Joint Dynamic Passive Beamforming and Resource Allocation for IRS-Aided Full-Duplex WPCN

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Abstract

This paper studies intelligent reflecting surface (IRS)-aided full-duplex (FD) wireless-powered communication network (WPCN), where a hybrid access point (HAP) broadcasts energy signals to multiple devices for their energy harvesting in the downlink (DL) and meanwhile receives information signals in the uplink (UL) with the help of IRS. Particularly, we propose three types of IRS beamforming configurations to strike a balance between the system performance and signaling overhead as well as implementation complexity. We first propose the fully dynamic IRS beamforming, where the IRS phase-shift vectors vary with each time slot for both DL wireless energy transfer (WET) and UL wireless information transmission (WIT). To further reduce signaling overhead and implementation complexity, we then study two special cases, namely, partially dynamic IRS beamforming and static IRS beamforming. For the former case, two different phase-shift vectors can be exploited for the DL WET and the UL WIT, respectively, whereas for the latter case, the same phase-shift vector needs to be applied for both DL and UL transmissions. We aim to maximize the system throughput by jointly optimizing the time allocation, HAP transmit power, and IRS phase shifts for the above three cases. Two efficient algorithms based on alternating optimization and penalty-based algorithms are respectively proposed for both perfect self-interference cancellation (SIC) case and imperfect SIC case by applying successive convex approximation and difference-of-convex optimization techniques. Simulation results demonstrate the benefits of IRS for enhancing the performance of FD-WPCN, especially with fully dynamic IRS beamforming, and also show that the IRS-aided FD-WPCN is able to achieve significantly performance gain compared to its counterpart with half-duplex when the self-interference (SI) is properly suppressed.

Index Terms

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Intelligent reflecting surface, full-duplex, WPCN, dynamic versus static IRS beamforming, resource allocation.

I. INTRODUCTION

The number of Internet-of-Things (IoT) devices such as temperature sensors, humidity sensors, and illuminating light sensors, have rapidly skyrocketed recently due to their tremendous demands required in various application scenarios. Such a massive number of wireless devices thus requires a scalable solution for providing ubiquitous communication connectivity and perpetual energy supply in the future. Although the lifetimes of devices can be extended by replacing and/or recharging the embedded batteries, it is unsafe and inconvenient especially in a toxic environment and rural areas. To achieve self-sustainable communication, a variety of wireless technologies has been proposed in the past such as wireless power transfer and simultaneous information and power transfer (SWIPT) [1], [2]. However, the efficiencies of wireless energy transfer (WET) and wireless information transmission (WIT) are severely affected by the distance based path loss and/or the multi-path fading. Although several technologies have been proposed to overcome this issue, which include massive multiple-input (MIMO), ultra-dense network (UDN), etc., [3], [4], they also face other challenges in practical implementation such as high power circuit consumption and high hardware cost.

To boost the spectral efficiency of wireless systems, full-duplex (FD) transmission is a promising technology to potentially double the spectral efficiency if the self-interference (SI) is perfectly cancelled [5]. Different from the half-duplex (HD) mode that the wireless node operates in a time division manner, i.e., the transmitter either transmits or receives signals at one time, it is able to transmit signal and receive signal over the same frequency simultaneously for the FD mode. However, due to the simultaneous transmission and reception at the same wireless node, its receiver antenna will receive the undesirable signals transmitted by its nearby transmitter antennas, thus interfering with the desired signal received at the same time. In fact, the performance of an FD system may be even worse than that of an HD system if the SI is not well suppressed. Fortunately, several SI cancellation (SIC) techniques have been proposed in the literature [6]–[9], which generally based on the analog-domain SIC and the digital-domain SIC. It was reported in [9] that the art-of-the-state of SI suppression can be up to $-110$ dB by combing the analog domain (i.e., SIC before analog-to-digital conversion (ADC) by using analog signal processing techniques) with digital domain (SIC after ADC by using digital signal
processing techniques). Various works have investigated the applications of FD in the different setups, such as WET and SWIPT systems [10]–[14]. In particular, the authors in [11] studied FD wireless-powered communication network (WPCN) and aimed at maximizing the weighted sum rate over all users by jointly optimizing the time allocation and transmit power allocation at a hybrid access point (HAP). The results showed that the FD-WPCN outperforms the HD-WPCN if SI can be suppressed below a certain level. Subsequently, [12] derived closed-form solutions in the FD-WPCN with perfect SIC case.

Recently, intelligent reflecting surfaces (IRSs) have been proposed as a promising cost-effective solution to improve both spectral- and energy-efficiency of wireless communication systems [15]–[20]. IRS is composed of 2-D planar arrays of sub-wavelength metallic or dielectric scatterers, each of which is able to independently and smartly induce different reflection amplitudes, phases, and polarization responses on the incident signals and thereby improving quality of services of users by forming the fine-grained directions of beam towards to the desirable users. In addition, IRS also has several other appealing advantages such as low profile, lightweight, and conformal geometry. More importantly, IRS can be composed of large numbers of dielectric scatterers with a very limited size. For example, it was shown in [21] that for a large IRS with $100 \times 102$ reflecting elements, the electrical sizes are about 1 square meter, which is attractive for the practical deployment. As such, the IRS can be installed on the ceilings to enhance personal WiFi network and also can be attached to the facades of buildings to assist the cellular network. Due to the above advantages, IRS has been exploited for different applications by optimizing its reflection coefficients, such as physical layer security [22]–[24], multi-cell cooperation [25]–[27], and unmanned aerial vehicle communication [28], [29]. While the above works focused on leveraging IRS for enhancing information transmission, IRS is also beneficial for WET and SWIPT [30]–[34]. By exploiting its large aperture with grained-fine tunable phase shifts, high passive beamforming gains can be achieved by the IRS to effectively compensate the end-to-end signal attenuation. For example, [33] studied an IRS-assisted SWIPT system, where a set of IRSs are deployed to assist the downlink (DL) WIT and WET from a multi-antenna AP to multiple information and energy users, respectively. The results showed that the transmission range is significantly enlarged with the help of IRSs.

By far, there are only a handful of works paying attention to studying IRS-aided WPCN [35]–[40]. The authors in [35] and [36] studied IRS-aided WPCN, where an orthogonal protocol for DL WET and uplink (UL) WIT was proposed with the goal of maximizing the common and
weighted sum throughput, respectively. The authors in [37] studied an IRS-empowered WPCN, where the IRS is allowed to harvest energy from an HAP, and then considered two schemes, namely, time-switching and power splitting, to support DL WET from the HAP to the distributed users and UL WIT from the users to the HAP. In [40], a new optimization framework on dynamic passive beamforming was firstly proposed to compromise the performance and complexity for implementing IRS-aided WPCNs. However, all the above works focus on the HD system, which suffers from a low spectral and energy efficiencies.

In this paper, we study an IRS-aided FD WPCN for further improving the system throughput. As shown in Fig. 1, the HAP operates in an FD mode with two antennas, which are use for DL WET and UL WIT, respectively. In addition, the IRS is deployed nearby the distributed devices to enhance DL WET from the HAP to the devices and UL WIT from the devices to the HAP simultaneously. Note that although there were several works [41]–[43] studied IRS-aided FD systems for some applications, such as the cognitive radio system, the point-to-point system, and the multi-user multiple-input single-output system, the above works assumed that the SI is either a constant or is perfectly canceled by ignoring the practical quantization error introduced by the strong SI under the limited dynamic range of the ADC converter. To the best of our knowledge, it is the first work to study the IRS-aided FD-WPCN with finite SI. It is worth pointing out that different from the WPCN without IRS where the channels of all devices remain static within a channel coherence block, we are able to proactively generate optimized artificial time-varying channels by properly designing the IRS reflection coefficients over different time slots within each channel coherence block, thus enhancing the multiuser diversity and improving the system throughput. The main contributions of this paper are summarized as follows.

- First, we study an IRS-aided FD-WPCN and propose three types of IRS beamforming configurations based on how the IRS is allowed to adjust its phase shifts across time. We first consider the fully dynamic IRS beamforming, where the phase-shift vectors vary with each time slot for DL WET and UL WIT. To further reduce signaling overhead and implementation complexity, we then study two special cases, namely, partially dynamic IRS beamforming and static IRS beamforming. For the former case, there are two different phase-shift vectors during the whole period with one for DL WET and the other for UL WIT. For the latter case, DL WET and UL WIT are assumed to adopt the same phase-shift vector. For the above three cases, we formulate the corresponding system throughput maximization problems by jointly optimizing the time allocation, HAP transmit power, and
IRS phase shifts. It is worth noting that such a thorough study in terms of different dynamic IRS beamforming configurations have not been studied yet in the literature.

