ROBUST BEAMFORMING WITH DECENTRALIZED INTERFERENCE COORDINATION IN COGNITIVE RADIO NETWORKS

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ABSTRACT

This paper considers an underlay cognitive radio network where primary and secondary networks coexist. The optimization target is to minimize the sum power of secondary transmitters while satisfying the worst case minimum SINR constraint for each secondary user (SU) and maximum aggregate interference constraint for each primary user (PU). Imperfect channel state information (CSI) is assumed, and the corresponding CSI errors are bounded by ellipsoids. We propose an alternating direction method of multipliers-based decentralized beamforming algorithm which relies only on local imperfect CSI and limited backhaul signaling. The convergence behavior of the proposed algorithm is studied via numerical examples.

Index Terms— Alternating direction method of multipliers, cognitive multi-cell beamforming, underlay cognitive radio systems.

1. INTRODUCTION

The utilization of the radio spectrum can be improved by using a well-known concept of cognitive radio (CR) [1–3]. The idea is that cognitive secondary users (SUs) are allowed to opportunistically utilize the bandwidth of licensed primary users (PUs). In many CR approaches, secondary network aims to exploit the unoccupied frequencies of the licensed band. However, higher spectrum efficiency is provided in underlay cognitive radio networks (CRNs) where the primary network allows the secondary network to access the occupied primary bandwidth, provided that the generated interference towards PUs is under tolerable threshold. Within this interference limitation, secondary network can optimize its own system performance. A wide range of algorithms has been recently proposed with various system optimization objectives and quality-of-service (QoS) requirements. Most of the algorithms aim to solve one of the following optimization targets: the maximization of weighted sum rate [4, 5], the maximization of weighted minimum rate/SINR [6, 7] and the minimization of sum transmission power with QoS constraints [8–14].

The aforementioned algorithms require perfect channel state information (CSI) in order to operate properly. In practice, CSI is imperfect, mainly due to errors in channel estimation and quantization. If the imperfections in the CSI are not taking into account in the beamforming design, it may cause significant performance degradation and violation of the QoS constraints. In the CR literature, CSI uncertainty is usually modeled by bounding all the error realizations with a known region (e.g., spherical or ellipsoidal) [15] or assuming that the error realizations are drawn from a known distribution [16]. Various cognitive beamforming problems with these error modeling approaches have been handled by either worst-case optimization [15, 17–24] or stochastic optimization [16, 22]. Single-cell and multi-cell CRNs were considered in [15–17, 19–22] and [18, 22–24], respectively. All these algorithms are centralized except the one in [23]. In general, decentralized algorithms are more practical than centralized ones due their potentially simpler network structure and reduced signaling/computational loads. In [23], the sum mean square error was minimized in underlay CRN with imperfect CSI between secondary transmitters and PUs. However, perfect CSI was assumed between secondary transmitters and SUs. The focus of this paper is on the sum power minimization via the worst-case optimization. Beamforming designs where this non-convex problem is reformulated as a convex one are proposed in [15, 20, 21, 24]. In [20], the problem is approximated conservatively leading to sub-optimal algorithms. In [15, 21, 24], the proposed algorithms use the standard semidefinite relaxation (SDR) method for the convex approximation. Global optimality is guaranteed for the cases when the solution of the approximated problem is rank-one. It was shown in [24] that rank-one solutions can be always guaranteed for the cognitive interference channel. Unfortunately, there are no decentralized robust algorithms proposed in the literature for the sum power minimization problem in multi-cell CRNs.

In this paper, we address this challenge by proposing a decentralized beamforming algorithm for multi-cell multiuser MISO CRNs where the CSI errors are bounded by ellipsoids. The non-convex problem is reformulated as a combined consensus and sharing problem, and then, approximated as a convex SDP. To solve this problem, we propose an alternating direction method of multipliers (ADMM)-based algorithm, which needs only local imperfect CSI at each transmitter and limited information exchange between transmitters via backhaul. If the optimal solution, provided by the proposed algorithm, is rank-one, it is also optimal for the original problem.

2. SYSTEM MODEL

Consider a CR system where a primary network with L PUs and a secondary network with K SUs coexist. Each user is equipped with a single antenna. Secondary network consists of B secondary transmitters, each equipped with T antennas. For simplicity of notation, the number of primary transmitters is not explicitly presented. Consequently, by writing "transmitter", we refer to the secondary transmitter. The sets of all secondary transmitters, SUs and PUs are denoted by $\mathcal{B}$, $\mathcal{K}$ and $\mathcal{L}$, respectively. Each SU is served by a single transmitter, and the serving transmitter for the SU k is denoted by b_k. SU association is assumed to be fixed. The set $\mathcal{K}_b$ with size $|\mathcal{K}_b| = K_b$ includes all the SUs served by its respective transmitter b. The received signal at the SU k is given by

$$\begin{aligned} r_k \quad &= \mathbf{h}_{b_k,k}\mathbf{m}_k s_k + \textstyle\sum_{i\in\mathcal{K}_{b_k}\setminus\{k\}} \mathbf{h}_{b_i,k}\mathbf{m}_i s_i + \\ &\textstyle\sum_{b\in\mathcal{B}\setminus\{b_k\}} \sum_{i\in\mathcal{K}_b} \mathbf{h}_{b,k}\mathbf{m}_i s_i + z_k \end{aligned} \qquad (1)$$

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where $\mathbf{m}_k \in \mathbb{C}^{T\times 1}$ and $s_k \in \mathbb{C}$ denote the beamforming vector and the data symbol with $\mathrm{E}[|s_k|^2] = 1$ for the SU k. The term $z_k \in \mathbb{C}$ with power σ_k^2 includes the additive noise and interference from primary network. The first, second and third terms in (1) are the desired signal, intra-cell and inter-cell interferences, respectively.

