Energy-Efficient Resource Allocation and Antenna Selection for IRS-Assisted Multicell Downlink Networks

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***Abstract*—This letter considers a network-assisted intelligent reflecting surface (IRS) technology. We aim to adopt an energy-efficient strategy via an antenna selection (AS) framework that determines which base station (BS) antennas transmit the data to the user equipment. In particular, we select the best set of antennas to increase energy efficiency (EE) while reducing power consumption. Also, the network takes advantage of the IRS system to increase the coverage and overall throughput of the network. We first propose an efficient algorithm for the considered scenario based on the successive convex approximation (SCA). Then we employ the Dinkelbach method that jointly selects the best set of antennas and optimizes their beamforming. Second, by introducing the slack variable and SCA method, we propose a tight approximation to solve the passive beamforming at the IRS. Simulation results unveil the performance of the proposed method and its influence on the power consumption at each antenna's RF chain.**

***Index Terms*—Intelligent reflecting surface (IRS), antenna selection (AS), energy efficiency (EE).**

I. Introduction

INTELLIGENT reflecting surface (IRS) recently has received significant attention as a promising technology for the sixth-generation (6G) cellular networks [1]. In particular, IRS consists of adjustable reflecting elements which can set the radio frequency (RF) signal reflection via controlling phase shifts [2].

There is a plethora of work that considers the IRS-assisted system. For example, the authors in [3] considered a multiple-input single-output (MISO) IRS-aided network. The authors performed the joint transmit beamforming and reflective beamforming at the BS and IRS to minimize the total transmit power. Since IRS operates in a full-duplex mode and is a passive element requiring low power consumption, it is a candidate solution to improve energy and spectral efficiencies. Regarding this, some recent works focused on improving the EE of the system. The authors in [4] considered a MISO IRS-aided multi-cell multi-user system intending to optimize the transmit beamforming and reflective beamforming, assuming the max-min SINR fairness concept. The authors in [5] considered a single-cell MISO IRS-aided simultaneous wireless information and power transfer (SWIPT) system where the power splitting (PS) was adopted to harvest energy. The authors in [6] investigated a resource allocation for an IRS-assisted MISO network that minimizes the transmit power considering both the beamforming vectors at the BS and phase shifts at the IRS while taking into account the minimum quality of service for each user. However, the above works considered the IRS-aided single base station (BS), in which the user association was not considered. Some works studied the user association (UA) in IRS-aided multi-BS to improve network performance by managing the interference. In [7], the authors examined joint BS-IRS-user association to maximize the utility of a multi-IRS aided wireless network. In [8], the authors designed IRS-UA to optimally balance the passive beamforming between different communication links for the BS-user via driving a lower bound based on the average signal to average interference plus noise ratio. In [9], the authors proposed the joint design of UA and passive beamforming in an IRS-aided heterogeneous network to maximize the weighted sum rate while considering statistical channel state information. The authors in [10] optimized both UA and reflecting beamforming to maximize the sum rate. However, the works in [9], [10] did not consider the power consumptions issue and RF chain concerns in real scenarios.

On the other hand, there are some practical issues in future networks based on the IRS-aided massive MIMO. For example, sharply focused energy beams need a large number of active radio frequency (RF) chains in transmit antennas [12]. Especially for the massive-MIMO-based networks, it is critical to activate or deactivate antennas in each BS based on a cost-effective algorithm that decreases the hardware complexity, the required signaling overhead, and energy consumption. The authors in [13] considered a hybrid network based on coordinated multipoint (CoMP) technology to maximize the throughput of the network in which the best cooperative set of antennas is selected.

However, some challenging issues still need to be addressed and lead to significant performance enhancement for IRS-assisted multi-cell systems. Specifically, since there is an essential algorithm to perform radio access network (RAN) moderation in such network, we consider this issue in IRS-assisted multi-cell networks. In this letter, we investigate a problem formulation to maximize the EE to facilitate

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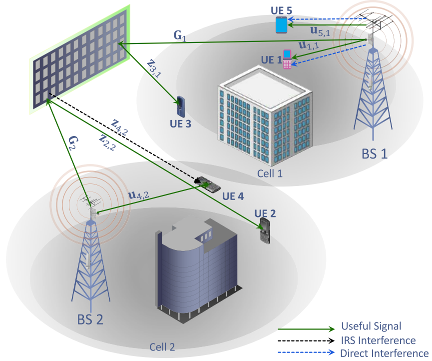

