Abstract—We consider a full-duplex bi-directional communication between two nodes that suffer from self-interference, where the nodes are equipped with multiple antennas. We focus on the effect of a residual self-interference due to independent and identically distributed (i.i.d.) channel estimation errors and limited dynamic ranges of the transmitters and receivers. We consider the design of source covariance matrices at the nodes for sum-rate maximization problem subject to multiple generalized linear constraints. The non-convex sum-rate optimization problem is solved using two sup-optimal techniques, which are proven to converge to a local optimum point. These algorithms exploit both spatial and temporal freedoms of the source covariance matrices of the multiple-input multiple-output (MIMO) links between the nodes to achieve higher sum-rate.

Index Terms—Bi-directional, full-duplex, MIMO, self interference, transceiver designs.

I. INTRODUCTION

Full-duplex (FD) multiple-input multiple-output (MIMO) bi-directional communication systems has attracted increasing research attention, since it has the potential to nearly double the system spectral efficiency compared to half duplex (HD) systems [1]. The main difficulty in implementing a FD system is that the strong self-interference exceeds the limited dynamic range at the receiver.

The theoretical works shown in [2]-[5] exploit multiple antennas for self-interference cancellation based on transmit beamforming. The basic idea behind this approach is that one could cancel the radio self-interference at the RF front-end of a receiver by generating an accurate RF cancellation signal based on the source of interference known in the baseband.

By exploiting both spatial and temporal freedoms of the source covariance matrices of the MIMO links, the authors of [6] maximize the lower bound of the achievable rates for FD bi-directional MIMO channels under transmit and receiver distortions using Gradient Projection (GP) method. The work in [7] later extended the findings in [6], under a simpler transmit distortion model, to fast fading channels, where instantaneous channel state information (CSI) is not known at the transmitters. Using the same transmit/receive distortion model in [6], the authors in [8] consider the weighted sum-rate (WSR) maximization problem subject to total power constraint of the FD system. Based on the relationship between WSR and weighted minimum mean squared-error problem established in [9], a low complexity iterative alternating algorithm is proposed.

Unlike the individual power constraints and the total power constraint assumed in the aforementioned papers, this paper considers the source covariance matrix design so as to maximize the sum-rate of the FD MIMO bi-directional system subject to multiple generalized linear constraints. Multiple linear constraints appear in systems with per-antenna power constraints, interference constraints, etc. Since the sum-rate optimization problem is non-convex, we use two suboptimal techniques to solve this problem. Unlike the method used in [8], [9] which is shown to have a slow convergence rate due to alternating updates between transmit and receive filters [10], we first apply soft interference nulling (SIN) technique [11] that solves a convex optimization problem. Secondly, unlike the GP method in [6], [7] which require a centralized approach and only handles the individual or sum-power constraint, we use a distributed iterative algorithm by linearizing the non-convex term [12] under the assumption that each receiver uses a linear minimum mean square error (MMSE) filters. These two suboptimal algorithms are shown to converge to a local optimum point.

The following notations are used in this paper. $(\cdot)^T$ and $(\cdot)^H$ are the transpose and conjugate transpose, respectively. $\mathbb{E}\{\cdot\}$, $I_N$, $\text{tr}(\cdot)$ and $|\cdot|$ denote the statistical expectation, $N$ by $N$ identity matrix, the trace and the determinant, respectively. $\text{diag}(\mathbf{A})$ is the diagonal matrix with the same diagonal elements as $\mathbf{A}$.

II. SYSTEM MODEL

We consider FD bi-directional MIMO wireless channels, where two nodes exchange information simultaneously as seen in Fig. 1. We assume that each node has $N$ physical antennas that can be used for simultaneous receiving and transmitting at the same carrier frequency [13].

We partition the data transmission period into two time slots ($t = 1, 2$). The use of two distinct time slots gives the freedom to switch between FD and HD signaling depending
on the power of the self-interference channel, while one time slot forces FD signaling, regardless of the power of the self-interference channel [6]-[8]. All the channel matrices are random and independent, where the entries of each matrix are i.i.d. complex Gaussian variables with zero mean with unit variance. It is assumed that both nodes have the estimated CSI. We use the FD channel model in [2]-[3], where the receiver $i \in \{1, 2\}$ performs MMSE estimation of $H_{ij}$. Let us denote the MMSE estimate as $\tilde{H}_{ij}$ and the estimation error as $\Delta H_{ij} = H_{ij} - \tilde{H}_{ij}$, where $H_{ij}$ and $\Delta H_{ij}$ are uncorrelated, and the entries of $\Delta H_{ij}$ are zero mean circularly symmetric complex Gaussian with variance $\sigma_v^2$. We will assume that the channel matrices remain constant over two consecutive time slots, but change randomly over an interval of many multiples of two time slots.

