ENERGY BEAMFORMING WITH ONE-BIT FEEDBACK

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ABSTRACT

Wireless energy transfer (WET) via far-field radio signal has emerged as a new solution for powering wireless networks. To overcome the significant path loss in wireless channels, multi-antenna or multiple-input multiple-output (MIMO) techniques have been proposed to enhance the transmission efficiency and distance for WET. However, in order to reap the large energy beamforming gain in WET, acquiring channel state information (CSI) at the energy transmitter (ET) is an essential task. This task is particularly challenging for WET systems, since existing channel training and feedback methods used for communication receivers cannot be implemented at the energy receiver (ER) due to the hardware limitation. To tackle this problem, in this paper we consider a point-to-point MIMO WET system with transmit energy beamforming, and propose a new channel learning method that requires only one feedback bit from the ER to ET per feedback interval. Each feedback bit indicates the increase or decrease of the harvested energy by the ER between the present and previous intervals, which can be measured without changing the existing hardware at the ER. Based on such feedback information, the ET adjusts transmit energy beamforming in different intervals and at the same time obtains an improved estimate of the MIMO channel by applying the analytic center cutting plane method (ACCPM). By numerical examples, we show the performance of our proposed new channel learning algorithm for MIMO WET systems in terms of convergence speed and energy transfer efficiency, as compared to existing algorithms.

1. INTRODUCTION

Harvesting energy in nature has received an upsurge of interest for the design of energy efficient wireless communication. In particular, radio signal is a viable new source for wireless energy harvesting. In order to achieve radio signal enabled energy harvesting for wireless devices that require constant and continuous power supplies, a new technique by employing dedicated energy transmitters (ETs) to send wireless power to a set of distributed energy receivers (ERs), termed far-field wireless energy transfer (WET), has drawn significant attention recently [1–3].

How to combat the significant signal path loss in wireless channels is one key challenge in implementing practical WET systems of both high energy transfer efficiency and long operating range. To overcome this issue, multi-antenna or multiple-input multiple-output (MIMO) technique, which has been successfully applied in wireless communication to improve the transmission rate and reliability over wireless channels, is also an appealing solution for WET (see e.g. [4–6]). However, the benefit of MIMO in WET crucially relies on the availability of channel state information (CSI) at the ET via the channel feedback from the ER, but acquiring such information is particularly challenging due to the hardware limitation of the ER

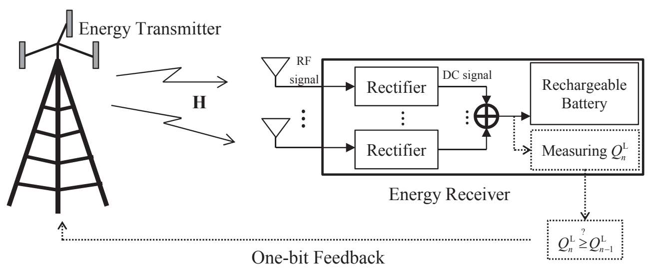

Fig. 1: A point-to-point MIMO system for wireless energy transfer (WET).

in practice. As shown in Fig. 1, one ER with multiple antennas harvests the energy from the signal sent by one multiple-antenna ET by applying the rectenna at each receive antenna [7], by which the radio frequency (RF) signal from each receive antenna is converted to a direct current (DC) signal via a rectifier, and then the DC signals from all receive antennas are combined to charge the battery. Since no baseband signal processing is implementable at the ER, existing channel training and feedback methods (see e.g. [8] and the references therein) for the receiver in wireless communication cannot be applied at the ER in WET and thus new channel learning and feedback schemes need to be designed, which motivates this work.

In this paper, we study a point-to-point MIMO WET system with transmit energy beamforming, as shown in Fig. 1. We propose a two-phase transmission protocol in the MIMO WET system for channel learning and energy transmission, respectively. We propose a new channel learning algorithm that requires only one feedback bit from the ER to ET per feedback interval. Each feedback bit indicates the increase or decrease of the harvested energy at the ER between the present and previous intervals. Based on such feedback information, the ET adjusts transmit energy beamforming in different intervals and at the same time obtains an improved estimate of the MIMO channel via applying the analytic center cutting plane method (ACCPM) [9]. By numerical examples, we show the performance of our proposed new channel learning algorithm in terms of convergence speed and energy transfer efficiency, as compared to existing algorithms.