- Second, we consider fully dynamic IRS beamforming optimization with perfect SIC. Since the formulated problem is non-convex due to the highly coupled optimization variables in the objective function and non-convex unit-modulus constraints of phase shifts, there are no standard methods for solving such non-convex optimization problem optimally. To solve this difficulty, we propose an efficient alternating optimization (AO) algorithm by first decomposing the entire variables into two blocks, namely, time allocation and phase shifts, and then optimize each block alternately, until convergence is achieved.

- Third, we consider fully dynamic IRS optimization with imperfect SIC, where the corresponding problem is more challenging than the former one due to the additional HAP transmission power involved in the objective function. To address this issue, we propose a novel penalty-based algorithm, which includes a two-layer iteration, i.e., an inner layer iteration and an outer layer iteration. The inner layer solves the penalized optimization problem, while the outer layer updates the penalty coefficient over iterations to guarantee convergence.

- Fourth, we respectively study partially dynamic IRS beamforming and static IRS beamforming, respectively. Since the formulated problems are different from that of the fully dynamic IRS beamforming, we extend the AO and penalty-based algorithms to solve them. In particular, a difference-of-convex (DC) optimization method is proposed to address unit-modulus phase-shift constraints, which guarantees to converge to locally optimal solutions.

- Finally, simulation results demonstrate the benefits of the IRS used for enhancing the performance of the FD-WPCN, especially when the fully dynamic IRS beamforming is adopted. We also show that the IRS-aided FD-WPCN is able to achieve significantly performance gain compared to the IRS-aided half-duplex (HD)-WPCN when the SI is well suppressed. Furthermore, it is found that the system with static IRS beamforming achieves almost the same performance as the case with partially dynamic IRS beamforming when the HAP has a large transmit power budget.

The rest of this paper is organized as follows. Section II introduces the system model and problem formulations for FD-WPCN with three types of IRS beamforming configurations. In Section III, we propose an AO based algorithm to solve the problem with fully dynamic
IRS beamforming under perfect SIC. In Section IV, we propose a penalty-based algorithm to solve the problem with fully dynamic IRS beamforming with imperfect SIC. In Section V, we extend the algorithms to solve the problems with partially dynamic IRS beamforming and static IRS beamforming, respectively. Numerical results are provided in Section VI and the paper is concluded in Section VII.

Notations: Boldface upper-case and lower-case letter denote matrix and vector, respectively. \( \mathbb{C}^{d_1 \times d_2} \) stands for the set of complex \( d_1 \times d_2 \) matrices. For a complex-valued vector \( x \), \( \|x\| \) represents the Euclidean norm of \( x \), \( \text{arg}(x) \) denotes the phase of \( x \), and \( \text{diag}(x) \) denotes a diagonal matrix whose main diagonal elements are extracted from vector \( x \). For a vector \( x \), \( x^* \) and \( x^H \) stand for its conjugate and conjugate transpose respectively. For a square matrix \( X \), \( \text{Tr}(X) \), \( \|X\|_2 \) and \( \text{rank}(X) \) respectively stand for its trace, Euclidean norm and rank, while \( X \succeq 0 \) indicates that matrix \( X \) is positive semi-definite. A circularly symmetric complex Gaussian random variable \( x \) with mean \( \mu \) and variance \( \sigma^2 \) is denoted by \( x \sim \mathcal{CN}(\mu, \sigma^2) \). \( \mathcal{O}(\cdot) \) is the big-O computational complexity notation.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider an IRS-aided full-duplex WPCN consisting of an HAP, \( K \) single-antenna devices, and an IRS, as shown in Fig. 1. We assume that the HAP operates in the FD mode to enhance the spectral efficiency and is equipped with two antennas, i.e., a transmitter antenna and a receiver antenna. The transmitter antenna broadcasts energy to the distributed devices in the DL and
meanwhile the receiver antenna receives the information from the distributed devices in the UL simultaneously over the same frequency band. In addition, the distributed devices are assumed to operate in a time-division HD mode due to their limited signal processing capability, where the devices first harvest energy in the DL and then transmit information in the UL.

We consider a quasi-static flat-fading channel in which the channel state information remains constant in a channel coherence frame, but may change in the subsequent frames. As shown in Fig. 2, each channel coherence frame consists of multiple blocks and each transmission period of one block of interest denoted by $T$ is divided into $K + 1$ time slots each with duration of $\tau_i, i \in K_1$, where $K_1 = \{0, \ldots, K\}$. The 0th slot is a dedicated time slot used to broadcast energy to all distributed devices in the DL, while the $i$th ($i \neq 0$) time slot is used for both DL WET and UL WIT. Since there are two antennas at the HAP, the DL and UL channels are different in general. In the DL transmission, denote by $g \in \mathbb{C}^{M \times 1}$, $h^H_{r,k} \in \mathbb{C}^{1 \times M}$, and $h_{d,k} \in \mathbb{C}^{1 \times 1}$ the complex equivalent baseband channel between the HAP and the IRS, between the IRS and the $k$th device, and between the HAP and the $k$th device, $k \in K_2$, where $K_2 = \{1, \ldots, K\}$, respectively. In the UL transmission, denote by $\bar{g}^H \in \mathbb{C}^{1 \times M}$, $\bar{h}_{r,k} \in \mathbb{C}^{M \times 1}$, and $\bar{h}_{d,k} \in \mathbb{C}^{1 \times 1}$ the complex equivalent baseband channel between the HAP and the IRS, between the IRS and the $k$th device, and between the HAP and the $k$th device, $k \in K_2$, respectively. In addition, the channel reciprocity is assumed and thus we have $\bar{h}_{r,k} = h^*_{r,k}$ for IRS-device links.

In this paper, we consider three types of IRS beamforming configurations, namely, fully dynamic IRS, partially dynamic IRS, and static IRS. In the following, we first provide the details for modeling the fully dynamic IRS case, and the other two cases are discussed in Section II-B.
1) DL WET: During DL WET, the received signal by device $k$ in time slot $i$ is given by

$$y_{d,k}^{i} = \sqrt{P_i} (h_{d,k} + h_{r,k}^H \Theta_i g) s_i + n_{k,i}^d,$$  \hspace{1cm} (1)$$

where $s_i$ is a pseudo-random signal which is a priori known at the HAP satisfying $\mathbb{E}\{|s_i|^2\} = 1$, $P_i$ represents the HAP’s transmit power at time slot $i$, $\Theta_i = \text{diag}(e^{j\theta_1}, \ldots, e^{j\theta_M})$ represents a diagonal reflection coefficient matrix in the $i$th time slot, where the reflection amplitude is fixed as 1 and $\theta_{i,m}$ denotes the $m$th reflecting element of the IRS phase shifts in the $i$th time slot, and $n_{k,i}^d \sim \mathcal{CN}(0, \sigma^2)$ stands for the additive white Gaussian noise at device $k$ in the $i$th time slot. For ease of exposition, we assume that the $k$th time slot is occupied by device $k$ for UL WIT, $k \in K_2$. It is worth noting that as in [11], since we consider a periodic transmission protocol shown in Fig. 2, each device $k$ can harvest energy during all time slots except its own transmission time slot $k$. Particularly, the energy harvested by device $k$ after its own WIT in the previous transmission block (e.g., $n-1$th) will be used for its WIT in the next transmission block (e.g., $n$th). Under this protocol, the amount of harvested energy by device $k$ during $T$ can be equivalently expressed as

$$E_k = \eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + h_{r,k}^H \Theta_i g|^2,$$ \hspace{1cm} (2)$$

where $0 \leq \eta_k \leq 1$ denotes the energy conversion coefficient at device $k$.

On the other hand, when device $k$ is scheduled to transmit in the $k$th time slot, device $k$ will exhaust the total harvested energy for UL WIT. The average transmit power of device $k$ for UL WIT is thus given by

$$p_k = \eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + h_{r,k}^H \Theta_i g|^2 / \tau_k, \quad k \in K_2.$$ \hspace{1cm} (3)$$

2) UL WIT: During UL WIT, device $k$ transmits its own data to the HAP, the received signal by the HAP in time slot $k$ is given by

$$y_{r,k}^{i} = \sqrt{p_k} (\tilde{h}_{d,k} + \tilde{g}^H \Theta_k \tilde{h}_{r,k}) x_k + \sqrt{P_k} (f + \tilde{g}^H \Theta_k g) s_k + n_{k,i}^r,$$ \hspace{1cm} (4)$$

1Note that in practice, the device scheduling order for the UL WIT may be affected by many other factors. Thus, in Section VI, we study two scheduling strategies based on the power gain of direct links, and evaluate their impacts on the system performance.

