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Worst-case robust energy harvesting maximization in cellular networks

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Dear editor,

Wireless energy harvesting (EH) is considered as a promising approach to achieve power self-sustainability in energy restricted communications. In literature, most studies on wireless EH communications focused on the design of power minimization (PM) or rate maximization subject to EH constraints. In a different perspectives, recent studies investigated EH maximization (EHM) for MISO system [1], cognitive radio network [2], outage constrained secure MIMO systems [3], and MISO channels [4]. In these studies, Refs. [1, 2] considered perfect channel state information (CSI) and Refs. [3, 4] considered imperfect CSI with Gaussian CSI errors caused by noisy channel estimation.

In this study, we consider EHM for multi-cell system under bounded CSI uncertainties resulted from the quantization introduced error. In each cell, there are a group of EH mobile stations (MS) and another group of information receiver (IR) MS. The system is designed to maximize the harvested energy at EH MS subject to the constraints of the signal to interference-plus-noise ratio (SINR) at IR MS. The contribution of the letter lies in the design on EHM for an unexplored scenario of multi-cell networks inflicting bounded CSI uncertainties by using the well-established worst-case robust optimization algorithm and primal decomposition based decentralized method.

Notations. $\mathcal{C}^N$ and $\mathcal{H}^N$ denote the sets of N-dimensional complex vectors and Hermitian matrices, respectively. $\mathcal{CN}(0,\sigma^2)$ denotes the complex Gaussian distribution with zero mean and variance σ^2. $\mathcal{B} \triangleq \{1,\ldots,B\}$, $\mathcal{N} \triangleq \{1,\ldots,N\}$, $\mathcal{K} \triangleq \{1,\ldots,K\}$, for positive integers B, N, K.

System model. The multi-cell system consists of B coordinated base stations (BS) with each one equipped with $N_{\rm T}$ transmit antennas. In each cell, there are K IR MSs and N EH MSs with single antenna. The received signals at IR MS k and EH MS n in cell b are respectively given by

$$y_{{\rm I},bk} = \sum_{d=1}^{B}\sum_{j=1}^{K} \boldsymbol{h}_{dbk}^{\rm H}\boldsymbol{w}_{dj}x_{dj} + z_{{\rm I},bk}, \quad (1)$$

$$y_{{\rm E},bn} = \sum_{d=1}^{B}\sum_{j=1}^{K} \boldsymbol{g}_{dbn}^{\rm H}\boldsymbol{w}_{dj}x_{dj} + z_{{\rm E},bn}, \quad (2)$$

where $\boldsymbol{w}_{dj} \in \mathcal{C}^{N_{\rm T}}$ and $x_{dj} \in \mathcal{CN}(0,1)$ are the transmit beamforming vectors and data from BS b to its serviced IR MS j. $\boldsymbol{h}_{dbk} \in \mathcal{C}^{N_{\rm T}}$ and $\boldsymbol{g}_{dbn} \in \mathcal{C}^{N_{\rm T}}$ are the transmission channel vectors from BS d to IR MS k and EH MS n in cell b, respectively. $z_{{\rm I},bk} \in \mathcal{CN}(0,\sigma_{{\rm I},bk}^2)$ and $z_{{\rm E},bn} \in \mathcal{CN}(0,\sigma_{{\rm E},bn}^2)$ are the superimposed noise. In this study, we consider imperfect CSI case and assume the bounded channel model $\boldsymbol{h}_{dbk} = \bar{\boldsymbol{h}}_{dbk} + \Delta\boldsymbol{h}_{dbk}$, $\boldsymbol{g}_{dbn} = \bar{\boldsymbol{g}}_{dbn} + \Delta\boldsymbol{g}_{dbn}$, where $\bar{\boldsymbol{h}}_{dbk}$ and $\bar{\boldsymbol{g}}_{dbn}$ are the estimated channel vectors, $\Delta\boldsymbol{h}_{dbk}$ and $\Delta\mathbf{g}_{dbn}$

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are the error vectors respectively bounded in ellipsoids $\Delta \boldsymbol{h}_{dbk}^{\rm H}\boldsymbol{Q}\Delta\boldsymbol{h}_{dbk} \leqslant 1$ and $\Delta \boldsymbol{g}_{dbk}^{\rm H}\boldsymbol{Q}\Delta\boldsymbol{g}_{dbk} \leqslant 1$ with $\boldsymbol{Q} \in \mathcal{H}^{N_{\rm T}}$ reflecting the size and shape of the ellipsoid.

