Space-Division Multiple Access-Based Energy Beamforming for IoT Devices

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Batteryless Internet of Things, powered by wireless energy transfer (WET) from dedicated power beacons (PBs), has emerged as a promising approach to eliminate the need for frequent battery replacements and maintenance. This paper compares statistical channel state information (SCSI), space-division multiple access (SDMA)-based SCSI, and the omnidirectional switching antenna (SA) WET techniques. We define an optimization algorithm to minimize the energy consumption of the PB while meeting reliability and latency constraints under realistic Rician fading channel models. Results reveal optimal charging times for each strategy. While the SDMA approach leverages multiple antennas to enhance energy delivery efficiency in dense environments, the SA technique offers a simpler, yet efficient solution for dense deployments.

I. INTRODUCTION

The proliferation of the Internet of Things (IoT), in the context of 5G and future 6G networks, has been pivotal in the advancement of scalable and reliable communications for a wide range of connected devices. The growing demand for sustainable IoT solutions has called for the development of batteryless devices that operate without frequent maintenance or battery replacements. To this end, wireless energy transfer (WET) has emerged as a compelling solution to sustain low-power devices, supporting maintenance-free operations and extending devices lifetime [1, 2].

WET technologies relying on radio frequency (RF) have been extensively explored as a means to power batteryless IoT devices. The deployment of power beacons (PBs) enables both direct powering of sensors and energy storage for future use. However, efficient WET in such networks often hinges on the availability of accurate channel state information (CSI), which facilitates optimized energy beamforming and maximizes energy delivery to intended devices.

The literature on WET has predominantly focused on techniques that assume perfect or near-perfect CSI, such as full CSI (FCSI) strategies, which enable precise beamforming towards specific devices. These techniques maximize energy transfer efficiency by accurately directing energy beams, but the assumption of instantaneous and perfect CSI availability is often impractical due to the significant overhead and energy consumption required for channel estimation and feedback [1]. To address these challenges, more practical approaches have been developed, including statistical CSI (SCSI) techniques, which leverage average channel knowledge to design beamforming patterns that reduce the need for real-time channel estimation [3]. SCSI-based strategies offer a compromise between performance and complexity, especially as the number of devices increases and instantaneous CSI estimation becomes infeasible [4].

Furthermore, other studies have explored non-beamforming strategies, such as the switching antenna (SA) and all antennas active (AA) techniques, which do not depend on instantaneous CSI. The SA method, which involves sequentially switching between antennas with each transmitting at full power, has been shown to provide more predictable energy delivery [5]. In contrast, the AA technique, which transmits from all antennas simultaneously, suffers from high variance in energy delivery under non-line-of-sight (NLOS) conditions, limiting its effectiveness in unpredictable environments [6].

Building on the above, and assuming that FCSI is infeasible, this work provides an analysis of the performance and trade-offs between SCSI, SCSI combined with space division multiple access (SDMA), and SA strategies for WET in dense IoT networks. The SDMA approach, which partitions antennas into groups to simultaneously serve subsets of devices, represents a promising middle ground between the simplicity of non-beamforming methods and the efficiency of beamforming approaches [6]. To address existing literature gaps, we evaluate SCSI, SDMA, and SA strategies under varying network parameters, such as the number of IoT devices, the average distance of the devices to the PB, and the transmit power of the PB.

II. SYSTEM MODEL

Figure 1 illustrates a PB, equipped with a uniform linear array of M antennas, charging D IoT devices via RF, each indexed by $i \in [1, D]$. The IoT devices are batteryless and equipped with single rectennas to harvest power from the PB. Once powered, these devices transmit their collected data to the destination node, which processes the data for further use. We consider the IoT devices randomly spread around the PB within a circle of radius R_{wet}, following a uniform distribution, with a minimum radius of 1 m around the PB.

