A DISTRIBUTED ROBUST TRANSMIT BEAMFORMING DESIGN FOR FULL-DUPLEX RELAY-AIDED WIRELESS COMMUNICATION SYSTEMS

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ABSTRACT

In this paper, we consider a decode-and-forward (DF) full-duplex relay (FDR)-aided downlink wireless communication system consisting of one base station (BS) equipped with large scale antennas and multiple MIMO FDRs, which have been recognized as essential techniques in the fifth generation (5G) wireless communications. In view of the system performance not only limited by self-interference (SI) and inter-relay interference (IRI) caused by FDRs but also by channel state information uncertainty, a distributed worst-case robust design of FDR beamforming and total power minimization for downlink transmission is proposed subject to relays' and users' target rates, a centralized solution is presented, and then its distributed implementation using alternating direction method of multipliers (ADMM) is presented as well. Finally, some simulation results are provided to demonstrate the efficacy of the proposed algorithm.

Index Terms— Full-duplex relay (FDR), massive MIMO, robust beamforming, semidefinite relaxation (SDR), alternating direction method of multipliers (ADMM).

1. INTRODUCTION

The expeditious expansion of wireless networks has resulted in tremendous increase in energy consumption, and so the crucial need of high power efficiency in wireless communications has drawn extensive attention in both academia and industry recently. In the fifth generation cellular system, the transmit rate is required at least 10 Gbps and the power should be reduced by 90% in network energy usage [1]. Massive MIMO and full-duplex relay (FDR) have been regarded as two essential elements to boost the spectral and energy efficiency [2, 3], due to the fact that the former can provide very large spatial multiplexing gain [4, 5] and the latter can maximally double the spectral efficiency thanks to advanced self-interference (SI) cancellation techniques [6, 7].

State-of-the-art works on massive MIMO and FDR technologies mostly assume that FDRs are equipped with large scale antennas [8-10], which, however, may not be very practical because the massive MIMO used by FDR is prone to hardware impairments if it is realized with low-cost components [8]. In [9], closed-form expressions are derived for the ergodic achievable rate with imperfect channel state information (CSI) based maximum ratio transmission (MRT), maximum ratio combining (MRC) and zero-forcing beamforming (ZFBF) employed at two-way amplify-and-forward (AF) relays. In [10], an optimal power allocation scheme has been proposed to maximize the energy efficiency under power constraints.

In this paper, in view of potential practical scenarios in 5G [11] where relays and users can be machine-type devices (i.e., sensors), we consider an FDR-aided downlink cellular system (cf. Fig. 1) where users direct links from the BS are too weak for reliable signal reception. Recently, [12] considers the case of perfect CSI and the BS equipped with multiple antennas for such a system. Considering the CSI uncertainty and massive MIMO at BS, we further design a scheme for system power minimization and robust FDR transmit beamforming under relays' and users' target rates constraints. We propose a centralized solution by semidefinite relaxation (SDR) and S-Lemma as well as a distributed implementation by alternating direction method of multipliers (ADMM), followed by some simulation results for performance evaluation.

Notation: $\mathbb{E}\{\cdot\}$ denotes the expectation of a random variable; $\|\cdot\|$ denotes the Euclidean norm of a vector; $\mathcal{CN}(\cdot)$ denotes the complex Gaussian distribution; $\mathbf{X}^\dagger$ and $\mathrm{Tr}(\cdot)$ represent the pseudo-inverse and the trace of matrix $\mathbf{X}$, respectively; $(\cdot)^H$ denotes conjugate transpose of vectors or matrices; $\mathbf{X} \succeq 0$ means that $\mathbf{X}$ is a positive-definite matrix; $\mathbb{R}_+^n$ denotes the set of non-negative real n-vectors; $\mathcal{I}_L = \{1, \ldots, L\}$, $\{\lambda_{li}\}_l$ stands for the set $\{\lambda_{1i}, \ldots, \lambda_{Li}\}$, and $\{\lambda_{li}\}_{l\neq i} = \{\lambda_{li}\}_l \setminus \lambda_{ii}$.

