Joint Time Allocation and Beamforming Design for IRS-Aided Coexistent Cellular and Sensor Networks

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***Abstract*—Internet of things (IoT) technology is an essential enabler to realize ubiquitous connections and pervasive intelligence for the future wireless communication system. The energy self-sustainability based on the wireless power transfer technique and the coexistence with heterogeneous networks will become two predominant attributes of IoT networks. In this paper we consider the system design in a context of coexistence of a wireless powered sensor network and a cellular system, both of which share common spectrum bandwidth and are assisted by intelligent reflecting surface (IRS). Specifically, the wireless sensors exploit the harvested energy from the cellular base station (BS) to transfer information to a data sink. We aim to design a cooperation scheme via jointly optimizing the time allocation of channel use, collaborative beamforming across networks and IRS phase-shifting control to improve the sensing network's throughput while guaranteeing the cellular users' quality of service. This design problem leads to a highly nonconvex and difficult mathematical optimization problem. Via utilizing the penalty-duality-decomposition (PDD) and successive convex approximation (SCA) methods, we have managed to develop an alternative optimization solution. Numerical results verify the effectiveness of our algorithm and demonstrate the benefits that come from the cooperative network design.**

***Index Terms*—Internet of things (IoT), wireless sensor network (WSN), intelligent reflecting surface (IRS), wireless power transfer (WPT), beamforming.**

I. Introduction

Nowadays our wireless communication system is developing rapidly towards the next generation, i.e. 5.5G/6G, which aims at building up a novel network possessing the comprehensive capability of communication, computing and sensing to enable the pervasive intelligence for future society [1]. Towards this end, the Internet of things (IoT) technology, especially the wireless sensor networks (WSN), will become the essential enabler to realize the huge number of person-to-machine (P2M) and machine-to-machine (M2M) type communications that are indispensable to implement smart cities, Industry 4.0 and so on.

A predominant challenge for the IoT application is the power supply of tsunami amount of IoT nodes deployed widely in practice. Fortunately, the maturity of the wireless power transfer (WPT) technology will make the energy self-sustainability an essential feature for the future IoT networks. Wireless sensors can harvest energy from their nearby RF sources, e.g. the cellular access point or TV/FM station to charge the battery [2,3].

Besides, ultra dense networking, which is another inevitable evolving trend of wireless network, will lead to a more crowded sub-6GHz band, where huge number of wireless connections overlap in various dimensions of channels, including time, spectrum, space and so on. Therefore, exploring coexisting and cooperating schemes of heterogeneous networks, e.g. cellular mobile users and IoT devices, in joint beamforming and channel sharing will promote networks' time/space/energy efficiency.

Very recently, intelligent reflecting surface (IRS) as an emerging technology has attracted much attention from both academia and industry [4,5]. IRS is a surface comprising a large number of reflecting elements that are specially designed in size, material and layout topology. IRS can adjust the reflected electromagnetic waves in a configurable manner. Multitude recent research works have demonstrated the IRS' potential in improving system's energy efficiency [6], enlarging the cellular coverage [5], decreasing power consumption [7], boosting wireless power transferring efficiency [8] and so on. IRS is envisioned as a viable technique to enhance the wireless communication network's performance.

In this paper, we consider a wireless powered WSN cooperating with a cellular mobile user system that are assisted by IRS. Here the two heterogeneous networks coexist in the same spectral bandwidth and share the channel use both in time and space (i.e. beamforming). Some relevant scenarios have considered in the recent literature. For instance, [9] considers WSN's joint beamforming, while WPT is not considered. [10] studies the beamforming design with the IRS being absent. The latest work [11] considers IRS-aided wireless powered WSN, yet coexistent networks are not taken into account. To the best of our authors' knowledge, there exists no paper at this point that simultaneously considers the time allocation, joint beamforming across coexisting networks and IRS phase-shifting design. This is indeed one major contribution of this paper.

Though very meaningful, the considered problem contains a group of highly nonconvex constraints, which makes the optimization task very challenging. Via adopting the cutting-the-edge methods like penalty-duality-decomposition (PDD), majorization maximization (MM) and successive convex approximation (SCA), we have successfully developed an iterative algorithm which exhibits fast convergence. Moreover, extensive numerical results demonstrate that the introduction of IRS and the joint beamforming across both the WSN and the cellular network can bring significant performance gain.

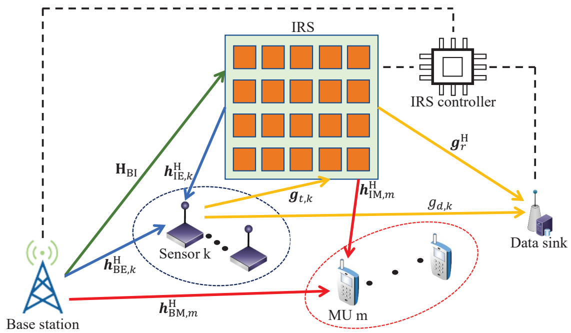

Fig. 1. System model.

II. System Model and Problem Formulation

This paper considers a wireless communication system comprising a base station (BS), multiple mobile users, a group of wireless sensors and a data sink as shown in Figure 1. The whole system works in a two-phase protocol, where the total time interval for every two-phase operation is T seconds. In the first phase, i.e., the downlink (DL) period, the M antenna BS transmits information to the K_M single-antenna mobile users and transfers energy to the K_E single-antenna sensors simultaneously. In the second phase, i.e., the uplink (UL) phase, the sensors collaboratively transfer information to the data sink. The two phases are specified in the following in detail.

A. Phase 1: The DL Period

The signal transmitted from the BS is

$$\boldsymbol{x}_{\mathrm{BS}} = \sum_{i=1}^{K_M} \boldsymbol{f}_i s_i, \tag{1}$$

where $s_i \in \mathbb{C}$ and $\boldsymbol{f}_i \in \mathbb{C}^{M\times 1}$ are the information symbol and its associated beamforming vector for the ith mobile user, respectively. Without loss of generality, we assume that $\mathbb{E}\{s_i\} = 0$ and $\mathbb{E}\{|s_i|^2\} = 1$. Besides, it's reasonable to suppose that different users have uncorrelated information, i.e., $\mathbb{E}\{s_i s_j^*\} = 0$.

