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Wireless Powered Sensor Networks: Collaborative Energy Beamforming Considering Sensing and Circuit Power Consumption

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***Abstract*—This letter studies a wireless powered sensor network, in which a number of sensor nodes send common information to a far apart information access point (AP) via distributed beamforming, by using the wireless energy transferred from a set of nearby multi-antenna energy transmitters (ETs). We consider practical sensing and circuit power consumption at sensor nodes, in addition to their transmission power. In this case, each sensor node is activated in information transmission only when its harvested power is larger than the sensing and circuit power. Under this setup, we aim to maximize the received signal-to-noise ratio (SNR) at the information AP, by jointly optimizing the collaborative energy beamforming at ETs, and the distributed information beamforming and the inactive/active status of sensor nodes, subject to individual power constraints at ETs and sensor nodes. We propose both optimal and suboptimal solutions to this problem based on the exhaustive search and the greedy algorithm for selecting active sensor nodes, respectively.**

***Index Terms*—Wireless sensor networks, wireless energy transfer, collaborative energy beamforming, distributed information beamforming, sensing and circuit power consumption.**

I. INTRODUCTION

Recently, radio frequency (RF) signal based wireless energy transfer (WET) has emerged as a perpetual and cost-effective solution to power wireless sensor networks [1], [2], where dedicated energy transmitters (ETs) broadcast wireless energy to power sensor nodes to sense and send information to access points (APs). In such networks, each sensor node's energy consumption for sensing and communication should not exceed its harvested wireless energy from ETs. By considering the new wireless energy harvesting constraints at sensor nodes, it is essential to jointly optimize the WET at the ETs and the information transmission at sensor nodes, so as to optimize the network performance (see, e.g., [3]–[7] for such joint optimizations under different setups).

The optimization of wireless powered sensor networks is fundamentally affected by the energy consumption model of sensor nodes. In the existing studies (e.g., [3]–[7]), the authors assumed that the transmission energy is their sole energy consumption. This assumption, however, cannot be true for most practical applications. In particular, practical sensor nodes have non-negligible sensing and circuit power consumption in addition to the transmission power [8]. It remains unknown how the sensing and circuit power consumption affects the joint WET and information transmission optimization for wireless powered sensor networks.

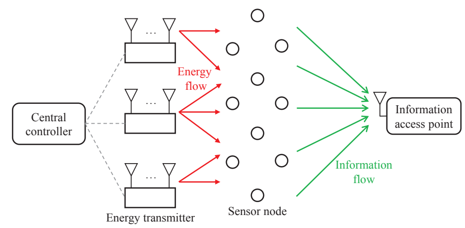

Fig. 1. System model of a wireless powered sensor network.

To overcome this issue, in this letter we consider a specific wireless powered sensor network as shown in Fig. 1, in which a number of sensor nodes send common information to a far apart AP,[1] by using the wireless energy transferred from a set of nearby multi-antenna ETs. The multiple ETs employ energy beamforming [10] in a collaborative manner to improve the energy transfer efficiency to sensor nodes, and the set of sensor nodes use distributed information beamforming [9] to improve the transmission range and data rates to the information AP. We consider practical sensing and circuit power consumption at sensor nodes, in addition to their transmission power. In this case, each sensor node is activated in information transmission only when its harvested power is larger than the sensing and circuit power.

Under this setup, we aim to maximize the received signal-to-noise ratio (SNR) at the information AP by jointly optimizing the collaborative energy beamforming at the ETs, and the distributed information beamforming and the active/inactive status of the sensor nodes, subject to individual power constraints at ETs and sensor nodes. This problem is non-convex and difficult to be solved in general. Despite this fact, we propose the optimal solution to this problem based on the exhaustive search for selecting active sensor nodes, which, however, has a high computation complexity. To overcome this issue, we further propose a suboptimal solution with lower complexity by using the greedy algorithm for selecting active sensor nodes. Numerical results show that the proposed optimal and suboptimal solutions significantly outperform the conventional design that ignores the non-zero sensing and circuit power consumption of sensor nodes, which is due to the fact that with non-zero sensing and circuit power consumption, certain sensor nodes should be inactivated in the

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[1]Practical examples include a sensor network transmitting measurements to an overflying unmanned aerial vehicle (UAV) [9].

design of collaborative energy beamforming, while all sensor nodes should be considered under the case with zero sensing and circuit power consumption. Furthermore, the suboptimal solution achieves a similar received SNR at the information AP as compared to the optimal solution.

