Joint Resource Allocation and Reflecting Design in IRS-UAV Communication Networks with SWIPT

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Abstract-Since the unmanned aerial vehicle (UAV) network and intelligent reflecting surface (IRS) technology can flexibly change wireless network links signal, the UAV-IRS network system is a potential solution to increase the communication performance gain. Motivated by the practicality of UAV-IRS networks, a non-orthogonal multiple access (NOMA) heterogeneous UAV communication system with simultaneous wireless information and power transfer (SWIPT) is considered, which consists of multiple UAV base stations (UBSs), a macro base station (MBS), and multiple IRSs for auxiliary communications. This paper pursues a goal to receive the system energy efficiency (EE) maximization by resource allocation and reflecting design of IRSs. Due to the strong coupling among multiple parameters in the original problem, this complex non-convex problem is decomposed into three stages. In the first stage, this paper decouples the problem into two subproblems of NOMA subchannel assignment and SIC decoding order to find the optimal solution separately. For the second stage, under the constraints of UAV's maximum transmit power, users' quality of service (QoS) requirements, user energy harvesting threshold and cross-layer interference constraints, a beamforming design based on Lagrangian duality is exploited. For the third stage, the power splitting (PS) factors and the reflecting phases of the IRS are jointly optimized using the penalty-SDR algorithm to approximate the suboptimal solution. Finally, the simulation curves exhibit the validity and excellent performance of the co-design scheme in improving the system EE.

Index Terms—UAV, IRS, SWIPT, reflecting design, energy efficiency, subchannel assignment, SIC decoding, beamforming design.

I. INTRODUCTION

UAV and IRS technology have emerged as a hotspot due to the flexible on-demand control and reconfigurable configuration of wireless communication environment [1] [2]. Compared with ground communication, UAV has a higher opportunity of establishing Line-of-Sight (LoS) communication link of air-ground, so it has an excellent wireless channel [3] [4]. IRS can assist in establishing a virtual communication

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G. K. Karagiannidis is with Department of Electrical and Computer Engineering, Aristotle University of Thessaloniki, Greece and also with Cyber Security Systems and Applied AI Research Center, Lebanese American University (LAU), Lebanon (e-mail: geokarag@auth.gr) link, with the potential to enhance the desired signal or restraining interference [5]. The combination of IRS and UAV has many advantages. Deploying IRS to reconfigure the UAV communication propagation environment can significantly improve the coverage and performance of air-ground networks [6]. In addition, in order to solve the possible link blockage of air-ground channels, applying IRS to the UAV-assisted airground network can obtain an outstanding communication environment and improve the communication quality of target users [1] [6].

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A. Related Works and Motivation

Exploiting a mass of inexpensive passive reflecting units, IRS can change the amplitude and phase of incident signal, which has a bright prospect of reconfiguring the wireless environment and improving network performance [7] [8]. Compared to active relays that assist communication through signal regeneration and retransmission, IRSs only passively reflect received signals, do not require any transmit radio frequency chain [9] [10]. Thus researches on IRS phase design have attracted tremendous attentions. For instance, in paper [11], the authors proposed a novel IRS-assisted coordinated multipoint system, which maximized the EE by jointly optimizing user association, subcarrier distribution, BS clustering, power control and IRS optimization design. The authors of [12] investigated an IRS-empowered multiple-input singleoutput (MISO) independent interference cooperative model. Maximizing EE was achieved by co-designing transmit and interferer beamforming matrices, IRS phase-shift matrices with ideal and incomplete channel state information (CSI). The authors of [13] proposed resource allocation involving distributed IRS. Under the premise of meeting the minimum rate requirement, unit modulus constraints and maximum transmit power, the IRS switching state, phase shift and transmit beamforming are jointly designed to maximize EE. In paper [14], the authors established an IRS-assisted multi-user MIMO uplink transmission network model that adopted only part of the channel information, including the instantaneous state information between IRS and the BS, and statistical state information between users and IRS. A joint design method based on user transmit covariance matrix and IRS phase matrix was adopted to maximize global EE of the system. The authors of [15] investigated a design for IRS deployment and passive beamforming with NOMA, and employed deep reinforcement learning to solve the problem.

Since the signal of the ground network link is interfered by obstacles now and then, the flexible deployment of UAV as an air base station has attracted remarkable attention [16]. The complementary advantages of IRS and UAV can bring noteworthy performance gains to wireless networks, which has aroused great enthusiasm among researchers [17] [18]. For example, sum-rate of the considered network was maximized by jointly designing transmit power, the reflecting matrix of the IRS, the 3D placement, the decoding design of NOMA [19]. On the premise of satisfying the minimum initial rate requirement, the joint optimization of IRS scheduling, IRS reflecting matrix and UAV trajectory was considered. The paper in [20] adopted relaxation algorithm and penalty method to investigate weighted sum bit error rate and fair bit error rate minimization, respectively. In paper [21], the authors formulated the joint design of IRS scheduling, UAV trajectory and resource management as a non-convex problem that maximized sum-rate while considering each user's heterogeneous QoS requirements. In [22], considering the continuous roaming of users, the use of NOMA techniques further improved the spectral efficiency. The energy consumption minimization problem was modeled by codesigning the motion of UAVs, the IRS phase design, the decoding order, and the power control strategy. Finally, the authors solved this problem using deep reinforcement learning algorithm.

In the age of information explosion, energy shortage is a significant and challenging problem, especially in dense heterogeneous networks consisting of multiple access points and devices [23]. To tackle this problem, researchers propose SWIPT technology, which uses radio frequency signals to synchronize information and energy transmission. SWIPT technology is the momentous technology to attain high EE transmission of ultra-dense network information with limited energy [24]. At present, researches on network EE based on SWIPT have received wide attention from researchers. In paper [25], the authors maximize the EE of NOMA heterogeneous networks by optimizing power control and subchannel allocation based on energy harvesting links and user QoS. The authors of paper [26] studied the problem of EE resource management in cell-free systems with layered multiplexing. With the aid of IRSs, paper [27] minimizes transmit power in SWIPT systems by designing transmit precoding and IRS reflecting design. The authors in [28] investigated the power allocation and subchannel assignment problems considering cross-laver/colayer interference suppression, energy harvesting, and incomplete CSI. By introducing a time-varying interference pricing method, the power control problem in heterogeneous networks was established as a non-cooperative game. In paper [29], a joint design problem based on secrecy EE with imperfect CSI and nonlinear energy harvesting models was adopted, the authors jointly optimized the beamforming vectors, dual-layer PS ratios and artificial noise matrixs to achieve a remarkable secrecy EE gain.

However, although introducing UAVs into the IRS network has improved the LoS propagation of signals, it has also introduced significant power consumption from UAVs. In addition, the power loss brought by the large-scale deployment of IRS components is equally significant and cannot be ignored. To ensure high energy efficiency gains in IRS-UAV networks, harvesting energy from ambient RF signals is

a candidate solution. By applying SWIPT, users can obtain information and energy at the same time. Therefore, SWIPTbased energy efficiency research for IRS-UAV heterogeneous networks is a very promising research direction, which can greatly facilitate the deployment of energy-limited user devices. There have been many studies on the EE research of IRS-assisted communications and throughput research of IRS-UAV in the aforementioned research. However, the study of energy efficiency in SWIPT-based IRS-UAV multi-layer heterogeneous cell downlink NOMA systems is just in its infancy, especially when cross-layer interference constraints, user nonlinear energy harvesting threshold constraints, QoS constraints, and discrete phase constraints are considered at the same time. Notably, this is the first attempt to use SWIPT to focus on EE optimization in IRS-assisted UAV heterogeneous network downlink NOMA systems. Due to the introduction of the PS-SWIPT nonlinear energy harvesting model, the PS factor will be strongly coupled with the SIC decoding factor, transmit beam, and IRS phase shift of the IRS-UAV downlink NOMA system under the objective function and multiple constraints, and this combined optimization problem is generally nonconvex and computationally difficult to solve, and the derivation of its optimization solution remains a challenging task. In this paper, the subchannel assignment, SIC decoding order, beamforming design, power splitting factor and IRS phase shift in the SWIPT-based IRS-UAV network are optimized with the objective of maximizing the system EE by considering cross-layer transmission interference, user energy harvesting threshold constraints, user QoS restrictions and discrete phase constraints.

B. Contributions

The contributions are enumerated as follows:

- First of all, this paper proposes a NOMA heterogeneous multiple IRS-UAV network system with SWIPT, which includes a MBS, multiple UBSs, and multiple IRSs for establishing virtual communication links to jointly provide communication services for users. Since the available energy of UAV is limited, we consider utilizing the energy harvested from the environment. Based on UAV transmit power, user QoS, cross-layer interference, user energy harvesting threshold, user decoding rules and IRS discrete phase constraints, a co-design optimization of subchannel assignment, SIC decoding order, beamforming design, PS factor and IRSs reflecting phase design to maximize the EE is proposed.
- Secondly, the proposed problem is a mixed integer nonlinear programming (MINLP) problem with strong coupling between the parameters, which is not easy to solve directly. Therefore, the proposed joint design problem is converted to three stages. In the first stage, a bilateral selection algorithm is proposed to achieve better channel gains. This is the first attempt to apply this algorithm to the IRS-UAV network optimization problem. In order to discuss the effect of IRS on the decoding order of SIC in NOMA, the decoding order of SIC is optimized using the penalty factor method. Then, In the second stage, under

the rigid limitation of the maximum UAV transmit power, user QoS requirements, cross-layer interference, and user energy harvesting threshold, a closed solution is sought by invoking the Lagrangian Dual method. In the third stage, with the solved subchannel assignment, SIC decoding order and beamforming design, the EE optimization problem on user QoS, user energy harvesting threshold constraints, discrete phase constraints is formulated as a innovative form only concerned with PS factor and the phase shift of IRSs. The penalty-SDR algorithm is used to handle the binary concave function including the PS factor and the phase shift, in order to approximate the original suboptimal solution.

• At last, various simulations curves unveil the attractive performance with fewer iterations, fast convergence of the proposed joint scheme. By comparing with existing schemes, the proposed scheme can notably elevate the EE of system and certify the superiority. Besides, the deployment of IRSs makes a noticeable impact on raising communication signal. The reflecting phase design and units numbers of IRSs can vastly contribute to the improvement of EE. In addition, the use of high resolution IRS discrete elements will not lead to an increase in EE gain, but will cause a decrease in EE. This is because high resolution IRS elements can cause significant changes in power consumption, especially when a large number of IRS elements are introduced. The algorithm proposed in this paper performs better in multi-cell and multiuser high-density areas, which is also more suitable for practical application scenarios.