Adopting the PB position as the reference and θ_i as the angle formed between the PB and a device i, the coordinate of the device is $(x_i, y_i) = (d_{i,\mathrm{wet}} \cos\theta_i, d_{i,\mathrm{wet}} \sin\theta_i)$, where $d_{i,\mathrm{wet}}$ is the distance between the PB and the i-th

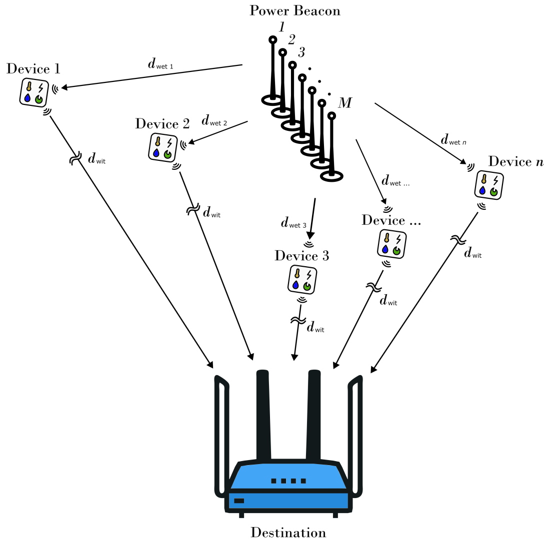

Figure 1: *Multi-antenna PB powering multiple IoT devices, which send data to a destination node. The distances between the PB and IoT devices are denoted as* $d_{i,\text{wet}}$, *while from each IoT device to the destination are denoted as* $d_{i,\text{wit}}$.

device. The distance between the PB and the destination node is d_{wit}, while the i-th device is at distance $d_{i,\text{wit}} = \sqrt{d_{i,\text{wet}}^2 + d_{\text{wit}}^2 - 2 d_{i,\text{wet}} d_{\text{wit}} \cos\theta_i}$ from the destination.

A. Channel Models

The WET link with respect to the i-th device is characterized by a Rician fading channel

$$\mathbf{h}_i = \sqrt{\beta_{i,\text{wet}}}(\mathbf{h}_{i,\text{LOS}} + \mathbf{h}_{i,\text{NLOS}}) \quad \in \mathbb{C}^{M\times 1}. \tag{1}$$

The deterministic LOS component is given by

$$\mathbf{h}_{i,\text{LOS}} = \sqrt{\frac{\kappa_{\text{wet}}}{1+\kappa_{\text{wet}}}}\, e^{j\varphi_{0,i}}\, [1, e^{j\psi_{1,i}}, \ldots, e^{j\psi_{M-1,i}}]^T, \tag{2}$$

where $[\cdot]^T$ is the transpose operation, κ_{wet} is the line-of-sight (LOS) factor, $\varphi_{0,i}$ is the initial phase shift of the first antenna with respect to the i-th device, and $\psi_{m,i}$, $m \in \{1, \ldots, M-1\}$, is the mean phase shift of the $(m+1)$-th array element with respect to the first. It is assumed that the antenna elements are equally spaced at a half-wavelength distance so that $\psi_{m,i} = -m\pi \sin\theta_i$. The NLOS component is

$$\mathbf{h}_{i,\text{NLOS}} \sim \sqrt{\frac{1}{1+\kappa_{\text{wet}}}}\mathcal{CN}(\mathbf{0}, \mathbf{R}), \tag{3}$$

where $\mathcal{CN}(\mathbf{0}, \mathbf{R})$ is a circularly-symmetric complex Gaussian vector with zero-mean and covariance $\mathbf{R} = \frac{1}{1+k_{\text{wet}}}\mathbf{I}$ [7].

The average power gain in the WET link is given by

$$\beta_{i,\text{wet}} = \frac{c^2}{16\pi^2 f_{\text{wet}}^2 d_{i,\text{wet}}^{\alpha_{\text{wet}}}}, \tag{4}$$

where c is the speed of light, f_{wet} is the WET frequency, and α_{wet} is the path-loss exponent for the WET link.