II. System Model and Problem Formulation

We consider a wireless sensor network as shown in Fig. 1, in which a total of K sensor nodes send common information to an information AP via distributed beamforming by using the wireless energy transferred from N distributed ETs.[2] Let $\mathcal{K} \triangleq \{1,\ldots,K\}$ and $\mathcal{N} \triangleq \{1,\ldots,N\}$ denote the sets of sensor nodes and ETs, respectively. The sensor nodes are each equipped with two antennas (one for energy harvesting and the other for information transmission), the information AP is equipped with a single antenna, and the ETs are each deployed with M antennas. We assume that the WET of the ETs and the information transmission of the sensor nodes operate over orthogonal frequency bands with identical bandwidth, and thus the sensor nodes can harvest energy and transmit information at the same time without co-channel interference between WET and information transmission links. For the purpose of initial investigation, we assume that there is a central controller that can gather the global channel state information (CSI) from the ETs to the sensor nodes and that from the sensor nodes to the information AP, and can thus coordinate the collaborative energy beamforming at ETs and the distributed information beamforming at sensor nodes, while each sensor node is only aware of its local CSI. We consider a block-based frequency-nonselective fading channel model, where wireless channels remain constant over each block of our interest. The block length is normalized for the ease of description, and the terms "energy" and "power" are used in the sequel without loss of generality.

First, consider the collaborative energy beamforming from the ETs to the sensor nodes. Let the transmitted energy signal by the ET $i \in \mathcal{N}$ be denoted as $\boldsymbol{x}_i^E = \sum_{j=1}^{d} \boldsymbol{v}_{ij} s_j^E$, where $\boldsymbol{v}_{ij} \in \mathbb{C}^{M\times 1}$ denotes the jth energy beamforming vector at ET i, s_j^E denotes the jth energy-carrying signal, $j \in \{1,\ldots,d\}$, and d represents the number of energy beams. Here, the energy-carrying signal s_j^E's are assumed to be *a priori* generated Gaussian random sequences with zero mean and unit variance [10]. Accordingly, s_j^E's are perfectly known by all the N ETs. We further aggregate the transmitted energy signal by all the N ETs as $\boldsymbol{x}^E = \left[\boldsymbol{x}_1^{E\,T},\cdots,\boldsymbol{x}_N^{E\,T}\right]^T = \sum_{j=1}^{d} \boldsymbol{v}_j s_j^E$, where $\boldsymbol{v}_j = \left[\boldsymbol{v}_{1j}^T,\cdots,\boldsymbol{v}_{Nj}^T\right]^T \in \mathbb{C}^{MN\times 1}$, and the superscript T denotes the transpose of a matrix. As a result, the transmit covariance matrix of the N ETs can be denoted as $\boldsymbol{S} = \mathbb{E}\left(\boldsymbol{x}^E \boldsymbol{x}^{E\,H}\right) = \sum_{j=1}^{d} \boldsymbol{v}_j \boldsymbol{v}_j^H$, which is positive semi-definite, i.e., $\boldsymbol{S} \succeq \boldsymbol{0}$. Here, $\mathbb{E}(\cdot)$ denotes the statistical expectation and the superscript H denotes the conjugate transpose of a matrix. Note that given any positive semi-definite matrix $\boldsymbol{S}$, the corresponding collaborative energy beam $\boldsymbol{v}_j$'s can be obtained based on the eigenvalue decomposition (EVD) of $\boldsymbol{S}$ with $d = \text{rank}(\boldsymbol{S})$ [10]. By letting $\boldsymbol{h}_k \in \mathbb{C}^{MN\times 1}$ denote the channel vector from the MN antennas of the N ETs to the sensor node k, the harvested energy at the sensor node k is expressed as $E_k = \eta_k \mathbb{E}\left(\left|\boldsymbol{h}_k^H \boldsymbol{x}^E\right|^2\right) = \eta_k \boldsymbol{h}_k^H \boldsymbol{S} \boldsymbol{h}_k, k \in \mathcal{K}$, where $0 < \eta_k \le 1$ denotes the energy harvesting efficiency at the sensor node k. Suppose that the maximum transmit power at each ET $i \in \mathcal{N}$ is denoted as $P_{\max,i}$. Therefore, we have

