Power Allocation for Channel Estimation and Energy Beamforming in Wirelessly Powered Sensor Networks

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***Abstract*—Wirelessly powered sensor networks (WPSNs) are becoming increasingly important to monitor many internet-of-things systems. In these WPSNs, dedicated base stations (BSs) with multiple antennas charge the sensor nodes without the need of replacing their batteries thanks to two essential procedures: i) getting of the channel state information of the nodes by sending pilots, and based on this, ii) performing energy beamforming to transmit energy to the nodes. However, the BSs have limited power budget and thus these two procedures are not independent, contrarily to what is assumed in some previous studies. In this paper, we investigate the novel problem of how to optimally allocate the power for channel estimation and energy transmission. Although the problem is non-convex, we provide a new solution approach and a performance analysis in terms of optimality and complexity. We also provide a closed form solution for the case where the channels are estimated based on a least square estimation. The simulations show a gain of approximately 10% in allocating the power optimally, and the importance of improving the channel estimation efficiency.**

I. INTRODUCTION

Wireless energy transmission (WET) [1], [2] can be used to charge the wireless devices remotely. It is a promising way to extend the lifetime of wireless sensor networks (WSNs), or even to support the WSNs to work as long as possible. WSNs with WET are called wirelessly powered sensor networks (WPSNs) [3].

In a typical WPSN as shown in Fig. 1, a base station (BS), acting as the energy source, provides energy to the nodes using WET, and the nodes use the received energy to make measurements and transmit them to a sink, which could be the energy source. Compared to traditional energy harvesting, because the energy source is dedicated, the process of the energy transmission is more controllable, predictable, and reliable. Consequently, the performance of the nodes is potentially more consistent.

A major problem of WET is the energy transmission efficiency, which greatly depends on the loss in the wireless channel [1]. As a result, the energy received at the node may be too limited for data transmission. To improve the efficiency, we can use energy beamforming techniques [4–6], which concentrate the power to the targets, and thus the nodes can collect more energy than the case where the BS broadcasts the energy. However, energy beamforming requires the knowledge of the channel state information (CSI) of the

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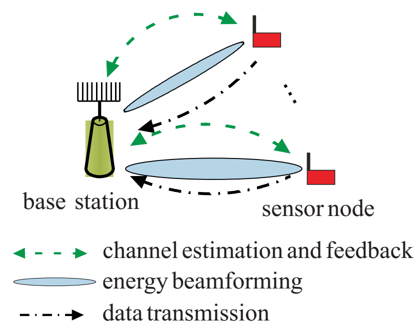


Fig. 1: The wirelessly powered sensor network considered in this paper. The base station uses energy beamforming to transmit energy to the nodes, and the nodes use the received energy for sensing and data transmission back to the base station.

nodes [7]. Therefore, besides WET, the BS must also spend some power to estimate the channel by sending pilots or energy probing [2], as shown in Fig. 1.

In general, the more energy the BS spends in channel estimation, the more accurate CSI it will have. In so doing, the BS can form a better energy beam to the nodes and thus increase the power received at the nodes. However, the BS has power limits imposed by national regulatory authorities and standards due to the safety issues [8], [9]. Consequently, it faces the crucial trade-off of using more power to get better CSI for higher WET efficiency but less power in energy transmission, or using more power in energy transmission with smaller WET efficiency due to less accurate CSI. In the literature, there are some works that focus on the cases with only one energy receiver. However, to the best of our knowledge, no investigations can be found to address such an important problem for the cases with multiple energy receivers.

Motivated by the problem above, we propose and investigate the power allocation problem for channel estimation and energy transmission. To summarize, the contributions of the paper are as follows:

- We propose the novel problem of power allocation for channel estimation and energy transmission for multiple sensor nodes, to maximize the monitoring performance of a WPSN.
- We show that the proposed power allocation problem is non-convex in general. Thus, we develop a novel

solution method based on solving a convex optimization iteratively. We show that our proposed algorithm can achieve a solution that possesses the desired optimality.
- We provide extensive numerical simulations to test the performance of the proposed algorithm. We show that the performance in terms of the data rate that the nodes can transmit is greatly improved. Besides, we also show how the power efficiency of channel estimation can greatly improve the performance of the sensor network.