C. Organization and Notations

The rest of this paper is arranged as below. Section II constructs the system model and the transformation of the codesign optimization problem. In Section III, efficient schemes are adopted to solve the three stages respectively. Section IV conducts comprehensive simulation experiments and compares existing algorithms to certify the superiority of this scheme. Finally, Section V makes the conclusion elaboration.

Notation: \mathbf{a}^{H} is the conjugate transpose of vector \mathbf{a} . $\|\mathbf{a}\|$ denotes the Euclidean norm. $\mathbf{Y} \succeq \mathbf{0}$ represents \mathbf{Y} as a positive semi-definite matrix. rank(·) and trace(·) are the rank and trace of matrix, respectively. (·)^t is the result of the parameter in the *t*-th iteration, where (·)* represents the optimal solution for the parameter.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Fig. 1 exhibits a downlink NOMA communication model in a heterogeneous IRS-UAV networks with SWIPT. The system considers a MBS and K hovering UAVs as air base stations, in which will serve multiple users together. It's assumed that each user equipment (UE) is equipped with hardware capable of transmitting information and energy simultaneously. The k-th UAV base station denotes UBS(k). The number of UE in the k-th cell is shown as M_k , $k \in K$, and the *i*-th UE of the corresponding k-th UAV cell is expressed as UE(k, i).



Fig. 1. IRS-UAV downlink communication system with SWIPT.

The system bandwidth is evenly divided into C subchannels, which the subchannel bandwidth is $B_{sc} = BW/C$, BW is the total bandwidth. It is assumed that each UAV cell contains an IRS to enhance the QoS of the user in the cell, that is, the number of IRSs is consistent with UAVs, which can be denoted by IRS(ℓ). The location coordinates of the UBS(k), IRS(ℓ) and UE(k, i) are $\mathbf{q}_k = [x_k^{UAV}, y_k^{UAV}, h_k^{UAV}]^T$, $\mathbf{I}_{\ell} = [x_\ell^{IRS}, y_\ell^{IRS}, h_\ell^{IRS}]^T$, $\mathbf{u}_{k,i} = [x_{k,i}^{UE}, y_{k,i}^{UE}]^T$ respectively.

$$\begin{split} &\Theta_{\ell} \text{ represents the reflecting phase matrix of IRS}(\ell), \Theta_{\ell} = &\operatorname{diag}(\theta_{1}^{\ell}, \cdots, \theta_{m}^{\ell}, \cdots, \theta_{M}^{\ell}), \Theta_{\ell} \in \mathbb{C}^{M \times M}, \theta_{m}^{\ell} = e^{j\varphi_{m}^{\ell}}, \theta_{m}^{\ell} \\ &\operatorname{represents the coefficient of the$$
m $-th element above IRS}(\ell), \\ &M \text{ denotes the quantity of reflecting elements on each IRS}, \\ &\varphi_{m}^{\ell} \text{ represents the phase of the$ *m* $-th unit on IRS}(\ell). Let \Theta = & & & & \\ & & & & \\ & & & & & \\ & & & & & \\ & & & & \\ & & & & \\ & & & & \\ & &$

Considering LoS and non-line-of-sight (NLoS) communications, the channel gain of the link UBS(k) between UE(k, i) on subchannel c can be expressed as follows

$$d_{k,i,c} = \sqrt{\frac{\rho_0}{\|\mathbf{q}_k - \mathbf{u}_{k,i}\|^{\alpha_{dl}}}} \left(\sqrt{\frac{\kappa_{dl}}{\kappa_{dl} + 1}} \overline{d}_{k,i,c} + \sqrt{\frac{1}{\kappa_{dl} + 1}} \overline{\overline{d}}_{k,i,c} \right)$$
(1)

where ρ_0 represents the path loss when the reference distance is 1 m, κ_{dl} is Rician factor of direct link, α_{dl} represents the path loss index of direct link. $\overline{d}_{k,i,c} = 1$ represents the deterministic LOS link component, $\overline{d}_{k,i,c}$ is random Rayleigh distribution NLoS components.

Similarly, the channel gain of the link $IRS(\ell)$ between UE(k, i) on subchannel *c* can be expressed

$$\mathbf{r}_{k,i,c}^{\ell} = \sqrt{\frac{\rho_0}{\|\mathbf{I}_{\ell} - \mathbf{u}_{k,i}\|^{\alpha_{rl}}}} \left(\sqrt{\frac{\kappa_{rl}}{\kappa_{rl} + 1}} \mathbf{\bar{r}}_{k,i,c}^{\ell} + \sqrt{\frac{1}{\kappa_{rl} + 1}} \mathbf{\bar{\bar{r}}}_{k,i,c}^{\ell} \right)$$
(2)

$$\bar{\mathbf{r}}_{k,i,c}^{\ell} = \left[1, e^{-j\frac{2\pi\varrho}{\lambda}\cos\phi_{k,i}^{\ell}}, ..., e^{-j\frac{2\pi(M-1)\varrho}{\lambda}\cos\phi_{k,i}^{\ell}}\right]^{T} \qquad (3)$$

where ϱ represents the IRS unit spacing, λ denotes the carrier wavelength. Note that when the condition of $\varrho \geq \frac{\lambda}{2}$ is satisfied, we can assume that the spatial correlation between IRS units is negligible. κ_{rl} is Rician factor of IRS-UE link, α_{rl} denotes the path loss index of IRS-UE link. $\mathbf{\bar{r}}_{k,i,c}^{\ell} \in \mathbb{C}^{M \times 1}$ denotes the deterministic LoS link component of IRS(ℓ)-UE(k, i). $\mathbf{\bar{r}}_{k,i,c}^{\ell} \in \mathbb{C}^{M \times 1}$ is random Rayleigh distribution NLoS components. $\cos \phi_{k,i}^{\ell} = \frac{\mathbf{u}_{k,i}^{*} - \mathbf{I}_{\ell}^{*}}{\|\mathbf{u}_{k,i} - \mathbf{I}_{\ell}\|}$ represents the cosine of the angle of departure (AoD) from the IRS(ℓ)-to-UE(k, i).

Besides, the channel gain of UBS(k)-IRS (ℓ) link on subchannel c is given by

$$\mathbf{G}_{k,c}^{\ell} = \sqrt{\frac{\rho_0}{\|\mathbf{q}_k - \mathbf{I}_{\ell}\|^2}} \overline{\mathbf{G}}_{k,c}^{\ell}$$
(4)

$$\overline{\mathbf{G}}_{k,c}^{\ell} = \left[1, e^{-j\frac{2\pi\varrho}{\lambda}\cos\psi_{k}^{\ell}}, ..., e^{-j\frac{2\pi(M-1)\varrho}{\lambda}\cos\psi_{k}^{\ell}}\right]^{T}$$
(5)

where $\cos \psi_k^{\ell} = \frac{\mathbf{I}_k^{\tau} - \mathbf{q}_k^{\pi}}{\|\mathbf{I}_{\ell} - \mathbf{q}_k\|}$ is the cosine of the angle of arrival (AoA) from the UBS(k)-to-IRS(ℓ), $\mathbf{G}_{k,c}^{\ell} \in \mathbb{C}^{M \times 1}$, $\overline{\mathbf{G}}_{k,c}^{\ell} \in \mathbb{C}^{M \times 1}$.

Considering the UE's intra-cell and inter-cell interference, the signal received by the *i*-th UE on subchannel c of UBS(k) by IRS(ℓ) is

$$y_{k,i,c}^{\ell} = \underbrace{\left(d_{k,i,c}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell}\right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell}\right) m_{k,i,c}^{\ell} w_{k,i,c}^{\ell} s_{k,i,c}^{\ell}}_{\text{desired signal}} + \underbrace{\left(d_{k,i,c}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell}\right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell}\right) \sum_{j=1, j \neq i}^{M_{k}} m_{k,j,c}^{\ell} w_{k,j,c}^{\ell} s_{k,j,c}^{\ell}}_{\text{intral-cellinterference}} + \underbrace{\sum_{b=1, b \neq k}^{K+1} \left(d_{k,i,c}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell}\right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell}\right) \sum_{v=1}^{M_{b}} m_{b,v,c}^{\ell} w_{b,v,c}^{\ell} s_{b,v,c}^{\ell}}_{\text{inter-cellinterference}}}$$

where $k, b \in K$, $i, j \in M_k$. $m_{k,i,c}$ is subchannel assignment coefficient, if UE(k, i) is assigned to subchannel c, then $m_{k,i,c}=1$, otherwise, $m_{k,i,c}=0$. $z_{k,i,c}^{\ell} \sim C\mathcal{N}(0, (\sigma_{k,i,c}^{\ell})_z^2),$ $w_{k,i,c}^{\ell}$ is the corresponding transmit beamforming of UE(k, i)on subchannel c by IRS (ℓ) .

In addition, each UE is equipped with a receiver architecture based on power splitting (PS), which divides the received signal power into an information decoding (ID) module and an energy harvesting (EH) module [24]. The signal received by each UE is divided into two parts, in which $\varepsilon_{k,i,c}^{\ell}$ is used for ID, and the remaining part $1 - \varepsilon_{k,i,c}^{\ell}$ is used for EH. Thus, the received signals of the ID and EH modules are $(y_{k,i,c}^{\ell})^{ID} = \sqrt{\varepsilon_{k,i,c}^{\ell}}y_{k,i,c}^{\ell} + n_{k,i,c}^{\ell}$ and $(y_{k,i,c}^{\ell})^{EH} = \sqrt{1 - \varepsilon_{k,i,c}^{\ell}}y_{k,i,c}^{\ell}$, respectively, where $n_{k,i,c}^{\ell} \sim C\mathcal{N}(0, (\sigma_{k,i,c}^{\ell})_{n}^{2})$.