$$\mathbb{E}\left(\left|\boldsymbol{x}_i^E\right|^2\right) = \text{tr}(\boldsymbol{B}_i \boldsymbol{S}) \le P_{\max,i}, \forall i \in \mathcal{N}, \qquad (1)$$

where $\text{tr}(\cdot)$ denotes the trace of a square matrix, and $\boldsymbol{B}_i \triangleq \text{Diag}\Bigg(\underbrace{0,\cdots,0}_{(i-1)M},\underbrace{1,\cdots,1}_{M},\underbrace{0,\cdots,0}_{(N-i)M}\Bigg)$, with $\text{Diag}(\boldsymbol{a})$ denoting a diagonal matrix with the diagonal elements given in the vector $\boldsymbol{a}$.

Next, consider the distributed information beamforming from the sensor nodes to the information AP. It is assumed that each sensor node has the common information s_I with zero mean and unit variance to be sent, and such common information can either be obtained by each sensor node measuring the same information (e.g., temperature information), or via them sharing such information with each other (to enable distributed information beamforming) [9]. It is also assumed that all sensor nodes are perfectly synchronized in both time and frequency, which may require the information AP to help send common reference signals. Let the channel coefficient from the sensor node k to the information AP be denoted as g_k. Then, each sensor node k sets its transmit information signal as $x_k^I = \sqrt{Q_k} g_k^H s^I/|g_k|$, where $Q_k \ge 0$ denotes the transmit power of sensor node k. Consequently, the transmitted information signals from all the K sensor nodes can be coherently combined at the information AP, for which the received SNR is denoted as $\gamma = \frac{\sum_{k\in\mathcal{K}}|g_k|^2 Q_k}{\sigma^2}$, where σ^2 denotes the noise power at the information AP receiver.

In practice, when each sensor node k is activated in information transmission (i.e., $Q_k > 0$), it also consumes sensing and circuit energy for maintaining its routine operation, in addition to the transmission power Q_k [11], [12].[3] For the ease of analysis, we denote the sensing and circuit energy consumption as a constant $\alpha_k > 0$. As a result, the total energy consumption for each sensor node k is expressed as $Q_k/\beta_k + \alpha_k \mathbf{1}(Q_k)$, where $0 < \beta_k < 1$ denotes the efficiency of the RF chain for sensor node k, and $\mathbf{1}(Q_k)$ is an indicator function given as $\mathbf{1}(Q_k) = \begin{cases} 1, & \text{if } Q_k > 0, \\ 0, & \text{if } Q_k = 0. \end{cases}$ Note that the energy consumed at each sensor node k cannot exceed that harvested from all the N ETs (i.e., E_k). As a result, we have the following wireless energy harvesting constraint for each sensor node k:[4]

$$Q_k/\beta_k + \alpha_k \mathbf{1}(Q_k) \le \eta_k \boldsymbol{h}_k^H \boldsymbol{S} \boldsymbol{h}_k, \forall k \in \mathcal{K}. \qquad (2)$$

Also suppose that each sensor node k is subject to a maximum

[2] Note that the ETs are dedicatedly designed for energy transmission, and not capable of decoding and forwarding the sent information of sensor nodes.

[3] Note that the CSI feedback also consumes energy at each sensor node k. We consider such energy consumption to be constant and included in Q_k.