2The energy harvested from the noise and the received UL WIT signals from other devices are assumed to be negligible, since both the noise power and device transmit power are much smaller than the transmit power of the HAP in practice [44], [45].
where $x_k$ denotes device $k$’s transmit signal, which is assumed to be of zero mean and unit power, i.e., $\mathbb{E}\{x_k\} = 0$ and $\mathbb{E}\{|x_k|^2\} = 1$, $f$ represents the effective loopback channel at the HAP that satisfies $\mathbb{E}\{|f|^2\} = \gamma$, and $n'_k \sim \mathcal{CN}(0, \sigma^2)$ denotes the received additive white Gaussian noise. It can be observed that the interference term in (4) consists of two parts. The first $\sqrt{P_k} s_k$ denotes the SI resulting from the DL transmission by the HAP and the second part $\sqrt{P_k} \bar{g}^H \Theta_k \bar{g}_s k$ denotes the interference introduced by the reflection of the DL transmit signal by the IRS. We assume that the IRS is deployed close to the devices and is far from the HAP by considering the following two facts. First, when the IRS is deployed close to the devices, the double propagation loss of the cascaded HAP-IRS-device link will be substantially reduced, which is beneficial for improving the signal-to-noise ratio (SNR). Second, when the IRS is deployed far from the HAP, the power of interference introduced by the reflection link, i.e., HAP-IRS-HAP link, will be significantly small compared to that of SI resulting from the DL transmission. As such, the second part of interference is neglected in the sequel of this paper.

3) SIC: In practice, the FD operation is often precluded by the significant quantization error introduced by the strong SI under the limited dynamic range of ADC at the receiver. Following [11], [46], this quantization error after ADC can be modeled as an independent white Gaussian noise denoted by $n_{error,k} \sim \mathcal{CN}(0, \beta \sigma^2_{error})$, $k \in K_2$, where $\beta \ll 1$ and $\sigma^2_{error}$ are given by

$$\sigma^2_{error,k} = p_k |\bar{h}_{d,k} + \bar{g}^H \Theta_k \bar{h}_{r,k}|^2 + \gamma P_k + \sigma^2 \overset{(a)}{\approx} \gamma P_k,$$

where $(a)$ holds due to the fact that the power of SI is generally much larger than that of the received signal from UL devices and the received noise. Expression (5) shows that the power of quantization error is proportional to that of transmit power at the HAP. In addition, we assume that the perfect loopback channel $f$ is available at the receiver of the HAP via using pilot-based channel estimation methods [46]. Therefore, subtracting SI from (4), the received signal at the HAP can be recast as

$$\tilde{y}_k = \sqrt{p_k} (\bar{h}_{d,k} + \bar{g}^H \Theta_k \bar{h}_{r,k}) x_k + n_{error,k} + n_r^k. \quad (6)$$

As a result, the achievable throughput of device $k$ in bits/Hz in time slot $k$ can be expressed as

$$R_k = \tau_k \log_2 \left(1 + \frac{p_k |\bar{h}_{d,k} + \bar{g}^H \Theta_k \bar{h}_{r,k}|^2}{\Gamma (\beta \gamma P_k + \sigma^2)} \right), \quad (7)$$

where $\Gamma$ represents the gap from channel capacity owing to the practical modulation and coding scheme.
B. Problem Formulation

Denote by sets $\mathcal{M} = \{1, \ldots, M\}$, $\tau = \{\tau_k, k \in \mathcal{K}_1\}$, $P = \{P_k, k \in \mathcal{K}_1\}$, and $v = \{v_i, i \in \mathcal{K}_1\}$, where $v^i = [v_{i,1}, \ldots, v_{i,M}]$ and $v_{i,m} = e^{j\theta_{i,m}}, i \in \mathcal{K}_1, m \in \mathcal{M}$. Let $q_k = \text{diag}(h^H_{r,k}) g$ and $\bar{q}_k = \text{diag}(\bar{g}^H) \bar{h}_{r,k}$. We thus have $|h_{d,k} + h^H_{r,k} \Theta_i g|^2 = |\bar{h}_{d,k} + \bar{q}_k|^2$ and $|\bar{h}_{d,k} + \bar{q}_k|^2$. The objective of this paper is to maximize the sum throughput of the IRS-aided FD-WPCN by jointly optimizing the time allocation, HAP transmit power, and IRS phase shifts.\(^3\)

We consider three types of IRS beamforming configurations, which are specified as follows.

1) **Fully Dynamic IRS Beamforming:** In this case, the phase-shift vectors change over each time slot during period of $T$. Mathematically, the problem is formulated as follows

$$\max_{\tau, P, v} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + v_{i}^H q_k|^2}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right)$$  \(8a\)

s.t. $\sum_{k=0}^{K} \tau_k \leq T$,  \(8b\)

$\tau_k \geq 0, k \in \mathcal{K}_1$,  \(8c\)

$0 \leq P_k \leq P_{\text{max}}, k \in \mathcal{K}_1$,  \(8d\)

$$\|v_{k,m}\| = 1, m \in \mathcal{M}, k \in \mathcal{K}_1,$$  \(8e\)

where $P_{\text{max}}$ in (8d) denotes the HAP transmit power budget.

2) **Partially Dynamic IRS Beamforming:** In this case, two different phase-shift vectors can be allowed to be used for DL WET and UL WIT, which are denoted by $v_d$ and $v_u$, respectively. We thus have $v_d = v_0, v_u = v_k, k \in \mathcal{K}_2$. Define $v_t = \{v_d, v_u\}$. Accordingly, the problem can be formulated as follows

$$\max_{\tau, P, v_t} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( P_0 \tau_0 |h_{d,k} + v_{d}^H q_k|^2 + \sum_{i=1, i \neq k}^{K} P_i \tau_i |h_{d,k} + v_{i}^H q_k|^2 \right)}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right)$$  \(9a\)

s.t. $\|v_{t,m}\| = 1, m \in \mathcal{M}, t \in \{u, d\}$,  \(9b\)

(8b), (8c), (8d),  \(9c\)

where $v_{t,m}$ denotes the $m$th entry of $v_t$.

\(^3\)Note that the considered problem formulation can be readily extended to take into account the fairness among devices by adding the different weighting factors on each device in the objective function, which does not affect our proposed algorithms. As such, we focus on the achievable sum throughput maximization problem instead.
3) Static IRS Beamforming: In this case, we adopt the same phase-shift vector for both UL and DL transmission, i.e., $v_0 = v_1 = \ldots = v_K$. Denote by $v_s$ the phase-shift vector for static IRS. Accordingly, the problem can be formulated as follows

$$
\max_{\tau, P, v_s} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( \sum_{i=0, i \neq k}^{K} P_i \tau_i \right) \left| h_{d,k} + v_s^H q_k \right|^2 \left| \bar{h}_{d,k} + v_s^H \bar{q}_k \right|^2}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right) \tag{10a}
$$

subject to

$$||v_{s,m}|| = 1, m \in M, \quad \text{(8b), (8c), (8d), (10b)} \tag{10b}$$

where $v_{s,m}$ denotes the $m$th entry of $v_s$.

The above three problems (8), (9) and (10) are all non-convex since the optimization variables are highly coupled in the objective functions, there are no standard methods for solving such non-convex optimization problems optimally in general. Although it looks like (8) and (10) have the similar objective function, the hidden structures are fundamentally different. Specifically, in (8a), $\sum_{i=0, i \neq k}^{K} P_i \tau_i \left| h_{d,k} + v_i^H q_k \right|^2$ and $\left| \bar{h}_{d,k} + v_s^H \bar{q}_k \right|^2$ are not coupled with respect to (w.r.t.) $v_k$. While $\left| h_{d,k} + v_s^H q_k \right|^2$ and $\left| \bar{h}_{d,k} + v_s^H \bar{q}_k \right|^2$ have the same phase-shift vector $v_s$ in (10a). Therefore, different algorithms are required. In the following two sections, we propose to two framework algorithms, namely AO and penalty-based algorithms, based on the successive convex approximation (SCA) and DC optimization techniques to solve problem (8). The extension to solve problems (9) and (10) will be studied in Section V.