Define $\boldsymbol{\theta}_{\mathrm{DL}} = [e^{j\theta_1^{\mathrm{DL}}}, \cdots, e^{j\theta_N^{\mathrm{DL}}}]^{\mathrm{T}}$, where θ_n^{DL} is the phase shift of the nth element in the DL period. Denote $\mathbf{H}_{\mathrm{BI}} \in \mathbb{C}^{N\times M}, \boldsymbol{h}_{\mathrm{BM},m}^{\mathrm{H}} \in \mathbb{C}^{1\times M}$ and $\boldsymbol{h}_{\mathrm{IM},m}^{\mathrm{H}} \in \mathbb{C}^{1\times N}$ as the channels from the BS to the IRS, from the BS to the mth mobile user and from the IRS to the mth mobile user, respectively, as shown in Figure 1. The received signal of the mth mobile user reads

$$y_m = (\boldsymbol{h}_{\mathrm{IM},m}^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{DL}} \mathbf{H}_{\mathrm{BI}} + \boldsymbol{h}_{\mathrm{BM},m}^{\mathrm{H}}) \boldsymbol{x}_{\mathrm{BS}} + n_m, \tag{2}$$

where $\boldsymbol{\Theta}_{\mathrm{DL}} = diag(\boldsymbol{\theta}_{\mathrm{DL}})$ and $n_m \sim \mathcal{CN}(0, \sigma_m^2)$ is the additive noise at the mth mobile user. In general, the information transmitted to each mobile user should be higher than a predefined threshold.

We use $\boldsymbol{h}_{\mathrm{BE},k}^{\mathrm{H}} \in \mathbb{C}^{1\times M}$ and $\boldsymbol{h}_{\mathrm{IE},k}^{\mathrm{H}} \in \mathbb{C}^{1\times N}$ to represent the channels from the BS to the kth sensor and from the IRS to the kth sensor, respectively. The received signal of the kth sensor is given as

$$y_k = (\boldsymbol{h}_{\mathrm{IE},k}^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{DL}} \mathbf{H}_{\mathrm{BI}} + \boldsymbol{h}_{\mathrm{BE},k}^{\mathrm{H}}) \boldsymbol{x}_{\mathrm{BS}}. \tag{3}$$

The sensor's received signal is fed into a rectifier circuit to charge its battery. The kth sensor's harvested energy from the BS is

$$E_k = \varepsilon_k \tau_0 \sum_{i=1}^{K_M} \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \boldsymbol{f}_i^{\mathrm{H}} \boldsymbol{h}_{\mathrm{E},k}, \tag{4}$$

where $\boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \triangleq \boldsymbol{h}_{\mathrm{IE},k}^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{DL}} \mathbf{H}_{\mathrm{BI}} + \boldsymbol{h}_{\mathrm{BE},k}^{\mathrm{H}}$, $0 < \varepsilon_k < 1$, $0 < \tau_0 < T$ are the energy harvesting efficiency at the kth sensor and time allocation for DL, respectively. Without loss of generality, it's assumed that $T = 1$s in this paper.

After the BS completes its transmission, the sensors exploit their harvested energy to simultaneously transmit information to the sink in the rest time slot $1 - \tau_0$.

B. Phase 2: The UL Period

All the sensors observe one common physical event and transfer its information to the data sink via collaboratively beamforming. Denote $z_k \in \mathbb{C}$ as the complex baseband signal transmitted by the kth sensor, which is given by

$$z_k = w_k(x + n_k), \tag{5}$$

where $x \in \mathbb{C}$ denotes the common source signal with $\mathbb{E}\{x\} = 0$ and $\mathbb{E}\{|x|^2\} = 1$, $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the local observation noise at the kth sensor and $w_k \in \mathbb{C}$ is the power coefficient of the kth sensor.

Denote P_k as the average transmit power of the kth sensor, which is given by

$$P_k = \frac{\eta_k E_k}{1 - \tau_0}, \tag{6}$$

where η_k denotes the fixed portion of the harvested energy which is used for its information transmission in the UL phase.

Denote $\boldsymbol{g}_{t,k} \in \mathbb{C}^{N\times 1}, g_{d,k} \in \mathbb{C}$ and $\boldsymbol{g}_r^{\mathrm{H}} \in \mathbb{C}^{1\times N}$ as the channels from the kth sensor to the IRS, from the kth sensor to the data sink and from the IRS to the data sink, respectively. Define $\boldsymbol{\theta}_{\mathrm{UL}} = [e^{j\theta_1^{\mathrm{UL}}}, \cdots, e^{j\theta_N^{\mathrm{UL}}}]^{\mathrm{T}}$ as the phase shift vector in the UL period. The received signal of the data sink is given by

$$y_{\mathrm{IR}} = \sum_{k=1}^{K_E} (\boldsymbol{g}_r^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{UL}} \boldsymbol{g}_{t,k} + g_{d,k}) z_k + n_{\mathrm{IR}}, \tag{7}$$

where $\boldsymbol{\Theta}_{\mathrm{UL}} = diag(\boldsymbol{\theta}_{\mathrm{UL}})$ and $n_{\mathrm{IR}} \sim \mathcal{CN}(0, \sigma_{\mathrm{IR}}^2)$ is the receive noise at the data sink.

The receiving signal-to-noise ratio (SNR) at the data sink is

$$\mathrm{SNR}_{\mathrm{IR}} = \frac{|\sum_{k=1}^{K_E} g_k w_k|^2}{\sum_{k=1}^{K_E} |g_k w_k|^2 \sigma_k^2 + \sigma_{\mathrm{IR}}^2}, \tag{8}$$

where $g_k \triangleq \boldsymbol{g}_r^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{UL}} \boldsymbol{g}_{t,k} + g_{d,k}$. Then the total transferred information obtained by the data sink in the UL phase is given by

$$R = (1 - \tau_0) \log_2 \left(1 + \frac{|\sum_{k=1}^{K_E} g_k w_k|^2}{\sum_{k=1}^{K_E} |g_k w_k|^2 \sigma_k^2 + \sigma_{\mathrm{IR}}^2}\right). \tag{9}$$

Here, we intend to maximize the transferred information from the sensors to the data sink while satisfying the mobile users' DL transmission requirement via jointly designing the BS's beamforming, IRS phase-shift in the DL and UL phases, the sensors' beamforming and the time allocation. The problem is formulated as

$$\text{(P1)} \quad \max_{\substack{\tau_0, \boldsymbol{\theta}_{\mathrm{DL}}, \boldsymbol{\theta}_{\mathrm{UL}}, \\ \mathbf{F}, \boldsymbol{w}}} R \tag{10}$$

$$\text{s.t.} \sum_{i=1}^{K_M} \| \boldsymbol{f}_i \|_2^2 \le P_{\max}, \tag{10a}$$

$$P_k \ge (1 + \sigma_k^2) |w_k|^2, \ \forall k, \tag{10b}$$

$$\tau_0 \log_2(1 + \mathrm{SINR}_m) \ge \gamma_m, \ \forall m, \tag{10c}$$

$$0 \le \tau_0 \le 1, \tag{10d}$$

$$0 \le \theta_n^{\mathrm{DL}} \le 2\pi, 0 \le \theta_n^{\mathrm{UL}} \le 2\pi, \ \forall n, \tag{10e}$$

where $\mathrm{SINR}_m \triangleq \frac{\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_m \boldsymbol{f}_m^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m}}{\sum_{i=1, i\neq m}^{K_M} \boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_i \boldsymbol{f}_i^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m} + \sigma_m^2}$, $\mathbf{F} \triangleq \{\boldsymbol{f}_i\}_{i=1}^{K_M}$, $\boldsymbol{w} \triangleq [w_1, \cdots, w_{K_E}]^{\mathrm{T}}$ and $\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \triangleq \boldsymbol{h}_{\mathrm{IM},m}^{\mathrm{H}} \boldsymbol{\Theta}_{\mathrm{DL}} \mathbf{H}_{\mathrm{BI}} + \boldsymbol{h}_{\mathrm{BM},m}^{\mathrm{H}}$.