2. SYSTEM MODEL

We consider a point-to-point MIMO WET system as shown in Fig. 1, where one ET with $M_T > 1$ transmit antennas delivers wireless energy to one ER with $M_R \geq 1$ receive antennas. We assume a quasi-static flat fading channel model, where the channel from the ET to ER remains constant within each transmission block and may change from one block to another. We denote each block duration as T, which is assumed to be sufficiently long for typical low-mobility and short-range WET applications.

We consider linear energy beamforming at the multiple-antenna ET. Without loss of generality, we assume that the ET sends $d \leq M_T$ energy beams. Let the jth beamforming vector be denoted

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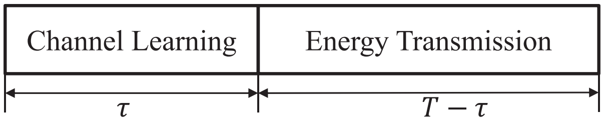

Fig. 2: The two-phase transmission protocol.

by $\boldsymbol{w}_j \in \mathbb{C}^{M_T \times 1}$ and its carried energy-modulated signal by s_j, $j \in \{1, \ldots, d\}$. Then the transmitted signal at ET is given by $\boldsymbol{x} = \sum_{j=1}^{d} \boldsymbol{w}_j s_j$. Since s_j's do not carry any information, they can be assumed to be independent sequences from an arbitrary distribution with zero mean and unit variance, i.e., $\mathbb{E}\left(|s_j|^2\right) = 1, \forall j$, where $\mathbb{E}(\cdot)$ denotes the expectation and $|\cdot|$ denotes the absolute value of a complex number. Furthermore, we denote the transmit covariance matrix as $\boldsymbol{S} = \mathbb{E}(\boldsymbol{x}\boldsymbol{x}^H) = \sum_{j=1}^{d} \boldsymbol{w}_j \boldsymbol{w}_j^H$ with the subscript H denoting the conjugate transpose. Note that given any positive semi-definite matrix $\boldsymbol{S}$, i.e., $\boldsymbol{S} \succeq \boldsymbol{0}$, the corresponding energy beams $\boldsymbol{w}_1, \ldots, \boldsymbol{w}_d$ can be obtained from the eigenvalue decomposition (EVD) of $\boldsymbol{S}$ with $d = \texttt{rank}(\boldsymbol{S})$. Assume that the ET has a transmit sum-power constraint P over all transmit antennas; then we have $\mathbb{E}(\|\boldsymbol{x}\|^2) = \sum_{j=1}^{d} \|\boldsymbol{w}_j\|^2 = \texttt{tr}(\boldsymbol{S}) \leq P$, where $\|\cdot\|$ denotes the Euclidean norm of a complex vector and $\texttt{tr}(\cdot)$ denotes the trace of a square matrix.

The ER harvests the wireless energy carried by all d energy beams from M_R receive antennas. By denoting the MIMO channel matrix from the ET to ER as $\boldsymbol{H} \in \mathbb{C}^{M_R \times M_T}$, then the total harvested energy at ER over one block of interest is expressed as [4]

$$Q = \eta T \mathbb{E}\left(\|\boldsymbol{H}\boldsymbol{x}\|^2\right) = \eta T \texttt{tr}(\boldsymbol{G}\boldsymbol{S}), \tag{1}$$

where $0 < \eta \leq 1$ denotes the energy harvesting efficiency of the rectifier at each receive antenna and $\boldsymbol{G} = \boldsymbol{H}^H \boldsymbol{H}$ is a positive semi-definite matrix, i.e., $\boldsymbol{G} \succeq \boldsymbol{0}$. Since η is a constant, we assume $\eta = 1$ in the sequel of the paper unless stated otherwise. It is assumed that the ER cannot estimate the MIMO channel $\boldsymbol{H}$ (or $\boldsymbol{G}$) given its low-complexity receiver (see Fig. 1); however, it can measure the average harvested energy amount over a certain period of time by simply connecting an "energy meter" at the combined DC signal output as shown in Fig. 1.

