Active IRS Aided WPCNs: A New Paradigm Towards Higher Efficiency and Wider Coverage

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Abstract—This paper considers an active intelligent reflecting surface (IRS)-aided wireless powered communication network (WPCN), where devices first harvest energy and then transmit information to a hybrid access point (HAP). Different from the existing works on passive IRS-aided WPCNs, this is the first work that introduces the active IRS in WPCNs. To guarantee the fairness, the problem is formulated as an amplifying power-limited weighted sum throughput (WST) maximization problem, which is solved by successive convex approximation technique and fractional programming alternatively. To balance the performance and complexity tradeoff, three beamforming setups are considered at the active IRS, namely user-adaptive IRS beamforming, uplink-adaptive IRS beamforming, and static IRS beamforming. Numerical results demonstrate the significant superiority of employing active IRS in WPCNs and the benefits of dynamic IRS beamforming. Specifically, it is found that compared to the passive IRS, active IRS not only improves the WST greatly, but also is more energy-efficient and can significantly extend the transmission coverage. Moreover, different from the symmetric deployment strategy of passive IRS, it is more preferable to deploy the active IRS near the devices.

Index Terms—active IRS, WPCN, dynamic beamforming.

I. INTRODUCTION

Intelligent reflecting surface (IRS) is a promising technology to enhance the performance of wireless powered communication networks (WPCNs) due to its ability to reshape the wireless propagation channels [1], [2], [3]. However, despite an asymptotic squared power gain brought by an IRS [4], the actual capacity gains for an IRS with hundreds of passive reflection elements (REs) is negligible when the direct link is not weak because of the “double fading” effect in IRS-aided cascaded channel [5]. Specifically, the equivalent path loss of the transmitter-IRS-receiver link is the product of the path losses of the transmitter-IRS link and IRS-receiver link, thus making the cascaded channel several orders of times worse than that of the direct link [5], [6]. Thanks to the recent advances in circuit manufacturing, a new type of IRS, i.e., active IRS, which is able to amplify the reflected signal’s amplitude by a low-cost set of active-load impedances, has recently been proposed to overcome the double-fading issue of conventional passive IRS [6], [7], [8].

It is demonstrated in [6], [7] that the higher downlink throughput of the active IRS-aided system is achieved with a modestly increased hardware cost and additional amplifying power budget. Since the energy consumption is a crucial issue in WPCNs, we are interested about whether deploying active IRS outperforms deploying passive IRS or not in terms of throughput performance. On the other hand, as revealed in [9], [10], for passive IRS-aided WPCNs, the uplink (UL)-adaptive scheme is equivalent to the static IRS beamforming scheme, which halves the number of IRS phase shifts (PSs) to be optimized and the signalling overhead practically required for the UL-adaptive scheme. However, for active IRS, the amplitude of the RE can also be adjusted smartly in addition to the PSs, which provides new degrees of freedom and imposes additional amplifying power constraints for system optimization. Therefore, whether the aforementioned conclusion still holds remains an open question when introducing active IRS in WPCNs.

Motivated by the above, in this paper we investigate an active IRS aided WPCN where an active IRS is deployed to assist the downlink (DL) wireless energy transmission (WET) and UL wireless information transmission (WIT) between a hybrid access point (HAP) and multiple devices, as shown in Fig. 1. To the best of our knowledge, this is the first work that introduces the active IRS in WPCNs. To guarantee the fairness, we aim to maximize the weighted sum throughput (WST) of all devices via jointly optimizing the resource allocation and the reflection coefficient matrix, subject to the new amplifying power and amplifying amplitude constraints at the active IRS. In particular, to trade off between the practical performance and implementation complexity, we investigate three beamforming setups at the active IRS, namely user-adaptive IRS beamforming, UL-adaptive IRS beamforming, and static IRS beamforming, as elaborated later.