III. PROPOSED SOLUTION FOR FULLY DYNAMIC IRS BEAMFORMING WITH PERFECT SIC

In this section, we study the fully dynamic IRS beamforming with perfect SIC, i.e., $\gamma = 0$, which also provides the performance upper bound for the case with imperfect SIC. Problem (8) can be simplified to

$$
\max_{P, \tau, v_s} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i \left| h_{d,k} + v_i^H q_k \right|^2 \left| \bar{h}_{d,k} + v_i^H \bar{q}_k \right|^2}{\Gamma \sigma^2 \tau_k} \right) \tag{11a}
$$

subject to

$$(8b), (8c), (8d), (8e). \tag{11b}$$

Problem (11) is a non-convex optimization problem since the optimization variables are coupled in (11a) and (8e) involves unit-modulus constraint, which makes it difficult to solve. We can
readily prove that at the optimal solution to (11), we must have $P_{k}^{\text{opt}} = P_{\text{max}}$, $k \in K$ since (11a) is monotonically increasing w.r.t. $P_i$. As such, problem (11) can be simplified to

$$\max_{\tau, v} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k P_{\text{max}} \sum_{i=0, i \neq k}^{K} \tau_i |h_{d,k} + v_i^H q_k|^2}{\Gamma \sigma^2 \tau_k} \right)$$

s.t. (8b), (8c). (12a)

Although problem (12) is still a non-convex optimization problem, it has less constraints and variables compared to (11). Additionally, it is observed that each optimization variable in (12) is involved in at most one constraint, which motivates us to apply AO method to solve it. Specifically, we divide all the variables into two blocks, i.e., 1) time allocation $\tau$, and 2) phase-shift vector $v$, and then optimize each block in an iterative way, until convergence is achieved.

A. Time Allocation Optimization

For any given phase-shift vector $v$, the time allocation optimization problem is given by

$$\max_{\tau} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k P_{\text{max}} \sum_{i=0, i \neq k}^{K} \tau_i |h_{d,k} + v_i^H q_k|^2}{\Gamma \sigma^2 \tau_k} \right)$$

s.t. (8b), (8c). (13a)

Lemma 1: The objective function of (13) is a jointly concave function of $\tau$.

Proof: It can be proved via checking its Hessian matrix, please refer to Appendix B of reference [12] for details.

Based on Lemma 1 and the fact that all constraints in (13) are linear, problem (13) is thus a convex optimization problem, which can be solved by the standard convex optimization techniques, such as interior-point method [47].

B. IRS Phase Shift Optimization

For any given time allocation $\tau$, the IRS phase shift optimization is given by

$$\max_{v} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k P_{\text{max}} \sum_{i=0, i \neq k}^{K} \tau_i |h_{d,k} + v_i^H q_k|^2}{\Gamma \sigma^2 \tau_k} \right)$$

s.t. (8e). (14a)
Problem (14) involves non-convex unit-modulus constraint (8e). To address this non-convexity, we relax the unit-modulus constraint (8e) as

\[ \|v_{k,m}\| \leq 1, \forall m \in \mathcal{M}, k \in \mathcal{K}_1, \]  

(15)

which is convex.

In addition, it is also observed that \( v_{i}, i \neq k \), does not appear in \( \sum_{i=0,i\neq k}^{K} \tau_{i} |h_{d,k} + v_{i}^{H} q_{k}|^{2} \) and \( |\bar{h}_{d,k} + v_{k}^{H} \bar{q}_{k}|^{2} \) simultaneously, which motivates us to apply AO algorithm to solve it. As such, we can partition the entire phase shifts into \( K + 1 \) blocks, i.e., \( \{v_{i}\}, i \in \mathcal{K}_1 \), and then alternately optimize each block until convergence is achieved. However, optimizing phase shift \( v_{0} \) for DL WET and \( v_{k}, k \in \mathcal{K}_2 \), for UL WIT are different. As such, we solve them separately with two cases in the following.

**Case 1:** Define \( y_{k,i} = |h_{d,k} + v_{i}^{H} q_{k}|^{2} \) and \( \bar{y}_{k} = |\bar{h}_{d,k} + v_{k}^{H} \bar{q}_{k}|^{2}, k \in \mathcal{K}_2, i \in \mathcal{K}_1 \). The phase shift optimization problem for DL WET, i.e., for \( v_{0} \), is given by

\[
\max_{v_{0}} \sum_{k=1}^{K} \tau_{k} \log_{2} \left( 1 + \frac{\eta_{k} P_{\max} (\tau_{0} |h_{d,k} + v_{0}^{H} q_{k}|^{2} + \sum_{i=1,i\neq k}^{K} \tau_{i} y_{k,i}) \bar{y}_{k})}{\Gamma \sigma^{2} \tau_{k}} \right)
\]

s.t. \( \|v_{0,m}\| \leq 1, \forall m \in \mathcal{M} \).  

(16a)

(16b)

It is observed that \( |h_{d,k} + v_{0}^{H} q_{k}|^{2} \) is a convex quadratic function of \( v_{0} \). Recall that any convex function is globally lower-bounded by its first-order Taylor expansion at any feasible point [47]. As a result, the SCA technique is applied. Specifically, for any local point \( v_{i}^{r} \) in the \( r \)th iteration, we have

\[
|h_{d,k} + v_{i}^{H} q_{k}|^{2} \geq - |h_{d,k} + v_{i}^{r,H} q_{k}|^{2} + 2 \text{Re} \left\{ (h_{d,k} + v_{i}^{H} q_{k})^{H} (h_{d,k} + v_{i}^{r,H} q_{k}) \right\}
\]

\[ \triangleq f_{k}(v_{i}), i \in \mathcal{K}_1, k \in \mathcal{K}_2, \]  

(17)

which is linear and convex w.r.t. \( v_{i} \).

For \( i = 0 \), \( f_{k}(v_{0}) \) is a lower bound of \( |h_{d,k} + v_{0}^{H} q_{k}|^{2} \). Substituting \( f_{k}(v_{0}) \) into (16a), we have the following convex optimization problem

\[
\max_{v_{0}} \sum_{k=1}^{K} \tau_{k} \log_{2} \left( 1 + \frac{\eta_{k} P_{\max} (\tau_{0} f_{k}(v_{0}) + \sum_{i=1,i\neq k}^{K} \tau_{i} y_{k,i}) \bar{y}_{k})}{\Gamma \sigma^{2} \tau_{k}} \right)
\]

s.t. (16b),  

(18a)

(18b)

which can be solved by the interior point method [47].
Case 2: The phase shift optimization problem for UL WIT, i.e., for $v_k, k \in \mathcal{K}_2$. We alternately update phase-shift vector over each UL time slot while others being fixed. The problem is given by

$$\max_{\tau_k} \tau_k \log_2 \left( 1 + \eta_k P_{\max} \sum_{i=0,i \neq k}^K \tau_i y_{k,i} \left| h_{d,k} + v_k^H \bar{q}_k \right|^2 / \Gamma \sigma^2 \tau_k \right) +$$

$$\sum_{j=1,j \neq k}^K \tau_j \log_2 \left( 1 + \eta_j P_{\max} \left( \tau_k h_{d,j} + v_k^H q_j \right) \bar{y}_j / \Gamma \sigma^2 \tau_j \right)$$

(19a)

s.t. $\|v_{k,m}\| \leq 1, \forall m \in \mathcal{M}$. (19b)

Similar to (17), taking the first-order Taylor expansion of $\left| h_{d,k} + v_k^H \bar{q}_k \right|^2$ at any feasible point $v^*_k$, we have its lower bound given by

$$\left| h_{d,k} + v_k^H \bar{q}_k \right|^2 \geq -\left| h_{d,k} + v_k^r H \bar{q}_k \right|^2 + 2 \text{Re} \left\{ \left( h_{d,k} + v_k^H \bar{q}_k \right) H \left( h_{d,k} + v_k^r H \bar{q}_k \right) \right\}$$

$$\triangleq \tilde{f}_k (v_k), k \in \mathcal{K}_2.$$ (20)

It can be readily checked that $\tilde{f}_k (v_k)$ is linear and convex w.r.t. $v_k$. Based on (17) and (20), problem (19) can be approximated by

$$\max_{\tau_k} \tau_k \log_2 \left( 1 + \eta_k P_{\max} \sum_{i=0,i \neq k}^K \tau_i y_{k,i} \tilde{f}_k (v_k) / \Gamma \sigma^2 \tau_k \right) +$$

$$\sum_{j=1,j \neq k}^K \tau_j \log_2 \left( 1 + \eta_j P_{\max} \left( \tau_k \tilde{f}_j (v_k) + \sum_{i=0,i \neq j,i \neq k}^K \tau_i y_{j,i} \right) \bar{y}_j / \Gamma \sigma^2 \tau_j \right)$$

(21a)

s.t. $\|v_{k,m}\| \leq 1, \forall m \in \mathcal{M}$, (21b)

which is convex and can be solved by interior-point method [47].