[4] We assume that each sensor node only has limited-capacity energy storage and consider its used energy at each time to be no larger than its harvested energy for ensuring the "energy causality" constraint. Dynamic energy storage management over time and the associated storage structure are beyond the scope of this letter.

transmit power $Q_{\max,k} > 0$. Therefore, we have

$$Q_k \leq Q_{\max,k}, \forall k \in \mathcal{K}. \quad (3)$$

We are interested in maximizing the received SNR at the information AP (i.e., γ) by jointly optimizing the collaborative energy beamforming at ETs (i.e., the transmit energy covariance matrix $\boldsymbol{S}$) and the distributed information beamforming at sensor nodes (i.e., the transmit power Q_k's). As a result, we formulate the optimization problem of our interest as

$$\text{(P1)}: \max_{\boldsymbol{S} \succeq \mathbf{0}, \{Q_k\}} \frac{\sum_{k \in \mathcal{K}} |g_k|^2 Q_k}{\sigma^2}$$
$$\text{s.t. } (1), (2), \text{ and } (3).$$

Note that with α_k's being non-zero, problem (P1) is in general a difficult problem to be solved, since the constraints in (2) are non-convex due to the indicator function $\mathbf{1}(Q_k)$'s. There exists a trade-off in optimizing $\boldsymbol{S}$ and $\{Q_k\}$ to maximize the received SNR at the information AP: spreading the energy beams to activate more sensor nodes can achieve higher distributed information beamforming gain, but in turn consume higher sensing and circuit energy.

III. Optimal Solution

In this section, we present the optimal solution to problem (P1). For each sensor node k, we introduce an auxiliary variable $\rho_k \in \{0, 1\}$ to denote its inactive/active status, where $\rho_k = 0$ represents that the sensor node k is not activated with $Q_k = 0$, whereas $\rho_k = 1$ means that it is activated with $Q_k > 0$. As a result, we can reformulate problem (P1) as

$$\text{(P2)}: \max_{\boldsymbol{S} \succeq \mathbf{0}, \{\rho_k, Q_k\}} \frac{\sum_{k \in \mathcal{K}} |g_k|^2 Q_k}{\sigma^2}$$
$$\text{s.t. } Q_k + \rho_k \alpha_k \leq \eta_k \boldsymbol{h}_k^H \boldsymbol{S} \boldsymbol{h}_k, \forall k \in \mathcal{K} \quad (4)$$
$$Q_k \leq \rho_k Q_{\max,k}, \ \forall k \in \mathcal{K} \quad (5)$$
$$\rho_k \in \{0, 1\}, \forall k \in \mathcal{K} \quad (6)$$
$$(1).$$

Problem (P2) is a mixed integer semi-definite program (MI-SDP), which is still non-convex. To optimally solve the MI-SDP (P2), we use a two-step approach by first optimizing the collaborative energy beamforming $\boldsymbol{S}$ and the distributed information beamforming $\{Q_k\}$ under any given $\{\rho_k\}$, and then optimizing the inactive/active status of sensor nodes $\{\rho_k\}$ via the exhaustive search.

First, we consider the joint collaborative energy beamforming and distributed information beamforming optimization problem under any given $\{\rho_k\}$, which is expressed as

$$f(\{\rho_k\}) = \max_{\boldsymbol{S} \succeq \mathbf{0}, \{Q_k\}} \frac{\sum_{k \in \mathcal{K}} |g_k|^2 Q_k}{\sigma^2} \quad (7)$$
$$\text{s.t. } (1), (4), \text{ and } (5),$$

where the optimal value $f(\{\rho_k\})$ denotes the maximum SNR at the information AP under given $\{\rho_k\}$. Problem (7) is a convex semi-definite program (SDP), which can be solved via standard convex optimization techniques such as the interior point method. Here, we employ the convex optimization tool named CVX [13] to solve this problem for obtaining $f(\{\rho_k\})$ under any given $\{\rho_k\}$. Note that under certain $\{\rho_k\}$, problem (7) may be infeasible. For example, when too many sensor nodes are activated with $\rho_k = 1$, the collaborative energy beamforming cannot support all the nodes' sensing and circuit power, and accordingly the constraints in (4) cannot be all ensured at the same time. In this case, the objective value is set as $f(\{\rho_k\}) = -\infty$. Also note that when problem (7) is feasible, we denote its optimal solution as $\boldsymbol{S}^{(\{\rho_k\})}$ and $\{Q_k^{(\{\rho_k\})}\}$.

