# Data Precoding and Energy Transmission for Parameter Estimation in MIMO Wireless Powered Sensor Networks

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***Abstract*—In this paper, we study parameter estimation in multiple-input multiple-output (MIMO) wireless powered sensor networks (WPSN). The sensor nodes are powered exclusively by harvesting the radio frequency signals transmitted from the energy access points. We propose a joint design of the sensor data precoders and energy covariance matrices to minimize the mean square error (MSE) of the parameter estimate. This design also incorporates optimal allocation of the harvested power for data acquisition and data transmission. We employ a zero-forcing precoding based estimation framework and the alternating minimization technique to compute the precoders, power allocation, and energy covariance matrices. Simulation results demonstrate that the proposed method achieves a superior estimation performance in comparison to the conventional energy transfer techniques for estimation in WPSNs.**

## I. Introduction

A major limitation of the wireless sensor networks (WSN) is the short lifetime due to the expensive cost of replacing the batteries and the inaccessibility of sensor nodes [1]. With the recent advances in wireless energy transfer (WET) technologies, dedicated energy access points (E-AP) can remotely recharge the sensor nodes and extend the network lifetime. In particular, radio frequency (RF) signals transmission based WET is well suited for WSNs because a large number of sensors can be recharged simultaneously [2]. WET has also been investigated for traditional communication networks in [3]–[6].

An important application of WSNs is to estimate a parameter of interest by transmitting the noisy observations at the sensor nodes to a remote fusion center (FC) over a multiple access channel (MAC). In such networks, one can intelligently design the sensor data preprocessing, uplink transmission, and receive processing at the FC to estimate the parameter to a high degree of accuracy [7], [8]. For a wireless powered sensor network (WPSN), which operates by harvesting the energy from the RF signals transmitted from the E-APs, an additional goal is to recharge the sensor nodes towards minimizing the parameter estimation error.

To that end, optimal energy management and sharing schemes were studied in [9] to minimize the finite-horizon total mean square error (MSE) of the estimate at the FC. Considering a fixed codebook of energy-beam directions, [10] derived optimal power allocation to energy-beam directions to minimize the MSE. Whereas, [11] examined energy beamforming to maximize the active probability of the WSN, and [12] presented energy beamforming and power allocation to the sensor nodes to maximize the received signal-to-noise ratio (SNR) at the FC. However, [11] and [12] do not consider the final task of the sensor network while designing the energy beamformers.

Existing works in [9]–[13] assume that the power consumption at the sensor nodes is only due to data communication. But, in a practical sensor node, data acquisition subsystems also a consume significant amount of power, and the acquisition power has a direct bearing on the estimation accuracy [14]. Therefore, unlike [9]–[13], we consider a system where the power harvested at the sensors can be optimally allocated between data acquisition and data transmission to enhance the estimation accuracy.

In this paper, we propose a joint design of precoders, energy covariance matrices, and power allocation between data acquisition and transmission for estimation of the vector parameters in a multi-antenna WPSN. We minimize the MSE of the parameter estimate subject to a power constraint at the E-APs. The joint design based on the optimal minimum mean square error (MMSE) estimation of vector parameters is intractable. To overcome this problem, we employ the alternating minimization technique to compute the precoders, energy covariance matrices, and power allocation that minimize the MSE of the estimate based on zero-forcing precoding. We show that the proposed algorithm yields a better estimate with only a marginal increase in the computational complexity.

For performance comparison, we present a conventional framework where the energy covariance matrices are designed to maximize the number of active sensors, but oblivious to observation statistics and channel state information (CSI) between the sensors and the FC. Finally, through simulation results, we demonstrate the MSE gains attained by the joint design over the conventional approaches for WPSN.

*Notation*: $(\cdot)^T$, $(\cdot)^H$, and $\text{tr}(\cdot)$ denote transpose, Hermitian, and trace of a matrix respectively. $\mathbf{I}_n$ represents an identity matrix of dimension $n$. The operator $\mathcal{V}(\mathbf{A})$ creates a column vector from matrix $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n]$ by stacking the col-

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umn vectors $\mathbf{a}_i$ and $\mathcal{V}_m^{-1}(\mathbf{a})$ rearranges the vector $\mathbf{a} \in \mathbb{C}^{mn\times 1}$ into a matrix with $m$ rows and $n$ columns.