To simulate the actual characteristics of the user energy harvester, a practical non-linear energy harvesting model is considered as follows

$$\Pi_{k,i,c}^{\ell} = \frac{\frac{\Omega_{k,i,c}^{\ell}}{1 + e^{-u_{k,i,c}^{\ell}} (\Xi_{k,i,c}^{\ell} - v_{k,i,c}^{\ell})} - \frac{\Omega_{k,i,c}^{\ell}}{1 + e^{u_{k,i,c}^{\ell}} v_{k,i,c}^{\ell}}}{1 - \frac{1}{1 + e^{u_{k,i,c}^{\ell}} v_{k,i,c}^{\ell}}}$$
(7)

where $\Omega_{k,i,c}^{\ell}$ indicates the maximum collected power of UE(k, i) on subchannel c by IRS(ℓ) when energy harvesting reaches saturation. $u_{k,i,c}^{\ell}$ and $v_{k,i,c}^{\ell}$ take into account circuit limitations and current leakage. $u_{k,i,c}^{\ell}$ indicates the charging rate with respect to the input RF power and $v_{k,i,c}^{\ell}$ relates to the sensitivity. $\Omega_{k,i,c}^{\ell}$, $u_{k,i,c}^{\ell}$ and $v_{k,i,c}^{\ell}$ can be determined by a curve fitting tool based on the measured data. In addition, the receives power $\Xi_{k,i,c}^{\ell}$ of UE(k, i) on subchannel c by IRS(ℓ) is

$$\Xi_{k,i,c}^{\ell} = \left(1 - \varepsilon_{k,i,c}^{\ell}\right) \times \left(\sum_{i=1}^{M_{k}} \left|H_{k,i,c}^{\ell} w_{k,i,c}^{\ell}\right|^{2} + \sum_{b=1,b\neq k}^{K+1} \left|H_{b,i,c}^{\ell}\right|^{2} \sum_{v=1}^{M_{b}} \left|w_{b,v,c}^{\ell}\right|^{2}\right) \right)$$
(8)

Due to the fact that NOMA allows multiple users to occupy a subchannel and can be decoded at the receiver by successive interference cancelation (SIC), NOMA can reduce interference in certain orders depending on the channel gain or power of different users. The user with the stronger channel gain decodes the signal of the user with the weaker channel gain before decoding its own signal [31]. However, due to the introduction of IRS in the system, IRS is able to change the cascaded channel gain of NOMA users. Since the decoding order of the NOMA system is determined by the channel quality, the SIC decoding order is the key in the IRS-NOMA system.

Specifically, if the message of UE(k, i) is the *n*-th signal to be decoded on subchannel c at the receiver, then there is $\pi_c(k,i) = n$. That is, the UE (k,i) will first decode the signals of all (n-1) previous users on subchannel c and then subtracts their signals in turn to decode the signal it wants. For example, a subchannel is occupied by two different UE, for a pair of users in UAV cell k, $UE_c(k, \{i, j\})$. Assignment to subchannel c in decoding order $\pi_c(k, i) < \pi_c(k, j)$, which indicates that $UE_c(k, \{i\})$ can treat the signal of $UE_c(k, \{j\})$ as interference and decode its signal directly. By applying SIC to eliminate $UE_c(k, \{i\})$'s signal, $UE_c(k, \{j\})$ can decode its own signal without co-channel interference. In this case, $|H_{k,i,c}^{\ell}|^2 \leq |H_{k,j,c}^{\ell}|^2$ should be satisfied to enure that the SIC can be successfully executed, otherwise, the decoding order is $\pi_c(k,i) > \pi_c(k,j)$, and $|H_{k,i,c}^\ell|^2 \ge |H_{k,j,c}^\ell|^2$ should be satisfied.

Let $\{1, ..., K\}$ denote UBS, the (K+1)-th base station represents the MBS. Let $H_{k,i,c}^{\ell}$ represents the channel gain from UBS(k) to UE(k, i) on subchannel c, $H_{k,i,c}^{\ell} = d_{k,i,c}^{H} + (\mathbf{r}_{k,i,c}^{\ell})^{H} \Theta_{\ell} \mathbf{G}_{k,c}^{\ell}$. Assuming that each user is sorted in descending order, then the relevant received signal-to-noise ratio (SINR) of UE(k, i) is represented by

$$SINR_{k,i,c}^{\ell} = \frac{m_{k,i,c}^{\ell} \left| H_{k,k,i,c}^{\ell} w_{k,i,c}^{\ell} \right|^{2}}{\left(\begin{array}{c} \left| H_{k,k,i,c}^{\ell} \right|^{2} \sum_{\pi_{c}(k,i) < \pi_{c}(k,j)} m_{k,j,c}^{\ell} \left| w_{k,j,c}^{\ell} \right|^{2} \right. \\ \left. + \sum_{b=1, b \neq k}^{K+1} \left| H_{k,b,i,c}^{\ell} \right|^{2} \sum_{v=1}^{M_{b}} m_{b,v,c}^{\ell} \left| w_{b,v,c}^{\ell} \right|^{2} \\ \left. + \left(\sigma_{k,i,c}^{\ell} \right)_{n}^{2} \middle/ \varepsilon_{k,i,c}^{\ell} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} \right) \right]$$
(9)

Authorized licensed use limited to: Aristotle University of Thessaloniki. Downloaded on September 26,2023 at 19:45:29 UTC from IEEE Xplore. Restrictions apply. © 2023 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information. where $H_{k,b,i,c}^{\ell}$ is the channel gain between BS *b* and UE *i* on subchannel *c* of base station *k*, $w_{k,i,c}^{\ell}$, $w_{k,j,c}^{\ell}$ are the transmit beamforming of the UBS(*k*) at UE(*k*, *i*) and UE(*k*, *j*) on subchannel *c* respectively.

B. Problem Formulation

The goal of this paper is to maximize system EE and ultimately reduce the energy consumption while considering user subchannel assignment, SIC decoding order, UAV transmit beamforming, power splitting factor and IRS discrete reflecting phase design. In addition, the energy harvesting function of the user equipment is also considered. The rate of UE(k, i) is stated as

$$R_{k,i,c}^{\ell} = B_{sc} \log_2(1 + SINR_{k,i,c}^{\ell}) \tag{10}$$

$$R(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \sum_{k=1}^{K+1} \sum_{i=1}^{M_k} \sum_{c=1}^C R_{k,i,c}^\ell$$
(11)

where $\boldsymbol{\pi} = \{\pi_c(k, i), \forall k, i, c\}$ is the set of SIC decoding order, consisting of matrix $\boldsymbol{\pi}_c \in \mathbb{C}^{M_k \times (K+1)}, \boldsymbol{\Gamma} = \{m_{k,i,c}^{\ell}, \forall k, i, c, \ell\}$ is the set of user subchannel assignment coefficients, consisting of matrix $\boldsymbol{\Gamma}_c^{\ell} \in \mathbb{C}^{M_k \times (K+1)}, \boldsymbol{W} = \{w_{k,i,c}^{\ell}, \forall k, i, c, \ell\}$ is the set of transmit beamforming matrix of the UBS, consisting of matrix $\boldsymbol{W}_c^{\ell} \in \mathbb{C}^{M_k \times (K+1)}, \boldsymbol{\varepsilon} = \{\varepsilon_{k,i,c}^{\ell}, \forall k, i, c, \ell\}$ is the set of power splitting factors, consisting of matrix $\boldsymbol{\varepsilon}_c^{\ell} \in \mathbb{C}^{M_k \times (K+1)}, \boldsymbol{\Theta} = \{\theta_m^{\ell}, \forall m, \ell\}$ denotes the set of phase shift matrix of IRSs, consisting of matrix $\boldsymbol{\Theta}_{\ell} \in \mathbb{C}^{M \times M}, \forall k \in \{1, ..., K, K+1\}, c \in \{1, ..., C\}, \ell \in \{1, ..., L\}.$

The total consumed transmit power can be obtained by

$$Q(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \sum_{k=1}^{K+1} \sum_{i=1}^{M_k} \sum_{c=1}^{C} m_{k,i,c}^{\ell} \left| w_{k,i,c}^{\ell} \right|^2 + P_{IRS} + P_H$$
(12)

where $P_{IRS} = LMp_{irs}(Bit)$, represents the power consumption of the IRS components, $p_{irs}(Bit)$ denotes hardware power loss of IRS components with (Bit)-bit resolution phase shifter [32]. $P_H = Kp_h$, p_h represents the mechanical energy consumed by the UAV to hover against gravity in unit time, which is generally considered to be a constant [33].

The total system energy consumption is represented as

$$EE(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \frac{R(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})}{Q(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})}$$
(13)

The joint optimization problem in this paper is transformed

into as follows

$$P: \max_{\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}} EE(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})$$

$$s.t. \quad C1: \sum_{i=1}^{M_k} \sum_{c=1}^{C} m_{k,i,c}^{\ell} \left| w_{k,i,c}^{\ell} \right|^2 \leq P_k^{UAV}, \forall k$$

$$C2: \left| w_{k,i,c}^{\ell} \right|^2 \geq 0, \forall k, i, c$$

$$C3: m_{k,i,c}^{\ell} \in \{0, 1\}, \forall k, i, c$$

$$C4: \sum_{k=1}^{K} m_{k,i,c}^{\ell} \leq N, \forall k, c$$

$$C5: \sum_{i=1}^{M_k} \sum_{c=1}^{C} m_{k,i,c}^{\ell} R_{k,i,c}^{\ell} \geq R_{k,\min}, \forall k$$

$$C6: \sum_{k=1}^{K} \sum_{i=1}^{M_k} \sum_{c=1}^{C} m_{k,i,c}^{\ell} \left| w_{k,i,c}^{\ell} H_{k,K+1,c}^{\ell} \right|^2 \leq I_{\max}$$

$$C7: \left| \theta_m^{\ell} \right| = 1, \theta_m^{\ell} \in \mathcal{F}_D, \forall m, \ell$$

$$C8: \pi_c(k, i) \leq \pi_c(k, j), \left| H_{k,i,c}^{\ell} \right|^2 \leq \left| H_{k,j,c}^{\ell} \right|^2$$

$$C9: 0 < \varepsilon_{k,i,c}^{\ell} < 1, \forall k, i, c$$

$$C10: \Pi_{k,i,c}^{\ell} \geq \left(\Pi_{k,i,c}^{\ell} \right)_{\min}, \forall k, i, c$$

$$(14)$$
here C1, C2 represent transmit power constraints, P_{L}^{UAV}

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where C1, C2 represent transmit power constraints, P_k^{UAV} represents the maximum transmit power of the k-th UAV, the sum power of UE cannot overtake each P_k^{UAV} , and the power of UE is non-negative. C3, C4 represent the limit of the number of users associated to each UBS. This paper stipulates that the maximum number of users that each UBS can serve is N. C5 specifies the heterogeneous QoS requirements of users, and $R_{k,\min}$ represents the minimum rate requirement. C6 is cross-layer interference limit, $|H_{b,K+1,c}^{\ell}|^2$ is the channel gain of users from UBS to MBS, and I_{\max} is the maximum interference constraint. C7 is the phase shift constraint of IRSs. C8 is to ensure that SIC decoding can be carried out successfully. C9 is the PS factor constraint for UE receiver in SWIPT. C10 is the UE energy harvesting threshold constraint.

