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Low-Complexity Statistical-CSI Wireless Energy Transfer for Indoor IoT: Power Beacon Placement and Beamsharing-Aware Charging Scheduling

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Abstract

Wireless Energy Transfer (WET) is a promising solution for sustaining large-scale Internet of Things (IoT) deployments, but reducing charging time requires coordinated Power Beacon (PB) placement, energy beamforming, and device scheduling under limited channel knowledge. This work develops a structured low-complexity framework for indoor WET networks in which K-means clustering is used as a distance-based surrogate for PB placement, while phase-only analog beamforming relies on Statistical Channel State Information (S-CSI), avoiding instantaneous small-scale CSI acquisition. Device scheduling is performed by the proposed Intelligent Power Distribution Model (IPDM), which employs a distance-based priority rule. Primary and secondary energy contributions due to beamsharing are explicitly incorporated into the nonlinear energy-harvesting dynamics, allowing secondary energy to influence subsequent charging rounds. Simulations show charging-time reductions of up to 50% relative to the random benchmark. For small-scale scenarios, the proposed method remains within 9.22% and 7.55% of a grid-based exhaustive-search benchmark for $N = 3$ and $N = 4$, respectively, while preserving polynomial computational complexity. These

results indicate that the proposed framework offers an effective low-complexity solution for quasi-static indoor IoT deployments.

Keywords: Wireless Energy Transfer, Power Beacon Placement, Statistical CSI, Beamsharing, Charging Scheduling

1 Introduction

The rapid growth of Internet of Things (IoT) applications in areas such as environmental monitoring, agriculture, industrial automation, and smart cities has increased the demand for reliable, scalable, and sustainable energy solutions capable of supporting large-scale device deployments [1, 2]. Although technologies such as Backscatter Communication [3–6] and Reconfigurable Intelligent Surfaces (RIS) [5] have been investigated to improve the communication and energy efficiency of IoT networks, ensuring a continuous and dependable power supply remains a major challenge. Conventional approaches based on wired charging or periodic battery replacement require human intervention, increase maintenance and operational costs, and may be impractical in remote or difficult-to-access environments. Moreover, the large-scale use and replacement of batteries raise additional sustainability concerns, further motivating the development of alternative energy-supply mechanisms for future IoT networks [1, 7–9].

In this context, Wireless Energy Transfer (WET) has emerged as a promising solution for extending the operational lifetime of IoT devices by enabling contactless energy delivery and reducing dependence on conventional battery-maintenance procedures [1, 2, 7, 10, 11]. However, the efficient implementation of WET in large-scale networks depends on several interrelated design aspects, among which energy beamforming plays a central role. In contrast to omnidirectional transmission, which spreads the radiated energy over a broad area, beamforming exploits multiple antennas at the power beacon (PB) to concentrate energy toward selected devices, thereby increasing the received power and improving transfer efficiency and coverage [1, 12, 13]. The effectiveness of this approach, however, generally depends on the availability of channel state information (CSI) at the PB. Acquiring accurate instantaneous CSI from a large number of energy-constrained devices may introduce substantial signaling overhead, computational complexity, and additional energy consumption, which can offset part of the benefits provided by WET itself [1, 12, 14, 15]. This limitation motivates the development of WET strategies that can achieve efficient energy beamforming while relying on reduced or statistical CSI (S-CSI).

Another challenge is the optimized deployment of PBs to ensure uninterrupted device operation [16, 17]. Proper PB placement promotes uniform coverage and avoids excessive or insufficient beacon concentration in specific regions, which may increase charging time and device downtime [16, 18]. This problem is particularly relevant when IoT devices are non-uniformly distributed. Therefore, PB deployment strategies should account for device density and individual energy constraints to maximize WET efficiency [18, 19].

In beamforming-based WET systems, the radiated energy cannot be perfectly confined to the intended receiver because of side lobes, beamforming imperfections, reflections, and scattering. Consequently, nearby non-targeted devices may opportunistically harvest part of the transmitted energy, a phenomenon known as beamsharing [11]. This effect couples the charging processes of different devices and makes the charging sequence a key factor in the total charging time. For example, prioritizing devices with higher energy demands may allow neighboring devices to accumulate energy before their dedicated charging phases, whereas charging them later may reduce this benefit and prolong the process. Optimizing the charging order is therefore essential to exploit beamsharing, pre-charge multiple devices, avoid redundant charging phases, and minimize the total charging duration. Reducing this time improves energy efficiency, decreases device-availability latency, and supports the timely and sustainable operation of large-scale, energy-constrained IoT networks.

1.1 Related Work

Motivated by the challenges discussed above, the RF-based WET literature has extensively investigated energy beamforming and power beacon (PB) deployment to improve the energy supply of IoT systems. One major research direction concerns beamforming under limited channel knowledge. In [20], Rotary Antenna Beamforming was introduced, in which a PB equipped with a uniform linear array performs continuous or periodic rotation to provide effective omnidirectional coverage and more predictable harvested energy. Similarly, [21] proposed the All Antennas Same Signal (AASS) and All Antennas Independent Signal (AAIS) schemes, showing that AASS is more suitable for strong line-of-sight (LoS) conditions, whereas AAIS offers greater predictability for dispersed devices or weaker LoS components. In [15], CSI-free strategies such as One Antenna, All Antennas at Once, and Switching Antennas were compared with CSI-based schemes. The results showed that All Antennas at Once performs better under LoS, while Switching Antennas is more attractive under non-LoS conditions because of its lower harvested-energy variance. Moreover, CSI-free schemes approach CSI-based performance as the number of IoT devices increases, making them suitable for massive deployments. In [22], transmission diversity with phase scanning was shown to exploit fading and nonlinear RF-to-DC conversion to improve WET efficiency without CSI.

A related research line considers S-CSI-based beamforming. In [14], a low-complexity multi-user design based on average channel vectors and angular PB rotations was proposed to improve coverage and energy-distribution uniformity. In [23], the correlation among clustered devices and the Karhunen–Loève decomposition were exploited to maximize delivered power in massive machine-type communications under S-CSI. In addition, [11] proposed an analog beamforming strategy that minimizes total charging time while satisfying minimum harvested-energy constraints. By allowing neighboring devices to harvest energy while another device is actively charged, the scheme demonstrated the benefits of beamsharing under S-CSI.

Another major research direction addresses PB or charger placement in wireless-powered sensor and IoT networks, considering coverage, cost, and energy sustainability. In [16], omnidirectional PB placement was optimized without knowledge of device

locations or CSI to maximize the average minimum received energy over the coverage area. In [18], a Daubechies-wavelet-based method determined near-optimal PB positions and outperformed other wavelet-based approaches using fewer PBs. Likewise, [19] optimized the deployment and orientation of directional PBs through a greedy algorithm without CSI, whereas [24] jointly optimized PB locations and power adaptation to minimize data-transmission time in batteryless wireless sensor networks.

More sophisticated charger-placement formulations have also been investigated. In [17], cost-aware placement problems were formulated either to minimize deployment cost subject to charging requirements or to maximize charging utility under a budget constraint. In [25], charger placement in clustered RF-powered sensor networks was optimized to improve network lifetime, showing that chargers located near cluster heads substantially increase sustainable operation time. In [26], charger placement and sensor power allocation were jointly optimized to maximize task utility rather than only received charging power. More recently, [27] introduced omnidirectional charging with directional antennas and developed methods to guarantee a minimum harvested power regardless of receiver orientation. In [28], K-Means++ and Q-learning were combined to reduce the number of chargers while maintaining sustainable network operation. From a dynamic perspective, [29] formulated offline and online charger-placement problems, showing that online decisions can address scenarios with unknown future charging demands. These studies confirm the importance of PB deployment when multiple practical objectives must be balanced.