## II. System Model

We consider a WPSN consisting of $L$ sensor nodes with $N_S$ antennas each and a FC with $N_F$ antennas. This network operates by harvesting energy from the RF signals transmitted by $K$ E-APs employing $N_E$ antennas each.

During the energy transfer phase, the $j$th E-AP transmits the energy signal $\mathbf{s}_j \in \mathbb{C}^{N_E\times 1}$ with the covariance matrix $\mathbf{\Sigma}_j \in \mathbb{C}^{N_E\times N_E}$ and the transmit power limited to $\text{tr}(\mathbf{\Sigma}_j) \le P_{E,j}$. Denoting the channel matrix between $i$th node and $j$th E-AP by $\mathbf{G}_{ij} \in \mathbb{C}^{N_S\times N_E}$, the harvested power at node $i$ can be written as[1]

$$P_{H,i} = \eta_i \mathbb{E}\Big[\Big\| \sum_{j=1}^{K} \mathbf{G}_{ij}\mathbf{s}_j \Big\|_F^2\Big] = \eta_i \sum_{j=1}^{K} \text{tr}\left(\mathbf{G}_{ij}\mathbf{\Sigma}_j\mathbf{G}_{ij}^H\right), \quad (1)$$

where $\eta_i$ is the energy harvesting efficiency at node $i$. This power is utilized for data acquisition and data transmission. It is assumed that the sensor nodes consume all the energy harvested during a charging epoch and do not have long-term storage.

The sensor nodes measure the parameter $\boldsymbol{\theta} \in \mathbb{C}^{M_\theta\times 1}$ with statistics $\boldsymbol{\theta} \sim \mathcal{CN}(\mathbf{0}, \mathbf{R}_\theta)$. The observations $\mathbf{x}_i \in \mathbb{C}^{M\times 1}$ at the $i$th node are given by

$$\mathbf{x}_i = \mathbf{A}_i\boldsymbol{\theta} + \mathbf{n}_i, \quad (2)$$

where $\mathbf{A}_i \in \mathbb{C}^{M\times M_\theta}$ represents the observation matrix and $\mathbf{n}_i \in \mathbb{C}^{M\times 1}$ indicates the Gaussian observation noise with zero mean and uncorrelated at different sensors.

Let $\alpha_i$ be the fraction of the harvested power allocated for data acquisition at the $i$th sensor. Then, the local observation noise covariance matrix can be modeled as

$$\mathbb{E}[\mathbf{n}_i\mathbf{n}_i^H] = \frac{P_S\mathbf{R}_i}{P_S + \alpha_i P_{H,i}}, \quad (3)$$

where $P_{S,i} \triangleq \alpha_i P_{H,i}$ equals the data acquisition power and $\mathbf{R}_i$ is the noise covariance matrix when the sensor uses a predetermined power $P_S$ to acquire the observations.

We consider an estimation setting where the sensor nodes transmit linearly precoded observations to the FC over a MAC [7]. Let $\mathbf{B}_i \in \mathbb{C}^{N_S\times M}$ denote the data precoding matrix at node $i$. From (2), the received data $\mathbf{y} \in \mathbb{C}^{N_F\times 1}$ at the FC can be expressed as

$$\mathbf{y} = \sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{x}_i + \mathbf{v} = \sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{A}_i\boldsymbol{\theta} + \mathbf{n}, \quad (4)$$

where $\mathbf{H}_i \in \mathbb{C}^{N_F\times N_S}$ stands for the channel matrix between the $i$th node and the FC and $\mathbf{v} \in \mathbb{C}^{N_F\times 1}$ is the noise at the FC distributed as $\mathcal{CN}(\mathbf{0}, \mathbf{R}_{\mathsf{FC}})$. The total noise is represented by $\mathbf{n} = \sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{n}_i + \mathbf{v}$ with covariance matrix

$$\mathbf{R} = \mathbb{E}[\mathbf{n}\mathbf{n}^H] = \sum_{i=1}^{L} \frac{P_S\mathbf{H}_i\mathbf{B}_i\mathbf{R}_i\mathbf{B}_i^H\mathbf{H}_i^H}{P_S + \alpha_i\sum_{j=1}^{K}\eta_i \text{tr}\left(\mathbf{G}_{ij}\mathbf{\Sigma}_j\mathbf{G}_{ij}^H\right)} + \mathbf{R}_{\mathsf{FC}}. \quad (5)$$