The $N \times 1$ received signal at the $i$th receiver is written as

$$y_i(t) = \sqrt{\rho_i} H_{ii} x_i(t) + c_i(t) + \sqrt{\rho_i} H_{ij} (x_j(t) + c_j(t)) + e_i(t) + n_i(t)$$

$$= \sqrt{\rho_i} \tilde{H}_{ii} x_i(t) + \sqrt{\rho_i} \Delta H_{ii} x_i(t) + \sqrt{\rho_i} \tilde{H}_{ij} c_j(t) + \sqrt{\rho_i} \Delta H_{ij} x_j(t) + \sqrt{\rho_i} \tilde{H}_{ij} c_j(t) + e_i(t) + n_i(t), \quad i, j \in \{1, 2\} \text{ and } j \neq i \quad (1)$$

where $x_i(t)$ is $N \times 1$ signal vector transmitted by transmitter $i$ with covariance matrix $\mathbb{E}\{x_i(t)x_i(t)^H\} = Q_i(t)$ and $x_j(t)$ is $N \times 1$ signal vector transmitted by the transmitter $j$, $j \neq i$ with a covariance matrix $\mathbb{E}\{x_j(t)x_j(t)^H\} = Q_j(t)$, which incurs self-interference at the $i$th receiver. $n_i(t) \in \mathbb{C}^N$ is the additive white Gaussian noise (AWGN) vector at the $i$th receiver with zero mean and unit covariance matrix, $\mathbb{E}\{n_i(t)n_i(t)^H\} = I_N$ and it is uncorrelated to $x_i(t)$ and $x_j(t)$. $\rho_i$ denotes the average gain of the $i$th transmitter-receiver link, and $\eta_i$ denotes the average gain of the self-interference channel.

In (1), $c_k(t) \in \mathbb{C}^N$, $k = 1, 2$ is the transmitter noise at the $k$th transmitter, which models the effect of limited transmitter DR and closely approximates the effects of additive power-amplifier noise, non-linearities in the DAC and phase noise [6]. The covariance matrix of $c_k(t)$ is given by $\kappa$ ($\kappa \ll 1$) times the energy of the intended signal at each receive antenna, i.e. $c_k(t) \sim \mathcal{CN}(0, \kappa diag(Q_k(t)))$, and is independent of $x_k(t)$.

In (1), $e_k(t) \in \mathbb{C}^N$, $k = 1, 2$ is the additive receiver distortion at the $k$th receiver, which models the effect of limited receiver DR and closely approximates the combined effects of additive gain-control noise, non-linearities in the ADC and phase noise [6]. The covariance matrix of $e_k(t)$ is given by $\beta$ ($\beta \ll 1$) times the energy of the undistorted received signal at each receive antenna, i.e. $e_k(t) \sim \mathcal{CN}(0, \beta diag(\Omega_k(t)))$. $\Omega_k(t) = \text{Cov}\{u_k(t)\}$, where $u_k(t)$ is the $k$th receiver’s undistorted received vector, i.e. $u_k(t) = y_k(t) - e_k(t)$. $e_k(t)$ is independent of $u_k(t)$.

The receiver $i \in \{1, 2\}$ knows the interfering codewords $x_j(t)$ from transmitter $j \in \{1, 2\}$, $j \neq i$, so the self-interference term $\sqrt{\eta_i} \tilde{H}_{ij} x_j(t)$ is known and thus can be cancelled in the baseband as in [6]. The interference-canceled signal can then be written as

$$\tilde{y}_i(t) = y_i(t) - \sqrt{\eta_i} \tilde{H}_{ij} x_j(t)$$

$$= \sqrt{\rho_i} \tilde{H}_{ii} x_i(t) + \sqrt{\rho_i} \tilde{H}_{ij} c_j(t) + \sqrt{\eta_i} \Delta H_{ij} x_j(t) + e_i(t) + n_i(t) \quad (2)$$

where $v_i(t)$ is the unknown interference components of (2) after self-interference cancellation and given by

$$v_i(t) = \sqrt{\rho_i} \Delta H_{ii} x_i(t) + \sqrt{\rho_i} \tilde{H}_{ii} c_i(t) + \sqrt{\eta_i} \Delta H_{ij} x_j(t) + \sqrt{\eta_i} \tilde{H}_{ij} c_j(t) + e_i(t) + n_i(t) \quad (3)$$