Next, with $f(\{\rho_k\})$ obtained under any given $\{\rho_k\}$, we obtain the optimal inactive/active status for sensor nodes by solving the following problem:

$$\max_{\{\rho_k\}} f(\{\rho_k\}) \quad (8)$$
$$\text{s.t. } (6).$$

Since ρ_k's are binary variables, we use the exhaustive search to find the optimal inactive/active status of sensor nodes to problem (8), denoted by $\{\rho_k^*\}$. By combing this together with the optimal solution to problem (7), we have obtained the optimal solution to problem (P2) to be $\{\rho_k^*\}$, $\boldsymbol{S}^* = \boldsymbol{S}^{(\{\rho_k^*\})}$ and $Q_k^* = Q_k^{(\{\rho_k^*\})}, \forall k \in \mathcal{K}$.

Here, since the exhaustive search is employed to find the optimal $\{\rho_k^*\}$ in (8), the complexity for optimally solving (P2) increases exponentially as the number of sensor nodes K.

IV. Suboptimal Solution with Low Complexity

In this section, we propose a low-complexity suboptimal solution to solve problem (P2), by using a similar two-step approach as in Section III, in which problem (7) is solved to obtain $f(\{\rho_k\})$ under given $\{\rho_k\}$ (same as in Section III), and the greedy algorithm (different from the exhaustive search in Section III) is employed to select active sensor nodes for solving problem (8).

Specifically, in the greedy algorithm for selecting active sensor nodes, we first define a candidate set of sensor nodes, and initial it as $\mathcal{A} = \mathcal{K}$. Then, in each iteration, we try to activate one sensor node from $\mathcal{A}$, such that the received SNR at the information AP can be maximally improved. When the sensor node is activated, it is deleted from the candidate set $\mathcal{A}$. The iteration ends when the received SNR at the information AP cannot be further increased, or problem (7) becomes infeasible, or the candidate set $\mathcal{A}$ becomes null. We denote the obtained suboptimal solution to problem (P2) as $\{\rho_k^{**}\}$, $\boldsymbol{S}^{**}$ and $\{Q_k^{**}\}$. The detailed algorithm is listed in Table I.

Remark 4.1 (Complexity analysis): The suboptimal solution in Table I needs to solve problem (7) in a total of $K(K+1)/2$ times in the worst case, while the optimal solution needs to solve problem (7) in a total of 2^K times. As a result, the worst-case complexity of the proposed suboptimal solution is only a $\frac{K(K+1)}{2^{K+1}}$ portion of that of the optimal solution.

V. Numerical Results

In this section, we provide numerical results to validate the performance of our proposed optimal and suboptimal solutions. For comparison, we consider a benchmark scheme employed in the existing literature, which ignores the sensing and circuit power by assuming that $\alpha_k = 0, \forall k \in \mathcal{K}$. In this case, problem (P1) is a convex SDP and thus can be optimally solved by CVX, for which the optimal solution is denoted as $\boldsymbol{S}^\star$ and $\hat{Q}_k$. Then the benchmark scheme sets the transmit energy covariance matrix at ETs as $\boldsymbol{S}^\star$, and consequently the inactive/active status and the transmit power of each sensor node

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TABLE I
GREEDY ALGORITHM FOR SOLVING PROBLEM (P2)

1) **Initialization:** set the candidate set of sensor nodes as $\mathcal{A} = \mathcal{K}$, and an auxiliary parameter $\gamma^{(0)} = 0$.
2) **For** $k = 1 : K$
   a) Set the SNR at the information AP in the kth iteration as $\gamma^{(k)} = 0$;
   b) **For** $l = 1 : K$
      - **If** $l \in \mathcal{A}$
         – Set $\rho_l = 1$, $\rho_j = 1, \forall j \in \mathcal{K} \setminus \mathcal{A}$, and $\rho_j = 0, \forall j \in \mathcal{A} \setminus \{l\}$;
         – Under given $\{\rho_k\}$, solve problem (7) to obtain $f(\{\rho_k\})$;
         – If $f(\{\rho_k\}) > \gamma^{(k)}$, then set $\gamma^{(k)} = f(\{\rho_k\})$ and record the index of sensor node as $a^{(k)} = l$.
      - **End If**
   c) **End For**
   d) Compare $\gamma^{(k)}$ and $\gamma^{(k-1)}$. If $\gamma^{(k)} > \gamma^{(k-1)}$, update the candidate set of sensor nodes as $\mathcal{A} \leftarrow \mathcal{A} \setminus \{a^{(k)}\}$; otherwise, exit the "For" loop.
3) **End For**
4) **Set** the inactive/active status of sensor nodes as $\rho_k^{**} = 0, \forall k \in \mathcal{A}$, and $\rho_k^{**} = 1, \forall k \in \mathcal{K} \setminus \mathcal{A}$, and accordingly set $\boldsymbol{S}^{**} = \boldsymbol{S}^{(\{\rho_k^{**}\})}$ and $Q_k^{*} = Q_k^{(\{\rho_k^{**}\})}, \forall k \in \mathcal{K}$.