The transmit power required at the $i$th node is $P_{T,i} \triangleq \mathbb{E}\left[\|\mathbf{B}_i\mathbf{x}_i\|^2\right]$. Due to a limited budget at the sensor nodes, the power available for data transmission is $P_{T,i} \le (1-\alpha_i)P_{H,i} - P_S$, which leads to the constraint

$$\text{tr}\left(\mathbf{B}_i\left(\mathbf{A}_i\mathbf{R}_\theta\mathbf{A}_i^H + \frac{P_S\mathbf{R}_i}{P_S + \alpha_i P_{H,i}}\right)\mathbf{B}_i^H\right) \le (1-\alpha_i)P_{H,i} - P_S. \quad (6)$$

The FC estimates the parameter $\boldsymbol{\theta}$ using the fusion rule $\mathbf{W} \in \mathbb{C}^{N_F\times M_\theta}$ as $\hat{\boldsymbol{\theta}} = \mathbf{W}^H\mathbf{y}$. The optimal MMSE fusion rule can be written as [8]

$$\mathbf{W} = \left(\mathbf{R} + \sum_{i=1}^{L}\sum_{j=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{A}_i\mathbf{R}_\theta\mathbf{A}_j^H\mathbf{B}_j^H\mathbf{H}_j^H\right)^{-1} \sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{A}_i\mathbf{R}_\theta, \quad (7)$$

and the corresponding MSE of the estimate is given by

$$\mathcal{E}_{\text{MMSE}} = \text{tr}\left(\mathbf{R}_\theta^{-1} + \sum_{i=1}^{L}\sum_{j=1}^{L} \mathbf{A}_i^H\mathbf{B}_i^H\mathbf{H}_i^H\mathbf{R}^{-1}\mathbf{H}_j\mathbf{B}_j\mathbf{A}_j\right)^{-1}. \quad (8)$$

As evident from (6) and (8), power allocation $\{\alpha_i\}_{i=1}^L$ plays an important role in reducing the estimation error. Therefore, in this paper, we investigate a joint design of the precoders $\{\mathbf{B}_i\}_{i=1}^L$, energy transmit covariance matrices $\{\mathbf{\Sigma}_j\}_{j=1}^K$, and power allocation $\{\alpha_i\}_{i=1}^L$ to minimize the MSE of the parameter estimate subject to power constraints at the E-APs and the sensor nodes.

## III. Zero-Forcing Precoding for Vector Parameter Estimation

Due to intractability of the objective function in (8), joint optimization of $\{\mathbf{B}_i\}$, $\{\mathbf{\Sigma}_j\}$, and $\{\alpha_i\}$ with the MMSE estimation is infeasible. To circumvent this, we present a zero-forcing (ZF) precoding framework in which the number of antennas at the FC is set to the dimension of the parameter, $N_F = M_\theta$. Further, the precoders $\{\mathbf{B}_i\} \in \mathbb{C}^{N_S\times M}$ are designed such that the effective MAC output at the FC is diagonal

$$\sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{A}_i = \beta\mathbf{I}_{M_\theta}, \quad (9)$$

where $\beta$ is the precoding gain. With the ZF precoding, the received signal $\mathbf{y}_{\mathsf{ZF}} \in \mathbb{C}^{M_\theta\times 1}$ can be expressed as

$$\mathbf{y}_{\mathsf{ZF}} = \beta\boldsymbol{\theta} + \sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{n}_i + \mathbf{v}. \quad (10)$$

The ZF precoding framework offers two advantages. First, it leads to a low complexity fusion rule $\mathbf{W}_{\mathsf{ZF}} = 1/\beta\mathbf{I}_{N_F}$. The parameter can be estimated by a simple scaling of the data as

$$\hat{\boldsymbol{\theta}}_{\mathsf{ZF}} = \mathbf{y}_{\mathsf{ZF}}/\beta = \boldsymbol{\theta} + \frac{1}{\beta}\sum_{i=1}^{L} \mathbf{H}_i\mathbf{B}_i\mathbf{n}_i + \frac{1}{\beta}\mathbf{v}. \quad (11)$$

[1]Throughout this paper, we assume a unit time duration. Hence, the terms power and energy are used interchangeably.