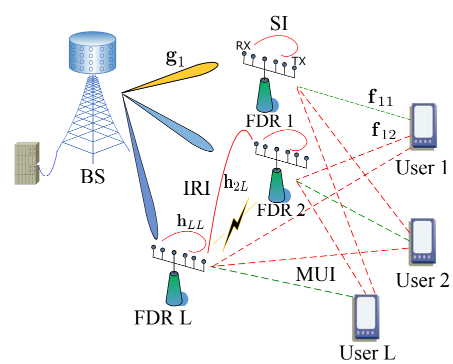

Fig. 1. An FDR aided wireless system with massive MIMO for BS

2. SIGNAL MODEL AND PROBLEM STATEMENT

Consider the FDR-aided downlink transmission system consisting of one BS equipped with N_B antennas and L FDRs, as illustrated in

This work is supported by the Ministry of Science and Technology, R.O.C., under Grant MOST 105-2221-E-007-020-MY2.

Fig. 1, and each relay equipped with N_t transmit and single receive antennas only serves one single-antenna user. Assume that all FDRs operate in decode-and-forward (DF) mode. When multiple relays are deployed in the network, the interference management is further complicated because self-interference (SI) at each relay, inter-relay interference (IRI) and multi-user interference (MUI) must be considered in addition to the interference across feeder links from BS to FDRs. Then the received signal at relay i is given by

$$y_i^R = \underbrace{\mathbf{g}_i^H \sqrt{p_i}\mathbf{v}_i q_i}_{\text{desired signal}} + \underbrace{\sum\nolimits_{j=1,j\neq i}^{L} \mathbf{g}_i^H \sqrt{p_j}\mathbf{v}_j q_j}_{\text{interference across feeder links}} + \underbrace{\mathbf{h}_{ii}^H \mathbf{w}_i s_i}_{\text{SI}} + \underbrace{\sum\nolimits_{k=1,k\neq i}^{L} \mathbf{h}_{ik}^H \mathbf{w}_k s_k}_{\text{IRI}} + n_i^R \quad (1)$$

where q_i, p_i and $\mathbf{v}_i \in \mathbb{C}^{N_B}$ are the transmit symbol, the power allocation and the normalized beamforming vector at the BS for the relay i; s_i and $\mathbf{w}_i \in \mathbb{C}^{N_t}$ are the transmit symbol and the beamforming vector at the relay i, respectively; $\mathbf{g}_i = \sqrt{\beta_i}\tilde{\mathbf{g}}_i \in \mathbb{C}^{N_B}$ denotes the channel between the BS and relay i (where β_i is large scale fading coefficient and $\tilde{\mathbf{g}}_i$ is small scale fading); $\mathbf{h}_{ii} \in \mathbb{C}^{N_t}$ and $\mathbf{h}_{ik} \in \mathbb{C}^{N_t}$ denote relay i's SI channel and IRI channel from relay k to relay i, respectively. Since relays are deployed at fixed places, we assume that all $\mathbf{g}_i$ and $\mathbf{h}_{ik}$ are perfectly known. Without loss of generality, assume $\mathbb{E}\left\{|q_i|^2\right\} = 1$, $\mathbb{E}\left\{|s_i|^2\right\} = 1$, $\|\mathbf{v}_i\|^2 = 1$ and $n_i^R \sim \mathcal{CN}\left(0, \sigma_{Ri}^2\right)$ is zero-mean additive white Gaussian noise (AWGN) with noise variance σ_{Ri}^2.

When N_B is large, the interference across feeder link is asymptotically orthogonal in massive MIMO system, so it can be eliminated by MRT or ZFBF [4]. Since ZFBF is asymptotically optimal, let $\mathbf{V} = \alpha_0 \mathbf{G}(\mathbf{G}^H\mathbf{G})^{-1}$ be the ZFBF from BS to FDRs, where $\alpha_0 = \sqrt{(N_B - L)/(\sum_{i=1}^{L} 1/\beta_i)}$ is a constant satisfying $\mathbb{E}\{\mathrm{Tr}(\mathbf{V}\mathbf{V}^H)\} = 1$ (cf. appendix in [13] for the proof) and $\mathbf{G} = [\mathbf{g}_1, \ldots, \mathbf{g}_L]$. Thus, the signal model of the relay i in (1) can be simplified as

$$y_i^R = \alpha_0\sqrt{p_i}q_i + \mathbf{h}_{ii}^H\mathbf{w}_i s_i + \sum_{k=1,k\neq i}^{L} \mathbf{h}_{ik}^H \mathbf{w}_k s_k + n_i^R \quad (2)$$

