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A Destination-Aided Wireless Energy Transfer Scheme in Multi-Antenna Relay Sensor Networks

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***Abstract*—We propose a destination-aided wireless energy transfer scheme in wireless relay sensor networks, where the power of the information collector who has stable power supply is fully exploited. Specifically, a multi-antenna three-node (S, R, D) relay system is considered, where the energy-constrained node R (sensor) assists to forward the message from S (sensor) to D (information collector), and also reports its own sensing information to D. To enhance the amount of scavenged energy at R, the strong energy stream is first transferred by D. The transmitter beamformers, receiver vectors and the relay processing matrix are jointly optimized to maximize the rate of R subject to the required rate of S and the power constraints. To solve this non-convex problem efficiently, these variables are alternatively optimized. Numerical results show that our proposed scheme greatly improves the capacity region, especially when the relay is close to the destination.**

***Index Terms*—Destination-aided wireless energy transfer, relay processing matrix, non-convex optimization**

I. Introduction

Wireless sensor networks, consisting of spatially distributed low-power sensors, have been widely deployed for environmental sensing and building structural monitoring, etc. These sensors need to periodically report their sensing results to the information collector. To enlarge the communication range, some sensors are frequently selected as relays to help forward the information. As a result, the energy of relay sensors can be consumed quickly, which shortens the lifetime of the whole network. However, replacing batteries of these sensors is inconvenient in some cases, such as the toxic environmental monitoring [1].

As a promising solution to prolong the lifetime, wireless energy transfer enables energy-constrained sensors to harvest the radio frequency (RF) energy from the ambient environment. Different from other renewable energy resources, RF electromagnetic wave makes the simultaneous wireless information and power transfer (SWIPT) possible. To implement it, the received stream is divided into two flows by the power splitting (PS) scheme with one for information decoding (ID) and the other for energy harvesting (EH) [2]. Based on the PS scheme, resource allocations in SWIPT relay networks have been widely investigated, where the energy-constrained relays can first harvest the energy from the source and then forward the message to the destination [3]. Nevertheless, for the information reporting process in wireless sensor networks, the scavenged energy at relay sensors is severely restricted by the low-power source sensors.

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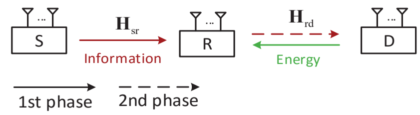

Fig. 1. Destination-aided energy transfer scheme in a MIMO relay network.

To tackle this energy shortage problem in some inconvenient battery-replacing scenarios, we propose a destination-aided wireless energy transfer scheme in sensor networks to fully exploit the power of the destination, i.e., the information collector with stable power supply. In particular, the energy-constrained relay is mainly powered by the strong energy stream sent by the destination. Different from [4] that the relay only helps to forward the message from source to destination, in this letter, we consider a more practical scenario where the relay sensor also reports its own sensing information to the destination. Then, the transmitter beamformers, the receiver vectors and the relay processing matrix are jointly optimized to maximize the relay rate subject to the required source rate and the power constraints. Alternating optimization method is adopted to handle this non-convex problem. Numerical results show that our proposed scheme greatly outperforms other schemes in terms of the capacity region.

Notations: $\|.\|_2$ and $\|.\|_F$ refer to the Euclidean norm and the Frobenius norm, respectively. $\otimes$ is the kronecker product.

II. System Model and Problem Formulation

This letter considers a wireless relay sensor network, which is modeled as a three-node multi-antenna relay system, as shown in Fig. 1. Nodes S and R are low-power sensors, and node D is an information collector with constant power supply. In this scenario, node R not only assists to forward the information of node S to node D, but also reports its own information to node D. To facilitate the information transmission, a destination-aided wireless energy transfer scheme is proposed, where the energy-constrained node R is powered by node D which has reliable power supply. The numbers of antennas at nodes S, R, D are denoted by N_s, N_r and N_d, respectively. The entire communication process consists of two equal phases, and each phase is normalized to be 1.

In the first phase, node S sends information signal x_s with $\mathbb{E}\left[|x_s|^2\right] = 1$ to node R for the information forwarding. Meanwhile, node D also transmits energy signal x_d with

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$\mathbb{E}\left[|x_d|^2\right]=1$ to power the energy-limited node R. As a result, the signal received at node R is expressed as

$$\mathbf{y}_r=\mathbf{H}_{sr}\mathbf{w}_s x_s+\mathbf{H}_{rd}^H\mathbf{w}_d x_d+\mathbf{n}_r, \quad (1)$$

where $\mathbf{w}_s\in\mathbb{C}^{N_s\times 1}$ and $\mathbf{w}_d\in\mathbb{C}^{N_d\times 1}$ are respectively the beamforming vectors at node S and D; $\mathbf{H}_{sr}\in\mathbb{C}^{N_r\times N_s}$ and $\mathbf{H}_{rd}^H\in\mathbb{C}^{N_r\times N_d}$ are respectively the channel matrices from S to R, and D to R; $\mathbf{n}_r\sim\mathcal{CN}(\mathbf{0},\sigma_r^2\mathbf{I}_{N_r})$ is the received noise vector at node R. To simultaneously decode the information and harvest the energy, the PS scheme is adopted at node R. Specifically, the received RF flow is divided into two streams, one for EH and the other for ID. Denote by ρ and $1-\rho$ the allocated power ratios for the ID stream and EH stream, respectively. Thus, the energy stream for EH is given as

