Optimization of STAR-RIS-assisted WET Systems Based on IoT Device Selection

Rogério Pereira Junior, Victoria Dala Pegorara Souto and Richard Demo Souza

Abstract— **In this paper, we evaluate a Wireless Energy Transfer (WET) system assisted by a Simultaneous Transmission and Reflection Reconfigurable Intelligent Surfaces (STAR-RIS) and consider the concept of beamsharing, which allows IoT devices to harvest energy even while others are actively being charged. Then, determining the optimal charging sequence is critical, as it directly impacts the total time required to charge all devices. To tackle this challenge, we propose an Ant Colony Optimization (ACO)-based approach to optimize the charging order, minimizing the overall system charging time. Furthermore, given that perfect Channel State Information (CSI) is challenging and often unavailable in practical scenarios, we propose a design methodology based on Statistical CSI (S-CSI) to optimize both the beamforming at the power beacon (PB) and the phase and amplitude configurations of the STAR-RIS elements. Our results demonstrate that the proposed solution achieves near-optimal performance and reduces the total charging time by at least 23% compared to a random selection benchmark.**

Keywords— **Wireless Energy Transfer, Ant Colony Optimization, Beamforming.**

I. INTRODUCTION

The growth of the Internet of Things (IoT) has highlighted the need for efficient and reliable solutions to power devices, especially in scenarios requiring uninterrupted operation [1]. Moreover, in certain environments, such as large agricultural areas or remote locations, frequent access to battery replacement or recharging is challenging, driving the need for innovative solutions [2]. In this context, Wireless Energy Transfer (WET) emerges as an appealing solution. The core idea of WET is to wirelessly transmit energy to devices using various techniques, such as solar, wind, inductive, and radio frequency (RF) [2]. Among the different approaches, the RF-based technique (RF-WET) stands out as the most compatible with the objectives of this study. This is due to its compact design, the simplicity of the hardware involved, and the ease of implementation for multi-user systems since a single RF signal can be simultaneously received by several sensors. Thus, RF-WET offers greater scalability and enables the continuous operation of IoT devices.

Although WET already represents a significant advancement, its efficiency can be further enhanced by introducing Reconfigurable Intelligent Surfaces (RISs), which consist of passive elements that dynamically adjust signal characteristics, such as phase, to optimize reflection and overcome obstacles or lack of line-of-sight (LoS) [3]. However, RISs only reflect signals, limiting their use to devices on the same side of the surface. In complex environments, like a mix of open areas and enclosed spaces, this reflection is insufficient to power indoor devices [4]. To overcome this, the Simultaneous Transmission and Reflection RIS (STAR-RIS) was introduced, enabling both reflection and transmission of signals, thus expanding system coverage and supporting more diverse deployment scenarios [4].

Despite the advantages of deploying STAR-RIS in WET systems, one of the main challenges is the need for accurate channel state information (CSI) to jointly design the beamforming at the power beacon (PB) and to determine the reflection and transmission coefficients of the STAR-RIS elements [2]. Although perfect CSI (P-CSI) allows optimal control of the PB and STAR-RIS beamforming, achieving it in practical scenarios is challenging due to the high power consumption required for CSI estimation and the high computational demands to process this information [5]. Furthermore, the presence of STAR-RIS significantly increases the complexity of the problem, since multiple channels need to be estimated.

To overcome the challenges of perfect CSI (P-CSI) in WET systems, statistical CSI (S-CSI) has been widely explored in WET systems without STAR-RIS [6]–[8]. Specifically, in [6], a beamforming strategy is developed using only average channel statistics to power IoT devices through a multi-antenna power beacon (PB). In [7], the authors propose a power allocation method that incorporates fairness, ensuring a minimum energy level for each IoT device and promoting equitable distribution across clusters. In addition, in [8], a beamforming design based only on S-CSI is proposed. The proposed approach, called “beamsharing”, considers that IoT devices can collect energy while other devices are being charged which significantly reduces the total charging time of all IoT devices. Finally, despite the advantages of the STAR-RIS, [6]–[8] does not consider the STAR-RIS architecture. Therefore, there is still a notable gap in the deployment of STAR-RISs in WET systems. Most studies focused on STAR-RIS have mainly addressed communication optimization [9]–[11], with little attention to its application in WET systems. Among the few studies that investigate the use of STAR-RIS in the context of WET, the authors in [12] explore an integrated scenario with Wireless Information Transfer (WIT). The work assumes perfect CSI knowledge and seeks to maximize the combined rate of two groups of sensor nodes connected to an access point.

