the definition of the pseudo-variance in Appendix A, we write the pseudo-variance of the received signal as

\[
\tilde{C}_{yk} = h_{kB}^H \tilde{C}_{x,B} h_{k,B}^* + \sum_{j=1}^{2} h_{kj}^H \tilde{C}_{x,j} h_{kj}^*, \quad \forall k \in C, \tag{20}
\]

\[
\tilde{C}_{z,j} = g_{jj}^H \tilde{C}_{x,j} g_{jj}^* + g_{jB}^H \tilde{C}_{x,B} g_{jB}^* + \Delta g_{jj}^H \tilde{C}_{x,j} \Delta g_{jj}^* + \kappa g_{jj}^H \tilde{C}_{x,j} g_{jj}^*, \quad \forall j, i \in D, i \neq j. \tag{21}
\]

The interference-plus-noise pseudo-variance is

\[
\tilde{C}_{w,k} = \tilde{C}_{yk} - h_{kB}^H \tilde{C}_{x,B} h_{k,B}^*, \quad \forall k \in C, \tag{22}
\]

\[
C_{q,j} = \tilde{C}_{z,j} - g_{jj}^H \tilde{C}_{x,j} g_{jj}^*, \quad \forall j, i \in D, i \neq j, \tag{23}
\]

where, \( \tilde{C}_{x,B} = v_{B_k} \mathbb{E} \{ d_{B_k} d_{B_j} \} v_{B_j}^T \).

Having the received signal and interference-plus-noise variance and pseudo-variance in (16)-(23), we can construct the augmented covariance matrix as in (68). We can simplify the determinant terms in (14) and (15) as follows:

\[
r_k \leq \frac{1}{2} \log \left( \frac{C_{yk}^2 - |\tilde{C}_{yk}|^2}{C_{uk}^2 - |\tilde{C}_{uk}|^2} \right), \quad \forall k \in C, \tag{24}
\]

\[
r_j' \leq \frac{1}{2} \log \left( \frac{C_{z,j}^2 - |\tilde{C}_{z,j}|^2}{C_{q,j}^2 - |\tilde{C}_{q,j}|^2} \right), \quad \forall j \in D. \tag{25}
\]

The achievable rates can be further simplified as,

\[
r_k \leq \frac{1}{2} \log \left( \frac{C_{yk}^2 (1 - C_{uk}^{-2} |\tilde{C}_{yk}|^2)}{C_{uk}^2 (1 - C_{uk}^{-2} |\tilde{C}_{yk}|^2)} \right) + \frac{1}{2} \log \left( \frac{1 - C_{yk}^{-2} |\tilde{C}_{yk}|^2}{1 - C_{uk}^{-2} |\tilde{C}_{yk}|^2} \right) := R_k, \quad \forall k \in C, \tag{26}
\]

\[
r_j' \leq \frac{1}{2} \log \left( \frac{C_{z,j}^2 (1 - C_{q,j}^{-2} |\tilde{C}_{z,j}|^2)}{C_{q,j}^2 (1 - C_{q,j}^{-2} |\tilde{C}_{z,j}|^2)} \right) + \frac{1}{2} \log \left( \frac{1 - C_{z,j}^{-2} |\tilde{C}_{z,j}|^2}{1 - C_{q,j}^{-2} |\tilde{C}_{z,j}|^2} \right) := R_j', \quad \forall j \in D, \tag{27}
\]

where the first terms in (26) and (27) correspond to the achievable rate bound in case of proper signaling, i.e., \( \tilde{C}_{ys} = 0 \) and \( \tilde{C}_{z,j} = 0 \). Allowing the transmission to be improper Gaussian, we can enhance the bound by improving the second terms in (26) and (27) [16, 17].

Based on (26) and (27), we can denote the achievable rate region of the users as the union of all achievable rates under certain power constraint while preserving the property of the covariance matrix (Hermitian positive semi-definite). Thus, the set of all achievable rates in the network is

\[
\mathcal{R} \triangleq \bigcup_{\substack{\text{Tr}(C_k) \leq P_k, \\ \text{Tr}(C_{q,j}) \leq P_B, \\ C_{x,B} \succeq 0, \quad \forall j \in D, \\ \tilde{C}_{x,B} \succeq 0, \quad \forall k \in C}} \{ r | 0 \leq r \leq \bar{r} \}, \tag{28}
\]

The problem is thus to find the rate-optimal transmit beamforming solution for the MISO full-duplex users and the BS by considering maximum transmit power and minimum received energy constraints.

The amount of captured energy of the incident signal at the users per unit time is written as

\[
e_k = E_k = h_{kB}^H C_{x,B} h_{k,B} + \sum_{j=1}^{2} h_{kj}^H C_{x,j} h_{kj}, \quad \forall k \in C, \tag{29}
\]

\[
e_j' = E_j' = g_{jj}^H C_{x,j} g_{jj} + g_{jB}^H C_{x,B} g_{jB} + \kappa g_{jj}^H \text{diag}(C_{x,j}) g_{jj}, \quad \forall j \in D, \tag{30}
\]

where \( E_k \) and \( E_j' \) are the incident signal energy at the \( k \)th cellular user and \( j \)th D2D user, respectively. The loaded energy is less than these amounts which are denoted by \( e_k \) and \( e_j' \).

Besides rate region, we define the rate-energy region of the \( j \)th D2D user as

\[
\mathcal{F}_j \triangleq \bigcup_{\substack{\text{Tr}(C_{x,j}) \leq P_j, \\ \text{Tr}(C_{q,j}) \leq P_B, \\ \tilde{C}_{x,j} \succeq 0, \quad \forall j \in D, \\ \tilde{C}_{x,B} \succeq 0, \quad \forall k \in C}} \{ f_j | 0 \leq f_j \leq \bar{f}_j \}, \tag{31}
\]

where \( f_j = [r_j' e_j'] \) is the achievable rate-energy tuple and \( \bar{f}_j = [\bar{r}_j' \bar{E}_j'] \) is the upper-bound.

By defining the rate region and rate-energy region of the users, we will discuss the problems in the next section.

