

Coordinated Uplink and Downlink Optimization for SWIPT-Enabled Cell-Free IIoT Systems

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Abstract—Cell-free architecture is a promising technology for overcoming the limitations of traditional dense small cells. Concurrently, the rapid development of the Industrial Internet of Things (IIoT) is an irresistible trend. However, a high density of active access points (APs) leads to significant interference and inefficient resource utilization. This paper considers coordinated uplink (UL) and downlink (DL) optimization for cell-free IIoT systems. In addition, the DL devices are capable of simultaneous wireless information and power transfer (SWIPT). Unfortunately, the mathematical model is not convex. To tackle this challenging problem, we use UL-DL duality (UDD) and a convex transformation to convert the non-convex problem into a convex one. The simulation results show energy minimization and sparsity at active APs.

Index Terms—Cell-free (CF), industrial Internet of Things (IIoT), simultaneous wireless information and power transfer (SWIPT), uplink-downlink duality (UDD).

I. INTRODUCTION

Cell-free (CF) MIMO has gained popularity as a transmission paradigm due to its performance at the service cell edge and the elimination of the macrocell [1]–[6]. In [2], the authors investigate an optimal problem subject to outage probability and time-allocation constraints in a CF network. Miretti et al. [3] investigated the distributed CF networks via uplink (UL)-downlink (DL) duality (UDD). In [4], the authors explored the full-duplex CF MIMO communication through the UDD approach. Wang et al. [5] proposed a deep reinforcement learning approach to address the green CF massive MIMO problem. In [6], the authors investigated energy-aware CF MIMO. However, the above literature has not investigated the Industrial Internet of Things (IIoT) communication.

Automation and unmanned operations have become widely recognized trends in both industry and academia [7]–[12]. The 3rd Generation Partnership Project (3GPP) is actively developing communication standards (including channel models) for the IIoT within Industry 5.0. The IIoT also encompasses automated guided vehicles (AGVs), autonomous shuttles, and computer numerical control (CNC). In [9], the authors investigated resource allocation for the CF MIMO UL in the IIoT environment. In [10], the authors explored the CF system in full-duplex IIoT communication. The authors in [11]

studied transmission trade-offs for short-packet communication in IIoT. Zhou et al. [12] considered UAV-assisted IIoT communication. However, the aforementioned studies have not yet investigated the simultaneous wireless information and power transfer (SWIPT) assisted IIoT in CF communication.

To efficiently exploit energy harvesting, beamforming plays a crucial role in modern wireless communication systems [13]–[17]. The authors in [13] analyzed open research questions in beam management beyond 5.5G. Lee et al. [14] used the concave-convex procedure and the Dinkelbach method to address the non-convex problem in an energy-harvesting D2D underlaid MIMO cellular network. In [15], the authors investigated the coexistence of human and machine in a dynamic time-division duplex (TDD) environment. The authors in [15] studied the low-complexity optimal designs, including a comparison between numerical computation (fixed-point method) and convex optimization (semidefinite relaxation (SDR) and second-order cone programming (SOCP)). The literature in [16] and [17] provides comprehensive surveys on energy consumption and beam design, covering convex, nonconvex, and beamforming neural network (BNN) methods. To the best of our knowledge, existing literature has not considered SWIPT-assisted IIoT in CF communication systems. To bridge this gap, this paper investigates the coordinated UL and DL optimization for SWIPT-enabled CF IIoT systems.

II. SYSTEM MODEL

As shown in Fig. 1, the system architecture is inspired by the frameworks proposed in [2], [18]. We assume the channel is TDD, i.e., the UL channel is merely the reverse of the DL channel. Let M and N denote the numbers of antennas and APs, with their corresponding index sets defined as $\mathcal{M} \triangleq \{1, \dots, M\}$ and $\mathcal{N} \triangleq \{1, \dots, N\}$, respectively. Both UL and DL machines are indexed by $i \in \mathcal{K} \triangleq \{1, \dots, K\}$ [18]. We consider the MISO system in which the machine is equipped with a single antenna [2], [18].