The channel vector from the transmitter b to the SU k is expressed as $\mathbf{h}_{b,k} = \hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k}, \forall b \in \mathcal{B}, \forall k \in \mathcal{K}$, where $\hat{\mathbf{h}}_{b,k} \in \mathbb{C}^{1\times T}$ and $\mathbf{u}_{b,k} \in \mathbb{C}^{1\times T}$ are the estimated channel at the transmitter and the CSI error, respectively. We assume that the CSI error is bounded by an ellipsoid [25]: $\mathcal{C}_{b,k} = \left\{\mathbf{u}_{b,k} : \mathbf{u}_{b,k}\mathbf{C}_{b,k}\mathbf{u}_{b,k}^{\mathrm{H}} \le 1\right\}$, $\forall b \in \mathcal{B}, \forall k \in \mathcal{K}$, where the positive definite matrix $\mathbf{C}_{b,k}$ is known at the transmitter b, and it determines the accuracy of the CSI by defining the shape and size of the bounding ellipsoid. The received SINR of the kth SU is given by $\Gamma_k = (\left|(\hat{\mathbf{h}}_{b_k,k} + \mathbf{u}_{b_k,k})\mathbf{m}_k\right|^2)/(\sigma_k^2 + \sum_{i\in\mathcal{K}_{b_k}\setminus\{k\}} \left|(\hat{\mathbf{h}}_{b_i,k} + \mathbf{u}_{b_i,k})\mathbf{m}_i\right|^2 + \sum_{b\in\mathcal{B}\setminus\{b_k\}} \chi_{b,k})$, where $\sum_{b\in\mathcal{B}\setminus\{b_k\}} \chi_{b,k}$ denotes the inter-cell interference caused by the secondary transmissions of other cells. The term $\chi_{b,k}$ denotes the inter-cell interference power from the transmitter b to the SU k, i.e., $\chi_{b,k} = \sum_{i\in\mathcal{K}_b} \left|(\hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k})\mathbf{m}_i\right|^2$. The previously introduced CSI uncertainty model is also used for the channel vectors from the secondary transmitters to the PU. In particular, the channel vector from the transmitter b to the PU l is given by $\mathbf{g}_{b,l} = \hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l}$, $\forall b \in \mathcal{B}$, $\forall l \in \mathcal{L}$, where $\hat{\mathbf{g}}_{b,k}$ and $\mathbf{v}_{b,l}$ are the estimated channel and the CSI error, respectively. Ellipsoid that bounds the CSI uncertainty is written as $\mathcal{D}_{b,l} = \left\{\mathbf{v}_{b,l} : \mathbf{v}_{b,l}\mathbf{D}_{b,l}\mathbf{v}_{b,l}^{\mathrm{H}} \le 1\right\}, \forall b \in \mathcal{B}, \forall l \in \mathcal{L}$, where $\mathbf{D}_{b,l} \succ 0$, and it is known at the transmitter. Each PU has a predefined maximum interference power level which the aggregate interference from the secondary network cannot exceed, i.e., $\Phi_l \ge \sum_{b\in\mathcal{B}} \phi_{b,l}, \forall l \in \mathcal{L}$, where $\phi_{b,l} = \sum_{i\in\mathcal{K}_b} \left|(\hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l})\,\mathbf{m}_i\right|^2$ denotes the interference power from the transmitter b to the PU l. The sum power of secondary network is given by $\sum_{b\in\mathcal{B}}\sum_{k\in\mathcal{K}_b} \mathrm{tr}(\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}})$.

3. PROBLEM FORMULATION

In this section, we first introduce the non-convex sum power minimization problem. Then, we equivalently rewrite the original problem in a form of combined consensus and sharing problem [26]. Lastly, the resulting problem is approximated as a tractable convex problem via SDR [25, 27] and S-procedure [27] methods. The optimization target is to minimize the sum power of secondary transmitters while satisfying the minimum SINR constraints of SUs $\{\gamma_k\}_{k\in\mathcal{K}}$ and the maximum aggregate interference power constraints of PUs $\{\Phi_l\}_{l\in\mathcal{L}}$. This problem can be written as

$$
\begin{aligned}
\min_{\substack{\{\mathbf{m}_k\}_{k\in\mathcal{K}},\\ \{\chi_{b,k}\}_{b\in\mathcal{B},k\in\bar{\mathcal{K}}_b},\\ \{\phi_{b,l}\}_{b\in\mathcal{B},l\in\mathcal{L}}}} \quad & \sum_{b\in\mathcal{B}}\sum_{k\in\mathcal{K}_b} \mathrm{tr}\left(\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}}\right)\\
\text{s. t.} \quad & \left(\hat{\mathbf{h}}_{b_k,k} + \mathbf{u}_{b_k,k}\right)\left(\tfrac{1}{\gamma_k}\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}} - \textstyle\sum_{i\in\mathcal{K}_{b_k}\setminus\{k\}} \mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\right)\\
& \left(\hat{\mathbf{h}}_{b_k,k} + \mathbf{u}_{b_k,k}\right)^{\mathrm{H}} \ge \sigma_k^2 + \textstyle\sum_{b\in\mathcal{B}\setminus\{b_k\}} \chi_{b,k},\\
& \forall k \in \mathcal{K}, \forall \mathbf{u}_{b_k,k} \in \mathcal{C}_{b_k,k}\\
& \textstyle\sum_{i\in\mathcal{K}_b} \left(\hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k}\right)\mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\left(\hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k}\right)^{\mathrm{H}} \le \chi_{b,k},\\
& \forall b \in \mathcal{B}, \forall k \in \bar{\mathcal{K}}_b, \forall \mathbf{u}_{b,k} \in \mathcal{C}_{b,k}\\
& \textstyle\sum_{i\in\mathcal{K}_b} \left(\hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l}\right)\mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\left(\hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l}\right)^{\mathrm{H}} \le \phi_{b,l},\\
& \forall b \in \mathcal{B}, \forall l \in \mathcal{L}, \forall \mathbf{v}_{b,l} \in \mathcal{D}_{b,l}\\
& \textstyle\sum_{b\in\mathcal{B}} \phi_{b,l} \le \Phi_l, \forall l \in \mathcal{L}.
\end{aligned} \tag{2}
$$