After certain SI cancellation processings at relay i are performed to suppress the SI, the residual SI (RSI) is still inevitable that can be modeled as AWGN with $Z_{\mathrm{RSI}} \sim \mathcal{CN}\left(0, \eta\left|\mathbf{h}_{ii}^H\mathbf{w}_i\right|^2\right)$, where $0 < \eta < 1$ is a hardware-dependent parameter characterizing the power level of RSI [12]. Thus, the signal-to-interference-plus-noise ratio (SINR) of relay i can be expressed as:

$$\mathsf{SINR}_i^R = \frac{\alpha_0^2 p_i}{\eta\left|\mathbf{h}_{ii}^H\mathbf{w}_i\right|^2 + \sum\limits_{k=1,k\neq i}^{L}\left|\mathbf{h}_{ik}^H\mathbf{w}_k\right|^2 + \sigma_{Ri}^2} \quad (3)$$

On the access link, provided that the direct link from BS to each user is negligible due to severe path loss, the received signal of user i is given by

$$y_i^U = \underbrace{\mathbf{f}_{ii}^H\mathbf{w}_i s_i}_{\text{desired signal}} + \underbrace{\sum_{l=1,l\neq i}^{L} \mathbf{f}_{il}^H \mathbf{w}_l s_l}_{\text{MUI}} + n_i^U \quad (4)$$

where $\mathbf{f}_{il} \in \mathbb{C}^{N_t}$ is the channel from the relay l to user i, and AWGN $n_i^U \sim \mathcal{CN}\left(0, \sigma_{Ui}^2\right)$. Due to the mobility of the cell-edge users, the CSI estimates (e.g., obtained through training) that are known to all the relays are imperfect. Hence, the uncertainty of channel $\mathbf{f}_{il}$ needs to be considered in the FDR beamforming design. Let

$$\mathbf{f}_{il} = \hat{\mathbf{f}}_{il} + \Delta\mathbf{f}_{il}, \forall i, l \in \mathcal{I}_L$$

where $\mathbf{f}_{il}$ are the true channels, $\hat{\mathbf{f}}_{il}$ are estimates of $\mathbf{f}_{il}$, and each CSI error vector $\Delta\mathbf{f}_{il}$ is confined within a hyper-spherical set Ω_{il} with radius ε_{il}, i.e.,

$$\Omega_{il} = \left\{\Delta\mathbf{f}_{il} \mid \|\Delta\mathbf{f}_{il}\|^2 \leq \varepsilon_{il}^2\right\} \quad (5)$$

Then SINR of user i can be expressed as:

$$\mathsf{SINR}_i^U = \frac{\left|(\hat{\mathbf{f}}_{ii} + \Delta\mathbf{f}_{ii})^H\mathbf{w}_i\right|^2}{\sum\limits_{l=1,l\neq i}^{L}\left|(\hat{\mathbf{f}}_{il} + \Delta\mathbf{f}_{il})^H\mathbf{w}_l\right|^2 + \sigma_{Ui}^2} \quad (6)$$

Under the preceding scenario (shown in Fig. 1) and premises, the worst-case robust design can be formulated as the following nonconvex power minimization problem:

$$\min_{p_i,\mathbf{w}_i} \sum_{i=1}^{L}\left(p_i + \|\mathbf{w}_i\|^2\right) \quad (7a)$$

$$\text{s.t.} \quad \log_2\left(1 + \mathsf{SINR}_i^R\right) \geq \gamma_{Ri}, \forall i \in \mathcal{I}_L \quad (7b)$$

$$\log_2\left(1 + \mathsf{SINR}_i^U\right) \geq \gamma_{Ui}, \forall i \in \mathcal{I}_L \quad (7c)$$

$$\|\Delta\mathbf{f}_{il}\|^2 \leq \varepsilon_{il}^2, \forall i, l \in \mathcal{I}_L \quad (7d)$$

where γ_{Ri} and γ_{Ui} denote the required relays' and users' target rates, respectively.