Fig. 1. An IRS-assisted multi-cell downlink network.

analyzing that all BSs antennas do not necessarily need to be activated. Hence, the proposed algorithm only activates a set of BS antennas that can boost the EE effectively based on the load of the network. In particular, the network is flexible enough to raise the sleep mode for the unnecessary antennas, which determines the proper solution regarding the data rate and energy consumption. To be more clear, this scenario considers the power consumption in the RF changes as well as the IRS system while providing the diversity for the network in an efficient manner. Furthermore, we demonstrate the efficiency of our proposed scenario where antenna selection (AS) can exploit for better utilization of limited resources. Finally, we compare the performance of our proposed method with three benchmark algorithms, i.e., [4], [10], and the random phase shift. The simulation results reveal that resource allocation and AS can increase the performance gain of the IRS-assisted multi-cell downlink networks.

Notations: The Hadamard product of two vectors is defined $\circ$ while the common matrix multiplication is presented by $*$. Moreover, the inner product of two vectors is represented by $\langle \mathbf{a}, \mathbf{b} \rangle$, and $\mathbf{B} \succeq 0$ indicates that $\mathbf{B}$ is a positive semidefinite (PSD) matrix. Furthermore, the Frobenius norm of the matrix and Euclidean norm of a vector are presented by $\|.\|_F$, $\|.\|$, respectively. Trace $[\mathbf{B}]$, $\mathbf{B}^H$ denote the trace matrix, the conjugate transpose of a matrix, respectively. The complex space of n-dimensional vectors is $\mathbb{C}^n$.

II. System Model

We consider the system model shown in Fig. 1 with N BSs whose indices are collected in set $\mathcal{N} = \{1, \ldots, N\}$, where each BS has T_n antennas. We define the set of user equipments (UEs) as $\mathcal{K} = \{1, \ldots, K\}$ and the set of users in the coverage area of the n^{th} BS is $\mathcal{K}_n$. Also, $\mathbf{G}_n \in \mathbb{C}^{T_n \times M}$ defines as the channel matrix between the BS n and the IRS with M reflecting elements. $\mathbf{u}_{k,n} \in \mathbb{C}^{T_n \times 1}$ and $\mathbf{z}_{k,n} \in \mathbb{C}^{M \times 1}$ are the channel vectors from the BS n and the IRS to the user k, respectively. Define $\boldsymbol{\theta} = \mathrm{diag}(e^{j\theta_1}, \ldots, e^{j\theta_M})$ as the reflection-coefficients matrix at the IRS where $\theta_m \in (0,\ 2\pi]$ is the phase shift of the m^{th} element at the IRS.[1] We assume that all BSs can use the IRS simultaneously where the IRS phase shifts are determined to increase the constructive effect for the critical users belonging to all cells. Besides, due to the orthogonal frequency division multiple (OFDM) technique, all the users located in the same cell experience the interference effect of the others in the same cell. Let us define $\boldsymbol{\rho}_{k,n} = [\rho^a_{k,n}] \in \mathbb{Z}^{T_n}$ where $\rho^a_{k,n}$ is an integer variable that characterizes that the a-th antenna of BS n, with cardinality of a being $|\mathcal{A}|$, are assigned to the user k in the case that $\rho^a_{k,n} = 1$, and otherwise, $\rho^a_{k,n} = 0$.

Consequently, the SINR of UE k is given by

$$\Gamma_{k,n} = \frac{|\mathbf{h}^H_{k,n}(\mathbf{w}_{k,n} \circ \boldsymbol{\rho}_{k,n})|^2}{\sum_{i \neq k, i \in \mathcal{K}_n} |\mathbf{h}^H_{k,n}(\mathbf{w}_{i,n} \circ \boldsymbol{\rho}_{i,n})|^2 + \sigma^2_{k,n}}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \quad (1)$$

where $\sigma^2_{k,n}$ is the noise power at the user k. We define $\mathbf{h}_{k,n} \triangleq \mathbf{u}_{k,n} + \mathbf{G}_n \boldsymbol{\Theta} \mathbf{z}_{k,n}$ and $\mathbf{w}_{k,n} \in \mathbb{C}^{T_n}$ represents the beamforming vector of the n^{th} BS to the k^{th} UE. We aim to design an algorithm for AS where each antenna can optionally be employed in the MISO transmission process for the k-th user in the massive MIMO communication.