Signal model of DL: The received signal at the i th DL machine is then expressed as

$$y_i^D = \mathbf{h}_i^H \mathbf{w}_i s_i^D + \mathbf{h}_i^H \sum_{j \neq i}^K \mathbf{w}_j s_j^D + n_i^D, \quad i = 1, \dots, K, \quad (1)$$

where $\mathbf{h}_i = [(\mathbf{h}_{i,1})^T, \dots, (\mathbf{h}_{i,N})^T]^T \in \mathbb{C}^{MN \times 1}$ is the channel vector for machine i , and $\mathbf{h}_{i,n} \in \mathbb{C}^{M \times 1}$ is the channel at the

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n th AP for the i th machine. $\mathbf{w}_i = [(\mathbf{w}_{i,1})^T, \dots, (\mathbf{w}_{i,N})^T]^T \in \mathbb{C}^{MN \times 1}$ is the aggregate beamforming vector for machine i , and $\mathbf{w}_{i,n} \in \mathbb{C}^{M \times 1}$ is the beamforming vector at the n th AP for the i th machine. n_i^D denotes the additive white Gaussian noise (AWGN) at the i th DL machine ($n_i^D \sim \mathcal{CN}(0, \sigma_i^2)$).

The received signal at the i th DL machine for information decoding (ID) is given by

$$\hat{y}_i^D = \sqrt{\rho_i} y_i^D + \tilde{n}_i^D, \quad i = 1, \dots, K, \quad (2)$$

where $\rho_i \in [0, 1]$ is a power splitting (PS) ratio [14], [15]. $\tilde{n}_i^D$ is the ID processing noise ($\tilde{n}_i^D \sim \mathcal{CN}(0, \tilde{\sigma}_i^2)$). The signal-to-interference-plus-noise ratio (SINR) at the i th DL machine can be expressed as

$$\text{SINR}_i^D = \frac{\rho_i |\mathbf{h}_i^H \mathbf{w}_i|^2}{\rho_i \left(\sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) + \tilde{\sigma}_i^2}, \quad i = 1, \dots, K. \quad (3)$$

The harvested energy at the i th DL machine can be expressed as follows:

$$\tilde{y}_i^{\text{EH}} = (1 - \rho_i) \left(\sum_{j=1}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right), \quad i = 1, \dots, K. \quad (4)$$

Signal model of UL: Following [2] and [18], the received signal at all APs is given by

$$\mathbf{y}^U = \sum_{i=1}^K \mathbf{g}_i \sqrt{p_i^U} s_i^U + \mathbf{n}^U. \quad (5)$$

Upon receiving the UL signal, a receive beamforming vector $\mathbf{v}_i$ is applied to (5). Then, the UL SINR for machine i can be expressed as follows:

$$\text{SINR}_i^U = \frac{|\mathbf{v}_i^H \mathbf{g}_i|^2 p_i^U}{\sum_{j \neq i}^K |\mathbf{v}_i^H \mathbf{g}_j|^2 p_j^U + \sigma_i^2 \|\mathbf{v}_i\|^2}, \quad i = 1, \dots, K. \quad (6)$$

Group-sparse model for AP selection: Following [18], the total energy consumption of the network can generally be expressed as

$$\left(\sum_{n=1}^N \xi_n \sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{v}_{i,n}\|^2) + \sum_{i=1}^K \|\mathbf{w}_i\|^2} \right) + \lambda \sum_{i=1}^K p_i^U, \quad (7)$$

where

$$\xi_n = \frac{P_c}{t_n + \epsilon}, \quad n = 1, \dots, N. \quad (8)$$

ξ_n denotes the weighting factor for the penalty term corresponding to AP n [18]. It follows that

$$\sum_{n=1}^N \xi_n t_n \approx |\mathcal{N}_{\text{on}}| P_c. \quad (9)$$

$|\mathcal{N}_{\text{on}}|$ denotes the cardinality of the active AP set. Since $\xi_n = \frac{P_c}{t_n + \epsilon}$, $\forall n$, we have $\xi_n t_n \approx P_n$ for active APs with $t_n \gg$

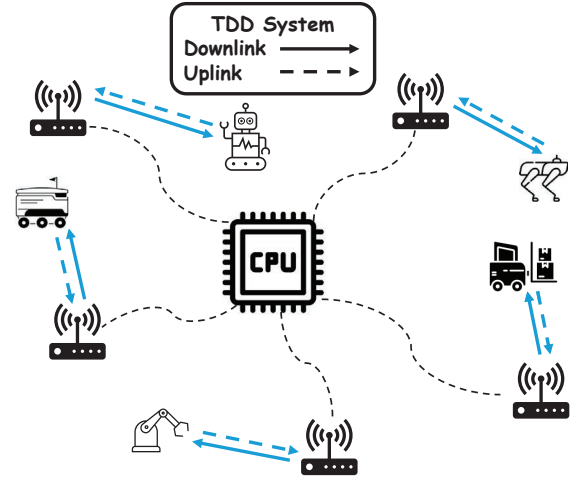


Fig. 1. The system model of Cell-Free (CF) IIoT systems. A CF IIoT system consists of five APs linked to a central processing unit (CPU).