Similar to the proof in [6], the covariance matrix of $v_i(t)$, $(i, j, t) \in \{1, 2\}$ and $i \neq j$ can be approximated as

$$\Sigma_i(t) \approx \rho_i \kappa H_{ii} \text{diag}(Q_i(t)) \tilde{H}^H_{ii} + \rho_i \sigma_v^2 \text{tr}(Q_i(t)) I_N + \eta_i \kappa H_{ij} \text{diag}(Q_j(t)) \tilde{H}^H_{ij} + \eta_i \sigma_v^2 \text{tr}(Q_j(t)) I_N + \rho_i \kappa \text{diag}(H_{ii} Q_i(t) H_{ii}^H) + \beta \rho_i \kappa \text{diag}(H_{ij} Q_j(t) H_{ij}^H)$$

$$\triangleq \Psi_i(t) + I_N \quad (4)$$

As a result of the channel estimation errors and limited dynamic ranges in (3), the noise $v_i(t)$ is generally non-Gaussian. To the best of our knowledge, the exact capacity of MIMO channels with channel estimation errors is still an open problem even for point-to-point MIMO systems [14]. However, assuming $v_i(t)$ as Gaussian, we can obtain useful lower bounds [14]. A lower bound of the achievable rate of the $i$th node at time $t$ can be written as

$$I_i(Q_1(t), Q_2(t))$$

$$= \log_2 |I_N + \rho_i \tilde{H}_{ii} Q_i(t) \tilde{H}^H_{ii} \Sigma_i(t)^{-1}|$$

$$= \log_2 \left| \rho_i \tilde{H}_{ii} Q_i(t) \tilde{H}^H_{ii} + \Sigma_i(t) \right| - \log_2 |\Sigma_i(t)| \quad (5)$$

The sum-rate optimization problem for $M$ general linear constraints is formulated as

$$\max_{Q} \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} I_i(Q_1(t), Q_2(t))$$

$$\text{s.t.} \quad \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr}(\Phi_{im}(t) Q_i(t)) \leq P_m, \quad m = 1, \ldots, M \quad (6)$$

$$Q_i(t) \geq 0, \quad (i, t) \in \{1, 2\} \quad (7)$$

$$\Phi_{im}(t) \in \mathbb{C}^{N \times N}, \quad m = 1, \ldots, M \text{ is a weight matrix}$$

Fig. 1. A bi-directional full-duplex MIMO system
and the matrices $\sum_{m=1}^{M} \Phi_{im}(t)$ are positive definite for all $(i,t) \in \{1,2\}$ so that the system is guaranteed to not transmit infinite power in any direction. For example, the sum-power constraint of the system over two time slots can be defined by choosing the matrix $\Phi_{im}(t)$ to be an identity matrix. The per-antenna power constraint at the $i$th antenna can be defined by choosing the matrix $\Phi_{im}(t)$ to be a diagonal matrix having all diagonal elements being zero except the $i$th element being 1.

In cognitive radio networks, the interference constraint from secondary users to primary users can be defined by choosing $\Phi_{im}(t) = hh^H$, where $h$ is the channel response from the secondary user to the primary user [15].

### III. Soft Interference Nulling

The first technique to solve (6)-(8) is SIN formulation, which is based on linearizing the optimization problem (6)-(8) about some given point, $Q_i(t), (i,t) \in \{1,2\}$. (5) is non-convex due to the presence of the second term $\log_2 |\Sigma_i(t)|$, which is indeed a concave function of the source covariance matrices. An approximate solution is found in [11] via an iterative scheme where the term $\log_2 |\Sigma_i(t)|$ is approximated using a first-order Taylor expansion about $Q_i(t)$:

$$\log_2 \left| \Sigma_i(t) \right| \approx \log_2 \left| \Sigma_i(t) \right|$$

$$+ \text{tr} \left\{ \Sigma_i(t)^{-1} \left( \rho_t \hat{H}_{ii} \text{diag} \left( Q_i(t) - Q_i(t) \right) \hat{H}_{ii}^H \right) \right\}$$