Wireless Information Transfer (WIT) refers to the transmission of data over wireless channels. The WIT link between the i-th IoT device and the destination is also modeled as a Rician fading channel

$$z_i = \sqrt{\beta_{i,\text{wit}}}(z_{i,\text{LOS}} + z_{i,\text{NLOS}}) \quad \in \mathbb{C}, \tag{5}$$

where $z_{i,\text{LOS}} = \sqrt{\frac{\kappa_{\text{wit}}}{1+\kappa_{\text{wit}}}} e^{j\phi_i}$, with LOS factor κ_{wit} and ϕ_i being the phase shift, while $z_{i,\text{NLOS}} = \sqrt{\frac{1}{1+\kappa_{\text{wit}}}}\mathcal{CN}(0,1)$. Moreover, the average power gain in the WIT link, $\beta_{i,\text{wit}}$ can be obtained from (4) replacing the subscripts wet by wit.

B. Transceiver Model

In the IoT device circuitry, the power usage of low-power transceivers is typically represented as a function that includes the drain efficiency η of the power amplifier (PA) and a constant power consumption P_{circ} related to other components within the transceiver circuit. The transmit power P_i is the effective power that the i-th device uses to transmit data through the WIT link to the destination node, given by:

$$P_{i,b} = \min\left\{\left[\eta\left(P_{i,b,\text{harv}} - P_{\text{circ}}\right)\right]^+, P_{\max}\right\}, \tag{6}$$

where $[x]^+ = \max\{0, x\}$, and $P_{i,b,\text{harv}}$ is the total power harvested by the rectenna of the i-th device, which depends on the WET scheme $b \in \{\text{SA}, \text{SCSI}, \text{SDMA}\}$, assuming that all of the harvested power is used by the transceiver. Notice that (6) only holds when $P_{i,b,\text{harv}} > P_{\text{circ}}$; furthermore, the transceiver has a maximum transmission power $P_{\max}$.

C. Outage Probability

An outage occurs when γ_i, the signal-to-noise ratio (SNR) at the destination given a transmission from device i, falls below a certain threshold $\gamma_{0,i}$, resulting in failure to decode the data. Assuming the Shannon limit, then $\gamma_{0,i} = 2^{R_i} - 1$, where R_i is the normalized transmission rate, given by:

$$R_i = \frac{N}{B\,T_i}, \tag{7}$$

with N being the number of bits transmitted to the destination node, B being the bandwidth of the WIT link, and T_i being the transmission time of the i-th device. The SNR for a given device, in its turn, is given by

$$\gamma_i = \frac{P_i\,\beta_{i,\text{wit}}\,|z_i|^2}{N_{\text{f}}\,N_0\,B}, \tag{8}$$

where N_{f} is the noise figure and N_0 is the noise power spectral density. Hence, the outage probability can be written as:

$$\mathcal{O}_i = \mathbb{P}\{\gamma_i < \gamma_{0,i}\} = \mathbb{P}\left\{|z_i|^2 < \frac{(2^{R_i}-1)N_{\text{f}}N_0B}{P_i\,\beta_{i,\text{wit}}}\right\}. \tag{9}$$

III. WET MODELS

The RF power the i-th device can harvest, $\mathcal{P}_{b,i}$, is determined by the WET technique used by the PB and the channel conditions, as

$$\mathcal{P}_{b,i} = |\mathbf{w}_{i,b}^H\,\mathbf{h}_i|^2, \tag{10}$$

where $\mathbf{w}_{i,b}$, $b \in \{\mathrm{SA}, \mathrm{SCSI}, \mathrm{SDMA}\}$ is the WET precoder, and $(\cdot)^H$ denotes the Hermitian transpose.

In addition, the DC power harvested by the i-th device follows a practical non-linear model defined as [2]

$$\mathcal{G}(\mathcal{P}_{b,i}) = \frac{(1 - e^{-c_0 \mathcal{P}_{b,i}})\mathcal{W}}{1 + e^{-c_0(\mathcal{P}_{b,i} - c_1)}}, \tag{11}$$

where $\mathcal{W}$ is the saturation level, and c_0 and c_1 are unitless constants to fit the rectenna characteristics.