By (1) and (2), the SINR at IR MS k and the harvested energy at EH MS n in cell b are respectively written as

$$\gamma_{bk} = \left(\left|\boldsymbol{h}_{bbk}^{\rm H}\boldsymbol{w}_{bk}\right|^2\right) \Big/ \left(\sum_{j\neq k}^{K}\left|\boldsymbol{h}_{bbk}^{\rm H}\boldsymbol{w}_{bj}\right|^2 + \sum_{d\neq b}^{B}\sum_{j=1}^{K}\left|\boldsymbol{h}_{dbk}^{\rm H}\boldsymbol{w}_{dj}\right|^2 + \sigma_{{\rm I},bk}^2\right),$$

$$E_{bn} = \lambda\left(\sum_{d=1}^{B}\sum_{j=1}^{K}\left|\boldsymbol{g}_{dbn}^{\rm H}\boldsymbol{w}_{dj}\right|^2\right),$$

where $\lambda \in (0,1]$ is the energy harvesting efficiency. For system design, we formulated an EHM problem with SINR constraints below.

$$\begin{aligned} \max\ & \textstyle\sum_{b,n} E_{bn} \\ {\rm s.t.}\ & \gamma_{bk} \geqslant \bar{\gamma}_{bk}, b\in\mathcal{B}, k\in\mathcal{K}, \\ & \textstyle\sum_{j} ||\boldsymbol{w}_{bj}||^2 \leqslant \bar{P}_b, b\in\mathcal{B}, \end{aligned} \tag{3}$$

where $\bar{\gamma}_{bk}$ and $\bar{P}_b$ are the SINR threshold for IR MS k in cell b and the power budget of cell b.

Problem solving. For robust optimization, introducing auxiliary variables $\{t_{dbn}\}$, $\{s_{dbk}\}_{d\neq b}$, additional constraints $\sum_j |\boldsymbol{g}_{dbn}^{\rm H}\boldsymbol{w}_{dj}|^2 \geqslant t_{dbn}$, $\sum_j |\boldsymbol{h}_{dbk}^{\rm H}\boldsymbol{w}_{dj}|^2 \leqslant s_{dbk}$, and replacing rank-1 matrix $\boldsymbol{w}_{dj}\boldsymbol{w}_{dj}^{\rm H}$ by semi-definite matrix $\boldsymbol{W}_{dj}$ with general rank, problem (3) can be expressed as a semidefinite programming (SDP):

$$\begin{aligned} \max\ & \textstyle\sum_{b,d,n} \lambda t_{bdn} \\ {\rm s.t.}\ & {\rm (a)}\ \boldsymbol{h}_{bbk}^{\rm H}\boldsymbol{U}_{bk}\boldsymbol{h}_{bbk} \geqslant \textstyle\sum_{d\neq b} s_{dbk} + \sigma_{{\rm I},bk}^2, \\ & {\rm (b)}\ \boldsymbol{g}_{bdn}^{\rm H}\boldsymbol{V}_b\boldsymbol{g}_{bdn} \geqslant t_{bdn}, \\ & {\rm (c)}\ \boldsymbol{h}_{bdk}^{\rm H}\boldsymbol{V}_b\boldsymbol{h}_{bdk} \leqslant s_{bdk}, \quad \forall b\neq d, \\ & {\rm (d)}\ {\rm Tr}(\boldsymbol{V}_b) \leqslant \bar{P}_b, \\ & \quad b\in\mathcal{B}, d\in\mathcal{B}, n\in\mathcal{N}, k\in\mathcal{K}, \end{aligned} \tag{4}$$

where $\boldsymbol{U}_{bk} \triangleq (\boldsymbol{W}_{bk}/\bar{\gamma}_{bk} - \sum_{j\neq k}\boldsymbol{W}_{bj})$, $\boldsymbol{V}_b \triangleq \sum_j \boldsymbol{W}_{bj}$. By S-Lemma [5], the constraints (4)(a)–(c) relating to bounded channel uncertainties can be respectively reformulated to be the following linear matrix inequalities (LMI):