The rest of the paper is organized as follows. In Section II, we summarize the related works on wireless energy transmission, especially for sensor networks. We provide a detailed description of the WPSN system and formulate the novel power allocation problem in Section III. Then, we provide a solution approach and the corresponding analysis of the approach in Section IV, followed by the numerical simulations in Section V. Last, we conclude our work and discuss the future directions in Section VI.

II. Related Works

WET is an important technique to recharge the sensor nodes. It allows us to transmit energy with the electromagnetic waves, and it is a promising way to provide energy to rechargeable sensor networks constantly. Compared to the ambient energy harvesting, WET has advantages in terms of better predictability and controllability [10]. More specifically, the energy sources can control the transmission of radio signals to carry energy in a form of electromagnetic radiation to the sensor nodes. Thus, there is a rich body of literature investigating charging wireless devices with WET.

The structures of WET systems can be broadly divided into two types, according to the transmission of the data: simultaneous wireless information and power transfer (SWIPT) [11] and wirelessly powered communication networks (WPCN) [7]. In SWIPT, the transmitter transmits data and energy at the same time, thus the receiver could allocate time, power, or antennas for decoding information and harvesting energy [12]. On the other hand, in WPCN [7], [13], the receivers transmit data using the energy harvested from the transmitters. In WPCN, most of the studies focus on maximizing the throughput of wireless devices by properly allocating the frequency or scheduling time for energy transmission and data transmission [13–16].

Since in WET the energy is carried by electromagnetic waves, the energy transfer efficiency greatly suffers path loss. To improve the efficiency, energy beamforming [4], [5] can be used to steer the signals towards the receivers. With perfect CSI, the work in [17] shows that the optimal energy beamforming in terms of received energy of a point-to-point MIMO system can be achieved by the eigenvector corresponding to the largest eigenvalue of the channel matrix. For a WPCN with multiple energy receivers, the authors of [14] study a joint time allocation and energy beamforming problem to maximize the network sum-throughput, and provide a solution approach based on semi-definite relaxation. However, in practice, the energy transmitter always needs power and time to achieve CSI, and the performance of WET depends on the channel estimation or learning that provides CSI. The accuracy of CSI estimation for WET has thus been investigated in [2], [5], [18]. In particular, the work in [18] considers the training design of WET for a single transmitter and single receiver system, such that the channel is sufficient accurate for energy beamforming whilst the energy consumption is not too high. The work is further extended in terms of multiple transmitters case in [5]. However, the considered network consists only one energy receiver.

In this paper, we investigate WPSN [3], which is the case of WPCN for sensor networks. Since sensor nodes are low power devices, we do not consider the maximum achievable rate as it is commonly done in WPCN. Instead, the metrics for sensor networks are usually lifetime and monitoring performance, which have not been considered in [2], [5], [18]. Important instances of studies concerning lifetime and monitoring performance are in [6], [19–21]. Such works considered the WET schedules to prolong WSN lifetime or improve monitoring performance. However, they assume that the wireless charger has perfect CSI or do not take channel estimation into account.

The work in [22] investigates the relationship of the power that is used in channel estimation and the expected received energy at the receiver. However, the power allocation for channel estimation and energy transmission to maximize the network performance has not been studied for WSNs. The case for a point-to-point network is studied in [18], [23]. However, the problem of how to allocate the power for different energy receivers has not been addressed. This means that, with the current approaches, it might happen that the BS transmits more power than needed to some nodes whilst it transmits not enough power to other nodes. This will significantly degrades the performance of the entire network. Thus, the power allocation for multiple energy receivers is still an open question. Therefore, in this paper we study the new problem of power allocation for channel estimation and energy transmission in a WPSN. The optimization takes the performance of all sensor nodes in the network into account, as opposed to what are done in the previous studies that only considered a single node's performance. To address the problem, we develop an binary searching based algorithm that iteratively checks the feasibility on the power, which is substantially different from the approaches in [18], [23].