$$+ \rho_t \sigma_t^2 \text{tr} \left\{ Q_i(t) - Q_i(t) \right\} I_N$$

$$+ \eta_i \left( \hat{H}_{ij} \text{diag} \left( Q_j(t) - Q_j(t) \right) \hat{H}_{ij}^H \right)$$

$$+ \beta \rho_i \text{diag} \left( \hat{H}_{ii} \left( Q_i(t) - Q_i(t) \right) \hat{H}_{ii}^H \right)$$

$$+ \beta \eta_i \text{diag} \left( \hat{H}_{ij} \left( Q_j(t) - Q_j(t) \right) \hat{H}_{ij}^H \right) \right\}$$

(9)

where we have applied $\log \left| I_N + XX^H \right| \approx \log \left| I_N + \tilde{X} \right| + \text{tr} \left\{ \left( I_N + XX^H \right)^{-1} \left( XX^H - \tilde{X} \right) \right\}$, which follows from the concavity of the log-determinant function [16]. $\Sigma_i(t)$ is the estimated covariance of the interference plus noise, same as $\Sigma_i(t)$ in (4) with $Q_i(t)$ replaced by $Q_i(t)$. Plugging (9) into (5), the optimization problem (6)-(8) can be rewritten as

$$\max_Q \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \left[ \log_2 \left| \rho_t \hat{H}_{ii} Q_i(t) \hat{H}_{ii}^H + \Sigma_i(t) \right| \right. \right.$$

$$\left. - \text{tr} \left\{ \Sigma_i(t)^{-1} \Psi_i(t) \right\} \right\}$$

(10)

$$\text{s.t.} \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \left\{ \Phi_{im}(t) Q_i(t) \right\} \leq P_m, \ m = 1, \ldots, M \right\}$$

$$Q_i(t) \succ 0, \ (i,t) \in \{1,2\}$$

(12)

where $\Psi_i(t)$ in (10) is defined in (4). Note that the optimization problem (10)-(12) is a convex, so its solution can be efficiently computed using standard convex optimization numerical techniques, e.g., by the interior-point method [16]. The iterative algorithm is summarized below:

#### Soft Interference Nulling Algorithm

- Initialize $Q_i(t) = 0, \ (i,t) \in \{1,2\}$.
- for
  - Compute $Q_i^+(t), (i,t) \in \{1,2\}$ by solving (10)-(12).
  - if $\frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \left( I_i (Q_i^+(t), Q_i^+(t)) - I_i (Q_i(t), \tilde{Q}_i(t)) \right) < \epsilon$
    - break
  - else
    - $Q_i(t) = Q_i^+(t)$
  - end if
- end loop

Following the same arguments as those in [11], we can show that SIN algorithm surely converges to a local optimum from any starting point.

### IV. SDP Relaxation

The second technique to solve (6)-(8) is based on SDP relaxation. Using the matrix inversion lemma $(A + BCD)^{-1} = A^{-1} - A^{-1}B (DA^{-1}B + C^{-1})^{-1}DA^{-1}$, (6)-(8) can be reformulated as

$$\min_Q \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \log_2 \left| I_N - \rho_t \hat{H}_{ii} Q_i(t) \hat{H}_{ii}^H \right| \right.$$

$$\times \left( \Sigma_i(t) + \rho_t \hat{H}_{ii} Q_i(t) \hat{H}_{ii}^H \right)^{-1} \right\}$$

(13)

$$\text{s.t.} \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \left\{ \Phi_{im}(t) Q_i(t) \right\} \leq P_m, \ m = 1, \ldots, M \right\}$$

$$Q_i(t) \succ 0, \ (i,t) \in \{1,2\}$$

(15)

Similar to [9], we reformulate (13)-(15) by further introducing new optimization variables $W_i(t) \in \mathbb{C}^{N \times N}$, $(i,t) \in \{1,2\}$ to obtain the following equivalent optimization problem

$$\min_{Q_i, W_i} \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \left[ \text{tr} \left\{ W_i(t) G_i(t) \right\} - \log_2 |W_i(t)| \right] \right.$$