$$\mathbf{y}_r^{EH}=\sqrt{1-\rho}(\mathbf{H}_{sr}\mathbf{w}_s x_s+\mathbf{H}_{rd}^H\mathbf{w}_d x_d+\mathbf{n}_r) \quad (2)$$

with the harvested energy

$$P_r^{EH}(\mathbf{w}_s,\mathbf{w}_d)=(1-\rho)\xi\left(\|\mathbf{H}_{sr}\mathbf{w}_s\|_2^2+\left\|\mathbf{H}_{rd}^H\mathbf{w}_d\right\|_2^2+\sigma_r^2\right), \quad (3)$$

where $0<\xi\leq 1$ is the energy harvesting efficiency. Besides, the information flow can be expressed as

$$\mathbf{y}_r^{ID}=\sqrt{\rho}(\mathbf{H}_{sr}\mathbf{w}_s x_s+\mathbf{H}_{rd}^H\mathbf{w}_d x_d+\mathbf{n}_r)+\mathbf{n}_c, \quad (4)$$

where $\mathbf{n}_c\sim\mathcal{CN}(\mathbf{0},\sigma_c^2\mathbf{I}_{N_r})$ is the circuit noise vector due to the signal frequency conversion from RF to the baseband.

In the second phase, node R not only forwards the message from S to D using the amplify-and-forward (AF) protocol, but also sends its own information x_r with $\mathbb{E}\left[|x_r|^2\right]=1$ to node D. Mathematically, the signal transmitted by node R is

$$\begin{aligned}\mathbf{x}_r^{ID}&=\mathbf{F}\mathbf{y}_r^{ID}+\mathbf{w}_r x_r \quad (5)\\ &=\mathbf{F}\left(\sqrt{\rho}(\mathbf{H}_{sr}\mathbf{w}_s x_s+\mathbf{H}_{rd}^H\mathbf{w}_d x_d+\mathbf{n}_r)+\mathbf{n}_c\right)+\mathbf{w}_r x_r,\end{aligned}$$

where $\mathbf{F}\in\mathbb{C}^{N_r\times N_r}$ is the relay processing matrix and $\mathbf{w}_r\in\mathbb{C}^{N_r\times 1}$ is the beamforming vector for node R's own message x_r. Hence, the power consumption at node R is given as

$$\begin{aligned}P_r(\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r,\mathbf{F})=&\rho\Big(\|\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s\|_2^2+\left\|\mathbf{F}\mathbf{H}_{rd}^H\mathbf{w}_d\right\|_2^2 \quad (6)\\ &+\sigma_r^2\|\mathbf{F}\|_F^2\Big)+\sigma_c^2\|\mathbf{F}\|_F^2+\|\mathbf{w}_r\|_2^2.\end{aligned}$$

Assuming that node D can successfully cancel its self-interference signal x_d, the received signal at node D is

$$\mathbf{y}_d=\mathbf{H}_{rd}(\sqrt{\rho}\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s x_s+\sqrt{\rho}\mathbf{F}\mathbf{n}_r+\mathbf{F}\mathbf{n}_c+\mathbf{w}_r x_r)+\mathbf{n}_d, \quad (7)$$

where $\mathbf{H}_{rd}$ is the channel matrix from node R to D, and $\mathbf{n}_d\sim\mathcal{CN}(\mathbf{0},\sigma_d^2\mathbf{I}_{N_d})$ is the received noise vector at node D. The received signal to interference plus noise ratios (SINRs) at node D to decode the information of node S and node R are respectively given as

$$\gamma_s(\mathbf{w}_s,\mathbf{w}_r,\mathbf{F},\mathbf{v}_s)= \quad (8)$$
$$\frac{\rho\left|\mathbf{v}_s^H\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s\right|^2}{\left|\mathbf{v}_s^H\mathbf{H}_{rd}\mathbf{w}_r\right|^2+(\sigma_r^2\rho+\sigma_c^2)\left\|\mathbf{v}_s^H\mathbf{H}_{rd}\mathbf{F}\right\|_2^2+\sigma_d^2\|\mathbf{v}_s\|_2^2},$$

and $\gamma_r(\mathbf{w}_s,\mathbf{w}_r,\mathbf{F},\mathbf{v}_r)=$ (9)

$$\frac{\left|\mathbf{v}_r^H\mathbf{H}_{rd}\mathbf{w}_r\right|^2}{\rho\left|\mathbf{v}_r^H\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s\right|^2+(\sigma_r^2\rho+\sigma_c^2)\left\|\mathbf{v}_r^H\mathbf{H}_{rd}\mathbf{F}\right\|_2^2+\sigma_d^2\|\mathbf{v}_r\|_2^2},$$

where $\mathbf{v}_s\in\mathbb{C}^{N_d\times 1}$ and $\mathbf{v}_r\in\mathbb{C}^{N_d\times 1}$ are receiver vectors for the information of node S and R, respectively. Hence, the rate of node R is $R_r=\log_2(1+\gamma_r)$.