3. PROPOSED DISTRIBUTED ROBUST ALGORITHM

3.1. Solving (7) by SDR and S-Lemma

By applying SDR (i.e., replacing $\mathbf{w}_i\mathbf{w}_i^H$ by $\mathbf{W}_i \succeq \mathbf{0}$) to problem (7), (7c) can be converted into two convex quadratic constraints via auxiliary variables. Then each of the resulting two constraints together with the quadratic constraint (7d) can be further converted into a linear matrix inequality (LMI) by S-Lemma [14, 15]. Then we come up with the following semidefinite program (SDP):

$$\min_{\substack{\mathbf{W}_i \succeq \mathbf{0},\\ \{p_i, \{\lambda_{il}\}_l\} \in \mathbb{R}_+}} \sum_{i=1}^{L} p_i + \mathrm{Tr}\left(\mathbf{W}_i\right) \quad (8a)$$

$$\text{s.t.} \quad \frac{\alpha_0^2 p_i}{2^{\gamma_{Ri}} - 1} \geq \eta\left(\mathbf{h}_{ii}^H\mathbf{W}_i\mathbf{h}_{ii}\right) + \sum_{k=1,k\neq i}^{L} \mathbf{h}_{ik}^H\mathbf{W}_k\mathbf{h}_{ik} + \sigma_{Ri}^2, \ \forall i \in \mathcal{I}_L \quad (8b)$$

$$\Phi_i(\mathbf{W}_i, T_i, \lambda_{ii}) \succeq \mathbf{0}, \ \forall i \in \mathcal{I}_L \quad (8c)$$

$$\Psi_{il}(\mathbf{W}_l, t_{il}, \lambda_{il}) \succeq \mathbf{0}, \ \forall i, l \in \mathcal{I}_L, \ l \neq i \quad (8d)$$

where the two LMIs $\Phi_i(\mathbf{W}_i, T_i, \lambda_{ii})$ and $\Psi_{il}(\mathbf{W}_l, t_{il}, \lambda_{il})$ are defined in (9a) and (9b), respectively (on top of the next page), in which $\lambda_{il} \geq 0, \theta_i = 1/(2^{\gamma_{Ui}} - 1), \forall i \in \mathcal{I}_L$, and

$$T_i = \sum_{l=1,l\neq i}^{L} t_{il}, \ \ t_{il} = (\hat{\mathbf{f}}_{il} + \Delta\mathbf{f}_{il})^H\mathbf{W}_l(\hat{\mathbf{f}}_{il} + \Delta\mathbf{f}_{il})$$

Note that t_{il} is the interference power from relay l to user i for $l \neq i$, and T_i is the sum of MUIs at user i.

$$\Phi_i(\mathbf{W}_i, T_i, \lambda_{ii}) \triangleq \begin{bmatrix} \theta_i \mathbf{W}_i + \lambda_{ii}\mathbf{I} & \theta_i \mathbf{W}_i \hat{\mathbf{f}}_{ii} \\ \theta_i \Big(\mathbf{W}_i \hat{\mathbf{f}}_{ii}\Big)^H & \theta_i \hat{\mathbf{f}}_{ii}^H \mathbf{W}_i \hat{\mathbf{f}}_{ii} - T_i - \sigma_{Ui}^2 - \lambda_{ii}\varepsilon_{ii}^2 \end{bmatrix} \succeq \mathbf{0} \tag{9a}$$

$$\Psi_{il}(\mathbf{W}_l, t_{il}, \lambda_{il}) \triangleq \begin{bmatrix} -\mathbf{W}_l + \lambda_{il}\mathbf{I} & -\mathbf{W}_l \hat{\mathbf{f}}_{il} \\ \Big(-\mathbf{W}_l \hat{\mathbf{f}}_{il}\Big)^H & -\hat{\mathbf{f}}_{il}^H \mathbf{W}_l \hat{\mathbf{f}}_{il} + t_{il} - \lambda_{il}\varepsilon_{il}^2 \end{bmatrix} \succeq \mathbf{0}. \tag{9b}$$