The literature has also considered specialized WET architectures. For wireless-powered underground sensor networks, [30] investigated CSI-free multiantenna schemes, including Switching Antennas, All-Antennas Independent Signals, All-Antennas Same Signal, and Rotary Antenna Beamforming, combined with a distributed multi-PB architecture. Under strong LoS conditions, the distributed Rotary Antenna Beamforming strategy approached and sometimes outperformed a full-CSI benchmark, while its deployment method performed close to or better than K-Means without prior node-location information. For indoor near-field WET, [31] jointly optimized transmit-antenna deployment and power allocation under a max-min criterion, showing that continuous apertures are unnecessary and that a finite number of antennas is sufficient in one-dimensional deployments. Radio-stripe architectures have also emerged as promising solutions for indoor RF-WET. In [32], radio-stripe geometry was optimized to maximize the minimum received power at hotspot locations while accounting for near-field propagation and fairness. In [33], multiple radio stripes were jointly designed with hotspot clustering and beamforming to maximize the minimum hotspot power. These works demonstrate that distributed antenna architectures can improve charging fairness and hotspot coverage.

Another group of studies addresses application-driven WET scenarios. In batteryless machine-type communications, [34] considered a PB-assisted architecture in which harvested energy is immediately used for uplink transmission and jointly optimized harvesting time and packet replication under average-CSI-based beamforming. In multi-hop RF-EH IoT networks, [35] showed that routing, link scheduling, and energy transfer must be jointly optimized to satisfy traffic and harvesting constraints.

Table 1: Review of state-of-the-art approaches for energy beamforming design and PB deployment.

Reference	S-CSI	MISO	PBs' Deployment	Charging Coordination
[20]	×	×	×	×
[16–18, 24–29, 39, 40]	×	×	✓	×
[15, 21, 22]	×	✓	×	×
[19, 30–33]	×	✓	✓	×
[14, 23]	✓	✓	×	×
[11]	✓	✓	×	<i>Beamsharing</i>
Proposed	✓	✓	✓	<i>Beamsharing & Device Selection</i>

Similarly, [36] incorporated battery-recharging time into route selection to reduce end-to-end recharging delay. For WET-aided federated learning, [37] jointly optimized charging duration, computing resources, and the number of local iterations, demonstrating the coupling between energy delivery and learning performance. Finally, [38] investigated energy-efficient routing and load balancing in wireless sensor networks, highlighting the importance of network-level coordination for extending operational lifetime.

Finally, hybrid and alternative deployment scenarios have been examined. In [39], a hybrid framework combined omnidirectional PBs in dense regions with directional PBs for isolated or sparse devices in batteryless wireless sensor networks applied to IoT-enabled e-commerce. The resulting optimization reduced the required number of PBs and improved deployment efficiency. In [40], PB placement in bistatic backscatter networks was optimized to maximize the guaranteed coverage distance. By accounting for the interaction between the energy-transfer and backscatter links, the authors derived analytical tools and low-complexity algorithms for positioning PBs around a central reader, showing that symmetric multi-PB deployments can substantially improve coverage. Table 1 summarizes the main characteristics of the reviewed works.

Overall, the literature shows that WET performance depends on the interaction among beamforming, PB deployment, receiver nonlinearity, and charging coordination. Nevertheless, these dimensions are commonly optimized separately or under objectives such as coverage, fairness, network lifetime, or received-power maximization. The problem considered here differs from a conventional coverage-oriented placement problem because the performance metric is the time required for all active devices to reach a prescribed energy threshold. Consequently, PB locations affect path loss and the available beamsharing opportunities, whereas the charging order determines how long neighboring devices can accumulate secondary energy before becoming primary targets. We therefore formulate a coupled deployment-and-scheduling design problem, but solve it through a structured sequential low-complexity decomposition that combines a distance-based placement surrogate with S-CSI beamforming and iterative scheduling under a common charging-time objective.

1.2 Contributions

Motivated by the above gaps, this work studies a coupled RF-based WET design in which PB deployment, S-CSI analog beamforming, nonlinear energy harvesting,

and device scheduling jointly determine the total system charging time. The original design is non-convex and combinatorial because PB positions affect both the intended received power and beamsharing opportunities, while the charging sequence changes the residual energy of all devices over time. Instead of claiming a globally optimal joint solution, we develop a structured sequential heuristic tailored to quasi-static indoor deployments, where PB placement is an offline design decision and charging assignments are updated online as devices reach their energy targets.

The proposed framework comprises three main stages: i) K-means clustering of the IoT-device coordinates, ii) PB placement at the resulting cluster centroids, and iii) iterative device assignment through the Intelligent Power Distribution Model (IPDM). K-means is used as a computationally efficient spatial surrogate. The current IPDM instantiation prioritizes PB-device assignments according to distance. Primary and secondary harvested-power components are then evaluated explicitly in each charging round, so beamsharing affects the energy accumulated by non-targeted devices and consequently the composition of subsequent rounds. The beamforming vectors are obtained only from S-CSI, avoiding instantaneous small-scale CSI acquisition.

As summarized in Table 1, unlike studies that optimize PB placement without exploiting multi-antenna transmission [16–18, 24–29, 39, 40], the proposed framework employs multi-antenna PBs to increase the spatial degrees of freedom for WET. Moreover, while previous works mainly consider beamforming alone [11, 14, 15, 20–23], PB deployment alone [16–18, 24–29, 39, 40], or partial joint formulations [19, 30–33], this work jointly addresses beamforming, PB deployment, and device prioritization. Its novelty therefore lies not in PB-assisted charging, S-CSI, or beamsharing individually, but in their integration into a practical, structured, and low-complexity framework for multi-PB indoor WET systems.

Therefore, the main contributions of this paper are summarized as follows.

- We formulate a coupled charging-time minimization problem that accounts for PB deployment, IoT-device scheduling, S-CSI-based analog beamforming, nonlinear RF-to-DC conversion, receiver sensitivity, and explicit primary and secondary harvested-power contributions. To avoid the signaling overhead and energy consumption associated with instantaneous CSI acquisition, the proposed framework relies only on long-term statistical channel information.
- We develop a structured low-complexity solution for PB deployment and charging coordination. K-means clustering is employed as a physically motivated placement surrogate, since shorter PB-device distances generally increase the average received power under LoS-aligned analog beamforming.
- We introduce the IPDM, a distance-aware scheduling strategy that determines the PB-device assignments during successive charging rounds. Although the scheduling metric itself is distance-based, both primary and secondary harvested-energy contributions are explicitly incorporated into the energy-state evolution, allowing beamsharing to pre-charge non-targeted devices and influence subsequent charging decisions. We further establish finite termination of the proposed procedure and derive a worst-case computational complexity of $\mathcal{O}(i_{\text{iter}}KN + KN^2)$ for a fixed number of PB antennas.

- Extensive numerical results demonstrate that the proposed S-CSI framework reduces the total charging time by up to 50% compared with the random benchmark and consistently outperforms the considered omnidirectional and wavelet-based schemes. Moreover, for the small-scale cases $N = 3$ and $N = 4$, the proposed solution remains only 9.22% and 7.55% above the corresponding grid-based exhaustive-search benchmark, respectively, demonstrating a favorable trade-off between charging performance and computational complexity.

The remainder of this paper is structured as follows. Section 2 introduces the system model and formally defines the optimization problem. Section 3 presents the proposed solution framework for minimizing the total charging time under S-CSI availability at the PBs. Section 4 provides a comprehensive performance evaluation through simulation results, illustrating the effectiveness of the proposed approach. Finally, Section 5 concludes the paper and outlines promising avenues for future research.

Notation: Throughout this paper, scalar variables are denoted by lowercase italic letters (*e.g.*, a), vectors are represented by lowercase boldface letters (*e.g.*, $\mathbf{a}$), and matrices are denoted by uppercase boldface letters (*e.g.*, $\mathbf{A}$). The superscript $(\cdot)^H$ represents the Hermitian (conjugate transpose) operation. The operators $|\cdot|$ and $\|\cdot\|$ denote the absolute value and the Euclidean norm, respectively. The imaginary unit is denoted by the upright symbol $i = \sqrt{-1}$, so as to distinguish it from the italic indices used throughout the paper. Unless otherwise specified, all vectors are assumed to be column vectors.