Second, it simplifies the objective function for jointly optimizing the energy covariance matrices and precoders. From (11), the MSE of the estimate $\hat{\boldsymbol{\theta}}_{\mathsf{ZF}}$ is derived as

$$\mathcal{E}_{\mathsf{ZF}}\left(\{\mathbf{B}_i\}_{i=1}^L, \beta, \{\boldsymbol{\Sigma}_j\}_{j=1}^K, \{\alpha_i\}_{i=1}^L\right) \triangleq \mathbb{E}\left[\|\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}_{\mathsf{ZF}}\|^2\right],$$
$$= \sum_{i=1}^L \frac{P_S \text{tr}(\mathbf{H}_i\mathbf{B}_i\mathbf{R}_i\mathbf{B}_i^H\mathbf{H}_i^H)}{P_S + \alpha_i \sum_{j=1}^K \eta_i \text{tr}(\mathbf{G}_{ij}\boldsymbol{\Sigma}_j\mathbf{G}_{ij}^H)} + \frac{\text{tr}(\mathbf{R}_{\mathsf{FC}})}{\beta^2}. \quad (12)$$

Since $\{\mathbf{B}_i\}$ are directly proportional to $\beta$, precoding gain $\beta$ does not occur in the first term of (12). In contrast to (8), the MSE of the estimate from the ZF precoding is a convex quadratic function with respect to $\{\mathbf{B}_i\}$ and $\beta$.

## IV. Joint Design of Precoders and Energy Covariance Matrices

Now, the objective is to find $\{\mathbf{B}_i\}, \{\alpha_i\}$, and $\{\boldsymbol{\Sigma}_j\}$ that minimize the MSE in (12) subject to the transmit power constraints at the sensors and E-APs and the zero-forcing constraint (9). This optimization problem can be formulated as

$$\begin{aligned}
\min_{\substack{\{\mathbf{B}_i\},\{\alpha_i\}\\ \{\boldsymbol{\Sigma}_j\},\beta}} \quad & \sum_{i=1}^L \frac{P_S \text{tr}(\mathbf{H}_i\mathbf{B}_i\mathbf{R}_i\mathbf{B}_i^H\mathbf{H}_i^H)}{P_S + \alpha_i \sum_{j=1}^K \eta_i \text{tr}(\mathbf{G}_{ij}\boldsymbol{\Sigma}_j\mathbf{G}_{ij}^H)} + \frac{\text{tr}(\mathbf{R}_{\mathsf{FC}})}{\beta^2} \\
\text{s. t.} \quad & \sum_{i=1}^L \mathbf{H}_i\mathbf{B}_i\mathbf{A}_i = \beta \mathbf{I}_{M_\theta}, \\
& \text{constraint (6)}, \; i = 1, \ldots, L, \\
& 0 \le \alpha_i \le 1, i = 1, \ldots, L, \\
& \text{tr}(\boldsymbol{\Sigma}_j) \le P_{E,j} \text{ and } \boldsymbol{\Sigma}_j \succeq \mathbf{0}, j = 1, \ldots, K.
\end{aligned} \quad (13)$$

The problem in (13) does not have a closed form solution and is difficult to solve. However, either for a given $\{\alpha_i\}$ or $\{\boldsymbol{\Sigma}_j\}$, it is convex. Therefore, we fix one set of the variables and optimize the other set, alternately. In the subsequent sections, we show that the solutions to the partial optimization problems can be obtained efficiently.