### IV. Optimization Problems

In what follows we present an overview of the considered optimization problems. In section

A. the optimal operating rates for the cellular users while fulfilling energy constraints is investigated.

B. we optimize the operating rate tuples for the full-duplex D2D users given rate demands for the cellular users.

C. the optimal operating rate-energy pairs of D2D users under cellular users’ rate constraints is delivered.

D. the optimization problem considers operating rates and energies of the network jointly under transmit power constraints.
A. Broadcast Users’ Rate Region under EH Constraint

Cellular users are capable of simultaneous ID and EH which can be achieved by AS receiver structure. In this section, we study the optimal achievable rate for these users while fulfilling their energy demands. Our goal is to find the optimal rate pairs for the cellular users while fulfilling their energy constraints. For this, we need to find the Pareto boundary of the rate region, in which all the rate pairs are optimal. Here, the Pareto boundary defines the frontier for the achievable rate tuples, such that an increment in the rate of one user inevitably coincides with a decrement in the rate of at least one of the other users. One way to find the Pareto boundary is to maximize sum of the weighted rates, \( \text{[19]} \). In what follows, we formulate sum of the weighted rates maximization problem under transmit power and harvested energy constraints.

\[
\begin{align*}
\max_{C_x, C_y} & \sum_{k=1}^{K} \alpha_k R_k \\
\text{s.t.} & \quad \Psi_k \leq h_{kB}^H C_{xB} h_{kB} + \sum_{j=1}^{2} h_{kj}^H C_{xj} h_{kj}, \quad \forall k \in C, \\
& \quad P_{xj} \geq \text{Tr}(C_{xj}) \geq 0, \quad \forall j \in D, \\
& \quad P_{xB} \geq \text{Tr}(C_{xB}) \geq 0, \\
& \quad \hat{C}_{xj} \succeq 0, \quad \forall j \in D, \\
& \quad \hat{C}_{xB} \succeq 0, \\
& \quad \text{rank}(C_{xj}) = 1, \quad \forall j \in D, \\
& \quad \text{rank}(C_{xB}) = 1, \quad \forall k \in C, \\
\end{align*}
\tag{32}
\]

where \( \alpha_k \) are the elements of vector \( \alpha \), which prioritize the maximization of the sum of individual weighted rates. In other words, \( \alpha \) specifies the direction of optimization over the field \( \mathbb{R}^K \). We define the set \( \mathcal{A} \) as, \( \mathcal{A} = \{ \alpha \in \mathbb{R}^K | ||\alpha||_1 = 1 \} \). Solving (32) and scanning the rate region in different directions by means of setting \( \alpha \in \{ \mathcal{A} \} \) with a predefined resolution will deliver the Pareto-optimal operating points. The collection of the Pareto-optimal points specify the Pareto boundary of the rate region. Note that, the union of all achievable Pareto rate tuples describes the achievable rate region defined in (28).

In problem (32), the transmission power is limited due to (32b), (32c). On the other hand, the cellular users are required to capture at least \( \Psi_k \) energy from the received RF signal for full functionality. The energy that has to be obtained by user \( k \) is represented in (32a) which needs to be provided by the BS and D2D users. The constraints (32b) and (32c) are due to the feasibility of beamforming vector reconstruction from the optimum covariance matrices, \( C_{xj} \) and \( C_{xB} \), i.e., feasible beamforming vectors can only be reconstructed from any matrix in the set of rank-1 positive semi-definite matrices. Note that, the optimization parameters are \( C_{xj}, \hat{C}_{xj} \), \( \forall j \in D \) and \( C_{xB}, \hat{C}_{xB} \), \( \forall k \in C \), but we refer to them as \( C_x \) and \( \hat{C}_x \) in the formulations.

Remark 1. The energy requirement \( \Psi_k, \forall k \in C \) might exceed the BS capability and should be provided to the cellular users by the D2D users. However, this turns the system to a broadcast interference channel. Thus, on one hand, the energy constraint would be fulfilled, and on the other hand the achievable rate would demolish.

Apparently (32) is a non-convex problem. This can be verified by plugging the entities in (16)-(19) and (20)-(23) into (26) and (27). Then we observe that, the objective function is neither convex nor concave function with respect to the optimization parameters, i.e., \( C_{xj}, \hat{C}_{xj}, C_{xB} \) and \( \hat{C}_{xB} \).

Remark 2. The objective function is non-convex even in case of proper Gaussian signaling where the achievable rates are bounded by \( R_k^{\text{proper}} \) and \( R_j^{\text{proper}} \) in (26) and (27). In this case the objective function is the difference of concave functions which is not necessarily convex or concave.

Problem (32) suffers from non-convexity in the constraint set as well. This is due to the rank-1 constraints (32b) and (32c). Thus, the optimization problem (32) can not be solved except by exhaustive search over the feasible set. However, the computational complexity of exhaustive search is high due to the dimensions of the optimization variables, i.e., \( M \times M \) and \( N \times N \) complex matrices. Maximizing sum of the weighted rates and maximizing the minimum of the rates (known as weighted Chebyshev goal function) are both able to manifest the Pareto boundary. \([19]\). Here, we focus on the latter which can be solved more efficiently. Therefore, the optimization problem that characterizes the Pareto boundary of the achievable rate region is formulated as the weighted Chebyshev problem as

\[
\begin{align*}
\max_{C_x, \hat{C}_x} & \min_{k \in C} \frac{R_k}{\alpha_k} \\
\text{s.t.} & \quad (32a) - (32g), \\
\end{align*}
\tag{33}
\]

Defining, \( \Lambda = \min_{k \in C} \left( \frac{R_k}{\alpha_k} \right) \), the problem is reformulated as

\[
\begin{align*}
\max_{\Lambda, C_x, \hat{C}_x} & \quad \Lambda \\
\text{s.t.} & \quad \Lambda \leq \frac{R_k}{\alpha_k}, \quad \forall k \in C, \\
(34a) - (34g), \\
\end{align*}
\tag{34}
\]

where the objective function is translated into the constraint set in the expense of adding an extra scalar parameter. The auxiliary scalar variable \( \Lambda \) is maximized in the direction of \( \alpha \) in order to get the Pareto-optimal operating point in that direction. This is illustrated in Fig. 3.

Using the rate expressions in (26) we have

\[
\begin{align*}
\max_{\Lambda, C_x, \hat{C}_x} & \quad \Lambda \\
\text{s.t.} & \quad \Lambda \leq \frac{1}{\alpha_k} \left( \log \left( \frac{C_{wk}}{C_{w_k}} \right) + \frac{1}{2} \log \left( \frac{1 - C_{wk}^{-2} \hat{C}_{wk}^2}{1 - C_{w_k}^{-2} \hat{C}_{w_k}^2} \right) \right), \quad \forall k \in C, \\
(32a) - (32g). \\
\end{align*}
\tag{35}
\]

This resembles a linear objective function with convex and non-convex constraints.

In order to make the problem solvable with less complexity,
we proceed with the following separate optimization method:

a) In the first step, we decouple the optimization problem into two optimization problems. The first problem contains the first term in the rate expression in constraint (35a), therefore the optimization variable would only be the transmit covariance matrices. In the second step, we rewrite the problem as a semi-definite program and solve them numerically by interior point methods. The solution of this problem is used in the second problem which involves the second term of constraint (35a). Note that the only optimization parameter in the second problem are the transmit pseudo-covariance matrices.

b) In the first step, the solutions of (a), i.e. covariance matrices obtained from (a), are used in the second optimization problem which involves the second term of constraint (35a). Note that the only optimization parameter in the second problem are the transmit pseudo-covariance matrices. In the second step, after some definitions we rewrite the problem as a semi-definite program and solve them numerically by interior point methods.