2 System Model

We consider the indoor WET scenario illustrated in Fig. 1, where a set $\mathcal{K} = \{1, \dots, K\}$ of ceiling-mounted PBs powers a set $\mathcal{N} = \{1, \dots, N\}$ of single-antenna IoT devices. Each PB is equipped with a uniform linear array (ULA) of M antennas and employs phase-only analog beamforming. The PB height is fixed at $z_k = 2.5$ m, whereas the device height is fixed at $z_n = 0.5$ m. The horizontal PB coordinates (x_k, y_k) are design variables during network commissioning, whereas the IoT-device coordinates are assumed quasi-static and available at this stage, for example from installation records or a localization subsystem. Once deployed, the PB positions remain fixed during the charging process. Physical PB relocation in response to device mobility is outside the scope of this work, although the charging schedule can be recomputed whenever the active-device set or the long-term channel conditions change.

The charging process is organized into successive rounds indexed by $c \in \{0, 1, \dots, C-1\}$. At the beginning of each round c , $E_n^{(c)}$ denotes the energy stored by device n , while $\mathcal{N}_c = \{n \in \mathcal{N} : E_n^{(c)} < E_{\min}\}$ represents the set of devices that have not yet reached the required energy level. The charging process continues until the first round C for which $\mathcal{N}_C = \emptyset$, indicating that all devices have satisfied their energy requirements. During each round, the binary variable $\delta_{j,k}^{(c)} \in \{0, 1\}$ indicates whether PB k selects device $j \in \mathcal{N}_c$ as its primary charging target. Since each PB can generate at most one primary energy beam at a time, the assignment variables satisfy $\sum_{j \in \mathcal{N}_c} \delta_{j,k}^{(c)} \leq 1$, $\forall k \in \mathcal{K}$ and $\forall c$. The available PBs remain active whenever $\mathcal{N}_c \neq \emptyset$;

consequently, when the number of remaining devices becomes smaller than the number of PBs, i.e., $|\mathcal{N}_c| < K$, multiple PBs may simultaneously target the same device. This strategy avoids unnecessary PB idling and allows the available transmit power to be exploited during the final charging rounds.

Therefore, let $\mathbf{h}_{n,k} \in \mathbb{C}^{M \times 1}$ denote the normalized small-scale channel vector from PB k to device n . A Rician channel model is adopted as

$$\mathbf{h}_{n,k} = \sqrt{\frac{\kappa}{1+\kappa}} \mathbf{h}_{n,k}^{\text{LoS}} + \sqrt{\frac{1}{1+\kappa}} \mathbf{h}_{n,k}^{\text{NLoS}}, \quad (1)$$

where κ is the Rician factor and the entries of $\mathbf{h}_{n,k}^{\text{NLoS}}$ are independent circularly symmetric complex-Gaussian random variables with zero mean and unit variance. For a half-wavelength-spaced ULA, the deterministic LoS response is expressed as $\mathbf{h}_{n,k}^{\text{LoS}} = e^{i\phi_0} [1, e^{-i\pi \sin \theta_{n,k}}, \dots, e^{-i(M-1)\pi \sin \theta_{n,k}}]^T$, where $\theta_{n,k}$ is the long-term azimuth direction from PB k to device n , and ϕ_0 is a common initial phase.

The corresponding large-scale path-loss coefficient is

$$\beta_{n,k} = \beta_0 \left(\frac{d_{n,k}}{d_0} \right)^{-\alpha}, \quad \beta_0 = \frac{c_0^2}{16\pi^2 f^2 d_0^2}, \quad (2)$$

where c_0 is the speed of light, f is the carrier frequency, $d_{n,k}$ is the distance between PB k and device n , and α is the path-loss exponent. A log-distance model referenced to $d_0 = 1$ m is adopted, so that β_0 is the free-space path gain at d_0 and (2) remains dimensionally consistent for any value of α . Throughout this work, S-CSI refers to long-term channel knowledge comprising the large-scale coefficient $\beta_{n,k}$, the Rician factor κ , and the deterministic LoS/mean array response $\mathbf{h}_{n,k}^{\text{LoS}}$. Thus, the PBs require device geometry or long-term angular information, but they do not require instantaneous realizations of $\mathbf{h}_{n,k}^{\text{NLoS}}$.

Finally, let $\mathbf{w}_{j,k}^{(c)} \in \mathbb{C}^{M \times 1}$ denote the analog beamforming vector at the PB k when targeting device j during round c , with $\|\mathbf{w}_{j,k}^{(c)}\|^2 = P_T$. The K PBs transmit mutually independent unit-power energy waveforms s_k , satisfying $\mathbb{E}[|s_k|^2] = 1$ and $\mathbb{E}[s_k s_l^*] = 0$ for $k \neq l$. Consequently, coherent distributed beamforming among different PBs is not assumed. Phase coherence is required only among the antenna elements of each individual PB, avoiding the tight inter-PB frequency and phase synchronization required by coherent distributed WET. Receiver noise is neglected, as its power is orders of magnitude below the harvested RF power. Therefore, the signal observed by device n during charging round c is

$$y_n^{(c)} = \sum_{k \in \mathcal{K}} \sum_{j \in \mathcal{N}_c} \delta_{j,k}^{(c)} \sqrt{\beta_{n,k}} \mathbf{h}_{n,k}^H \mathbf{w}_{j,k}^{(c)} s_k, \quad (3)$$

where the terms for which $j = n$ represent signals transmitted by PBs that intentionally target device n , whereas the terms with $j \neq n$ represent energy incident on device n from beams intended for other devices, i.e., the beamsharing contribution.

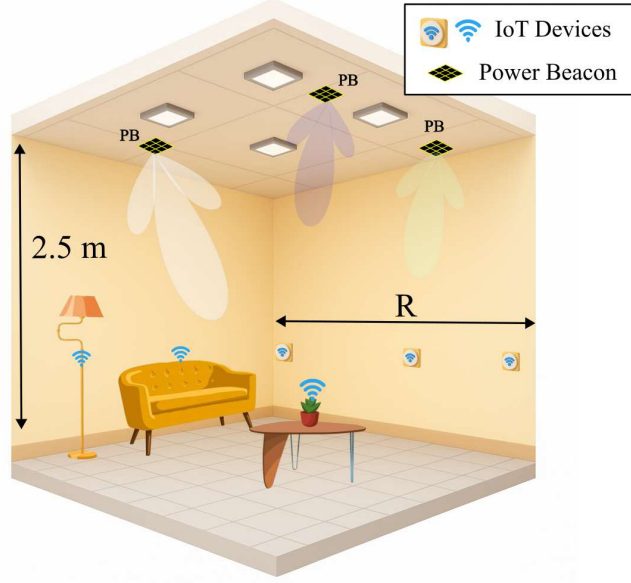


Fig. 1: Evaluated quasi-static indoor system with K ceiling-mounted PBs at $z = 2.5$ m powering N single-antenna IoT devices at $z = 0.5$ m. PB positions are determined during the offline deployment stage, whereas charging assignments are updated over time.

2.1 Energy Harvested by IoT Devices

Considering (3) and the mutual independence of the PB waveforms, the RF power available at device n during charging round c is given by

$$P_n^{(c)} = \mathbb{E} \left[\left| y_n^{(c)} \right|^2 \right] = \underbrace{\sum_{k \in \mathcal{K}} \delta_{n,k}^{(c)} \beta_{n,k} \left| \mathbf{h}_{n,k}^H \mathbf{w}_{n,k}^{(c)} \right|^2}_{P_{\text{PRIM},n}^{(c)}} + \underbrace{\sum_{k \in \mathcal{K}} \sum_{\substack{j \in \mathcal{N}_c \\ j \neq n}} \delta_{j,k}^{(c)} \beta_{n,k} \left| \mathbf{h}_{n,k}^H \mathbf{w}_{j,k}^{(c)} \right|^2}_{P_{\text{SEC},n}^{(c)}}, \quad (4)$$

where $P_{\text{PRIM},n}^{(c)}$ denotes the power received from PBs whose primary target is device n , whereas $P_{\text{SEC},n}^{(c)}$ represents the secondary power harvested from beams directed toward other active devices. The expectation in (4) is taken over the energy waveforms s_k only, so that $P_n^{(c)}$ is conditioned on a given realization of the small-scale channels $\mathbf{h}_{n,k}$. The S-CSI assumption therefore constrains the information available for the beamforming design in (10), not the fading actually experienced by the devices, which is generated explicitly in the simulations. The latter term captures the beamsharing effect. Its magnitude depends on the PB-device distances, the angular separation between the targeted and non-targeted devices, and the radiation pattern of the antenna array.

