Robust Transceiver Design for Full Duplex Multi-user MIMO Systems

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Abstract—We consider a weighted sum-rate maximization problem for a multi-user multiple-input multiple-output (MIMO) cellular system where a full-duplex (FD) base-station (BS) serves multiple half-duplex (HD) uplink (UL) and downlink (DL) users simultaneously while taking the imperfect channel knowledge into consideration. By exploiting the relationship between weighted sum-rate and weighted minimum-mean-squared-error problems, joint design of transceiver matrices can be obtained through an iterative convergent algorithm. Simulation results confirmed the importance of accurate channel estimation in FD systems.

Keywords—Full-duplex, imperfect CSI, MIMO, multi-user.

I. INTRODUCTION

Amongst the emerging technologies for next-generation wireless networks, full-duplex (FD) communication is considered as a promising technique to potentially double the speed of wireless systems, since it enables available spectral resources to be fully utilized in time and frequency [1].

FD multi-user systems, where a FD capable base-station (BS) communicates with half-duplex (HD) uplink (UL) and downlink (DL) users at the same time slot over the same frequency band, have been investigated in [2]-[6]. The authors in [2]-[6] assume that perfect channel-state-information (CSI) is available at the transmitters, which is practically impossible due to the inaccurate channel estimation. Therefore, robust transceiver designs that take into account imperfect channel knowledge are of interest, which have not been reported (to the best of our knowledge) so far for FD cellular systems. In this work, we propose a robust precoder scheme for the FD multiple-input multiple-output (MIMO) multi-user system to maximize the weighted sum-rate of the network subject to power constraints at the BS and UL users under norm-bounded channel estimation errors. Similar to [7], we adopt a convex optimization problem which is proven to converge, wherein a convex subproblem is solved at each step. Numerical results are presented to show the importance of channel estimation in FD systems.

Notation: Matrices and vectors are denoted as bold capital and lowercase letters, respectively. $(\cdot)^T$ is the transpose, and $(\cdot)^H$ is the conjugate transpose. $I_N$ and $0_{N \times M}$ are the $N \times N$ identity and $N \times M$ zero matrix, respectively; $\text{tr}(\cdot)$ is the trace; $|.|$ is the determinant; $\text{vec}(\cdot)$ stacks the elements of a matrix to one long column vector. $\otimes$ denotes the Kronecker product. $\|X\|_F$ and $\|x\|_2$ denote the Frobenius norm of matrix $X$ and the Euclidean norm of vector $x$, respectively.

II. SYSTEM MODEL

We consider a multi-user MIMO system, in which a BS operating in FD mode serves $K$ UL and $J$ DL HD users simultaneously. The BS is equipped with $M_B$ and $N_B$ transmit and receive antennas, respectively. The number of antennas at the $k$-th UL and the $j$-th DL user are denoted by $M_k$ and $N_j$, respectively. $H_{UL}^{k} \in \mathbb{C}^{N_B \times M_k}$ and $H_{DL}^{k} \in \mathbb{C}^{N_j \times N_B}$ represent the $k$-th UL and the $j$-th DL channel, respectively. $H_0 \in \mathbb{C}^{N_B \times M_B}$ is the self-interference channel between the transmitter and receiver antennas of BS. $H_{DU}^{k} \in \mathbb{C}^{N_B \times M_k}$ is the co-channel interference (CCI) channel from the $k$-th UL user to the $j$-th DL user.

The source symbols $s_{UL}^{k} \in \mathbb{C}^{d_{UL}^{k}}$ and $s_{DL}^{j} \in \mathbb{C}^{d_{DL}^{j}}$ for the $k$-th UL and the $j$-th DL user, respectively, are assumed to be independent and identically distributed (i.i.d.) with unit power. Denoting the precoders for the data streams of the $k$-th UL and $j$-th DL user as $V_{UL}^{k} = [v_{UL}^{k,1}, \ldots, v_{UL}^{k,J}] \in \mathbb{C}^{M_k \times d_{UL}^{k}}$, and $V_{DL}^{j} = [v_{DL}^{j,1}, \ldots, v_{DL}^{j,J}] \in \mathbb{C}^{M_j \times d_{DL}^{j}}$, respectively, the signal received by the BS and the $j$-th DL user can be written, respectively, as