III. Modelling and Problem Formulation

We consider a WPSN as shown in Fig. 1. The network has one BS and $N > 1$ sensor nodes, $v_1, v_2, \ldots, v_N$, demanding low energy consumption rates. The BS has N_{t} antennas and uses energy beamforming to transmit RF energy to the sensor nodes. Accordingly, the sensor nodes use the received energy to make measurements and to transmit data. Here we consider a star topology network where the sensor nodes transmit their measurements directly to the BS[1]. Thus, the data rate of the

[1]We should note that for a multihop WSN, when the routing table is fixed, the results of the paper still valid.

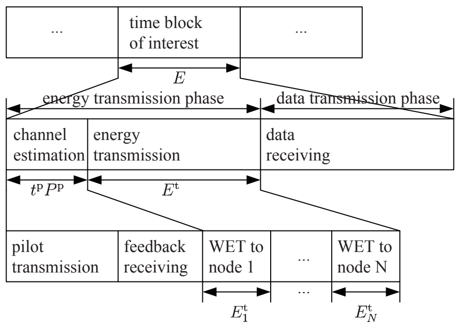


Fig. 2: In each time block of interest, the base station allocates its power for estimating the channels of the sensor nodes, and the power for energy transmission for each sensor node.

sensor nodes can be considered as the sampling rate of the nodes. Since energy of the sensor nodes is supplied by the BS, the nodes' performance depends on how the BS utilizes its power, as we describe below.

We consider a block-fading channel where the channels from the BS to the sensor nodes remain constant in a time block [17]. The duration of the time block is normalized as 1. In each time block of interest, the BS has a total energy E for channel estimation and energy transmission. It uses power $P^{\rm p}$ to send energy pilots for CSI estimation in the first $t^{\rm p}$ time, and then uses the rest of the energy $E^{\rm t}$ to transmit energy to the sensors, as shown in Fig. 2. Based on the estimation of the channels, the BS can form energy beams using the existing approaches [2], [6] with a certain power. Thus, the harvested energy depends on the transmitted power, the exact channel gains, and the accuracy of the channel estimation. Specifically, the BS uses a standard least square estimation to estimate the channels, as described in the following.

Consider a fading channel $\boldsymbol{h}_i$ with additive white Gaussian noise. The BS transmits pilots (for simplicity the pilots are the column vectors of identical matrix $\boldsymbol{I}$) with power $P^{\rm p}$, then the signal received by node v_i is $\boldsymbol{y}_i = \sqrt{P^{\rm p}/N_{\rm t}}\boldsymbol{h}_i + \boldsymbol{n}_i$, where $\boldsymbol{h}_i$ is the channel, $\boldsymbol{n}_i$ is the noise with covariance $\sigma_{\rm n}^2\boldsymbol{I}_{N_{\rm t}}$. The node transmits back $\boldsymbol{y}_i$ and the BS uses the least square estimator to estimate, i.e., $\hat{\boldsymbol{h}}_i = \boldsymbol{y}_i/\sqrt{P^{\rm p}/N_{\rm t}} = \boldsymbol{h}_i + \boldsymbol{n}_i/\sqrt{P^{\rm p}/N_{\rm t}}$. Then, during the energy transmission, the BS transmits energy $E_i^{\rm t}$ to v_i with beamforming $\hat{\boldsymbol{h}}_i$. The expected harvested energy of v_i would be $E_i^{\rm t} = \mathbb{E}[\eta|\hat{\boldsymbol{h}}_i^H\boldsymbol{h}_i|^2E_i^{\rm t}/\|\hat{\boldsymbol{h}}_i\|^2]$, where η is the RF-DC conversion rate of the node. When the BS has massive antenna, $E_i^{\rm t}$ converges to

$$E_i^{\rm r} = \eta\frac{N_{\rm t}g_i^2P^{\rm p}}{g_iP^{\rm p} + N_{\rm t}\sigma_{\rm n}^2}E_i^{\rm t}\,,$$

where $g_i = \mathbb{E}[\boldsymbol{h}_i^H\boldsymbol{h}_i]/{N_{\rm t}}^2$.