In the following we discuss the steps in details.

\textbf{a) Optimization of Covariance Matrix:} \textbf{Step 1}: First we focus on the first term in the rate expression in (26) and (27) to optimize the covariance matrices individually. Thus, assuming \( R_{k}^{\text{improper}} = \alpha_k \), we replace \( C_{y_k}, C_{w_k}, C_{s} \), and \( C_{q_j} \) with the corresponding expressions in (16) and (19). Consequently, problem (33) simplifies to

\[ \max_{\alpha_k} \min_{\mathbf{C} \in \mathcal{C}} \frac{R_{\text{proper}}}{\alpha_k} \]

s.t., \( \Psi_k \leq \mathbf{h}_k^H \mathbf{C}_{x_k} \mathbf{h}_k + \sum_{j=1}^{\mathcal{D}} \mathbf{h}_j^H \mathbf{C}_{x_j} \mathbf{h}_j, \forall k \in \mathcal{C}, \]

\( C_{x_j} \geq 0, \forall j \in \mathcal{D}, \)

\( C_{x_k} \geq 0, \quad \) or \( k \in \mathcal{C}, \)

\( (36a) \)

By defining \( \Gamma = \min_{\alpha_k} \left( \frac{R_{\text{proper}}}{\alpha_k} \right) \), we rewrite the problem as

\[ \max_{\Gamma, \mathcal{C}} \Gamma \]

s.t. \( \Gamma \leq \Gamma_k^{(1)} \left( C_{x_{B_k}}, C_{x_j} \right), \forall k \in \mathcal{C}, \)

\[ \Psi_k \leq \mathbf{h}_k^H \mathbf{C}_{x_k} \mathbf{h}_k + \sum_{j=1}^{\mathcal{D}} \mathbf{h}_j^H \mathbf{C}_{x_j} \mathbf{h}_j, \forall k \in \mathcal{C}, \]

\( C_{x_j} \geq 0, \forall j \in \mathcal{D}, \)

\( C_{x_k} \geq 0, \quad \) or \( k \in \mathcal{C}, \)

\( (37a) \)

where the BS transmits covariance matrix for a particular user, say user \( k \), is denoted by \( C_{x_{B_k}} \). The problem is still non-convex due to the rank-1 constraints, i.e., (32a), (32g). We define \( \Gamma_k^{(1)} \) as a function of transmit covariance matrices, i.e.,

\[ \Gamma_k^{(1)} \left( C_{x_{B_k}}, C_{x_j} \right) \quad \text{on top of next page by (39).} \]

\textbf{Step 2}: Now, we have the separate optimization problem which only depends on the transmit signal covariance matrices. Now, we apply trace operation to (37b) and the numerator and denominator of the expression inside the logarithm in (28). By using the shift property of trace and defining \( \mathbf{H}_{ij} = \mathbf{h}_i \mathbf{h}_j^H \), the optimization problem reduces to

\[ \max_{\Gamma, \mathcal{C}} \Gamma \]

s.t. \( \Gamma \leq \Gamma_k^{(2)} \left( C_{x_{B_k}}, C_{x_j} \right), \forall k \in \mathcal{C}, \)

\[ \Psi_k \leq \text{Tr}(\mathbf{H}_k \mathbf{C}_{x_k}) + \sum_{j=1}^{\mathcal{D}} \text{Tr}(\mathbf{H}_j \mathbf{C}_{x_j}), \forall k \in \mathcal{C}, \]

\( C_{x_j} \geq 0, \forall j \in \mathcal{D}, \)

\( C_{x_k} \geq 0, \quad \) or \( k \in \mathcal{C}, \)

\( (39a) \)

where, \( \Gamma_k^{(2)} \left( C_{x_{B_k}}, C_{x_j} \right) \) is given on top of the next page by (39). By relaxing the rank-1 constraints, i.e., (32a), (32g), problem (39) becomes a semi-definite program (SDP) for given \( \Gamma \), since the constraint set is convex. In order to get the optimal \( \Gamma \) that makes the constraint set feasible, we utilize bisection method. By bisecting over the objective, i.e., \( \Gamma \), the only optimizing variables are \( C_{x_i}, \forall j \in \mathcal{D} \) and \( C_{x_{B_k}}, \forall k \in \mathcal{C} \).
Therefore, optimization problem (39) can be solved efficiently by checking the feasibility of the constraint set for a given \( \Gamma \). Thus, we solve the following feasibility problem for a given \( \Gamma \):

\[
\begin{align*}
\text{find} & \quad C_{x_j} \in S^N \text{ and } C_{x_{B_k}} \in S^M, \quad \forall j \in D \text{ and } \forall k \in C, \\
\text{s.t.} & \quad (39a) - (39d), \quad (42a) - (42c),
\end{align*}
\]

where \( S^M \) and \( S^N \) are the cone of \( M \times M \) and \( N \times N \) Hermitian positive semi-definite matrices, respectively. The solution of problem (39) coincides with the solution of (41) for the maximum \( \Gamma \) that makes the constraint set non-empty when the rank-1 constraints are relaxed. In the rest of the paper we denote the optimal covariance matrices of (39) by \( C^*_{x_j}, \forall j \in D \) and \( C^*_{x_{B_k}}, \forall k \in C \), and the solution of problem (39) by \( \Gamma^* \).

The optimal covariance matrices are valid if and only if they are rank-1. We proceed with the two following feasible solutions,

I. **The solutions are intrinsically rank-1**: Then the corresponding rates are achievable, i.e. all the points on the Pareto boundary can be achieved by beamforming [32]. Thus, an eigenvalue decomposition of a particular optimal solution, say \( C^*_{x_j} \), yields:

\[
C^*_{x_j} = u_j \beta_j u_j^H = u_j \beta_j^2 u_j^H = t_j t_j^H,
\]

where \( u_j \) is the eigenvector corresponding to the single eigenvalue \( \beta_j \). Notice that, the beamforming vector for the \( j^{th} \) D2D user is represented by \( t_j \).

II. **The solutions have higher ranks**: We utilize the Gaussian randomization procedure, [20], which finds sub-optimal rank-1 solutions. Gaussian randomization starts with generating finite number of vectors from the Gaussian distribution with zero mean and \( C^*_{x_j} \) covariance matrix, i.e. \( \mathcal{N} \sim (0, C^*_{x_j}) \). Then, out of the feasible beamforming solutions, the optimal one is chosen. Gaussian randomization provides a sub-optimal solution and the quality of the sub-optimality depends on the number of randomizations.