The set $\bar{\mathcal{K}}_b = \mathcal{K} \setminus \mathcal{K}_b$ consists of all the SUs except for those served by the transmitter b. In (2), the first three sets of constraints can be equivalently written as inequalities since they hold with equality at the optimal solution. The problem (2) is non-convex and has infinitely many constraints due to the CSI uncertainty.

3.1. Equivalently reformulated problem

In this subsection, the original problem (2) is equivalently rewritten as a combined consensus and sharing problem [26]. This is a key step for achieving a decentralized algorithm via ADMM in Section 4. First, we introduce $\tilde{\chi}_{b,k}^{b'}$ and $\tilde{\phi}_{b',l}$ as the local copies of $\chi_{b,k}$ and $\phi_{b',l}$ at the transmitter b', respectively. Note that each $\chi_{b,k}$ couples exactly two transmitters, i.e., the serving transmitter b_k and the interfering transmitter b. Whereas, each $\phi_{b,l}$ couples all the transmitters. Consequently, the aim of the reformulated problem is to enforce consensus between each pair of transmitter-level copies of $\tilde{\chi}_{b,k}^{b}$ and $\tilde{\chi}_{b,k}^{b_k}$, as well as, optimally share resources $\{\tilde{\phi}_{b,l}\}_{b\in\mathcal{B},l\in\mathcal{L}}$ between the transmitters. The resulting problem is expressed as

$$
\begin{aligned}
\min_{\substack{\{\mathbf{m}_k\}_{k\in\mathcal{K}},\\ \{\chi_{b,k}\}_{b\in\mathcal{B},k\in\bar{\mathcal{K}}_b},\\ \{\phi_{b,l},\tilde{\phi}_{b,l}\}_{b\in\mathcal{B},l\in\mathcal{L}},\\ \{\tilde{\chi}_{b,k}^{b'}\}_{b\in\mathcal{B},k\in\bar{\mathcal{K}}_b,\forall b'\in\{b_k,b\}}}} \quad & \sum_{b\in\mathcal{B}}\sum_{k\in\mathcal{K}_b} \mathrm{tr}\left(\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}}\right)\\
\text{s. t.} \quad & \left(\hat{\mathbf{h}}_{b_k,k} + \mathbf{u}_{b_k,k}\right)\left(\tfrac{1}{\gamma_k}\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}} - \textstyle\sum_{i\in\mathcal{K}_{b_k}\setminus\{k\}} \mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\right)\\
& \left(\hat{\mathbf{h}}_{b_k,k} + \mathbf{u}_{b_k,k}\right)^{\mathrm{H}} \ge \sigma_k^2 + \textstyle\sum_{b\in\mathcal{B}\setminus\{b_k\}} \tilde{\chi}_{b,k}^{b_k},\\
& \forall k \in \mathcal{K}, \forall \mathbf{u}_{b_k,k} \in \mathcal{C}_{b_k,k}\\
& \textstyle\sum_{i\in\mathcal{K}_b} \left(\hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k}\right)\mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\left(\hat{\mathbf{h}}_{b,k} + \mathbf{u}_{b,k}\right)^{\mathrm{H}} \le \tilde{\chi}_{b,k}^{b},\\
& \forall b \in \mathcal{B}, \forall k \in \bar{\mathcal{K}}_b, \forall \mathbf{u}_{b,k} \in \mathcal{C}_{b,k}\\
& \textstyle\sum_{i\in\mathcal{K}_b} \left(\hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l}\right)\mathbf{m}_i\mathbf{m}_i^{\mathrm{H}}\left(\hat{\mathbf{g}}_{b,l} + \mathbf{v}_{b,l}\right)^{\mathrm{H}} \le \phi_{b,l},\\
& \forall b \in \mathcal{B}, \forall l \in \mathcal{L}, \forall \mathbf{v}_{b,l} \in \mathcal{D}_{b,l}\\
& \textstyle\sum_{b\in\mathcal{B}} \phi_{b,l} \le \Phi_l, \forall l \in \mathcal{L}\\
& \tilde{\chi}_{b,k}^{b'} = \chi_{b,k}, \forall b \in \mathcal{B}, \forall k \in \bar{\mathcal{K}}_b, \forall b' \in \{b_k, b\}\\
& \tilde{\phi}_{b,l} = \phi_{b,l}, \forall b \in \mathcal{B}, \forall l \in \mathcal{L}.
\end{aligned} \tag{3}
$$