Note that different from the existing works on passive IRS [9], the ability to amplify the incident signal for active IRS brings new degrees of freedom, which adds the variables to be optimized. Besides, the additional constraints of amplifying power budget and the maximum amplifying amplitude at the active IRS further increase the difficulty and complexity for IRS beamforming optimization. Moreover, in passive IRS-aided WPCNs, the energy harvested from the noises is usually ignored since it is extremely low. However, due to the use of active amplifying REs at the IRS, the thermal noises introduced by active REs are amplified in the meantime and thereby cannot be ignored as that in passive IRS-aided WPCNs. Specifically, in DL WET, the wireless-powered devices can harvest the additional energy from the amplified noise power; whereas in UL WIT, the active REs’ reflecting coefficients have to balance the two conflicting goals to maximize the
communication throughput, i.e., the received signal power maximization and the noise power minimization. Therefore, the joint design of resource allocation and IRS beamforming in the considered active IRS aided WPCNs is much more challenging than its counterpart in conventional passive IRS-aided WPCNs, thus calling for non-trivial efforts.

To solve the formulated WST maximization problem, we decompose the coupled joint optimization into two subproblems and propose an alternating optimization (AO)-based algorithm, where successive convex approximation (SCA) technique and fractional programming (FP) are utilized to solve the two subproblems respectively. Numerical results reveal that employing the active IRS in WPCNs performs much better than its passive IRS counterpart and validate the advantage of dynamic IRS beamforming, which is different from the conclusion in [9]. Specifically, it is found that: 1) Active IRS can improve the WST significantly by alleviating the double-fading effects suffered by passive IRS; 2) Even less transmit energy and amplifying energy is required to achieve the higher throughput and/or the larger coverage with the assist of the active IRS; 3) Different from the symmetric deployment strategy for passive IRS, the joint design of resource allocation and IRS beamforming is more challenging than its counterpart in conventional passive IRS-based systems.

Different from the existing passive IRS architecture, we consider that the IRS is supported by an external power source, and thus the REs in the IRS can exploit the active loads to amplify the incident signal so as to alleviate the double-fading attenuation [6], [7]. In particular, the reflecting coefficient of the \(n\)-th RE at the IRS is denoted by \(\phi_0,n = a_0,n e^{j\theta_0,n}, \forall n \in \mathcal{N} \triangleq \{1, \ldots, N\}\), where \(a_0,n \in [0, a_{\max}]\) and \(\theta_0,n \in [0, 2\pi]\) represent the amplitude and the PS of \(\phi_0,n\), respectively [6]. The amount of harvested energy at device \(k\) during DL WET is thereby expressed as

\[
E_k(\nu_0) = \tau_0 \eta \left( P_k |h_{d,k}^H + b_{0,k}^H \nu_0^2| + \sigma_0^2 |v_{Q_2,k}^H \nu_0| \right),
\]

where \(Q_{2,k} \triangleq \text{diag}([|h_{r,k}|^2, \ldots, |h_{r,k}|^N]^T)\) and \(\eta \in (0, 1]\) is the energy conversion efficiency of the devices.

For UL WIT, each device transmits its own information signal to the HAP for a duration of \(\tau_k\) with transmit power \(p_k\). In the following, we investigate three cases of IRS beamforming setups, namely the user-adaptive IRS beamforming, UL-adaptive IRS beamforming and static IRS beamforming, depending on how the active IRS reconfigures its REs over time during UL WIT.

III. PROBLEM FORMULATION

To guarantee the fairness, we aim at maximizing the WST of the considered WPCN by jointly optimizing the IRS coefficient matrix, the time allocation and the transmit powers.

1) For the user-adaptive IRS beamforming case, the active IRS is allowed to reconfigure its reflecting vectors \(K\) times in UL WIT and each vector is dedicated to one device. The achievable throughput of the \(k\)-th device in bits/Hz is computed as

\[
\tau_k(\tau_k, p_k, \nu_k) = \tau_k \log_2 \left( 1 + \frac{p_k |h_{d,k}^H + b_{0,k}^H \nu_k^2|}{\sigma_0^2 |v_{Q_2,k}^H \nu_k| + \sigma_2^2} \right).
\]

where \(Q_1 \triangleq \text{diag}([|g_1|^2, \ldots, |g|^N]^T)\), \(p_k\) and \(\nu_k \triangleq [\phi_{k,1}, \ldots, \phi_{k,N}]^H\) are the transmit power and the IRS beamforming vector of the \(k\)-th device during \(\tau_k\) in UL WIT, respectively.