We aim at designing the energy beams at the ET to maximize the transferred energy to the ER, i.e., Q given in (1), over each transmission block subject to a given transmit sum-power constraint. The problem is thus formulated as

$$\begin{aligned} &\max_{\boldsymbol{S}} \; T\texttt{tr}(\boldsymbol{G}\boldsymbol{S}) \\ &\texttt{s.t.} \; \texttt{tr}(\boldsymbol{S}) \leq P, \; \boldsymbol{S} \succeq \boldsymbol{0}. \end{aligned} \tag{2}$$

It has been shown in [4] that the optimal solution to (2) is given by $\boldsymbol{S}^* = P\boldsymbol{v}_E \boldsymbol{v}_E^H$, which achieves the maximum harvested energy $Q_{\max} = TP\lambda_E$, with λ_E and $\boldsymbol{v}_E$ denoting the dominant eigenvalue and its corresponding eigenvector of $\boldsymbol{G}$, respectively. Since $\texttt{rank}\,(\boldsymbol{S}^*) = 1$, this solution implies that sending one energy beam (i.e., $d = 1$) in the form of $\boldsymbol{w}_1 = \sqrt{P}\boldsymbol{v}_E$ is optimal for the point-to-point MIMO WET setup. This solution is thus referred to as the *optimal energy beamforming (OEB)* for a given $\boldsymbol{G}$.

However, implementing the OEB requires that the ET perfectly knows the MIMO channel, which needs to be estimated in practical systems. In this paper, we propose a two-phase transmission protocol as shown in Fig. 2: in the first phase, the ET implements channel learning (to be specified next) to estimate the MIMO channel; and in the second phase, based on the estimated MIMO channel the ET transmits with the corresponding OEB for WET. We explain the two phases in more detail as follows.

The channel learning phase corresponds to the first τ amount of time in each block of duration T, which is further divided into N_L feedback intervals each of length T_s, i.e., $\tau = N_L T_s$. For convenience, we assume that $N = T/T_s$ is an integer denoting the total block length in the number of feedback intervals. During this phase, the ET transmits with different covariance matrices (or sets of energy beamforming vectors) over N_L feedback intervals. Let the transmit covariance at ET in interval $n \in \{1, \ldots, N_L\}$ be denoted by $\boldsymbol{S}_n^{\mathrm{L}}$. Then the transferred energy to ER over the nth interval is given by $Q_n^{\mathrm{L}} = T_s \texttt{tr}(\boldsymbol{G}\boldsymbol{S}_n^{\mathrm{L}})$. At the same time, the ER measures its harvested energy amount Q_n^{L} and then feeds back one bit, denoted by $f_n \in \{0, 1\}$, to indicate whether the harvested energy in the nth interval is larger (i.e., $f_n = 0$) or smaller (i.e., $f_n = 1$) than that in the $(n-1)$th interval, $n = 1, \ldots, N_L$. For the convenience of our analysis later, we set $f_n \leftarrow 2f_n - 1$ such that $f_n \in \{-1, 1\}$. More specifically, if $Q_n^{\mathrm{L}} \geq Q_{n-1}^{\mathrm{L}}$, then $f_n = -1$; while if $Q_n^{\mathrm{L}} < Q_{n-1}^{\mathrm{L}}$, then $f_n = 1$. Also we denote $Q_0^{\mathrm{L}} \triangleq 0$ and equivalently $\boldsymbol{S}_0^{\mathrm{L}} = \boldsymbol{0}$ for convenience. Notice that the feedback interval T_s should be designed considering the practical feedback link rate from the ER to ET as well as the sensitivity of the energy meter at the ER. For the purpose of exposition, we assume in this paper that Q_n^{L}'s are all perfectly measured at the ER, and thus f_n's are all accurately determined at the ER and then sent back to the ET without any error, and furthermore the consumed energy for sending back f_n's is negligible at the ER as compared to its average harvested energy. Also notice that during the channel learning phase, the ER transmits the feedback bits to the ET over a dedicated communication channel and at the same time also receives the wireless energy from the ET over another orthogonal frequency channel.

The subsequent energy transmission phase in each block corresponds to the remaining $T - \tau$ amount of time. Let the estimate of $\boldsymbol{v}_E$ from the estimated channel matrix of $\boldsymbol{G}$ in the channel learning phase be denoted by $\tilde{\boldsymbol{v}}_E$. Then based on the principle of OEB, the ET sets the (rank-one) transmit covariance in the energy transmission phase as $\boldsymbol{S}^{\mathrm{E}} = P\tilde{\boldsymbol{v}}_E \tilde{\boldsymbol{v}}_E^H$. Accordingly, the total harvested energy at ER during this phase is expressed as $Q^{\mathrm{E}} = (T - \tau)P\tilde{\boldsymbol{v}}_E^H \boldsymbol{G} \tilde{\boldsymbol{v}}_E$.