To fill the gap in the literature, in this paper, we investigate

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the integration of STAR-RIS into WET systems. Specifically, the main goal of this paper is to minimize the total charging time required to meet the minimum energy requirements of all IoT devices. As we consider the beamsharing concept proposed in [8], to achieve the paper's goal, it is necessary to define the charging order of the IoT devices, which is a difficult problem to solve due to the number of IoT devices. Therefore, we propose an emerging solution based on the Ant Colony Optimization (ACO) technique to define the suboptimal charging order of the IoT devices, which minimizes the total charging time of the system. In addition, the proposed solution optimizes the beamforming at the PB and the phase and amplitudes at the STAR-RIS based only on the S-CSI knowledge, which is viable in practical scenarios. Finally, the results demonstrate that the proposed approach effectively reduces the total charging time of IoT devices by efficiently utilizing the beamsharing effect. The main contributions of this work are: (i) A novel ACO-based strategy is proposed to minimize the total charging time using only S-CSI; (ii) It is shown that appropriate selection of the charging sequence significantly outperforms existing benchmarks in reducing system recharge time; and (iii) It is highlighted that poor device selection can substantially increase the overall charging duration, even surpassing the time required by a random selection strategy.

II. System Model

In this paper, we consider a scenario where a PB, equipped with a Uniform Linear Array (ULA) composed of N antennas, transfers energy to K devices with the help of a STAR-RIS composed by M elements. We adopt analog beamforming at the power beacon (PB), which restricts the PB to generating a single beam at any given time. The total number of IoT devices in the system is denoted by $K = K_\mathrm{r} + K_\mathrm{t}$, where K_r and K_t represent the number of devices located on the reflection and transmission sides of the STAR-RIS, respectively. Devices on the reflecting side, referred to as "r-device", are represented by the set $\mathcal{R} \in \{1, 2, \ldots, K_\mathrm{r}\}$, while those on the transmitting side, referred to as "t-device", are represented by the set $\mathcal{T} \in \{1, 2, \ldots, K_\mathrm{t}\}$.

In addition, we define $\mathbf{w}_k \in \mathbb{C}^{N\times 1}$ as the beamforming at the PB pointed to the k-th device and $\mathbf{\Theta}_k^{(p)} \in \mathbb{C}^{M\times M}$ is the diagonal matrix that defines the reflection and transmission pattern of STAR-RIS for the k-th device with $p \in \{\mathrm{r}, \mathrm{t}\}$. We can express $\mathbf{\Theta}_k^{(p)}$ as follows

$$\mathbf{\Theta}_k^{(p)} = \mathrm{diag}\left(\sqrt{\beta_{k,1}^{(p)}} e^{j\theta_{k,1}^{(p)}}, \ldots, \sqrt{\beta_{k,M}^{(p)}} e^{j\theta_{k,M}^{(p)}}\right), \quad (1)$$

where $\beta_{k,m}^{(p)} \in \{0, 1\}$ and $\theta_{k,m}^{(p)} \in [0, 2\pi)$ represent the amplitude and phase of the transmission and reflection STAR-RIS' coefficients, respectively. The phase adjustments of the transmission and reflection coefficients can be optimized independently, enabling individual control of the beams. However, the signal amplitudes are coupled by the law of energy conservation, i.e., $\beta_{k,m}^{(\mathrm{r})} + \beta_{k,m}^{(\mathrm{t})} = 1 \ \forall m \in \{1, \ldots, M\}$ [4].