ϵ .¹ Therefore, the weighted term $\sum_n \xi_n t_n$ approximately represents the total static power consumption of active APs. P_c is the static power consumption of each AP. Furthermore, t_n is an auxiliary variable satisfying:

$$\sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{v}_{i,n}\|^2)} \leq t_n, \quad n = 1, \dots, N. \quad (10)$$

λ is a regularization parameter used to balance the energy consumption of active APs and machines.

III. PROBLEM FORMULATION

To minimize the total power consumption of the CF system, we jointly consider the DL SINR, UL SINR, energy harvesting, and group sparsity for AP selection in the following optimization problem.

$$\min \left(\sum_{n=1}^N \xi_n t_n + \sum_{i=1}^K \|\mathbf{w}_i\|^2 \right) + \lambda \sum_{i=1}^K p_i^U \quad (11a)$$

$$\text{s.t.} \quad \frac{\rho_i |\mathbf{h}_i^H \mathbf{w}_i|^2}{\rho_i \left(\sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) + \tilde{\sigma}_i^2} \geq \gamma_i^D, \quad \forall i, \quad (11b)$$

$$\frac{|\mathbf{v}_i^H \mathbf{g}_i|^2 p_i^U}{\sum_{j \neq i}^K |\mathbf{v}_i^H \mathbf{g}_j|^2 p_j^U + \sigma_i^2 \|\mathbf{v}_i\|^2} \geq \gamma_i^U, \quad \forall i, \quad (11c)$$

$$(1 - \rho_i) \left(\sum_{j=1}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) \geq E_i, \quad \forall i, \quad (11d)$$

$$\sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{v}_{i,n}\|^2)} \leq t_n, \quad \forall n, \quad (11e)$$

$$0 \leq \rho_i \leq 1, \quad \forall i. \quad (11f)$$

¹ ϵ is a small positive number to ensure stability during iterations [18].

The decision variables are $\{\mathbf{w}_i\}$, $\{\mathbf{v}_i\}$, non-negative UL powers $\{p_i^U\}$, $\{t_n\}$, and $\{\rho_i\}$. Unfortunately, problem (11) is not a convex problem [15]–[17], [19].

IV. ALGORITHM

In this section, we propose the UDD and the SOCP technique to convert the non-convex problem into a convex one. One of the challenges in problem (11) is to simultaneously satisfy both the UL and DL constraints, which cannot be directly transformed into a convex form. Therefore, we address this issue by using the UDD method to first convert the pure UL problem into a virtual DL problem. Following [18], the UL problem can be expressed as:

$$\min_{\substack{\{\mathbf{v}_i\}, \\ \{p_i^U \geq 0\}}} \sum_{i=1}^K p_i^U \quad (12a)$$

$$\text{s.t.} \quad \frac{|\mathbf{v}_i^H \mathbf{g}_i|^2 p_i^U}{\sum_{j \neq i}^K |\mathbf{v}_i^H \mathbf{g}_j|^2 p_j^U + \sigma_i^2 \|\mathbf{v}_i\|^2} \geq \gamma_i^U, \quad \forall i \in \mathcal{K}. \quad (12b)$$

By leveraging the Lagrangian dual, problem (12) can be transformed from the UL domain into a virtual DL domain. The transformed optimization problem is formalized in the following proposition.