Combining the above two phases, the total harvested energy at ER over one particular block is given by

$$Q_{\text{total}} = \sum_{n=1}^{N_L} T_s \texttt{tr}(\boldsymbol{G}\boldsymbol{S}_n^{\mathrm{L}}) + (T - \tau)P\tilde{\boldsymbol{v}}_E^H \boldsymbol{G} \tilde{\boldsymbol{v}}_E. \tag{3}$$

In (3), we observe that if the estimated MIMO channel is accurate with given finite N_L (or τ), then it follows that $\tilde{\boldsymbol{v}}_E^H \boldsymbol{G} \tilde{\boldsymbol{v}}_E \approx \lambda_E$. In this case, we have $Q_{\text{total}} \to Q_{\max}$ by increasing the block duration, i.e., $N \to \infty$ or $T \to \infty$. However, given finite N, there is in general a trade-off in time allocation, i.e., N_L versus $N - N_L$, between channel learning and energy transmission phases in order to maximize Q_{total} in (3).

3. CHANNEL LEARNING WITH ONE-BIT FEEDBACK

In this section, we propose a new channel learning algorithm for the ET to estimate the matrix $\boldsymbol{G}$ based on the one-bit feedback from the ER over each feedback interval in the channel learning phase. The proposed algorithm is based on the celebrated ACCPM in convex optimization [9]. To the authors' best knowledge, this paper is the first attempt to apply this technique to channel learning with one-bit feedback. In the following, we first introduce ACCPM,[1] and then present the ACCPM based channel learning algorithm with one-bit feedback.

[1] We refer the readers to [9] for more details of ACCPM.

3.1. Introduction of ACCPM

ACCPM is an efficient localization and cutting plane method for solving general convex or quasi-convex optimization problems [9, 10], with the goal of finding one feasible point in a convex target set $\mathcal{X} \subseteq \mathbb{R}^{m\times 1}, m \geq 1$, where $\mathcal{X}$ can be the set of optimal solutions to the optimization problem. Suppose that any point in the target set $\mathcal{X}$ is known *a priori* to be contained in a convex set $\mathcal{P}_0$, i.e., $\mathcal{X} \subseteq \mathcal{P}_0$. $\mathcal{P}_0$ is referred to as the initial working set. The basic idea of ACCPM is to query an *oracle* for localizing the target set $\mathcal{X}$ through finding a sequence of convex working sets, denoted by $\mathcal{P}_1, \cdots, \mathcal{P}_i, \cdots$. At each iteration $i \geq 1$, we query the oracle at a point $\boldsymbol{x}^{(i)} \in \mathbb{R}^{m\times 1}$, where $\boldsymbol{x}^{(i)}$ is chosen as the analytic center of the previous working set $\mathcal{P}_{i-1}$. If $\boldsymbol{x}^{(i)} \in \mathcal{X}$, then the algorithm ends. Otherwise, the oracle returns a *cutting plane*, i.e., $\boldsymbol{a}_i \neq \boldsymbol{0}$ and b_i satisfying that

$$\boldsymbol{a}_i^T \boldsymbol{z} \leq b_i \text{ for } \boldsymbol{z} \in \mathcal{X}, \tag{4}$$

which indicates that $\mathcal{X}$ should lie in the half space of $\mathcal{H}_i = \{\boldsymbol{z} | \boldsymbol{a}_i^T \boldsymbol{z} \leq b_i\}$ with the subscript T denoting the transpose. After the querying, the working set is then updated as $\mathcal{P}_i = \mathcal{P}_{i-1} \cap \mathcal{H}_i$. By properly choosing the cutting plane in (4) based on $\boldsymbol{x}^{(i)}$, we can have $\mathcal{P}_0 \supseteq \cdots \supseteq \mathcal{P}_i \supseteq \mathcal{X}$. Therefore, the returned working set $\mathcal{P}_i$ will be reduced and eventually approach the target set $\mathcal{X}$ as $i \to \infty$.

It is worth noting that given query point $\boldsymbol{x}^{(i)}$, if the cutting plane $\boldsymbol{a}_i^T \boldsymbol{z} = b_i$ in (4) contains $\boldsymbol{x}^{(i)}$, then it is referred to as a *neutral cutting plane*; if $\boldsymbol{a}_i^T \boldsymbol{x}^{(i)} > b_i$, i.e., $\boldsymbol{x}^{(i)}$ lies in the interior of the cut half space, then it is named a *deep cutting plane*; otherwise, it is called as a *shallow cutting plane*. For ACCPM, a deep or at least neutral cutting plane is required in each iteration.