$${\rm C}_{bk}^1: \begin{bmatrix} \boldsymbol{U}_{bk}+\beta_{bk}\boldsymbol{Q} & \boldsymbol{U}_{bk}\boldsymbol{h}_{bbk} \\ \boldsymbol{h}_{bbk}^{\rm H}\boldsymbol{U}_{bk} & \boldsymbol{h}_{bbk}^{\rm H}\boldsymbol{U}_{bk}\boldsymbol{h}_{bbk} - c_{bk} \end{bmatrix} \succeq 0,$$

$${\rm C}_{bdn}^2: \begin{bmatrix} \boldsymbol{V}_b+\alpha_{bdn}\boldsymbol{Q} & \boldsymbol{V}_b\boldsymbol{g}_{bdn} \\ \boldsymbol{g}_{bdn}^{\rm H}\boldsymbol{V}_b & \boldsymbol{g}_{bdn}^{\rm H}\boldsymbol{V}_b\boldsymbol{g}_{bdn} - d_{bdn} \end{bmatrix} \succeq 0,$$

$${\rm C}_{bdk}^3: \begin{bmatrix} -\boldsymbol{V}_b+\mu_{bdk}\boldsymbol{Q} & -\boldsymbol{V}_b\boldsymbol{h}_{bdk} \\ -\boldsymbol{h}_{bdk}^{\rm H}\boldsymbol{V}_b & -\boldsymbol{h}_{bdk}^{\rm H}\boldsymbol{V}_b\boldsymbol{h}_{bdk} - e_{bdk} \end{bmatrix} \succeq 0,$$

where $c_{bk} \triangleq \beta_{bk} + \sum_{d\neq b} s_{dbk} + \sigma_{{\rm I},bk}^2$, $d_{bdn} \triangleq \alpha_{bdn} + t_{bdn}$, $e_{bdk} \triangleq \mu_{bdk} - s_{bdk}$. $\{\beta_{bk}\}$, $\{\alpha_{bdn}\}$, $\{\mu_{bdk}\}_{b\neq d}$ are non-negative auxiliary variables.

The reformulated SDP with LMI constraints is convex and can be solved by off-the-shelf convex optimization solver. Solving (4) requires all the CSI of the coordinated networks, and the associated centralized algorithm incurs heavy overhead on sharing the CSI together with beamforming vectors. In contrast, decentralized algorithm can reduce this overhead by decomposing the original problem into a group of subproblems coordinated by a master problem [6]. Primal decomposition, which has been widely used in conventional PM problems [7, 8], is appropriate for the problems with coupling variables, and when the coupling variables are fixed, the constraints decouple. Primal decomposition is applicable for the considered problem (4) in which the constraint relating to each cell couples with the other cells by the inter-cell interference s_{dbk}. By fixing s_{dbk} and under the framework of primal decomposition, problem (4) is decomposed into B subproblems:

$$\begin{aligned} \max\ & \textstyle\sum_{d,n} \lambda t_{bdn} \\ {\rm s.t.}\ & {\rm C}_{bk}^1, {\rm C}_{bdn}^2, {\rm C}_{bdk}^3, (4)({\rm d}), \end{aligned} \tag{5}$$

for $b = 1, 2, \ldots, B$, that are coordinated by a master problem:

$$\begin{aligned} \max\ & \textstyle\sum_{b} f_b^*(\{s_{dbk}\}_{d\neq b}) \\ {\rm s.t.}\ & s_{dbk} > 0, \quad d\neq b, k\in\mathcal{K}. \end{aligned} \tag{6}$$

In the decomposition, we have assumed the availability at a specific BS of the CSI from that BS to all the MS in the coordinated networks, which can be achieved by periodically transmitted pilot signaling under the coordinated multi-cell framework. Note that unlike the PM problem in conventional cellular systems, the objective function in the considered EHM problem is not naturally decomposable. Nevertheless, it can be decoupled by defining a group of local auxiliary variables with each one relating to the EH contribution of a specific cell. In (6), $f_b^*(\{s_{dbk}\}_{d\neq b})$ is defined as the optimal objective value of subproblem b with fixed $\{s_{dbk}\}_{d\neq b}$. The optimized solution to (6) can be updated by project sub-gradient $s_{dbk}^{(i+1)} = \mathcal{P}(s_{dbk}^{(i)} + \delta^{(i)}\eta_{dbk})$, $d\neq b$, where $\mathcal{P}(\cdot)$ is the project operator, i and $\delta^{(i)}$ denote iteration index and step size, η_{dbk} is the associated sub-gradient, which can be obtained by $\eta_{dbk} = \varsigma_{dbk} - \zeta_{bk}$ with ς_{dbk} and ζ_{bk} the optimal Lagrange multipliers associated with the constraints C^3_{bdk} of subproblem d and with the constraints C^1_{bk} of subproblem b, respectively. For approaching the optimal solution, the master problem and the subproblems are alternatingly optimized in an iterative manner. Note that the signaling overhead is significantly reduced compared with the centralized method in which the exchanged singling is in the form of scalars instead of vectors, and therefore, the computational complexity for the decentralized algorithm is mainly determined by the SDP solving at each cell.