(16)

$$\text{s.t.} \left\{ \frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \left\{ \Phi_{im}(t) Q_i(t) \right\} \leq P_m, \ m = 1, \ldots, M \right\}$$

$$Q_i(t) \succ 0, \ (i,t) \in \{1,2\}$$

(18)

where $W_i \triangleq \left[ W_1^T(1), W_1^T(2), W_2^T(1), W_2^T(2) \right]^T$ and $G_i(t)$ is defined as

$$G_i(t) = I_N - \rho_t \hat{H}_{ii} Q_i(t) \hat{H}_{ii}^H \left( \Sigma_i(t) + \rho_t \hat{H}_{ii} Q_i(t) \hat{H}_{ii}^H \right)^{-1}$$

Since the optimization problem (16)-(18) is convex in $W_i(t), (i,t) \in \{1,2\}$, the optimal $W_i(t)$ is found by taking the derivative of (16) with respect to $W_i(t)$ and make it equal to zero.

$$W_i^*(t) = \left[ \frac{1}{\ln 2} G_i(t) \right]^{-1}$$

(19)
By plugging (19) back in (16), we can see the equivalence of (16)-(18) and (13)-(15). In order to have a distributed approach, we let the nodes optimize their covariance matrices independently. Therefore, for fixed $W_i(t)$, node $i$ can solve the following problem

$$
\max_{Q_i(t)} \frac{1}{2} \sum_{t=1}^{2} \text{tr} \left\{ A_i(t) \left( \Sigma_i(t) + \rho_i \bar{H}_{ii} Q_i(t) \bar{H}_{ii}^H \right)^{-1} \right\}
+ \frac{1}{2} \sum_{t=1}^{2} \text{tr} \left\{ A_j(t) \left( \Sigma_j(t) + \rho_j \bar{H}_{jj} Q_j(t) \bar{H}_{jj}^H \right)^{-1} \right\}
$$

subject to

$$
\frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \{ \Phi_{im}(t) Q_i(t) \} \leq P_m, \ m = 1, \ldots, M
$$

where

$$
A_k(t) = \rho_k W_k(t) \bar{H}_{kk} Q_k(t) \bar{H}_{kk}^H, \quad k = 1, 2.
$$

The objective function (20) is not convex, so we use an iterative approach by linearizing the second term in (20) similar to SIN in Section III.

$$
\text{tr} \left\{ A_j(t) \left( \Sigma_j(t) + \rho_j \bar{H}_{jj} Q_j(t) \bar{H}_{jj}^H \right)^{-1} \right\}
\approx \text{tr} \left\{ A_j(t) \left( (C_j(t) + D_j(t))^{-1} - (C_j(t) + D_j(t))^{-1} D_j(t) (C_j(t) + D_j(t))^{-1} \right) \right\}
$$

where

$$
C_j(t) = \rho_j \bar{H}_{jj} Q_j(t) \bar{H}_{jj}^H + \rho_j \kappa \bar{H}_{jj} \text{diag} (Q_j(t)) \bar{H}_{jj}^H + \bar{I}_N + \rho_j \sigma_e^2 \text{tr} \{ Q_j(t) \} \bar{I}_N + \beta \text{tr} \left\{ \bar{H}_{jj} Q_j(t) \bar{H}_{jj}^H \right\}
$$

and $D_j(t)$ is same as $D_i(t)$ with $Q_i(t)$ replaced with $Q_j(t)$.

By plugging (24) into (20) and simplifying the resulting optimization problem, we get

$$
\min_{Q_i(t)} \frac{1}{2} \sum_{t=1}^{2} \text{tr} \left\{ W_i(t) \Sigma_i(t) \left( \Sigma_i(t) + \rho_i \bar{H}_{ii} Q_i(t) \bar{H}_{ii}^H \right)^{-1} \right\}
+ \frac{1}{2} \sum_{t=1}^{2} \text{tr} \{ B_j(t) Q_i(t) \}
$$

subject to

$$
\frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \{ \Phi_{im}(t) Q_i(t) \} \leq P_m, \ m = 1, \ldots, M
$$

where $B_j(t)$ is given by

$$
B_j(t) = \eta_j \kappa \text{diag} \left( \bar{H}_{jj}^H (C_j(t) + D_j(t))^{-1} A_j(t) \right)
$$

The objective function in (25) considers the effect of the source covariance matrix of node $i$ on not only its own rate, but also on the rate of $j$th node, $(i, j) \in \{1, 2\}$, $i \neq j$.