3.2. ACCPM Based Channel Learning Algorithm

In this subsection, we present the proposed channel learning algorithm based on ACCPM. First, we define the target set for our problem of interest. Since any positively scaled estimate of $\boldsymbol{G}$ results in the same OEB $\tilde{\boldsymbol{v}}_E$ for the energy transmission phase, we define the target set as $\mathcal{X} = \{\bar{\boldsymbol{G}} | \boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I},\ \bar{\boldsymbol{G}} = \beta \boldsymbol{G}, \forall \beta > 0\}$, which contains all scaled matrices of $\boldsymbol{G}$ satisfying that $\boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I}$. Since $\boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I}$ is known *a priori*, we have the initial convex working set as $\mathcal{P}_0 = \{\bar{\boldsymbol{G}} | \boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I}\}$, i.e., $\mathcal{X} \subseteq \mathcal{P}_0$.

Next, we show that the one-bit feedback f_n's in the N_L feedback intervals play the role of oracle in ACCPM for our problem, which return a series of working sets $\{\mathcal{P}_n\}$ to help localize the target set $\mathcal{X}$. Consider each feedback interval as one iteration. Then, for any feedback interval $n \in \{2, \ldots, N_L\}$,[2] by querying the one-bit feedback f_n, the ET can obtain the following inequality for Q_n^{L} and Q_{n-1}^{L} (recall that $Q_n^{\mathrm{L}} = T_s \mathtt{tr}(\boldsymbol{G}\boldsymbol{S}_n^{\mathrm{L}})$):

$$f_n \mathtt{tr}\left(\boldsymbol{G}(\boldsymbol{S}_n^{\mathrm{L}} - \boldsymbol{S}_{n-1}^{\mathrm{L}})\right) \leq 0, \tag{5}$$

which can be regarded as a cutting plane such that $\boldsymbol{G}$ lies in the half space of $\mathcal{H}_n = \{\bar{\boldsymbol{G}} | f_n \mathtt{tr}\left(\bar{\boldsymbol{G}}(\boldsymbol{S}_n^{\mathrm{L}} - \boldsymbol{S}_{n-1}^{\mathrm{L}})\right) \leq 0\}$. Accordingly, by denoting $\mathcal{P}_1 = \mathcal{P}_0$, we can obtain the working set $\mathcal{P}_n$ at interval $n \geq 2$ by updating $\mathcal{P}_n = \mathcal{P}_{n-1} \cap \mathcal{H}_n$, or equivalently,

$$\mathcal{P}_n = \left\{\bar{\boldsymbol{G}} | \boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I},\ f_i \mathtt{tr}\left(\bar{\boldsymbol{G}}\left(\boldsymbol{S}_i^{\mathrm{L}} - \boldsymbol{S}_{i-1}^{\mathrm{L}}\right)\right) \leq 0, 2 \leq i \leq n\right\}. \tag{6}$$

It is evident that $\mathcal{P}_0 = \mathcal{P}_1 \supseteq \mathcal{P}_2 \supseteq \cdots \supseteq \mathcal{P}_{N_L} \supseteq \mathcal{X}$.

From (6), we can obtain the analytic center of $\mathcal{P}_n$, denoted as $\tilde{\boldsymbol{G}}^{(n)}$, which is explicitly given by [10]

[2]Note that for interval $n = 1$, it always holds that $Q_1^{\mathrm{L}} \geq Q_0^{\mathrm{L}} = 0$, and thus the one-bit feedback information is always $f_1 = -1$, which does not contain any useful information for localizing the target set $\mathcal{X}$.

Table 1: ACCPM Based Channel Learning Algorithm

Algorithm I
1) **Initialization:** Set $n = 0$, $Q_0^{\mathrm{L}} = 0$, and $\boldsymbol{S}_1^{\mathrm{L}} = \frac{P}{M_T}\boldsymbol{I}$.
2) **Repeat:**
a) $n \leftarrow n + 1$;
b) The ET transmits with $\boldsymbol{S}_n^{\mathrm{L}}$;
c) The ER feeds back $f_n = -1$ (or 1) if $Q_n^{\mathrm{L}} \geq Q_{n-1}^{\mathrm{L}}$ (or otherwise);
d) The ET computes the query point $\tilde{\boldsymbol{G}}^{(n)}$ given in (7);
e) The ET computes $\boldsymbol{b}_{n+1}$ from (10), obtains $\boldsymbol{B}_{n+1} = \mathrm{smat}(\boldsymbol{b}_{n+1})$, and updates $\boldsymbol{S}_{n+1}^{\mathrm{L}} = \boldsymbol{S}_n^{\mathrm{L}} + \boldsymbol{B}_{n+1}$.
3) **Until** $n \geq N_L$.
4) The ET estimates $\tilde{\boldsymbol{G}} = \tilde{\boldsymbol{G}}^{(N_L)}$.