C. Overall Algorithm and Computational Complexity Analysis

Finally, we need to reconstruct the obtained phase shifts as unit-modulus solutions. The reconstruction scheme is given by

$$v^opt_{k,m} = \frac{v_{k,m}}{|v_{k,m}|}, k \in \mathcal{K}_1, m \in \mathcal{M}.$$ (22)

Based on the solutions to the above subproblems, an AO algorithm is proposed, which is summarized in Algorithm 1.

The mainly computational complexity lies from steps 3, 4, and 6. Specifically, in step 3, (13) can be solved by the interior-point method, whose complexity is $O((K+1)^3.5)$ [48], where $K + 1$
Algorithm 1 AO for solving (11).

1: Initialize IRS phase-shift vector $v_k^r$, $k \in K_1$, and threshold $\varepsilon$.

2: repeat
3:   Update time allocation by solving (13).
4:   Update DL WET phase shift vector $v_0$ by solving (18).
5:   for $k = 1, \ldots, K$
6:     Update UL WIT phase shift vector $v_k$ by solving (21).
7:   end
8: until the fractional increase of the objective function of (11) is below a threshold $\varepsilon$.

9: Reconstruct phase shifts based on (22).

10: Update time allocation by solving (13) based on the newly obtained phase shifts.

11: Output: time allocation $\tau$, and phase-shift vector $v$.

denotes the number of variables. In steps 4 and 6, the complexity for solving (18) and (21) by
the interior-point method is the same with $O(M^{3.5})$, where $M$ denotes the number of variables.
Therefore, the total complexity of Algorithm 1 is $O(L_{iter} ((K+1)M^{3.5} + (K+1)^{3.5}))$, where
$L_{iter}$ stands for the number of iterations required to reach convergence. Since at steps 3, 4, and
6, each subproblem is optimally solved, the objective function is non-decreasing over iterations.
In addition, the maximum objective value of (11) is upper bounded by a finite value due to
the limited HAP transmit power. As such, by applying the proposed Algorithm 1, the objective
value is guaranteed to be non-decreasing over the iterations and terminated finally.

IV. PROPOSED SOLUTION FOR FULLY DYNAMIC IRS BEAMFORMING WITH IMPERFECT SIC

For the fully dynamic IRS beamforming with imperfect SIC, i.e., $\gamma \neq 0$, the formulated
problem is more challenging than that with perfect SIC since the HAP transmission power $P$
is involved in the objective function of (8). To solve this problem, we extend the proposed AO
algorithm in Section III to a novel penalty-based algorithm, which includes a two-layer iteration,
i.e., an inner layer iteration and an outer layer iteration. The inner layer solves the penalized
optimization problem by exploiting the AO algorithm, while the outer layer updates the penalty
coefficient over iterations to guarantee convergence. Specifically, by introducing a new auxiliary
variable \( z = \{ z_k, k \in K_2 \} \), problem (8) is rewritten as

\[
\max_{\tau, P, \nu, z} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + \nu_i^H q_k|^2}{\sigma^2 z_k \tau_k} \right)
\]

\[
\text{s.t. } z_k = \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right), k \in K_2,
\]

\[
(8b), (8c), (8d), (8e).
\]

We then use (23b) as a penalty term that is added to the objective function of (23), yielding the following optimization problem

\[
\max_{\tau, P, \nu, z} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + \nu_i^H q_k|^2}{\sigma^2 z_k \tau_k} \right)
\]

\[
- \frac{1}{2\rho} \sum_{k=1}^{K} |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right)|^2
\]

\[
\text{s.t. } (8b), (8c), (8d), (8e),
\]

where \( \rho > 0 \) is a penalty coefficient that penalizes the violation equality constraint (23b). By gradually decreasing the value of \( \rho \) in the outer layer, as \( \rho \to 0 \), it follows that \( \frac{1}{2\rho} \to \infty \). In this case, equality in (23b) is guaranteed in the optimal solution to problem (24). For any given \( \rho > 0 \), (23) is still a non-convex optimization problem due to the non-convex objective function as well as non-convex unit-modulus constraint (8e). However, it is observed that each optimization variable is involved in at most one constraint, which motivates us to apply AO algorithm to solve it in the inner layer. Specifically, we first relax unit-modulus constraint (8e) as (15). We then divide all the optimization variables into four blocks, i.e., 1) time allocation \( \tau \), 2) HAP transmission power \( P \), 3) auxiliary variable \( z \), and 4) IRS phase shift \( \nu \), and then alternately optimize each block, until convergence is achieved.

1) Optimizing \( \tau \) for given \( P, \nu, z \): Ignoring irrelevant terms w.r.t. \( \tau \), this subproblem can be expressed as

\[
\max_{\tau} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + \nu_i^H q_k|^2}{\sigma^2 z_k \tau_k} \right)
\]

\[
\text{s.t. } (8b), (8c).
\]

Problem (25) has a similar form to problem (13) discussed in Section III-A, which thus can be solved similarly.
2) Optimizing $P$ for given $\tau, v, z$: This subproblem is written as

$$\max_{P} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0,i\neq k}^{K} P_i \tau_i |h_{d,k} + v_i^H q_k|^2}{\sigma^2 z_k \tau_k} \right)$$

$$- \frac{1}{2 \rho} \sum_{k=1}^{K} |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right)|^2$$

s.t. (8d).

It is observed that both the objective function and constraints are convex, which thus can be efficiently solved by interior-point method [47].

3) Optimizing $z$ for given $P, \tau, v$: This subproblem can be expressed as

$$\max_{z} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0,i\neq k}^{K} P_i \tau_i |h_{d,k} + v_i^H q_k|^2}{\sigma^2 z_k \tau_k} \right)$$

$$- \frac{1}{2 \rho} \sum_{k=1}^{K} |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right)|^2$$

(27)

It is observed that (27) has no constraints and the auxiliary optimization variables \( \{z_k, k \in K_2\} \) can be solved in parallel. Without loss of generality, the $k$th subproblem of (27) is given by

$$\max_{z_k} \tau_k \log_2 \left( 1 + \frac{a_k}{z_k} \right) - \frac{1}{2 \rho} |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right)|^2$$

(28)

where $a_k = \eta_k \sum_{i=0,i\neq k}^{k-1} P_i \tau_i |h_{d,k} + v_i^H q_k|^2 / \tau_k \sigma^2$, $k \in K_2$. The key observation in (28) is that the function $\log_2 \left( 1 + \frac{a_k}{z_k} \right)$ is convex w.r.t. $z_k$, and its lower bound can be obtained by taking its first-order Taylor expansion at any feasible point. As a result, the SCA technique is applied here. Specifically, for any given point $z_k^r$ in the $r$th iteration, we have

$$\log_2 \left( 1 + \frac{a_k}{z_k} \right) \geq \log_2 \left( 1 + \frac{a_k}{z_k^r} \right) - \frac{a_k \log_2 e}{z_k^r (z_k^r + a_k)} (z_k - z_k^r).$$

(29)

Replacing $\log_2 \left( 1 + \frac{a_k}{z_k} \right)$ by its lower bound, we have the newly formulated optimization problem as follows

$$\max_{z_k} \tau_k \left( \log_2 \left( 1 + \frac{a_k}{z_k} \right) - \frac{a_k \log_2 e}{z_k^r (z_k^r + a_k)} (z_k - z_k^r) \right) - \frac{1}{2 \rho} |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 + 1 \right)|^2$$

(30)

which is convex. By taking the first-order derivative of (30) w.r.t. $z_k$ and setting it to zero, the closed-form optimal solution to (30) can be obtained as

$$z_k^{opt} = \Gamma \left( \frac{\beta \gamma P_k}{\sigma^2 + 1} - \frac{\rho a_k \tau_k \log_2 e}{z_k^r (z_k^r + a_k)} \right), k \in K_2.$$
4) Optimizing $v$ for given $P, \tau, z$: Ignoring irrelevant terms w.r.t. $v$, this subproblem can be expressed as

$$\max_v \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \sum_{i=0, i \neq k}^{K} P_i \tau_i |h_{d,k} + v_i^H q_k|^2}{\sigma^2 z_{k} \tau_k} \right)$$

s.t. (15).