The problem can be accordingly formulated as

\[
(P_{UE}) \quad \max_{\tau_k, (p_k), (\nu_k)} \sum_{k=1}^{K} \omega_k \tau_k(\tau_k, p_k, \nu_k)
\]

s.t. \(p_k \tau_k \leq \tau_0 \eta (P_k |h_{d,k}^H + b_{0,k}^H \nu_0^2| + \sigma_0^2 |v_{Q_2,k}^H \nu_0|), \forall k, (4a)\)

\(P_k^H Q_1^H \nu_0 + \sigma_0^2 |v_{Q_2,k}^H \nu_0^2| \leq P_k, (4b)\)

\(p_k v_{Q_2,k}^H \nu_k + \sigma_0^2 |v_{Q_2,k}^H \nu_k| \leq P_k, \forall k, (4c)\)

\(\tau_0 + \sum_{k=1}^{K} \tau_k \leq T_{\text{max}}, (4d)\)

\(\tau_0 \geq 0, \tau_k \geq 0, p_k \geq 0, \forall k, (4e)\)

\(a_{t,n} \leq a_{\max}, \quad t = 0, 1, \ldots, K, \quad \forall n \in \mathcal{N}. (4f)\)

In \((P_{UE}), (4f)\) represents the energy causality constraints. \((4b)\) and \((4c)\) are the IRS amplifying power constraints for DL WET and UL WIT, respectively. \((4f)\) is the total time constraints. \((4b)\) and \((4c)\) are non-negativity constraints. \((4b)\) are the amplitude constraints of the active REs. It can be seen that, by employing active IRS, the amplitude and PS of the reflecting coefficient vectors \(\nu_0\) and \(\{\nu_k\}\) need to be optimized in the meantime, and they are coupled with \(\tau_0, \{\tau_k\}\) and \(\{p_k\}\) in the objective as well as the constraint \((4f)\) and \((4c)\). Therefore,
problem (4) is a challenging non-convex optimization problem and difficult to solve optimally in general.

2) For UL-adaptive IRS beamforming case, all the devices share the common IRS coefficient vector in UL WIT, i.e., $v_1 = \cdots = v_K$. The corresponding problem can be formulated similarly to (5) as

\[
(P_{UL}) : \max_{r_0, \{r_k\}, \{p_k\}, v_0} \sum_{k=1}^{K} \omega_k r_k (\tau_k, p_k, v_1)
\]

s.t. $p_k v_k^H Q_{2,k} v_1 + \sigma_n^2 v_1^H v_1 \leq P_k, \forall k$, $a_{t,n} \leq a_{\max}$, $t = 0, 1$, $\forall n \in N$, (5) \[1\), \[2\), \[3\), \[4\].

3) For static IRS beamforming case, all the devices need to share the same IRS coefficient vector as that in DL WET, i.e., $v_0 = v_1 = \cdots = v_K$. Accordingly, the problem is formulated as

\[
(P_{ST}) : \max_{\tau_0, \{\tau_k\}, \{p_k\}, v_0} \sum_{k=1}^{K} \omega_k \tau_k (\tau_0, \tau_k, p_k, v_0)
\]

s.t. $p_k v_0^H Q_{2,k} v_0 + \sigma_n^2 v_0^H v_0 \leq P_k, \forall k$, $a_{0,n} \leq a_{\max}$, $\forall n \in N$, (5) \[1\), \[2\), \[3\), \[4\).