A. Switching Antenna (SA)

In SA, the PB transmits without beamforming and, consequently, without using any CSI [5]. Then, the total charging time is the time until all D devices are charged enough to ensure transmission with outage probability $\mathcal{O}^\star$, *i.e.*,

$$\tau_{\mathrm{SA}} = \max_i \; T_i. \tag{12}$$

The transmission is done with full power by one antenna at a time, and all antennas are used during a block. Thus, each m-th PB antenna, $m \in [1, \ldots, M]$, provides $\mathcal{P}_{i,m,\mathrm{SA}} = \beta_{i,\mathrm{wet}} \, \Gamma_{\mathrm{P}} \, |h_{i,m}|^2$ [5], where $h_{i,m}$ represents the m-th element of $\mathbf{h}_i$ and Γ_{P} is the transmit power of the PB. At the i-th device, the power harvested from the m-th antenna is $\mathcal{G}(\mathcal{P}_{i,m,\mathrm{SA}})$. Assuming equal-time allocation for each antenna, the total power harvested by the i-th device is

$$P_{i,\mathrm{SA,harv}} = \frac{1}{M} \sum_{m=1}^{M} \mathcal{G}(\beta_{i,\mathrm{wet}} \Gamma_{\mathrm{P}} |h_{i,m}|^2). \tag{13}$$

Finally, the transmit power of the i-th device, $P_{i,\mathrm{SA}}$, is given by (6) using (13).

B. SCSI Beamforming

With SCSI, the PB uses statistical information to perform beamforming towards one device at a time, time multiplexing to serve multiple devices. The total charging time is

$$\tau_{\mathrm{SCSI}} = \sum_{i=1}^{D} T_i. \tag{14}$$

The precoder for SCSI is $\mathbf{w}_{i,\mathrm{SCSI}} = \sqrt{\Gamma_{\mathrm{P}}} \frac{\mathbf{h}_{i,\mathrm{LOS}}}{||\mathbf{h}_{i,\mathrm{LOS}}||}$, which substituted into (10) with a few algebraic manipulations yields [7]

$$\mathcal{P}_{i,\mathrm{SCSI}} = \beta_{i,\mathrm{wet}} \Gamma_{\mathrm{P}} \left| ||\mathbf{h}_{i,\mathrm{LOS}}|| + \frac{\mathbf{h}_{i,\mathrm{LOS}}^H \, \mathbf{h}_{i,\mathrm{NLOS}}}{||\mathbf{h}_{i,\mathrm{LOS}}||} \right|^2. \tag{15}$$

With SCSI only, $\mathbf{h}_{i,\mathrm{NLOS}}$ is unknown at the PB, representing an uncertainty in the beamforming design. Thus, SCSI performs better when the LOS component is dominant in (15).

The power harvested by the i-th device is $P_{i,\mathrm{SCSI,harv}} = \mathcal{G}(\mathcal{P}_{i,\mathrm{SCSI}})$, so the transmit power $P_{i,\mathrm{SCSI}}$ follows from (6).

C. SDMA-Based SCSI Beamforming

The SDMA technique enables simultaneous energy transfer to multiple devices by creating individual energy beams. Thus, the system can potentially overcome the limitations of time multiplexing and offer a more efficient WET solution in dense scenarios. The PB antennas are divided into G groups, so the number of antennas in each group $g \in \{1, 2, \ldots, G\}$ is $\frac{M}{G}$. The total charging time with SDMA becomes

$$\tau_{\mathrm{SDMA}} = \sum_{g=1}^{G} \max_{i \in g} \; T_i. \tag{16}$$

Then, only a subset of the channel vector $\mathbf{h}_i$ is used for each group, so that we denote the channel subset vectors by $\mathbf{b}_{i,\mathrm{LOS}}$ and $\mathbf{b}_{i,\mathrm{NLOS}}$, each containing $\frac{M}{G}$ elements of $\mathbf{h}_{i,\mathrm{LOS}}$ and $\mathbf{h}_{i,\mathrm{NLOS}}$, respectively. Therefore, the SDMA precoder is equivalent to the SCSI precoder, with the proper channel subset substitutions,