To address the above non-convex problem, an iterative method is invoked to seek out a suboptimal solution in section III.

III. PROPOSED SCHEME

Due to the system model is non-convex and the target function present in fractional form, the inequality approximation convex transform is adopted to represent the lower bound on the UE rate [34]. For any $SINR_{k,i,c}^{\ell} \geq 0$, the inequality form can be presented as

$$a_{k,i,c}^{\ell} \log_2(SINR_{k,i,c}^{\ell}) + b_{k,i,c}^{\ell} \le \log_2(1 + SINR_{k,i,c}^{\ell}),$$
(15)

where $a_{k,i,c}^{\ell}$ and $b_{k,i,c}^{\ell}$ are respectively

$$a_{k,i,c}^{\ell} = \frac{\widetilde{SINR}_{k,i,c}^{\ell}}{1 + \widetilde{SINR}SINR_{k,i,c}^{\ell}}$$
(16)

$$b_{k,i,c}^{\ell} = \log_2(1 + \widetilde{SINR}_{k,i,c}^{\ell}) - \frac{\widetilde{SINR}_{k,i,c}^{\ell}}{1 + \widetilde{SINR}_{k,i,c}^{\ell}} \log_2(\widetilde{SINR}_{k,i,c}^{\ell})$$
(17)

where $\widetilde{SINR}^{\ell}_{k,i,c}$ is the value of the last iteration of $SINR^{\ell}_{k,i,c}$.

According to Eq.(15), the lower bound of UE(k, i) rate as

$$\ddot{R}^{\ell}_{k,i,c} = B_{sc} a^{\ell}_{k,i,c} \log_2(SINR^{\ell}_{k,i,c}) + b^{\ell}_{k,i,c}$$
(18)

Then the rate is $\ddot{R}(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \sum_{k=1}^{K+1} \sum_{i=1}^{M_k} \sum_{c=1}^{C} \ddot{R}_{k,i,c}^{\ell}$. The problem of (14) can be rewritten as

$$P': \max_{\substack{\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta} \\ s.t}} EE(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \frac{R(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})}{Q(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})}$$

$$s.t \quad C1 - C4, C6, C7, C8, C9, C10$$

$$C5': \sum_{i=1}^{M_k} \sum_{c=1}^C m_{k,i,c}^{\ell} \ddot{R}_{k,i,c}^{\ell} \ge R_{k,\min}, \forall k$$
(19)

Obviously, the target function in the above equation is a nonlinear fraction. Introduce an operation to convert fractions into subtractions to reduce computational complexity [35].

$$\eta^{*} = \max_{\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta}} \frac{\ddot{R}(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})}{Q(\boldsymbol{\pi}, \boldsymbol{\Gamma}, \mathbf{W}, \boldsymbol{\varepsilon}, \boldsymbol{\Theta})} = \frac{\ddot{R}(\boldsymbol{\pi}^{*}, \boldsymbol{\Gamma}^{*}, \mathbf{W}^{*}, \boldsymbol{\varepsilon}^{*}, \boldsymbol{\Theta}^{*})}{Q(\boldsymbol{\pi}^{*}, \boldsymbol{\Gamma}^{*}, \mathbf{W}^{*}, \boldsymbol{\varepsilon}^{*}, \boldsymbol{\Theta}^{*})}$$
(20)
$$\ddot{R}(\boldsymbol{\pi}^{*}, \boldsymbol{\Gamma}^{*}, \mathbf{W}^{*}, \boldsymbol{\varepsilon}^{*}, \boldsymbol{\Theta}^{*}) - \eta^{*}Q(\boldsymbol{\pi}^{*}, \boldsymbol{\Gamma}^{*}, \mathbf{W}^{*}, \boldsymbol{\varepsilon}^{*}, \boldsymbol{\Theta}^{*}) = 0$$
(21)

Thus, the problem of (19) can be restated as

$$P'': \max_{\substack{\boldsymbol{\pi},\boldsymbol{\Gamma},\mathbf{W},\boldsymbol{\varepsilon},\boldsymbol{\Theta}\\s.t}} \ddot{R}(\boldsymbol{\pi},\boldsymbol{\Gamma},\mathbf{W},\boldsymbol{\varepsilon},\boldsymbol{\Theta}) - \eta Q(\boldsymbol{\pi},\boldsymbol{\Gamma},\mathbf{W},\boldsymbol{\varepsilon},\boldsymbol{\Theta})$$

$$s.t \qquad C1 - C4, C5', C6, C7, C8, C9, C10$$
(22)

A. Subchannel Assignment and SIC decoding order

Referring to the method in [36], this paper designs the problem of subchannel assignment in NOMA to associate users, UBS and subchannels. This subsection proposes a suboptimal low-complexity subchannel bilateral selection algorithm. The proposed algorithm consists of two steps as follow.

1) Assign users to corresponding subchannels according to subchannel gain. Specifically, according to the CSI of each user, a occupy request is sent to the subchannel that can provide it with the optimal subchannel gain, and the user with the most suitable channel status is allocated to the wellmatched subchannel.

2) Subhannels accept or reject users based on the channel EE of various combinations of users. To optimize the energy efficiency of a subchannel, select a group of N users that can be connected to it, where the maximum number of users allowed on the subchannel is set to N. Then the user matching scheme of each subchannel is obtained. The EE formula for the subchannel c on the UBS(k) with IRS (ℓ) is given by

$$EE_{k,c}^{\ell} = \frac{\sum_{i=1}^{M_k} R_{k,i,c}^{\ell}}{\sum_{i=1}^{M_k} m_{k,i,c}^{\ell} \left| w_{k,i,c}^{\ell} \right|^2}$$
(23)

SIC decoding order is critical to correctly determine the decoding order after the channel assignment is complete, as the reflecting phase shift of the IRS elements will affect the optimal decoding order. For the whole system, the optimal decoding order will be any one of N! different orders, and the computational complexity of solving the original problem

grows exponentially as the number of UE increases, which is prohibitive. Therefore, the paper proposes a low-complexity algorithm to determine the decoding order by finding an optimal phase shift that maximizes the sum of the combined channel gains. The optimisation problem can thus be transformed into

$$P(A_{\boldsymbol{\pi}}) : \max_{\boldsymbol{\Theta}} \sum_{c=1}^{C} \sum_{i=1}^{M_{k}} \left| \left(d_{k,i}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell} \right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell} \right) \right|^{2}$$

s.t
$$C7 : \left| \boldsymbol{\theta}_{m}^{\ell} \right| = 1, \boldsymbol{\theta}_{m}^{\ell} \in \mathcal{F}_{D}, \forall m, \ell$$
$$C8 : \pi_{c}(k,i) \leq \pi_{c}(k,j), \left| \boldsymbol{H}_{k,i,c}^{\ell} \right|^{2} \leq \left| \boldsymbol{H}_{k,j,c}^{\ell} \right|^{2}$$
(24)

Let $\Phi_{\ell} = \check{\boldsymbol{\theta}}_{\ell}\check{\boldsymbol{\theta}}_{\ell}^{H}, \ \Phi_{\ell} \in \mathbb{C}^{(M+1)\times(M+1)}$ introduce a dummy variable γ with $|\gamma| = 1, \ \check{\boldsymbol{\theta}}_{\ell} = [\ \boldsymbol{\theta}_{\ell}^{T} \ \gamma \]^{T},$ where $\boldsymbol{\theta}_{\ell} = [\ \boldsymbol{\theta}_{1}^{\ell}, \cdots, \boldsymbol{\theta}_{m}^{\ell}, \cdots, \boldsymbol{\theta}_{M}^{\ell}]^{H}$. Let $\mathbf{X}_{k,i,c}^{\ell} = [\ (\operatorname{diag}((\mathbf{r}_{k,i,c}^{\ell})^{\mathrm{H}})\mathbf{G}_{k,c}^{\ell})^{T} \ (d_{k,i,c}^{\ell})^{*} \]^{T}, \ \mathbf{X}_{k,i,c}^{\ell} \in \mathbb{C}^{(M+1)\times 1},$ then we have

$$\left| \left(d_{k,i}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell} \right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell} \right) \right|^{2} \stackrel{\Delta}{=} \operatorname{trace} \left(\boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell} \left(\mathbf{X}_{k,i,c}^{\ell} \right)^{H} \right) \\
= \operatorname{trace} \left(\left(\mathbf{X}_{k,i,c}^{\ell} \right)^{H} \boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell} \right) \tag{25}$$

Next, for the unit modulus constraint of C7, we can convert to the following form

$$C7(a) : \operatorname{diag}(\mathbf{\Phi}_{\ell}) = \mathbf{1}_{M+1}$$

$$C7(b) : \mathbf{\Phi}_{\ell} \succeq 0$$

$$C7(c) : \operatorname{rank}(\mathbf{\Phi}_{\ell}) = 1$$
(26)

The above constraint is a non-convex problem. Referring to [37], we transform the above rank 1 problem into

$$\|\mathbf{\Phi}_{\ell}\|_{*} - \|\mathbf{\Phi}_{\ell}\|_{2} \le 0 \tag{27}$$

where $\|\Phi_{\ell}\|_{*} = \sum_{\tau} \sigma_{\tau} \geq \|\Phi_{\ell}\|_{2} = \max_{\tau} \{\sigma_{\tau}\}, \sigma_{\tau}$ represents the τ -th singular value of Φ_{ℓ} [38] [39]. The minimum value of Eq. (27) can be obtained by imposing a very small penalty term, the equation holds if and only if Φ_{ℓ} reaches rank 1, so the problem based on penalty term is given by

$$P'(A_{\boldsymbol{\pi}}):\min \frac{1}{2\mu} (\|\boldsymbol{\Phi}_{\ell}\|_{*} - \|\boldsymbol{\Phi}_{\ell}\|_{2}) - \sum_{c=1}^{C} \sum_{i=1}^{M_{k}} \operatorname{trace}((\mathbf{X}_{k,i,c}^{\ell})^{H} \boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell}) \qquad (28)$$

s.t. C8
C7': diag($\boldsymbol{\Phi}_{\ell}$) = 1_{M+1}, $\boldsymbol{\Phi}_{\ell} \succeq 0$

where μ is the penalty factor. Note that although the rank 1 constraint is relaxed in problem (28), the solution obtained by solving problem (28) is the optimal solution when $\mu \to 0$. On the other hand, for sufficiently small values of μ , solving problem (28) yields a rank 1 solution only. For the above closed form, we define a lower bound $Z = \|\Phi_{\ell}\|_2$ to deal with this problem

$$Z\left(\boldsymbol{\Phi}_{\ell}\right) \geq Z\left(\boldsymbol{\Phi}_{\ell}^{(t)}\right) + \operatorname{trace}\left(\nabla_{\boldsymbol{\Phi}_{\ell}}^{H} Z\left(\boldsymbol{\Phi}_{\ell}^{(t)}\right)\left(\boldsymbol{\Phi}_{\ell} - \boldsymbol{\Phi}_{\ell}^{(t)}\right)\right) \\ \stackrel{\Delta}{=} \tilde{Z}\left(\boldsymbol{\Phi}_{\ell}\right)$$
(29)