$$y_{UL}^{k} = \sum_{k=1}^{K} H_{UL}^{k} V_{UL}^{k} s_{UL}^{k} + H_{0}^{k} V_{UL}^{k} s_{UL}^{k} + n_{UL}^{k}, \quad (1)$$

$$y_{DL}^{j} = H_{DL}^{j} V_{DL}^{j} s_{DL}^{j} + \sum_{k=1}^{K} H_{DU}^{k} V_{UL}^{k} s_{UL}^{k} + n_{DL}^{j}, \quad (2)$$

where $n_{UL}^{k} \sim \mathcal{CN}(0, \sigma_n^2 I_{N_B})$ and $n_{DL}^{j} \sim \mathcal{CN}(0, \sigma_n^2 I_{N_j})$ denote the additive white Gaussian noise vector at the BS and the $j$-th DL user, respectively.

The received signals are processed by linear decoders, denoted as $U_{UL}^{k} = [u_{UL}^{k,1}, \ldots, u_{UL}^{k,J}, d_{UL}^{k}] \in \mathbb{C}^{N_B \times d_{UL}^{k}}$, and $U_{DL}^{j} = [u_{DL}^{j,1}, \ldots, u_{DL}^{j,J}, d_{DL}^{j}] \in \mathbb{C}^{N_j \times d_{DL}^{j}}$ by the BS and the $j$-th DL user, respectively. Therefore, the estimate of data streams of the $k$-th UL and the $j$-th DL user are given as $\hat{s}_{UL}^{k} = (U_{UL}^{k})^H y_{UL}^{k}$ and $\hat{s}_{DL}^{j} = (U_{DL}^{j})^H y_{DL}^{j}$, respectively. Using these estimates, the signal-to-interference-plus-noise ratio (SINR) values of the $m$-th stream of the $k$-th user in the
where $\Sigma_{UL}^k$ denotes the covariance matrix of the interference-plus-noise terms at the $k$-th UL user given as
\[
\Sigma_{UL}^k = \sum_{j=1}^{J_U} \mathbf{H}_j^U \mathbf{V}_j^U (\mathbf{V}_j^U)^H (\mathbf{H}_j^U)^H + \sum_{j \neq m}^{J_U} \mathbf{H}_j^U \mathbf{V}_j^U (\mathbf{V}_j^U)^H (\mathbf{H}_j^U)^H + \sum_{j \neq m}^{J_D} \mathbf{H}_j^D \mathbf{V}_j^D (\mathbf{V}_j^D)^H (\mathbf{H}_j^D)^H + \sigma_n^2 \mathbf{I}_{N_0}.
\]

The WSFR optimization problem can be formulated as:
\[
\max_{\mathbf{v}_k^U, \mathbf{d}_k^U} \sum_{k=1}^{K} w_k^U \sum_{m=1}^{U_k} \log (1 + \gamma_{k,m}^U)
\]
\[
+ \sum_{j=1}^{J} \sum_{m=1}^{d_j^U} \log (1 + \gamma_{j,m}^U)
\]
subject to
\[
\sum_{m=1}^{d_j^U} \mathbf{v}_j^U (\mathbf{v}_j^U)^H \mathbf{u}_j^U \leq P_k, \quad k \in \mathcal{S}^U,
\]
\[
\sum_{j=1}^{J} \sum_{m=1}^{d_j^U} \mathbf{v}_j^U (\mathbf{v}_j^U)^H \mathbf{d}_j^U \leq P_0,
\]

where $w_k^U$ and $d_j^U$ are the weights of the $k$-th UL and the $j$-th DL user, respectively, and $\mathbf{v}_k^U = \{\mathbf{v}_{k,m}^U : \forall (k,m)\}$ and $\mathbf{U}^U = \{\mathbf{u}_{k,m}^U : \forall (k,m)\}$, $X \in \{UL, DL\}$. The constraints $P_k$ and $P_0$ are the transmit power constraints at the $k$-th UL user and at the BS, respectively. We use $\mathcal{S}^U$ and $\mathcal{S}^D$ to represent the set of $K$ UL and $J$ DL channels, respectively.