It can be seen that the optimal p_i (denoted by $\tilde{p}_i$) is obtained when (8b) holds with equality, i.e.,

$$\tilde{p}_i = \frac{2^{\gamma_{Ri}} - 1}{\alpha_0^2}\Big\{\eta \mathbf{h}_{ii}^H \mathbf{W}_i \mathbf{h}_{ii} + \sum_{k=1, k\neq i}^{L} \mathbf{h}_{ik}^H \mathbf{W}_k \mathbf{h}_{ik} + \sigma_{Ri}^2\Big\} \tag{10}$$

Thus, problem (8) can be further simplified as the following SDP

$$\min_{\substack{\mathbf{W}_i \succeq \mathbf{0}, \\ \{\lambda_{il}\}_l \subset \mathbb{R}_+}} \sum_{i=1}^{L} \tilde{p}_i + \mathrm{Tr}\left(\mathbf{W}_i\right) \tag{11a}$$

$$\text{s.t.} \quad \Phi_i(\mathbf{W}_i, T_i, \lambda_{ii}) \succeq \mathbf{0}, \ \forall i \in \mathcal{I}_L \tag{11b}$$

$$\Psi_{il}(\mathbf{W}_l, t_{il}, \lambda_{il}) \succeq \mathbf{0}, \ \forall i, l \in \mathcal{I}_L, \ l \neq i \tag{11c}$$

Problem (11) is a convex optimization problem and is readily solved using off-the-shelf convex optimization software, e.g., CVX [16]. However, when the obtained optimal $\mathbf{W}_i^\star$ is of rank one (i.e., $\mathbf{W}_i^\star = \mathbf{w}_i^\star (\mathbf{w}_i^\star)^H$ for some $\mathbf{w}_i^\star \in \mathbb{C}^{N_t}, \ \forall i \in \mathcal{I}_L$), the obtained $\mathbf{w}_i^\star$ is optimal to the original problem (7). This is the case to problem (7) as stated in the proposition below without need of Gaussian randomization to find an approximate rank-one solution.

Proposition 1: *Suppose that the SDR problem* (11) *is feasible. Then, a rank-one solution* $(\mathbf{W}_i^\star = \mathbf{w}_i^\star (\mathbf{w}_i^\star)^H, \ \forall i \in \mathcal{I}_L)$ *to problem* (11) *exists.*

This proposition can be proven through the Karush-Kuhn-Tucker (KKT) conditions associated with problem (11) in a similar fashion to the proof for a worst-case multicell coordinated beamform design in [17]. However, the proof is omitted here due to space limitations.

3.2. Distributed Algorithm by ADMM

By interchanging the indices of i and l in $\Psi_{il}(\mathbf{W}_l, t_{il}, \lambda_{il})$ (cf. (9b)), the feasible set of problem (11) can be re-expressed in a more compact form needed for distributed implementation. To this end, we define the following convex constraint set associated with relay i:

$$\mathcal{C}_i = \Big\{(\mathbf{W}_i, \{\lambda_{li}\}_l, T_i, \{t_{li}\}_{l\neq i}) \mid \\ \Phi_i(\mathbf{W}_i, T_i, \lambda_{ii}) \succeq \mathbf{0}, \ \mathbf{W}_i \succeq \mathbf{0} \\ \Psi_{li}(\mathbf{W}_i, t_{li}, \lambda_{li}) \succeq \mathbf{0}, \ \lambda_{li} \geq 0, \ \forall l \in \mathcal{I}_L, \ l \neq i\Big\}, \ \forall i \in \mathcal{I}_L$$

Let

$$\mathbf{t} = [t_{12}, \ldots, t_{1L}, t_{21}, t_{23}, \ldots, t_{2L}, t_{L1}, \ldots, t_{L(L-1)}]^T \in \mathbb{R}_+^{L(L-1)}$$
$$\mathbf{t}_i = [T_i, t_{1i}, \ldots, t_{(i-1)i}, t_{(i+1)i}, \ldots, t_{Li}]^T \in \mathbb{R}_+^L, \ \forall i \in \mathcal{I}_L$$