The MOSEK solver is used to solve the above convex optimisation problem. The decoding order is then determined by comparing the effective channel gain of each subchannel

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Algorithm 1 Stage 1: Subchannel Assignment and SIC Decoding Order Optimization

- 1: Initialize the matching list of Γ , maximum iterations Δ_1 , $t_1 = 0$, Φ^0 and SIC decoding order matrix π .
- 2: Subproblem 1: Subchannel Assignment
- 3: for k = 1 to K+1 do
- 4: Initialize UE sets $U_k(c)$ and \overline{U}_k , which represent whether UE(k) is assigned to channel c respectively.
- 5: while $U_k \neq \emptyset$ do
- 6: **for** i=1 to M_k **do**
- 7: Look for c^* meets $|H_{k,k,i,c^*}|^2 \ge |H_{k,k,i,c}|^2$.
- 8: if $|U_k(c^*)| < N$ then
- 9: Assign UE(k) to c subchannel, and delete UE(k) in \overline{U}_k , let $m_{k,i,c^*} = 1$.

10: end if

12:

11: **if** $|U_k(c^*)| = N$ then

(1) The subchannel c* picks N UE that make the EE^ℓ_{k,c} keep the largest, and rejects other UE;
(2) Remove these two UE from set Ū_k and set their subchannel assignment factor to 1 to mark these UE as having completed subchannel assignment;

(3) The UE who is not successfully assigned to subchannel c^* is put into set \overline{U}_k , and set the subchannel assignment factor of this user to 0.

- 13: **end if**
- 14: **end for**
- 15: end while
- 16: **end for**
- 17: Subproblem 2: SIC Decoding Order Optimization
- 18: repeat
- 19: Update $\tilde{Z}(\Phi)$ by Eq.(29).
- 20: Solve problem $P'(A_{\pi})$ to obtain Φ^{t_1} .
- 21: Update $t_1 = t_1 + 1$
- 22: **until** Convergence or $t_1 = \Delta_1$.

user. Finally, the constraint C8 for successful SIC decoding is equivalently converted to

$$\operatorname{trace}((\mathbf{X}_{k,i,c}^{\ell})^{H} \boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell}) \leq \operatorname{trace}((\mathbf{X}_{k,j,c}^{\ell})^{H} \boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,j,c}^{\ell})$$
(30)

The two subproblems of the first stage are optimized in turn as shown in Algorithm 1, where $U_k(c)$ is the set of UE assigned to subchannel c in cell k, \bar{U}_k indicates the set of UE in cell k who are not yet assigning subchannels.

B. Beamforming Design

Since the subchannel matching results have been obtained in the previous subsection, the user subchannel assignment coefficient is regarded as a constant, the phase shift of IRSs and SIC decoding order is fixed, and the beamforming design problem in heterogeneous networks is considered.

Let $|\widehat{w}_{k,i,c}^{\ell}|^2 = m_{k,i,c}^{\ell} |w_{k,i,c}^{\ell}|^2$, then the objective function

can be simplified as

$$\ddot{R}(\widehat{\mathbf{w}}) - \eta Q(\widehat{\mathbf{w}}) =$$

$$\sum_{k=1}^{K+1} \sum_{i=1}^{M_k} \sum_{c=1}^C \left[\widehat{R}_{k,i,c}^\ell - \eta \left| \widehat{w}_{k,i,c}^\ell \right|^2 \right] - \eta (P_{IRS} + P_H)$$

$$(31)$$

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Then the problem of (22) can be transformed into

$$P(B): \max_{\mathbf{w}} \ddot{R}(\widehat{\mathbf{w}}) - \eta Q(\widehat{\mathbf{w}})$$
s.t
$$C1': \sum_{i=1}^{M_k} \left| \widehat{w}_{k,i,c}^\ell \right|^2 \leq P_k^{UAV}, \forall k$$

$$C5'': \sum_{i=1}^{M_k} \widehat{R}_{k,i,c}^\ell \geq R_{k,\min}, \forall k$$

$$C6': \sum_{k=1}^{K} \sum_{i=1}^{M_k} \sum_{c=1}^{C} \left| \widehat{w}_{k,i,c}^\ell H_{k,K+1,\ell} \right|^2 \leq I_{\max}$$

$$C10: \Pi_{k,i,c}^\ell \geq \left(\Pi_{k,i,c}^\ell \right)_{\min}, \forall k, i, c$$
(32)

C10 can be converted as follows

$$\frac{\sum_{j=1}^{M_{k}} \left| H_{k,i,c}^{\ell} \widehat{w}_{k,j,c}^{\ell} \right|^{2} + \sum_{b=1,b\neq k}^{K+1} \left| H_{b,i,c}^{\ell} \right|^{2} \sum_{v=1}^{M_{b}} \left| \widehat{w}_{b,v,c}^{\ell} \right|^{2} \ge \frac{1}{1-\varepsilon_{k,i,c}^{\ell}} \left[v_{k,i,c}^{\ell} - \frac{1}{u_{k,i,c}^{\ell}} \ln \left(\frac{e^{u_{k,i,c}^{\ell} v_{k,i,c}^{\ell}} \left(\Omega_{k,i,c}^{\ell} - \left(\Pi_{k,i,c}^{\ell} \right)_{\min} \right) \right) \right] \right]$$

$$(33)$$

According to the above transformation, the four constraints are linear constraints on $\left| w_{k,i,c}^{\ell} \right|^2$, and the problem P(B) is convex. Therefore, the Lagrangian dual theory is adopted to resolve the problem.

Then the Lagrangian function of P(B) is established as Eq.(34), where $\alpha, \beta, \varpi, \varkappa$ is the Lagrange multiplier corresponding to C1', C5'', C6' and C10.

$$\begin{aligned} &f_{L}\left(\widehat{\mathbf{w}}, \alpha, \beta, \varpi, \varkappa\right) \\ &= \sum_{k=1}^{K+1} \sum_{i=1}^{M_{k}} \sum_{c=1}^{C} \left[\widehat{R}_{k,i,c}^{\ell} - \eta \Big| \widehat{w}_{k,i,c}^{\ell} \Big|^{2} \right] - \eta (P_{IRS} + P_{H}) \\ &+ \sum_{k=1}^{K+1} \alpha_{k} (\sum_{i=1}^{M_{k}} \Big| \widehat{w}_{k,i,c}^{\ell} \Big|^{2} - P_{k}^{UAV}) + \sum_{k=1}^{K+1} \beta_{k} (R_{k,\min} - \sum_{i=1}^{M_{k}} \widehat{R}_{k,i,c}^{\ell}) \\ &+ \varpi \left(\sum_{k=1}^{K} \sum_{i=1}^{M_{k}} \sum_{c=1}^{C} \Big| \widehat{w}_{k,i,c}^{\ell} H_{k,K+1,c}^{\ell} \Big|^{2} - I_{\max} \right) \\ &+ \varkappa \left(\left(\Pi_{k,i,c}^{\ell} \right)_{\min} - \Pi_{k,i,c}^{\ell} \right) \end{aligned}$$

where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, ..., \alpha_{K+1}]^T, \boldsymbol{\beta} = [\beta_1, \beta_2, ..., \beta_{K+1}]^T$.

The dual function of f_L is formulated as $f_D(\alpha, \beta, \varpi, \varkappa) = \max f_L(\widehat{\mathbf{w}}, \alpha, \beta, \varpi, \varkappa)$, thus the dual problem is obtained by $\min_{\alpha, \beta, \varpi, \varkappa} f_D(\alpha, \beta, \varpi, \varkappa)$. The partial derivative of the Lagrangian function is obtained as follows

$$\frac{\partial f_L(\widehat{\mathbf{w}}, \alpha, \beta, \overline{\omega}, \varkappa)}{\partial \left| \widehat{w}_{k,i,c}^{\ell} \right|^2} = + \varpi \left| H_{k,K+1,c}^{\ell} \right|^2 - \varkappa \left| H_{k,i,c}^{\ell} \right|^2 + \frac{B_{sc} a_{k,i,c}^{\ell} (1 - \beta_k)}{\ln 2 \left| \widehat{w}_{k,i,c}^{\ell} \right|^2} - \sum_{j=1, j \neq i}^{i-1} \frac{B_{sc} a_{k,i,c}^{\ell} (1 - \beta_k)}{\ln 2 \left| \widehat{w}_{k,i,c}^{\ell} \right|^2} - \eta + \alpha_k - \sum_{b=1, b \neq k}^{K+1} \sum_j^{M_b} \frac{B_{sc} a_{k,i,c}^{\ell} (1 - \beta_b) \widehat{SINR}_{k,i,c}^{\ell} \left| H_{b,k,j,c}^{\ell} \right|^2}{\ln 2 \left| \widehat{w}_{k,i,c}^{\ell} H_{b,b,j,c}^{\ell} \right|^2} \right|^2 \tag{35}$$

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Algorithm 2 Stage 2: Beamforming Design