(32a)

$$\rho^r = c \rho^{r-1}, \quad 0 \leq c \leq 1,$$

(33)

where $c$ is a step size. Generally, a larger value of $c$ can achieve better performance but at the cost of more iterations in the outer layer. It is worth pointing out that if $c$ is chosen very small, the penalty-based algorithm will be eventually diverged with a high possibility. Empirically, choosing $c$ from 0.7 to 0.9 is a good choice to balance the convergence speed and performance.

5) Overall Algorithm and Computational Complexity Analysis: In the outer layer, we gradually decrease the value of penalty coefficient $\rho^r$ in the $r$th iteration as follows

(32b)

$$\xi = \max_{k \in K_2} \left\{ |z_k - \Gamma \left( \beta \gamma P_k / \sigma^2 \right) + 1| \right\} .$$

(34)

The algorithm is terminated when $\xi$ is below a predefined threshold. The details of this algorithm are summarized in Algorithm 2. Note that with the proper variable partition in our proposed algorithm, there is no constraint coupling between the variables in different blocks, as seen in (25), (26), (31), and (32). In addition, each subproblem is either locally or optimally solved. As such, based on the results in [49], the obtained solution converges to a point fulfilling the Karush–Kuhn–Tucker (KKT) optimality conditions of original problem (8).

The complexity of Algorithm 2 can be analyzed as follows. In the inner layer, the main complexity of Algorithm 2 comes from steps 4, 5 and 7, which can be calculated similarly as Algorithm 1 discussed in Section III-C. Therefore, the total complexity of Algorithm 2 is $O \left( L_{\text{outer}} L_{\text{inner}} \left( 2(K+1)^{3.5} + (K+1) M^{2.5} \right) \right)$, where $L_{\text{inner}}$ and $L_{\text{outer}}$ denote the numbers of iterations required for reaching convergence in the inner layer and outer layer, respectively.
Algorithm 2: Penalty-based algorithm for solving problem (8).

1: Initialize $v^r$, $P^r$, $z^r$, $c$, $\rho$, $\varepsilon_1$, and $\varepsilon_2$.

2: repeat: outer layer
3: \hspace{1em} repeat: inner layer
4: \hspace{2em} Update $\tau$ by solving (25).
5: \hspace{2em} Update $P$ by solving (26).
6: \hspace{2em} Update $z$ based on (31).
7: \hspace{2em} Update $v$ by solving (32).
8: until the fractional increase of the objective value of (24) is below a threshold $\varepsilon_1$.
9: Update penalty coefficient $\rho$ based on (33).
10: until penalty violation $\xi$ is below a threshold $\varepsilon_2$.
11: Reconstruct phase shifts based on (22).
12: Update time allocation $\tau$, power allocation $P$, and auxiliary variable $z$ by solving (25), (26), and (31), respectively, based on the new phase shifts.
13: Output: time allocation $\tau$, power allocation $P$, and phase shift $v$.

V. EXTENSION TO PARTIALLY DYNAMIC AND STATIC IRS BEAMFORMING

In this section, we study two special cases, namely, partially dynamic IRS beamforming and static IRS beamforming, for both perfect SIC and imperfect SIC. Since the problem formulations of the above two special cases are different from that of fully dynamic IRS beamforming in (8), the new algorithms are required. However, it can be easily observed that the resource allocation (transmit power $P$ and time allocation $\tau$) optimization of problems (9) and (10) can be solved in the same way as (8) for both perfect SIC and imperfect case discussed in Section III and Section IV, respectively. As such, in this section, we only focus on the phase shift optimization for the partially dynamic IRS beamforming and static IRS beamforming as below. Without loss of generality, we first solve the phase shift optimization for the static IRS case. Then, we will show later that the phase shift optimization for the partially dynamic beamforming can be solved by a combination of that for fully dynamic beamforming and static beamforming.

A. Phase Shift Optimization for Static IRS Beamforming with Imperfect SIC

For the static IRS beamforming with the imperfect SIC, problem (10) is more challenging than problem (8) since phase-shift vector $v$ appears in both $|h_{d,k} + v_s^H q_k|^2$ and $|\bar{h}_{d,k} + v_s^H \bar{q}_k|^2$. 
As a result, the proposed SCA for the phase shift optimization in (8) cannot be applied to (10). To tackle this difficulty, a DC optimization method is proposed with at least a locally optimal solution guaranteed. Specifically, the phase shift optimization subproblem for (10) is given by

$$\max_{\mathbf{v}_s} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( \sum_{i=0,i\neq k}^{K} P_i \tau_i \right) |h_{d,k} + v_s^H q_k|^2 |\bar{h}_{d,k} + v_s^H \bar{q}_k|^2}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right)$$

s.t. (10b).

(35a)

Let $|h_{d,k} + v_s^H q_k|^2 = |\tilde{v}^H h_k|^2$ and $|\bar{h}_{d,k} + v_s^H \bar{q}_k|^2 = |\tilde{v}^H \bar{h}_k|^2$, where $\tilde{v}^H = [1 \hspace{1cm} v_s^H]$, $h_k^H = [h_{d,k}^H \hspace{1cm} v_s^H]$ and $\bar{h}_k^H = [\bar{h}_{d,k}^H \hspace{1cm} \bar{q}_k^H]$. Define $\mathbf{H}_k = h_k h_k^H$, $\bar{\mathbf{H}}_k = \bar{h}_k \bar{h}_k^H$, $\tilde{v}^H = \tilde{v} \bar{v}^H$, which needs to satisfy $\tilde{V} \succeq 0$ and rank$(\tilde{V}) = 1$. We thus have

$$|h_{d,k} + v_s^H q_k|^2 |\bar{h}_{d,k} + v_s^H \bar{q}_k|^2 = |\tilde{v}^H h_k|^2 |\tilde{v}^H \bar{h}_k|^2 = \text{tr} \left( \tilde{V} \bar{H}_k \tilde{V} \mathbf{H}_k \right).$$

(36)

As such, we can rewritten (35) as

$$\max_{\mathbf{v} \succeq 0} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( \sum_{i=0,i\neq k}^{K} P_i \tau_i \right) \text{tr} \left( \tilde{V} \bar{H}_k \tilde{V} \mathbf{H}_k \right)}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right)$$

s.t. $\tilde{V}_{m,m} = 1, m = 1, \ldots, M + 1,$

$$\text{rank}(\tilde{V}) = 1.$$  

(37b)

(37c)

Problem (37) is still non-convex due to the non-convexity of the objective function (37a) and rank-one constraint (37c). The key observation in (37) is that $\text{tr} \left( \tilde{V} \bar{H}_k \tilde{V} \mathbf{H}_k \right)$ is convex w.r.t. $\tilde{V}$, which motivates us to apply SCA technique to linearize it into a linear form. Specifically, for any given point $\tilde{V}^r$, we have the following lower bound

$$\text{tr} \left( \tilde{V} \bar{H}_k \tilde{V} \mathbf{H}_k \right) \geq \text{tr} \left( \tilde{V}^r \bar{H}_k \tilde{V}^r \mathbf{H}_k \right) + 2 \text{tr} \left( \bar{H}_k \tilde{V}^r \mathbf{H}_k \left( \tilde{V} - \tilde{V}^r \right) \right) \triangleq f_k \left( \tilde{V} \right), k \in K_2,$$

(38)

where the right-hand-side of (38) is linear w.r.t $\tilde{V}$.

With (38), problem (37) is approximated as

$$\max_{\mathbf{v} \succeq 0} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( \sum_{i=0,i\neq k}^{K} P_i \tau_i \right) f_k \left( \tilde{V} \right)}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right)$$

s.t. (37b), (37c).