Remark 1: Denote the optimal objective of (P_{UL}), (P_{UL}) and (P_{ST}) as $R_{UL}^*$, $R_{UL}^*$ and $R_{ST}^*$, respectively. For passive IRS-aided WPCNs, it was shown in [9] that $R_{UL}^* \geq R_{UL}^* = R_{ST}^*$, and thus the number of IRS Ps to be optimized can be saved for UL-adaptive IRS beamforming [9]. However, due to the new design flexibility and amplifying power/amplitude constraints imposed by the active IRS, $R_{UL}^* = R_{ST}^*$ does not hold anymore. Specifically, let us take the single device’s case for illustration. For the UL-adaptive IRS beamforming, to maximize the harvesting energy in DL WET, by utilizing the Cauchy-Schwarz inequality we can derive the optimal $a_{0,n}$ as $a_{0,n}^* = \min \left\{ \frac{1}{\left| |g_{0,n}|^2 + |h_{0,n}|^2 \right|}, a_{\max} \right\}$, where $c_0^2 = P_k / \sum_{n=1}^{N} \left( \frac{P_k}{|g_{0,n}|^2 + |h_{0,n}|^2} \right)$. Similarly, to maximize the achievable throughput, the optimal $a_{1,n}$ is given by $a_{1,n}^* = \min \left\{ \frac{1}{\left( |g_{0,n}|^2 + |h_{0,n}|^2 \right)}, a_{\max} \right\}$, where $c_1^2 = P_k / \sum_{n=1}^{N} \left( \frac{1}{|g_{0,n}|^2 + |h_{0,n}|^2} \right)$. Obviously $a_{0,n}^* \neq a_{1,n}^*, \forall n \in N$. Therefore, we have $v_0^* \neq v_1^*$, which validates the necessity of UL-adaptive IRS beamforming in active IRS-aided WPCNs. In addition, among the three cases, (P_{ST}) is the most challenging problem to solve, since $v_0$ in (P_{ST}) is not only coupled in all devices’ achievable throughput in the objective function but also in the energy harvesting constraints (4b), as well as the amplifying power constraints for DL WET and UL WIT, i.e., (4b) and (5), respectively. Nevertheless, we propose efficient algorithms to solve the three problems in the following sections.

IV. PROPOSED SOLUTION FOR (P_{UL})

For the problem of employing user-adaptive IRS beamforming, i.e., (P_{UL}), to simplify the highly coupled non-convex optimization problem, the original problem is first decomposed into two subproblems and then solved separately in an alternative manner.

A. Optimizing $\tau_0, \{\tau_k\}, \{p_k\}$ and $v_0$ with the given $\{v_k\}$

For a given set of $\{v_k\}$, the signal-to-interference-plus-noise ratio (SINR) of each device is a constant, which is denoted as $\gamma_k(v_k) \triangleq |h_{d,k}^H + b_k^H v_k|^2 / (\sigma_n^2 + \sigma_2^2 v_k^H Q_k v_k).$ To proceed, we introduce a new set of variables $\{f_k\}$, where $f_k = p_k \tau_k, \forall k$, and $W_0 = \tau_0 v_0$, where $v_0 = v_0^* v_0^H$ and $v_0 = [v_0^H, 1]^H$, which needs to satisfy $W_0 \geq 0$ and rank($W_0$) = 1. Note that $\text{Tr}(W_0) = \tau_0 v_0^H v_0 - 1$. Then the subproblem can be reformulated as

\[
\max_{\tau_0, \{\tau_k\}, \{p_k\}, W_0} \sum_{k=1}^{K} \omega_k \tau_k \log_2 \left[ 1 + \gamma_k(v_k) f_k / \tau_k \right]
\]

s.t. $f_k + \eta \tau_0 \sigma_n^2 \leq \eta \text{Tr}(P_k B_k + \sigma_n^2 \tilde{Q}_k) W_0$, $\forall k$, (7) \[A\), \[B\), \[C\).

B. Optimizing $\{v_k\}$ with the given $\tau_0, \{\tau_k\}, \{p_k\}$ and $v_0$

For this subproblem, the optimal $\{v_k\}$ can be independently obtained by solving $K$ subproblems in parallel, each with only one reflecting coefficient vector. Specifically, for $v_k$, the optimal solution can be obtained by maximizing the SINR $\gamma_k(v_k).$ To deal with this fraction-formed objective, we utilize FP in [13] by introducing an auxiliary variables $\iota_k$. Then the subproblem is equivalent to the following problem

\[
\max_{v_k, \iota_k} 2 \Re \{ f_k (h_{d,k}^H + b_k^H v_k) \} - |\iota_k|^2 (\sigma_n^2 v_k^H Q_k v_k + \sigma_2^2 v_k^H v_k)
\]

s.t. \[A\), \[B\), \[C\).