The power received by the k-th device on the reflection side when the j-th device is being charged, i.e., the beamforming vector at the PB is designed to point to the j-th device, can be expressed as

$$P_{k,j}^{(\mathrm{r})} = \xi_{\mathrm{RD}_k} \left|\mathbf{v}_k^{\mathrm{H}} \Theta_j^{(\mathrm{r})} \mathbf{H} \mathbf{w}_j\right|^2 \xi_{\mathrm{PR}} + \xi_{\mathrm{PD}_k} \left|\mathbf{p}_k^{\mathrm{H}} \mathbf{w}_j\right|^2 \quad \forall k, j \in \mathcal{R}. \quad (2)$$

where ξ_{PD_k}, ξ_{PR}, and ξ_{RD_k} denotes the path-loss of the link between the PB and the IoT devices (PD), PB and STAR-RIS (PR), and STAR-RIS and devices (RD), respectively. In this paper, we consider the log-distance path-loss for all links, i.e., $\xi_{\ell_k} = \frac{\lambda^2}{16\pi^2} d_\ell^{-\alpha_\ell}$ where $\ell \in \{\mathrm{RD}, \mathrm{PR}, \mathrm{PD}\}$, $d_\ell \geq 1$ is the distance between the involved network elements, α_ℓ is the path loss exponent of each link, $\lambda = \frac{c}{f}$ is the wavelength with c being the speed of light and f the carrier frequency. Moreover, $\mathbf{p}_k^{\mathrm{H}} \in \mathbb{C}^{1\times N}$ and $\mathbf{v}_k^{\mathrm{H}} \in \mathbb{C}^{1\times M}$ denote the channel vector between the PB and the k-th IoT device and between the STAR-RIS and the k-th IoT device, respectively. In addition, $\mathbf{H} \in \mathbb{C}^{M\times N}$ denotes the channel matrix between the PB and the STAR-RIS. Similar to (2), the power harvested by the k-th device on the transmission side is given by

$$P_{k,j}^{(\mathrm{t})} = \xi_{\mathrm{RD}_k} \left|\mathbf{v}_k^{\mathrm{H}} \Theta_j^{(\mathrm{r})} \mathbf{H} \mathbf{w}_j\right|^2 \xi_{\mathrm{PR}} \quad k, j \in \mathcal{T}. \quad (3)$$

In this paper, all channel links are modeled according to the Rician fading model which can be given by

$$\mathbf{H} = \sqrt{\frac{\kappa_{\mathrm{PR}}}{1+\kappa_{\mathrm{PR}}}} \bar{\mathbf{H}} + \sqrt{\frac{1}{1+\kappa_{\mathrm{PR}}}} \tilde{\mathbf{H}}, \quad (4)$$

where κ_{PR} is the Rice factor, $\tilde{\mathbf{H}} \in \mathbb{C}^{M\times N}$ represents the NLoS components modeled with Rayleigh fading and $\bar{\mathbf{H}} \in \mathbb{C}^{M\times N}$ represents the LoS components of the channel matrix. Finally, $\mathbf{p}_k$ and $\mathbf{v}_k$ are modeled in the same way as $\mathbf{H}$ in (4) and κ_{PR} is replaced by κ_{PD} or κ_{RD} for $\mathbf{p}_k$ and $\mathbf{v}_k$, respectively.

Therefore, the energy collected by the k-th IoT device considering beamsharing is given by

$$\Phi_k = \underbrace{\left[t_k \left(\frac{\Gamma_{k,k} - \mu\Omega}{1-\Omega}\right)\right]}_{\mathcal{Q}_k} + \sum_{j=1, j\neq k}^{k-1} t_j \underbrace{\left[\frac{\Gamma_{k,j} - \mu\Omega}{1-\Omega}\right]}_{\mathcal{Q}_j}, \quad (5)$$

where $\mathcal{Q}_k$ denotes the energy harvested by the k-th IoT device when the beamforming vector is designed to the k-th IoT device and $\mathcal{Q}_j$ is the total energy harvested by the k-th IoT device while the j-th device is being charged. It is important to highlight that j and k denotes the index of the IoT devices in the reflection or transmission plane, i.e., if the k-the IoT device is in the reflection side, $\mathcal{Q}_j$ for the k-th device is computed only considering the neighboring devices in the reflection plane ($j, k \in \mathcal{R}$). The same consideration is done for $k \in \mathcal{T}$. Moreover, t_k and t_j denote the time in which the PB is focusing on the k-th or j-th device, respectively. $\Omega = \frac{1}{1+e^{ab}}$ is a constant that ensures a zero-input/zero-output response, where a and b are parameters that model the specific characteristics of the circuit. Furthermore, μ represents the maximum power that the IoT device can harvest when reaching saturation, limiting its ability to store energy efficiently [13]. Finally, $\Gamma_{k,j}$ denotes the traditional logistic function, which is given by

$$\Gamma_{k,j} = \frac{\mu}{1 + e^{-a\left(P_{k,j}^{(p)} - b\right)}}. \quad (6)$$