3.2. Approximated problem

The problem (3) can be turned into a tractable convex form by using the standard SDR and S-procedure methods [24, 25, 28]. Using the SDR [25], (3) is approximated as an SDP by replacing the rank-one matrix $\mathbf{m}_k\mathbf{m}_k^{\mathrm{H}}$ by a semidefinite matrix $\mathbf{Q}_k$ without a rank-one constraint. The resulting problem is still intractable due to the infinite number of constraints. Since the constraints are quadratic w.r.t. the corresponding CSI error vectors, the S-Procedure [27] can be applied to equivalently reformulate these constraints as linear matrix inequalities (LMIs) [24]. Further details on this derivation can be found in [24]. The resulting problem is a tractable convex SDP

$$
\begin{aligned}
\min_{\substack{\{\mathbf{Q}_k,\alpha_k\}_{k\in\mathcal{K}},\\ \{\chi_{b,k},\beta_{b,k}\}_{b\in\mathcal{B},k\in\bar{\mathcal{K}}_b},\\ \{\phi_{b,l},\tilde{\phi}_{b,l},\delta_{b,l}\}_{b\in\mathcal{B},l\in\mathcal{L}},\\ \{\tilde{\chi}_{b,k}^{b'}\}_{b\in\mathcal{B},k\in\bar{\mathcal{K}}_b,\forall b'\in\{b_k,b\}}}} \quad & \sum_{b\in\mathcal{B}}\sum_{k\in\mathcal{K}_b} \mathrm{tr}\left(\mathbf{Q}_k\right)\\
\text{s. t.} \quad & \mathbf{Q}_k \succeq 0, \mathbf{\Delta}_k \succeq 0, \alpha_k \ge 0, \forall b \in \mathcal{B}, \forall k \in \mathcal{K}_b\\
& \mathbf{\Theta}_{b,k} \succeq 0, \beta_{b,k} \ge 0, \forall b \in \mathcal{B}, \forall k \in \bar{\mathcal{K}}_b\\
& \mathbf{\Lambda}_{b,l} \succeq 0, \delta_{b,l} \ge 0, \forall b \in \mathcal{B}, \forall l \in \mathcal{L}\\
& \textstyle\sum_{b\in\mathcal{B}} \phi_{b,l} \le \Phi_l, \forall l \in \mathcal{L}\\
& \tilde{\chi}_{b,k}^{b'} = \chi_{b,k}, \forall b \in \mathcal{B}, \forall k \in \bar{\mathcal{K}}_b, \forall b' \in \{b_k, b\}\\
& \tilde{\phi}_{b,l} = \phi_{b,l}, \forall b \in \mathcal{B}, \forall l \in \mathcal{L}
\end{aligned} \tag{4}
$$

where the matrixes $\mathbf{\Delta}_k$, $\mathbf{\Theta}_{b,k}$ and $\mathbf{\Lambda}_{b,l}$ are denoted by

$$\mathbf{\Delta}_k \triangleq \begin{bmatrix} \mathbf{A}_k + \alpha_k \mathbf{C}_{b_k,k} & \mathbf{A}_k \hat{\mathbf{h}}_{b_k,k}^{\mathrm{H}} \\ \hat{\mathbf{h}}_{b_k,k} \mathbf{A}_k & \hat{\mathbf{h}}_{b_k,k} \mathbf{A}_k \hat{\mathbf{h}}_{b_k,k}^{\mathrm{H}} - \sum_{b' \in \mathcal{B} \setminus b_k} \tilde{\chi}_{b',k}^{b_k} - \sigma_k^2 - \alpha_k \end{bmatrix} \tag{5}$$

$$\mathbf{\Theta}_{b,k} \triangleq \begin{bmatrix} -\mathbf{B}_b + \beta_{b,k} \mathbf{C}_{b,k} & -\mathbf{B}_b \hat{\mathbf{h}}_{b,k}^{\mathrm{H}} \\ -\hat{\mathbf{h}}_{b,k} \mathbf{B}_b & -\hat{\mathbf{h}}_{b,k} \mathbf{B}_b \hat{\mathbf{h}}_{b,k}^{\mathrm{H}} + \tilde{\chi}_{b,k}^{b} - \beta_{b,k} \end{bmatrix} \tag{6}$$

$$\mathbf{\Lambda}_{b,l} \triangleq \begin{bmatrix} -\mathbf{B}_b + \delta_{b,l} \mathbf{D}_{b,l} & -\mathbf{B}_b \hat{\mathbf{g}}_{b,l}^{\mathrm{H}} \\ -\hat{\mathbf{g}}_{b,l} \mathbf{B}_b & -\hat{\mathbf{g}}_{b,l} \mathbf{B}_b \hat{\mathbf{g}}_{b,l}^{\mathrm{H}} + \tilde{\phi}_{b,l} - \delta_{b,l} \end{bmatrix} \tag{7}$$

where $\mathbf{A}_k \triangleq \frac{1}{\gamma_k} \mathbf{Q}_k - \sum_{i \in \mathcal{K}_{b_k} \setminus \{k\}} \mathbf{Q}_i$ and $\mathbf{B}_b \triangleq \sum_{i \in \mathcal{K}_b} \mathbf{Q}_i$. The sets $\{\alpha_k\}_{k \in \mathcal{K}}$, $\{\beta_{b,k}\}_{b \in \mathcal{B}, k \in \bar{\mathcal{K}}_b}$ and $\{\delta_{b,l}\}_{b \in \mathcal{B}, l \in \mathcal{L}}$ consist of slack variables. If global imperfect CSI is available, (4) can be optimally solved using an SDP solver. If the optimal $\{\mathbf{Q}_k\}_{k \in \mathcal{K}}$ are all rank-one (i.e., the SDR is tight), then the solution of the relaxed problem (4) is also globally optimal for the original non-convex problem (2). In general, the solution of (4) cannot be guaranteed to be rank-one. However, it was shown in [24] that rank-one solutions can always be achieved in a cognitive interference channel (i.e., each transmitter serves only a single user). In case the solution of (4) is higher-rank, a feasible rank-one solution may be achieved via approximation methods [28]. For example, a simple approximation method in [7] can be extended for (4). In the rest of the paper, only local imperfect CSI is assumed to be available.