III. Problem Formulation

Based on the proposed scenario, we consider the EE of the considered network that is the ratio between the total achievable rate and the total power consumption given as $\eta = R_{\mathrm{tot}}/P_{\mathrm{tot}}$, where the numerator and denominator are respectively given by

$$R_{\mathrm{tot}} = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \log_2(1 + \Gamma_{k,n}) = \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} r_{k,n}, \quad (2)$$

$$P_{\mathrm{tot}} = \sum_{n \in \mathcal{N}} P^{\mathrm{stc}}_n + \sum_{n=1}^{N} \sum_{a=1}^{T_n} (P^{\mathrm{ant}}_{a,n} \sum_{k \in \mathcal{K}_n} \rho^a_{k,n}) + \frac{1}{\zeta} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \|(\mathbf{w}_{k,n} \circ \boldsymbol{\rho}_{k,n})\|^2 + P^{\mathrm{IRS}}, \quad (3)$$

where P^{stc}_n is the static power required to support the basic circuit operations, $0 < \xi < 1$ denotes the efficiency of the power amplifier, and $P^{\mathrm{ant}}_{a,n}$ denotes the dissipated power per antenna. Also, $P^{\mathrm{IRS}} = P^{\mathrm{IRS}}_{\mathrm{stc}} + MP^{\mathrm{IRS}}_{\mathrm{dyc}}$ where $P^{\mathrm{IRS}}_{\mathrm{stc}}$ and $P^{\mathrm{IRS}}_{\mathrm{dyc}}$ are the required static power for the basic operations of the IRS circuit and the dynamic power for each reflecting component, respectively. The optimization problem for the considered network for improving the EE metric is given by[2]

$$\mathrm{P}_1\colon \max_{\mathbf{w}, \boldsymbol{\rho}, \boldsymbol{\Theta}} \ \eta$$

$$s.t.\colon \sum_{k \in \mathcal{K}} \|(\mathbf{w}_{k,n} \circ \boldsymbol{\rho}_{k,n})\|^2 \leq P^n_{\max}, \forall n \in \mathcal{N}, \quad (4a)$$

$$\sum_{k \in \mathcal{K}} \rho^a_{k,n} \leq L_a, \forall a \in \mathcal{A}, \forall n \in \mathcal{N} \quad (4b)$$

$$\sum_{a \in \mathcal{A}} \rho^a_{k,n} \leq a_{\max}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \forall a \in \mathcal{A}, \quad (4c)$$

$$|\theta_{mm}| = 1, \forall m \in \mathcal{M}, \quad (4d)$$

$$\rho^a_{k,n} \in \{0, 1\}, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \forall a \in \mathcal{A}. \quad (4e)$$

Constraint (4a) indicates a limitation on the total transmit power of each BS, where $P^n_{\max}$ is the maximum transmit power budget. The vector of beamforming and antennas

[1]It should be noted that the discrete phase shift at the IRS is more practical and cost-effective [11]. However, the misalignment of IRS-reflected and non-IRS-reflected signals caused by the discrete phase shifts deteriorate the performance gain.

[2]This problem formulation could be extended to take into account the minimum QoS for each user.

selection are presented respectively as $\mathbf{w}$ and $\boldsymbol{\rho}$. We further denote L_a as the maximum number of UEs that each antenna can serve. Then, we impose constraint (4b) in the optimization problem due to technical hardware limitations. Moreover, we limit the number of antennas $a_{\max}$ for each user via (4c). Constraint guarantees that the diagonal phase shift matrix (4d) has M unit-modulus elements on its main diagonal. Constraint (4e) shows $\rho_{k,n}^a$ only takes integer values. Optimization problem P_1 is a mixed-integer nonlinear programming (MINLP) problem, and we solve it by an alternative optimization (AO) framework, which includes two subproblems [5]. The outputs of first subproblem are $\boldsymbol{\rho}^*$ and $\mathbf{w}^*$. Then, the phase shift design based on the previous phase is performed. Please note that this iterative solution is continued until the problem converges to a feasible solution of $\{\boldsymbol{\rho}^*, \mathbf{w}^*, \boldsymbol{\theta}^*\}$.