A. Optimization Problem

The main objective of this paper is to minimize the total time required to charge K IoT devices $\left(t_{\mathrm{T}} = \sum_{k=1}^{K} t_k\right)$ by optimizing the beamforming vector at the PB (w_k), the phase and amplitude of the STAR-RIS' elements $\left(\boldsymbol{\Theta}_k^{(\mathrm{r})} \text{ and } \boldsymbol{\Theta}_k^{(\mathrm{t})}\right)$, and the time allocated for each IoT device (t_k). To minimize t_{T}, we consider the minimum energy constraint for each IoT device, analog beamforming constraint, and the conservation of energy law constraint for the amplitude of the STAR-RIS-RIS' elements. Then, the proposed optimization problem is

$$\begin{aligned} \underset{\{w_k\},\{\boldsymbol{\Theta}_k^{(\mathrm{r})}\},\{\boldsymbol{\Theta}_k^{(\mathrm{t})}\},\{t_k\}}{\text{Minimize}} \quad & t_T = \sum_{k=1}^{K} t_k \\ \text{Subject to} \quad & \Phi_k \geq E_k \ \forall k \in \{1,\ldots,K\} \\ & |w_{k,n}|^2 = \frac{P_T}{N} \ \forall n \in \{1,\ldots,N\}, \\ & \beta_{k,m}^{(\mathrm{r})} + \beta_{k,m}^{(\mathrm{t})} = 1 \ \forall m \in \{1,\ldots,M\}, \\ & t_k \geq 0, \ \forall k, \end{aligned} \tag{7}$$

where E_k is the minimum energy constraint of the k-th device, and $|w_{k,n}|^2 = \frac{P_T}{N}$ denotes the analog beamforming constraint, and $\beta_{k,m}^{(\mathrm{r})} + \beta_{k,m}^{(\mathrm{t})} = 1$ is the conservation of energy law constraint for the amplitude of the STAR-RIS-RIS' elements. To find the optimal solution of (7) it is necessary to have perfect knowledge of the CSI, which becomes a challenge for WET systems especially due to the energy and time constraints in the estimation process [14]. In this sense, we will use only the knowledge of the S-CSI since it is a simpler and more practical approach.

The channels between the PB and the IoT devices on the reflection side of the STAR-RIS are assumed to be quasi-blocked. Consequently, the PB's beamforming vector is designed to direct energy toward the STAR-RIS, following the Equal Gain Transmitter (EGT) method [8], and is given by

$$\mathbf{w}_k = \sqrt{\frac{P_{\mathrm{T}}}{N}} \left[\frac{\sum_{m=1}^{M} \bar{H}_{m,1}}{\left|\sum_{m=1}^{M} \bar{H}_{m,1}\right|}, \ldots, \frac{\sum_{m=1}^{M} \bar{H}_{m,N}}{\left|\sum_{m=1}^{M} \bar{H}_{m,N}\right|} \right]^{\mathrm{T}}, \tag{8}$$

where $\mathbf{w}_k$ is computed based on the sum of the M channels for each of the N antennas at the PB.

For the STAR-RIS, we adopt a scenario known as uniform power division [4], where the transmission and reflection amplitude coefficients of the STAR-RIS elements are equal, that is, $\beta_{k,m}^{(p)} = \beta^{(p)}$. Furthermore, the STAR-RIS operates based on the Time Switching (TS) protocol [4]. In this protocol, the surface alternates between two main phases: transmission and reflection. Thus, the incident signal is not divided into two parts simultaneously; all the energy of the incident signal is used exclusively in one mode at a time (reflection or transmission). Therefore, the amplitude coefficient $\beta^{(p)}$ is equal to 1 during the time interval applied to each mode. The choice of the time-switching protocol was made to exploit the full potential of STAR-RIS in the charging process, allowing both sides (transmitter and reflector) to utilize all the surface resources during a dedicated time interval. As for the phase adjustments of these coefficients, they are determined by means of an optimal continuous adjustment, that is, they are adjusted to compensate for the phase of the channels, according to