4. DECENTRALIZED BEAMFORMING DESIGN

In this section, we propose an ADMM-based decentralized algorithm to solve the combined consensus and sharing problem (4). In general, ADMM can combine the decomposability of dual decomposition and the convergence properties of the method of multipliers [26]. In particular, ADMM can converge under more general conditions than dual decomposition, e.g., without the requirements of strict convexity or finiteness of the objective function [26].

For simplicity of notation, we first write (4) in a compact form:

$$\begin{array}{ll} \underset{\{\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b, \boldsymbol{\chi}_b, \boldsymbol{\phi}_b\}_{b \in \mathcal{B}}}{\min.} & \sum_{b \in \mathcal{B}} f_b\left(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b\right) \\ \text{s. t.} & \tilde{\boldsymbol{\chi}}_b = \boldsymbol{\chi}_b, \forall b \in \mathcal{B} \\ & \tilde{\boldsymbol{\phi}}_b = \boldsymbol{\phi}_b, \forall b \in \mathcal{B} \\ & \sum_{b \in \mathcal{B}} \phi_{b,l} \leq \Phi_l, \forall l \in \mathcal{L}. \end{array} \tag{8}$$

We have collected all the optimization variables into transmitter b specific matrixes and vectors: $\bar{\mathbf{Q}}_b = [\mathbf{Q}_{\mathcal{K}_b(1)}, \ldots, \mathbf{Q}_{\mathcal{K}_b(K_b)}]$, $\tilde{\boldsymbol{\phi}}_b = [\tilde{\phi}_{b,\mathcal{L}(1)}, \ldots, \tilde{\phi}_{b,\mathcal{L}(L)}]^{\mathrm{T}}$, $\boldsymbol{\phi}_b = [\phi_{b,\mathcal{L}(1)}, \ldots, \phi_{b,\mathcal{L}(L)}]^{\mathrm{T}}$, $\bar{\mathbf{F}}_b = [\boldsymbol{\alpha}_b, \boldsymbol{\beta}_b, \boldsymbol{\delta}_b]$, $\boldsymbol{\alpha}_b = [\alpha_{\mathcal{K}_b(1)}, \ldots, \alpha_{\mathcal{K}_b(K_b)}]^{\mathrm{T}}$, $\boldsymbol{\beta}_b = [\beta_{b,\bar{\mathcal{K}}_b(1)}, \ldots, \beta_{b,\bar{\mathcal{K}}_b(|\bar{\mathcal{K}}_b|)}]^{\mathrm{T}}$, $\boldsymbol{\delta}_b = [\delta_{b,\mathcal{L}(1)}, \ldots, \delta_{b,\mathcal{L}(L)}]^{\mathrm{T}}$. The elements of the vector $\tilde{\boldsymbol{\chi}}_b$ are taken from the sets $\{\tilde{\chi}_{b',k}^{b}\}_{b' \in \mathcal{B} \setminus \{b_k\}, k \in \mathcal{K}_b}$ and $\{\tilde{\chi}_{b,k}^{b}\}_{k \in \bar{\mathcal{K}}_b}$ in a specific order. Similarly, the vector $\boldsymbol{\chi}_b$ is composed of the sets $\{\chi_{b',k}\}_{b' \in \mathcal{B} \setminus \{b_k\}, k \in \mathcal{K}_b}$ and $\{\chi_{b,k}\}_{k \in \bar{\mathcal{K}}_b}$ using the same ordering. The function f_b is defined as

$$f_b\left(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b\right) = \begin{cases} \sum_{k \in \mathcal{K}_b} \operatorname{tr}(\mathbf{Q}_k), & \left(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b\right) \in \mathcal{S}_b \\ \infty, & \text{otherwise.} \end{cases} \tag{9}$$

The set $\mathcal{S}_b$ is defined as

$$\mathcal{S}_b = \left\{ \bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b \;\middle|\; \begin{array}{l} \mathbf{Q}_k \succeq 0, \mathbf{\Delta}_k \succeq 0, \alpha_k \geq 0, \\ \forall k \in \mathcal{K}_b \\ \mathbf{\Theta}_{b,k} \succeq 0, \beta_{b,k} \geq 0, \forall k \in \bar{\mathcal{K}}_b \\ \mathbf{\Lambda}_{b,l} \succeq 0, \delta_{b,l} \geq 0, \forall l \in \mathcal{L} \end{array} \right\}. \tag{10}$$

The first step in ADMM is to write the augmented Lagrangian [26]. The (partial) augmented Lagrangian for (8) is given by

$$\begin{aligned} & L_\rho\left(\left\{\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b, \boldsymbol{\chi}_b, \boldsymbol{\phi}_b, \boldsymbol{\mu}_b, \boldsymbol{\nu}_b\right\}_{b \in \mathcal{B}}\right) \\ & = \textstyle\sum_{b \in \mathcal{B}} \Big(f_b(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b) + \boldsymbol{\mu}_b^{\mathrm{T}}(\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b) \\ & + \boldsymbol{\nu}_b^{\mathrm{T}}(\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b) + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b\big\|_2^2 + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b\big\|_2^2 \Big) \end{aligned} \tag{11}$$

where $\boldsymbol{\mu}_b$ and $\boldsymbol{\nu}_b$ are the dual variables associated with the interference equality constraints of (8). The last two terms of (11) are quadratic penalty terms with penalty parameter $\rho > 0$, and they penalize for the violation of the equality constraints of (8). The augmented Lagrangian (11) can be seen as a standard Lagrangian of (8) where the quadratic penalty terms are added to the objective function. Due to the added penalty terms, ADMM is able to converge without the need of strict convexity or finiteness of the original objective function of (8). ADMM operates iteratively via the following steps: 1) update of local primal variables, 2) update of global primal variables and 3) update of local dual variables. At iteration $t+1$, these steps are given by