Proposition 1 Suppose that problem (12) is feasible. Then, the equivalent virtual DL problem can be expressed as:

$$\min_{\{\mathbf{u}_i\}} \sum_{i=1}^K \|\mathbf{u}_i\|^2 \quad (13a)$$

$$\text{s.t.} \quad \frac{|\mathbf{g}_i^H \mathbf{u}_i|^2}{\sum_{j \neq i}^K |\mathbf{g}_i^H \mathbf{u}_j|^2 + \sigma_i^2} \geq \gamma_i^U, \quad \forall i \in \mathcal{K}. \quad (13b)$$

Proof: The proof is omitted due to space limitations and can be derived by following similar steps as in [15], [20]. ■

Based on the virtual DL transformation in Proposition 1, problem (11) can be reformulated as

$$\min_{\substack{\{\mathbf{w}_i\}, \{\mathbf{u}_i\} \\ \{\rho_i\}, \{t_n\}}} \left(\sum_{n=1}^N \xi_n t_n + \sum_{i=1}^K \|\mathbf{w}_i\|^2 \right) + \lambda \sum_{i=1}^K \|\mathbf{u}_i\|^2 \quad (14a)$$

$$\text{s.t.} \quad \frac{\rho_i |\mathbf{h}_i^H \mathbf{w}_i|^2}{\rho_i \left(\sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) + \tilde{\sigma}_i^2} \geq \gamma_i^D, \quad \forall i, \quad (14b)$$

$$\frac{|\mathbf{g}_i^H \mathbf{u}_i|^2}{\sum_{j \neq i}^K |\mathbf{g}_i^H \mathbf{u}_j|^2 + \sigma_i^2} \geq \gamma_i^U, \quad \forall i, \quad (14c)$$

$$(1 - \rho_i) \left(\sum_{j=1}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) \geq E_i, \quad \forall i, \quad (14d)$$

$$\sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{u}_{i,n}\|^2)} \leq t_n \quad \forall n, \quad (14e)$$

$$0 \leq \rho_i \leq 1, \quad \forall i. \quad (14f)$$

Problem (14) is still non-convex. Therefore, the constraints need to be transformed into convex forms. Let $\alpha_i^2 = \rho_i$ and $\beta_i^2 = 1 - \rho_i$, where $\alpha_i > 0$ and $\beta_i > 0$. Problem (14) can be equivalently expressed as:

$$\min_{\substack{\{\mathbf{w}_i\}, \{\mathbf{v}_i\} \\ \{\rho_i\}, \{t_n\}}} \left(\sum_{n=1}^N \xi_n t_n + \sum_{i=1}^K \|\mathbf{w}_i\|^2 \right) + \lambda \sum_{i=1}^K \|\mathbf{u}_i\|^2 \quad (15a)$$

$$\text{s.t.} \quad \frac{|\mathbf{h}_i^H \mathbf{w}_i|^2}{\sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 + \frac{\tilde{\sigma}_i^2}{\alpha_i^2}} \geq \gamma_i^D, \quad \forall i, \quad (15b)$$

$$\frac{|\mathbf{g}_i^H \mathbf{u}_i|^2}{\sum_{j \neq i}^K |\mathbf{g}_i^H \mathbf{u}_j|^2 + \sigma_i^2} \geq \gamma_i^U, \quad \forall i, \quad (15c)$$

$$\left(\sum_{j=1}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 \right) \geq \frac{E_i}{\beta_i^2}, \quad \forall i, \quad (15d)$$

$$\sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{u}_{i,n}\|^2)} \leq t_n \quad \forall n, \quad (15e)$$

$$0 \leq \rho_i \leq 1, \quad \forall i, \quad (15f)$$

$$\alpha_i^2 + \beta_i^2 \leq 1, \quad \forall i. \quad (15g)$$

The following addresses the transformation of non-convex constraints to convex ones.

- *Constraint (15b):* By defining $r_i^2 = \frac{\tilde{\sigma}_i^2}{\alpha_i^2}$, constraint (15b) can be rearranged as follows:

$$\frac{|\mathbf{h}_i^H \mathbf{w}_i|^2}{\gamma_i^D} \geq \sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 + r_i^2, \quad \forall i. \quad (16)$$