The nonlinear RF-to-DC conversion model is described using the logistic function $\mathcal{L}_n(P) = \mu/[1 + e^{-a(P-b)}]$, where μ is the saturation DC power, whereas a and b are circuit-dependent fitting parameters [41]. Therefore, defining $\Omega = (1 + e^{ab})^{-1}$, the effective harvested DC power is given by

$$g_n(P) = \frac{\mathcal{L}_n(P) - \mu\Omega}{1 - \Omega} u(P - P_s), \quad (5)$$

where $u(\cdot)$ denotes the Heaviside function and P_s is the receiver sensitivity. Consequently, $g_n(P) = 0$ whenever the received RF power is below the sensitivity threshold.

Moreover, during each charging round c , the received power and the corresponding RF-to-DC conversion rate are assumed to remain constant until the next charging event. This is consistent with the quasi-static indoor scenario considered here, in which the devices and the PBs are fixed and the dominant LoS component, which carries most of the harvested power under the beamforming rule adopted below, is determined by a geometry that does not change during the charging process. The model therefore tracks the energy accumulated over each round through the round-averaged harvesting rate, rather than resolving the fluctuations of the residual NLoS component within the round. Accordingly, for every active device $n \in \mathcal{N}_c$, the stored energy evolves as

$$E_n^{(c+1)} = E_n^{(c)} + \Delta t_c g_n(P_n^{(c)}). \quad (6)$$

Once a device reaches the energy threshold $E_{\min}$, it is removed from the active set and no longer considered in subsequent charging rounds. Therefore, an explicit maximum storage-capacity parameter is not required in the considered charging process.

2.2 Proposed Optimization Problem

The objective of this work is to minimize the total time required for all IoT devices to reach the prescribed energy level $E_{\min}$. For a given PB assignment and beamforming configuration during charging round c , the remaining time required for an active device $n \in \mathcal{N}_c$ to reach $E_{\min}$ is given by

$$t_n^{(c)} = \begin{cases} \frac{E_{\min} - E_n^{(c)}}{g_n(P_n^{(c)})}, & g_n(P_n^{(c)}) > 0, \\ +\infty, & g_n(P_n^{(c)}) = 0. \end{cases} \quad (7)$$

Since $n \in \mathcal{N}_c$ implies $E_n^{(c)} < E_{\min}$, the numerator in (7) is always strictly positive for every active device. Therefore, the duration of charging round c is determined by the first device to reach the required energy level, i.e., $\Delta t_c = \min_{n \in \mathcal{N}_c} t_n^{(c)}$. Consequently, at least one active device reaches $E_{\min}$ at the end of each feasible charging round, after which the active set is updated as $\mathcal{N}_{c+1} = \{n \in \mathcal{N}_c : E_n^{(c+1)} < E_{\min}\}$,

and the process continues until $\mathcal{N}_C = \emptyset$. Accordingly, the total charging time is

$$t_{\text{sum}} = \sum_{c=0}^{C-1} \Delta t_c. \quad (8)$$

It is important to note that neither $t_n^{(c)}$ nor Δt_c is an independent optimization variable. Both quantities are induced by the current energy states, PB-device assignments, beamforming vectors, and corresponding harvested powers. From (4)–(8), it follows that the total charging time depends on three interdependent design components: the PB positions, the per-round PB-device assignments, and the energy beamforming vectors. The PB coordinates determine the large-scale attenuation and the relative angular geometry of the WET links, thereby affecting both the primary and secondary harvested-power components. The assignment matrices determine which devices are selected as primary targets in each round, whereas the beamforming vectors determine the spatial distribution of the transmitted energy. These variables therefore jointly affect the energy-state evolution in (6) and, consequently, the duration of the subsequent charging rounds.

Based on these definitions, the proposed charging-time minimization problem can be expressed as

$$\begin{aligned} & \underset{\{(x_k, y_k)\}, \{\Delta^{(c)}\}, \{\mathbf{w}_{j,k}^{(c)}\}}{\text{minimize}} & t_{\text{sum}} &= \sum_{c=0}^{C-1} \Delta t_c \\ & \text{subject to} & E_n^{(C)} &\geq E_{\min}, \quad \forall n \in \mathcal{N}, \\ & & E_n^{(c+1)} &= E_n^{(c)} + \Delta t_c g_n(P_n^{(c)}), \quad \forall n \in \mathcal{N}_c, \forall c, \\ & & \Delta t_c &= \min_{n \in \mathcal{N}_c} t_n^{(c)}, \quad \forall c, \\ & & |w_{j,k,m}^{(c)}|^2 &= \frac{P_T}{M}, \quad \forall j \in \mathcal{N}_c, \forall k, \forall m, \forall c, \\ & & \delta_{j,k}^{(c)} &\in \{0, 1\}, \quad \forall j \in \mathcal{N}_c, \forall k, \forall c, \\ & & \sum_{j \in \mathcal{N}_c} \delta_{j,k}^{(c)} &\leq 1, \quad \forall k \in \mathcal{K}, \forall c, \\ & & 0 \leq x_k, y_k &\leq R, \quad \forall k \in \mathcal{K}, \end{aligned} \quad (9)$$

where $P_n^{(c)}$ is obtained from (4), while $g_n(\cdot)$ and $t_n^{(c)}$ are defined in (5) and (7), respectively. In addition, the terminal-energy constraint guarantees that all IoT devices reach the required energy level by the end of the charging process, whereas the constant-modulus constraint enforces equal power allocation across the M antenna elements, consistent with the adopted analog beamforming architecture. The binary variable $\delta_{j,k}^{(c)}$ identifies the primary target selected by PB k during round c , and the corresponding assignment constraint limits each PB to at most one primary beam at a time. Devices that are not selected as primary targets may nevertheless harvest secondary energy through the beamsharing term in (4). Finally, the IoT-device coordinates are treated as fixed parameters of the deployment scenario, while the horizontal PB coordinates (x_k, y_k) remain the spatial design variables.

Directly adapting the beamforming vectors in (9) to each instantaneous channel realization would require instantaneous CSI at the PBs, resulting in additional channel-estimation, feedback, and signaling overhead. To avoid this requirement, the proposed framework adopts the S-CSI-based phase-only beamforming strategy [11]. Specifically, when PB k targets device j during round c , its beamforming vector is given by

$$\mathbf{w}_{j,k}^{(c)} = \sqrt{\frac{P_T}{M}} \left[\frac{h_{j,k,1}^{\text{LoS}}}{|h_{j,k,1}^{\text{LoS}}|}, \dots, \frac{h_{j,k,M}^{\text{LoS}}}{|h_{j,k,M}^{\text{LoS}}|} \right]^T. \quad (10)$$

Thus, considering (10) into (9), the practical problem considered in this work reduces to determining the PB locations and the sequence of PB–device assignment matrices, and can be written as

$$\begin{aligned} & \underset{\{(x_k, y_k)\}, \{\mathbf{\Delta}^{(c)}\}}{\text{minimize}} & t_{\text{sum}} &= \sum_{c=0}^{C-1} \Delta t_c \\ & \text{subject to} & E_n^{(C)} &\geq E_{\min}, \quad \forall n \in \mathcal{N}, \\ & & E_n^{(c+1)} &= E_n^{(c)} + \Delta t_c g_n(P_n^{(c)}), \quad \forall n \in \mathcal{N}_c, \forall c, \\ & & \Delta t_c &= \min_{n \in \mathcal{N}_c} t_n^{(c)}, \quad \forall c, \\ & & \delta_{j,k}^{(c)} &\in \{0, 1\}, \quad \forall j \in \mathcal{N}_c, \forall k, \forall c, \\ & & \sum_{j \in \mathcal{N}_c} \delta_{j,k}^{(c)} &\leq 1, \quad \forall k \in \mathcal{K}, \forall c, \\ & & 0 \leq x_k, y_k &\leq R, \quad \forall k \in \mathcal{K}. \end{aligned} \quad (11)$$