### III. Joint Beamforming Design

We will first simplify the notations similar to [3] by combining UL and DL channels. Denoting
\[
\mathbf{H}_{ij} = \begin{cases} 
\mathbf{H}_{ij}^U, & i \in \mathcal{S}^U, \quad j \in \mathcal{S}^U, \\
\mathbf{H}_{ij}^D, & i \in \mathcal{S}^D, \quad j \in \mathcal{S}^D,
\end{cases}
\]
\[
\mathbf{n}_i = \begin{cases} 
\mathbf{n}_i^U, & i \in \mathcal{S}^U, \\
\mathbf{n}_i^D, & i \in \mathcal{S}^D,
\end{cases}
\]
\[
\tilde{N}_i(\tilde{M}_i) = \begin{cases} 
\mathbf{N}_i(\mathbf{M}_i), & i \in \mathcal{S}^U, \\
\mathbf{N}_i(\mathbf{M}_0), & i \in \mathcal{S}^D,
\end{cases}
\]

and referring to $\mathbf{v}_i^X, \mathbf{U}_i^X, \mathbf{X}_i^X, \mathbf{d}_j^X, X \in \{UL, DL\}$ as $\mathbf{V}_i, \mathbf{U}_i, \mathbf{X}_i, \mathbf{d}_j$, the SINR of the $m$-th stream in the $i$-th link, $i \in \mathcal{S} \triangleq \mathcal{S}^U \cup \mathcal{S}^D$, can be written as
\[
\gamma_{i,m} = \frac{|\mathbf{H}_{i,m}^H |^2}{\mathbf{d}_m^H \mathbf{H}_{i,m}^H + \sigma_n^2},
\]

where $\mathbf{H}_{i,m}$ is the channel matrix associated with the $i$-th UL user and $\mathbf{d}_m$ is the channel matrix associated with the $m$-th DL user.

### III. Joint Beamforming Design

We will now transform the optimization problem into a form that can be solved using the convex optimization tools available in [8, Theorem 1].

**Proposition 1:** For any $\mathbf{v}_i$ that is a solution of (11)-(13), there is a solution of (4)-(6) that share the same objective and constraint values, and thus (4)-(6) and (11)-(13) are equivalent. In particular, $\mathbf{v}_{i,m}$ can be obtained by taking the $m$-th column of $\mathbf{V}_i = \mathbf{V}_i^U \mathbf{V}_i^D$, where $\mathbf{D} \mathbf{A}^H$ is the eigen-decomposition of $\mathbf{V}_i^H \mathbf{H}_i^H \mathbf{H}_i \mathbf{V}_i$, and $\mathbf{u}_{i,m}$ can be obtained from $\mathbf{u}_{i,m} = \mathbf{V}_i^{-1} \mathbf{H}_i \mathbf{v}_{i,m}$, where $\mathbf{V}_i$ is defined in (7).

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**Theorem 2:** We will now transform the optimization problem into a form that can be solved using the convex optimization tools available in [8, Theorem 1].
where $\hat{H}_{ij}$ and $\Delta_{ij}$ denote the estimated CSI and the channel error matrix with uncertainty bound $\tau_{ij}$, respectively.

With the imperfect CSI, the objective function of the optimization problem (11)-(13) is replaced with

$$\max \mathbf{V} \quad \min \sum_{i \in S} w_i \log |I_{d_j} + V_i^H \hat{H}_{ii} V_i| \ . \ (15)$$

By using the well-known relationship between the weighted sum-rate and weighted minimum mean-squared-error (MSE) problems [9], we transform the robust weighted sum-rate problem in (15) into an equivalent robust weighted MSE problem, which is expressed as

$$\max \mathbf{V} \quad \min \sum_{i \in S} w_i (-tr \{W_i E_i\} + \log |W_i| + d_i) \ . \ (16)$$

where $U(W) = \{ U_i(W_i) : i \in S \}$, $W_i \in \mathbb{C}^d \times d_i$ is a weight matrix, and $E_i$ is the MSE matrix of the $i$-th link defined as

$$E_i = (U_i^H H_{ii} V_i - I_{d_i}) (U_i^H H_{ii} V_i - I_{d_i})^H + U_i^H \Sigma_i U_i.$$