(10a) is the power constraint at the BS with $P_{\max}$ denoting the maximum power supply. (10b) reflects the fact that the sensors' transmit energy cannot exceed its harvested energy in the first phase.

III. Proposed Algorithm

The problem (P1) is highly nonconvex and difficult to solve. Inspired by the WMMSE method [12], we first reformulate (P1) into a more tractable form, which is more amiable to BCD type algorithm development. Suppose a feasible solution for (10) can be found, which is set as the starting point of our iterative algorithm.

By introducing auxiliary variables u_{IR} and v_{IR}, the original problem (P1) can be equivalently transformed into

$$(\mathrm{P2}) \quad \min_{\substack{\tau_0, \boldsymbol{\theta}_{\mathrm{DL}}, \boldsymbol{\theta}_{\mathrm{UL}}, \\ \mathbf{F}, \boldsymbol{w}, u_{\mathrm{IR}}, v_{\mathrm{IR}}}} (1-\tau_0)(u_{\mathrm{IR}} e_{\mathrm{IR}} - \log_2 u_{\mathrm{IR}}) \tag{11}$$

$$\text{s.t.} \sum_{i=1}^{K_M} \| \boldsymbol{f}_i \|_2^2 \leq P_{\max}, \tag{11a}$$

$$P_k \geq (1+\sigma_k^2) \mid w_k \mid^2, \ \forall k, \tag{11b}$$

$$\tau_0 \log_2(1+\mathrm{SINR}_m) \geq \gamma_m, \ \forall m, \tag{11c}$$

$$0 \leq \tau_0 \leq 1, \tag{11d}$$

$$0 \leq \theta_n^{\mathrm{DL}} \leq 2\pi, 0 \leq \theta_n^{\mathrm{UL}} \leq 2\pi, \ \forall n, \tag{11e}$$

where the mean square error function e_{IR} is defined as

$$e_{\mathrm{IR}} = \left| 1 - v_{\mathrm{IR}}^* \sum_{k=1}^{K_E} g_k w_k \right|^2 + v_{\mathrm{IR}}^* \left(\sum_{k=1}^{K_E} g_k w_k \sigma_k^2 w_k^* g_k^* + \sigma_{\mathrm{IR}}^2 \right) v_{\mathrm{IR}}. \tag{12}$$

In the following, we proceed to utilize BCD framework to design optimization of each block variable of (P2).

A. Optimize Auxiliary Variable v_{IR} with Others being Fixed

Function (12) is convex with respect to (w.r.t.) v_{IR}. By defining $\tilde{g} = \sum_{k=1}^{K_E} g_k w_k$ and checking the first-order optimality condition w.r.t. v_{IR} in (12), we can get the optimal v_{IR} as

$$v_{\mathrm{IR}}^{\mathrm{opt}} = \left(\tilde{g}\tilde{g}^* + \sum_{k=1}^{K_E} g_k w_k \sigma_k^2 w_k^* g_k^* + \sigma_{\mathrm{IR}}^2 \right)^{-1} \tilde{g}. \tag{13}$$

B. Optimize Auxiliary Variable u_{IR} with Others being Fixed

Due to the convexity of problem (11) w.r.t. u_{IR}, the closed form solution can be again obtained by (14) via checking the first-order optimality condition, which is

$$u_{\mathrm{IR}}^{\mathrm{opt}} = (e_{\mathrm{IR}} \ln 2)^{-1}. \tag{14}$$

C. Optimize Time Allocation τ_0 with Others being Fixed

Fixing other variables, the optimization problem of τ_0 can be given as follows

$$\min \tau_0 \tag{15}$$

$$\text{s.t.} \frac{\eta_k \varepsilon_k \tau_0 \sum_{i=1}^{K_M} \mid \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \mid^2}{1-\tau_0} \geq (1+\sigma_k^2) \mid w_k \mid^2, \ \forall k, \tag{15a}$$

$$\tau_0 \log_2(1+\mathrm{SINR}_m) \geq \gamma_m, \ \forall m, \tag{15b}$$

$$0 \leq \tau_0 \leq 1. \tag{15c}$$

Under the assumption that (15) has a feasible solution, i.e., $\tau_0^{\mathrm{opt}} \leq 1$, the closed form solution of the above linear optimization problem is given as follows

$$\tau_0^{\mathrm{opt}} = \max \left\{ \frac{(1+\sigma_k^2) \mid w_k \mid^2}{\eta_k \varepsilon_k \sum_{i=1}^{K_M} \mid \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \mid^2 + (1+\sigma_k^2) \mid w_k \mid^2}, \frac{\gamma_m}{\log_2(1+\mathrm{SINR}_m)} \right\}, \forall k, \forall m. \tag{16}$$

D. Optimize Sensor Beamforming $\boldsymbol{w}$ with Others being Fixed

Denote $a_{ij} \triangleq g_i^* v_{\mathrm{IR}} u_{\mathrm{IR}} v_{\mathrm{IR}}^* g_j$, $b_i \triangleq u_{\mathrm{IR}} g_i$, $c_i \triangleq \sigma_i^2 g_i^* v_{\mathrm{IR}} u_{\mathrm{IR}} v_{\mathrm{IR}}^* g_i$, $\mathbf{A} \triangleq [a_{ij}]_{i,j=1}^{K_E}$, $\boldsymbol{b} \triangleq [b_1, \cdots, b_{K_E}]^{\mathrm{T}}$, $\mathbf{C} \triangleq diag\{c_1, \cdots, c_{K_E}\}$, $e_i \triangleq 1+\sigma_i^2$, $\tilde{c}_1 \triangleq u_{\mathrm{IR}} + \sigma_{\mathrm{IR}}^2 v_{\mathrm{IR}} u_{\mathrm{IR}} v_{\mathrm{IR}}^*$ and $\mathbf{D}_i = diag\{\mathbf{O}_{i-1}, e_i, \mathbf{O}_{K_E-i+1}\}$. Then the optimization problem w.r.t. $\boldsymbol{w}$ can be written in a compact form as

$$\min_{\boldsymbol{w}} \boldsymbol{w}^{\mathrm{H}}(\mathbf{A}+\mathbf{C})\boldsymbol{w} - 2\mathcal{R}e\{v_{\mathrm{IR}}^* \boldsymbol{b}^{\mathrm{T}} \boldsymbol{w}\} + \tilde{c}_1 \tag{17}$$

$$\text{s.t.} \ \boldsymbol{w}^{\mathrm{H}} \mathbf{D}_k \boldsymbol{w} \leq P_k, \ \forall k. \tag{17a}$$