**b) Optimization of Pseudo-covariance matrix**

**Step 1**: By considering the optimal covariance matrix of problem (39), we have the optimal value for the first term in the rate expression in (26) which is denoted by \( \Gamma^* \). By plugging \( \Gamma^* \) into the first term of (26) we optimize the pseudo-covariance matrix. Thus, the optimization problem is written as

\[
\begin{align*}
\max_{\Lambda, C_x} & \quad \Lambda \\
\text{s.t.} & \quad \Lambda \leq \Gamma^* + \frac{1}{2\alpha_k} \log \left( \frac{1 - C_{x_{y_k}}^{-2} |C_{x_{y_k}}'|^2}{1 - C_{x_{w_k}}^{-2} |C_{x_{w_k}}'|^2} \right), \quad \forall k \in C, \quad (42a) \\
& \quad \tilde{C}_{x_j} \succeq 0, \quad \forall j \in D, \quad (42b) \\
& \quad \tilde{C}_{x_{B_k}} \succeq 0, \quad (42c)
\end{align*}
\]

where the power and energy constraints are dropped since they are embedded in the covariance part of the augmented covariance matrix.

**Step 2**: This step is described in Appendix B.

**B. Rate Region of the D2D users**

The coexistence of D2D communication in the crowd of cellular users requires the study of the achievable rate region of the full-duplex D2D users while guaranteeing rate demands of the other users. We can resemble this case as a cognitive network with cognitive users where, the cellular users are the primary users and the D2D users are the secondary users. Particularly, we consider underlay cognitive network where D2D users are active only in case of fulfilling the primary users’ demands. In this section we assume that the primary users request only information and we formulate the maximum achievable rate-tuples for the D2D users. The problem is written as

\[
\begin{align*}
\max_{C_x, \tilde{C}_{x_{j}} \in D} & \quad \frac{R_j'}{\alpha_j} \\
\text{s.t.} & \quad \Sigma_k \leq \Sigma_k^{(1)} (C_{x_{B_k}}, C_{x_j}), \quad \forall k \in C, \quad (43a) \\
& \quad (32a) - (32c)
\end{align*}
\]

where, \( R_j' \) is the achievable rate for the \( j^{th} \) full-duplex D2D user that is given in (27) and \( \Sigma_k \) is the rate demand for \( k^{th} \) cellular user. Note that, \( \Sigma_k^{(1)} (C_{x_{B_k}}, C_{x_j}) \) is given on top of next page by (44). Hence, the objective functions composed of the covariance and pseudo-covariance matrices of the transmit signals. To solve this problem we proceed with the same procedure as described in the last section. First we optimize the covariance matrix assuming \( R_j'_{\text{improper}} = 0 \), which is
By defining, \(D_2D\) users assuming self-interference and transmitter noise problem (35) which is elaborated in Appendix B. The pseudo-covariance matrices for this problem is similar to previous sections. Please see Appendix B for details.

Achieving the Pareto boundary of the rate-energy region as

\[
\max \min_{C_x} \frac{R_j^{\text{proper}}}{\alpha_j} \quad \text{s.t.} \quad \Sigma_k \leq \Sigma_k^{(2)} \left( C_{x B_k}, C_{x_j} \right), \quad \forall k \in \mathcal{C},
\]

(32a) - (32b)

By defining, \(\Gamma = \min_{j \in \mathcal{D}} \frac{R_j^{\text{proper}}}{\alpha_j}\) we formulate the respective SDP problem as

\[
\max \Gamma \quad \text{s.t.} \quad \Gamma \leq \Gamma_k^{(3)} \left( C_{x B_k}, C_{x_j} \right), \quad \forall j \in \mathcal{D}, i \neq j,
\]

(46a)

\[
\Sigma_k \leq \Sigma_k^{(2)} \left( C_{x B_k}, C_{x_j} \right), \quad \forall k \in \mathcal{C},
\]

(32a) - (32b)

where \(\Gamma_k^{(3)}\) and \(\Sigma_k^{(2)}\) are defined on top of the next page by (37) and (48), respectively. By ignoring the rank-1 constraints, we solve the SDP efficiently. Furthermore we compensate the relaxation by Gaussian randomization method in order to get a feasible optimal solution. Note that the optimization problem of (46) yields the optimal transmit covariance matrices while the rate region can be further improved by optimization over the pseudo-covariance matrices. Optimizing pseudo-covariance matrices for this problem is similar to problem (35) which is elaborated in Appendix B.

C. Joint Rate-Energy Optimization (full-duplex D2D users)

In this subsection we present the rate-energy region of the D2D users assuming self-interference and transmitter noise with active base station. The full-duplex D2D users are equipped with a single receive antenna. In a single-antenna receiver, either information out of the received signal can be extracted or the energy unless by power splitting (PS) or time sharing (TS). First, we study the PS receiver structure, where each D2D user splits the received signals power and decodes the information of one portion and captures the energy of the other portion. We formulate the optimization problem that achieves the Pareto boundary of the rate-energy region as

\[
\max \min_{C_x, C_{z_j}} \frac{R_j^{\prime} \left( \eta \right)}{\alpha_1 \alpha_2} \quad \text{s.t.} \quad \Sigma_k \leq \Sigma_k^{(2)} \left( C_{x B_k}, C_{x_j} \right), \quad \forall k \in \mathcal{C},
\]

(49a)

where, 0 \(\leq\) \(\alpha_1\) \(\leq\) 1 and \(\alpha_2 = 1 - \alpha_1\).

Remark 3. In order to formulate \(R_j^{\prime} \forall j \in \mathcal{D}\), we should consider the fact that, given linear self-interference channel estimation, the residual self-interference i.e., \(\Delta g_{ij} x_j\), is orthogonal to the observations i.e., \(z_j\). Thus, the optimization process knows the error variance only which is

\[
\Delta^2_{RSI} = \Delta g_{ij} H_{x_j} \Delta g_{jj}.
\]

Assuming error to be proper Gaussian, we can write

\[
\Delta g_{ij} \hat{C}_{x_j} \Delta g_{jj}^* = 0.
\]

We define \(\eta\) as the power splitting factor, so that \(\eta = 1\) for pure information detection and \(\eta = 0\) for pure energy harvesting. Thus, joint EH and ID occurs by setting \(0 < \eta < 1\). By this definition, we first optimize the covariance matrices as,

\[
\max \min_{\Gamma, C_x, \eta} \left( \frac{R_j^{\prime} \left( \eta \right) \left( \eta \right)}{\alpha_1 \alpha_2} \right) \quad \text{s.t.} \quad \Gamma \leq \Gamma_k^{(4)} \left( \eta, C_{x B_k}, C_{x_j} \right), \quad \forall j \in \mathcal{D}, i \neq j,
\]