Since the formulation in (16) is intractable, we look at the lower bound of the inner min-max problem by interchanging the min-max terms, and express the problem as

$$\max \mathbf{W}, \mathbf{U} \quad \min \sum_{i \in S} w_i (-tr \{W_i E_i\} + \log |W_i| + d_i). \ (17)$$

To simplify the problem further, we write $tr \{W_i E_i\}$ as

$$tr \{W_i E_i\} \leq \sum_{j \in S} tr \{W_i (U_i^H H_{ij} V_j - \delta_{ij} I_{d_i}) (U_i^H H_{ij} V_j - \delta_{ij} I_{d_i})^H \} + \sigma^2_{n_i} tr \{W_i^2 U_i U_i^H \} \ . \ (18)$$

where (a) is obtained by plugging $\Sigma_i$ in (7) and using $\delta_{ij}$ as the Kronecker delta function; (b) is obtained by using the equality $tr \{A^H A\} = ||A||^2_F$ and writing $W_i = B_i B_i^H$, and (c) is obtained by using the identities $||A||^2_F = vec(A)^2_F$ and $vec(ABC) = (C^T \otimes A) vec(B)$. Using (18), the inner minimization problem in (17) can be rewritten as

$$\max \mathbf{V, B, U, A, \epsilon} \quad \sum_{i \in S} w_i \left(- \sum_{j \in S} \lambda_{ij} - \sigma^2_{n_i} ||U_i B_i||^2_F + 2 \log |B_i| + d_i \right). \ (19)$$

Using epigraph form and introducing slack variable $\lambda_{ij}$, the problem (19) can be written as

$$\max_{\mathbf{A}, \mathbf{B}, \mathbf{U}, A, \epsilon} \sum_{i \in S} w_i \left(- \sum_{j \in S} \lambda_{ij} - \frac{\sigma^2_{n_i}}{A} ||U_i B_i||^2_F + 2 \log |B_i| + d_i \right) \ . \ (20)$$

s.t. $-||d_{ij} + D_{ij} vec(\Delta_{ij})||^2_F \leq \lambda_{ij}, \ ||\Delta_{ij}||^2_F \leq \tau_{ij}, \ \forall (i,j),$ where $A = \{ \lambda_{ij} : \forall (i,j) \}$. Using Schur complement lemma, the constraint in (20) is expressed in linear matrix inequalities (LMI) form:

$$\begin{bmatrix} \lambda_{ij} & d_{ij}^H \\ d_{ij} & 0 \end{bmatrix} \geq 0. \ (21)$$

To further simplify (21), we use the following lemma:

Lemma 1 ([10]): Given matrices $P$, $Q$, $A$ with $A = A^H$, the semi-infinite LMI of the form

$$(22)$$

A \succeq P \ X Q + Q^H X^H P, \ \forall X : ||X||_F \leq \rho,$

holds if and only if $\exists \epsilon \geq 0$ such that

$$(23)$$

$$A - \epsilon H^T Q - \epsilon P^H \succeq 0.$$ 

By choosing $A = \begin{bmatrix} \lambda_{ij} & d_{ij}^H \\ d_{ij} & I_{d_i \times d_j} \end{bmatrix}$, $P = \begin{bmatrix} 0_{N_i \times N_j \times 1} & D_{ij}^H \end{bmatrix}$, $X = vec(\Delta_{ij})$, $Q = \begin{bmatrix} -1, & 0_{1 \times d_i \times d_j} \end{bmatrix}$, we can apply Lemma 1 to (21), and the resulting overall optimization problem is formulated as

$$\max \mathbf{V, B, U, A, \epsilon} \quad \sum_{i \in S} w_i \left(- \sum_{j \in S} \lambda_{ij} - \frac{\sigma^2_{n_i}}{A} ||U_i B_i||^2_F + 2 \log |B_i| + d_i \right). \ (25)$$