By writing in an epigraph form and introducing a slack variable s, the problem can be eventually formulated into a standard SOCP problem as

$$\min_{\boldsymbol{w},t,s} t \tag{18}$$

$$\text{s.t.} \ s - 2\mathcal{R}e\{v_{\mathrm{IR}}^* \boldsymbol{b}^{\mathrm{T}} \boldsymbol{w}\} + \tilde{c}_1 \leq t, \tag{18a}$$

$$\sqrt{\| (\mathbf{A}+\mathbf{C})^{\frac{1}{2}} \boldsymbol{w} \|_2^2 + \frac{(s-1)^2}{4}} \leq \frac{s+1}{2}, \tag{18b}$$

$$\sqrt{\| \mathbf{D}_k^{\frac{1}{2}} \boldsymbol{w} \|_2^2 + \frac{(P_k-1)^2}{4}} \leq \frac{P_k+1}{2}, \ \forall k, \tag{18c}$$

which can be efficiently solved by numerical solvers, e.g., CVX.

E. Optimize IRS in the UL Period $\boldsymbol{\theta}_{\mathrm{UL}}$ with Others being Fixed

Denote $\boldsymbol{\phi}_{\mathrm{UL}} \triangleq [\phi_1^{\mathrm{UL}}, \cdots, \phi_N^{\mathrm{UL}}]^{\mathrm{H}}$, where $\phi_n^{\mathrm{UL}} \triangleq e^{j\theta_n^{\mathrm{UL}}}$, $\boldsymbol{p}_k \triangleq diag(\boldsymbol{g}_r^{\mathrm{H}})\boldsymbol{g}_{t,k} w_k$ and $q_k \triangleq g_{d,k} w_k$. After some manipulations, the update of $\boldsymbol{\phi}_{\mathrm{UL}}$ can be compactly written as

$$\min_{\boldsymbol{\phi}_{\mathrm{UL}}} \boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} \mathbf{P} \boldsymbol{\phi}_{\mathrm{UL}} + 2\mathcal{R}e\{\boldsymbol{q}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{UL}}\} + \tilde{c}_2 \tag{19}$$

$$\text{s.t.} \ \mid \phi_n^{\mathrm{UL}} \mid = 1, \ \forall n, \tag{19a}$$

where the parameters in (19) are defined as follows

$$\mathbf{P} \triangleq u_{\mathrm{IR}} v_{\mathrm{IR}}^* \left(\sum_{i=1}^{K_E} \sum_{j=1}^{K_E} \boldsymbol{p}_i \boldsymbol{p}_j^{\mathrm{H}} + \sum_{k=1}^{K_E} \sigma_k^2 \boldsymbol{p}_k \boldsymbol{p}_k^{\mathrm{H}} \right) v_{\mathrm{IR}}, \tag{20}$$

$$\boldsymbol{q}^{\mathrm{H}} \triangleq u_{\mathrm{IR}} v_{\mathrm{IR}}^* \left(\sum_{i=1}^{K_E} \sum_{j=1}^{K_E} q_i \boldsymbol{p}_j^{\mathrm{H}} + \sum_{k=1}^{K_E} \sigma_k^2 q_k \boldsymbol{p}_k^{\mathrm{H}} \right) v_{\mathrm{IR}} - u_{\mathrm{IR}} \sum_{k=1}^{K_E} \boldsymbol{p}_k^{\mathrm{H}} v_{\mathrm{IR}}, \tag{21}$$

$$\tilde{c}_2 \triangleq u_{\mathrm{IR}} \left(\sum_{i=1}^{K_E} \sum_{j=1}^{K_E} v_{\mathrm{IR}}^* q_i q_j^* v_{\mathrm{IR}} + \sum_{k=1}^{K_E} \left(v_{\mathrm{IR}}^* q_k \sigma_k^2 q_k^* v_{\mathrm{IR}} - 2\mathcal{R}e\{v_{\mathrm{IR}}^* q_k\} \right) + v_{\mathrm{IR}}^* \sigma_{\mathrm{IR}}^2 v_{\mathrm{IR}} + 1 \right). \tag{22}$$

The problem (19) is still difficult to solve due to its constant modulus constraints. We employ MM method to tackle the above problem [13]. Assume that $\boldsymbol{\phi}_{\mathrm{UL}}^{(j)}$ is the optimal $\boldsymbol{\phi}_{\mathrm{UL}}$ obtained in the jth iteration. In the $(j+1)$th iteration, the following inequality holds

$$\boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} \mathbf{P} \boldsymbol{\phi}_{\mathrm{UL}} \leq \boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} \mathbf{X} \boldsymbol{\phi}_{\mathrm{UL}} - 2\mathcal{R}e\{\boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} (\mathbf{X}-\mathbf{P}) \boldsymbol{\phi}_{\mathrm{UL}}^{(j)}\} + (\boldsymbol{\phi}_{\mathrm{UL}}^{(j)})^{\mathrm{H}} (\mathbf{X}-\mathbf{P}) \boldsymbol{\phi}_{\mathrm{UL}}^{(j)}, \tag{23}$$

where $\mathbf{X} = \lambda_{\max}\mathbf{I}$ and $\lambda_{\max}$ denotes the maximum eigenvalue of $\mathbf{P}$. Define $f(\boldsymbol{\phi}_{\mathrm{UL}}, \boldsymbol{\phi}_{\mathrm{UL}}^{(j)}) \triangleq \boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} \mathbf{X} \boldsymbol{\phi}_{\mathrm{UL}} - 2\mathcal{R}e\{\boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}} (\mathbf{X}-\mathbf{P})(\boldsymbol{\phi}_{\mathrm{UL}}^{(j)})\} + (\boldsymbol{\phi}_{\mathrm{UL}}^{(j)})^{\mathrm{H}} (\mathbf{X}-\mathbf{P})(\boldsymbol{\phi}_{\mathrm{UL}}^{(j)})$. We replace the original objective function in (19) with the tight upper bound given in the right hand side of (23). The optimization of $\boldsymbol{\phi}_{\mathrm{UL}}$ now becomes

$$\min_{\boldsymbol{\phi}_{\mathrm{UL}}} f(\boldsymbol{\phi}_{\mathrm{UL}}, \boldsymbol{\phi}_{\mathrm{UL}}^{(j)}) + 2\mathcal{R}e\{\boldsymbol{q}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{UL}}\} + \tilde{c}_2 \tag{24}$$

$$\text{s.t.} \ \mid \phi_n^{\mathrm{UL}} \mid = 1, \ \forall n. \tag{24a}$$

By omitting the constants that are independent of $\boldsymbol{\phi}_{\mathrm{UL}}$, the problem can be simplified as follows

$$\max_{\boldsymbol{\phi}_{\mathrm{UL}}} \mathcal{R}e\{\boldsymbol{\phi}_{\mathrm{UL}}^{\mathrm{H}}((\lambda_{\max}\mathbf{I}-\mathbf{P})\boldsymbol{\phi}_{\mathrm{UL}}^{(j)} - \boldsymbol{q})\} \tag{25}$$

$$\text{s.t.} \ \mid \phi_n^{\mathrm{UL}} \mid = 1, \ \forall n. \tag{25a}$$

The above problem has a closed form solution given by

$$\boldsymbol{\phi}_{\mathrm{UL}}^{(j+1)} = e^{j\ arg((\lambda_{\max}\mathbf{I}-\mathbf{P})\boldsymbol{\phi}_{\mathrm{UL}}^{(j)}-\boldsymbol{q})}. \tag{26}$$