$$\begin{aligned} & \bar{\mathbf{Q}}_b^{t+1}, \tilde{\boldsymbol{\chi}}_b^{t+1}, \tilde{\boldsymbol{\phi}}_b^{t+1}, \bar{\mathbf{F}}_b^{t+1} \\ & = \underset{\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b}{\operatorname{argmin}} \; L_\rho(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b, \boldsymbol{\chi}_b^t, \boldsymbol{\phi}_b^t, \boldsymbol{\mu}_b^t, \boldsymbol{\nu}_b^t), \forall b \in \mathcal{B} \end{aligned} \tag{12}$$

$$\begin{aligned} & \{\boldsymbol{\chi}_b^{t+1}, \boldsymbol{\phi}_b^{t+1}\}_{b \in \mathcal{B}} \\ & = \underset{\{\boldsymbol{\chi}_b, \boldsymbol{\phi}_b\}_{b \in \mathcal{B}}}{\operatorname{argmin}} \; L_\rho(\{\bar{\mathbf{Q}}_b^{t+1}, \tilde{\boldsymbol{\chi}}_b^{t+1}, \tilde{\boldsymbol{\phi}}_b^{t+1}, \bar{\mathbf{F}}_b^{t+1}, \boldsymbol{\chi}_b, \boldsymbol{\phi}_b, \boldsymbol{\mu}_b^t, \boldsymbol{\nu}_b^t\}_{b \in \mathcal{B}}) \end{aligned} \tag{13}$$

$$\boldsymbol{\mu}_b^{t+1} = \boldsymbol{\mu}_b + \rho(\tilde{\boldsymbol{\chi}}_b^{t+1} - \boldsymbol{\chi}_b^{t+1}), \forall b \in \mathcal{B} \tag{14}$$

$$\boldsymbol{\nu}_b^{t+1} = \boldsymbol{\nu}_b + \rho(\tilde{\boldsymbol{\phi}}_b^{t+1} - \boldsymbol{\phi}_b^{t+1}), \forall b \in \mathcal{B}. \tag{15}$$

The steps (12), (14) and (15) are separable between transmitters, and thus, they can be solved independently in parallel at each transmitter. The step (13) needs network-level coordination, i.e., information exchange between transmitters via backhaul. In particular, transmitter b signals the local copies $\tilde{\boldsymbol{\chi}}_b^{t+1}$ and $\tilde{\boldsymbol{\phi}}_b^{t+1}$ to the coupled transmitters. Next, we explain how to optimally solve the steps (12) and (13).

The local primal variables in (12) are updated by solving the following problem

$$\begin{aligned} \underset{\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b}{\min.} \quad & f_b(\bar{\mathbf{Q}}_b, \tilde{\boldsymbol{\chi}}_b, \tilde{\boldsymbol{\phi}}_b, \bar{\mathbf{F}}_b) + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b^t + \mathbf{v}_b^t\big\|_2^2 \\ & + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b^t + \mathbf{w}_b^t\big\|_2^2. \end{aligned} \tag{16}$$

For simplicity of presentation, we have used the scaled ADMM formulation [26] in (16) by combining the linear and quadratic terms of (11): $(\boldsymbol{\mu}_b^t)^{\mathrm{T}}(\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b^t) + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b^t\big\|_2^2 = \frac{\rho}{2}\big\|\tilde{\boldsymbol{\chi}}_b - \boldsymbol{\chi}_b^t + \mathbf{v}_b^t\big\|_2^2 - \frac{\rho}{2}\big\|\mathbf{v}_b^t\big\|_2^2$ and $(\boldsymbol{\nu}_b^t)^{\mathrm{T}}(\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b^t) + \frac{\rho}{2}\big\|\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b^t\big\|_2^2 = \frac{\rho}{2}\big\|\tilde{\boldsymbol{\phi}}_b - \boldsymbol{\phi}_b^t + \mathbf{w}_b^t\big\|_2^2 - \frac{\rho}{2}\big\|\mathbf{w}_b^t\big\|_2^2$, where $\mathbf{v}_b^t = \frac{1}{\rho}\boldsymbol{\mu}_b^t$ and $\mathbf{w}_b^t = \frac{1}{\rho}\boldsymbol{\nu}_b^t$. The last constant terms were dropped from (16) since they do not have any impact on finding the optimal points. The problem (16) can be recast as an SDP via the following steps. After writing (16) in the epigraph form [27], the resulting quadratic constraint

$\sum_{k\in\mathcal{K}_b}\mathrm{tr}\left(\mathbf{Q}_k\right)+\frac{\rho}{2}\left\|\tilde{\boldsymbol{\chi}}_b-\boldsymbol{\chi}_b^t+\mathbf{v}_b^t\right\|_2^2+\frac{\rho}{2}\left\|\tilde{\boldsymbol{\phi}}_b-\boldsymbol{\phi}_b^t+\mathbf{w}_b^t\right\|_2^2-q_b\leq 0$ can be reformulated as an SOC constraint [29]: $\|\mathbf{y}_b\|_2 \leq x_b$, where $\mathbf{y}_b = [(1+(\sum_{k\in\mathcal{K}_b}\mathrm{tr}\left(\mathbf{Q}_k\right)-q_b))/2, \sqrt{\frac{\rho}{2}}(\tilde{\boldsymbol{\chi}}_b-\boldsymbol{\chi}_b^t+\mathbf{v}_b^t)^{\mathrm{T}}, \sqrt{\frac{\rho}{2}}(\tilde{\boldsymbol{\phi}}_b-\boldsymbol{\phi}_b^t+\mathbf{w}_b^t)^{\mathrm{T}}]^{\mathrm{T}}$ and $x_b = (1-(\sum_{k\in\mathcal{K}_b}\mathrm{tr}\left(\mathbf{Q}_k\right)-q_b))/2$. Now the SOC constraint can be written as a linear matrix inequality (LMI) form [30]. The optimal points $\bar{\mathbf{Q}}_b^\star$, $\tilde{\boldsymbol{\chi}}_b^\star$ and $\tilde{\boldsymbol{\phi}}_b^\star$ are found by solving the resulting SDP