which can be solved by alternately optimizing $\iota_k$ and $v_k$ until the objective converges. Specifically, the optimal $\iota_k$ can be obtained by setting its first-order derivative to zero, which is given by

\[
\iota_k = \frac{(h_{d,k}^H + b_k^H v_k)}{\sigma_n^2 v_k^H Q_k v_k + \sigma_2^2 v_k^H v_k}
\]

(9)

Then the optimal $v_k$ can be obtained by solving problem (8) with the updated $\iota_k$, which is a quadratically constrained quadratic program (QCQP) problem and can also be solved with interior-point algorithm.

C. Convergence and Complexity Analysis

The convergence of this AO-based algorithm is ensured since the objective value of problem (4) is non-decreasing over the iterations and the maximum objective value is upper bounded by a finite value. The computational complexity of the proposed algorithm for (P_{UL}) is given by $O(I_{AO} \ln(1/\varepsilon) m \sqrt{AK} + 2 N (AK + N^3 + m (AK + N^2 + N))$.
where $v$ we turn to optimize which can be formulated as the following convex problem.

Equation (10)

$\max_{v_1(\chi_k), \tau_k} \sum_{k=1}^{K} \omega_k \tau_1 \log_2 (1 + \chi_k) - \omega_k \tau_1 \chi_k + u_k(v_1, \chi_k, \tau_k)$

subject to

$\omega_1, \omega_\ell \leq \omega_\max, \quad \forall n \in \mathcal{N}.$

where $u_k(v_1, \chi_k, \tau_k) \triangleq 2R \left\{ \ell_k \sqrt{\omega_1 \tau_1 (1 + \chi_k) p_k (h_{d,k}^H + b_k^H v_1)} - |v_k|^2 (p_k |h_{d,k}^H + b_k^H v_1|^2 + \sigma_{\text{n}_k}^2 v_k Q_1 v_1 + \sigma_{\text{e}_k}^2) \right\}.$

Equation (11)

After optimizing $\tau_0, \tau_1, \{p_k\}$ and $v_0$ with the given $v_1$, we turn to optimize $v_1$ with the given $\tau_0, \{\tau_k\}, \{p_k\}$ and $v_0$. Note that instead of the fraction-formed objective as for the second subproblem in $\mathcal{P}_{\text{UL}}$, now we have to deal with the sum of logarithm function and fractions in the objective. Still, FP method can be used to tackle with this problem.

Concretely, by introducing two auxiliary sets of variables $\{\chi_k\}$ and $\{\ell_k\}$, the subproblem is equivalent to

Equation (12)

Equation (13)

Equation (14)

Equation (15)

Equation (16)

Equation (17)

Equation (18)

For the subproblem of optimizing $v_0$ with the given $\tau_0, \{\tau_k\}$ and $\{p_k\}$, the objective can be reformulated similarly as given in (10), except replacing $v_1$ with $v_0$, which is given by

$$\max_{v_0(\chi_k)} \sum_{k=1}^{K} \omega_h \tau_1 \log_2 (1 + \chi_k) - \omega_h \tau_1 \chi_k + u_h(v_0, \chi_k, \ell_k)$$

subject to

$$f_k \leq E_k(v_0), \quad \forall k,$$

Equation (19)

where $u_k(v_0, \chi_k, \ell_k)$ is as given in (11), $\{\chi_k\}$ and $\{\ell_k\}$ are updated by (12) and (13), respectively.