Although the beamforming rule is fixed, Problem (11) remains challenging because PB deployment and charging scheduling are coupled through the energy-harvesting dynamics. In particular, the PB locations determine the path loss and angular relationships of the WET links and therefore affect both $P_{\text{PRIM},n}^{(c)}$ and $P_{\text{SEC},n}^{(c)}$. At the same time, the charging sequence determines how long non-targeted devices can accumulate secondary energy before becoming primary targets. As a result, the effectiveness of a given charging sequence depends on the PB deployment, while the performance of a particular PB deployment also depends on the adopted charging order. In addition, the binary assignment variables introduce a combinatorial component, while the nonlinear RF-to-DC conversion model, receiver-sensitivity threshold, and beamsharing-induced coupling prevent the total charging time from being decomposed into independent per-device optimization problems. These characteristics make the direct search for the global optimum of (11) computationally prohibitive as the number of IoT devices increases.

Accordingly, the following section outlines the proposed approach aimed at minimizing the total charging time by establishing a charging order for IoT devices and the optimal placement of PBs. Lastly, it is important to note that a mechanism must be implemented to notify the PBs when an IoT device has been fully charged. The adopted solution to this challenge is for the n -th device to send a message via a control channel upon reaching full charge. This notification is a single low-rate message sent once per device, and its energy cost is not included in the energy dynamics of Section 2.

Since at most N such messages are transmitted over the whole charging process, and each of them is orders of magnitude shorter than the corresponding charging interval, neglecting this cost does not affect the comparison among the evaluated schemes, all of which require the same mechanism.

3 Proposed Approach

To address the coupled design problem in (11), the proposed method adopts a structured low-complexity procedure composed of two operational stages. In the first stage, the quasi-static spatial distribution of the IoT devices is exploited during network commissioning to determine the PB locations. Once the PBs are deployed, their positions remain fixed, and the second stage dynamically updates the PB-device charging assignments as devices progressively reach the required energy level $E_{\min}$. This separation reflects the different time scales associated with infrastructure deployment and charging-schedule adaptation, while avoiding the need for repeated PB relocation during operation. The individual steps that constitute the proposed solution are presented in the following subsections.

3.1 Clustering of IoT Devices and PBs Placement

In the deployment stage, K-means partitions the N device coordinates into K groups, and each PB is placed at the centroid of one group. The procedure is:

1. Initialize K centroids within the deployment region.
2. Assign each device to its nearest centroid using Euclidean distance.
3. Recompute each centroid as the mean position of the devices assigned to the corresponding cluster.
4. Repeat Steps 2–3 until the centroid displacement is below the stopping tolerance.
5. Place PB k at the final centroid of cluster k .

Although K-means does not directly minimize the total charging time t_{sum} , its use for PB placement can be physically justified by the dependence of the received power on the PB-device distance. In particular, under the LoS-aligned beamforming strategy in (10) and assuming independent unit-variance NLoS channel components, the average primary RF power delivered by PB k to its intended device n is given by $\mathbb{E}[P_{\text{PRIM},n,k}] = \beta_{n,k} P_T (\kappa M + 1) / (1 + \kappa)$. Since $\beta_{n,k} \propto d_{n,k}^{-\alpha}$, the average primary received power decreases as the PB-device distance increases. Furthermore, because the PB and device heights are fixed, reducing the horizontal distance between them also reduces the corresponding three-dimensional distance. This provides a direct physical motivation for positioning the PBs close to groups of IoT devices, as naturally promoted by K-means clustering.

The resulting distance reduction is also consistent with the charging-time objective. In particular, a higher received RF power generally leads to a higher harvested DC power $g_n(P)$ when the receiver operates above its sensitivity threshold. According to (7), increasing $g_n(P)$ reduces the residual time required for an active device to reach $E_{\min}$. Therefore, reducing the PB-device distances tends to decrease the charging time, which motivates the use of K-means as a computationally efficient placement

Algorithm 1: Distance-aware IPDM assignment for charging round c .

Input : $\mathcal{K}, \mathcal{N}_c$, distances $d_{n,k}$
Output: $\Delta^{(c)}$

```
1 Initialize  $\Delta^{(c)} \leftarrow \mathbf{0}^{N \times K}$  and  $\mathcal{D}_{\text{PB}} \leftarrow \emptyset$ 
2 for  $k = 1$  to  $K$  do
3    $\mathcal{C}_k \leftarrow \mathcal{N}_c \setminus \mathcal{D}_{\text{PB}}$ 
4   if  $\mathcal{C}_k = \emptyset$  then
5      $\mathcal{C}_k \leftarrow \mathcal{N}_c$ 
6   end
7    $n^* \leftarrow \arg \min_{n \in \mathcal{C}_k} d_{n,k}$ 
8    $\delta_{n^*,k}^{(c)} \leftarrow 1$ 
9    $\mathcal{D}_{\text{PB}} \leftarrow \mathcal{D}_{\text{PB}} \cup \{n^*\}$ 
10 end
11 return  $\Delta^{(c)}$ 
```

surrogate, even though the overall charging process also depends on beamsharing, the nonlinear RF-to-DC conversion characteristic, receiver sensitivity, and the charging sequence.

The proposed placement strategy is particularly suitable for planned or quasi-static indoor IoT deployments, in which device locations are available during network commissioning, and the PBs remain fixed during normal operation. Consequently, continuous device tracking or physical PB relocation is not required.

3.2 Definition of IoT Device Charging Order

After the PB locations are fixed, the scheduler determines the primary target of each PB in every charging round. The proposed IPDM defines the assignment matrix $\Delta^{(c)} = [\delta_{n,k}^{(c)}]$ using a distance-based priority rule. Importantly, the current IPDM instantiation does not rank devices using P_{PRIM} or P_{SEC} . Instead, distance is used to select primary targets, whereas both power components are subsequently included in (4) and therefore affect the energy update (6). As a consequence, beamsharing changes which devices leave the active set $\mathcal{N}_c$ and thereby influences the assignments in later rounds.

For each PB, IPDM preferentially selects the nearest device that has not already been chosen as a primary target by another PB in the same round. If all remaining devices have already been assigned and some PBs are still available, target reuse is allowed. This rule preserves primary-target diversity whenever $|\mathcal{N}_c| \geq K$ while avoiding PB idling when $|\mathcal{N}_c| < K$. Algorithm 1 summarizes the procedure.

It is important to emphasize, however, that the IPDM framework is not inherently restricted to distance-based prioritization and may be extended to incorporate other decision metrics, such as residual energy demand, channel correlation, nonlinear-EH operating conditions, QoS requirements, or explicitly beamsharing-aware utilities. The investigation of such alternative prioritization criteria is left for future work.

3.3 Complete Proposed Approach

The complete framework combines the one-time deployment stage with the iterative charging stage. Let $E_n^{(0)}$ be the initial stored energy (zero in the simulations unless stated otherwise). At each round, IPDM determines the primary assignments, the S-CSI beamformers are constructed, the total received powers are evaluated including beamsharing, and the next event time is obtained from the smallest residual charging time. The energy of every active device is then updated over the same interval Δt_c . Algorithm 2 summarizes this event-driven procedure.

Algorithm 2: Complete low-complexity PB deployment and charging scheduling framework.