(39a)

(39b)

Note that by removing the rank-one constraint (37c), problem (39) becomes a convex semidefinite programming (SDP) problem, which can be efficiently solved by the standard convex techniques.
However, the obtained $\tilde{V}$ may not be a rank-one solution. Although the Gaussian randomization technique can be applied to construct a rank-one solution from the obtained high-rank solution $\tilde{V}$, it may not be able to guarantee a locally and/or globally optimal solution, especially when the dimension of matrix $\tilde{V}$ is large [50]. To address this issue, we apply the DC optimization method to solve (39), which guarantees to converge to a KKT point [51]. The main idea behind of DC optimization method lies in the following equivalence

$$\text{rank} \left( \tilde{V} \right) = 1 \iff \text{tr} \left( \tilde{V} \right) - \left\| \tilde{V} \right\|_2 = 0, \quad (40)$$

which indicates that the rank-one constraint can be equivalently replaced by a DC framework. Adding $\text{tr} \left( \tilde{V} \right) - \left\| \tilde{V} \right\|_2$ as the penalty term in the objective function (39a), problem (39) can be transformed as

$$\max_{\tilde{V} \succeq 0} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \left( \sum_{i=0, i \neq k}^{K} P_i \tau_i \right) \tilde{f}_k \left( \tilde{V} \right)}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right) - \frac{1}{2\rho} \left( \text{tr} \left( \tilde{V} \right) - \left\| \tilde{V} \right\|_2 \right) \quad (41a)$$

subject to (37b),

$$\frac{1}{2\rho} \text{tr} \left( \left( I - \lambda H \left( \tilde{V}^r \right) \right) \tilde{V} \right) \quad (42a)$$

subject to (37b),

where $\rho$ is a penalty coefficient that is defined in (24). Since $\left\| \tilde{V} \right\|_2$ is convex w.r.t. $\tilde{V}$, we can apply SCA to linearize $\left\| \tilde{V} \right\|_2$. According to [52], for any given point $\tilde{V}^r$ in the rth iteration, by ignoring irrelevant terms w.r.t. $\tilde{V}$, we have the following lower bound

$$\max_{\tilde{V} \succeq 0} \sum_{k=1}^{K} \tau_k \log_2 \left( 1 + \frac{\eta_k \tilde{f}_k \left( \tilde{V} \right)}{\Gamma (\beta \gamma P_k + \sigma^2) \tau_k} \right) -$$

$$\frac{1}{2\rho} \text{tr} \left( \left( I - \lambda H \left( \tilde{V}^r \right) \right) \tilde{V} \right) \quad (42a)$$

subject to (37b),

where $\lambda H \left( \tilde{V}^r \right)$ denotes the eigenvector corresponding to the largest eigenvalue of $\tilde{V}^r$. It can be seen that both the objective function and constraints are convex, which thus can be efficiently solved by the standard convex optimization techniques [47]. By gradually decreasing $\rho$ and successively updating $\tilde{V}$ by solving (42), the convergence will be finally reached to obtain at least a locally optimal solution [51], [52].

**Remark 1:** Note that the above proposed DC optimization is irrespective of the HAP transmit power $P$ when it is fixed, it is thus applicable to the static IRS beamforming with perfect SIC. Therefore, we can solve problem (10) for perfect SIC similarly as in Algorithm 1 and for
imperfect SIC similarly as in Algorithm 2, with slight modifications, which are omitted here for brevity.

B. Phase Shift Optimization for Partially Dynamic IRS Beamforming

It can be observed that phase-shift vectors $v_d$ and $v_u$ in (9) are intricately coupled, which motivates us to alternately optimize each phase-shift vector. For the fixed $v_d$, it can be seen in the objective function of (9), two quadratic functions (i.e., $|h_{d,k} + v_u^H q_k|^2$ and $|ar{h}_{d,k} + v_u^H q_k|^2$) w.r.t. $v_u$ are multiplied together. As such, it can also be solved by the DC optimization method proposed in Section V-A. For the fixed $v_u$, there exists one quadratic function (i.e., $|h_{d,k} + v_d^H q_k|^2$) w.r.t. $v_d$, which can be solved by the SCA technique proposed in Section III-B.

Remark 2: Similarly, the combination of DC optimization and SCA techniques for phase shift optimization is also applicable to the partially dynamic IRS beamforming with perfect SIC. Therefore, we can solve (10) for perfect SIC similarly as in Algorithm 1 and for imperfect SIC similarly as in Algorithm 2, with slight modifications, which are omitted here for brevity.

VI. Numerical Results

In this section, we provide numerical results to demonstrate the effectiveness of the proposed algorithms and to provide useful insights for the IRS-aided FD-WPCN. We consider a system that operates on a carrier frequency of 750 MHz with the system bandwidth of 1 MHz and effective noise power density $-150$ dBm/Hz [33]. We assume that the IRS is equipped with a uniform rectangular array with $M = M_x M_z$ reflecting elements, where $M_x$ and $M_z$ denotes the numbers of reflecting elements along the $x$-axis and $z$-axis, respectively. We fix $M_x = 5$ and increase $M_z$ linearly with $M$. We assume that the antenna spacing is half of the wavelength, i.e., $\lambda/2 = 0.2$ m. A three dimensional coordinate setup is considered, where the HAP and the IRS are located at $(0, 0, 0)$, $(10 \text{ m}, 0, 2.5 \text{ m})$ measured in meter (m), while the devices are uniformly and randomly distributed in a circle centered at $(10 \text{ m}, 0, 0)$ with a radius 1.5 m. The distance-dependent path loss model is given by $L(d) = c_0 (d/d_0)^{-\alpha}$, where $c_0 = (\lambda/(4\pi))^2$ is the path loss at the reference distance $d_0 = 1$ m, $d$ is the link distance, and $\alpha$ is the path loss exponent. We assume that the HAP-IRS link, the IRS-device link, and the HAP-device link follow Rician fading with a Rician factor of 3 dB. In addition, the path loss exponents for the HAP-IRS link, the IRS-device link, and the HAP-device link are set as 2.2, 2.2, and 2.6,
respectively. Unless otherwise specified, we set $T = 1 \text{ s}$, $\beta = -60 \text{ dB}$, $\Gamma = 9.8 \text{ dB}$, $\rho = 100$, $c = 0.85$, $\varepsilon = \varepsilon_1 = 10^{-2}$, and $\varepsilon_2 = 10^{-5}$.

A. Fully Dynamic IRS Beamforming

In this subsection, we study fully dynamic IRS beamforming and compare the IRS-aided FD-WPCN with several benchmarks in terms of throughput under different setups such as device scheduling, transmit power $P$ and the number of IRS reflecting elements $M$.

Before discussing the system performance of the IRS-aided WPCN, we first verify the effectiveness of penalty-based Algorithm 2 for the dynamic IRS beamforming with imperfect SIC. The constraint violation and convergence behaviour of Algorithm 2 for one snapshot with $P_{\text{max}} = 30 \text{ dBm}$ with the different number of IRS reflecting elements $M$, namely, $M = 20$, $M = 40$, and $M = 60$, are plotted in Fig. 3. From Fig. 3(a), it is observed that constraint violation $\xi$ converges very fast with the value decreasing to predefined accuracy $10^{-5}$ after about 53 iterations for $M = 20$, which indicates that the equality constraint (23b) in problem (23) can be eventually satisfied. Even for $M = 60$, only about 65 iterations are required for reaching the violation predefined accuracy, which again demonstrates its effectiveness. Note that there exists fluctuations of the penalty violation in the initial few iterations. This is mainly because when the initial penalty $\rho$ is relatively large, the solution obtained by the penalty-based algorithm does not satisfy the equality in (23b). While as $\rho$ decreases with the iteration number increases, the penalty violation $\max_{k \in K_2} \{|z_k - \Gamma (\beta \gamma P_k/\sigma^2 + 1)|\}$ is forced to approach the predefined accuracy $\varepsilon_2 = 10^{-5}$. As such, the penalty-based algorithm is guaranteed to converge finally. This can also
be observed more clearly in Fig. 3(b), where the penalized objective values of (24) obtained by different $M$ all increase quickly with the number of iterations and finally converge.

1) Effect of device scheduling: In Fig. 4, we study the impact of device scheduling on the sum throughput of the IRS-aided FD-WPCN. We consider two scheduling schemes: (a) increasing order of SNR, where the device with the highest SNR of the HAP-device link is scheduled to transmit first; (b) decreasing order of SNR, where the device with the lowest SNR of the HAP-device link is scheduled to transmit first. In addition, we also study the effects of scheduling under different setups, such as $\gamma$ and the number of reflecting elements $M$, on the system performance. It is observed from Fig. 4 that the sum throughput obtained by all schemes increases when the HAP transmit power budget $P_{\text{max}}$ increases. The performance gap between increasing order and decreasing order for perfect SIC case is negligible, even $M$ is large. For imperfect SIC, the increasing order scheduling scheme still achieves a negligible sum throughput compared to the decreasing order scheduling scheme, even for $M = 40$. This indicates that the scheduling order is not significant in the considered system model. As such, we adopt the increasing order scheduling as our scheduling strategy in the following simulations.