Notice that the right-hand-side of the constraint (16) is a convex function with respect to $v_0$, thus is globally lower-bounded by its first-order Taylor expansion at the fixed point $v_0$, which is given by

$$P_\ell |h_{d,k}^H + b_k^H v_0|^2 + \sigma_{\text{n}_k}^2 v_k Q_2 k v_0 \geq - \sigma_{\text{n}_k}^2 v_k Q_2 k v_0 + 2 \sigma_{\text{n}_k}^2 \Re \{ v_k Q_2 k v_0 \} - P_\ell |h_{d,k}^H + b_k^H v_0|^2$$

$$+ 2 P_\ell \Re \{ (h_{d,k}^H + b_k^H v_0)(h_{d,k}^H + b_k^H v_0) \} \triangleq q_k(v_0).$$

If $P_\ell |h_{d,k}^H + b_k^H v_0|^2 + \sigma_{\text{n}_k}^2 v_k Q_2 k v_0$ with $q_k(v_0)$ in constraint (16), the problem (15) turns into a QCQP problem and can be solved with interior-point algorithm.

To sum up, the computational complexity of solving $\mathcal{P}_{\text{ST}}$ with the proposed algorithm is $\mathcal{O}(I_{\text{AO}} \ln(1/\epsilon)(2K + 1)^{3.5} + I_{\text{FP}} 2 \sqrt{2K + N(N^3 + KN^2 + N^2 + KN^2)})$.

VI. SIMULATION RESULTS

We consider a WPCN with one HAP located at $(0, 0, 0)$ meter (m), one active IRS located at $(x_{\text{IRS}}, 0, 2)$ m, and $K$ devices which are randomly distributed in a circle centered at $(x_{\text{UE}}, 0, 0)$ m with a radius of 1 m. We adopt the path loss model in [14] and the path loss exponent is set to be 2.2 for $P_\ell$ and $h_{d,k}, \forall k$. For small scale fading, Rayleigh fading is adopted for $h_{d,k}, \forall k$. Whereas for $g$ and $h_{r,k}, \forall k$, Rician fading is adopted with a Rician factor of 10.

Other parameters are set as follows: $P_\ell = 20$ dBm, $P_\ell = 5$ dBm, $\sigma_{\text{n}_k}^2 = \sigma_{\text{e}_k}^2 = \sigma_{\text{n}_k}^2 = \sigma_{\text{e}_k}^2 = -90$ dBm, $T_{\text{max}} = 1$ s, $x_{\text{IRS}} = x_{\text{UE}} = 10$ m, $\eta = 0.8$, $K = 4$ and $N = 10$, if not specified otherwise. For the purpose of comparison, we consider the following schemes.

1) UE active: proposed algorithm for $\mathcal{P}_{\text{UE}}$; 2) UL active: proposed algorithm for $\mathcal{P}_{\text{UL}}$; 3) Static active: proposed algorithm for $\mathcal{P}_{\text{ST}}$; 4) UE passive: employing a passive IRS with the user-adaptive beamforming via the algorithm proposed in [9]; 5) UL/Static passive: employing a passive IRS with the static beamforming via the algorithm proposed in [9].

A. Active or Passive IRS for WPCNs?

In Fig. 2(a), we plot the achievable sum throughput of the IRS-aided WPCN system versus the HAP's transmit power $P_\ell$. For active IRS, we consider two cases with $A_{\text{max}} = 10$ and 25 dB [15]. It can be seen that employing the active IRS in WPCN performs much better than the traditional passive IRS-aided WPCN, and this performance gain is more significant when the HAP's transmit power $P_\ell$ is low and with larger constraint $A_{\text{max}}$, because the active RE can amplify the incident signal's amplitude and enhance the transmission links.

As for the three different beamforming strategies, it is shown that employing the UL-adaptive beamforming for the active IRS achieves an additional gain compared with employing...
static beamforming for the active IRS, which is different from the conclusion in [9], where these two beamforming setups have the same performance in the passive IRS-aided WPCN. This phenomenon results from the following two reasons. First, the active IRS amplifies the noise at the IRS, which can no longer be neglect in the optimization problem and brings an additional term in the constraint \(4(b)\). Second, the IRS amplification power constraints for DL WET and UL WIT, i.e., \(4(b)\) and \(4(c)\), respectively, further influence the symmetry of DL channels and the UL channels. Thus, the proof of Proposition 1 in [9] does not apply for the active IRS-aided WPCN. Besides, the performance gap is more significant when the constraint \(a_{\text{max}}\) is large, since \(a_{\text{max}}\) limits the amplification amplitude at the IRS and thereby reduces the achievable performance gain brought by the active IRS. This suggests that when \(a_{\text{max}}\) is large, employing more reconfigurable beamforming patterns at the active IRS can realize more performance gain. Whereas employing dynamic beamforming may not be necessary with the low \(a_{\text{max}}\) since the performance gaps of employing different IRS reflecting patterns are relatively small in this case.