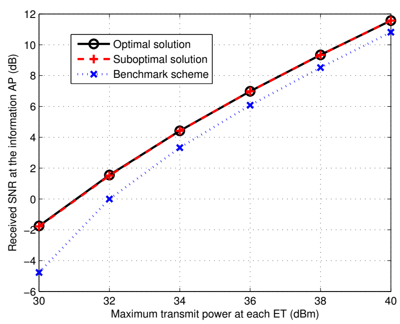

Fig. 2. The received SNR γ at the information AP versus the maximum transmit power $P_{\max}$ at each ET.

$k \in \mathcal{K}$ are expressed as $\rho_k^{\star} = \begin{cases} 0, & \text{if } \eta_k \boldsymbol{h}_k^H \boldsymbol{S}^{\star} \boldsymbol{h}_k < \alpha_k \\ 1, & \text{if } \eta_k \boldsymbol{h}_k^H \boldsymbol{S}^{\star} \boldsymbol{h}_k \geq \alpha_k, \end{cases}$ and $Q_k^{\star} = \min\left(\beta_k \left(\eta_k \boldsymbol{h}_k^H \boldsymbol{S}^{\star} \boldsymbol{h}_k - \alpha_k\right)^+, Q_{\max,k}\right)$, respectively.

In the simulation, we consider a wireless sensor network consisting of $K = 10$ sensor nodes that are randomly distributed within a circle with the radius being 15 meters. There are $N = 4$ ETs uniformly distributed in the circle, and each ET is equipped with $M = 4$ antennas. Furthermore, we consider that the information AP is an overflying UAV far away from the sensor nodes, located 3000 meters away from the center of the circle [9]. Also, we set the sensing and circuit power consumption, the energy harvesting efficiency, the RF efficiency, and the maximum transmit power at each sensor node k as $\alpha_k = 0.5$ mW, $\eta_k = 0.5$, $\beta_k = 0.5$, and $Q_{\max,k} = 20$ dBm, respectively, $\forall k \in \mathcal{K}$.

Fig. 2 shows the received SNR γ at the information AP versus the maximum transmit power $P_{\max}$ at each ET, where $P_{\max} = P_{\max,i}, \forall i \in \mathcal{N}$. It is observed that the received SNR γ at the information AP increases as the maximum transmit power $P_{\max}$ at each ET becomes large. Specifically, the proposed optimal and suboptimal solutions are observed to significantly outperform the benchmark scheme, especially when the maximum transmit power $P_{\max}$ at each ET is small (e.g., $P_{\max} = 30$ dBm). This is due to the fact that the proposed optimal and suboptimal solutions can properly choose active sensor nodes to balance the distributed information beamforming gain and the non-zero sensing and circuit power consumption cost, while the benchmark scheme fails to do so. Furthermore, the suboptimal solution is observed to achieve a similar received SNR γ at the information AP as compared to the optimal solution. This, together with the complexity analysis in Remark 4.1, shows that the proposed suboptimal solution is very promising from the practical implementation perspective.

VI. CONCLUSION

This letter considered a wireless powered sensor network, where a number of sensor nodes send common information to an information AP, by using the harvested wireless power from dedicatedly deployed ETs. By taking into account the practical non-zero sensing and circuit power consumption at each sensor node, we jointly optimize the collaborative energy beamforming at the ETs and the distributed information beamforming at the sensor nodes (together with their inactive/active status), to maximize the received SNR at the information AP. Our proposed design improves the system performance significantly, as compared to the conventional design that ignores the non-zero sensing and circuit power consumption of sensor nodes.

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