For a node v_i, it uses a predetermined fixed power to transmit data. We denote the power consumption to transmit a unit data to the sink node by $e_i > 0$. Besides of the energy consumption for data transmission, its static power consumption is c_i, which accounts for sensing, local data processing, circuits, and also sending feedback to the BS. Denote the data rate of node v_i by w_i. Then, we have that the total energy consumption of v_i is $e_iw_i + c_i$[3].

Regarding the monitoring performance of the WPSN, we hope to have that the nodes make measurements as much as possible. Besides, we do not want to have some nodes make little measurements. Thus, we use the minimum sampling rate of the nodes, $w_{\min}$, as the monitoring performance metric of the WPSN. Denote $\boldsymbol{w} = [w_1, w_2, \ldots, w_N]^T$, and $\boldsymbol{E}^{\rm t} = [E_1^{\rm t}, \ldots, E_N^{\rm t}]^T$. Then, we are ready to formulate the power allocation problem as follows:

$$\max_{w_{\min},\boldsymbol{w},\boldsymbol{E}^{\rm t},P^{\rm p}} \quad w_{\min} \tag{1a}$$

$$\text{s.t.} \quad w_i \geq w_{\min}\,, \forall i, \tag{1b}$$

$$e_iw_i + c_i \leq E_i^{\rm r}\,, \forall i, \tag{1c}$$

$$t^{\rm p}P^{\rm p} + \sum_i E_i^{\rm t} \leq E\,, \tag{1d}$$

$$w_i, E_i^{\rm t}, P^{\rm p} \geq 0\,, \forall i\,, \tag{1e}$$

where the objective is to maximize the minimum data rate of all the nodes, $w_{\min}$; Constraint (1c) is the energy causality, i.e., the consumed energy of a node should be no larger than the energy it receives; Constraint (1d) is the energy limit of the BS; and Constraint (1e) is the non negative constraint of the data rates, the training powers, and the transmitting powers. The problem is to allocate the power of channel estimation and energy transmission for each sensor node such that the minimum rate of the nodes is maximized. If we check Constraint (1c), we have that the Hessian matrix is not positive semidefinite. Consequently, Problem (1) is not a convex optimization and the solution approach is non-trivial. Notice also that when $N = 1$, such a problem can be simplified to a convex optimization. Therefore, the difficulty of Problem (1) mainly comes from the power allocation for multiple nodes. Even though the problem is non-convex, we propose a solution algorithm to find the solution to the problem, as will be presented in the next section.

IV. Solution Approach

In this section, we investigate a solution approach to solve Problem (1). Then, we show the correctness and efficiency of the algorithm by analysing its computational complexity.

To develop the solution algorithm, we first study a sub problem to check the feasibility on the power, based on the assumption that the rate is given.

[2]Although the scheme for channel acquisition is forward-link channel estimation based on least square, our approach is valid for general cases including power probing scheme as long as $E_i^{\rm r}$ is a monotone increasing and concave function of $P^{\rm p}$. More discussion can be found in our journal version.

[3]This model is commonly used for WSNs [20], [24], [25] due to that the power that the sensor nodes use for data transmission is very limited, compared to other cases such as mobile phones. However, with proper modifications, our approach still valid for the Shannon capacity based model.