In this letter, the transmitter beamformers $\{\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r\}$, the relay processing matrix $\mathbf{F}$ and the receiver vectors $\{\mathbf{v}_s,\mathbf{v}_r\}$ are jointly optimized to maximize the achieved rate of node R, subject to the minimum required rate of node S, $R_s^{\min}$, and the energy consumption in the system. The optimization problem can be formulated as ($\mathcal{P}1$)

$$\max_{\mathbf{v}_r,\mathbf{v}_s,\mathbf{w}_r,\mathbf{w}_s,\mathbf{w}_d,\mathbf{F}} \quad \gamma_r(\mathbf{w}_s,\mathbf{w}_r,\mathbf{F},\mathbf{v}_r) \quad (10a)$$
$$\text{s. t.} \quad \gamma_s(\mathbf{w}_s,\mathbf{w}_r,\mathbf{F},\mathbf{v}_s)\geq\gamma_s^{\min}, \quad (10b)$$
$$P_r(\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r,\mathbf{F})\leq P_r^{EH}(\mathbf{w}_s,\mathbf{w}_d), \quad (10c)$$
$$\|\mathbf{w}_s\|_2^2\leq P_s,\;\;\|\mathbf{w}_d\|_2^2\leq P_d, \quad (10d)$$

where $\gamma_s^{\min}=2^{R_s^{\min}}-1$ is the minimum SINR of node S; P_s and P_d are respectively the maximum allowed power of nodes S and D. (10c) is the energy causality constraint and (10d) are the energy consumption constraints.

III. Problem Solution

Obviously, problem $\mathcal{P}1$ is non-convex and hard to directly solve. To tackle this difficulty, in this section, we alternatively optimize the transmit beamforming vectors $\{\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r\}$, the relay processing matrix $\mathbf{F}$ and the receiver vectors $\{\mathbf{v}_s,\mathbf{v}_r\}$ until problem converges.

A. The Optimization of Receiver Vectors

With given $\{\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r\}$ and $\mathbf{F}$, we first optimize the receiver vectors $\{\mathbf{v}_r,\mathbf{v}_s\}$. Define $\mathbf{a}_r=\mathbf{H}_{rd}\mathbf{w}_r,\mathbf{B}_r=\rho\mathbf{b}_r\mathbf{b}_r^H+(\sigma_r^2\rho+\sigma_c^2)\mathbf{H}_{rd}\mathbf{F}\mathbf{F}^H\mathbf{H}_{rd}^H+\sigma_d^2\mathbf{I}_{N_d},\mathbf{b}_r=\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s,\mathbf{B}_s=\mathbf{H}_{rd}\mathbf{w}_r\mathbf{w}_r^H\mathbf{H}_{rd}^H+(\sigma_r^2\rho+\sigma_c^2)\mathbf{H}_{rd}\mathbf{F}\mathbf{F}^H\mathbf{H}_{rd}^H+\sigma_d^2\mathbf{I}_{N_d},\mathbf{a}_s=\sqrt{\rho}\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s$, the original problem is rewritten as ($\mathcal{P}2$)

$$\max_{\mathbf{v}_r,\mathbf{v}_s}\frac{\mathbf{v}_r^H\mathbf{a}_r\mathbf{a}_r^H\mathbf{v}_r}{\mathbf{v}_r^H\mathbf{B}_r\mathbf{v}_r},\;\; s.\;t.\;\frac{\mathbf{v}_s^H\mathbf{a}_s\mathbf{a}_s^H\mathbf{v}_s}{\mathbf{v}_s^H\mathbf{B}_s\mathbf{v}_s}\geq\gamma_s^{\min}, \quad (11)$$

where both the objective function and the left hand of the constraint are generalized Rayleigh quotients. Hence, the optimal $\mathbf{v}_r^*$ and $\mathbf{v}_s^*$ can be respectively obtained in closed-forms:

$$\mathbf{v}_r^*=\mathbf{q}_{\max}\left(\mathbf{B}_r^{-1}\mathbf{a}_r\mathbf{a}_r^H\right)=\frac{\mathbf{B}_r^{-1}\mathbf{a}_r}{\left\|\mathbf{B}_r^{-1}\mathbf{a}_r\right\|_2},\;\mathbf{v}_s^*=\frac{\mathbf{B}_s^{-1}\mathbf{a}_s}{\left\|\mathbf{B}_s^{-1}\mathbf{a}_s\right\|_2}, \quad (12)$$

where $\mathbf{q}_{\max}(\mathbf{A})$ is the eigenvector corresponding to the maximum eigenvalue of $\mathbf{A}$.