Input : $\mathcal{K}, \mathcal{N}$, device coordinates, system parameters
Output: t_{sum}

- 1 Cluster the IoT-device coordinates using K-means and place the K PBs at the resulting centroids
- 2 Initialize $c \leftarrow 0$, $t_{\text{sum}} \leftarrow 0$, and $E_n^{(0)} \leftarrow E_{n,0}, \forall n \in \mathcal{N}$
- 3 Set $\mathcal{N}_0 \leftarrow \{n \in \mathcal{N} : E_n^{(0)} < E_{\min}\}$
- 4 **while** $\mathcal{N}_c \neq \emptyset$ **do**
- 5 Determine $\Delta^{(c)}$ using Algorithm 1
- 6 Construct the active beamforming vectors $\mathbf{w}_{j,k}^{(c)}$ according to (10)
- 7 Compute $P_n^{(c)}$ for every $n \in \mathcal{N}_c$ using (4)
- 8 Compute $g_n(P_n^{(c)})$ and $t_n^{(c)}$ for every $n \in \mathcal{N}_c$ using (5) and (7)
- 9 **if** $t_n^{(c)} = +\infty$ for all $n \in \mathcal{N}_c$ **then**
- 10 Declare the current charging state infeasible and stop
- 11 **end**
- 12 Determine $\Delta t_c \leftarrow \min_{n \in \mathcal{N}_c} t_n^{(c)}$
- 13 Update $t_{\text{sum}} \leftarrow t_{\text{sum}} + \Delta t_c$
- 14 Update $E_n^{(c+1)}$ for every $n \in \mathcal{N}_c$ using (6)
- 15 Update $\mathcal{N}_{c+1} \leftarrow \{n \in \mathcal{N}_c : E_n^{(c+1)} < E_{\min}\}$
- 16 $c \leftarrow c + 1$
- 17 **end**
- 18 **return** t_{sum}

The sequential structure reflects the timescale separation of the considered deployment. PB placement is an offline decision based on quasi-static coordinates and therefore remains unchanged during charging. The scheduling stage, in contrast, is adaptive: after each completion event, the active-device set changes, IPDM is recomputed, and new primary and secondary harvested-power values result. Reapplying K-means after every charging round would reproduce the same PB locations because

the physical device coordinates are unchanged; therefore, an alternating deployment/scheduling loop would add computational cost without changing the installed PB positions in the considered static model.

3.4 Computational Complexity Analysis

The computational complexity of the proposed framework is determined by the PB-placement stage and the iterative charging-scheduling procedure. The K-means algorithm is executed once during network commissioning and has complexity $\mathcal{O}(i_{\text{iter}}KN)$, where i_{iter} denotes the number of iterations required for centroid convergence. Once the PB positions are fixed, the IPDM is executed at each charging round to determine the PB-device assignments. For an active set $\mathcal{N}_c$, Algorithm 1 evaluates at most $|\mathcal{N}_c|$ candidate devices for each of the K PBs, resulting in a complexity of $\mathcal{O}(K|\mathcal{N}_c|)$. For a fixed number of antennas M , the subsequent computation of the beamforming vectors, received powers, residual charging times, and energy-state updates has the same asymptotic order.

The number of charging rounds is also bounded by the number of IoT devices. Specifically, whenever the current charging state is feasible, Δt_c is defined by the smallest finite residual charging time among the active devices. Consequently, at least one device reaches $E_{\min}$ at the end of each round and is removed from $\mathcal{N}_{c+1}$. Since the process starts with at most N active devices, it requires no more than N charging rounds. Therefore, $\sum_{c=0}^{C-1} |\mathcal{N}_c| = \mathcal{O}(N^2)$ in the worst case, yielding an overall computational complexity of $\mathcal{O}(i_{\text{iter}}KN + KN^2)$ for fixed M . In the typical operating regime where $K \ll N$, the iterative charging stage dominates and the proposed framework scales approximately quadratically with the number of IoT devices.

This polynomial complexity contrasts with an exhaustive optimization of the charging order, whose search space grows factorially with N . Even considering only the possible device-charging permutations, an exhaustive search would require evaluating up to $N!$ candidate orders, corresponding to approximately 2.43×10^{18} possibilities for $N = 20$ and more than 10^{157} for $N = 100$. Jointly searching over PB locations and charging assignments would further increase this computational burden. Thus, exhaustive optimization becomes impractical even for moderately sized IoT networks, whereas the proposed sequential framework remains computationally tractable.

Finally, the proposed method is intended as a low-complexity heuristic for the coupled and non-convex design problem in (11), and no constant-factor approximation ratio or global-optimality guarantee is claimed. Instead, its solution quality is evaluated empirically against the grid-based exhaustive-search benchmark in small-scale scenarios where such a comparison remains computationally feasible.

4 Results and Discussions

This section evaluates the proposed S-CSI framework and compares it with the following reference schemes.

- **P-CSI:** the K-means PB placement and IPDM scheduling structure are retained, but instantaneous perfect CSI (P-CSI) is assumed for beamforming and charging-time calculation as in [11]. This scheme is an idealized benchmark for the effect of channel knowledge; because PB placement and scheduling are still restricted to the same structural rules, it is not claimed to be a global lower bound on (9).
- **Random:** PB positions and the device-charging order are randomized, while P-CSI beamforming is retained. This is intentionally a strong random baseline because it separates the benefit of deployment/scheduling structure from the benefit of perfect channel knowledge.
- **Omnidirectional:** the same K-means deployment and IPDM scheduling are used, but each PB has a single antenna and radiates omnidirectionally. This benchmark isolates the gain associated with multi-antenna directional WET.
- **Wavelets:** the Daubechies-wavelet PB-placement method of [18] is adapted to the considered multi-antenna setting and combined with P-CSI beamforming. The best admissible coverage-radius setting of that method is used for comparison.

The proposed scheme relies exclusively on the S-CSI model defined in Section 2. Unless otherwise stated, each reported data point is obtained by averaging over 10^3 independent channel realizations and 10^2 independent spatial configurations of the IoT devices, and the resulting curves therefore represent ensemble-averaged performance. To provide a representative assessment under different spatial deployment conditions, the device locations are generated according to a mixed spatial model in which 50% of the configurations follow a uniform distribution over the considered indoor area, while the remaining 50% are generated according to a hotspot-based distribution. This setup enables the proposed framework and the considered benchmarks to be evaluated under both spatially homogeneous and clustered device deployments while maintaining the same channel and energy-harvesting assumptions across all schemes.

Table 2: Simulation Parameters.

Parameter	Variable	Value
Number of antennas at the PBs	M	4
Number of PBs	K	4
Coverage radius	R	10 m
Number of IoT devices	N	20
Carrier frequency [42]	f	915 MHz
Rician factor	κ	1.0
Transmission power [42]	P_T	3 W
Maximum energy harvested [8]	μ	10.73 mW
Circuit constant [8]	a	0.2308
Circuit constant [8]	b	5.365
Harvesting sensitivity [43]	P_s	-20 dBm
Minimum energy constraint	$E_{\min}$	100 μ J
Path loss exponent	α	2.0

4.1 Grid-Based Exhaustive-Search Analysis

To assess the quality of the low-complexity solution in scenarios where exhaustive evaluation remains feasible, we use a grid-based exhaustive-search benchmark with $K = 2$ PBs, $R = 5$ m, and $N \in \{3, 4\}$. The deployment region is discretized into candidate PB coordinates and, for each candidate deployment, all feasible PB-to-device assignments are evaluated using the same S-CSI beamforming rule, nonlinear RF-to-DC model, sensitivity threshold, and beamsharing equations as the proposed method. The exhaustive-search results are averaged over 10 independent channel realizations because of their combinatorial cost. Throughout this subsection, the gap is defined as $(t_{\text{sum}}^{\text{prop}} - t_{\text{sum}}^{\text{ex}})/t_{\text{sum}}^{\text{prop}}$, that is, the excess charging time of the proposed solution expressed as a fraction of its own charging time. For $N = 3$, the proposed method achieves a total charging time of 16.81 s, whereas the grid-based exhaustive benchmark achieves 15.26 s, corresponding to a 9.22% gap. For $N = 4$, the corresponding values are 23.44 s and 21.67 s, yielding a 7.55% gap. These results show that the proposed heuristic is close to the best solution found on the adopted finite grid in the evaluated small-scale cases.