Assume that $w_{\min}$ is given. Then, we want to find the minimum power to satisfies such a rate, and formulate the sub problem as follows:

$$\min_{E_{\mathrm{s}}, \boldsymbol{E}^{\mathrm{t}}, \boldsymbol{P}^{\mathrm{p}}} \quad E_{\mathrm{s}} \tag{2a}$$

$$\text{s.t.} \quad e_i w_{\min} + c_i \leq \frac{\eta N_{\mathrm{t}} g_i^2 P^{\mathrm{p}} E_i^{\mathrm{t}}}{g_i P^{\mathrm{p}} + N_{\mathrm{t}} \sigma_{\mathrm{n}}^2}, \forall i \,, \tag{2b}$$

$$t^{\mathrm{p}} P^{\mathrm{p}} + \sum_i E_i^{\mathrm{t}} \leq E_{\mathrm{s}} \,, \tag{2c}$$

$$w_i, P^{\mathrm{p}}, E_i^{\mathrm{t}} \geq 0, \forall i \,. \tag{2d}$$

Constraint (2b) gives us that E_i^{t} should be no less than $(e_i w_{\min} + c_i)\left(g_i P^{\mathrm{p}} + N_{\mathrm{t}} \sigma_{\mathrm{n}}^2\right)(\eta g_i^2 N_{\mathrm{t}} P^{\mathrm{p}})^{-1}, \forall i$. Define $f_i(w_{\min}) = (e_i w_{\min} + c_i)(\eta g_i N_{\mathrm{t}})^{-1}$, and $\tilde{N}_i = N_{\mathrm{t}} \sigma_{\mathrm{n}}^2 / g_i$. Then, Problem (2) is equivalent to the following one:

$$\min_{0 \leq P^{\mathrm{p}}} \quad E_{\mathrm{s}}(P^{\mathrm{p}} | w_{\min}) \triangleq t^{\mathrm{p}} P^{\mathrm{p}} + \sum_i f_i(w_{\min}) \left(1 + \frac{\tilde{N}_i}{P^{\mathrm{p}}}\right) \,, \tag{3}$$

where $E_{\mathrm{s}}(P^{\mathrm{p}} | w_{\min})$ is the total power to satisfy the required sampling rate $w_{\min}$, where the BS uses power P^{p} for channel estimation. We have the following proposition for Problem (3):

Proposition 1: Problem (3) is a convex optimization, and $P^{p,*}(w_{\min}) = \sqrt{\sum_i f_i(w_{\min}) \tilde{N}_i / t^{\mathrm{p}}}$ is the optimal solution [4].

Remark 1: Proposition 1 gives us that the optimum of Problem (3) is

$$E^*(w_{\min}) = \sum_i f_i(w_{\min}) + 2\sqrt{\sum_i f_i(w_{\min}) \tilde{N}_i t^{\mathrm{p}}} \,. \tag{4}$$

Let $E^*(w)$ be the optimum of Problem (3) given w, and $w_{\min}^*$ be the optimum of Problem (1). If $E^*(w) < E$, we have that $w < w_{\min}^*$; otherwise $w \geq w_{\min}^*$. This gives us the solution algorithm for Problem (1) based on binary searching. The idea is as follows:

We first find the lower bound and upper bound of $w_{\min}$, which is denoted by $w_{\min}^{\mathrm{l}}$ and $w_{\min}^{\mathrm{u}}$ respectively. For the lower bound, we can easily choose $w_{\min}^{\mathrm{l}} = 0$. For the upper bound, one can choose $w_{\min}^{u}$ to be the optimal solution of the following linear optimization problem:

$$\max_{w_{\min}, \boldsymbol{E}^{\mathrm{t}}} \quad w_{\min} \tag{5a}$$

$$\text{s.t.} \quad e_i w_{\min} + c_i \leq \eta N_{\mathrm{t}} g_i E_i^{\mathrm{t}}, \forall i \,, \tag{5b}$$

$$\sum_i E_i^{\mathrm{t}} \leq E \,, \tag{5c}$$

$$w_{\min}, E_i^{\mathrm{t}} \geq 0, \forall i \,. \tag{5d}$$

The interpretation of Problem (5) is that the BS has perfect CSI beforehand, thus it will not consume any power for channel estimation, and has more power to charge the nodes.