B. The Optimization of Transmitter Beamformers

Then, the transmitter beamformers $\{\mathbf{w}_s,\mathbf{w}_d,\mathbf{w}_r\}$ are optimized with the fixed $\mathbf{F}$ and $\{\mathbf{v}_r,\mathbf{v}_s\}$. Let $\mathbf{h}_{rrd}^H=\mathbf{v}_r^H\mathbf{H}_{rd},\mathbf{h}_{rsd}^H=\mathbf{v}_r^H\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr},\mathbf{h}_{ssd}^H=\mathbf{v}_s^H\mathbf{H}_{rd}\mathbf{F}\mathbf{H}_{sr},\mathbf{h}_{srd}^H=\mathbf{v}_s^H\mathbf{H}_{rd}$, the original problem $\mathcal{P}1$ can be recasted as ($\mathcal{P}3$)

$$\max_{\mathbf{w}_r,\mathbf{w}_s,\mathbf{w}_d}\frac{\left|\mathbf{h}_{rrd}^H\mathbf{w}_r\right|^2}{\rho\left|\mathbf{h}_{rsd}^H\mathbf{w}_s\right|^2+a}\;\;\text{s. t.}\frac{\rho\left|\mathbf{h}_{ssd}^H\mathbf{w}_s\right|^2}{\left|\mathbf{h}_{srd}^H\mathbf{w}_r\right|^2+b}\geq\gamma_s^{\min}, \quad (13a)$$

$$\rho\left(\|\mathbf{F}\mathbf{H}_{sr}\mathbf{w}_s\|_2^2+\left\|\mathbf{F}\mathbf{H}_{rd}^H\mathbf{w}_d\right\|_2^2\right)+\|\mathbf{w}_r\|_2^2+c\leq$$
$$(1-\rho)\xi\left(\|\mathbf{H}_{sr}\mathbf{w}_s\|_2^2+\left\|\mathbf{H}_{rd}^H\mathbf{w}_d\right\|_2^2\right),\;\;(10d), \quad (13b)$$

where $a = (\sigma_r^2\rho + \sigma_c^2)\left\|\mathbf{h}_{rrd}^H\mathbf{F}\right\|_2^2 + \sigma_d^2\left\|\mathbf{v}_r\right\|_2^2, b = (\sigma_r^2\rho + \sigma_c^2)\left\|\mathbf{h}_{srd}^H\mathbf{F}\right\|_2^2 + \sigma_d^2\left\|\mathbf{v}_s\right\|_2^2, c = (\sigma_r^2\rho+\sigma_c^2)\left\|\mathbf{F}\right\|_F^2 - (1-\rho)\xi\sigma_r^2$.

To solve this non-convex problem, we first relax it to a semi-definite programming (SDP) problem. Let $\mathbf{W}_s = \mathbf{w}_s\mathbf{w}_s^H$, $\mathbf{W}_d = \mathbf{w}_d\mathbf{w}_d^H$ and $\mathbf{W}_r = \mathbf{w}_r\mathbf{w}_r^H$, problem $\mathcal{P}3$ can be relaxed as ($\mathcal{P}4$)

$$\max_{\mathbf{W}_r,\mathbf{W}_s,\mathbf{W}_d} \frac{\mathrm{Tr}(\mathbf{H}_{rrd}\mathbf{W}_r)}{\rho\mathrm{Tr}(\mathbf{H}_{rsd}\mathbf{W}_s) + a} \tag{14a}$$

$$\text{s. t.} \quad \rho\mathrm{Tr}(\mathbf{H}_{ssd}\mathbf{W}_s) \geq \gamma_s^{\min}\left(\mathrm{Tr}(\mathbf{H}_{srd}\mathbf{W}_r) + b\right), \tag{14b}$$

$$\mathrm{Tr}(\mathbf{H}_s\mathbf{W}_s) + \mathrm{Tr}(\mathbf{H}_d\mathbf{W}_d) + \mathrm{Tr}(\mathbf{W}_r) \leq -c, \tag{14c}$$

$$\mathrm{Tr}(\mathbf{W}_s) \leq P_s, \ \mathrm{Tr}(\mathbf{W}_d) \leq P_d, \tag{14d}$$

where $\mathbf{H}_{rrd} = \mathbf{h}_{rrd}\mathbf{h}_{rrd}^H, \mathbf{H}_{rsd} = \mathbf{h}_{rsd}\mathbf{h}_{rsd}^H, \mathbf{H}_{ssd} = \mathbf{h}_{ssd}\mathbf{h}_{ssd}^H, \mathbf{H}_{srd} = \mathbf{h}_{srd}\mathbf{h}_{srd}^H, \mathbf{H}_{fsr} = \mathbf{H}_{sr}^H\mathbf{F}^H\mathbf{F}\mathbf{H}_{sr}, \mathbf{H}_{frd} = \mathbf{H}_{rd}\mathbf{F}^H\mathbf{F}\mathbf{H}_{rd}^H, \bar{\mathbf{H}}_{sr} = \mathbf{H}_{sr}^H\mathbf{H}_{sr}, \bar{\mathbf{H}}_{rd} = \mathbf{H}_{rd}\mathbf{H}_{rd}^H, \mathbf{H}_s = \rho\mathbf{H}_{fsr} - (1-\rho)\xi\bar{\mathbf{H}}_{sr}, \mathbf{H}_d = \rho\mathbf{H}_{frd} - (1-\rho)\xi\bar{\mathbf{H}}_{rd}$. Note that problem $\mathcal{P}4$ is a linear fractional programming problem and can be dealt with the Charnes-Cooper transformation. Introduce a slack variable $t > 0$ and define $\hat{\mathbf{W}}_r = t\mathbf{W}_r$, $\hat{\mathbf{W}}_s = t\mathbf{W}_s$, $\hat{\mathbf{W}}_d = t\mathbf{W}_d$, problem $\mathcal{P}4$ can be equivalently rewritten as ($\mathcal{P}5$)