(55a)

\[
\Gamma \leq \Gamma_k^{(5)} \left( \eta, C_{x B_k}, C_{x_j} \right), \quad \forall j \in \mathcal{D}, i \neq j,
\]

(55b)

\[
\Sigma_k \leq \Sigma_k^{(2)} \left( C_{x B_k}, C_{x_j} \right), \quad \forall k \in \mathcal{C},
\]

(32a) - (32b)

where \(\Gamma_k^{(4)}\) and \(\Gamma_k^{(5)}\) are defined on top of the next page by (56) and (57), respectively. By exhaustive search over \(\eta\) and bisection over \(\Gamma\), we solve the problem. Problem (55) can be solved in the same way as the Problem (32). If the optimal solutions does not fulfill the rank-1 constraints, the Gaussian randomization procedure finds a suboptimal solution correspondingly. The pseudo-covariance matrices are optimized using the similar to previous sections. Please see Appendix B for details.

Time sharing is the other strategy that could be utilize for joint ID and EH in a single antenna receivers. The achievable rate-energy region for TS receivers can be found by determining
In this case, the problem is expressed as scanning the rate-energy in the positive quadrant of interested in the rate-energy region (user 2, detects information and vice versa. Therefore, we are user, say user 1, harvests energy while the other user, say other user to purely harvest energy, we can study the trade-off between the objectives of different users. Suppose one antennas at the receivers for improving achievable rates of the users. Thus, we stick to a single-antenna information reception system and an auxiliary antenna for energy harvesting. The problem delivers the (2K + 2)-dimensional rate-energy region, where K cellular users simultaneously harvest energy and decode information by AS and 2 full-duplex D2D users are decoding information only. We formulate the following optimization problem,

\[
\max \min_{C_x, C_s} \left( \frac{R_1'}{\alpha_1}, \frac{E_1'}{\alpha_2} \right)
\]

s.t. \( \Sigma_k \leq \Sigma_k^{(2)} (C_{xk}, C_{xj}), \forall k \in C, \) (58a)

where, \( 0 \leq \alpha_1 \leq 1 \) and \( \alpha_2 = 1 - \alpha_1. \) It is important to note that, not only the optimum covariance and pseudo-covariance but also the optimum rate-energy pair is crucial, so that one could decide which user to detect information and which user to harvest energy. This problem is solved similarly and we skip reformulations.

**D. Joint Rate-Energy Optimization Simultaneously**

Simultaneous optimization of the rates and the energies jointly might be considered if the nodes are capable of EH and ID at the same time. We can think of it by implementing one extra antenna at the receivers. Thus, one antenna is used for information detection, while the other harvests energy, (AS). In this paper we do not discuss the optimality of using both antennas at the receivers for improving achievable rates of the users. Thus, we stick to a single-antenna information reception system and an auxiliary antenna for energy harvesting. The problem delivers the (2K + 2)-dimensional rate-energy region,
suffers from interference caused by the D2D users which are

Remark 4. The broadcast channel investigated in this paper suffers from interference caused by the D2D users which are

TABLE I: Channel realizations

|    | $h_{11}$ | $h_{12}$ | $h_{21}$ | $g_{11}$ | $g_{12}$ | $g_{21}$ | $h_{12}$ | $h_{22}$ | $g_{12}$ | $g_{22}$ |
|----|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|    | 0.896e-1 | 2.3215   | 0.1702e+1 | 5.380e+1 | 2.440e-1 | 0.247e-1 | 0.328e+1 | 0.947e+1 | 0.947e+1 | 0.947e+1 |
| $b_{12}$ | 0.985e-1 | 2.3215   | 0.1702e+1 | 5.380e+1 | 2.440e-1 | 0.247e-1 | 0.328e+1 | 0.947e+1 | 0.947e+1 | 0.947e+1 |

Self-interference channel estimates

Inter-user interference channels

In this section, the capacity region is bounded by the dotted black frontier. The capacity of broadcast channel is achievable by dirty paper coding (DPC) and proper Gaussian signaling at the BS and TIN at the receivers.

A. Cellular Users’ Rate Region

In this subsection, we discuss the rate region improvement of the cellular users when allowing improper Gaussian signaling. We assume that an extra receive antenna is employed in the cellular users in order to obtain the required amount of energy from the RF signals. The channel that is experienced by the information decoding chain and energy harvesting chain is assumed to be fully correlated. The discussions in this section are based on the solution of problem (33).

It is of importance to note that, the capacity of the MIMO broadcast Gaussian channel is achieved by treating interference as noise (TIN) in the receivers and dirty paper coding (DPC) at the transmitter with proper Gaussian signaling, [33], [34]. In order to show the performance of Gaussian signaling with linear precoding, we compare the achievable rate region with the optimal scheme (DPC which is a nonlinear precoding scheme) that achieves the capacity. Figure 5 compares the achievable rate region of improper Gaussian signaling, proper Gaussian signaling and DPC scheme.

Fig. 5: Rate region improvement by improper signaling under EH constraint. Transmission power of the BS is limited by 4 units while the D2D users might transmit with maximum power of 2 units. Noise variance is unity. The cellular users are assumed to capture 6 units of energy from the RF signal.

Now, it is required that, the cellular users obtain particular RF energy from the environment. The case might happen that the required energy is far more than that exists in their surroundings. Hence power should be transmitted to the cellular users in order to fulfill the energy demands. If the demanded energy can be provided by the BS, it is rate-optimal for the cellular users if the D2D users remain silent. But if the demanded energy is more than the BS capability, the D2D users get activated to fulfill the cellular users’ energy demands. In this case, on one hand the interference from the D2D users fulfills the energy demands of the cellular users and on the other hand, this interference reduces the achievable rates of the cellular users. Hence, in order to guarantee the cellular users’ demands, simultaneous information and energy transmission is required to fulfill the network constraints. If the interference from the D2D users appear, improper Gaussian signaling helps in enlarging the achievable rate region. Figure 5 illustrates the rate region improvement by allowing improper Gaussian signaling. Considering energy demands, the rate region of DPC is improved by improper Gaussian signaling which is depicted in Fig. 6a. The convex hull of all achievable rates by both encoding orders is also achieved by time sharing which is shown by black dashed curves. The performance of utilizing and not utilizing DPC in the energy constrained broadcast channel is given in Fig. 6b. When the BS utilizes DPC, it codes the message in a way that the received signal in one user is free from the interference from the other user. This type of coding is beneficial from information rate perspective but it is detrimental from the energy viewpoint. In this case, if the cellular users’ energy demands are high enough, DPC becomes an inefficient coding scheme. The inefficiency of DPC is shown in Fig. 6b where the rate region of the cellular users is almost the same as the case of not utilizing DPC.
B. Full-Duplex D2D