$$\mathcal{P}_{i,\mathrm{SDMA}} = \beta_{i,\mathrm{wet}} \Gamma_{\mathrm{P}} \left| ||\mathbf{b}_{i,\mathrm{LOS}}|| + \frac{\mathbf{b}_{i,\mathrm{LOS}}^H \mathbf{b}_{i,\mathrm{NLOS}}}{||\mathbf{b}_{i,\mathrm{LOS}}||} \right|^2, \tag{17}$$

with transmit power $P_{i,\mathrm{SDMA}}$ coming from (6) using $\mathcal{G}(\mathcal{P}_{i,\mathrm{SDMA}})$.

D. Problem Formulation

Our goal is to minimize the energy consumption at the PB, while efficiently charging D IoT devices, which must transmit data to a destination given a target outage probability $\mathcal{O}^\star$. The energy consumption of the PB is given by $E = \Gamma_{\mathrm{P}} \tau_b$, for $b \in \{\mathrm{SA}, \mathrm{SCSI}, \mathrm{SDMA}\}$. Since Γ_{P} is fixed, this optimization problem can be written as

$$\begin{aligned}
\tau_b^\star = \underset{\tau_b}{\text{minimize}} \quad & E = \Gamma_{\mathrm{P}} \tau_b && \text{(18a)}\\
\text{s.t.} \quad & \mathcal{O}_i = \mathcal{O}^\star, \quad \forall i \in \mathcal{D} && \text{(18b)}\\
& \tau_b \leq \tau_{\max}, && \text{(18c)}\\
& R_i \leq R_{\max}, \quad \forall i \in \mathcal{D} && \text{(18d)}
\end{aligned}$$

in which (18b) denotes a set of constraints in order to satisfy a target outage probability $\mathcal{O}^\star$ for each i-th device. Also, a maximal charging time and a maximal transmission rate per device are imposed by conditions (18c) and (18d).

IV. RESULTS

In this section, we compare the SDMA-based beamforming technique with SCSI and SA. We assume that $\mathcal{W} = 10.73$ mW, $c_0 = 0.2308$, $c_1 = 5.365$, $\eta = 33\%$, $P_{\mathrm{circ}} = 1.33$ mW and $P_{\max} = 3.3$ dBm. In addition, $M = 24$, $d_{\mathrm{wit}} = 100$ m, $\kappa_{\mathrm{wet}} = 4$ dB, $\kappa_{\mathrm{wit}} = 2$ dB, $\alpha_{\mathrm{wet}} = \alpha_{\mathrm{wit}} = 3$, $f_{\mathrm{wet}} = 915$ MHz, $f_{\mathrm{wit}} = 2.45$ GHz, $N_{\mathrm{f}} = 10$ dBm, $N_0 = -204$ dB/Hz, $N = 23$ bytes, and $B = 100$ kHz. Furthermore, for the optimization $\mathcal{O}^\star = 10^{-3}$, $\tau_{\max} = 1$ s, and $R_{\max} = 8$ bps/Hz.

Figure 2 shows the optimal charging time $\tau_b^\star$, with $G \in \{2, 3\}$ groups for SDMA, as a function of the number of IoT devices D. We observe that the SA technique remains constant regardless of the number of users, once the WET is omnidirectional and $\tau_{\mathrm{SA}}^\star$ is the time until all devices have enough