F. Optimize BS Beamforming $\mathbf{F}$ *with Others being Fixed*

The optimization of $\mathbf{F}$ with the remaining variables being fixed is given as follows

$$\text{Find } (\mathbf{F}) \tag{27}$$

$$\text{s.t.} \sum_{i=1}^{K_M} \parallel \boldsymbol{f}_i \parallel_2^2 \leq P_{\max}, \tag{27a}$$

$$\frac{\eta_k \varepsilon_k \tau_0 \sum_{i=1}^{K_M} \mid \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \mid^2}{1-\tau_0} \geq (1+\sigma_k^2) \mid w_k \mid^2, \ \forall k, \tag{27b}$$

$$\tau_0 \log_2\left(1+\frac{\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_m \boldsymbol{f}_m^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m}}{\sum_{i=1,i\neq m}^{K_M} \boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_i \boldsymbol{f}_i^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m} + \sigma_m^2}\right) \geq \gamma_m, \forall m. \tag{27c}$$

This problem is actually a feasibility characterization problem. Note that (27c) can be changed into an SOCP form which is presented by (30c) and (30d) [14]. The only difficulty to solve (27) lies in the nonconvex constraint (27b).

By moving the left-hand-side of (27b) to the right-hand-side in (28), the constraint has a form of difference of convex (DC) functions as

$$\frac{(1-\tau_0)(1+\sigma_k^2) \mid w_k \mid^2}{\eta_k \varepsilon_k \tau_0} - \sum_{i=1}^{K_M} \mid \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \mid^2 \leq 0, \ \forall k. \tag{28}$$

To tackle the above problem, we adopt SCA method. Denote $\mathbf{F}^{(j)}$ as the $\mathbf{F}$ obtained in the jth iteration. We utilize the following first-order Taylor expansion

$$\boldsymbol{h}^{\mathrm{H}} \boldsymbol{f} \boldsymbol{f}^{\mathrm{H}} \boldsymbol{h} = \boldsymbol{h}^{\mathrm{H}} \boldsymbol{f}^{(j)} (\boldsymbol{f}^{(j)})^{\mathrm{H}} \boldsymbol{h} + 2\mathcal{R}e\{(\boldsymbol{f}^{(j)})^{\mathrm{H}} \boldsymbol{h} \boldsymbol{h}^{\mathrm{H}} (\boldsymbol{f}-\boldsymbol{f}^{(j)})\} \tag{29}$$

to convexify the constraint (28) and yield a conservative version of the problem (27) given as

$$\min_{\mathbf{F},\tilde{t}} \ \tilde{t} \tag{30}$$

$$\text{s.t.} \sum_{i=1}^{K_M} \parallel \boldsymbol{f}_i \parallel_2^2 - P_{\max} \leq \tilde{t}, \tag{30a}$$

$$\frac{(1-\tau_0)(1+\sigma_k^2) \mid w_k \mid^2}{\eta_k \varepsilon_k \tau_0} - \sum_{i=1}^{K_M} \Big(2\mathcal{R}e\{(\boldsymbol{f}_i^{(j)})^{\mathrm{H}} \boldsymbol{h}_{\mathrm{E},k} \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i\} - \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i^{(j)} (\boldsymbol{f}_i^{(j)})^{\mathrm{H}} \boldsymbol{h}_{\mathrm{E},k} \Big) \leq \tilde{t}, \ \forall k, \tag{30b}$$

$$\sqrt{\sum_{i=1,i\neq m}^{K_M} \boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_i \boldsymbol{f}_i^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m} + \sigma_m^2} - \frac{1}{\sqrt{2^{\frac{\gamma_m}{\tau_0}}-1}} \times \mathcal{R}e\{\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_m\} \leq \tilde{t}, \ \forall m, \tag{30c}$$

$$\mathcal{I}m\{\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_m\} = 0, \ \forall m. \tag{30d}$$

The above problem can be numerically solved by CVX and $\mathbf{F}^{(j+1)}$ can be determined. Due to the feasible initial point assumption, the solution newly obtained must still be feasible.

G. Optimize IRS in the DL Period $\boldsymbol{\theta}_{\mathrm{DL}}$ *with Others being Fixed*

When other variables are given, the update of $\boldsymbol{\theta}_{\mathrm{DL}}$ is equivalent to solving the following problem

$$\text{Find } (\boldsymbol{\theta}_{\mathrm{DL}}) \tag{31}$$

$$\text{s.t.} \ \frac{\eta_k \varepsilon_k \tau_0 \sum_{i=1}^{K_M} \mid \boldsymbol{h}_{\mathrm{E},k}^{\mathrm{H}} \boldsymbol{f}_i \mid^2}{1-\tau_0} \geq (1+\sigma_k^2) \mid w_k \mid^2, \ \forall k, \tag{31a}$$

$$\tau_0 \log_2\left(1+\frac{\boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_m \boldsymbol{f}_m^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m}}{\sum_{i=1,i\neq m}^{K_M} \boldsymbol{h}_{\mathrm{M},m}^{\mathrm{H}} \boldsymbol{f}_i \boldsymbol{f}_i^{\mathrm{H}} \boldsymbol{h}_{\mathrm{M},m} + \sigma_m^2}\right) \geq \gamma_m, \forall m, \tag{31b}$$

$$0 \leq \theta_n^{\mathrm{DL}} \leq 2\pi, \ \forall n, \tag{31c}$$

which is again a feasibility check problem.