Once we have known the upper bound and lower bound of $w_{\min}$, we can check the feasibility of $w_{\min} = 0.5(w_{\min}^{\mathrm{l}} + w_{\min}^{\mathrm{u}})$ for Problem (3). If $w_{\min}$ is feasible, we update the new lower bound by $w_{\min}$; otherwise, we update the new upper bound by $w_{\min}$. This proceeds iteratively, until the lower bound and upper bound converge. The summary of the algorithm is shown in Algorithm 1.

[4] All the proofs can be found in our technical report [26]

Algorithm 1 Power allocation of channel estimation and energy transmission

Input: $\alpha_i, e_i, c_i, \eta_i(\cdot), \eta_{i,\max}, \forall i, E, \varepsilon$
Output: $E_i^{\mathrm{t}}, \forall i, P^{\mathrm{p}}, w_{\min}$

Set $w_{\min}^{\mathrm{l}} = 0$
if $\sum_i c_i / (\eta N_{\mathrm{t}} g_i) > E$ **then**
    The problem is infeasible and return $w = 0$.
else
    Find the initial upper bound $w_{\min}^{\mathrm{u}}$ by solving Problem (5)
    while $w_{\min}^{\mathrm{u}} - w_{\min}^{\mathrm{l}} \geq \varepsilon$ **do**
        Set $w_{\min} = 0.5(w_{\min}^{\mathrm{u}} + w_{\min}^{\mathrm{l}})$
        Solve Problem (3) and achieve $E^*(w_{\min})$ according to (4)
        if $E^*(w_{\min}) - E > 0$ **then**
            Update $w_{\min}^{\mathrm{u}} = w_{\min}$
        else
            Update $w_{\min}^{\mathrm{l}} = w_{\min}$
        end if
    end while
    Set $w_{\min} = w_{\min}^{\mathrm{l}}$, and set $P^{\mathrm{p}} = \sqrt{\sum_i f_i(w_{\min}) \tilde{N}_i / t^{\mathrm{p}}}$
    Set $E_i^{\mathrm{t}} = f_i(w_{\min})(1 + \tilde{N}_i (P^{\mathrm{p}})^{-1}), \forall i$.
    return $E_i^{\mathrm{t}}, P^{\mathrm{p}}, \forall i, w_{\min}$.
end if

Remark 2: According to Remark 1, the optimal $w_{\min}$ should satisfy that $E^*(w_{\min}^*) = E$. This equation has a unique and close form solution, which is $w_{\min} = (a_2 - \sqrt{a_2^2 - 4 a_1 a_3})(2a_1)^{-1}$, where $a_1 = \left(\sum_i e_i (\eta N_{\mathrm{t}} g_i)^{-1}\right)^2$, $a_2 = 2 \sum_i e_i (\eta N_{\mathrm{t}} g_i)^{-1} \left(E - \sum_i c_i (\eta N_{\mathrm{t}} g_i)^{-1}\right) + 4 \sum_i e_i t^{\mathrm{p}} (\eta g_i)^{-1}$, and $a_3 = \left(E - \sum_i c_i (\eta N_{\mathrm{t}} g_i)^{-1}\right)^2 - 4 \sum_i c_i t^{\mathrm{p}} (\eta g_i)^{-1}$. However, we keep the binary searching part in Algorithm 1, such that the solution can be applied to other channel models and estimation approaches (which leads to a different form of $P^{p,*}(w_{\min})$), by appropriate modification. Due to the limited space, we skip the detailed discussion here.

Now, we are ready to analyze the performance of Algorithm 1 to solve Problem (1). The performance is in terms of optimality of the solution provided by the algorithm, and algorithm's complexity.