- 1: Initialize maximum iterations of the outer layer Δ_2 , set $t_2=0$, EE $\eta^{(0)}$, and maximum tolerance χ .
- 2: while $|\ddot{R}(\hat{w}^{t_2}) \eta^{t_2-1}U(\hat{w}^{t_2})| > \chi \text{ or } t_2 \leq \Delta_2 \text{ do}$
- 3: Initialize maximum iterations of the inner layer Δ_3 , set $t_3=0$, and Lagrange multiplier $\alpha_k, \beta_k, \varpi, \varkappa$.
- 4: repeat
- for k = 1 to K+1 do 5: for i = 1 to M_k do 6: Update $\widehat{w}_{k,i,c}^{\ell}, \alpha_k, \beta_k, \varpi, \varkappa$, respectively. 7: end for 8: end for 9: $t_3 = t_3 + 1.$ 10: until The objective function converges. 11: Update $\eta^{(t_2)} = \frac{\ddot{R}(\hat{w}^{t_2-1})}{U(\hat{w}^{t_2-1})}.$ 12: Update $t_2 = t_2 + 1$ 13: 14: end while

Let $\partial f_L(\widehat{\mathbf{w}}, \alpha, \beta, \varpi, \varkappa) / \partial \left| \widehat{w}_{k,i,c}^{\ell} \right|^2 = 0$, the update formula for getting about $\left| \widehat{w}_{k,i,c}^{\ell} \right|^2$ is as Eq.(36), where $\zeta \left(\widehat{w}_{k,i,c}^{\ell} \right) = B_{sc} a_{k,j,c}^{\ell} (1 - \beta_b) \widehat{SINR}_{k,j,c}^{\ell} / \ln 2 \left| \widehat{w}_{k,j,c}^{\ell} \right|^2$, where

$$\frac{\left|\widehat{w}_{k,i,c}^{\ell}\right|^{2}}{\left(\frac{\ln 2\left[\eta - \alpha_{k} - \varpi\left|H_{k,K+1,c}^{\ell}\right|^{2} + \varkappa\left|H_{k,i,c}^{\ell}\right|^{2}\right] + \right]}{\sum_{j=1}^{i-1} \zeta\left(\widehat{w}_{k,j,c}^{\ell}\right) + \sum_{b=1,b\neq k}^{K+1} \sum_{j=1}^{M_{b}} \zeta\left(\widehat{w}_{b,j,c}^{\ell}\right) \left|\frac{H_{b,k,j,c}^{\ell}}{H_{b,b,j,c}^{\ell}}\right|^{2}\right)}$$
(36)

The updated Lagrange multiplier $\alpha, \beta, \varpi, \varkappa$ can be written as

$$\alpha_{k}^{t+1} = \alpha_{k}^{t} - \tau_{1}^{t} (P_{k}^{UAV} - \sum_{i=1}^{M_{k}} |(\widehat{w}_{k,i,c}^{\ell})^{t}|^{2})$$
(37)

$$\beta_k^{t+1} = \beta_k^t - \tau_2^t \left(\sum_{i=1}^{M_k} \left(\widehat{R}_{k,i,c}^\ell\right)^t - R_{k,\min}\right)$$
(38)

$$\varpi^{t+1} = \varpi^t - \tau_3^t (I_{\max} - \sum_{k=1}^K \sum_{i=1}^{M_k} \sum_{c=1}^C \left| \left(\widehat{w}_{k,i,c}^\ell \right)^t H_{k,K+1,c}^\ell \right|^2 \right)$$
(39)

$$\begin{aligned} \varkappa^{t+1} &= \varkappa^{t} - \\ \tau_{4}^{t} \begin{pmatrix} \left| H_{k,i,c}^{\ell} (\widehat{w}_{k,i,c}^{\ell})^{t} \right|^{2} + \sum_{b=1,b\neq k}^{K+1} \left| H_{b,i,c}^{\ell} \right|^{2} \sum_{v=1}^{M_{b}} \left| \widehat{w}_{b,v,c}^{\ell} \right|^{2} + \\ \sum_{j=1,j\neq i}^{M_{k}} \left| H_{k,i,c}^{\ell} \widehat{w}_{k,j,c}^{\ell} \right|^{2} - \frac{v_{k,i,c}^{\ell}}{1 - \varepsilon_{k,i,c}^{\ell}} + \frac{v_{k,i,c}^{\ell}}{(1 - \varepsilon_{k,i,c}^{\ell})u_{k,i,c}^{\ell}} \times \\ \ln \left(\frac{e^{u_{k,i,c}^{\ell} v_{k,i,c}^{\ell}} (\Omega_{k,i,c}^{\ell} - (\Pi_{k,i,c}^{\ell})_{\min})}{e^{u_{k,i,c}^{\ell} v_{k,i,c}^{\ell}} (\Pi_{k,i,c}^{\ell})_{\min} + \Omega_{k,i,c}^{\ell}} \right) \end{aligned}$$

$$(40)$$

where t is the number of iterations, and τ_1^t , τ_2^t , τ_3^t , τ_4^t represents the step size of the t-th iteration. The beamforming design process is summarized as Algorithm 2.

C. Power Splitting Factor and Reflecting Optimization

This subsection jointly studies PS factor and the phase design of multiple IRSs. The phases of IRSs are optimized synchronously in a parallel manner. Fixed subchannel assignment coefficients, SIC decoding order and beamforming parameters, the problem of stage 3 is reformulated as

$$P(C) : \max_{\substack{\boldsymbol{\varepsilon}, \boldsymbol{\Theta} \\ \boldsymbol{\varepsilon}, \boldsymbol{\Theta}}} \widehat{R}(\boldsymbol{\varepsilon}, \boldsymbol{\Theta}) - \eta Q(\boldsymbol{\varepsilon}, \boldsymbol{\Theta})$$

s.t C5, C7, C9, C10 (41)

Let $Y_{k,i,c}^{\ell} = (\mathbf{X}_{k,i,c}^{\ell})^H \mathbf{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell}$ and $\widehat{W}_{k,i,c}^{\ell} = \widehat{w}_{k,i,c}^{\ell} \left(\widehat{w}_{k,i,c}^{\ell} \right)^H$, the following transformation formula can be obtained

$$\left| \left(d_{k,i}^{H} + \left(\mathbf{r}_{k,i,c}^{\ell} \right)^{H} \boldsymbol{\Theta}_{\ell} \mathbf{G}_{k,c}^{\ell} \right) \widehat{w}_{k,i,c}^{\ell} \right|^{2} \\ \stackrel{\Delta}{=} \operatorname{trace} \left(\widehat{W}_{k,i,c}^{\ell} \left(\mathbf{X}_{k,i,c}^{\ell} \right)^{H} \boldsymbol{\Phi}_{\ell} \mathbf{X}_{k,i,c}^{\ell} \right) = \operatorname{trace} \left(\widehat{W}_{k,i,c}^{\ell} Y_{k,i,c}^{\ell} \right)$$
(42)

Thus C10 can be converted to C10' as

$$\sum_{j=1}^{M_{k}} \operatorname{trace}(\widehat{W}_{k,i,c}^{\ell} Y_{k,j,c}^{\ell}) + \sum_{b=1,b\neq k}^{K+1} \sum_{v=1}^{M_{b}} \operatorname{trace}(\widehat{W}_{b,v,c}^{\ell} H_{k,b,i,c}^{\ell}) \geq \frac{1}{1-\varepsilon_{k,i,c}^{\ell}} \left[v_{k,i,c}^{\ell} - \frac{1}{u_{k,i,c}^{\ell}} \ln \left(\frac{e^{u_{k,i,c}^{\ell} v_{k,i,c}^{\ell}} (\Omega_{k,i,c}^{\ell} - (\Pi_{k,i,c}^{\ell})_{\min})}{e^{u_{k,i,c}^{\ell} v_{k,i,c}^{\ell}} (\Pi_{k,i,c}^{\ell})_{\min} + \Omega_{k,i,c}^{\ell}} \right) \right]$$

$$(43)$$

Therefore, the following transformation can be obtained as

$$\sum_{i=1}^{M_{k}} \sum_{c=1}^{C} \hat{R}_{k,i,c}^{\ell} = \left\{ \begin{cases} \sum_{j=i}^{M_{k}} \left| H_{k,k,i,c}^{\ell} \hat{w}_{k,j,c}^{\ell} \right|^{2} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \frac{M_{b}}{2} \right) \right| \\ \sum_{j=i+1}^{K+1} \sum_{c=1}^{M_{b}} \left| H_{k,k,i,c}^{\ell} \hat{w}_{k,j,c}^{\ell} \right|^{2} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{M_{k}} \left| H_{k,k,i,c}^{\ell} \hat{w}_{k,j,c}^{\ell} \right|^{2} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \frac{M_{b}}{2} \right) \right| \\ \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\frac{\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\frac{\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\frac{\sigma_{k,i,c}^{\ell} \right)_{z}^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{M_{b}} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c}^{\ell} \right|^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c} \right|^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1} \left| H_{k,b,i,c}^{\ell} \hat{w}_{b,v,c} \right|^{2} + \left(\sum_{j=i+1}^{K+1} \sum_{j=i+1}^{K+1}$$

where $f\left(\Phi_{\ell}, \varepsilon_{k,i,c}^{\ell}\right)$ and $g\left(\Phi_{\ell}, \varepsilon_{k,i,c}^{\ell}\right)$ are as Eq.(45) and Eq.(46), respectively.

$$\begin{aligned} f\left(\boldsymbol{\Phi}_{\ell}, \varepsilon_{k,i,c}^{\ell}\right) \\ = \log_{2} \begin{pmatrix} \sum_{j=i}^{M_{k}} \operatorname{trace}(\widehat{W}_{k,j,c}^{\ell} \mathbf{Y}_{k,k,i,c}^{\ell}) + \left(\sigma_{k,i,c}^{\ell}\right)_{z}^{2} \\ + \sum_{b=1, b \neq k}^{K+1} \sum_{v=1}^{M_{b}} \operatorname{trace}(\widehat{W}_{b,v,c}^{\ell} H_{k,b,i,c}^{\ell}) + \frac{\left(\sigma_{k,i,c}^{\ell}\right)_{n}^{2}}{\varepsilon_{k,i,c}^{\ell}} \end{pmatrix} \\ = \log_{2} \begin{pmatrix} \sum_{j=i+1}^{M_{k}} \operatorname{trace}(\widehat{W}_{k,j,c}^{\ell} \mathbf{Y}_{k,k,i,c}^{\ell}) + \left(\sigma_{k,i,c}^{\ell}\right)_{z}^{2} \\ + \sum_{b=1, b \neq k}^{K+1} \sum_{v=1}^{M_{b}} \operatorname{trace}(\widehat{W}_{b,v,c}^{\ell} H_{k,b,i,c}^{\ell}) + \frac{\left(\sigma_{k,i,c}^{\ell}\right)_{n}^{2}}{\varepsilon_{k,i,c}^{\ell}} \end{pmatrix} \\ \end{aligned}$$
(45)