$$\begin{array}{ll}\underset{\bar{\mathbf{Q}}_b,\tilde{\boldsymbol{\chi}}_b,\tilde{\boldsymbol{\phi}}_b,\bar{\mathbf{F}}_b,q_b}{\min.} & q_b \\ \text{s. t.} & \begin{bmatrix} x_b & \mathbf{y}_b^{\mathrm{H}} \\ \mathbf{y}_b & x_b\mathbf{I}\end{bmatrix}\succeq 0, \forall k\in\mathcal{K}_b \\ & \mathbf{Q}_k\succeq 0, \boldsymbol{\Delta}_k\succeq 0, \alpha_k\geq 0, \forall k\in\mathcal{K}_b \\ & \boldsymbol{\Theta}_{b,k}\succeq 0, \beta_{b,k}\geq 0, \forall k\in\bar{\mathcal{K}}_b \\ & \boldsymbol{\Lambda}_{b,l}\succeq 0, \delta_{b,l}\geq 0, \forall l\in\mathcal{L}.\end{array} \tag{17}$$

Now the local primal variables can be updated: $\bar{\mathbf{Q}}_b^{t+1} = \bar{\mathbf{Q}}_b^\star$, $\tilde{\boldsymbol{\chi}}_b^{t+1} = \tilde{\boldsymbol{\chi}}_b^\star$ and $\tilde{\boldsymbol{\phi}}_b^{t+1} = \tilde{\boldsymbol{\phi}}_b^\star$.

The global primal variables in (13) are updated with the optimal points of the following problem

$$\begin{array}{ll}\underset{\{\boldsymbol{\chi}_b,\boldsymbol{\phi}_b\}_{b\in\mathcal{B}}}{\min.} & \sum_{b\in\mathcal{B}}\Big((\boldsymbol{\mu}_b^t)^{\mathrm{T}}(\tilde{\boldsymbol{\chi}}_b^{t+1}-\boldsymbol{\chi}_b)+\frac{\rho}{2}\left\|\tilde{\boldsymbol{\chi}}_b^{t+1}-\boldsymbol{\chi}_b\right\|_2^2 \\ & +(\boldsymbol{\nu}_b^t)^{\mathrm{T}}(\tilde{\boldsymbol{\phi}}_b^{t+1}-\boldsymbol{\phi}_b)+\dfrac{\rho}{2}\|\tilde{\boldsymbol{\phi}}_b^{t+1}-\boldsymbol{\phi}_b\|_2^2\Big) \\ \text{s. t.} & \sum_{b\in\mathcal{B}^{\mathrm{S}}}\phi_{b,l}\leq\Phi_l, \forall l\in\mathcal{L}.\end{array} \tag{18}$$

Since the objective and constraint functions of (18) are separable in $\boldsymbol{\chi}_b$ and $\boldsymbol{\phi}_b$, these variables can be solved independently. Since the optimization problem is unconstrained and quadratic in $\boldsymbol{\chi}_b$, the optimal point $\boldsymbol{\chi}_b^\star$ is found by setting the gradient of (18) w.r.t. $\boldsymbol{\chi}_b$ to zero. The resulting solution is expressed in component wise as

$$\chi_{b,k}^\star = \frac{1}{2}\left(\tilde{\chi}_{b,k}^{b,t+1}+\tilde{\chi}_{b,k}^{b_k,t+1}+\frac{1}{\rho}(\mu_{b,k}^{b,t}+\mu_{b,k}^{b_k,t})\right) \tag{19}$$

and the update is $\chi_{b,k}^{t+1} = \chi_{b,k}^\star$. Note that $\mu_{b,k}^{b,t}+\mu_{b,k}^{b_k,t} = 0$ by substituting $\chi_{b,k}^{t+1}$ in (14). Hence, $\chi_{b,k}^{t+1}$-update simplifies to $\chi_{b,k}^{t+1} = 1/2(\tilde{\chi}_{b,k}^{b,t+1}+\tilde{\chi}_{b,k}^{b_k,t+1})$. The optimal point $\boldsymbol{\phi}_b^\star$ is found by solving the following convex quadratic optimization problem

$$\begin{array}{ll}\underset{\{\boldsymbol{\phi}_b\}_{b\in\mathcal{B}}}{\min.} & \sum_{b\in\mathcal{B}}\Big((\boldsymbol{\nu}_b^t)^{\mathrm{T}}(\tilde{\boldsymbol{\phi}}_b^{t+1}-\boldsymbol{\phi}_b)+\frac{\rho}{2}\left\|\tilde{\boldsymbol{\phi}}_b^{t+1}-\boldsymbol{\phi}_b\right\|_2^2\Big) \\ \text{s. t.} & \sum_{b\in\mathcal{B}}\phi_{b,l}\leq\Phi_l, \forall l\in\mathcal{U}^{\mathrm{P}}.\end{array} \tag{20}$$

The update is $\boldsymbol{\phi}_b^{t+1} = \boldsymbol{\phi}_b^\star$. Using the updated primal variables, the local dual variables can be updated as presented in (14) and (15). Finally, the proposed decentralized ADMM-based beamforming approach is summarized in *Algorithm 1*.