$$\max_{\hat{\mathbf{W}}_r,\hat{\mathbf{W}}_s,\hat{\mathbf{W}}_d,t>0} \mathrm{Tr}(\mathbf{H}_{rrd}\hat{\mathbf{W}}_r) \tag{15a}$$

$$\text{s. t.} \quad \rho\mathrm{Tr}(\mathbf{H}_{rsd}\hat{\mathbf{W}}_s) + at = 1, \tag{15b}$$

$$\rho\mathrm{Tr}(\mathbf{H}_{ssd}\hat{\mathbf{W}}_s) \geq \gamma_s^{\min}\left(\mathrm{Tr}(\mathbf{H}_{srd}\hat{\mathbf{W}}_r) + bt\right), \tag{15c}$$

$$\mathrm{Tr}(\mathbf{H}_s\hat{\mathbf{W}}_s) + \mathrm{Tr}(\mathbf{H}_d\hat{\mathbf{W}}_d) + \mathrm{Tr}(\hat{\mathbf{W}}_r) \leq -ct, \tag{15d}$$

$$\mathrm{Tr}(\hat{\mathbf{W}}_s) \leq tP_s, \ \mathrm{Tr}(\hat{\mathbf{W}}_d) \leq tP_d, \tag{15e}$$

which is a convex SDP, and can be solved by CVX [5].

However, the ranks of achieved optimal matrices may be higher than one. Based on the Theorem 3.2 in [6], there always exists optimal solution to problem $\mathcal{P}5$ satisfying $\mathrm{Rank}^2(\hat{\mathbf{W}}_r^*) + \mathrm{Rank}^2(\hat{\mathbf{W}}_s^*) + \mathrm{Rank}^2(\hat{\mathbf{W}}_d^*) \leq 4$, where 4 is the number of generalized constraints. Thus, ignoring the trivial rank-zero case, there always exists optimal rank-one solution. According to Appendix A in [6], the rank-one solution can be found via the rank-reduction procedure. Consequently, the optimal $\mathbf{w}_s^*$, $\mathbf{w}_d^*$ and $\mathbf{w}_r^*$ can be obtained.

C. The Optimization of Relay Processing Matrix

Finally, with the given $\{\mathbf{w}_s, \mathbf{w}_d, \mathbf{w}_r\}$ and $\{\mathbf{v}_s, \mathbf{v}_r\}$, we design the relay processing matrix $\mathbf{F}$. Define $\mathbf{h}_{srs} = \mathbf{H}_{sr}\mathbf{w}_s, \mathbf{h}_{rdd} = \mathbf{H}_{rd}^H\mathbf{w}_d$, problem $\mathcal{P}1$ is equivalently rewritten as ($\mathcal{P}6$)

$$\min_{\mathbf{F}} \ \rho\left|\mathbf{h}_{rrd}^H\mathbf{F}\mathbf{h}_{srs}\right|^2 + (\sigma_r^2\rho + \sigma_c^2)\left\|\mathbf{h}_{rrd}^H\mathbf{F}\right\|_2^2 \tag{16a}$$

$$\text{s. t.} \ \rho\left|\mathbf{h}_{srd}^H\mathbf{F}\mathbf{h}_{srs}\right|^2 \geq \gamma_s^{\min}\left((\sigma_r^2 + \sigma_c^2)\rho\left\|\mathbf{h}_{srd}^H\mathbf{F}\right\|_2^2 + a'\right), \tag{16b}$$

$$\rho\left(\left\|\mathbf{F}\mathbf{h}_{srs}\right\|_2^2 + \left\|\mathbf{F}\mathbf{h}_{rdd}\right\|_2^2 + \sigma_r^2\left\|\mathbf{F}\right\|_F^2\right) + \sigma_c^2\left\|\mathbf{F}\right\|_F^2 \leq b', \tag{16c}$$

where $a' = \left|\mathbf{v}_s^H\mathbf{H}_{rd}\mathbf{w}_r\right|^2 + \sigma_d^2\left\|\mathbf{v}_s\right\|_2^2, b' = (1-\rho)\xi\left(\left\|\mathbf{h}_{srs}\right\|_2^2 + \left\|\mathbf{h}_{rdd}\right\|_2^2 + \sigma_r^2\right) - \left\|\mathbf{w}_r\right\|_2^2$.