Following [15], the non-convex constraint (16) can be transformed into an SOCP-compliant form as

$$\left\| \begin{bmatrix} \mathbf{h}_i^H \mathbf{W} \\ \sigma_i \\ r_i \end{bmatrix} \right\| \leq \sqrt{1 + \frac{1}{\gamma_i^D} \mathbf{h}_i^H \mathbf{w}_i}, \quad \forall i \in \mathcal{K}, \quad (17a)$$

$$\sqrt{(r_i - \alpha_i)^2 + 4\tilde{\sigma}_i^2} \leq r_i + \alpha_i, \quad \forall i \in \mathcal{K}, \quad (17b)$$

$$\text{Re}(\mathbf{h}_i^H \mathbf{w}_i) \geq 0, \quad \forall i \in \mathcal{K}, \quad (17c)$$

$$\text{Im}(\mathbf{h}_i^H \mathbf{w}_i) = 0, \quad \forall i \in \mathcal{K}, \quad (17d)$$

where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_K]$. Specifically, we utilize the following algebraic equivalence:

$$ab \geq z^2 \iff \sqrt{(a-b)^2 + 4z^2} \leq a+b \quad (18)$$

where $\forall a, b \geq 0$. Without loss of generality, constraints (17c) and (17d) can be omitted hereafter for brevity.

- *Constraint (15c):* According to the method in [15], constraint (15c) can be transformed from a non-convex form into the following SOCP constraints:

$$\left\| \begin{bmatrix} \mathbf{g}_i^H \mathbf{U} \\ \sigma_i \end{bmatrix} \right\| \leq \sqrt{1 + \frac{1}{\gamma_i^U} \mathbf{g}_i^H \mathbf{u}_i}, \quad \forall i, \quad (19)$$

where $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_K]$.

Algorithm 1 Proposed Algorithm for Joint AP Selection and Beamforming Optimization

- 1: **Initialize:** $l = 0$. Initialize the topologies of all APs and IoT devices, as well as the channel coefficients.
 - 2: **while** convergence criterion is not satisfied **do**
 - 3: Obtain $t_n^{(l)}$ by solving problem (22).
 - 4: $\xi_n^{(l+1)} = \frac{P_n}{t_n^{(l)} + \epsilon}$, $n = 1, \dots, N$.
 - 5: $l \leftarrow l + 1$
 - 6: **end while**
 - 7: Let t^* denote the optimal sparse solution, and let $\mathcal{N}_{\text{on}}$ denote the set of active APs.
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- *Constraint (15d):* By combining (15d) and (16), we obtain the following inequality.

$$(1 + \frac{1}{\gamma_i^D}) |\mathbf{h}_i^H \mathbf{w}_i|^2 \geq \frac{E_i}{\beta_i^2} + r_i^2. \quad (20)$$

Let $q_i^2 = \frac{E_i}{\beta_i^2}$. Based on the algebraic equivalence in (18), we obtain

$$\sqrt{q_i^2 + r_i^2} \leq \sqrt{1 + \frac{1}{\gamma_i^D}} \mathbf{h}_i^H \mathbf{w}_i, \quad (21a)$$

$$\sqrt{(q_i - \beta_i)^2 + 4\sqrt{E_i}} \leq q_i + \beta_i. \quad (21b)$$

Therefore, the convex optimization problem can be expressed as:

$$\min_{\{\mathbf{w}_i\}, \{\mathbf{v}_i\}, \{\rho_i\}, \{t_n\}} \left(\sum_{n=1}^N \xi_n t_n + \sum_{i=1}^K \|\mathbf{w}_i\|^2 \right) + \lambda \sum_{i=1}^K \|\mathbf{u}_i\|^2 \quad (22a)$$

$$\text{s.t.} \quad \sqrt{\sum_{i=1}^K (\|\mathbf{w}_{i,n}\|^2 + \|\mathbf{u}_{i,n}\|^2)} \leq t_n \quad \forall n, \quad (22b)$$

$$\left\| \begin{bmatrix} \mathbf{h}_i^H \mathbf{W} \\ \sigma_i \\ r_i \end{bmatrix} \right\| \leq \sqrt{1 + \frac{1}{\gamma_i^D}} \mathbf{h}_i^H \mathbf{w}_i, \quad \forall i, \quad (22c)$$

$$\sqrt{(r_i - \alpha_i)^2 + 4\tilde{\sigma}_i} \leq r_i + \alpha_i, \quad \forall i, \quad (22d)$$

$$\left\| \begin{bmatrix} \mathbf{g}_i^H \mathbf{U} \\ \sigma_i \end{bmatrix} \right\| \leq \sqrt{1 + \frac{1}{\gamma_i^U}} \mathbf{g}_i^H \mathbf{u}_i, \quad \forall i, \quad (22e)$$