Introduce the notations $\boldsymbol{\phi}_{\mathrm{DL}} \triangleq [\phi_1^{\mathrm{DL}}, \cdots, \phi_N^{\mathrm{DL}}]^{\mathrm{H}}$, where $\phi_n^{\mathrm{DL}} \triangleq e^{j\theta_n^{\mathrm{DL}}}$ and $\boldsymbol{p}_{k,i} \triangleq diag(\boldsymbol{h}_{\mathrm{IE},k}^{\mathrm{H}}) \mathbf{H}_{\mathrm{BI}} \boldsymbol{f}_i$, $q_{k,i} \triangleq \boldsymbol{h}_{\mathrm{BE},k}^{\mathrm{H}} \boldsymbol{f}_i$, $\boldsymbol{x}_{m,i} \triangleq diag(\boldsymbol{h}_{\mathrm{IM},m}^{\mathrm{H}}) \mathbf{H}_{\mathrm{BI}} \boldsymbol{f}_i$, $y_{m,i} \triangleq \boldsymbol{h}_{\mathrm{BM},m}^{\mathrm{H}} \boldsymbol{f}_i$. The constraints (31a) and (31b) are nonconvex and again can be expressed as DC forms. We again adopt the SCA method to solve this problem. Denote $\boldsymbol{\phi}_{\mathrm{DL}}^{(j)}$ as the $\boldsymbol{\phi}_{\mathrm{DL}}$ obtained in jth iteration. Then, the $(j+1)$th update of $\boldsymbol{\phi}_{\mathrm{DL}}$ is performed by solving the problem

$$\min_{\boldsymbol{\phi}_{\mathrm{DL}},\beta} \ \beta \tag{32}$$

$$\text{s.t.} \ 2\mathcal{R}e\{\boldsymbol{a}_{1,k}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{1,k} \leq \beta, \ \forall k, \tag{32a}$$

$$\boldsymbol{\phi}_{\mathrm{DL}}^{\mathrm{H}} \boldsymbol{\Xi}_m \boldsymbol{\phi}_{\mathrm{DL}} + 2\mathcal{R}e\{\boldsymbol{a}_{2,m}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{2,m} \leq \beta, \ \forall m, \tag{32b}$$

$$\mid \phi_n^{\mathrm{DL}} \mid = 1, \ \forall n, \tag{32c}$$

where the parameters in (32a) and (32b) are given as follows

$$\boldsymbol{\Xi}_m \triangleq (2^{\frac{\gamma_m}{\tau_0}}-1) \sum_{i=1,i\neq m}^{K_M} \boldsymbol{x}_{m,i} \boldsymbol{x}_{m,i}^{\mathrm{H}}, \tag{33}$$

$$\boldsymbol{a}_{1,k}^{\mathrm{H}} \triangleq -\sum_{i=1}^{K_M} \Big((\boldsymbol{\phi}_{\mathrm{DL}}^{(j)})^{\mathrm{H}} \boldsymbol{p}_{k,i} \boldsymbol{p}_{k,i}^{\mathrm{H}} + q_{k,i} \boldsymbol{p}_{k,i}^{\mathrm{H}} \Big), \tag{34}$$

$$c_{1,k} \triangleq \frac{(1-\tau_0)(1+\sigma_k^2) \mid w_k \mid^2}{\eta_k \varepsilon_k \tau_0} + \sum_{i=1}^{K_M} \Big((\boldsymbol{\phi}_{\mathrm{DL}}^{(j)})^{\mathrm{H}} \boldsymbol{p}_{k,i} \boldsymbol{p}_{k,i}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}^{(j)} - q_{k,i} q_{k,i}^* \Big), \tag{35}$$

$$\boldsymbol{a}_{2,m}^{\mathrm{H}} \triangleq (2^{\frac{\gamma_m}{\tau_0}}-1) \sum_{i=1,i\neq m}^{K_M} y_{m,i} \boldsymbol{x}_{m,i}^{\mathrm{H}} - (\boldsymbol{\phi}_{\mathrm{DL}}^{(j)})^{\mathrm{H}} \boldsymbol{x}_{m,m} \boldsymbol{x}_{m,m}^{\mathrm{H}} - y_{m,m} \boldsymbol{x}_{m,m}^{\mathrm{H}}, \tag{36}$$

$$c_{2,m} \triangleq (2^{\frac{\gamma_m}{\tau_0}}-1) \Big(\sum_{i=1,i\neq m}^{K_M} y_{m,i} y_{m,i}^* + \sigma_m^2 \Big) - y_{m,m} y_{m,m}^* + (\boldsymbol{\phi}_{\mathrm{DL}}^{(j)})^{\mathrm{H}} \boldsymbol{x}_{m,m} \boldsymbol{x}_{m,m}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}^{(j)}. \tag{37}$$

The constant modulus constraint (32c) makes the problem difficult. We adopt the PDD method to attack this problem. To this end, we first introduce an auxiliary variable $\boldsymbol{\psi}_{\mathrm{DL}}$ and rewrite the problem as [7]

$$\min_{\boldsymbol{\phi}_{\mathrm{DL}},\boldsymbol{\psi}_{\mathrm{DL}},\beta} \ \beta \tag{38}$$

$$\text{s.t.} \ 2\mathcal{R}e\{\boldsymbol{a}_{1,k}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{1,k} \leq \beta, \ \forall k, \tag{38a}$$

$$\boldsymbol{\phi}_{\mathrm{DL}}^{\mathrm{H}} \boldsymbol{\Xi}_m \boldsymbol{\phi}_{\mathrm{DL}} + 2\mathcal{R}e\{\boldsymbol{a}_{2,m}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{2,m} \leq \beta, \ \forall m, \tag{38b}$$

$$\boldsymbol{\phi}_{\mathrm{DL}} = \boldsymbol{\psi}_{\mathrm{DL}}, \tag{38c}$$

$$\mid \psi_n^{\mathrm{DL}} \mid = 1, \ \forall n, \tag{38d}$$

$$\mid \phi_n^{\mathrm{DL}} \mid \leq 1, \ \forall n. \tag{38e}$$

Via penalizing the equality constraint (38c), we can obtain the augmented Lagrangian problem of (38) as follows

$$\min_{\boldsymbol{\phi}_{\mathrm{DL}},\boldsymbol{\psi}_{\mathrm{DL}},\boldsymbol{\lambda},\beta} \ \beta + \frac{1}{2\rho} \parallel \boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}} \parallel_2^2 + \mathcal{R}e\{\boldsymbol{\lambda}^{\mathrm{H}} (\boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}})\} \tag{39}$$

$$\text{s.t.} \ 2\mathcal{R}e\{\boldsymbol{a}_{1,k}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{1,k} \leq \beta, \ \forall k, \tag{39a}$$

$$\boldsymbol{\phi}_{\mathrm{DL}}^{\mathrm{H}} \boldsymbol{\Xi}_m \boldsymbol{\phi}_{\mathrm{DL}} + 2\mathcal{R}e\{\boldsymbol{a}_{2,m}^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{DL}}\} + c_{2,m} \leq \beta, \forall m, \tag{39b}$$

$$\mid \psi_n^{\mathrm{DL}} \mid = 1, \ \forall n, \tag{39c}$$

$$\mid \phi_n^{\mathrm{DL}} \mid \leq 1, \ \forall n. \tag{39d}$$

The PDD method is a two-layer iterative procedure [15], with its inner layer alternatively updating $\boldsymbol{\phi}_{\mathrm{DL}}$ and $\boldsymbol{\psi}_{\mathrm{DL}}$ and its outer layer updating the dual variables $\boldsymbol{\lambda}$ or the penalty cofficient ρ.