To make problem $\mathcal{P}6$ tractable, we adopt equations $\mathrm{vec}(\mathbf{AXB}) = (\mathbf{B}^T \otimes \mathbf{A})\mathrm{vec}(\mathbf{X})$ and $\mathrm{Tr}(\mathbf{X}_1^T\mathbf{X}_2) = \mathrm{vec}(\mathbf{X}_1)^T\mathrm{vec}(\mathbf{X}_2)$ to further reformulate problem $\mathcal{P}6$ as ($\mathcal{P}7$)

$$\min_{\mathbf{f}} \ \mathbf{f}^H\mathbf{A}_f\mathbf{f} \ \text{s. t.} \ \mathbf{f}^H\mathbf{B}_f\mathbf{f} + \gamma_s^{\min}a' \leq 0, \ \mathbf{f}^H\mathbf{C}_f\mathbf{f} \leq b', \tag{17}$$

where $\mathbf{f} = \mathrm{vec}(\mathbf{F}), \mathbf{A}_f = \left(\rho(\mathbf{h}_{srs}\mathbf{h}_{srs}^H)^T + (\sigma_r^2\rho + \sigma_c^2)\mathbf{I}\right) \otimes (\mathbf{h}_{rrd}\mathbf{h}_{rrd}^H), \mathbf{B}_f = \left(-\rho(\mathbf{h}_{srs}\mathbf{h}_{srs}^H)^T + \Gamma_s^{\min}(\sigma_r^2\rho + \sigma_c^2)\mathbf{I}\right) \otimes (\mathbf{h}_{srd}\mathbf{h}_{srd}^H), \mathbf{C}_f = \rho\left((\mathbf{h}_{srs}\mathbf{h}_{srs}^H)^T + (\mathbf{h}_{rdd}\mathbf{h}_{rdd}^H)^T\right) \otimes \mathbf{I}_{N_r\times N_r} + (\rho\sigma_r^2 + \sigma_c^2)\mathbf{I}_{N_r^2\times N_r^2}$. Note that matrice $\mathbf{A}_f$ and $\mathbf{C}_f$ are positive-definite, while matrix $\mathbf{B}_f$ is only hermitian but indefinite. Thus, problem $\mathcal{P}7$ is a non-convex quadratically constrained quadratic programming (QCQP) problem. It is easy to observe that this non-convex problem can be handled by the semi-definite relaxation (SDR) and the rank-reduction procedure, which is similar to problem $\mathcal{P}3$. However, the computation complexity will become extremely high when the number of relay antennas increases.

To lower the complexity, we propose a parallel algorithm based on the alternating directions method of multipliers (ADMM) [7], which can also directly yield the semi-closed form rank-one solution. The basic idea is to introduce local variables for each constraint and convert this QCQP problem into several QCQP problems with one constraint (QCQP-1), which can be solved efficiently. Let us introduce local variables $\{\mathbf{f}_1, \mathbf{f}_2\}$ and rewrite $\mathcal{P}7$ as a consensus-ADMM form ($\mathcal{P}8$)

$$\min_{\mathbf{f}} \quad \mathbf{f}^H\mathbf{A}_f\mathbf{f} \tag{18a}$$

$$\text{s. t.} \quad \mathbf{f}_1^H\mathbf{B}_f\mathbf{f}_1 \leq -\gamma_s^{\min}a', \ \mathbf{f}_2^H\mathbf{C}_f\mathbf{f}_2 \leq b', \tag{18b}$$

$$\mathbf{f} = \mathbf{f}_1, \quad \mathbf{f} = \mathbf{f}_2. \tag{18c}$$

According to [7], this consensus problem can be iteratively solved by following steps:

$$\mathbf{f} \leftarrow (\mathbf{A}_f + 2\theta\mathbf{I})^{-1}\left(\theta\sum\nolimits_{i=1}^{2}(\mathbf{f}_i + \boldsymbol{\alpha}_i)\right), \tag{19}$$

$$\mathbf{f}_1 \leftarrow \arg\min_{\mathbf{f}_1}\left\|\mathbf{f}_1 - \mathbf{f} + \boldsymbol{\alpha}_1\right\|_2^2, \text{s. t.} \ \mathbf{f}_1^H\mathbf{B}_f\mathbf{f}_1 \leq -\gamma_s^{\min}a', \tag{20}$$

$$\mathbf{f}_2 \leftarrow \arg\min_{\mathbf{f}_2}\left\|\mathbf{f}_2 - \mathbf{f} + \boldsymbol{\alpha}_2\right\|_2^2, \text{s. t.} \ \mathbf{f}_2^H\mathbf{C}_f\mathbf{f}_2 \leq b', \tag{21}$$

$$\boldsymbol{\alpha}_i = \boldsymbol{\alpha}_i + \mathbf{f}_i - \mathbf{f}, \ i \in \{1, 2\}, \tag{22}$$

where $\boldsymbol{\alpha}_i$ is the scaled dual variable for equation constraint $\mathbf{f} = \mathbf{f}_i$ and θ is the penalty factor. Note that there are two block variables, i.e., global variable $\mathbf{f}$ and local variables $\{\mathbf{f}_i\}$, to be alternatively optimized. Hence, the ADMM-based algorithm can converge to a KKT point of non-convex problem $\mathcal{P}7$ [7].