Interestingly, we notice that employing static beamforming for the active IRS with \(a_{\text{max}} = 25\, \text{dB}\) performs distinguishably from the others, which presents an U-shaped curve as \(x_{\text{UE}}\) increases, which verifies the effectiveness of employing active IRS in WPCNs.

To gain more insights, we examine the effect of the deployment of IRS. Specifically, we plot the sum throughput versus the distance between the HAP and the center of the devices cluster, i.e., \(x_{\text{UE}}\), where IRS is deployed above the center of the devices cluster, i.e., \(x_{\text{UE}} = x_{\text{IRS}}\). It can be seen that, by using the active IRS, the transmission coverage improves greatly compared with employing passive IRS. For example, to achieve 4 bits/Hz throughput, the distance between the HAP and the center of the devices cluster cannot exceed 4 m. Whereas this distance is extended to 12 m with the help of active IRS when the amplification constraint is set as \(a_{\text{max}} = 10\, \text{dB}\). Moreover, the coverage can be further enlarged with a larger \(a_{\text{max}}\), which verifies the effectiveness of employing active IRS in WPCNs.

B. Coverage Extension and Asymmetric Deployment

In Fig. 2(c), we plot the sum throughput versus the distance between the HAP and the center of the devices cluster, i.e., \(x_{\text{UE}}\), where IRS is deployed above the center of the devices cluster, i.e., \(x_{\text{UE}} = x_{\text{IRS}}\). It can be seen that, by using the active IRS, the transmission coverage improves greatly compared with employing passive IRS. For example, to achieve 4 bits/Hz throughput, the distance between the HAP and the center of the devices cluster cannot exceed 4 m. Whereas this distance is extended to 12 m with the help of active IRS when the amplification constraint is set as \(a_{\text{max}} = 10\, \text{dB}\). Moreover, the coverage can be further enlarged with a larger \(a_{\text{max}}\), which verifies the effectiveness of employing active IRS in WPCNs.

Besides, we investigate the total energy consumption among the different schemes versus transmit power \(P_{\Lambda}\) in Fig. 2(b), where the parameters are the same as given in Fig. 2(a). Note that the total energy consumption with the passive IRS is calculated as \(E_{\text{passive}} = P_{\Lambda}\tau_{0}\). Whereas the total energy consumption with the active IRS is calculated as \(E_{\text{active}} = \tau_{0}P_{\Lambda} + \tau_{0}(P_{\Lambda}v_{0}^{2}Q_{1}v_{0} + \sigma_{v_{0}^{2}}v_{0} + \sum_{k=1}^{K}	au_{k}(p_{k}v_{k}^{2}Q_{2}v_{k} + \sigma_{v_{k}^{2}}v_{k})\). Surprisingly, employing passive IRS consumes more energy than that with the active IRS, due to a longer time is needed for DL WET, i.e., a larger \(\tau_{0}\) in passive IRS-aided WPCNs. This validates the superiority of utilizing active IRS compared with passive IRS, since the former one not only achieves higher throughput but also consumes less transmit/amplifying energy under the given setups.

VII. CONCLUSIONS

In this paper, we investigated the joint beamforming and resource allocation optimization for an amplifying power limited active IRS-aided WPCN. We considered three different beamforming setups and solved the corresponding WST maximization problems via SCA technique and FP method with AO-based algorithm. Numerical results not only demonstrated the significant superiority of adopting active IRS in WPCNs, but also validated the benefits of employing dynamic IRS beamforming. Particularly, it was found that by introducing active IRS, the WPCNs could achieve much higher throughput with less transmit/amplifying energy consumption compared to the passive IRS-aided WPCNs. Moreover, it was unveiled that the active IRS should be deployed near devices in practice.
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