The performance of full-duplex D2D users is evaluated in this subsection. We consider the case, where D2D users behave as underlay cognitive radios. Hence they are allowed to be active just in case that the demands of the primary users (cellular users) are fulfilled. Having this in mind that the primary users are supposed to fulfill certain rate constraints, D2D users maximize the achievable rates and energies. By utilizing improper signaling, the rate region of the D2D users is enlarged as is Fig. 7. Rate-energy region for a full-duplex node is studied where, PS and TS are the joint ID and EH phases in a particular D2D user, the black straight line consists of the outermost achievable rate and energy tuples. We studied Gaussian signaling from the rate and energy perspective is vivid. If we share time (TS structure) between EH and ID phases for joint ID and EH. The rate-energy regions are achievable for unity noise variance and unity residual self interference (RSI) variance.

Fig. 6: Improper signaling boosts the achievable rate region of DPC when EH constraints for the cellular users accedes a threshold. The cellular users are assumed to capture 6 units of energy from the RF signal. Antenna separation is the receiver structure for ID and EH purposes.

Fig. 7: Rate region of D2D users. Improper signaling improves the achievable rates when the BC users are guaranteed with data rate of 0.7 bits per channel use. The rate-energy regions are achievable for unity noise variance and unity residual self interference (RSI) variance.

Fig. 8: Rate-energy region of a full-duplex node in the network. Other users are neither demanding information nor energy. Power splitting (PS) and time sharing between EH and ID phases are the receiver structure for joint ID and EH. The rate-energy regions are achievable for unity noise variance and unity residual self interference (RSI) variance.
received signal energy at the first D2D user, i.e., $E'_1$, while this type of transmission is not rate optimal for the second D2D users, i.e., $R_2$. Thus, due to the priority weights of the rate and the energy optimization, all the points on the rate-energy region boundaries are achievable by optimum beamforming vectors.

C. Joint rate and energy maximization

In this subsection, we discuss the performance of the investigated setup, when each receive antenna either decodes information or extracts the energy of the incident RF signal. Cellular users are able to harvest energy from the RF signal in the environment and decode information simultaneously with maximum power through AS receiver structure. However, D2D users are equipped with a single receive antenna and the receivers consume the whole received signal with its maximum power for ID purpose. In other words, D2D users are not demanding energy at a particular time and their main concern is information, (refer to problem 59).

For two cellular users (demanding information and energy) and two D2D users (demanding information only), some interesting operating point on the boundary of six-dimensional rate-energy region is depicted in Table II.

![Fig. 9: Rate-energy region. One D2D user is capturing RF energy and the other one decodes the information. Broadcast users are guaranteed with 0.5 and 0.8 bits per channel use. $\sigma_n^2 = \sigma_{RS1}^2 = 1$.](image)

| $r_1$ | $r_2$ | $r_1$ | $r_2$ | $c_1$ | $c_2$ | Impr. of sum-rate |
|-------|-------|-------|-------|-------|-------|------------------|
| 1.00  | 0.00  | 0.03  | 0.29  | 1.01  | 1.33  | 0%               |
| 0.1   | 0.09  | 0.43  | 0.40  | 6.99  | 6.99  | 12%              |
| 0.068 | 0.095 | 0.87  | 1.00  | 3.98  | 3.17  | 15%              |
| 0.26  | 0.31  | 0.48  | 0.37  | 4.94  | 8.00  | 23%              |

TABLE II: Pareto-optimal operating points for different Chebyshev weights.

APPENDIX A

We introduce proper/improper Gaussian signals, we will discuss their entropy and the possible benefits of improper signaling, which will be utilized in the setup considered in this paper. Let $x$ be a zero-mean complex-valued Gaussian random vector (RV) which is a vector of random variables with the $k^{th}$ element as, $x_k = x_{k'} + j x_{k''}$. The second-order moments of $x$ are given by

$C_x = \mathbb{E}\{xx^H\}$, \hspace{1cm} (61)
$\hat{C}_x = \mathbb{E}\{xx^T\}$, \hspace{1cm} (62)

where $C_x$ and $\hat{C}_x$ specify the covariance and pseudocovariance matrices of $x$, respectively. For instance, for a RV of length two (two independent random entries), $x = (x_1 \ x_2)^T$, the second-order moment is written as

$C_x = \mathbb{E}\left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \end{bmatrix}^* \right\}$
$= \begin{bmatrix} \mathbb{E}\{x_1x_1^*\} & \mathbb{E}\{x_1x_2^*\} \\ \mathbb{E}\{x_2x_1^*\} & \mathbb{E}\{x_2x_2^*\} \end{bmatrix}$, \hspace{1cm} (63)

$\hat{C}_x = \mathbb{E}\left\{ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} x_1 & x_2 \end{bmatrix} \right\}$
$= \begin{bmatrix} \mathbb{E}\{x_1x_1\} & \mathbb{E}\{x_1x_2\} \\ \mathbb{E}\{x_2x_1\} & \mathbb{E}\{x_2x_2\} \end{bmatrix}$, \hspace{1cm} (64)

For a proper Gaussian random variable $x_k = x_{k'} + j x_{k''}$, we have

$\mathbb{E}\{x_kx_k^*\} = \mathbb{E}\{x_{k'}x_{k'}^*\} + \mathbb{E}\{x_{k''}x_{k''}^*\} = P_{k'} + P_{k''} = 2P_{k''}, \forall k \in \{1, 2\}$, \hspace{1cm} (65)

$\mathbb{E}\{x_kx_{k'}\} = \mathbb{E}\{x_{k'}x_{k'}\} - \mathbb{E}\{x_{k'}x_{k''}\} + 2j\mathbb{E}\{x_{k''}x_{k'}\} = P_{k'} - P_{k''} + 2j\text{Cov}(x_{k'}, x_{k''}) = 0$, \hspace{1cm} (66)

$\mathbb{E}\{x_kx_l^*\} = 0, \hspace{0.5cm} \forall l \neq k$, \hspace{1cm} (67)