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Convert $q(\mathbf{\Phi}_{\ell})$ using SCA as follows

$$g\left(\boldsymbol{\Phi}_{\ell}, \varepsilon_{k,i,c}^{\ell}\right) \leq g\left(\boldsymbol{\Phi}_{\ell}^{(t)}, \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right) + \operatorname{trace}\left(\left(\nabla_{\boldsymbol{\Phi}}^{H}g\left(\boldsymbol{\Phi}_{\ell}^{(t)}, \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right)\right)\left(\boldsymbol{\Phi}_{\ell} - \boldsymbol{\Phi}_{\ell}^{(t)}\right)\right) + \operatorname{trace}\left(\left(\partial_{\varepsilon_{k,i,c}^{\ell}}g(\boldsymbol{\Phi}_{\ell}^{(t)}, \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right)\right)\left(\varepsilon_{k,i,c}^{\ell} - \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right)\right) \\ \triangleq \tilde{g}\left(\boldsymbol{\Phi}_{\ell}, \varepsilon_{k,i,c}^{\ell}\right)$$

$$(47)$$

where

$$\nabla_{\widetilde{\Phi}_{\ell}}^{H} g\left(\Phi_{\ell}^{(t)}, \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right) = \frac{\sum_{j=i+1}^{M_{k}} \mathbf{x}_{k,i,c}^{\ell} \widehat{W}_{k,j,c}^{\ell} \left(\mathbf{x}_{k,i,c}^{\ell}\right)^{H} / \ln 2}{\left(\sum_{j=i+1}^{M_{k}} \operatorname{trace}(\mathbf{W}_{k,j,c}^{\ell} \left(\mathbf{x}_{k,i,c}^{\ell}\right)^{H} (\Phi_{\ell})^{(t)} \mathbf{x}_{k,i,c}^{\ell}) + \left(\sigma_{k,i,c}^{\ell}\right)_{z}^{2}\right)} + \sum_{b=1, b \neq k}^{K+1} \sum_{v=1}^{M_{b}} \operatorname{trace}(\widehat{W}_{b,v,c}^{\ell} H_{k,b,i,c}^{\ell}) + \frac{\left(\sigma_{k,i,c}^{\ell}\right)_{z}^{2}}{\left(\varepsilon_{k,i,c}^{\ell}\right)^{t}}\right)} \\ \partial_{\varepsilon_{k,i,c}^{\ell}} g\left(\Phi_{\ell}^{(t)}, \left(\varepsilon_{k,i,c}^{\ell}\right)^{(t)}\right) = \frac{\left(\sigma_{k,i,c}^{\ell}\right)_{z}^{2} / \ln 2\left[\left(\varepsilon_{k,i,c}^{\ell}\right)^{t}\right]^{2}}{\left(\varepsilon_{k,i,c}^{\ell}\right)^{t}}\right)^{2}}$$

$$\frac{\left(\sum_{j=i+1}^{M_{k}}\operatorname{trace}(\mathbf{W}_{k,j,c}^{\ell}(\mathbf{X}_{k,i,c}^{\ell})^{H}(\boldsymbol{\Phi}_{\ell})^{(t)}\mathbf{X}_{k,i,c}^{\ell})+(\sigma_{k,i,c}^{\ell})^{2}\right)}{+\sum_{b=1,b\neq k}^{K+1}\sum_{v=1}^{M_{b}}\operatorname{trace}(\widehat{W}_{b,v,c}^{\ell}H_{k,b,i,c}^{\ell})+\frac{(\sigma_{k,i,c}^{\ell})^{2}_{n}}{(\varepsilon_{k,i,c}^{\ell})^{t}}\right)}$$
(49)

Consequently, the problem P(C) can be replaced by

$$P'(C) : \max_{\substack{\boldsymbol{\varepsilon},\boldsymbol{\Theta}\\\boldsymbol{\varepsilon},\boldsymbol{\Theta}}} R(\boldsymbol{\varepsilon},\boldsymbol{\Theta}) - \eta Q(\boldsymbol{\varepsilon},\boldsymbol{\Theta})$$

$$s.t.C5 : \sum_{i=1}^{M_k} \sum_{c=1}^{C} B_{sc}(f(\boldsymbol{\Phi}_{\ell},\varepsilon_{k,i,c}^{\ell}) - g(\boldsymbol{\Phi}_{\ell},\varepsilon_{k,i,c}^{\ell})) \ge R_{k,\min}$$

$$C7 : \operatorname{diag}(\boldsymbol{\Phi}_{\ell}) = 1_{M+1}, \boldsymbol{\Phi}_{\ell} \succeq 0, \operatorname{rank}(\boldsymbol{\Phi}_{\ell}) = 1$$

$$C9, C10'$$
(50)

where the objective function can be converted to

$$R(\boldsymbol{\varepsilon}, \boldsymbol{\Theta}) - \eta Q(\boldsymbol{\varepsilon}, \boldsymbol{\Theta}) = \sum_{k=1}^{K+1} \sum_{i=1}^{M_k} \sum_{c=1}^{C} \left[B_{sc} f(\boldsymbol{\Phi}_{\ell}, \boldsymbol{\varepsilon}_{k,i,c}^{\ell}) - g(\boldsymbol{\Phi}_{\ell}, \boldsymbol{\varepsilon}_{k,i,c}^{\ell}) - \eta | \widehat{w}_{k,i,c}^{\ell} |^2 \right] - \eta (P_{I\!R\!S} + P_H)$$
(51)

Apply Eq.(29) to convert the above rank 1 constraint. Then the problem of P'(C) can be rewritten as

$$P''(C) : \min \frac{1}{2\mu} \left(\left\| \mathbf{\Phi}_{\ell} \right\|_{*} - \widetilde{Z} \left(\mathbf{\Phi}_{\ell} \right) \right) + \eta Q(\boldsymbol{\varepsilon}, \boldsymbol{\Theta}) - \widehat{R}(\boldsymbol{\varepsilon}, \boldsymbol{\Theta})$$

s.t C5, C9, C10'
C7 : diag $(\mathbf{\Phi}_{\ell}) = 1_{M+1}, \mathbf{\Phi}_{\ell} \succeq 0$ (52)

Since this optimization problem is convex, the optimization solver CVX is adopted to solve it. The third stage of the joint problem is executed as in Algorithm 3.

D. Convergence and Complexity Analysis

This energy-efficient joint optimization algorithm consists of three sub-stages that are optimized sequentially to improve the overall solution quality while reducing the complexity.

Algorithm 3 Stage 3: Power Splitting Factor and Reflecting Optimization

1: Initialize maximum iterations Δ_4 , $t_4 = 0$, ε^0 , Φ^0

- 2: repeat
- 3: Update $\tilde{Z}(\Phi)$ by Eq.(29).
- 4: Solve problem P''(C) to obtain ε^{t_4} , Φ^{t_4} .
- 5: Update $t_4 = t_4 + 1$
- 6: **until** Convergence or $t_4 = \Delta_4$.

It can be seen that the optimized solution throughout the optimization algorithm from the previous sub-stage is used in the latter sub-stage of the algorithm. As we apply approximate optimization methods during the transformation of the three sub-stages, the solution results are sub-optimal solutions to the initial model and the results obtained for each scenario are iterated as the input values for the next scenario. The optimization values for the three stages of this paper are defined as follows

$$\eta^{t} = \begin{cases} \eta_{1}^{t}; & P(A) \text{ is solved} \\ \eta_{1,2}^{t}; & P(A) \text{ and } P(B) \text{ are solved} \\ \eta_{1,2,3}^{t}; & P(A), P(B) \text{ and } P(C) \text{ are solved} \end{cases}$$
(53)

Thus, in the *t*-th iteration, we can obtain three stages of optimization results with $\eta^t \leq \eta_1^t \leq \eta_{1,2}^t \leq \eta_{1,2,3}^t$. It is shown that the value of the objective function tends not to decrease after each iteration. Since the initial problem has limited UAV transmit power and limited cross-layer interference, the original upper bound on the problem is a finite value, so that the scheme proposed in this paper can eventually converge with the following computational complexity.

The algorithm complexity of this paper is composed of three stages as follows. For stage 1, in the subchannel assignment algorithm, it is assumed that there are K+1 BSs, each BS serves M_k users, and the number of subchannels is C, so the algorithm complexity of the first subproblem in stage1 is $O(CM_k(K+1))$. For subproblem 2, CVX is adopted to solve the SDP problem, the complexity for a SDP problem under S_1 SDP restraints which contains an $S_2 \times S_2$ positive semi-definite matrix is $O(\sqrt{S_2}\log(1/\iota)(S_1S_2^3 + S_1^2S_2^2 + S_1^3))$, where ι is the non-negative accuracy parameters. Thus, solving the SIC decoding optimisation problem requires $O(\log(1/\iota)(KM^{3.5} + K^2M^{2.5} + K^3M^{0.5}))$. In stage 2, the proposed algorithm updates the transmit beamforming param-) eters, assuming that I_1 and I_2 are the number of outer loops and inner loops in Algorithm 2, respectively, then the whole computational complexity is $O(I_1I_2CM_k(K+1))$. For stage 3, as to P''(C), with $S_2 = M$, $S_1 = 3KM_k + K$, calculate the complexity of P''(C) as $O(\log(1/\iota)(M^{3.5}(3KM_k+K)+K))$ $M^{2.5}(3KM_k + K)^2 + M^{0.5}(3KM_k + K)^3)$. Therefore, the total complexity of the multi-stage joint optimization algorithm proposed in this paper is $O(\log(1/\iota)(KM^{3.5}(3M_k +$ $2) + K^2 M^{2.5} ((3M_k + 1)^2 + 1) + K^3 M^{0.5} ((3M_k + 1)^3 + 1))).$

IV. SIMULATION RESULTS

Some of the main simulation parameters are given as follows. The system is composed of a ground MBS, multiple



Fig. 2. The convergence of the proposed scheme for different cases.