Then it can be seen that there exists a matrix $\mathbf{E}_i \in \{0,1\}^{L\times L(L-1)}$, that satisfies $\mathbf{t}_i = \mathbf{E}_i \mathbf{t}, \ \forall i \in \mathcal{I}_L$. Moreover, $\mathbf{E}_i$ can be shown to be of full column rank, and $\sum_{i=1}^{L} \tilde{p}_i = \sum_{i=1}^{L} G_i$ where G_i is also given by (10) except that the indices i and k are interchanged in the summation term. Hence, problem (11) can be alternatively represented as:

$$\min \ \sum_{i=1}^{L} G_i + \mathrm{Tr}(\mathbf{W}_i) \tag{13a}$$

$$\text{s.t.} \ \mathcal{Z}_i \triangleq (\mathbf{W}_i, \{\lambda_{li}\}_l, \mathbf{t}_i) \in \mathcal{C}_i, \ \forall i \in \mathcal{I}_L \tag{13b}$$

$$\mathbf{t}_i = \mathbf{E}_i \mathbf{t}, \ \forall i \in \mathcal{I}_L \tag{13c}$$

To meet the convergence conditions of ADMM, we solve the following penalty terms augmented problem instead of (13) by introducing auxiliary variables $\rho_i \geq 0, i \in \mathcal{I}_L$.

$$\min \sum_{i=1}^{L} G_i + \mathrm{Tr}(\mathbf{W}_i) + \frac{c}{2}\|\mathbf{E}_i \mathbf{t} - \mathbf{t}_i\|^2 + \frac{c}{2}\big(\rho_i - \mathrm{Tr}(\mathbf{W}_i)\big)^2 \tag{14a}$$

$$\text{s.t.} \ \mathcal{Z}_i \in \mathcal{C}_i, \ \forall i \in \mathcal{I}_L \tag{14b}$$

$$\mathcal{X}_i \triangleq \Big(\mathbf{t} = \mathbf{E}_i^\dagger \mathbf{t}_i, \rho_i = \mathrm{Tr}(\mathbf{W}_i)\Big) \in \mathbb{R}_+^{L(L-1)+1}, \ \forall i \in \mathcal{I}_L \tag{14c}$$

where $c > 0$ is a preassigned parameter. The corresponding ADMM for solving (14) actually solves the dual optimization problem of (14), which is also a max-min problem defined as:

$$\max_{\substack{\boldsymbol{\nu}_i \in \mathbb{R}^L, \mu_i \in \mathbb{R} \\ \forall i \in \mathcal{I}_L}} \Big\{ \min_{\substack{\mathcal{Z}_i \in \mathcal{C}_i, \mathcal{X}_i \\ \forall i \in \mathcal{I}_L}} \sum_{j=1}^{L} g(\mathcal{Z}_j, \mathcal{X}_j, \boldsymbol{\nu}_j, \mu_j)\Big\} \tag{15}$$

where

$$g(\mathcal{Z}_j, \mathcal{X}_j, \boldsymbol{\nu}_j, \mu_j) \triangleq G_j + \mathrm{Tr}(\mathbf{W}_j) + \frac{c}{2}\|\mathbf{E}_j \mathbf{t} - \mathbf{t}_j\|^2 \\ + \frac{c}{2}\big(\rho_j - \mathrm{Tr}(\mathbf{W}_j)\big)^2 + \boldsymbol{\nu}_j^T(\mathbf{E}_j \mathbf{t} - \mathbf{t}_j) + \mu_j(\rho_j - \mathrm{Tr}(\mathbf{W}_j))$$

in which $\boldsymbol{\nu}_j \in \mathbb{R}^{L(L-1)}$ and $\mu_j \in \mathbb{R}$ are dual variables associated with (14c). The resulting distributed algorithm is summarized in Algorithm 1. In Algorithm 1, Steps 4-6 update the primal variables, $\mathcal{Z}_i$ and $\mathcal{X}_i$ by solving the inner minimization problem of (15). Specifically, Step 4 updates the primal variables $\mathcal{Z}_i$ by solving the following convex subproblem using CVX:

$$\mathcal{Z}_i(q+1) = \arg\min_{\mathcal{Z}_i \in \mathcal{C}_i} g\big(\mathcal{Z}_i, \mathcal{X}_i(q), \boldsymbol{\nu}_i(q), \mu_i(q)\big) \tag{16}$$

where q denotes the iteration number. Step 5 is interchange of the MUI information at each user among all the relays[1]. Step 6 solves the following quadratic convex subproblem:

$$\mathcal{X}_i(q+1) = \arg\min_{\mathcal{X}_i} \sum_{j=1}^{L} g\big(\mathcal{Z}_j(q+1), \mathcal{X}_i, \boldsymbol{\nu}_j(q), \mu_j(q)\big), \ \forall i \in \mathcal{I}_L \tag{17}$$