The near optimality of the algorithm is given by the following theorem:

Theorem 1: Let Problem (1) be feasible and let its optimum be $w_{\min}^{\mathrm{o}} > 0$. Given any arbitrary small gap ε, Algorithm 1 will find a feasible solution $(w_{\min}, \boldsymbol{w}, \boldsymbol{E}^{\mathrm{t}*}, P^{\mathrm{p}*})$ that satisfies $w_{\min}^{\mathrm{o}} - w_{\min} < \varepsilon$.

Remark 3: Although the channels are estimated by least square based approach, the proposed approach is still valid (by proper modification) for other channel models or estimation approaches, such as the ones in [18], [22], [27], as long as the variance of estimation error is a convex decreasing function with P^{p}. Due to the limited space, we skip the detailed discussion here.

Regarding the complexity of Algorithm 1, we have the following proposition:

Proposition 2: Let Problem (1) be feasible and let its optimum be $w > 0$. The time complexity of Algorithm 1 is at most $O(N \log(E/N))$, where recall that N is the number of nodes, and E is the total energy that the BS has in a time block.

Consequently, we conclude that Algorithm 1 is an efficient approach to find a close optimal solution for Problem (1). In the next section, we will test the performance of the proposed algorithm by numerical simulations.

V. Numerical Simulations

In this section, we numerically evaluate the performance of Algorithm 1 to solve Problem (1). We use Matlab for performing numerical simulations. We first describe the set-ups of the simulations. Then, we test the convergence of the algorithm. Finally, we evaluate the average minimum data rates achieved by the algorithm with different network parameters.

1) Simulation Set-ups: The set-ups of the simulations are given as follows. We deploy $N = 20$ sensor nodes in a disk region with radius 50 meters. One BS with $N_{\rm t} = 100$ antennas is located at the centre of the region to transmit energy and to collect data. The total energy available at the BS for the time slot of 1 second is 3 Joule. The frequency of the RF energy carrier is 915 MHz, and the path loss depends on the distance between the BS and the node, and is calculated according to the Friis equation. The RF-DC conversion rate, i.e., ratio of received energy to the stored energy of a node, is $\eta = 0.1$ by default. For a sensor node, it transmit data with the standard 2.4 GHz frequency. The power consumption to transmit a unit size data to the BS is $10^{-7}d^2$ Watts, where d is the distance of the node to the BS. The static energy consumption of a node, c_i, is 3×10^{-7} Watts. $t^{\rm p}$ is 0.1 second.

2) Convergence Tests: First, we will show the convergence of the algorithm. In the running case, we set the channel estimation noise is $\sigma_{\rm n}^2 = -90$ dBm. The sensor nodes are randomly deployed in the region. The termination parameter ε in Line 6 of the algorithm is set to be 0.001 bit/s. Then, in Fig. 3(a), we plot $w_{\min}$ and the corresponding needed power $P^*(w_{\min})$ achieved by Algorithm 1 in each iteration step. Initially, the rate is $w = 24.7$ bits/s, and it requires energy 2.4346 Joules. Since it is smaller than the power the BS can allocate, the threshold data rate increases from the 2nd iteration until the 7th iteration, where the needed power is slightly above $E = 3$ Joule. Then, the threshold rate starts decreasing. The algorithm terminates at the 14-th iteration, where the resulting rate is 31.5 bits/s. The corresponding energy is slightly less than 3 Joules, which indicates the rate is near optimal and feasible. The total number of iterations is not too large, which indicates that the algorithm is efficient.

3) Performance Tests: To evaluate the performance of Algorithm 1, we make simulations with different noise level of channel estimation. For each combination of parameter, we simulate 1000 times with different deployments of the nodes, and take the average.