Observing from (19)-(22), the update of $\mathbf{f}$ and $\{\boldsymbol{\alpha}_i\}$ can be easily calculated. In the following, we focus on the update of $\mathbf{f}_1$, which is a QCQP-1 problem. As proved in [5], QCQP-1 problem satisfies the strong duality and can be solved optimally. Since $\mathbf{B}_f$ is hermitian matrix, it yields that $\mathbf{B}_f = \mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^H$, where $\boldsymbol{\Lambda}$ is a real diagonal matrix and $\mathbf{Q}$ is a unitary matrix. Define $\boldsymbol{\beta}_1 = \mathbf{f} - \boldsymbol{\alpha}_1, \bar{\boldsymbol{\beta}}_1 = \mathbf{Q}^H\boldsymbol{\beta}_1, \bar{\mathbf{f}}_1 = \mathbf{Q}^H\mathbf{f}_1$, the update of $\bar{\mathbf{f}}_1$ can be reformulated as

$$\min_{\bar{\mathbf{f}}_1} \left\|\bar{\mathbf{f}}_1 - \bar{\boldsymbol{\beta}}_1\right\|_2^2 \ \text{s. t.} \ \bar{\mathbf{f}}_1^H\boldsymbol{\Lambda}\bar{\mathbf{f}}_1 \leq -\gamma_s^{\min}a'. \tag{23}$$

The corresponding Lagrangian function is

$$\mathcal{L}(\bar{\mathbf{f}}_1; \mu) = \left\|\bar{\mathbf{f}}_1 - \bar{\boldsymbol{\beta}}_1\right\|_2^2 + \mu\left(\bar{\mathbf{f}}_1^H\boldsymbol{\Lambda}\bar{\mathbf{f}}_1 + \gamma_s^{\min}a'\right), \tag{24}$$

where μ is the multiplier. Taking the derivative of Lagrangian function with respect to $\bar{\mathbf{f}}_1$, we have

$$\nabla\mathcal{L}(\bar{\mathbf{f}}_1; \mu) = \left(\bar{\mathbf{f}}_1 - \bar{\boldsymbol{\beta}}_1\right) + \mu\boldsymbol{\Lambda}\bar{\mathbf{f}}_1 = 0. \tag{25}$$

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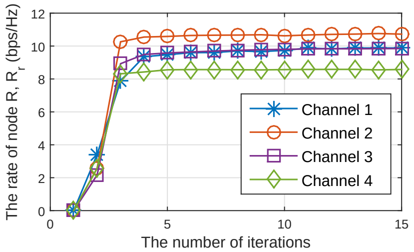

Fig. 2. The convergence performance with $d_{rd}/d_{sd} = 1/3$, $R_s^{min} = 1$ bps/Hz and $\rho = 0.2$.

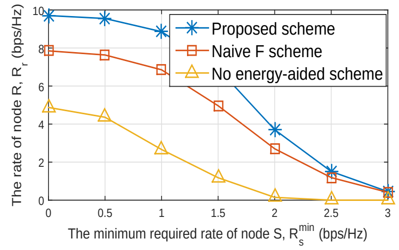

Fig. 3. Node R-Node S rate regions with $d_{rd}/d_{sd} = 1/3$.

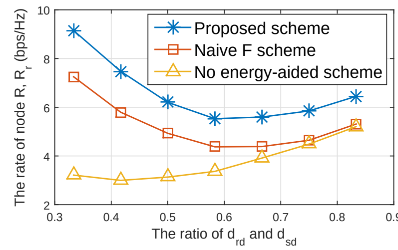

Fig. 4. Rate of node R versus d_{rd}/d_{sd} with $R_s^{min} = 1$ bps/Hz.

Thus, $\bar{\mathbf{f}}_1 = (\mathbf{I}+\mu\mathbf{\Lambda})^{-1}\bar{\boldsymbol{\beta}}_1$. From the dual problem of QCQP-1, we know that $\mathbf{I}+\mu\mathbf{\Lambda} \succeq 0$. That is $1+\mu\lambda_n \geq 0, \forall n \in \{1..., N_r^2\}$, where λ_n is the n-th eigenvalue of $\mathbf{B}_f$. Substituting the expression of $\bar{\mathbf{f}}_1$ to the constraint of (23), we have $h(\mu) = \bar{\boldsymbol{\beta}}_1^H(\mathbf{I}+\mu\mathbf{\Lambda})^{-1}\mathbf{\Lambda}(\mathbf{I}+\mu\mathbf{\Lambda})^{-1}\bar{\boldsymbol{\beta}}_1 + \gamma_s^{\min}a' \leq 0$, which is also equal to

$$h(\mu) = \sum_{n=1}^{N_r^2} \frac{\lambda_n}{(1+\mu\lambda_n)^2} \left|\bar{\beta}_{1n}\right|^2 + \gamma_s^{\min}a' \leq 0, \tag{26}$$

where $\bar{\beta}_{1n}$ is the element of vector $\bar{\boldsymbol{\beta}}_1$. Taking the derivative of (26), we have

$$h'(\mu) = -\sum_{n=1}^{N_r^2} \frac{2\lambda_n^2}{(1+\mu\lambda_n)^3} \left|\bar{\beta}_{1n}\right|^2 < 0. \tag{27}$$