For the inner layer, we alternatively update $(\boldsymbol{\phi}_{\mathrm{DL}}, \beta)$ and $\boldsymbol{\psi}_{\mathrm{DL}}$.

Algorithm 1: PDD Algorithm to Solve (32)

Initialize $\beta^{(0)}$, $\boldsymbol{\phi}_{\mathrm{DL}}^{(0)}$, $\boldsymbol{\psi}_{\mathrm{DL}}^{(0)}$, $\boldsymbol{\lambda}^{(0)}$, $\rho^{(0)}$ and $k=0$;
repeat
  set $\boldsymbol{\phi}_{\mathrm{DL}}^{(k,0)} := \boldsymbol{\phi}_{\mathrm{DL}}^{(k)}$, $\boldsymbol{\psi}_{\mathrm{DL}}^{(k,0)} := \boldsymbol{\psi}_{\mathrm{DL}}^{(k)}$, $\beta^{(k,0)} := \beta^{(k)}$, $t=0$;
  repeat
    update $\left(\boldsymbol{\phi}_{\mathrm{DL}}^{(k,t+1)}, \beta^{(k,t+1)}\right)$ by solving (40);
    update $\boldsymbol{\psi}_{\mathrm{DL}}^{(k,t+1)}$ by (43); $t++$;
  until *convergence*
  set $\boldsymbol{\phi}_{\mathrm{DL}}^{(k+1)} := \boldsymbol{\phi}_{\mathrm{DL}}^{(k,\infty)}$, $\boldsymbol{\psi}_{\mathrm{DL}}^{(k+1)} := \boldsymbol{\psi}_{\mathrm{DL}}^{(k,\infty)}$, $\beta^{(k+1)} := \beta^{(k,\infty)}$;
  if $\|\boldsymbol{\phi}_{\mathrm{DL}}^{(k+1)} - \boldsymbol{\psi}_{\mathrm{DL}}^{(k+1)}\|_\infty \le \delta$ **then**
    $\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)} + \frac{1}{\rho^{(k)}}\left(\boldsymbol{\phi}_{\mathrm{DL}}^{(k+1)} - \boldsymbol{\psi}_{\mathrm{DL}}^{(k+1)}\right)$, $\rho^{(k+1)} := \rho^{(k)}$;
  else
    $\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)}$, $\rho^{(k+1)} := c \cdot \rho^{(k)}$;
  end if
  $k++$;
until $\|\boldsymbol{\phi}_{\mathrm{DL}}^{(k)} - \boldsymbol{\psi}_{\mathrm{DL}}^{(k)}\|_2$ is sufficiently small

When $\boldsymbol{\psi}_{\mathrm{DL}}$ is fixed, the problem of updating $(\boldsymbol{\phi}_{\mathrm{DL}}, \beta)$ is given by

$$\min_{\boldsymbol{\phi}_{\mathrm{DL}},\beta} \beta + \frac{1}{2\rho} \parallel \boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}} \parallel_2^2 + \mathcal{R}e\{\boldsymbol{\lambda}^{\mathrm{H}}(\boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}})\} \tag{40}$$

$$\text{s.t. } 2\mathcal{R}e\{\boldsymbol{a}_{1,k}^{\mathrm{H}}\boldsymbol{\phi}_{\mathrm{DL}}\} + c_{1,k} \le \beta,\ \forall k, \tag{40a}$$

$$\boldsymbol{\phi}_{\mathrm{DL}}^{\mathrm{H}}\boldsymbol{\Xi}_m\boldsymbol{\phi}_{\mathrm{DL}} + 2\mathcal{R}e\{\boldsymbol{a}_{2,m}^{\mathrm{H}}\boldsymbol{\phi}_{\mathrm{DL}}\} + c_{2,m} \le \beta,\ \forall m, \tag{40b}$$

$$|\ \phi_n^{\mathrm{DL}}\ | \le 1,\ \forall n, \tag{40c}$$

which is a convex problem and can be numerically solved.

When $\boldsymbol{\phi}_{\mathrm{DL}}$ and β is fixed, the optimization with respect to $\boldsymbol{\psi}_{\mathrm{DL}}$ is given as follows

$$\min_{\boldsymbol{\psi}_{\mathrm{DL}}} \frac{1}{2\rho} \parallel \boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}} \parallel_2^2 + \mathcal{R}e\{\boldsymbol{\lambda}^{\mathrm{H}}(\boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}})\} \tag{41}$$

$$\text{s.t. } |\ \psi_n^{\mathrm{DL}}\ | = 1,\ \forall n, \tag{41a}$$

which can be equivalently written as

$$\max_{\boldsymbol{\psi}_{\mathrm{DL}}} \mathcal{R}e\{(\boldsymbol{\phi}_{\mathrm{DL}} + \rho\boldsymbol{\lambda})^{\mathrm{H}}\boldsymbol{\psi}_{\mathrm{DL}}\} \tag{42}$$

$$\text{s.t. } |\ \psi_n^{\mathrm{DL}}\ | = 1,\ \forall n. \tag{42a}$$

The optimal solution of $\boldsymbol{\psi}_{\mathrm{DL}}$ is given in a closed form as

$$\boldsymbol{\psi}_{\mathrm{DL}}^{\mathrm{opt}} = e^{j\ arg(\boldsymbol{\phi}_{\mathrm{DL}} + \rho\boldsymbol{\lambda})}. \tag{43}$$

For the outer layer, if the equality $\boldsymbol{\phi}_{\mathrm{DL}} = \boldsymbol{\psi}_{\mathrm{DL}}$ approximately holds, we update $\boldsymbol{\lambda}$ by $\boldsymbol{\lambda} := \boldsymbol{\lambda} + \rho^{-1}(\boldsymbol{\phi}_{\mathrm{DL}} - \boldsymbol{\psi}_{\mathrm{DL}})$. Otherwise we need to increase the penalty coefficient ρ^{-1}, forcing $\boldsymbol{\phi}_{\mathrm{DL}} = \boldsymbol{\psi}_{\mathrm{DL}}$ to be approached. The PDD algorithm is given in Algorithm 1.

In this way, we can obtain $\boldsymbol{\theta}_{\mathrm{DL}}^{(j+1)}$. Following the feasible initial point assumption again, we conclude that the update of $\boldsymbol{\theta}_{\mathrm{DL}}$ in (31) can guarantee its feasibility.

The overall algorithm to solve (P2) is summarized in Algorithm 2 in detail.