$$\tilde{\boldsymbol{G}}^{(n)} = \mathtt{arg} \min_{\boldsymbol{0} \preceq \bar{\boldsymbol{G}} \preceq \boldsymbol{I}} -2\log\det\left(\bar{\boldsymbol{G}}\right) - 2\log\det\left(\boldsymbol{I} - \bar{\boldsymbol{G}}\right) - \sum_{i=2}^{n} \log\left(-f_i \mathtt{tr}\left(\bar{\boldsymbol{G}}\left(\boldsymbol{S}_i^{\mathrm{L}} - \boldsymbol{S}_{i-1}^{\mathrm{L}}\right)\right)\right), \tag{7}$$

where $\det(\cdot)$ denotes the determinant of a square matrix. Since the problem in (7) can be shown to be convex, it can be solved by standard convex optimization techniques, e.g., CVX [11]. Notice that $\tilde{\boldsymbol{G}}^{(n)}$ is the query point for the next feedback interval $n + 1$.

Up to now, we have obtained the query point at each interval n, $\tilde{\boldsymbol{G}}^{(n-1)}$, and the cutting plane given by (5) for ACCPM. To complete our algorithm, we also need to ensure that the resulting cutting plane is at least neutral given $\tilde{\boldsymbol{G}}^{(n-1)}$. This is equivalent to constructing the transmit covariance $\boldsymbol{S}_n^{\mathrm{L}}$'s such that

$$\mathtt{tr}\left(\tilde{\boldsymbol{G}}^{(n-1)}\left(\boldsymbol{S}_n^{\mathrm{L}} - \boldsymbol{S}_{n-1}^{\mathrm{L}}\right)\right) = 0, n = 2, \ldots, N_L. \tag{8}$$

We find such $\boldsymbol{S}_n^{\mathrm{L}}$'s by setting $\boldsymbol{S}_1^{\mathrm{L}} = \frac{P}{M_T}\boldsymbol{I}$ for interval $n = 1$ and

$$\boldsymbol{S}_n^{\mathrm{L}} = \boldsymbol{S}_{n-1}^{\mathrm{L}} + \boldsymbol{B}_n \tag{9}$$

for the remaining intervals $n = 2, \ldots, N_L$, where $\boldsymbol{B}_n \in \mathbb{C}^{M_T \times M_T}$ is a probing matrix that is neither positive nor negative semi-definite in general. With the above choice, finding a pair of $\boldsymbol{S}_n^{\mathrm{L}}$ and $\boldsymbol{S}_{n-1}^{\mathrm{L}}$ to satisfy (8) is simplified to finding the probing matrix $\boldsymbol{B}_n$ satisfying $\mathtt{tr}(\tilde{\boldsymbol{G}}^{(n-1)}\boldsymbol{B}_n) = 0, n = 2, \ldots, N_L$. To find such a $\boldsymbol{B}_n$ for the nth interval, we define a vector operation $\mathrm{svec}(\cdot)$ that maps a complex Hermitian matrix $\boldsymbol{X} \in \mathbb{C}^{m\times m}$ to a real vector $\mathrm{svec}(\boldsymbol{X}) \in \mathbb{R}^{m^2\times 1}, m \geq 1$, with $\mathtt{tr}(\boldsymbol{XY}) = (\mathrm{svec}(\boldsymbol{X}))^T \mathrm{svec}(\boldsymbol{Y})$ for any given complex Hermitian matrix $\boldsymbol{Y}$. Accordingly, we can express $\tilde{\boldsymbol{g}}^{(n-1)} = \mathrm{svec}\left(\tilde{\boldsymbol{G}}^{(n-1)}\right)$ and $\boldsymbol{b}_n = \mathrm{svec}\left(\boldsymbol{B}_n\right)$, where $\tilde{\boldsymbol{g}}^{(n-1)T}\boldsymbol{b}_n = \mathtt{tr}(\tilde{\boldsymbol{G}}^{(n-1)}\boldsymbol{B}_n) = 0$. Due to the one-to-one mapping of $\mathrm{svec}(\cdot)$, finding $\boldsymbol{B}_n$ is equivalent to finding $\boldsymbol{b}_n$ that is orthogonal to $\tilde{\boldsymbol{g}}^{(n-1)}$. Define a projection matrix $\boldsymbol{F}_n = \boldsymbol{I} - \frac{\tilde{\boldsymbol{g}}^{(n-1)}\tilde{\boldsymbol{g}}^{(n-1)T}}{\|\tilde{\boldsymbol{g}}^{(n-1)}\|^2}$. Then we can express $\boldsymbol{F}_n = \boldsymbol{V}_n\boldsymbol{V}_n^T$, where $\boldsymbol{V}_n \in \mathbb{R}^{M_T^2 \times (M_T^2 - 1)}$ satisfies $\boldsymbol{V}_n^T\tilde{\boldsymbol{g}}^{(n-1)} = \boldsymbol{0}$ and $\boldsymbol{V}_n^T\boldsymbol{V}_n = \boldsymbol{I}$. Thus, $\boldsymbol{b}_n$ can be any vector in the subspace spanned by $\boldsymbol{V}_n$. Specifically, we set