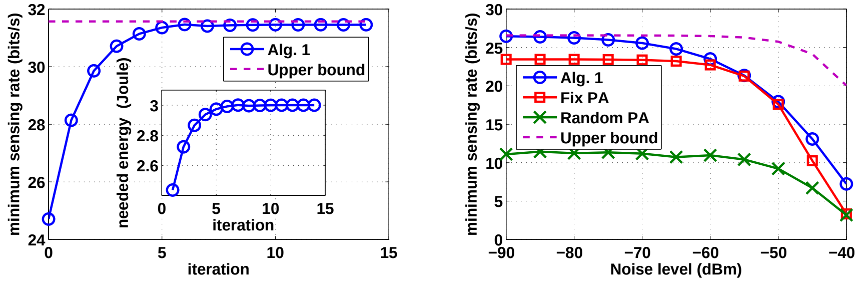
The performance is compared to an upper bound, a data rate achieved by a random based power allocation, a rate achieved by a fixed power allocation, and a rate achieved by energy broadcasting. The upper bound corresponds to the solution of Problem (5), which is the case where the BS has perfect CSI. For the random based power allocation, the idea is that the BS first allocates the power for channel estimation $P^{\rm p}$ randomly, and then finds the solution of Problem (1) with $P^{\rm p}$ fixed. The fixed power allocation is similar to the random based power allocation, where the difference is that the BS always uses a fixed ratio of the total power (in the simulation we use 0.3 Watts) for channel estimation. Regarding the energy broadcasting case, the BS spends no power in channel estimation and just broadcast energy with a fixed power 3 Watts.

We test the performance of the algorithm with different channel estimation noise, which could be considered as the power efficiency of channel estimation. The lower noise level, the higher efficiency it is for channel estimation. We change the noise level from -40 dBm to -90 dBm, and the results are shown in Fig. 3(b). The blue line with circles, the green line with crosses, the red line with squares, the yellow line with diamond marks, and the dashed purple line represents the average minimum data rate achieved by Algorithm 1, the random based power allocation, the fixed power allocation, the energy broadcasting, and the upper bound, respectively. We observe that, when the noise level is high, e.g. $\sigma_{\rm n}^2 = -50$ dBm, the gap of the data rate Achieved by 1 to the upper bound is large. The reason is that, in such cases, the BS needs to spend more power to learn the channel for a good enough CSI for energy beamforming. However, this leads to insufficient power in energy transmission, and the performance of WET deteriorate. However, when $\sigma_{\rm n}^2$ reduces to -70 dBm, we observe that the gap reduces to be almost negligible. The reason is that the BS needs much less energy in channel estimation to get a good enough CSI. We also compare the data rate achieved by Algorithm 1, the fixed power allocation, and the random based power allocation. We observe that the rate achieved by the random based power allocation is much worse than the optimal case. If the pilot power is fixed, the performance is close to the optimal one at certain noise level. However, at other levels, the rate achieved by Algorithm 1 is approximately 10% higher than the fixed PA.

To summarize, the simulation results show the convergence of the algorithm, and its performance is close to the upper bound if we have large power efficiency in channel estimation. Also, Algorithm 1 outperforms other power allocations scheme in terms of the data rate.

VI. Conclusions and Future Works

We considered a wirelessly powered sensor network where a BS uses energy beamforming to supply energy to sensor nodes for sensing and data uploading. To acquire channel state information for energy beamforming, the BS needs to consume energy. Thus, we studied the problem of power allocation on channel estimation and energy transmission for



(a) (b)

Fig. 3: (a) Convergence of Algorithm 1; (b) Comparison of Algorithm 1 to other approaches with different noise level in channel estimation

each node, such that the monitoring performance, in terms of data rate, is maximized. We showed that the problem is non convex in general. To solve the problem, we proposed a solution algorithm of low complexity, based on a binary search approach, to calculate the optimal solution numerically. The simulation results showed that significant performance gains can be obtained by the proposed algorithm, compared to a fixed ratio power allocation. Also, the performance is close to the upper bound of the data rate if the power efficiency of channel estimation is large enough.

In the future, we will study the case with multiple BSs, and the cases with general channel acquisition methods.

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