### A. Energy Covariance Matrices

Let us define $\mathbf{b}_i = \mathcal{V}(\mathbf{B}_i) \in \mathbb{C}^{N_S M \times 1}$ and assume that $\{\alpha_i\}$ are known. Then, from the relationship $\text{tr}\left(\mathbf{A}^H\mathbf{B}\mathbf{C}\mathbf{D}^H\right) = \mathcal{V}(\mathbf{A})^H((\mathbf{D}^H)^T \otimes \mathbf{B})\mathcal{V}(\mathbf{C})$ and $\mathcal{V}(\mathbf{A}\mathbf{X}\mathbf{B}) = (\mathbf{B}^T \otimes \mathbf{A})\mathcal{V}(\mathbf{X})$, the problem in (13) can be recast as

$$\begin{aligned}
\min_{\substack{\{\mathbf{b}_i\},\{Q_i\}\\ \{\boldsymbol{\Sigma}_j\},\beta}} \quad & \sum_{i=1}^L \frac{P_S \mathbf{b}_i^H(\mathbf{R}_i^T \otimes \mathbf{H}_i^H\mathbf{H}_i)\mathbf{b}_i}{P_S + \alpha_i Q_i} + \frac{\text{tr}(\mathbf{R}_{\mathsf{FC}})}{\beta^2} \\
\text{s. t.} \quad & \sum_{i=1}^L (\mathbf{A}_i^T \otimes \mathbf{H}_i)\mathbf{b}_i = \beta \mathcal{V}(\mathbf{I}_{M_\theta}), \\
& \mathbf{b}_i^H\mathbf{Z}_i\mathbf{b}_i + \frac{P_S \mathbf{b}_i^H\left(\mathbf{R}_i^T \otimes \mathbf{I}_{N_S}\right)\mathbf{b}_i}{P_S + \alpha_i Q_i} \\
& \qquad \le (1-\alpha_i)Q_i - P_S, \; i = 1, \ldots, L, \\
& \eta_i \sum_{j=1}^K \text{tr}(\mathbf{G}_{ij}\boldsymbol{\Sigma}_j\mathbf{G}_{ij}^H) \ge Q_i, \; i = 1, \ldots, L, \\
& \text{tr}(\boldsymbol{\Sigma}_j) \le P_{E,j} \text{ and } \boldsymbol{\Sigma}_j \succeq \mathbf{0}, j = 1, \ldots, K,
\end{aligned} \quad (14)$$

**Algorithm 1** Alternating Minimization based Algorithm

Initialize $n = 0$ and $\alpha_i^{(0)}$ for $i = 1, \ldots, L$.
**Repeat**
Obtain $\{\boldsymbol{\Sigma}_j^{(n+1)}\}$ and $\{Q_i^{(n+1)}\}$ from (14) with $\alpha_i = \alpha_i^{(n)}$, $\forall i$.
Determine $\{\mathbf{b}_i^{(n+1)}\}$ and $\{\alpha_i^{(n+1)}\}$ from (15) with $Q_i = Q_i^{(n+1)}$, $\forall i$.
Set $n = n + 1$.
**Until** convergence

where $\mathbf{Z}_i \triangleq (\mathbf{A}_i\mathbf{R}_\theta\mathbf{A}_i^H)^T \otimes \mathbf{I}_{N_S}$. The above problem can be expressed as a semidefinite program (SDP) and addressed efficiently using the interior point methods [15].

### B. Sensor Precoders and Power Allocation

Now, for a fixed $\{\boldsymbol{\Sigma}_j\}$, the optimization problem to calculate $\{\mathbf{b}_i\}$, $\{\alpha_i\}$, and $\beta$ is written as

$$\begin{aligned}
\min_{\{\mathbf{b}_i\},\{\alpha_i\},\beta} \quad & \sum_{i=1}^L \frac{P_S \mathbf{b}_i^H(\mathbf{R}_i^T \otimes \mathbf{H}_i^H\mathbf{H}_i)\mathbf{b}_i}{P_S + \alpha_i Q_i} + \frac{\text{tr}(\mathbf{R}_{\mathsf{FC}})}{\beta^2} \\
\text{s. t.} \quad & \sum_{i=1}^L (\mathbf{A}_i^T \otimes \mathbf{H}_i)\mathbf{b}_i = \beta \mathcal{V}(\mathbf{I}_{M_\theta}), \\
& \mathbf{b}_i^H\mathbf{Z}_i\mathbf{b}_i + \frac{P_S \mathbf{b}_i^H\left(\mathbf{R}_i^T \otimes \mathbf{I}_{N_S}\right)\mathbf{b}_i}{P_S + \alpha_i Q_i} \\
& \qquad \le (1-\alpha_i)Q_i - P_S, \; i = 1, \ldots, L, \\
& 0 \le \alpha_i \le 1, i = 1, \ldots, L.
\end{aligned} \quad (15)$$

This is a generalized quadratic convex program that can be solved easily [16].