s.t. $-||d_{ij} + D_{ij} vec(\Delta_{ij})||^2_F \leq \lambda_{ij}, \ ||\Delta_{ij}||^2_F \leq \tau_{ij}, \ \forall (i,j),$ where $\epsilon = \{ \epsilon_{ij} : \forall (i,j) \}$, and $B = \{ B_i : i \in S \}$. Although the problem in (25)-(28) is non-convex, it becomes a convex function of each optimization variable when the other two are fixed. Therefore we can apply the coordinate ascend method to update the transceiver matrices iteratively. In particular, when $V$ and $U$ are fixed, $B$ can be solved using MAXDET algorithm [11], when $B$ and $U$ ($B$ and $V$) are fixed, $V$ ($U$) can be computed by solving the resulting Semidefinite programming (SDP) problem. Since the alternating iterative updates lead to a monotonic increase of the objective function in (25), and the fact that it is bounded above guarantees the convergence of the proposed algorithm to a stationary point.
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B. Computational Complexity

Since the proposed algorithm solves a SDP problem in each step (SDP is a special case of MAX-DET [11]), we focus on the complexity analysis of a standard SDP problem:

$$\min_{x \in \mathbb{R}^n} c^T x \quad \text{s.t.} \quad A_0 + \sum_{i=1}^{n} x_i A_i \succeq 0, \quad \|x\|_2 \leq R,$$

(29)

where $A_i$ denotes the symmetric block-diagonal matrices with $L$ diagonal blocks of size $a_l \times a_l$, $l = 1, \ldots, L$. The number of elementary arithmetic operations necessary for solving this problem is upper-bounded by [12]

$$\mathcal{O}(1) \left( \sum_{i=1}^{L} a_l \right)^{1/2} n \left( n^2 + \sum_{i=1}^{L} a_l^2 + \sum_{i=1}^{L} a_l^2 \right).$$

(30)

For example, in computing $V_L$, the number of diagonal blocks $L$ is equal to $|S|^2 + |S|^{UL} + 1$. For the $|S|^2$ LMI constraints in (26), the dimension of blocks are $a_l = d_j + N_i M_f + 1, \quad (i,j) \in S$. For the UL power constraint, the dimension of the block is $a_l = M_0 j^{UL} + 1, \quad i \in S^{UL}$. For the BS power constraint, the dimension of the block is $a_l = M_0 \sum_{j \in S^{UL}}^j + 1$. The unknown variables to be determined are of size $n = \sum_{i \in S} 2M_i d_i + 2|S|^2$. The analysis of the other subproblems can be carried out in a similar manner. Then, the complexity parameters for solving the problem (25)-(28) using SDP method are given in Table I.

IV. SIMULATION RESULTS

In this section, we compare the proposed FD setup with the equivalent HD system under the 3GPP LTE specifications for small cell deployments, which is considered to be especially suitable for deployment of FD technology due to low transmit powers, short transmission distances and low mobility [2]. A single hexagonal cell having a BS in the center with randomly distributed UL and DL users is simulated. The parameters for the system model and the path-loss model for each link are adopted from [13, Table II]. The elements of the nominal small-scale fading channels, except the self-interference channel, are randomly generated according to zero-mean, unit-variance, i.i.d. Gaussian distributions. For the nominal self-interference channel, we adopt the model in [1], in which the self-interference channel is distributed as $H_0 \sim \mathcal{CN} \left( \sqrt{\sigma_j^2} K_R H_0, \sqrt{\sigma_j^2} L_0 \otimes I_{M_0} \right)$, where $K_R$ is the Rician factor, $H_0$ is a deterministic matrix, and $\sigma_j^2$ is introduced to parametrize the capability of a certain self-interference cancellation design. The uncertainty sizes are related to the quality of channels, i.e., $\tau_{ij} = s\|H_{ij}\|_F$, $s \in [0, 1]$. We apply the following values as our system parameters: $M_0 = N_f = 2, K_0 = N_0 = 2, K = J = 2, K_R = 1$ and $H_0$ to be the matrix of all ones for all experiments. The resulting system performance is averaged over 100 channel realizations.

It can be seen from Fig. 1 that as the size of the uncertainty region increases, the FD system suffers more, and the gap between FD and HD systems decreases. This degradation in performance of the FD system is explained as follows. Since there are more interference channels (self-interference and CCI) in FD systems, as the uncertainty level of the channels increases, the system performance of the FD system degrades more. This indicates that the channel estimation is a critical factor for successful deployment of FD systems.

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