$$\sqrt{q_i^2 + r_i^2} \leq \sqrt{1 + \frac{1}{\gamma_i^D}} \mathbf{h}_i^H \mathbf{w}_i, \quad \forall i, \quad (22f)$$

$$\sqrt{(q_i - \beta_i)^2 + 4\sqrt{E_i}} \leq q_i + \beta_i, \quad \forall i, \quad (22g)$$

$$\sqrt{\alpha_i^2 + \beta_i^2} \leq 1, \quad \forall i. \quad (22h)$$

To solve the optimization problem (22), we iteratively solve problems (22) and (8). The iteration will stop when $|\xi_n^{(l+1)} - \xi_n^{(l)}| < \eta$. l represents the l th iteration and η denotes the convergence threshold. After convergence, the active APs and the corresponding optimal beamforming vectors are obtained. The detailed implementation steps for the proposed joint AP selection and beamforming optimization are summarized

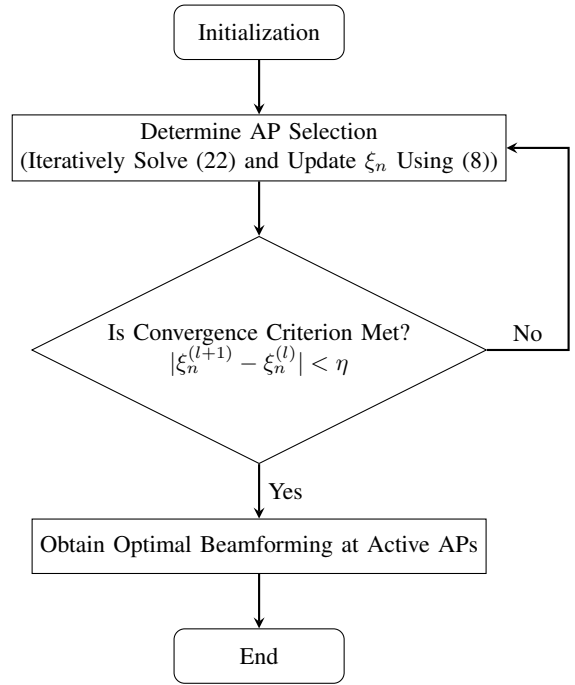


Fig. 2. Flowchart of the proposed iterative AP selection and beamforming optimization algorithm.

in Algorithm 1, while the overall conceptual framework is illustrated in Fig. 2.

V. PERFORMANCE EVALUATION

In this section, we present simulation results to validate the mathematical model and algorithm. The channel is modeled using Rayleigh fading. The receiver noise power is set to -50 dBm. The static power consumption of each AP is $P_n = 5$ W. The minimum level of harvested energy is $E_i = -20$ dBm. A small positive number is set to $\epsilon = 10^{-7}$. The convergence tolerance is chosen as $\eta = 0.001$. The simulation setup can be extended to arbitrary settings if the optimization problem is feasible. The numerical simulations are implemented in MATLAB and solved via the CVX toolbox [19], [20].

Fig. 3 shows the performance evaluation. (a) Topology of APs and IoT devices. (b) Trade-off curve. (c) SINR versus total power (dBm). As illustrated in Fig. 3(a), we consider a CF network topology where all APs and IoT devices are randomly distributed within a square area of $1000 \times 1000 \text{m}^2$. Fig. 3(a) also shows the sparse result of the proposed algorithm for joint AP selection. Fig. 3(b) illustrates the simulation results of (22a), and λ can be an arbitrary value. We can see that as λ increases from left to right, the total power consumption of IoT devices decreases. Therefore, the simulation results demonstrate the power-consumption trade-off between APs and IoT devices. Moreover, the proposed algorithm exhibits stable trade-off behavior across representative channel/topology realizations when the optimization problem is feasible. Fig. 3(c) shows the total transmit power versus the SINR target. The observed trend can be explained by the