VI. CONCLUSION

In this paper, we studied the rate and energy performance of a two-tier network which is composed of a full-duplex device-to-device communication incorporated in a macro-cell with a base station. Furthermore, we investigated the advantage of full-duplex D2D uses in aiding the cellular users. Due to the energy and information demands of the users, different practical receiver structures for joint energy harvesting and information detection are investigated, namely, antenna separation, power splitting and time sharing. The performance of these types of receivers are manifested while improper Gaussian signaling is proposed to be utilized at the transmitters. We observed that, if the energy demands of the cellular users is out of the capability of the BS, the full-duplex D2D users aid in fulfilling the demands and it is not necessary to utilize non-linear dirty paper coding at the BS in case of high-enough energy demands. The achievable rate region of the users in the network and the achievable rate-energy region of the full-duplex users are studied and the optimal beamforming and resource allocation solutions are delivered.
where $P_h$ and $P_k$ are the power of the real and imaginary components, respectively. Therefore, $\hat{C}_x = 0$ for proper Gaussian signals due to equal power allocation for the real and imaginary components and zero correlation between them. Allowing the freedom for unequal power allocation and correlation between the real and imaginary components of the complex signal, the pseudo-covariance matrix is not a zero matrix, i.e., $\hat{C}_x \neq 0$, and it is complex-valued in general. In this case, $\hat{C}_x$ can not solely describe the second-order moment of $x$, but the pseudo-covariance matrix ($\hat{C}_x$) is required as well. Authors in [29] introduce an augmented covariance matrix that includes both of the covariance and pseudo-covariance of the complex random vector which is given by

$$\hat{C}_x = \begin{pmatrix} C_x & \hat{C}_x \\ \hat{C}_x^* & C_x^* \end{pmatrix}. \tag{68}$$

It is of importance to mention that, the augmented covariance matrix holds all of the properties of a covariance matrix, i.e., positive semi-definite and Hermitian.

**Entropy of an improper Gaussian random vector:** Now, we can express the entropy of a complex Gaussian random vector $x$ as, [29]:

$$h(x) = \frac{1}{2} \log \left( (2\pi e)^{2M} |C_x| \right), \tag{69}$$

where $x \in \mathbb{C}^{M \times 1}$. For the case of proper Gaussian where $\hat{C}_x = 0$, the entropy expression reduces to $h(x) = \log((\pi e)^M |C_x|)$.

By considering the differences between the proper and improper Gaussian signals. Here we show the sub-optimality of proper signaling for networks in which the receive nodes suffer from interference which is treated as noise. To this end, consider the two-user full-duplex MISO channel as in Fig. 2.

We write the mutual information between the transmit and receive signal of the D2D users as follows [35]:

$$I(z_j; x_j | x_i, g_{ji}, g_{ji}) = h(z_j | x_j, g_{ji}, g_{ji}) - h(z_j | x_i, x_j, g_{ji}, g_{ji}), \quad \forall j, i \in \mathcal{D}, i \neq j. \tag{70}$$

We need to maximize the mutual information over the distribution of the transmit signal, while receivers utilize TIN strategy. We study the following two cases.

**Case 1.** Assuming an active BS, perfect SI cancellation and absence of transmitter noise. (70) is given by

$$I(z_j; x_j | x_i, g_{ji}, g_{jj}) = h(g_{ji}^H x_i) - h(n_j), \quad \forall j, i \in \mathcal{D}, i \neq j. \tag{71}$$

We observe that the second term does not depend on the transmit signals. In this case, the optimal transmission scheme would be proper Gaussian transmission [35]. Since, either non-equal power allocation or any correlation between the real and imaginary components of the complex Gaussian signal reduces the first entropy expression in (71) which results in reducing the mutual information.

**Case 2.** Assuming an active BS, for the two-user full-duplex with RSI and transmitter noise, we can explain (70) as follows: Considering (70), it is not clear that proper Gaussian signaling is the optimal Gaussian signaling. It might turn out that, by switching from proper to improper Gaussian signals, the terms $h(z_j | x_j, x_i, g_{ji}, g_{ji})$, $\forall i \in \mathcal{D}, i \neq j$ decrease more than the decrement of $h(z_j | x_j, x_i, g_{ji}, g_{ji})$, $\forall j \in \mathcal{D}$, which would result in an overall increase in (70).

Therefore, in scenario 2 we have the opportunity to maximize the rates of the users by improper Gaussian transmission.

**APPENDIX B**

For converting the problem into a SDP, we use similar Lemma as in [18].

**Lemma 1.** The positive semi-definite constraint is satisfied if and only if $\hat{C}_x = S_j \tilde{t}_j \tilde{t}_j^H \forall j \in \mathcal{D}$ and $\hat{C}_{xy_k} = S_{B_k} \tilde{t}_{B_k} \tilde{t}_{B_k}^H \forall k \in \mathcal{C}$, where $S_j$ and $S_{B_k}$ are complex scalar variables satisfying $|S_j| \leq ||t_j||^2$ and $|S_{B_k}| \leq ||t_{B_k}||^2$, and $\tilde{t}_j = \frac{t_j}{||t_j||}$ and $\tilde{t}_{B_k} = \frac{t_{B_k}}{||t_{B_k}||}$, where $t_j$ and $t_{B_k}$ are defined as is [42].

**Proof:** similar to the proof of Lemma 1 in [18].

By using this lemma, optimizing over positive semi-definite matrices of sizes $M \times M$ and $N \times N$ reduces to optimizing over a complex scalar, $S$. We rewrite the pseudo-variance of the received signal as:

$$\hat{C}_{yk} = \sum_{m=1}^{K} (h_k^H \tilde{t}_{B_m})^2 S_{B_m} + \sum_{j=1}^{2} (h_{kj}^H \tilde{t}_j)^2 S_j, \forall k \in \mathcal{C}, \tag{72}$$

$$\hat{C}_{zj} = (g_{ji}^H \tilde{t}_j)^2 S_i + \sum_{m=1}^{K} (g_{ji}^H \tilde{t}_{B_m})^2 S_{B_m} + \kappa (g_{ji}^H \tilde{t}_j)^2 S_j, \forall j \in \mathcal{D}. \tag{73}$$

The pseudo-variance of the interference-plus-transmitter noise ($\hat{C}_{wk}$ and $\hat{C}_{qj}$) is written as,

$$\hat{C}_{wk} = \sum_{m=1}^{K} (h_k^H \tilde{t}_{B_m})^2 S_{B_m} + \sum_{j=1}^{2} (h_{kj}^H \tilde{t}_j)^2 S_j, \forall k \in \mathcal{C}, \tag{74}$$

$$\hat{C}_{qj} = \sum_{m=1}^{K} (g_{ji}^H \tilde{t}_{B_m})^2 S_{B_m} + \kappa (g_{ji}^H \tilde{t}_j)^2 S_j, \forall j \in \mathcal{D}. \tag{75}$$

For simplicity in formulation and without loss of generality, we assume two active cellular users, i.e., $K = 2$.