$$\boldsymbol{\theta}_k^{(p)} = \angle\bar{\mathbf{v}}_k - \angle\bar{\mathbf{H}}\mathbf{w}_k, \tag{9}$$

where $\boldsymbol{\theta}_k^{(p)} = \left[\theta_{k,1}^{(p)}, \ldots, \theta_{k,M}^{(p)}\right] \in \mathbb{C}^{M\times 1}$ is the phase adjustment vector of the STAR-RIS' elements.

Therefore, substituting (8) and (9) into (7), the suboptimal allocated time for each IoT device can be computed by

$$t_1^* = \left\lceil \frac{E_k(1-\Omega)}{\Gamma_{k,k} - \mu\Omega} \right\rceil \quad \text{for } k = 1, \tag{10}$$

$$t_k^* = \left\lceil \frac{\left(E_k - \sum_{j=1}^{k-1} \mathcal{Q}_j\right)(1-\Omega)}{\Gamma_{k,k} - \mu\Omega} \right\rceil \quad \text{for } k > 1. \tag{11}$$

Equations (10) and (11) show that the charging order of IoT devices directly affects the total charging time due to the beamsharing effect, represented by the term Q_j. Devices can continue to accumulate energy while others are being charged, making an optimal sequence crucial for efficiency. To address this, a new strategy is proposed to optimize the charging process.

III. Proposed Approach based on ACO

To minimize the total charging time t_{T}, it is necessary to determine the optimal charging order for IoT devices. To achieve this, we propose a novel approach based on the Ant Colony Optimization (ACO) technique [15]. ACO is an optimization technique based on the collective behavior of ant colonies, which find more efficient paths by leaving chemical trails called pheromones. Over time, the most efficient paths in terms of lower cost or higher efficiency (such as shorter distance or time) accumulate more pheromones, encouraging more ants to follow them [15]. The artificial ants construct solutions based on probabilities, influenced by two factors: the pheromone $\tau_{i,l}$, which reflects the quality of the path between position i and l, and the heuristic $\eta_{i,l}$, which represents problem-specific information such as distances or times. Then, the probability of an ant n choosing a device l when leaving device i is given by [15]

$$\Upsilon_{i,l}^{n} = \frac{\tau_{i,l}^{\sigma} \cdot \eta_{i,l}^{\psi}}{\sum_{k\in K} \tau_{i,k}^{\sigma} \cdot \eta_{i,k}^{\psi}}, \tag{12}$$

where σ and ψ are parameters that control the influence of the pheromone and the heuristic, respectively. Moreover, after the ants construct their paths, the pheromone is updated to reflect the quality of the solutions found. Therefore, the pheromone is updated based on [16]

$$\tau_{i,l} = (1-\rho)\cdot\tau_{i,l} + \sum_{n=1}^{L} \Delta\tau_{i,l}^{n}, \tag{13}$$

where ρ is the pheromone evaporation rate, which decreases over time, while L represents the number of ants used. The term $\Delta\tau_{i,l}$ is the amount of pheromone added on the path between device i and l by ant n, calculated based on the quality of the solution found (the better the solution, the greater the increase in pheromone). The process is repeated until the stopping criterion is reached.

The main steps of the proposed solution based on ACO algorithm to define the suboptimal selection order of the IoT devices which minimize $t_{\rm T}$ are described next.

1) Initialize $\tau_{i,l}$ with values equal to 1.
2) Construct the charging sequence for each ant from (12).
3) For each defined sequence, the beamforming vector at the PB and the STAR-RIS coefficients for each IoT device are determined based on (8) and (9), respectively.
4) The charging time of each device is defined based on (10) and (11), obtaining total charging time ($t_{\rm T}$).
5) Save the sequence that obtained the lowest $t_{\rm T}$.
6) Update pheromone trails from equation (13).
7) Check the stopping criterion: If the maximum number of iterations is reached or the solution does not improve significantly, the algorithm execution is terminated. Otherwise, return to Step 2.