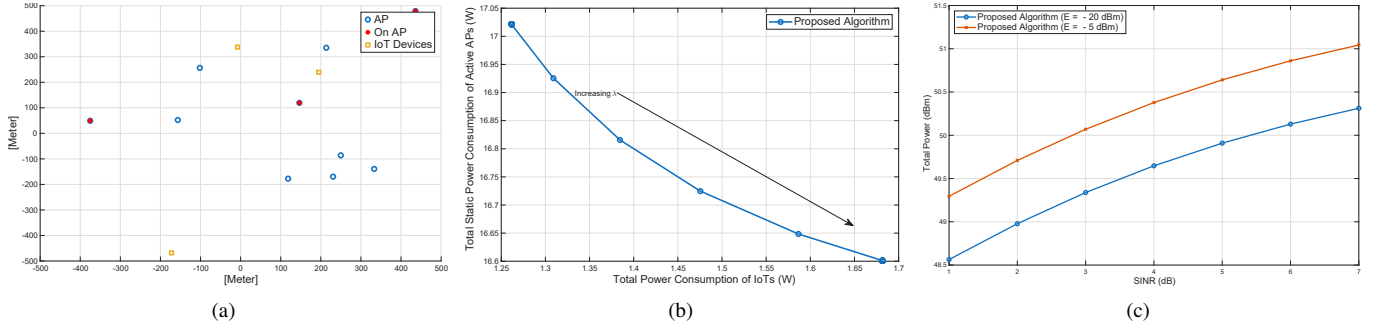


Fig. 3. Performance evaluation. (a) Topology of APs and IoT devices. (b) Active APs versus total IoT transmit power. (c) SINR versus total power (dBm).

DL SINR and energy harvesting constraints. Specifically, from (11b) and (11d), the PS ratio satisfies

$$\underbrace{\frac{\gamma_i^D \bar{\sigma}_i^2}{S_i - \gamma_i^D I_i}}_{\text{Lower bound}} \leq \rho_i \leq \underbrace{1 - \frac{E_i}{Q_i}}_{\text{Upper bound}} \quad (23)$$

where $S_i \triangleq |\mathbf{h}_i^H \mathbf{w}_i|^2$, $I_i \triangleq \sum_{j \neq i}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2$, and $Q_i \triangleq \sum_{j=1}^K |\mathbf{h}_i^H \mathbf{w}_j|^2 + \sigma_i^2 = S_i + I_i$. As the DL SINR target γ_i^D increases, the lower bound of ρ_i becomes larger. This can be observed from (11b), which can be rewritten as

$$\frac{S_i}{I_i + \bar{\sigma}_i^2 / \rho_i} \geq \gamma_i^D. \quad (24)$$

Conversely, increasing the harvesting-energy requirement decreases the upper bound of ρ_i . Consequently, the feasible interval of ρ_i shrinks, requiring higher transmit power to satisfy both constraints simultaneously. This observation is consistent with the simulation results shown in Fig. 3(c).

VI. CONCLUSION

In this paper, we consider coordinated UL and DL optimization for SWIPT-enabled CF IIoT systems. We formulate the optimization problem, which is nonconvex. Fortunately, the UDD method and algebraic properties can help transform the challenging problem into a convex one. Then, we propose a joint optimization algorithm for AP selection and beamforming. In the simulations, we examine the AP sparsity and the SWIPT capability. We also compare AP on/off states, the trade-off curve, and SINR versus total power (dBm). This algorithm can help the future IIoT achieve lower power consumption.