A. Joint Antenna Selection and Beamforming

To solve the problem P_1, we define the product of two variables, where one of them is integer as a new auxiliary variable $\tilde{\mathbf{w}}_{k,n} = \mathbf{w}_{k,n} \circ \boldsymbol{\rho}_{k,n}$. Besides, we employ the semidefinite relaxation (SDR) that imposes $\mathbf{H}_{k,n} = \mathbf{h}_{k,n}\mathbf{h}_{k,n}^H$ and $\tilde{\mathbf{W}}_{k,n} = \tilde{\mathbf{w}}_{k,n}\tilde{\mathbf{w}}_{k,n}^H$. On the other side, we exploit the big-M approach to decompose the multiplicative terms [15]. Hence, $\tilde{\mathbf{W}}_{k,n}$ can be decomposed using the following additional constraints:

$$0 \preceq \tilde{\mathbf{W}}_{k,n} \preceq P_{\max}^n \mathrm{diag}(\boldsymbol{\rho}_{k,n}), \tag{5a}$$

$$\mathbf{W}_{k,n} - \mathrm{diag}(\mathbf{1} - \boldsymbol{\rho}_{k,n}) P_{\max}^n \preceq \tilde{\mathbf{W}}_{k,n} \preceq \mathbf{W}_{k,n}. \tag{5b}$$

Because of the integer variable $\rho_{k,n}^a$, (4e) is a non-convex binary constraint. Hence, we relaxed $\rho_{k,n}^a$ into a continuous one and impose the following additional constraints [15]:

$$\sum_{n\in\mathcal{N}}\sum_{a\in\mathcal{A}}\sum_{k\in\mathcal{K}} \rho_{k,n}^a - \sum_{n\in\mathcal{N}}\sum_{a\in\mathcal{A}}\sum_{k\in\mathcal{K}} (\rho_{k,n}^a)^2 \le 0, \tag{6a}$$

$$0 \le \rho_{k,n}^a \le 1, \forall k \in \mathcal{K}, \forall n \in \mathcal{N}, \forall a \in \mathcal{A}. \tag{6b}$$

Since (6a) is a difference of two convex functions, problem P_1 can be rewritten as

$$\mathrm{P}_2\colon \max_{\mathbf{W},\boldsymbol{\rho},\tilde{\mathbf{W}}} \ \eta - \kappa\Big(Q(\rho_{k,n}^a) - E(\rho_{k,n}^a)\Big),$$

$$s.t.\colon \sum_{k\in\mathcal{K}} \mathrm{trace}[\tilde{\mathbf{W}}_{k,n}] \le P_{\max}^n, \forall n \in \mathcal{N}, \tag{7a}$$

$$\mathrm{Rank}(\tilde{\mathbf{W}}_{k,n}) = 1, \tag{7b}$$

$$\text{(4b), (4c), (5a), (5b), and (6b),} \tag{7c}$$

where $Q(\rho_{k,n}^a) = \sum_{n\in\mathcal{N}}\sum_{a\in\mathcal{A}}\sum_{k\in\mathcal{K}} \rho_{k,n}^a$ and $E(\rho_{k,n}^a) = \sum_{n\in\mathcal{N}}\sum_{a\in\mathcal{A}}\sum_{k\in\mathcal{K}}(\rho_{k,n}^a)^2$. Moreover, $\kappa \gg 1$ is a large constant which acts as a penalty factor. However, the objective function is still non-convex. To tackle this issue, at first, we rewrite the rate function as the difference of two concave functions (D.C.) $r_{k,n} = f_{k,n} - g_{k,n}$. In this case, $f_{k,n} = \log_2(\mathrm{trace}[\mathbf{H}_{k,n}\tilde{\mathbf{W}}_{k,n}] + \sum_{i\neq k, i\in\mathcal{K}_n} \mathrm{trace}[\mathbf{H}_{k,n}\tilde{\mathbf{W}}_{i,n}] + \sigma_{k,n}^2)$ and $g_{k,n} = \log_2(\sum_{i\neq k, i\in\mathcal{K}_n} \mathrm{trace}[\mathbf{H}_{k,n}\tilde{\mathbf{W}}_{i,n}] + \sigma_{k,n}^2)$. Employing the D.C. approximation, $g_{k,n}$ is approximated as $\tilde{g}_{k,n}(\tilde{\mathbf{W}}_{k,n}) \approx g_{k,n}(\tilde{\mathbf{W}}_{k,n}^{[t]}) + \mathrm{trace}[\langle \nabla g_{k,n}(\tilde{\mathbf{W}}_{k,n}^{[t]}), (\tilde{\mathbf{W}}_{k,n} - \tilde{\mathbf{W}}_{k,n}^{[t]})\rangle]$ where $\nabla g(\tilde{\mathbf{W}}_{k,n}) = \beta_{k,n}^i \frac{\mathbf{H}_{k,n}^H}{\ln(2)(\sum_{i\neq k, i\in\mathcal{K}_n} \mathrm{trace}[\mathbf{H}_{k,n}\tilde{\mathbf{W}}_{i,n}^{[t]}] + \sigma_{k,n}^2)}$, in which $i \neq k$, $\beta_{k,n}^i = 1$ otherwise $\beta_{k,n}^i = 0$. Using the same structure $E(\rho_{k,n}^a)$ is approximated as $\tilde{E}(\rho_{k,n}^a) \approx E(\rho_{k,n}^{a[t]}) + 2\rho_{k,n}^{a[t]}(\rho_{k,n}^a - \rho_{k,n}^{a[t]})$. Now, we adopt the Dinkelbach algorithm to solve the nonlinear fractional programming method where $\lambda^* = \max\limits_{\tilde{\mathbf{W}}} \frac{f_{k,n} - \tilde{g}_{k,n}}{S}$. Thus, the problem can be restated as follow