[1]In practical applications (e.g., ad-hoc networks), this information interchange can be achieved through broadcasting.

thereby yielding the closed-form solutions:

$$\mathbf{t}(q+1) = \mathbf{E}^{\dagger}\left(\tilde{\mathbf{t}}(q+1) - \tilde{\boldsymbol{\nu}}(q)/c\right) \quad (18a)$$

$$\rho_i(q+1) = \mathrm{Tr}(\mathbf{W}_i(q+1)) - \mu_i(q)/c, \ \forall i \in \mathcal{I}_L \quad (18b)$$

where $\tilde{\mathbf{t}}(q+1) = [\mathbf{t}_1^T(q+1), \ldots, \mathbf{t}_L^T(q+1)]^T$, $\tilde{\boldsymbol{\nu}}(q) = [\boldsymbol{\nu}_1^T(q), \ldots, \boldsymbol{\nu}_L^T(q)]^T$ and $\mathbf{E} \triangleq [\mathbf{E}_1^T, \ldots, \mathbf{E}_L^T]^T$. Step 7 is the outer maximization for updating the dual variables $\{\boldsymbol{\nu}_i, \mu_i\}$ by the subgradient method as follows:

$$\boldsymbol{\nu}_i(q+1) = \boldsymbol{\nu}_i(q) + c\left(\mathbf{E}_i\mathbf{t}(q+1) - \mathbf{t}_i(q+1)\right) \quad (19a)$$

$$\mu_i(q+1) = \mu_i(q) + c\big(\rho_i(q+1) - \mathrm{Tr}(\mathbf{W}_i(q+1))\big) \quad (19b)$$

It can be shown that, when problem (11) is feasible, every limit point of $\mathbf{W}_i(q+1), \forall i \in \mathcal{I}_L$ yielded by Algorithm 1 is an optimal solution of problem (11) [17], and meanwhile the obtained optimal $\mathbf{W}_i^{\star}$ is of rank one by Proposition 1.

Algorithm 1 ADMM for solving (11)

1: **Input** $\{\boldsymbol{\nu}_i(0), \mu_i(0), \mathbf{t}(0), \rho_i(0)\}$, $\forall i \in \mathcal{I}_L$, and $0 < c < 1$.
2: Set $q = 0$.
3: **repeat**
4: Relay i updates primal variables[2] $\mathcal{Z}_i(q+1)$ by solving problem (16) $\forall i \in \mathcal{I}_L$;
5: Relay i sends $\mathbf{t}_i(q+1)$ to all the other relays $\forall i \in \mathcal{I}_L$;
6: Relay i updates primal variables $\mathcal{X}_i(q+1)$ by (18a) and (18b) $\forall i \in \mathcal{I}_L$;
7: Relay i updates dual variables $\boldsymbol{\nu}_i(q+1)$ and $\mu_i(q+1)$ by (19a) and (19b), respectively, $\forall i \in \mathcal{I}_L$;
8: Set $q := q+1$;
9: Set $c := \min\{qc, 1\}$;
10: **until** the predefined stopping criterion is met.
11: **Output** optimal $\mathbf{W}_i^{\star} = \mathbf{W}_i(q+1)$ (yielded in Step 4) and the associated beamformer $\mathbf{w}_i^{\star}$, and optimal $p_i^{\star}$ by (10).

4. SIMULATION RESULTS AND CONCLUSIONS

The simulation settings are similar to those in [12]. Number of FDRs $L = 2$, BS antennas $N_B = 100$, and $N_t = 3$ transmit antennas and $N_r = 1$ receive antenna for each FDR; inter-FDR distance is 500 m, and the distance between BS and each FDR is 600 m; users' locations are random with distance to the serving FDR at least 35 m; channel estimates are randomly generated with complex Gaussian distribution and CSI error radius $\varepsilon_{il} = \varepsilon$, $\forall i \in \mathcal{I}_L$ (cf. (5)); noise variances at each relay and each user are identical to -92 dBm; the power level parameter of RSI $\eta = 0.1$; the required target rates at all the FDR and users are identical ($\gamma_{Ri} = \gamma_{Ui} = \gamma$). Simulation results (average total power) were obtained over 5000 channel realizations that are feasible to problem (7).