### C. Alternating Minimization Algorithm

The alternating minimization algorithm to compute $\{\mathbf{b}_i\}$, $\{\alpha_i\}$, and $\{\boldsymbol{\Sigma}_j\}$ is summarized in Algorithm 1. The initializations $\{\alpha_i^{(0)}\}$ are chosen such that they satisfy $0 < \alpha_i^{(0)} < 1, \forall i$. The algorithm can be terminated when the MSE $\mathcal{E}_{\mathsf{ZF}}(\{\mathbf{b}_i^{(n)}\}, \beta^{(n)}, \{\boldsymbol{\Sigma}_j^{(n)}\}, \{\alpha_i^{(n)}\})$ converges, and the individual precoders are calculated as $\mathbf{B}_i = \mathcal{V}_{N_s}^{-1}(\mathbf{b}_i)$.

The FC executes the algorithm and feeds back the precoders and power allocation coefficients to the sensors and the energy covariance matrices to the E-APs. In addition, to further reduce the MSE, the FC can employ the MMSE estimator $\mathbf{W}_{\mathsf{ZF-M}} = \beta(\mathbf{R} + \beta^2\mathbf{R}_\theta)^{-1}\mathbf{R}_\theta$ on the received data (10), instead of scaling-only estimator.

*Convergence of Algorithm 1*: Due to the convexity of the optimization problems in (14) and (15), we can observe that

$$\begin{aligned}
\mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i^{(n)}\}, \beta^{(n)}, \{\boldsymbol{\Sigma}_j^{(n)}\}, \{\alpha_i^{(n)}\}\big) &\ge \min_{\mathbf{b},\beta,\boldsymbol{\Sigma}} \mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i\}, \beta, \{\boldsymbol{\Sigma}_j\}, \{\alpha_i^{(n)}\}\big) \\
&= \mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i^{(n+1)}\}, \beta^{(n+1)}, \{\boldsymbol{\Sigma}_j^{(n+1)}\}, \{\alpha_i^{(n)}\}\big) \\
&\ge \min_{\mathbf{b},\beta,\boldsymbol{\alpha}} \mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i\}, \beta, \{\boldsymbol{\Sigma}_j^{(n+1)}\}, \{\alpha_i\}\big) \\
&= \mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i^{(n+1)}\}, \beta^{(n+1)}, \{\boldsymbol{\Sigma}_j^{(n+1)}\}, \{\alpha_i^{(n+1)}\}\big).
\end{aligned}$$

The sequence $\mathcal{E}_{\mathsf{ZF}}\big(\{\mathbf{b}_i^{(n)}\}, \beta^{(n)}, \{\mathbf{\Sigma}_j^{(n)}\}, \{\alpha_i^{(n)}\}\big)$ monotonically decreases with iteration index $n$, and therefore, Algorithm 1 will converge.

The objective function in (13) is continuously differentiable and component-wise strictly quasi-convex. Further, for the given channel matrices $\mathbf{H}_i$ and observation matrices $\mathbf{A}_i$, the feasible sets in (14) and (15) are compact under a mild assumption that $\beta$ is bounded. Hence, the algorithm converges to at least a local minima regardless of the initial feasible point [17, Theorem 3].

*Computational Complexity:* The problem in (14) can be recast to a SDP with a positive semidefinite constraint on $K$ matrices of dimension $N_E \times N_E$ and an objective function that is a sum of $L$ quadratic-over-linear functions with $MN_S$ optimization variables. Thus, the worst-case computational complexity for (14) is given by $\mathcal{O}(L(MN_S)^3 + (KN_E)^{3.5} + (KN_E)^{2.5})$ [18]. The optimization problem (15) is a generalized quadratic convex program that can be evaluated with complexity $\mathcal{O}(L(MN_S)^3)$ [16]. Therefore, the total computational complexity of Algorithm 1 is $n\mathcal{O}(L(MN_S)^3 + (KN_E)^{3.5} + (KN_E)^{2.5})$, where $n$ is the number of iterations.