$$\mathrm{P}_3\colon \max_{\mathbf{W},\boldsymbol{\rho},\tilde{\mathbf{W}}} \ \sum_{k\in\mathcal{K}}\sum_{n\in\mathcal{N}} (f_{k,n} - \tilde{g}_{k,n}) - \kappa\Big(Q - \tilde{E}\Big) - \lambda S,$$

$$s.t.\colon \text{(4b), (4c), (5a), (5b), (6b), (7a),}$$

where $S = \sum_{n\in\mathcal{N}} P_n^{\mathrm{stc}} + \sum_{n=1}^N \sum_{a=1}^{T_n} (P_{a,n}^{\mathrm{ant}} \sum_{k\in\mathcal{K}_n} \rho_{k,n}^a) + \frac{1}{\zeta}\sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} \mathrm{trace}[\tilde{\mathbf{W}}_{k,n}] + P^{\mathrm{IRS}}$. The problem P_3 can be efficiently solved using **Algorithm 1**. It should be noted that if the solution does not approach a rank-one solution, the randomization method is adopted to obtain a feasible solution.

B. Phase Shift Optimization

In this subsection, we design the phase shifts at the IRS for the given optimal solutions $\{\mathbf{W}_{k,n}^*, \rho_{k,n}^*, \lambda^*\}$. As a result, the EE problem can be transformed to the rate function. However, constraint (4d) is a module constraint that makes solving the problem challenging. Let us define $x_m = e^{j\theta_m}, \forall m \in \mathcal{M}$ and $\mathbf{x} = [x_1, \ldots, x_M]^T$. We also rewrite $\mathbf{z}_{k,n}^H \boldsymbol{\Theta} \mathbf{G}_n \tilde{\mathbf{w}}_{k,n} \triangleq \boldsymbol{\psi}_{k,n}^{\mathrm{H}} \mathbf{x}$ and $\mathbf{u}_{k,n}^H \tilde{\mathbf{w}}_{k,n} \triangleq \tilde{u}_{k,n}$ where $\boldsymbol{\psi}_k^{\mathrm{H}} = (\mathrm{diag}(\mathbf{z}_{k,n}^H)\mathbf{G}_n \tilde{\mathbf{w}}_{k,n})^*$. Now, by introducing slack variable $\mu_{k,n}$, the optimization problem can be formulated as follows

$$\mathrm{P}_4\colon \underset{\mathbf{x},\ \mu}{\mathrm{maximize}} \ \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} \log_2(1 + \mu_{k,n})$$

$$s.t.\colon \ \frac{\left|\boldsymbol{\psi}_k^H \mathbf{x} + \tilde{u}_{k,n}\right|^2}{\sum\limits_{i\neq k} \left|\boldsymbol{\psi}_k^H \mathbf{x} + \tilde{u}_{i,n}\right|^2 + \sigma_k^2} \ge \mu_{k,n}, \forall k \in \mathcal{K}, \tag{8a}$$

$$|x_m| = 1, \forall m \in \mathcal{M}. \tag{8b}$$

P_4 is still non-convex due to non-convexity of the constraint (8b) as well as incorporating interference in the data rate. However, let us write the optimization problem into a more tractable form via the penalty method as

$$\mathrm{P}_5\colon \max_{\mathbf{x},\ \mu} \ \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} \log_2(1 + \mu_{k,n}) - \frac{1}{2\nu}\sum_{m=1}^M (|x_m|^2 - 1)$$

$$s.t.\colon \ |x_m| \le 1, \forall m \in \mathcal{M}, \text{ and (8a).} \tag{9a}$$