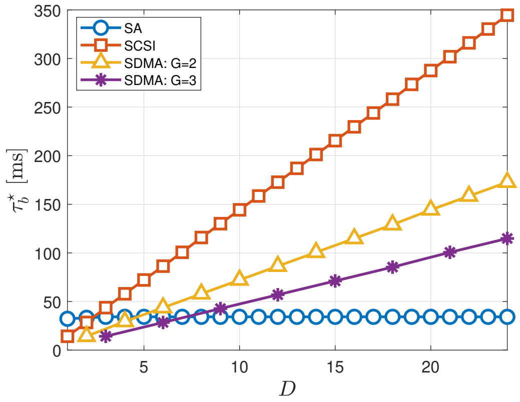

Figure 2: *Optimal charging time ($\tau_b^\star$) vs. number of devices (D) for SA, SCSI, and SDMA with $G \in \{2, 3\}$, $\Gamma_{\mathrm{P}} = 53$ dBm and $R_{\mathrm{wet}} = 3.5$ m.*

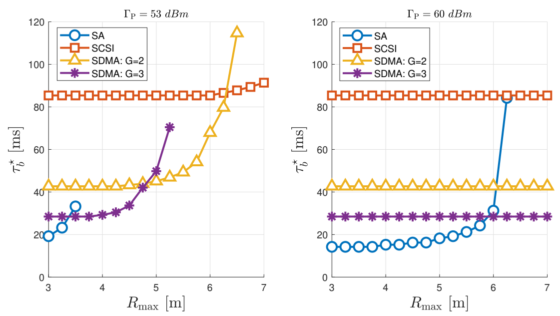

Figure 3: $\tau_b^\star$ *vs.* R_{wet} *with* $D = 6$ *devices.*

energy to transmit. Also, $\tau^\star_{\mathrm{SCSI}}$ and $\tau^\star_{\mathrm{SDMA}}$ increase with D and outperform SA when D is small. For instance, SDMA with $G = 3$ outperforms the other schemes when $D \leq 9$. On the other hand, the SA technique becomes more advantageous when the number of devices increases significantly. Let us remark that with $R_{\mathrm{wet}} = 3$ m the device density with $D = 24$ is of $D/(\pi R^2_{\mathrm{wet}}) \approx 0.85$ devices/m^2.

Figure 3 plots $\tau_b^\star$ as a function of R_{wet}. In the left figure, with $\Gamma_{\mathrm{P}} = 53$ dBm, the performance of SA significantly drops when $R_{\mathrm{wet}} > 3$ m, while SCSI and SDMA can extend the charging radius for a few meters. In addition, the right figure increases Γ_{P} to 60 dBm, in which we observe that all techniques benefit from this increase, but with SDMA being able to further extend the charging radius, with reduced energy consumption compared to SCSI.

Figure 4 shows the impact of Γ_{P} on $\tau_b^\star$ with $D = 6$ devices. As Γ_{P} increases, all techniques show a decrease in $\tau_b^\star$ up to a saturation point of minimal charging time. On the other hand, if Γ_{P} is too low, $\tau_b^\star$ tends to infinity. Furthermore, we also observe that for SA to be efficient, the power level must be considerably increased, while SDMA offers an important trade-off in performance.

V. CONCLUSION

This paper explores a batteryless IoT system powered by WET from a dedicated PB, comparing SCSI, SDMA, and SA beamforming in different environments. An optimization algorithm minimizes PB energy consumption while meeting WIT reliability. Results show optimal charging times for each WET strategy, with SDMA performing best in less dense networks and SA excelling in very dense ones due to its simplicity and lack of CSI requirements.

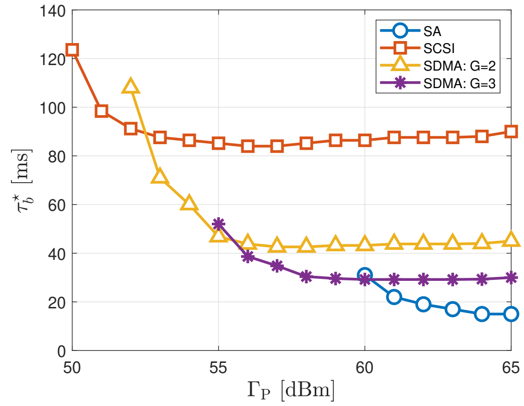

Figure 4: $\tau_b^\star$ *vs.* Γ_{P} *with* $R_{\mathrm{wet}} = 6$ *m.*

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