Due to the complementarity condition, i.e., $\mu h(\mu) = 0$, we can derive that, if $h(0) \leq 0$, $\mu = 0$; if $h(0) > 0$, $h(\mu) = \sum_{n=1}^{N_r^2} \frac{\lambda_n}{(1+\mu\lambda_n)^2}\left|\bar{\beta}_{1n}\right|^2 + \gamma_s^{\min}a' = 0$. Since $h(\mu)$ is a monotonic decreasing function, the solution for $h(\mu) = 0$ is unique and can be found via the Newtons method. Once the optimal μ^* is obtained, $\mathbf{f}_1^*$ can also be achieved.

Similarly, we can derive the $\mathbf{f}_2^*$ in (21). By alternatively updating the global variable $\mathbf{f}$, local variables $\{\mathbf{f}_1, \mathbf{f}_2\}$ and multipliers $\{\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2\}$ until the algorithm converges, $\mathbf{f}^*$ can be obtained. Subsequently, the relay processing matrix $\mathbf{F}^*$ can be achieved by reshaping the $\mathbf{f}^*$.

Notice that our proposed algorithm alternatively optimizes three blocks of variables. With each iteration, the achieved rate of node R, R_r, is improved. Besides, there exists an upper bound value of R_r due to the limitation of the transmission power. Therefore, the proposed algorithm can always converge, which is also verified in the numerical results.

IV. Numerical Results

Numerical examples are presented in this section to validate our results. We set the numbers of antennas as $N_s = N_r = N_d = 4$ and the transmission powers as $P_s = 30$ dBm and $P_d = 35$ dBm. The noise power is $\sigma_r^2 = \sigma_c^2 = \sigma_d^2 = 0$ dBm and the energy conversion efficiency is $\xi = 30\%$. Assume that $d_{sd} = d_{sr} + d_{rd} = 6$ m and the path-loss exponent is 3.5. All channel entries are independently generated from i.i.d. Rayleigh fading with the respective average power values. In the simulation, the optimal ρ is found via exhaustive search among 0.01:0.01:0.99.

The convergence performance is shown in Fig. 2. It can be seen that our proposed algorithm converges after 4 iterations. Then, Fig. 3 shows the achievable R-S rate regions. The 'naive F scheme' means $\mathbf{F} = \mathbf{I}$ and the 'no energy-aided scheme' represents $P_d = 0$ W. Clearly, our proposed scheme can improve the rate of node R up to 80%, as compared with the no energy-aided scheme. This validates the necessity of destination-aided wireless energy transfer for the information reporting process in low-power sensor networks.

The impact of node R's location on the rate of R is shown in Fig. 4. As compared with the 'no energy-aided scheme', our proposed scheme has significant advantage especially when node R is closer to node D. Furthermore, with the increase of d_{rd}/d_{sd}, the achieved rate of node R first decreases due to the reduction of harvested energy from node D, and then increases due to the enhanced signal strength from node S.

V. Conclusion

We have proposed a destination-aided wireless energy transfer scheme in wireless relay sensor networks, where the energy-limited relay sensor is powered by the information collector who has reliable power supply. The formulated problem, which aims to maximize the rate of the relay by jointly designing transmitter beamformers, receiver vectors and the relay processing matrix, has been effectively solved. It has been shown that the capacity region can be greatly improved with our proposed scheme. Moreover, the location of relay has a significant impact on the system rate. In the future, the relay selection scheme will be designed for destination-aided multi-relay energy-harvesting networks.

References

[1] L. Lei, Y. Kuang, X. Shen, K. Yang, J. Qiao, and Z. Zhong, "Optimal reliability in energy harvesting industrial wireless sensor networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 8, pp. 5399–5413, Aug. 2016.

[2] R. Zhang and C. K. Ho, "MIMO broadcasting for simultaneous wireless information and power transfer," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 1989–2001, May 2013.

[3] G. Zheng, Z. Ho, E. A. Jorswieck, and B. Ottersten, "Information and energy cooperation in cognitive radio networks," *IEEE Transactions on Signal Processing*, vol. 62, no. 9, pp. 2290–2303, Mar. 2014.

[4] Y. Huang and B. Clerckx, "Relaying strategies for wireless-powered MIMO relay networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 9, pp. 6033–6047, Sept. 2016.

[5] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge University Press, 2004.

[6] Y. Huang and D. P. Palomar, "Rank-constrained separable semidefinite programming with applications to optimal beamforming," *IEEE Transactions on Signal Processing*, vol. 58, no. 2, pp. 664–678, Feb. 2010.

[7] S. Boyd, N. Parikh, E. Chu, B. Peleato, J. Eckstein *et al.*, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends® in Machine learning*, vol. 3, no. 1, pp. 1–122, 2011.