Note that ν is a penalty factor that needs to be very small. One can readily verify that (P5) belongs to the class of DC function, and the SCA approach can be adapted to obtain a locally optimal solution. Therefore, we adopt the SCA method to make a convex objective function which can be approximated via first-order Taylor series as

$$\mathrm{P}_6\colon \max_{\mathbf{x},\ \mu} \ \sum_{n\in\mathcal{N}}\sum_{k\in\mathcal{K}} \log_2(1 + \mu_{k,n})$$

Algorithm 1 Joint Beamforming and Antenna Selection Algorithm

Input: Set maximum tolerance (ε) and the maximum iteration number $I_{\max}$. Choose a feasible $\mathbf{W}^{[0]}$ and $\boldsymbol{\rho}^{[0]}$. Define $i = 1$ and $\lambda^{[0]} = 0$.
repeat
  Calculate $\tilde{g}(\tilde{\mathbf{W}}, \mathbf{W}, \boldsymbol{\rho})$ and $\tilde{E}(\boldsymbol{\rho})$ via a successive convex approximation (SCA) structure.
  Solve problem P_3 for a given $\lambda^{[i-1]}$.
    if $|f^{[i]} - \tilde{g}^{[i]} - \lambda^{[i-1]} S^{[i]}| \leq \varepsilon$
      return $(\tilde{\mathbf{W}}^*, \mathbf{W}^*, \boldsymbol{\rho}^*) = (\tilde{\mathbf{W}}^{[i]}, \mathbf{W}^{[i]}, \boldsymbol{\rho}^{[i]})$, $\lambda^* = \lambda^{[i-1]}$.
    else $\lambda^{[i]} = \dfrac{f_{k,n}^{[i]} - \tilde{g}_{k,n}^{[i]}}{S^{[i]}}$.
  $i = i + 1$.
  until $i = I_{\max}$.
return $(\tilde{\mathbf{W}}^*, \mathbf{W}^*, \boldsymbol{\rho}^*)$.

$$- \frac{1}{2\nu} \sum_{m=1}^{M} \left[\left((x_m^{[t']})^2 - 1 \right) + 2(x_m^{[t']})(x_m - x_m^{[t']}) \right]$$
$$s.t.: \ (8\text{a}), \ (9\text{a}).$$

As the last step, we handle the non-convexity of constraint (8a) via introducing the slack variable $\alpha_{k,n}$. Thus (8a) can be translated into the following two inequalities

$$\sum_{i \neq k} \left| \boldsymbol{\psi}_i^H \mathbf{x} + \tilde{u}_{i,n} \right|^2 + \sigma_k^2 \leq \alpha_{k,n}, \tag{10}$$
$$\left| \boldsymbol{\psi}_k^H \mathbf{x} + \tilde{u}_{k,n} \right|^2 \geq \alpha_{k,n} \mu_{k,n}, \tag{11}$$

where, $\alpha_{k,n}\mu_{k,n} = \frac{1}{2}(\alpha_{k,n} + \mu_{k,n})^2 - \frac{1}{2}(\alpha_{k,n}^2 + \mu_{k,n}^2)$. It can be seen that (10) is a convex constraint whereas (11) is non-convex. To tackle the non-convexity of (11), we utilize DC approach that can be approximated as

$$\begin{aligned} &2\mathcal{R}\Big((\boldsymbol{\psi}_k^H \mathbf{x}^{[t']} + \tilde{u}_{k,n})^H \boldsymbol{\psi}_k^H \mathbf{x} \Big) - \Big| \boldsymbol{\psi}_k^H \mathbf{x}^{[t']} + \tilde{u}_{k,n} \Big|^2 \\ &\geq \frac{1}{2}(\alpha_{k,n} + \mu_{k,n})^2 - \frac{1}{2}\Big((\alpha_{k,n}^2)^{[t']} + (\mu_{k,n}^2)^{[t']} \Big) \\ &\quad - (\alpha_{k,n})^{[t']}(\alpha_{k,n} - (\alpha_{k,n})^{[t']}) - (\mu_{k,n})^{[t']}(\mu_{k,n} - (\mu_{k,n})^{[t']}), \end{aligned} \tag{12}$$

where $\mathbf{x}^{[t']}$, $\alpha_{k,n}^{[t']}$, and $\mu_{k,n}^{[t']}$ are the solution in $[t']$-th iteration. Now, we can solve the following convex problem instead of dealing with non-convex problem in P_6

$$\begin{aligned} \mathrm{P}_7 \colon \max_{\mathbf{x},\ \mu,\ \alpha} \ & \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} \log_2(1 + \mu_{k,n}) - \frac{1}{2\nu} \\ & \sum_{m=1}^{M} \left[\left((x_n^{[t']})^2 - 1 \right) + 2(x_n^{[t']})(x_n - x_n^{[t']}) \right] \\ s.t.: \ & (\mathbf{9a}), \ (\mathbf{10}), \ (\mathbf{12}). \end{aligned}$$