Simulations. The system parameters are chosen to be $B = 2$, $N_{\mathrm{T}} = 4$, $K = 2$, $N = 3$, $\lambda = 0.1$. The channel parameters are set the same as in [8]. Specifically, the channel vectors are generated to be i.i.d. complex Gaussian random vectors with zero mean and unit variance. The path losses in cells and across cells are set to be 0 and -10 dB, respectively, and the noise variance is 10^{-4}. Without the loss of generality, let $\bar{\gamma} \triangleq \bar{\gamma}_{bk}$ for $b \in \mathcal{B}$, $k \in \mathcal{K}$, $\bar{P} \triangleq \bar{P}_b$ for $b \in \mathcal{B}$, and $\boldsymbol{Q} \triangleq \varepsilon^{-2}\boldsymbol{I}$ symbolizing the CSI error to be bounded in a sphere of radius ε.

Figure 1(a) plots the harvested energy versus channel error bound ε under different transmission parameters of $\bar{\gamma}$ and $\bar{P}$. Since larger CSI errors require more power to compensate, less power is left for the EH under a fixed power budget. Thus we see from the plots that the harvested energy varies inversely proportionally with ε. Similarly, as $\bar{\gamma}$ increases, more transmit power should be allocated to the IR MS to satisfy the SINR constraints, and a less amount of power is available to the EH under a fixed power budget. Accordingly, the harvested energy varies in a similar manner with $\bar{\gamma}$ as with ε. On the other hand, increasing the power budget is certain to increase the harvested energy under invariant $\bar{\gamma}$ and ε, which is validated by the simulations.

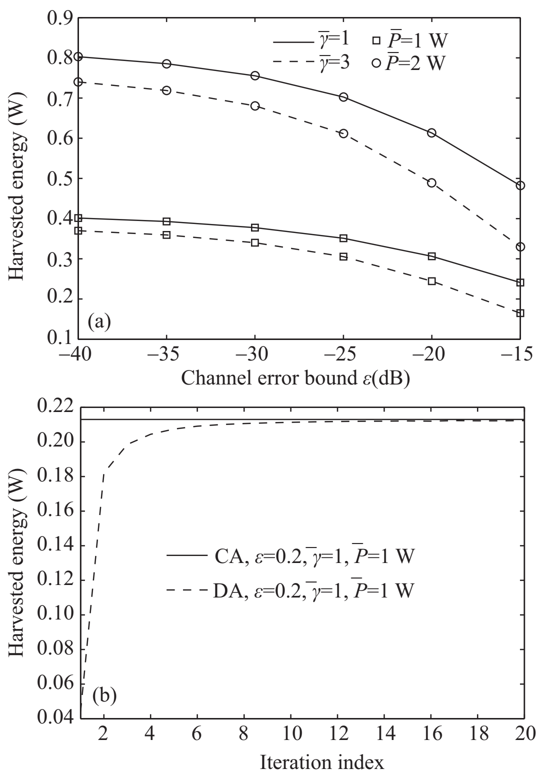

Figure 1 (a) Harvested energy versus channel error bound; (b) convergence property of distributed algorithm.

Figure 1(b) depicts the convergence property of decentralized algorithm (DA) under ε of 0.2. As a benchmark, the result of centralized algorithm (CA) is also presented for comparison. We see from the depicts that the decentralized algorithm converges monotonously to the centralized solution under the considered channel errors, and the effectiveness of the CA is thus verified.

Conclusion. We investigated EHM for multi-cell coordinated systems under a bounded channel error model. Both robust centralized and decentralized solutions were presented using SDP and S-Lemma techniques. Simulations verified the effectiveness of the proposed transmission scheme.

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