2) Effect of HAP transmit power: In Fig. 5, we compare the sum throughput obtained by all schemes versus $P_{\text{max}}$ with $K = 10$ and $M = 40$. In order to show the performance of IRS-aided FD-WPCN, we adopt the following schemes for comparison: (a) Perfect SIC: we study four cases, namely, “FD, No SI”, “FD, No SI, Fixed time”, “FD, No SI, Random phase”, and “FD, No SI, without IRS”. For “FD, No SI”, this is our proposed scheme by jointly optimizing the phase shifts and the time allocation, which is solved by Algorithm 1; For “FD, No SI,
For perfect SIC case, our proposed scheme outperforms than other schemes, which demonstrates the benefits of joint optimization of phase shifts and time allocation. In addition, it can be seen that the IRS with random phase achieves nearly the same performance as the case without IRS since the reflected signal is dissipated by the random phase adjustment at the IRS. Besides, for perfect SIC and imperfect SIC with $\gamma = -65$ dB, both of them outperform the IRS-aided HD-WPCN, which shows the superiority of IRS-aided FD-WPCN over the IRS-aided HD-WPCN if the SI is well suppressed. When $\gamma = -55$ dB, the IRS-aided FD-WPCN outperforms the IRS-aided HD-WPCN only when $P_{\text{max}}$ is smaller than about 27 dBm, but performs worse when $P_{\text{max}}$ becomes larger. This is because that as $P_{\text{max}}$ increases, a strong SI is imposed on the HAP receiver side and thus will degrade the system performance.

3) Effect of number of reflecting elements: In Fig. 6, we compare the sum throughput obtained by all schemes versus $M$ with $P_{\text{max}} = 30$ dBm and $K = 10$. It is observed that the sum throughput of the schemes with IRS phase optimization monotonically increases with $M$ since
more reflecting elements help achieve higher passive beamforming gain, which is beneficial for both DL WET and UL WIT. In addition, we can observe that for perfect SIC, the performance gap between the FD-WPCN with IRS and the FD-WPCN without IRS is magnified as $M$ increases. This is because the signal reflected by the IRS towards the desired devices becomes more focused with increasing $M$. In addition, the FD-WPCN with random IRS phase shifts outperforms that without IRS when $M$ becomes large, since the IRS is able to reflect some of the dissipated signals back to the desired devices. Furthermore, it is observed that the SIC plays a key role in the system performance. For example, the IRS-aided FD-WPCN with $\gamma = -65$ dB significantly outperforms the IRS-aided HD-WPCN in terms of sum throughput, especially when $M$ becomes large, the performance gap will be more pronounced. However, when $\gamma = -55$ dB, the achievable sum throughput of the IRS-aided FD-WPCN is smaller than that of the IRS-aided HD-WPCN. This indicates that the IRS-aided FD-WPCN is superior over the IRS-aided HD-WPCN when the effective SIC can be implemented.

**B. Dynamic versus Static IRS Beamforming**

In this subsection, we compare three types of IRS beamforming configurations in terms of sum throughput. In Fig. 7, we study the effect of the number of devices $K$ with $P_{\text{max}} = 30$ dBm and $M = 40$ on the system performance for both IRS-aided FD-WPCN and IRS-aided HD-WPCN. We can see that the sum throughput obtained by all the schemes increases as $K$ increases. This can be readily shown as follows. Denote $\{\tau^{\text{opt}}_k, k \in \mathbb{K}_K\}$, $\{P^{\text{opt}}_k, k \in \mathbb{K}_K\}$, and $\{v^{\text{opt}}_k, k \in \mathbb{K}_K\}$ as the optimal time allocation, transmit power, and phase shifts for $K$ devices. When the number of devices becomes $K + 1$, $\{\tau^{\text{opt}}_k \cup \tau^{\text{opt}}_{K+1}, k \in \mathbb{K}_K\}$, $\{P^{\text{opt}}_k \cup P^{\text{opt}}_{K+1}, k \in \mathbb{K}_K\}$, and $\{v^{\text{opt}}_k \cup v^{\text{opt}}_{K+1}, k \in \mathbb{K}_K\}$ with $\tau^{\text{opt}}_{K+1} = P^{\text{opt}}_{K+1} = 0$ are the feasible solutions for the $K + 1$ devices and achieve the same objective value compared to the $K$ devices case. This shows that the objective value obtained with the $K$ devices case serves as a lower bound for that of the case with $K + 1$ devices, and thus a higher sum throughput is achieved when $K$ becomes large.

In addition, several interesting insights are obtained. First, it is observed that for the perfect SIC, the performance gap between our proposed scheme and the fully dynamic IRS beamforming without time allocation optimization scheme increases with the increasing of $K$. In particular, when $K = 2$, the performance gap between two schemes is negligible, while for $K = 12$, the performance gap becomes significant. This indicates that the time allocation plays an important role when $K$ is large. Second, if the SI is well suppressed, e.g., $\gamma = -65$ dB, the performance
gap between HD and FD will be remarkably enlarged as $K$ becomes large. This implies that the effective SIC is indeed needed in practical applications. Third, it is observed that for the perfect SIC case, when $K \leq 4$, the partially dynamic IRS beamforming scheme achieves only a slight higher performance gain than the static IRS beamforming scheme, while the performance gap is even negligible when $K \geq 4$. This can be explained as follows. As $K$ is small, which indicates that the number of time slots for energy harvesting during UL WIT is small and the dedicated DL WET time slot plays a important role in improving system performance. As such, an exclusive IRS phase-shift vector set for DL WET will significantly improve the harvested energy of the devices. For the extreme case where $K = 1$, the dedicated DL WET time slot must be required, since otherwise, no energy can be harvested. Similar results can also be obtained for the case with imperfect SIC.

In Fig. 8, we study the sum throughput versus $M$ for the three types of the IRS beamforming configurations with $P_{\text{max}} = 30$ dBm and $K = 10$. First, it is observed that for the FD-WPCN with perfect SIC, the fully dynamic IRS beamforming case outperforms both partially dynamic and static IRS beamforming cases. This is expected since for former, the IRS is able to proactively generate artificial time-varying channels over each time slot to adapt to WET and WIT so as to improve the system performance. We also find that the static IRS beamforming case is able to achieve the same performance compared to the partially dynamic IRS beamforming case since the duration of DL WET time slot is almost zero if $P_{\text{max}}$ is sufficiently large. This conclusion is similar to the FD-WPCN without IRS derived in Corollary 3.1 of [11]. This unveils us that the dedicated DL WET stage and the DL IRS phase shift optimization are not needed in practice if $P_{\text{max}}$ is sufficiently large. For the FD-WPCN with imperfect SIC, we can obtain similar results. However, the results do not hold for the HD case. It is observed that the HD with partially dynamic IRS beamforming outperforms that with static IRS beamforming, and the performance gap becomes significant when $M$ is large. This can be explained as follows. Due to the adopted harvest-then-transmit protocol for the HD case, the dedicated DL WET time slot must be needed, i.e., $\tau_0 \neq 0$, since otherwise, no energy can be used for UL WIT. This indicates that the IRS phase shift optimization is beneficial for improving DL WET. In addition, for the partially dynamic IRS beamforming case, there are additional degrees of freedom of IRS phase shift optimization for UL WIT, thereby improving the UL throughput. Finally, we can observe that the IRS-aided FD-WPCN is able to achieve higher throughput compared to the IRS-aided HD-WPCN, which again demonstrates the benefits of exploiting both IRS and FD in the WPCN.
VII. CONCLUSION

In this paper, we proposed three types of IRS beamforming configurations for IRS-aided FD-WPCN, which strike a balance between the system performance and signaling overhead as well as implementation complexity. The sum throughput maximization problems for the three cases are formulated by jointly optimizing the time allocation, the HAP transmit power, and IRS phase shifts. We first investigated the fully dynamic IRS beamforming optimization with perfect SIC and proposed an efficient AO algorithm. Then, we extended it to the case with imperfect SIC and proposed a penalty-based algorithm. We also studied partially dynamic IRS beamforming and static IRS beamforming, and extended the proposed AO and penalty algorithms based on the DC framework optimization and SCA techniques. Simulation results demonstrated the benefits of the IRS for enhancing the performance of the FD-WPCN, especially when the fully dynamic IRS beamforming is adopted, and also showed that the IRS-aided FD-WPCN is able to achieve significantly performance gain compared to the IRS-aided HD-WPCN when the SI is well suppressed. The results in this paper can be further extended by considering multiple IRSs, frequency-selective channel model, imperfect CSI, etc., which will be left as future work.

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