UAVs and IRSs. The radius of the macro cell is set to 500 meters, and the MBS is deployed in the center, and the UBSs are stochastically deployed in the macro cell. The minimum distance from the UBS to the MBS is set to 50 m. The radius of UAV cell is 10 m, the IRS location is randomly set on the radius of each UAV cell, and the heights of UBS and IRS are 30 m and 20 m, respectively. The system bandwidth is 20 MHz. The hovering power consumption of each UAV is 0.1 W. The AWGN power spectral density is -174 dBm/Hz. The energy harvesting coefficient is 0.8. The path-loss index of UBS-UE and IRS-UE link are 2.5 and 2.2, respectively. The penalty factor is set to 10^{-5} , the total number of subchannels is set to 4, and the power consumption of the IRS element is set to 5dBm for resolution 1 and 15dBm for resolution 2. Let Rician factor $Kr = \kappa_{dl} = \kappa_{rl}$, and set the value to 10 dB. The parameter $u_{k,i,c}^{\ell} = 0.0086$ in the nonlinear energy harvesting model, $v_{k,i,c}^{\ell} = 11.8689 \mu$ W, and the maximum havesting power is set to $\Omega_{k,i,c}^{\ell} = 10.219 \mu$ W.

Fig. 2 exhibits the convergence of the proposed scheme via various scenarios. There are 4 UAVs in the network, each UAV cell serves 8 users, and the number of subchannels is 4. Four cases are considered: 1) M=30, $P_{max}=37$ dBm, Bit=1; 2) M=10, $P_{max}=37$ dBm, Bit=1; 3) M=10, $P_{max}=27$ dBm, Bit=1; 4) M=10, $P_{max}=27$ dBm, Bit=2. Fig. 2 illustrates that the algorithms proposed for these four cases converge as the iterations index increases. Furthermore, the EE elevates as numbers of IRS reflecting units on account of the proposed phase design can enable passive beamforming gain enhancement. Concretely, compared to case 1, case 2 increases the number of IRSs by 10, and the EE gain of the system increases by 31.2%. Due to the low cost of IRS deployment and high system performance gain, deploying IRS in the network can play a role in economical and energy saving to a large extent. Similarly, comparing case 2 and case 3, it can be perceived that rising transmit power of UBSs can also promote EE. Comparing case 3 and case 4, it can be observed that the resolution of the discrete phase greatly affects the EE gain of the system. This is because that the higher the resolution of the discrete phase, the more EE expression and a decrease in system EE.

Fig. 3 shows the impact of six existing algorithms on system



Fig. 3. Energy efficiency versus different maximum transmit power of UAV.



Fig. 4. Energy efficiency versus the number of users per UAV cell.

gains as the UAV transmit power varies. In the simulation, the number of UAVs is 4, the number of UE per UAV cell is 4, and subchannels number is set to 4. The six schemes increase the EE gain as the transmit power of UAVs increases. Comparing the EE gains of the proposed algorithms for different user energy harvesting threshold settings, it was found that the higher the user energy harvesting threshold, the lower the EE of the system, which is more evident in Fig. 5. In addition, Fig. 3 shows the system gain of the proposed algorithm compared to the four schemes of without SIC decoding optimization (No-SIC-opt), Fix-PS-factor, equal beamforming (EQ-beamforming), Random-phase respectively. The optimized decoding order results in a system gain of 24.4%, while the rest of the parameter optimizations result in a system gain greater than this value, especially the optimized design for the discrete phase results in the most significant gain. This embodies the significance of beamforming design and IRSs phase shift design.

Fig. 4 evaluates the impact of different schemes on the system EE as the number of users per UAV cell varies. It can be seen from the simulation curve that the system EE tends to increase as the UAV cell users increases. It can be observed from the simulation that the more UAVs, the better the system gain. Then the scheme performs better when there are many UAVs and users are intensive. Not only that, Fig. 4



Fig. 5. Energy efficiency versus different user harvested energy threshold



Fig. 6. Energy efficiency versus UAV hovering power consumption.

exhibits that as the horizontal axis user parameter changes, the more the count of IRS reflecting elements, the more significant the system EE gain. Both No-SIC-opt and the Random-phase scheme have little effect on the EE of the network in the presence of fluctuating numbers of users, and in particular the EE effect is weakest with fluctuating numbers of users in the random phase shift scheme.

Fig. 5 evaluates the influence of different cases on EE versus user harvested energy threshold. All schemes become less EE as the user energy harvesting threshold increases. Comparing the simulations with phase resolution Bit=1 and Bit=2, the EE gain becomes smaller as the IRS phase resolution increases, because the high resolution phase causes a dramatic increase in power consumption. Unlike discrete phase shifts, continuous phase shifts require infinite phase resolution with a hardware power consumption of 45dbm, which can have a catastrophic impact on EE, especially when the number of IRS elements is large and the denominator of Eq.(13) becomes infinitely large. The impact of IRS phase resolution on EE forms a very different result when comparing studies of the user sum-rate in paper [40].

Fig. 6 evaluates the effect of changes in the power consumed by the UAV while hovering on the system EE. The number of each IRS's reflecting elements are 10. Simulations show that the performance of the UAV network decreases with



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Fig. 7. Energy efficiency versus numbers of IRS reflecting elements.

the increase of hovering power consumption under the five different schemes. This is because the increase in hover consumed power leads to the total power consumption of growth and a decrease in the proportion of sum-rate to total power consumption. However, the gain of the proposed scheme still outperforms compared other schemes with IRS phase resolution Bit=1. Besides, the larger the phase resolution, the lower the EE of the system. Rand subchannel scheme (RAsubchannel) means that users randomly occupy subchannels without considering the subchannel state. In comparison with the RA-subchannel scheme and No-SIC-opt scheme, using the SIC decoding optimisation mentioned in the paper results in greater gain than the subchannel assignment algorithm. Moreover, compared with Random-phase scheme, the performance gain of this paper's algorithm is significant.

The simulation in Fig. 7 displays the change of the system EE as the IRS reflecting units increases. The transmit power of the UAV is 37 dBm. As the number of IRSs reflecting units increase, the system EE gain is significant. In addition, compared with the other five schemes, the EE gain of the proposed scheme is stupendous. That is to say, deploying plentiful lowcost IRSs in the network can effectively increase the EE of the system, save costs, and has economic significance. The subchannel allocation, SIC decoding optimization, beamforming design and IRS phase shift design proposed in this paper can significantly improve system EE. In particular, in simulation 7, the spatial correlation fading caused by the dense arrangement of IRS elements is considered, i.e., the distribution of NLoS components of the link IRS-UE is $\overline{\mathbf{r}}_{k,i,c}^{\ell} \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Lambda}_{k,i,c}^{\ell})$, $\Lambda_{k\,i\,c}^{\ell} \succeq 0$ is the spatial correlation matrix [41]. The correlation matrix between the elements of the u-th and v-th is $[\mathbf{\Lambda}_{\mathbf{k},\mathbf{i},\mathbf{c}}^{\ell}]_{u,v} = \sin (2\pi \|\mathbf{s}_u - \mathbf{s}_v\|/\lambda)/(2\pi \|\mathbf{s}_u - \mathbf{s}_v\|/\lambda), \ \mathbf{s}_u = [x(u)d_H, y(u)d_V]^T$ are the two-dimensional positional coordinates of element $u, x(u) = mod(u-1, N_H)$ is the horizontal position coordinate of element $u, y(u) = \lfloor (u-1)/N_V \rfloor$ is the coordinate of the vertical position of element u, d_H, d_V are the horizontal width and vertical height of each element, respectively, which is set to $d_H = d_V = \rho = \lambda/4$, N_H , N_V are the number of IRS elements in the horizontal and vertical directions, respectively, in this simulation $N_H = M$, $N_V = 1$. Notice that $|\cdot|$ is the truncation symbol, $mod(\cdot, \cdot)$ is the modu-



Fig. 8. Energy efficiency versus pathloss exponent of IRS-UE link.



Fig. 9. Energy efficiency versus the number of UAV cells.

lus operation. $\overline{\mathbf{r}}_{k,i,c}^{\ell} = (\mathbf{\Lambda}_{k,i,c}^{\ell})^{1/2} \mathbf{e}_{k,i,c}^{\ell}, \mathbf{e}_{k,i,c}^{\ell} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$. In this simulation, the spatially correlated fading scheme is compared with the uncorrelated fading case, and the system EE is lower than the uncorrelated fading case, but still shows an increasing trend with the increase of IRS elements. Spatial correlation causes the decay of system EE, and considering how to attenuate the spatial fading among IRS elements is also a topic worth studying in IRS systems in the future.

In Fig. 8, we compare the effects of different Rician factor and UAV maximum transmit power on the system EE as the path loss index of IRS-UE link changes. Fig. 8 exhibits that as the path loss index increases, the system EE in the four cases shows a rapid decline trend. It's true that as the path-loss index of the IRS-UE link increases, the reflecting signal of the IRS becomes weaker. In addition, the larger the Rician factor, the larger the EE gain of the system. Under the same Richin factor, the higher the transmit power of UAVs, the better the system EE gain.

Fig. 9 exhibits the change of EE gain with the increase of UAV cells for four schemes. The maximum transmit power of UAVs are 37 dBm, and each cell has 4 users. Comparing the system gain at different user energy harvesting thresholds, we find that larger thresholds lead to smaller system gains. Not only that, the IRS phase shift design proposed is significantly superior to No-SIC-opt scheme and Random-phase scheme.

The simulation effectively proves that the proposed joint optimization scheme is more suitable for dense scenes with UAV cells. This is because when the users become dense, UBSs need to serve a mass of users. In this situation, the energy harvesting unit can significantly alleviate the pressure on energy supply, which creates a noticeable EE gain.

V. CONCLUSION

This paper considers the constraints of cross-layer interference and energy harvesting threshold etc., focusing on subchannel assignment, SIC decoding order, beamforming design, power splitting factor and IRS discrete reflecting phase shift optimization to maximize the system EE. Due to the primal problem established is a non-convex function in fractional form, we convert it to a subtractive form to simplify the solution. According to the pros and cons of the channel conditions, an effective subchannel matching scheme is proposed. As the SIC decoding order in the IRS-NOMA system has a non-negligible impact on the system, the SIC decoding order is optimized in this paper. Then, when the subchannel assignment parameter and decoding order is fixed, the beamforming design is obtained through an algorithm by invoking the Lagrangian dual theory. Furthermore, the power splitting factor and the discrete phase shift of IRSs is jointly designed via a penalty-SDR method and obtains a significant performance gain. Finally, the validity of the proposed scheme is proved by extensive simulations. It is verified that the deployment of IRSs have a non-negligible impact on the system EE. Our future work will focus on the study of resource optimization methods for IRS-UAV networks under the imperfect cascade CSI model.

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