P_7 can now be solved by SCA. Therefore, we can employ optimization solvers such as CVX to solve it efficiently. Please note that the objective function of P_1 would be improved after this iterative algorithm or at least is monotonically non-decreasing after each iteration [16].

C. Computational Complexity Analysis

In this section, we investigate the complexity of the proposed algorithm. For P_3, the problem consists of $\mathcal{C} = N + T_n N + KN + KNT_n + 4KN$ convex constraints and $2KNT_n$ variables. Considering the SDP method, the total complexity is $O_1 = \mathcal{O}(\mathcal{C} J_{\mathrm{SCA}} J_{\mathrm{D}} (2KNT_n) \times (\sqrt{T_n N} \log(\frac{1}{\epsilon})(K'N'^3 + K'^3 N'^2 + K'^3))$ where J_{D} denotes the number of iterations for solving the Dinkelbach method and J_{SCA} is the number of iterations required for the SCA algorithm, $K' = 4K + 1$ and $N' = T_n N$. For the phase shift optimization the complexity of solving problem (P7) is $\mathcal{O}(VC)$ where $V = K + M$ is the total number of variables and $C = 2K + M$ is the total number of constraints. Besides, the number of iterations for SCA method is $\mathcal{O}(\sqrt{K+M} \log_2(\frac{1}{\epsilon}))$ in which ϵ is the accuracy for the SCA approach.

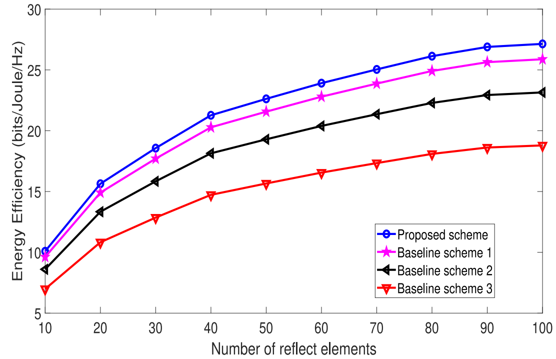

Fig. 2. EE versus the number of reflecting elements.

IV. SIMULATION RESULTS

This section presents the numerical results to investigate the performance of our proposed algorithm. We consider 2 base stations that are equipped with 4 antennas. The BSs are located at $(-100, 0)$ and $(100\frac{\sqrt{2}}{2}, -100\frac{\sqrt{2}}{2})$ in the cartesian coordinate. The channel model includes the line-of-sight(LOS) and non-line-of-sight(NLOS) as follows

$$\mathbf{G}_n = \sqrt{\frac{K_r}{1+K_r}} \mathbf{G}_n^{\mathrm{LOS}} + \sqrt{\frac{1}{1+K_r}} \mathbf{G}_n^{\mathrm{NLOS}}, \tag{13}$$
$$\mathbf{z}_{k,n} = \sqrt{\frac{K_r}{1+K_r}} \mathbf{z}_{k,n}^{\mathrm{LOS}} + \sqrt{\frac{1}{1+K_r}} \mathbf{z}_{k,n}^{\mathrm{NLOS}}, \tag{14}$$

where K_r is the Rician factor. Also, $\mathbf{z}_{k,n}^{\mathrm{NLOS}}$ and $\mathbf{G}_n^{\mathrm{NLOS}}$ denote the NLOS components which follow Rayleigh fading models [16]. Also, there is an IRS with 40 reflecting elements in the origin of the coordinate. As the channel characteristics, we consider that bandwith equals 500 MHz and $\Delta = 5$. Also, $\zeta_t = 9.82$ dBm, $\zeta_r = 0$ dBm, and γ_i follows the setting described in [10]. The number of user equipments in the network are assumed 12 which their location are selected randomly in a circular area at with a radius of 100 meter. Also, we preset $a_{max} = 4, L_a = 2, \kappa = 10^5, \nu = 10^{-4}, \sigma_{k,n}^2 = -90$ dBm, and $P_{\max} = 30$ dBm. Additionally, the static and dynamic power of IRS are determined as $P_{\mathrm{stc}}^{\mathrm{IRS}} = 100$ mW and $P_{\mathrm{dyc}}^{\mathrm{IRS}} = 0.33$ mW, $P_n^{\mathrm{stc}} = 30$ dBm, and $P_{a,n}^{\mathrm{ant}} = 20$ dBm. For comparison three baseline schemes are examined, namely, i) baseline scheme 1: Proposed method in [4]; ii) baseline scheme 2: Proposed method in [10]; iii) baseline scheme 3: max SINR AS strategy while considering random passive beamforming vectors for the IRS.