With the standard assumptions for ADMM [26], *Algorithm 1* converges to the optimal solution of (8). Note that *Algorithm 1* does not necessarily provide a feasible beamforming solution for the original primal problem (8) at intermediate iterations. This is due to an inherent characteristic of the ADMM that the local copies of the optimization variables, i.e., the interference terms, are not necessarily required to be equal at intermediate iterations leading to a violation of the QoS constraints. However, a feasible set of beamformers may be achieved at each iteration by enforcing consistency between the local interference values. This can be done by fixing $\tilde{\boldsymbol{\chi}}_b = \boldsymbol{\chi}_b$ and $\tilde{\boldsymbol{\phi}}_b = \boldsymbol{\phi}_b$, and solving (17) at the transmitter b, $\forall b\in\mathcal{B}$. At a cost of sub-optimal performance, *Algorithm 1* can be stopped at any (primal) feasible iterate to reduce delay and signaling/computational load. If the optimal solution of *Algorithm 1* is rank-one, it is also globally optimal for the original non-convex problem (2).

Algorithm 1 ADMM-based decentralized beamformer design

1: Set $t = 0$, $\boldsymbol{\mu}_b^0 = 0$, $\boldsymbol{\chi}_b^0 = 0$, $\boldsymbol{\nu}_b^0 = 0$ and $\boldsymbol{\phi}_b^0 = 0$.
2: **repeat**
3: Transmitter $b, \forall b\in\mathcal{B}$: Update local primal variables $\bar{\mathbf{Q}}_b^{t+1} = \bar{\mathbf{Q}}_b^\star$, $\tilde{\boldsymbol{\chi}}_b^{t+1} = \tilde{\boldsymbol{\chi}}_b^\star$ and $\tilde{\boldsymbol{\phi}}_b^{t+1} = \tilde{\boldsymbol{\phi}}_b^\star$ by solving (17).
4: Transmitter $b, \forall b\in\mathcal{B}$: Signal local copies $\tilde{\boldsymbol{\chi}}_b^{t+1}$ and $\tilde{\boldsymbol{\phi}}_b^{t+1}$ to the coupled transmitters via backhaul links.
5: Transmitter $b, \forall b\in\mathcal{B}$: Update global primal variables $\boldsymbol{\chi}_b^{t+1} = \boldsymbol{\chi}_b^\star$ and $\boldsymbol{\phi}_b^{t+1} = \boldsymbol{\phi}_b^\star$ via (19) and (20), respectively.
6: Transmitter $b, \forall b\in\mathcal{B}$: Update local dual variables $\boldsymbol{\mu}_b^{t+1}$ and $\boldsymbol{\nu}_b^{t+1}$ by solving (14) and (15), respectively. Set $t = t+1$.
7: **until** stopping criterion is satisfied

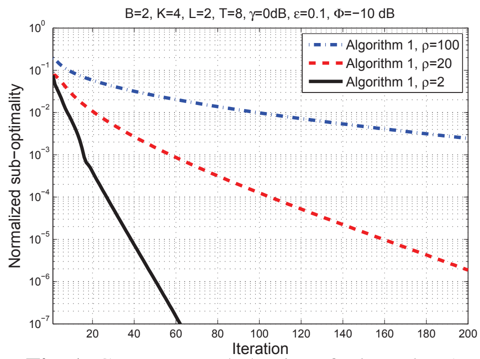

Fig. 1. Convergence behavior of *Algorithm 1*.

5. SIMULATION RESULTS

In this section, the performance of *Algorithm 1* is evaluated via numerical examples. The simulation model consists of $B = 2$ secondary transmitters, $K = 4$ SUs and $L = 2$ PUs. Each secondary transmitter serves a predefined set of two SUs. Each user is equipped with a single antenna, and each transmitter with $T = 8$ antennas. Each channel realization is uncorrelated and Rayleigh faded. The CSI errors are bounded by spherical regions, i.e., $\mathbf{C}_{b,k} = \left(1/\epsilon^2\right)\mathbf{I}_T$ and $\mathbf{D}_{b,l} = \left(1/\epsilon^2\right)\mathbf{I}_T$, $\forall b\in\mathcal{B}, \forall k\in\mathcal{K}, \forall l\in\mathcal{L}$, and $\epsilon = 0.1$. The SINR and interference constraints are: $\gamma_k = \gamma = 0$ dB, $\forall k\in\mathcal{K}$ and $\Phi_l = \Phi = -10$ dB, $\forall l\in\mathcal{L}$. The power of z_k is set to 1 for each SU, i.e., $\sigma_k^2 = \sigma^2 = 1$, $\forall k\in\mathcal{K}$. Fig. 1 illustrates the normalized sub-optimality of *Algorithm 1* as a function of iteration t. The normalized sub-optimality is defined as $\left(d^t - d^\star\right)/d^\star$, where d^t and $d^\star$ denote the value of the objective function at iteration t in *Algorithm 1* and the optimal objective value achieved by solving the centralized problem (4), respectively. Results demonstrate that the speed of convergence depends heavily on the choice of penalty parameter ρ. One can see that with $\rho = 2$ convergence is relatively fast. In Fig. 1, all the converged optimal solutions are rank-one, and thus, they are also globally optimal for the original problem (2).

6. CONCLUSIONS

In this paper, we proposed an ADMM-based decentralized robust algorithm for the sum power minimization in a cognitive multi-cell multiuser MISO network. In the proposed algorithm, each transmitter solves its corresponding optimization problems independently in parallel relying only on local imperfect CSI and limited backhaul signaling between transmitters. Numerical examples demonstrated relatively fast convergence for the proposed decentralized algorithm.

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