## V. Conventional Design of Precoders and Energy Covariance Matrices

In this section, we present a conventional framework for estimation in WSPNs. In the first step, the energy covariance matrices are designed to maximize the minimum harvested power by all the sensor nodes in the network [19] as

$$
\begin{aligned}
&\max_{\gamma, \{\mathbf{\Sigma}_j^{\mathsf{conv}}\}} \quad \gamma \\
&\text{s. t.} \quad \eta_i \sum_{j=1}^{K} \mathrm{tr}(\mathbf{G}_{ij}\mathbf{\Sigma}_j^{\mathsf{conv}}\mathbf{G}_{ij}^H) \geq \gamma + P_S,\ i = 1, \ldots, L, \\
&\qquad \mathrm{tr}(\mathbf{\Sigma}_j^{\mathsf{conv}}) \leq P_{E,j} \text{ and } \mathbf{\Sigma}_j^{\mathsf{conv}} \succeq \mathbf{0},\ j = 1, \ldots, K,
\end{aligned} \tag{16}
$$

which also increases the number of sensor nodes in operation. It should be noted that the energy covariance matrices obtained from (16) are independent of the local observation information and the CSI between the sensors and the FC. The power harvested at the $i$th sensor is $P_{H,i}^{\mathsf{conv}} = \eta_i \sum_{j=1}^{K} \mathrm{tr}(\mathbf{G}_{ij}\mathbf{\Sigma}_j^{\mathsf{conv}}\mathbf{G}_{ij}^H)$.

Next, the optimal joint MMSE precoders and the fusion rule are obtained from [8] with the data transmission power at the $i$th sensor node equal to $(1-\alpha_i)P_{H,i}^{\mathsf{conv}}$ and the observation noise covariance matrix as $\frac{P_S \mathbf{R}_i}{P_S + \alpha_i P_{H,i}^{\mathsf{conv}}}$, for a specified $\{\alpha_i\}$. This scheme is also an iterative algorithm, which requires solving a quadratic program in each iteration.

The computational complexity to evaluate (16) is $\mathcal{O}((KN_E)^{3.5} + (KN_E)^{2.5})$ and to obtain the precoders and fusion rule is $n\mathcal{O}(L(N_S^3 + LMN_S^2))$ [8]. Therefore, the total computational complexity of the conventional framework is $n\mathcal{O}(L(N_S^3 + LMN_S^2)) + \mathcal{O}((KN_E)^{3.5} + (KN_E)^{2.5})$, which is comparable with the complexity of the joint design.

Next, we provide simulation results to compare the performance of the framework derived in this section with the estimation scheme proposed in Section IV.

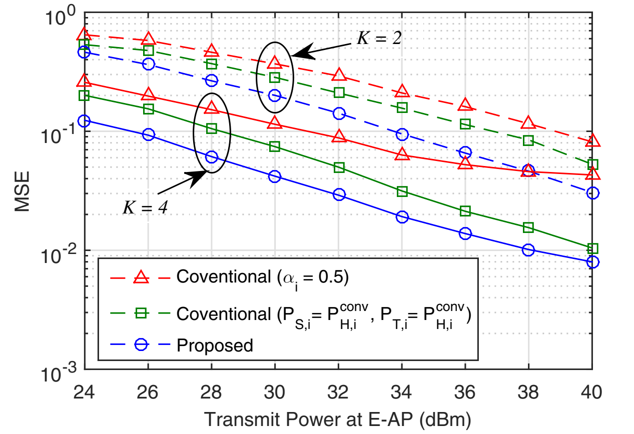


Fig. 1. MSE as a function of transmit power at the E-APs with $n = 15$, $M_\theta = 2$, $L = 15$, and $K$ E-APs.