$$\boldsymbol{b}_n = \boldsymbol{V}_n \boldsymbol{p}, \tag{10}$$

where $\boldsymbol{p} \in \mathbb{R}^{(M_T^2-1)\times 1}$ is a randomly generated vector in order to make $\boldsymbol{b}_n$ independently drawn from the subspace. With the obtained $\boldsymbol{b}_n$, we have the probing matrix $\boldsymbol{B}_n = \mathrm{smat}(\boldsymbol{b}_n)$,[3] where $\mathrm{smat}(\cdot)$

[3]Note that $\boldsymbol{B}_n$ in general contains both positive and negative eigenvalues. As a result, the update in (9) may not necessarily yield an $\boldsymbol{S}_n^{\mathrm{L}}$ that satisfies both $\mathtt{tr}(\boldsymbol{S}_n^{\mathrm{L}}) \leq P$ and $\boldsymbol{S}_n^{\mathrm{L}} \succeq \boldsymbol{0}$. Nevertheless, by setting $\|\boldsymbol{p}\|$ to be sufficiently smaller than P, we can always find a $\boldsymbol{p}$ and its resulting $\boldsymbol{S}_n^{\mathrm{L}}$ satisfying the above two conditions with only a few random trials. In this paper we choose $\|\boldsymbol{p}\| = P/10$.

denotes the inverse operation of $\mathrm{svec}(\cdot)$. Accordingly, $\boldsymbol{S}_n^{\mathrm{L}}$ that satisfies the neutral cutting plane in (8) is obtained.

To summarize, we present the ACCPM based channel learning algorithm for MIMO WET with one-bit feedback in Table 1 as Algorithm I. Note that in step 3) of the algorithm, the iteration terminates after N_L feedback intervals of the channel leaning phase, and in step 4), the estimated $\tilde{\boldsymbol{G}}$ is set as the analytic center of $\mathcal{P}_{N_L}$, i.e., $\tilde{\boldsymbol{G}} = \tilde{\boldsymbol{G}}^{(N_L)}$. Accordingly, we can use the dominant eigenvector of $\tilde{\boldsymbol{G}}$ as the corresponding OEB $\tilde{\boldsymbol{v}}_E$ for the energy transmission phase.

4. NUMERICAL EXAMPLES

In this section, we provide numerical examples to validate the performance of our proposed channel learning algorithm in the point-point MIMO WET system. We assume that the signal attenuation from the ET to ER is 40 dB corresponding to a distance of 5 meters. Given this transmission distance, the line-of-sight (LOS) signal is dominant, and thus Rician fading is used to model the channel. Furthermore, we assume $T_s = 1$ for convenience, and set $P = 30$ dBm (1 Watt), $\eta = 0.5$, $M_T = 4$ and $M_R = 2$.

In Fig. 3, we show the convergence performance of the ACCPM based channel learning algorithm with one-bit feedback as compared to two existing algorithms. These two benchmark algorithms apply the same one-bit feedback f_n over each interval as in the proposed algorithm whereas they use different methods instead of ACCPM to design the transmit signals in the channel learning phase to estimate the MIMO channel. Due to the page limitation, we introduce them briefly as follows and their details can be found in [12, 13].

- *Cyclic Jacobi Technique (CJT) based method [12]:* This method applies the CJT to update $\boldsymbol{S}_n^{\mathrm{L}}$'s based on feedback bit f_n's and perform a blind estimate of the EVD for $\boldsymbol{G}$, i.e., $\boldsymbol{G} = \boldsymbol{V}\boldsymbol{\Lambda}\boldsymbol{V}^H$. Specifically, the EVD is estimated via implementing several Jacobi sweeps each of which corresponds to a series of line searches each having the accuracy given by η. After each Jacobi sweep, the ET can obtain an updated approximation of $\boldsymbol{V}$.
- *Gradient sign method [13]:* In this method, the ET sends only one energy beam per interval (i.e., $\boldsymbol{S}_n^{\mathrm{L}}, n = 1, \ldots, N_L$, are all of rank-one). Over each interval n, the ET adapts the energy beam by either adding or subtracting a random perturbation based on f_n. The Euclidean norm of each generated perturbation vector is termed step size.