The scope of this comparison is limited by its cost. Even the PB-placement stage alone requires the evaluation of q^{2K} candidate configurations when q grid points are considered along each spatial coordinate, while the number of feasible charging assignments increases combinatorially with N . As a result, exhaustive evaluation rapidly becomes computationally prohibitive as the network size grows. The small-scale exhaustive-search results are therefore used only to benchmark the proposed solution in scenarios where such evaluation remains tractable, whereas the scalability of the proposed framework for larger deployments is supported by its polynomial computational complexity, as discussed in Section 3.4.

4.2 Clustering Strategy Analysis

To assess the suitability of K-means for the PB-placement stage, its performance is compared with hierarchical clustering and Density-Based Spatial Clustering of Applications with Noise (DBSCAN), representing centroid-based, hierarchical, and density-based clustering approaches, respectively. The purpose of this comparison is to evaluate representative clustering strategies as practical surrogates for PB deployment rather than to perform an exhaustive survey of clustering algorithms, since the primary performance metric is the total charging time rather than clustering quality itself. As shown in Fig. 2, K-means and hierarchical clustering achieve comparable values of t_{sum} and consistently outperform DBSCAN under the considered mixed spatial distribution. Although hierarchical clustering yields marginally lower charging times in a few cases, K-means offers lower computational and memory requirements together with more favorable scalability. In contrast, DBSCAN exhibits greater sensitivity to the choice of the neighborhood-radius and minimum-sample parameters, particularly when uniform and hotspot-based device distributions are jointly considered. Therefore, K-means is adopted as a practical compromise among charging performance, implementation complexity, robustness, and scalability.

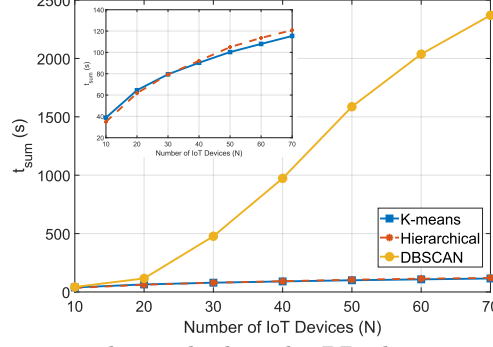


Fig. 2: Total charging time obtained when the PB-placement stage uses representative centroid-based (K-means), hierarchical, and density-based (DBSCAN) clustering strategies.

4.3 PBs Placement and IoT Device Selection

Figure 3 illustrates the two main stages of the proposed framework. First, K-means clustering determines three cluster centroids, at which the PBs are subsequently deployed. The distance-aware IPDM is then applied iteratively to define the PB-device assignments as the IoT devices progressively reach their required energy level $E_{\min}$. When at least K devices remain active, the IPDM preferentially assigns distinct primary targets to the PBs, whereas, for $|\mathcal{N}_c| < K$, target reuse is allowed so that the available PBs can remain active during the final charging rounds. The figure also highlights the contribution of beamsharing, since three out of the twenty devices, namely D_8 , D_{17} , and D_{20} , reach $E_{\min}$ exclusively through secondary harvested energy before requiring a dedicated primary-charging interval, corresponding to $\rho_{\text{SEC-only}} = 3/20 = 15\%$. This result does not imply that secondary power is explicitly used in the IPDM prioritization metric; rather, it illustrates how the secondary-power component in (4) can remove devices from the active set and thereby reduce the duration of subsequent charging rounds.

4.4 IoT Device Selection Analysis

To isolate the impact of the charging-order strategy, we consider an auxiliary configuration denoted as “Proposed with Random Device Selection.” This configuration should not be confused with the Random benchmark introduced earlier, in which both the PB locations and the device-charging order are randomized. Here, the K-means-based PB locations, S-CSI beamforming, nonlinear energy-harvesting model, beamsharing mechanism, and all remaining system assumptions are kept identical to those of the proposed method; the only modification is that the primary charging targets are selected randomly instead of according to the distance-aware IPDM. Hence, this configuration constitutes an ablation of the device-selection strategy and allows the contribution of the proposed charging order to be assessed under otherwise identical operating conditions.

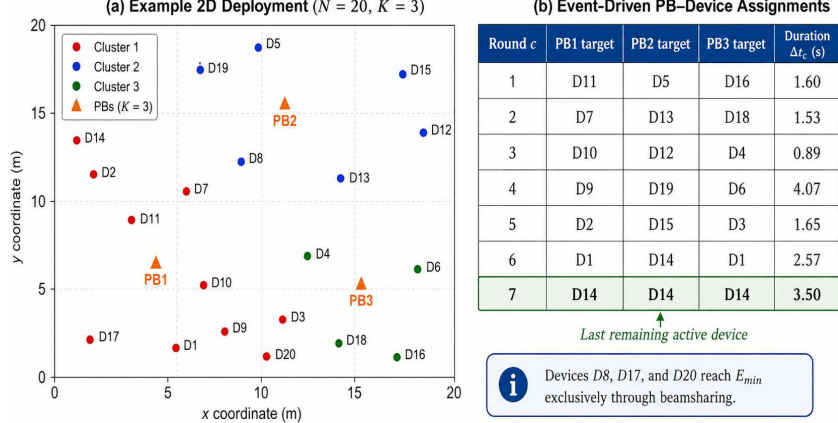


Fig. 3: Illustrative operation of the proposed WET framework for $N = 20$ devices and $K = 3$ PBs: (a) K-means-based PB placement and (b) event-driven PB-device assignments. Devices D_8 , D_{17} , and D_{20} reach $E_{\min}$ exclusively through beamsharing. The statistical evaluation uses the default $K = 4$ configuration.

As shown in Table 3, the proposed IPDM consistently achieves a lower mean total charging time t_{sum} for all evaluated network sizes at $R = 10$ m. Relative to random device selection, the reductions are approximately 41.7%, 30.0%, and 32.0% for $N = 10, 30$, and 50 , respectively. The persistence of this gain as the network size increases indicates that the proposed distance-aware ordering provides a systematic advantage rather than a benefit restricted to a particular device density or realization. In particular, by preferentially assigning PBs to nearby devices, IPDM exploits favorable propagation conditions for the primary links and accelerates the occurrence of charging-completion events, allowing the active set to evolve more efficiently over successive rounds.

Although the IPDM prioritization rule itself depends only on the PB-device distances, its effectiveness is further reinforced by the beamsharing-aware energy dynamics in (4). Devices that are not selected as primary targets may simultaneously accumulate secondary energy from beams directed toward other devices, thereby reducing their residual charging times and, in some cases, reaching $E_{\min}$ without requiring a dedicated primary-charging interval. Consequently, the structured charging order does not merely improve the energy transfer to the currently selected devices; it also shapes the amount of secondary energy accumulated by the remaining devices and therefore influences the composition of the active set $\mathcal{N}_c$ and the assignments in subsequent rounds. These results demonstrate that the proposed IPDM provides a simple yet effective scheduling mechanism that exploits spatial information together with the natural beamsharing dynamics of multi-PB WET systems, yielding substantial charging-time reductions without requiring additional instantaneous channel information or a more complex combinatorial scheduling procedure.

Table 3: Impact of the device-selection strategy on the mean total charging time for $R = 10$ m.

N	t_{sum} (s)	
	Proposed Method	Proposed, but with Random Device Selection
10	38.80	66.59
30	79.46	113.44
50	100.30	146.20

4.5 Number of IoT Devices

Figure 4a evaluates the impact of the number of IoT devices on the total charging time. As expected, t_{sum} increases with N , although the growth is not strictly linear due to the contribution of beamsharing. As the device density increases within the same deployment area, non-targeted devices are more likely to receive energy from the main lobes or sidelobes of beams directed toward other devices, partially compensating for the additional charging demand. The magnitude of this effect depends on both the PB-device distances and their relative angular geometry and is therefore associated with the secondary-energy component in (4), rather than with spatial proximity alone. Across the evaluated values of N , the proposed S-CSI scheme consistently outperforms the Random, Omnidirectional, and Wavelets benchmarks, achieving a reduction of up to approximately 26.5% in t_{sum} relative to Wavelets at $N = 50$. Moreover, its performance remains close to that of the P-CSI despite relying only on statistical channel information. Since the P-CSI benchmark adopts the same PB-placement and scheduling structure, this comparison quantifies the performance loss associated with using S-CSI instead of instantaneous CSI.