## VI. Simulation Results

For the simulations, we consider a WPSN with $L$ sensor nodes and $K$ E-APs distributed randomly over a geographical area of size 20m×20m. The effect of the random placement of the sensors and E-APs is averaged through Monte-Carlo simulations.

The number of antennas at the sensor nodes, the FC, and the E-APs are taken to be $N_S = 2$, $N_F = 2$, and $N_E = 4$, respectively. All the channels follow an independent and identically distributed (i.i.d.) Rayleigh fading with a path loss exponent $\omega = 3$ [20]. The energy harvesting efficiency at the sensors is set to $\eta_i = 0.5$, $\forall i$, and the minimum data acquisition power is equal to $P_S = 1$mW. The parameter is assumed to be Gaussian with $\boldsymbol{\theta} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_{M_\theta})$ and dimension $M_\theta = 2$. The observations size is fixed to $M = 2$ and the elements of observation matrix $\mathbf{A}_i$ are generated as i.i.d. $\mathcal{CN}(0, 10^{-3})$. The covariance matrix of the observation noise at the sensor nodes and the noise at the FC are taken as $\mathbf{R}_i = 0.05\mathbf{I}_M, \forall i$, and $\mathbf{R}_{\mathsf{FC}} = 0.05\mathbf{I}_{M_\theta}$, respectively. We choose the initializations for Algorithm 1 as $\alpha_i^{(0)} = 0.5, \forall i$, and for the algorithm in [8] as $\mathbf{B}_i^{(0)} = \sqrt{(1-\alpha_i)P_{H,i}^{\mathsf{conv}}/N_S M}\mathbf{1}_{N_S \times M}, \forall i$, where $\mathbf{1}_{N_S \times M}$ represents a $N_S \times M$ matrix of all ones. The number of iterations is set to $n = 15$ for both the algorithms.

Fig. 1 plots the MSE of the parameter estimate as a function of transmit power at the E-APs $(P_{E,j})$ with $L = 15$ and $K = \{2, 4\}$. For comparison, it also depicts the performance of the conventional approach with $\{\alpha_i\} = 0.5$, $\forall i$. It can be observed that the proposed joint design attains a lower MSE in comparison with the conventional scheme. This shows the importance of designing the energy covariance matrices taking into account the tradeoff between the data transmission power and data acquisition power. Even in an ideal scenario with the data transmission power $P_{T,i} = P_{H,i}^{\mathsf{conv}}$ and acquisition power $P_{S,i} = P_{H,i}^{\mathsf{conv}}$, the conventional framework performs worse than the joint design.

Fig. 2 illustrates the speed of convergence of the iterative algorithms. It can be seen that the algorithm requires only a

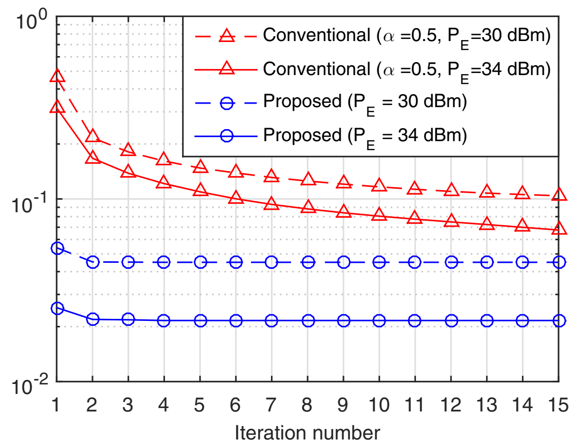


Fig. 2. Convergence of MSE with iteration number for $M_\theta = 2$, $L = 15$, and $K = 4$.

few iterations to converge. This demonstrates that a higher estimation accuracy is achieved with only a marginal increase in the computational complexity.

## VII. Conclusion

In this paper, we have investigated a joint design of sensor data precoders, energy covariance matrices, and power allocation between data acquisition and transmission for estimation of a vector parameter in WPSNs. A zero-forcing precoding in combination with the alternating minimization algorithm was presented to solve the MSE minimization problem. Simulation results confirm that the proposed scheme with power allocation leads to a significant improvement in estimation accuracy in comparison to the conventional energy transfer schemes for WPSNs.

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