In Fig. 3, we use the normalized error, given by $\frac{\lambda_E - \tilde{\boldsymbol{v}}_E^H \boldsymbol{G} \tilde{\boldsymbol{v}}_E}{\lambda_E}$, as the performance metric, where $\tilde{\boldsymbol{v}}_E$ denotes the OEB based on the estimated MIMO channel in each algorithm. From this figure, it is observed that the CJT based method results in discrete error points corresponding to different values of η and different numbers of implemented Jacobi sweeps. This is due to the fact that this method can obtain an updated estimate of $\boldsymbol{V}$ only after each complete Jacobi sweep over a certain number of feedback intervals. For the gradient sign method, it is observed that a larger step size of 0.05 yields faster convergence but also more notable fluctuations as compared to the case of smaller step size of 0.01. In contrast, ACCPM is observed to achieve an exponentially decreasing error over the number of feedback intervals, and also significantly outperform the other two algorithms.

Fig. 4 shows the average harvested power per block, i.e., Q_{total}/T with Q_{total} given in (3), over the block duration in N (recall that $N = T/T_s$), where N_L is chosen for each channel learning algorithm to maximize the average harvested power with each given N. For comparison, we also plot the harvested power, $Q_{\max}/T$, by the OEB assuming perfect CSI at the ET as a performance upper bound, as well as that in the case without CSI at the

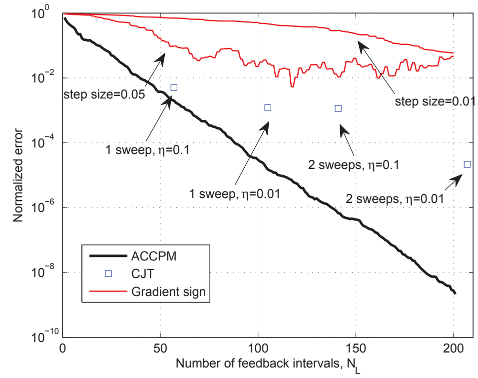

Fig. 3: Convergence performance for different schemes.

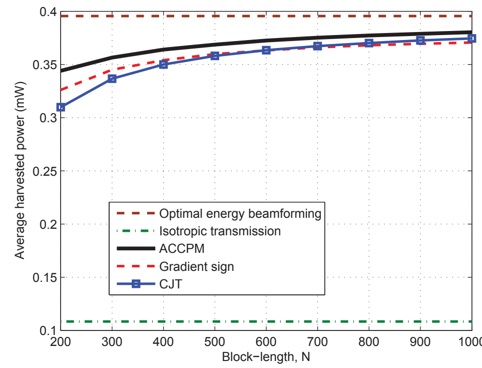

Fig. 4: Average harvested power versus block-length N.

ET by an isotropic transmission with $\boldsymbol{S} = \frac{P}{M_T}\boldsymbol{I}$ as a performance lower bound. For the three channel learning algorithms, namely the ACCPM, CJT, and gradient sign, it is observed that as N increases, the average harvested power increases to more closely approach the performance upper bound by the OEB with perfect CSI. This is due to the fact that with larger block duration, the MIMO channel can be estimated more accurately but with smaller percentage of time in each block. The proposed ACCPM based algorithm is observed to achieve higher average harvested power than the other two schemes of CJT and gradient sign. This is consistent with its best channel learning performance as shown in Fig. 3.

5. CONCLUDING REMARKS

This paper proposed a new channel learning algorithm for the point-to-point MIMO WET system. By requiring that the ER sends back to the ET only one bit per feedback interval to indicate the increase or decrease of its harvested energy, the ET is able to adjust the probing energy beams over different intervals to estimate the MIMO channel based on the method of ACCPM. It is hoped that this paper opens an avenue for further investigation of new feedback techniques for MIMO WET systems.

After the acceptance of this paper, the authors become aware of one parallel work [14] that will be presented in the same conference. [14] considered the one-bit feedback based channel learning in a point-to-point multiple-input single-output (MISO) system for wireless communication (versus WET). Although the core idea of using ACCPM for designing one-bit feedback based channel learning is essentially the same for the two papers, there are still sufficient differences in the feedback and training signal designs due to independent investigations.

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