IV. Simulation Results

As shown in Figure 2, we consider a system comprising 4 mobile users and 8 sensors in an indoor environment. An IRS is deployed on the ceiling to aid the communication system. Unless otherwise specified, the remaining parameters are fixed as: $M = 8$, $P_{\max} = 25$dBm, $\sigma_m^2 = \sigma_k^2 = \sigma_{\mathrm{IR}}^2 = -100$dBm, $\forall m, k$, $\gamma_m = 0.2, \forall m$, $\varepsilon_k = 0.99, \forall k$, $\eta_k = 1, \forall k$, $\rho = 0.5$. In the following discussion, we only use the 4 outer sensors expect for the experiment where the impact of different number of sensors are examined.

Algorithm 2: Overall Algorithm to Solve (P2)

Initialize feasible $\tau_0^{(0)}$, $\{\boldsymbol{f}_i^{(0)}\}_{i=1}^{K_M}$, $\boldsymbol{w}^{(0)}$, $\boldsymbol{\theta}_{\mathrm{DL}}^{(0)}$, $\boldsymbol{\theta}_{\mathrm{UL}}^{(0)}$ and $k=1$;
repeat
  update auxiliary variable $v_{\mathrm{IR}}^{(k)}$ by (13);
  update auxiliary variable $u_{\mathrm{IR}}^{(k)}$ by (14);
  update time allocation $\tau_0^{(k)}$ by (16);
  update sensor beamforming $\boldsymbol{w}^{(k)}$ by solving (18);
  update IRS in the UL period $\boldsymbol{\theta}_{\mathrm{UL}}^{(k)}$ by (26);
  update BS beamforming $\{\boldsymbol{f}_i^{(k)}\}_{i=1}^{K_M}$ by solving (30);
  update IRS in the DL period $\boldsymbol{\theta}_{\mathrm{DL}}^{(k)}$ by Algorithm 1;
  $k++$;
until convergence

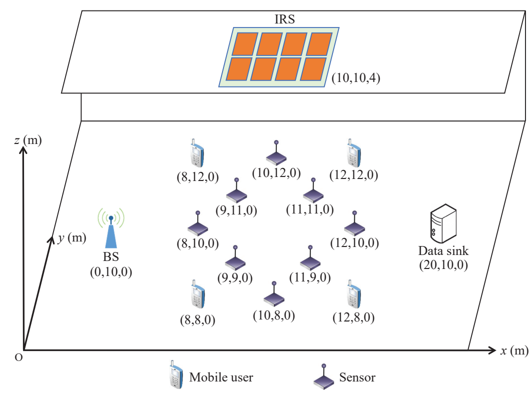

Fig. 2. Simulation setup.

A. Convergence Behaviour and the Impact of IRS

As shown in Figure 3, we illustrate our algorithm's convergence under different IRS settings. For a benchmark, we also present random phase shift scheme and no-IRS scheme. According to the result in Figure 3, it can be observed that the algorithm exhibits fast convergence. Besides, with the aid of IRS, the performance of system outperforms no-IRS scheme. Moreover, more reflecting elements bring more performance gain.

B. The Impact of QoS of Mobile Users

The impact of QoS of mobile users is plotted in Figure 4, where QoS stands for the information transferred from the BS to each mobile user. On the one hand, as the threshold of mobile users rises, the time allocation for DL is longer and the sensors can harvest more energy to transfer information to the data sink. On the other hand, less time is available for the sensors to perform UL transmission. Consequently, a modest QoS threshold will yield a maximal transferred information to the data sink. At the same time, more IRS elements will benefit the information transmission.

C. The Impact of Number of Wireless Sensors

We investigate the impact of the number of sensors on the information obtained by the data sink in Figure 5. As suggested by the results, the transferred information increases as the

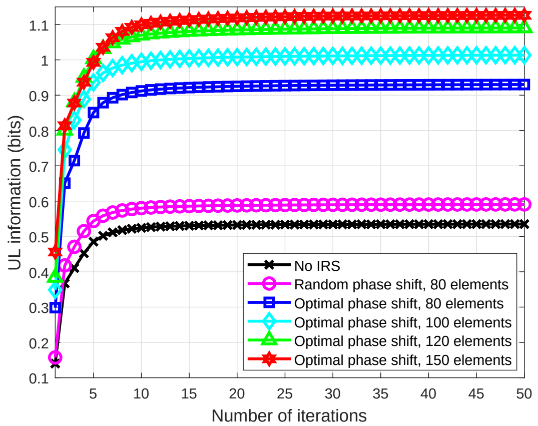

Fig. 3. Convergence behaviour and the impact of IRS.

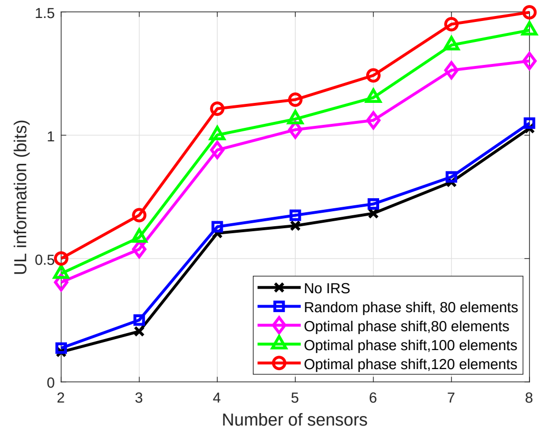

Fig. 5. The impact of number of wireless sensors.

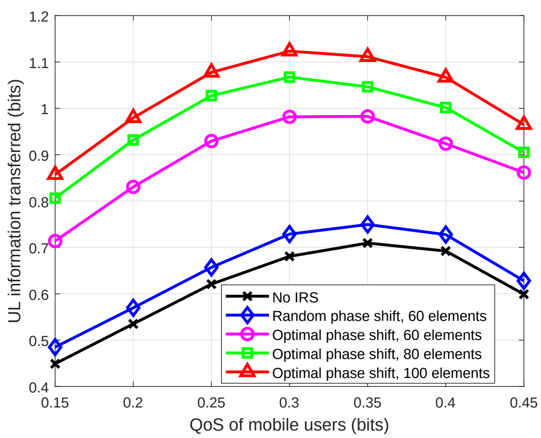

Fig. 4. The impact of QoS constraints.

number of sensors grows. The benefit of large-scale wireless sensor networks are two-fold. Firstly, more sensor nodes will harvest more energy and hence emit signals with larger total transmission power. Note that the curves rise rapidly at some points owing to the topology of the simulation scenario and the choice of the sensors. Secondly, more sensors will provide more antennas, which yields higher collaborative beamforming gain. Besides, we also observe a performance gain that comes along with the deployment of IRS and more reflecting elements.

V. Conclusion

In this paper, we consider the system design for the coexistence of a cellular network and a wireless powered WSN assisted by an IRS. We have developed an algorithm to solve the challenging problem of jointly designing the time allocation, cooperative beamforming across networks and IRS phase-shifting control. Numerical results suggest that the introducing IRS and jointly designing of WSN together with its associated coexistent system can effectively improve the system's performance.

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