4.6 Rician Factor

Figure 4b illustrates the impact of the Rician factor κ on the mean total charging time t_{sum} . The charging time decreases with κ for all evaluated schemes, which follows directly from the beamforming rule in (10). Since the beamformer is aligned with the deterministic LoS response, the average primary RF power delivered to the intended device is $\mathbb{E}[P_{\text{PRIM},n,k}] = \beta_{n,k} P_T (\kappa M + 1) / (1 + \kappa)$, which increases with κ whenever $M > 1$ and approaches the full array gain $\beta_{n,k} P_T M$ as $\kappa \rightarrow \infty$. A stronger LoS component therefore improves the match between the S-CSI beamformer and the realized channel, raising the harvested DC power and shortening the charging time. The nonlinear RF-to-DC characteristic in (5) and the sensitivity threshold P_s affect the magnitude of this gain, since deep fades that push the received power below P_s yield no harvested energy, but they do not change its direction. Across the evaluated range of κ , the proposed method consistently outperforms the Wavelets, Random, and Omnidirectional benchmarks, demonstrating that the proposed deployment and scheduling strategy remains effective under different LoS/NLoS conditions.

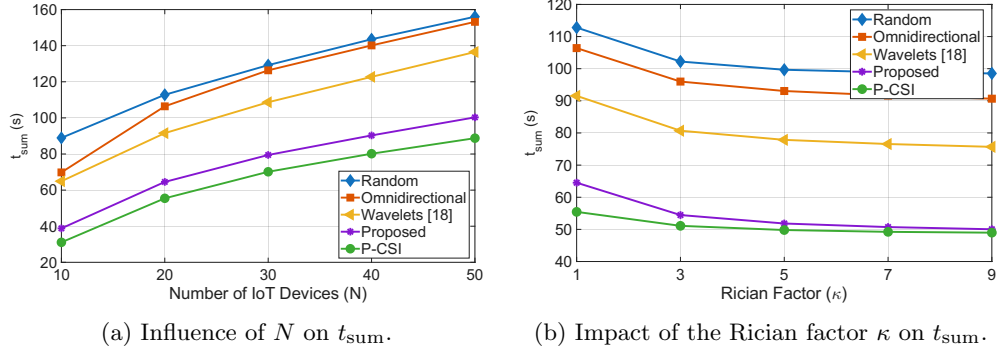


Fig. 4: Performance of the proposed framework under different network and channel conditions: (a) influence of the number of IoT devices and (b) impact of the Rician factor.

4.7 Number of PB Antennas

Figure 5a evaluates the impact of the number of PB antennas M on the mean total charging time t_{sum} . For the half-wavelength ULA and the phase-aligned beamforming strategy in (10), increasing M enhances the coherent beamforming gain toward the intended device while producing a narrower radiation pattern. Consequently, a larger antenna array can reduce the charging time of the primary target, but may also restrict the angular region over which non-targeted devices effectively harvest secondary energy. The overall effect therefore reflects a trade-off between increased primary beamforming gain and reduced beamsharing opportunities for angularly separated devices.

The trend in Fig. 5a reflects this trade-off. The charging time does not decrease monotonically over the whole evaluated range. For small arrays the beam is wide enough for non-targeted devices to harvest a substantial amount of secondary energy, so the initial narrowing of the radiation pattern can offset the additional primary gain. As M grows further, the coherent gain toward the primary target dominates and t_{sum} decreases steadily, with progressively smaller increments due to the reduced contribution of secondary harvesting and the saturation of the nonlinear EH process. Across the evaluated antenna range, the proposed S-CSI scheme consistently outperforms the Random and Wavelets benchmarks, achieving a maximum reduction of approximately 56.7% in t_{sum} relative to the Random scheme. Its performance also remains close to that of the P-CSI benchmark, indicating that the proposed framework can retain much of the benefit of directional beamforming without requiring instantaneous small-scale CSI.

4.8 Number of PBs

Increasing the number of PBs generally reduces the total charging time by allowing more devices to receive strong primary energy simultaneously while also decreasing

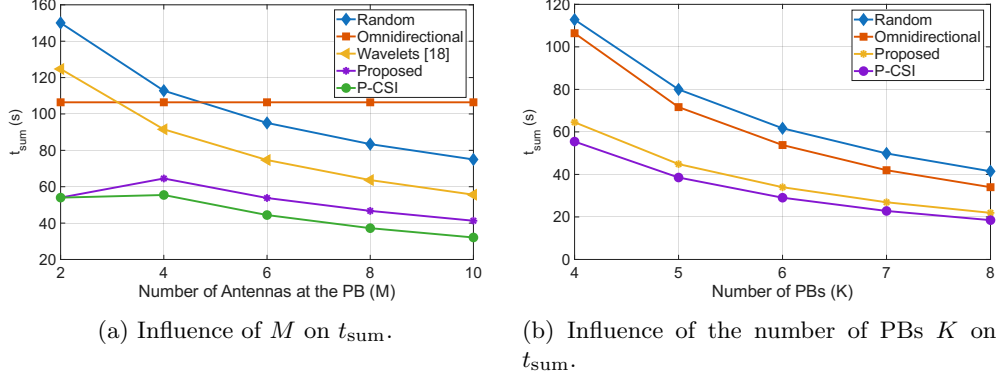


Fig. 5: Impact of the PB configuration on the mean total charging time: (a) influence of the number of antennas and (b) influence of the number of PBs.

the typical distance between an IoT device and its nearest PB. However, these performance gains must be balanced against the additional costs associated with PB installation, power supply, maintenance, and coordination. Figure 5b illustrates this trade-off. Over the evaluated range of PB counts, the proposed method reduces t_{sum} by up to 47.12% relative to the Random benchmark. Moreover, for a given charging-time requirement, the results indicate that the proposed deployment and scheduling strategy can reduce the number of required PBs by up to 37% compared with random deployment. These results demonstrate an empirical cost-performance advantage under the considered system configuration. The Wavelets benchmark is not included in this comparison because it exhibits consistently inferior performance over the evaluated operating range and, due to its specific construction, supports only a restricted set of PB configurations, preventing a consistent comparison across all values of K .

5 Conclusion

This work investigated the minimization of the total charging time in multi-PB indoor WET networks and proposed a structured low-complexity framework that jointly accounts for PB deployment, S-CSI-based analog beamforming, device scheduling, nonlinear RF-to-DC conversion, receiver sensitivity, and beamsharing. The proposed solution combines K-means-based PB placement with distance-aware IPDM scheduling, while explicitly incorporating both primary and secondary harvested-energy contributions into the device energy evolution. This formulation allows secondary energy to influence subsequent scheduling decisions through changes in the active-device set, without requiring instantaneous small-scale CSI. The resulting algorithm has worst-case complexity $\mathcal{O}(i_{\text{iter}}KN + KN^2)$ for fixed M and requires at most N charging rounds under the considered feasibility conditions, providing a scalable alternative to exhaustive joint optimization. Numerical results demonstrate consistent charging-time reductions over the Random, Omnidirectional, and Wavelets benchmarks across different network configurations, with gains of up to 50% relative to

random deployment and scheduling. Moreover, in the small-scale scenarios where grid-based exhaustive evaluation remains computationally feasible, the proposed approach achieves charging-time gaps of only 9.22% and 7.55% for $N = 3$ and $N = 4$, respectively, indicating a favorable trade-off between performance and computational complexity. The results further show that the proposed framework remains effective under variations in network size, Rician fading conditions, and antenna and PB counts. Future work will extend the framework to mobility-aware operation, beamsharing-aware scheduling metrics, adaptive transmit-power control, coherent multi-PB transmission with synchronization constraints, beam-switching overhead, RIS-assisted propagation, and broader heterogeneous channel conditions.

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