As only S-CSI is considered, the algorithm relies solely on the LoS component of the channels, which may lead to suboptimal charging performance and the risk of some devices not meeting the minimum power requirement. To address this, the proposed solution is executed iteratively until all devices confirm, through the control channel, that they are fully charged.

IV. Results and Discussions

In this section, we present the simulation results considering a STAR-RIS positioned at the center of the 2D plane with coordinates $(x_{\rm R}, y_{\rm R}) = (0, 0)$. The PB is fixed on the reflection side of STAR-RIS, located at a distance of 10 meters from STAR-RIS, at coordinates $(x_{\rm PB}, y_{\rm PB}) = (-10, 0)$. The IoT devices are evenly distributed between the reflection and transmitting sides. In addition, the $K_{\rm t}$ devices on the reflection side are arranged in a square structure of 3 meters wide. Finally, unless otherwise stated, the simulation parameters are: $K_t = 5$, $N = 6$, $M = 64$, $f = 915$ MHz, $\mu = 10.73$ mW, $a = 0.2308$, $b = 5.365$, $E_k = 10$ μJ $\forall k \in \{1, \ldots, K\}$, $\alpha_{\rm PD} = 3.5$, $\alpha_{\rm PR}$,$\alpha_{\rm RD} = 2.4$, $\kappa_{\rm PD} = 0.2$, $\kappa_{\rm PR}$ and $\kappa_{\rm RD} = 1.5$, $\rho = 0.3$, $\sigma = 1.5$, $\psi = 2$, and $L = 20$. The results presented in this section were obtained using Matlab®, and the curves represent the average of 10^3 independent channel realizations and 5 different topologies.

In addition, to evaluate the proposed solution *S-CSI (Beamsharing/ACO)*, we consider the following benchmarks: (i) *S-CSI (Beamsharing/Random Selection)*, where the sequence of devices to be charged is chosen randomly; (ii) *S-CSI (Beamsharing/Near)*, where the devices in the reflection/transmission side of the STAR-RIS are selected based on the shortest distance from the PB/STAR-RIS; and (iii) *S-CSI (Beamsharing/Far)*, where the devices in the reflection/transmission side of the STAR-RIS are selected based on the farthest distance from the PB/STAR-RIS; It is important to highlight that these benchmarks consider that the beamforming at the PB and the phase and amplitude of the STAR-RIS' elements are designed based only on the S-CSI knowledge. However, to obtain a lower bound of the proposed solution, we consider the *P-CSI (Beamsharing/ACO)* and *P-CSI (Beamsharing/Random Selection)* benchmarks where the devices are selected to be charged as previously described while the beamforming at the PB and at the STAR-RIS is designed based on the P-CSI knowledge.

To illustrate the impact of the number of IoT devices, Figure 1 depicts the $t_{\rm T}$ as a function of the number of IoT devices (K) for $M = 64$, $N = 6$ and $K_{\rm t} = 5$. In this analysis, we fix $K_{\rm t} = 5$ and vary the number of IoT devices on the reflection side of the STAR-RIS, i.e. $K_{\rm r} \in \{5, 10, 15, 20, 25\}$. From the results, we can observe that the proposed solution S-CSI (Beamsharing/ACO) achieves a close-to-optimal total charging time for all K configurations. Specifically, for $K \in \{10, 15, 20, 25, 30\}$ the proposed solution reduced $t_{\rm T}$ by 19.0%, 16.3%, 15.6%, 15.4%, and 15.0% compared to the S-CSI (Beamsharing/Far) benchmark. This outcome stems from ACO's capability to optimize the charging sequence, minimizing efficiency by effectively leveraging the potential of beamsharing. In addition, the results highlight the importance of developing novel solutions to smartly define the charging order of the IoT devices as, if the devices are randomly selected, the $t_{\rm T}$ increases by up to 24.2%, 23.8%, 23.5%, 23.3%, and 23.0% for $K \in \{10, 15, 20, 25, 30\}$ when compared to the proposed solution.