Fig. 2 shows the EE versus the number of reflecting elements. This figure for all schemes demonstrates that increasing the number of reflecting elements boosts the network's EE,

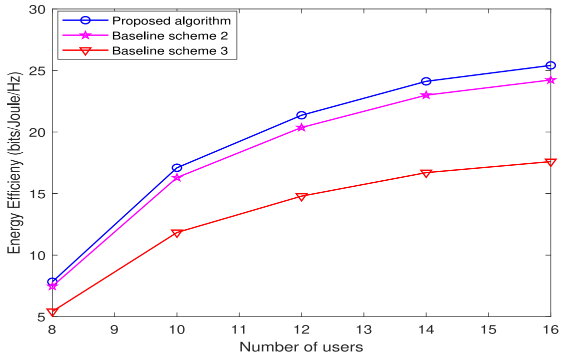

Fig. 3. EE versus the number of users.

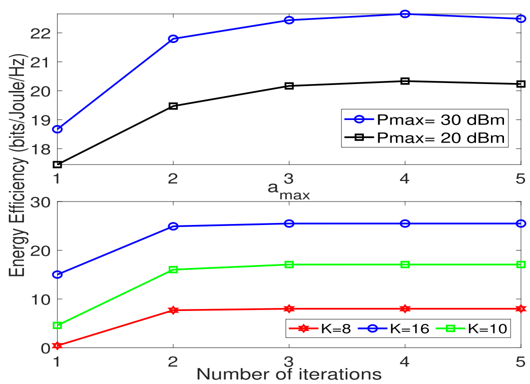

Fig. 4. Top plot: EE versus $a_{\max}$. Bottom plot: EE versus the number of iterations.

where the incremental process is limited in the massive number of reflecting elements. This is because increasing the number of reflecting elements yields to increase the data rate, which results in higher EE; however, for a higher value number of M, not only the interference term incorporated in the data rate increases which limits the data rate but also mounts the term of the power consumption. This figure also demonstrates that our proposed algorithm has a better performance than baseline scheme 2 due to adopting a novel framework for user association based on the AS strategy and proposing an algorithm for beamforming that yields an efficient sub-optimal solution. This figure also illustrates that the proposed algorithm outperforms baseline scheme 1 due to adopting AS strategy as well as solution methodology, which yields a locally optimal solution.

Fig. 3 illustrates the EE versus the number of users varying from 8 to 16. We can see that network's EE with a large number of the user equipment can achieve higher performance than the networks with a small number of users due to increasing the network's data rate while reducing the transmit power. It can be seen that the proposed algorithm reaches a higher EE as compared to baseline scheme 1. This is due to performing a novel approach for user association based on the AS in which not only can obtain a higher data rate but also consumes minor power, which returns in higher EE.

The top plot Fig. 4 illustrates the effect of $a_{\max}$ or (4c) on the network's performance for different maximum transmit power. It is observable that in the proposed algorithm, increasing the number of antennas in the MISO transmission increases the energy efficiency, which is rational since (4c) brings a degree of freedom into the network. It can be seen that for a large number of possible active antennas, the slope of the curve slows down. We can also see that increasing the maximum transmit power improves the EE. The bottom plot Fig. 4 presents the convergence of the proposed approach for a different number of users when $P_{\max}$ is fixed, which shows that the algorithm requires almost four iterations to converge.

V. Conclusion

In this letter, we studied the problem of joint antenna selection (AS) and active/passive beamforming for IRS-assisted multi-cell downlink to optimize the EE, which helps to the RAN moderation concept. The formulated problem is MINLP which is challenging to solve. Simulation results depicted that we obtained a higher EE via AS. They divulged we could save significant energy for the transmit power by increasing the sleep mode in the antennas. Further, they revealed the fast convergence of the proposed algorithm, outperforming the other baseline schemes.

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