Fig. 2 shows the average power performance of the robust design (distributed results denoted by "◯" and "□" using Algorithm 1 and centralized results by "×" and "+" by solving (11)) versus target rate γ and that of the non-robust design (as if all channel estimates were perfect) (denoted by "△"). One can see that the latter outperforms the former; their power performances degrade with γ basically in a similar trend and the performance gap (around 2.8∼4.0 dBm for $\varepsilon = 0.05$ and 4.0∼6.0 dBm for $\varepsilon = 0.1$) is slightly larger for larger γ. Moreover, the distributed results and the centralized results are close to each other, justifying the efficacy of Algorithm 1.

[2] Step 4 also yields the optimal $\{\lambda_{li}(q+1)\}_l$, though it is not needed in the algorithm operation at each iteration.

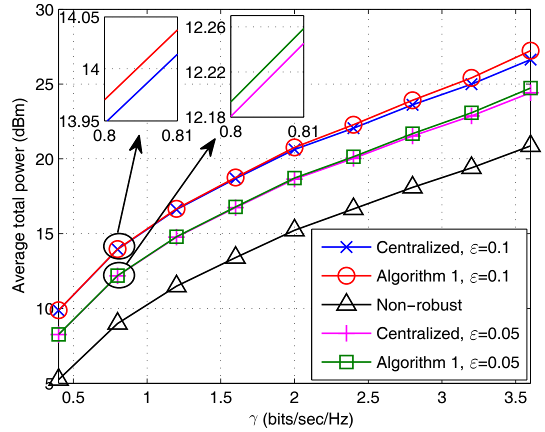

Fig. 2. Total transmit power (dBm) versus target rate γ for $N_B = 100$, $N_t = 3$, $N_r = 1$, $\eta = 0.1$, $\varepsilon = 0.1$

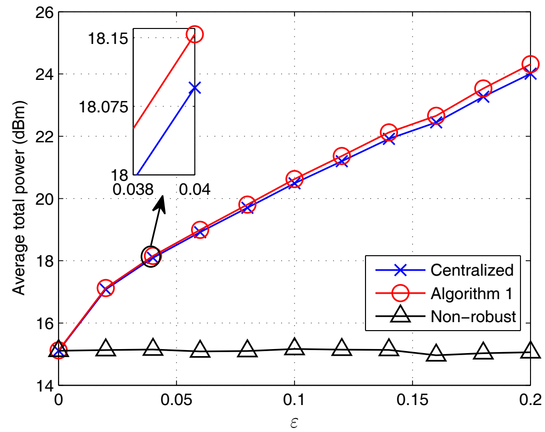

Fig. 3. Total transmit power (dBm) versus CSI error radius ε for $N_B = 100$, $N_t = 3$, $N_r = 1, \eta = 0.1,\ \gamma = 2$ bits/sec/Hz.

Fig. 3 shows the corresponding results versus ε for $\gamma = 2$ bits/sec/Hz. Again, one can observe that the distributed results using Algorithm 1 and the centralized results are close to each other, and their average power increases with CSI error radius ε, while the non-robust design nearly yields the same level (15 dBm) of total power for all ε. We would like to emphasize that though the non-robust design is more power efficient, most of the obtained solutions are not feasible to the required target rate (cf. (7b), (7c) and (7d)) due to CSI errors. For instance, its feasibility rate obtained by statistical testing is low as 28.64% for $\gamma = 2, \varepsilon = 0.2$, while the proposed robust design is 100% feasible in all the presented simulation results.

In conclusion, we have presented a distributed robust transmit beamforming design (Algorithm 1) for an FDR-aided wireless system (cf. Fig. 1), where BS is equipped with large scale antennas. The proposed algorithm is also an ADMM algorithm with convergence and optimal performance guarantee. Some simulation results were also provided to demonstrate its efficacy. However, to the best of our knowledge, there are no existing benchmark schemes for comparison. For the case of $N_r > 1$ (receive antennas) and/or multiple users served by each FDR, and the case of FDR operating in AF mode, the corresponding robust designs are left for future researches.

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