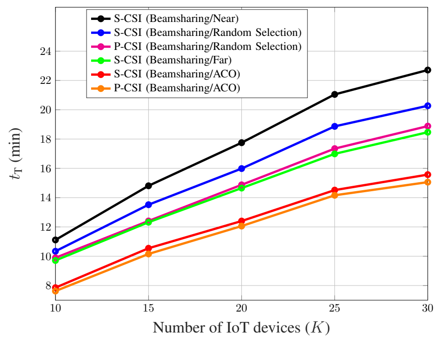

Fig. 1: $t_{\rm T}$ versus K for $M = 64$, $N = 6$ and $K_{\rm T} = 5$.

Figure 1 shows that the benchmark *S-CSI (Beamsharing/Far)* closely matches the performance of the proposed solution. This is because directing beamforming towards the most distant IoT device allows intermediate devices to harvest energy through beam scattering, reducing the total charging time. In contrast, *S-CSI (Beamsharing/Near)* performs worse, as devices closer to the STAR-RIS and PB are at small angles to the main beam, reducing beam scattering and energy harvesting. Overall, the results confirm that the proposed solution achieves near-optimal performance with only S-CSI knowledge, highlighting its practical feasibility in real-world scenarios.

Figure 2 illustrates the impact of the number of STAR-RIS elements (M) on $t_{\rm T}$. The results show that increasing M consistently reduces $t_{\rm T}$ across all benchmarks. This behavior is due to STAR-RIS's ability to focus energy beams toward IoT devices, enhancing transmission gain and optimizing energy harvesting. Furthermore, the proposed solution achieves a reduction in $t_{\rm T}$ by up to 13%, 15%, 16.5%, 20%, and 15% for $M \in \{36, 49, 64, 81, 100\}$ compared to the random selection approach. This further underscores the importance of the proposed solution in intelligently determining the optimal charging order for IoT devices. Finally, the results confirm that the proposed solution maintains near-optimal performance even for large M, highlighting its effectiveness in practical scenarios.

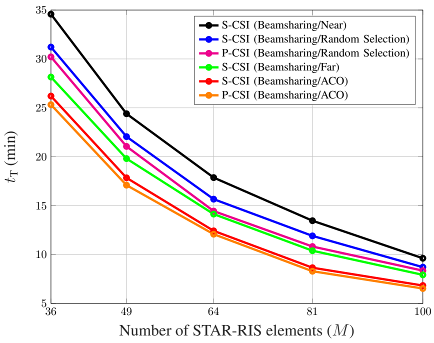

Fig. 2: t_{T} versus M for $N = 6$, $K_{\mathrm{t}} = 5$, and $K_{\mathrm{r}} = 15$.

Finally, Figure 3 demonstrates that increasing the number of PB antennas (N) reduces t_T, due to improved beam directivity and more efficient energy delivery to IoT devices and the STAR-RIS. However, the reduction in t_T becomes less significant as N increases, since concentrated beams reduce dependence on beamsharing. This suggests that in high-capacity PB scenarios, the charging sequence has less impact. Despite this, the proposed ACO-based solution consistently outperforms all benchmarks, achieving the lowest charging times for all values of N.

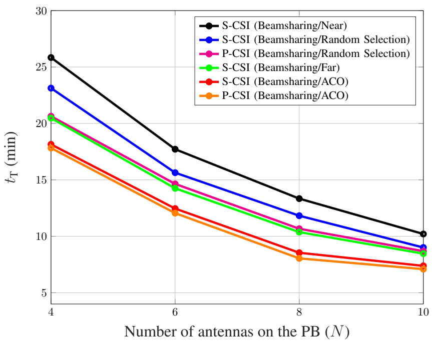

Fig. 3: t_T versus N for $M = 64$, $K_{\mathrm{t}} = 5$, and $K_{\mathrm{r}} = 15$.

V. Conclusion

This paper presents a novel solution based on the ACO algorithm for a WET system assisted by a STAR-RIS. The proposed method operates solely with S-CSI, thereby reducing computational complexity and making it suitable for practical scenarios where P-CSI is difficult to obtain. ACO is utilized to determine the optimal charging sequence of IoT devices by exploiting the beamsharing effect to minimize the total charging time. The results validate the proposed approach's efficiency in enabling effective energy transfer. As directions for future research, we intend to analyze the influence of PB positioning on system performance and explore alternative device selection strategies, such as reinforcement learning and clustering techniques, to further optimize charging efficiency.

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