By further simplifying the objective function, we have

$$
\min_{Q_i(t), Y_i(t)} \frac{1}{2} \sum_{t=1}^{2} \text{tr} \{ Y_i(t) \Sigma_i(t) \left( \Sigma_i(t) + \rho_i \bar{H}_{ii} Q_i(t) \bar{H}_{ii}^H \right)^{-1} \}
+ \frac{1}{2} \sum_{t=1}^{2} \text{tr} \{ B_j(t) Q_i(t) \}
$$

subject to

$$
\frac{1}{2} \sum_{i=1}^{2} \sum_{t=1}^{2} \text{tr} \{ \Phi_{im}(t) Q_i(t) \} \leq P_m, \ m = 1, \ldots, M
$$

where $Y_i(t) = W_i(t) \Sigma_i(t) \left( \Sigma_i(t) + \rho_i \bar{H}_{ii} Q_i(t) \bar{H}_{ii}^H \right)^{-1}$ and $Y_i(t) \triangleq \left[ Y_i^T(1), \ Y_i^T(2) \right]^T$. In (35), $\Sigma_i(t)$ and $W_i(t)$ are updated using (4) and (19), respectively. Hence, for fixed $W_i(t)$, $(i, t) \in \{1, 2\}$, node $i$ updates its source covariance matrix $Q_i(t)$ through solving (32)-(35).

Since the second term in (20) is a convex function of $Q_i(t)$, the local linear approximation is a lower bound which is tight at the feasible point $Q_i(t)$. So when we solve (32)-(35), we minimize a concave lower bound of the objective function (20), which follows that (20) is nondecreasing. Moreover, since (20) is bounded from above and this implies the proposed algorithm converges. It is shown in [12] that SDP algorithm converges to a stationary point. The SDP algorithm can be summarized as below.
problem with the HD constraint that results over realization or a tolerance factor of worse than the HD when to loose stopping criterion the proposed algorithms perform iterations for convergence at high INR. Moreover, the difference for the proposed algorithms under different power constraint.

Moreover, the difference for the proposed algorithms under different power constraint. To optimize the HD scheme, we solved the optimization function of signal-to-noise ratio (SNR), nominal interference-power constraint and individual power constraint is

\[ P = \text{full power constraint} \]

\[ \lambda = \text{individual power constraint} \]

In this section, we numerically investigate the sum-rate maximization problem for MIMO FD bi-directional systems as a function of signal-to-noise ratio (SNR), nominal interference-to-noise ratio (INR), transmitter/receiver distortion (\( \kappa / \beta \)). For brevity, we set the same average transmit power for each node \( P_1 = P_2 = 1W \). We also assumed \( \rho_1 = \rho_2 = \rho, \eta_1 = \eta_2 = \eta \). To optimize the HD scheme, we solved the optimization problem with the HD constraint that \( Q_1(2) = Q_2(1) = 0 \). “FP” stands for a full power constraint, i.e., the transmit power constraint of each transceiver over two time slots is 2W. “IP” stands for an individual power constraint where each transceiver’s peak transmit power per time slot is 1W. For simplicity, the stopping criterion is 30 iterations per channel realization or a tolerance factor of \( \epsilon = 0.01 \). We average the results over 100 independent channel realizations.

Fig. 2 demonstrates the achievable sum rate of the proposed algorithms as a function of the SNR. As the residual interference increases, the performance of the proposed algorithms degenerate to a half-duplex baseline. On the other hand, a significant FD gain is obtained when the INR is small. Moreover, the difference for the proposed algorithms under a full power constraint and individual power constraint is negligible, but as seen in Fig. 3, SIN algorithm requires more iterations for convergence at high INR. Note that in Fig. 2, due to loose stopping criterion the proposed algorithms perform worse than the HD when \( \eta = 60dB \).

\[ \text{V. SIMULATION RESULTS} \]

\begin{center}
\begin{tabular}{|c|c|}
\hline
\textbf{SDP Algorithm} & \\
\hline
\textbf{Initialize} & \textbf{Q}_i(t) = 0_N, (i,t) \in \{1,2\} \\
\hline
\textbf{repeat} & \\
\hline
\textbf{for} i=1, 2 & \\
\hline
\textbf{Update} & \textbf{W}_i(t) \textbf{from (19)} \\
\textbf{Update} & \textbf{Q}_i(t) \textbf{from (32)-(35)} \\
\textbf{Update} & \textbf{W}_i(t) \textbf{from (19)} \\
\textbf{until convergence} & \\
\hline
\end{tabular}
\end{center}

\section{REFERENCES}