REFERENCES

- [1] S. Jeong, J. Kang, O. Simeone, and S. Shamai, "Cell-free MIMO perceptive mobile networks: Cloud vs. edge processing," *IEEE Trans. Veh. Technol.*, vol. 74, no. 6, pp. 9520–9532, Jun. 2025.
- [2] G. Zhang, Y. Lu, M. Li, Z. Zhong, and T. Q. S. Quek, "Joint uplink and downlink robust transmission for cell-free networks," *IEEE Wireless Commun.*, vol. 23, no. 10, pp. 15 308–15 321, Oct. 2024.
- [3] L. Miretti, R. L. G. Cavalcante, E. Björnson, and S. Stańczak, "UL-DL duality for cell-free massive MIMO with per-AP power and information constraints," *IEEE Trans. Signal Processing*, vol. 72, pp. 1750–1765, 2024.
- [4] Z. Shu *et al.*, "Decoupled uplink-downlink multi-connectivity scheduling in full-duplex cell-free massive MIMO networks: A HGN-DRL approach," *IEEE Trans. Netw.*, vol. 33, no. 5, pp. 2367–2382, Oct. 2025.
- [5] G. Wang, P. Cheng, Z. Chen, B. Vucetic, and Y. Li, "Green cell-free massive MIMO: An optimization embedded deep reinforcement learning approach," *IEEE Trans. Signal Process.*, vol. 72, pp. 2751–2766, 2024.
- [6] Ö. T. Demir, M. Masoudi, E. Björnson, and C. Cavdar, "Cell-free massive MIMO in O-RAN: Energy-aware joint orchestration of cloud, fronthaul, and radio resources," *IEEE J. Sel. Areas Commun.*, vol. 42, no. 2, pp. 356–372, Feb. 2024.
- [7] T. Jiang *et al.*, "3GPP standardized 5G channel model for IIoT scenarios: A survey," *IEEE Internet Things J.*, vol. 8, no. 11, pp. 8799–8815, Jun. 2021.
- [8] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "A tutorial on beam management for 3GPP NR at mmWave frequencies," *IEEE Commun. Surveys and Tuts.*, vol. 21, no. 1, pp. 173–196, 1st Quart. 2019.
- [9] Q. Peng, H. Ren, C. Pan, N. Liu, and M. El-kashlan, "Resource allocation for uplink cell-free massive MIMO enabled URLLC in a smart factory," *IEEE Trans. Commun.*, vol. 71, no. 1, pp. 553–568, Jan. 2023.
- [10] B. Liu, P. Zhu, J. Wang, and X. You, "Cell-free network-assisted full-duplex enabled short-packet communications toward energy efficiency in IIoT networks," *IEEE Wireless Commun.*, vol. 24, no. 12, pp. 10 244–10 260, Dec. 2025.
- [11] P. He, X. Zhao, Y. Cui, D. Wu, R. Wang, and H. Gu, "Retransmission-throughput rate tradeoff for short-packet communications in industrial IoT," *IEEE Trans. Ind. Informat.*, vol. 21, no. 12, pp. 9957–9967, Dec. 2025.
- [12] L. Zhou, S. Leng, and T. Q. S. Quek, "VerDT: A versatile digital twins framework for UAVs-based industrial cyber-physical systems," *IEEE Trans. Mob. Comput.*, vol. 24, no. 10, pp. 10 099–10 117, Oct. 2025.
- [13] Y. Heng, J. G. Andrews, J. Mo, V. Va, A. Ali, B. L. Ng, and J. C. Zhang, "Six key challenges for beam management in 5.5G and 6G systems," *IEEE Commun. Mag.*, vol. 59, no. 7, pp. 74–79, Jul. 2021.
- [14] C.-H. Lee, R. Y. Chang, C.-T. Lin, and S.-M. Cheng, "Energy-efficient D2D underlaid MIMO cellular networks with energy harvesting," in *Proc. IEEE GLOBECOM*, Dec. 2018.
- [15] C.-H. Lee, R. Y. Chang, S.-M. Cheng, C.-H. Lin, and C.-H. Hsiao, "Joint beamforming and power allocation for M2M/H2H co-existence in green dynamic TDD networks: Low-complexity optimal designs," *IEEE Internet Things J.*, vol. 9, no. 6, pp. 4799–4815, Mar. 2022.
- [16] A. M. Elbir, K. V. Mishra, S. A. Vorobyov, and R. W. Heath, "Twenty-five years of advances in beamforming: From convex and nonconvex optimization to learning techniques," *IEEE Signal Process. Mag.*, vol. 40, no. 4, pp. 118–131, Jun. 2023.
- [17] Y.-F. Liu *et al.*, "A survey of recent advances in optimization methods for wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 42, no. 11, pp. 2992–3031, Nov. 2024.
- [18] S. Luo, R. Zhang, and T. J. Lim, "Downlink and uplink energy minimization through user association and beamforming in C-RAN," *IEEE Trans. Wireless Communications*, vol. 14, no. 1, pp. 494–508, Jan. 2015.
- [19] C.-H. Lee, D.-N. Yang, G.-S. Lee, C.-H. Wang, and W. Liao, "Joint view selection, multigroup multicast beamforming, and DIBR for RIS-aided multi-view videos," *IEEE Trans. Mob. Comput.*, vol. 24, no. 7, pp. 6376–6393, Jul. 2025.
- [20] A. B. Gershman, N. D. Sidiropoulos, S. Shahbazpanahi, M. Bengtsson, and B. Ottersten, "Convex optimization based beamforming," *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 62–75, May 2010.