We define the following vectors,

$$s = [S_1 \quad S_2 \quad S_{B_1} \quad S_{B_2}]^T, \tag{76}$$

$$a_1 = C_{y_1}^{-1} \left[ (h_{11}^H \tilde{t}_1)^2 (h_{12}^H \tilde{t}_2)^2 (h_{21}^H \tilde{t}_1)^2 (h_{22}^H \tilde{t}_2)^2 \right]^H, \tag{77}$$

$$a_2 = C_{y_2}^{-1} \left[ (h_{21}^H \tilde{t}_1)^2 (h_{22}^H \tilde{t}_2)^2 (h_{11}^H \tilde{t}_1)^2 (h_{12}^H \tilde{t}_2)^2 \right]^H, \tag{78}$$

$$a_1' = C_{z_1}^{-1} \left[ \kappa (g_{11}^H \tilde{t}_1)^2 (g_{12}^H \tilde{t}_2)^2 (g_{21}^H \tilde{t}_1)^2 (g_{22}^H \tilde{t}_2)^2 \right]^H, \tag{79}$$

$$a_2' = C_{z_2}^{-1} \left[ \kappa (g_{21}^H \tilde{t}_1)^2 (g_{22}^H \tilde{t}_2)^2 (g_{11}^H \tilde{t}_1)^2 (g_{12}^H \tilde{t}_2)^2 \right]^H. \tag{80}$$
We also define the transmit noise covariance matrices and the corresponding interference vectors.

\[ b_1 = C_{y_1}^{-1} \left[ (h_{11}^H \hat{f}_1)^2 \ (h_{12}^H \hat{f}_2)^2 \ 0 \ (h_{1B}^H \hat{f}_B)^2 \right]^H, \quad (81) \]
\[ b_2 = C_{y_2}^{-1} \left[ (h_{21}^H \hat{f}_1)^2 \ (h_{22}^H \hat{f}_2)^2 \ (h_{2B}^H \hat{f}_B)^2 \right]^H, \quad (82) \]
\[ b_3 = C_{\sigma_z}^{-1} \left[ \kappa (g_{11}^H \hat{f}_1)^2 \ 0 \ (g_{1B}^H \hat{f}_B)^2 \right]^H, \quad (83) \]
\[ b_4 = C_{\sigma_q}^{-1} \left[ 0 \ \kappa (g_{22}^H \hat{f}_2)^2 \ (g_{2B}^H \hat{f}_B)^2 \right]^H. \quad (84) \]

We define the matrices \( A, A', B, B', \) and \( S \) as,

\[ A_k = a_k a_k^H, \quad A'_j = a'_j a'_j^H, \quad (85) \]
\[ B_k = b_k b_k^H, \quad B'_j = b'_j b'_j^H, \quad (86) \]
\[ S = S S^H. \quad (87) \]

By the defined vectors and matrices, we can state the following equalities:

\[ C_{y_k}^{-2} \hat{C}_y | x_k |^2 = |a_k^H x|^2 = \text{Tr}(A_k S), \quad (88) \]
\[ C_{w_k}^{-2} \hat{C}_w | x_k |^2 = |b_k^H x|^2 = \text{Tr}(B_k S), \quad (89) \]
\[ C_{\sigma_z}^{-2} \hat{C}_{\sigma_z} | x_k |^2 = |a'_j x|^2 = \text{Tr}(A'_j S), \quad (90) \]
\[ C_{\sigma_q}^{-2} \hat{C}_{\sigma_q} | x_k |^2 = |b'_j x|^2 = \text{Tr}(B'_j S). \quad (91) \]

Considering lemma 1 and aforementioned equalities, we re-formulate (42a):

\[ \Gamma = \Lambda - \lambda_* \leq \frac{1}{2 \omega_i} \log \frac{1 - \text{Tr}(A_k S)}{1 - \text{Tr}(B_k S)}, \quad (92) \]

Constraint (42c) can also be reformulated as:

\[ \text{Tr}(M_i S) \leq ||t_j||^4, \quad \forall j \in \{1, 2\}, \quad (93) \]
\[ \text{Tr}(M_k S) \leq ||t_k||^4, \quad \forall k \in \{1, 2\}, \quad (94) \]

where \( M_i = m_i m_i^T \) and \( m_i \) is the \( i^\text{th} \) column of \( 4 \times 4 \) identity matrix.

Therefore, the optimization problem (42) can be written as a SDP as follows:

\[ \begin{align*}
\max_{\Gamma, S} & \quad \Gamma, S \succeq 0, \\
\text{s.t.} & \quad \Gamma \leq \frac{1}{2 \omega_k} \log \left( 1 - \frac{1 - \text{Tr}(A_k S)}{1 - \text{Tr}(B_k S)} \right), \quad \forall i \in \{1, 2\}, \quad (95a) \\
& \quad \text{Tr}(M_i S) \leq ||t_j||^4, \quad \forall j \in \{1, 2\}, \quad (95b) \\
& \quad \text{Tr}(M_k S) \leq ||t_k||^4, \quad \forall k \in \{1, 2\}, \quad (95c)
\end{align*} \]

where the rank-1 constraint of \( S \) is dropped. Thereof the solution is an upper bound for the original problem, unless the optimal \( S \) is rank-1. If the optimal \( S \) is not rank-1, the solution can be approximated by Gaussian randomization algorithm that is utilized in [37, 38 and 39]. The Gaussian randomization algorithm finds the suboptimal rank-1 solution.

**Theorem 1.** [18] For any matrix \( S \) that satisfies (95b), the following inequalities fulfill:

\[ 1 - \text{Tr}(A_k S) \geq C_{y_k}^{-2} \sigma^4 \geq 0, \quad \forall k \in \{1, 2\}, \quad (96) \]
\[ 1 - \text{Tr}(B_k S) \geq C_{w_k}^{-2} \sigma^4 \geq 0, \quad \forall k \in \{1, 2\}. \quad (97) \]

If (96) and (97) fulfills, then problem (42) is a quasi-convex problem and can be solved by bisection. [32] We consider the following feasibility problem by bisection over \( \Gamma \).

\[ \text{find } S \in S^2 \quad \text{s.t.} \quad (95a) - (97). \]

where \( S^* \) is found with a certain bisection accuracy.

If the solution, i.e. \( S^* \) is rank-1 the \( s^* \) can be calculated by eigen-value decomposition. Then, by replacing the elements of \( s^* \), i.e., \( S_j \) and \( S_{B_k} \), \( \forall j \in \{1, 2\} \), in the equation of lemma 1, that is, \( \hat{C}_{x_j} = S_j \hat{f}_j^T \hat{f}_j, \quad \forall j \in \{1, 2\} \) and \( \hat{C}_{x_{B_k}} = S_{B_k} \hat{f}_{B_k}^T \hat{f}_{B_k}, \quad \forall k \in \{1, 2\} \), the optimal pseudo-covariance matrices are delivered.

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