SCHOOL OF ELECTRICAL ENGINEERING AND TELECOMMUNICATIONS

IRS-Assisted Communication for B5G Networks

By

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Thesis submitted as a requirement for the degree Master of Engineering (Telecommunication Engineering)

Submitted: Aug. 17, 2021

Abstract

In practice, wireless signals are emitted for serving multiple users concurrently through multipath channels. However, due to the nature of multiple-channel broadcasting, the receiver signal quality is degraded by channel fading and other channel factors. In particular, the cell-edge users not only suffer from strong co-channel interference, but their performances are also affected by the weak desired signal strength. Nowadays, an advance technology, named intelligent reflection surface (IRS), has been introduced to assist the communication connection between the multi-antenna transmitters and the receivers, especially for cell-edge users. The impinging signal at the IRS is reflected with desired phase shifts for passive beamforming. Moreover, the Joint Process Coordinated Multipoint (JP-CoMP) downlink transmission can be adopted across multiple base stations for improving the quality of communication. Besides, energy efficiency is also a critical issue and a goal to achieve in this thesis. In general, it is challenging to realize energy efficient communications. In particular, the resource allocation design for energy efficiency maximization is often formulated as a non-convex optimization problem which is challenging. As a remedy, in this thesis, we aim to address the energy efficiency maximization problem of IRS-assisted communication with JP-COMP. In particular, we design a

suboptimal algorithm based on the Dinkelbach's method, SCA and SDR programming to optimize the result. It is necessary to obtain the simulation result under the reality circumstance to verify and get the conclusion that IRS can reflect and focus event signals to the users to facilitate energy efficiency, in other words, to maximize the amount of transmitted data with per unit energy.

Keywords: IRS, JP-CoMP, Energy Efficient, Cell edge user;

Acknowledgements

I’d like to express my gratitude to my Supervisor Wing Kwan Ng who patiently made a great contribution to the content of this paper. I really appreciate the courage and confidence Wing Kwan Ng gave me not only in the field of study, but also in life. Most importantly, he directed me on how to think by myself and provide effective introductions on how to solve the problem in the appropriate way. Professor Wing Kwan Ng shows me how to discuss equally, which gives me much more confidence to speak up and work effectively. It is my pleasure to be his mentee during my postgraduation learning.

Abbreviations

BS	Base station
AP	Access Point
5G	The fifth-generation
B5G	Beyond the fifth-generation
CSI	Channel State Information
IRS	Intelligent reflecting surface
SINR	Signal-to-interference-plus-noise ratio
QoS	Quality of service
JP-CoMP	Joint Process Coordinated Multipoint
AWGN	Additive white Gaussian noise
AO	Alternating Optimization
SCA	Successive convex approximation
SDR	Semi-definite relaxation
MIMO	Multiple-input multiple-output
mmWave	Millimeter wave
UDN	Ultra-dense network
UAV	Unmanned aerial vehicle
RRHS	Remote radio heads
NOMA	Non-orthogonal multiple access
MBB	Mobile broadband

Contents

I. INTRODUCTION

Currently, 5G has been widely used in various commercial fields and Internet of Things applications with high reliability, high data rate, high connection density and reliability, low latency and other characteristics. Beyond 5G (B5G) is a brand-new communication standard for supporting three-dimensional communications such as space-air communications, space-ground communications and maritime communications, aiming to increase communication data rate to exceed 1Tbit /s. While both 5G and B5G have made contributions to improving system performance, major concerns regarding cost, including energy and basic hardware devices, and the need for higher transmission power, remain unanswered. Hence, finding innovative and cost-effective methods for B5G network is imperative. In addition, due to the randomness and uncontrollability of signal propagation, 5G physical layer technology can normally adapt to the wireless environment with temporal and spatial changes. In the past decade, various wireless technologies have been proposed and thoroughly studied to meet the high standards of future communications, including the most prominent ultra-dense network (UDN), large-scale multiple-input multiple-output (MIMO), and millimeter wave (mmWAVE) communications. However, in real systems, network power consumption and hardware cost are still key issues in the existing communication systems. For example, UDN increases circuit and cooling energy consumption almost linearly as the number of deployed base stations (BSs) increases, while achieving high performance communications on MMWAVE frequencies requires expensive RF chains and complex signal processing, especially when large-scale MIMO is used to take advantage of small wavelengths. In addition, adding too many active components to a wireless network, such as small cellular base stations or relay or remote radio heads (RRHS), can also lead to more serious interference problems. Therefore, the search for innovative research on spectrum and energy efficiency technologies with low hardware costs remains a necessary condition for the development of sustainable wireless networks in the future. Accordingly, the intelligent reflecting surface (IRS) is considered a bright new technology for reconfiguring wireless communication environments by controlling software reflection. In fact, IRS has been studied in different systems to deal with various problems in existing research. IRS-Assisted UAV Communication system is able to serve multiple ground users with minimum of the average total power consumption [9]. IRS-NOMA Networks yield a good tradeoff between the sum-rate maximization and total power consumption minimization, which also mentions the NOMA could provide the better performance than conventional OMA-IRS system [3]. IRS is able to assist multiuser multiple-input single-output (MISO) system to achieve transmit power minimum [18]. IRS can be deployed in mitigating many types of interference in full-duplex (FD) cognitive radio systems [11]. Improving system security by analyzing maximum security rate can be reached by IRS-aided wireless system [7]. [27] results show that, for the single-user infrared auxiliary system, the receiving signal-to-noise ratio (SNR) increases twice with the increase of the number of infrared reflection units N.

Over the past few decades, communication networks and computing systems have proved their importance as fundamental drivers of economic growth. Over the years, they have expanded not only in size (such as geographic region and number of terminals), but also in the diversity of services, users, and deployment environments. The purpose of resource allocation is to intelligently and efficiently allocate the limited available resources between the terminals/clients to meet the business needs of the end users.

With the rapid development and dramatic development of communication networks and computing systems, resource allocation remains a fundamental challenge due to the need for better quality of service with the increasing demand for bandwidth and computation-intensive services. In particular, to deal with a variety of new system architectures, such as cognitive networks, mesh networks, multi-hop networks, point-to-point networks, multi-standard networks, cloud computing systems, data centers, etc., distributed intelligence in a variety of devices operating autonomously can transform the traditional centralized distribution mechanism into a fully distributed solution. In recent years, many tools including optimization theory, control theory, game theory, auction theory have been used to model and solve various practical resource allocation problems. Therefore, resource allocation in communication networks and computing systems is an urgent research topic with great application prospects. In order to ensure the best performance of these systems and networks, it is imperative to develop advanced resource allocation technology.

In the era of MBB (Mobile Broadband), with the popularity of mobile intelligent terminals, data traffic in wireless networks is growing exponentially, followed by the rapid expansion of wireless networks, geometric growth of site density, and the annual growth of equipment energy consumption costs of more than 20%, even beyond some of the gains from business growth, which states that increasing demand for network traffic is closely linked to energy consumption in power amplifiers, transceiver hardware, and baseband processing and etc. This relationship can be derived from the energy efficiency measure, in bits/joules, that describes how many bits of information can be transmitted per unit of energy. Moreover, from the perspective of architecture, the traditional network is generally divided into core layer, convergence layer and access layer. With the continuous expansion of the network scale, the network traffic explosively grows, and the core layer and convergence layer devices increase with the increase of the number of access layer devices, which makes the network more complex and the energy consumption becomes larger and larger. Hence, energy issue should be taken seriously and achieving energy efficiency should be the benchmark for achieving a smarter and healthier wireless environment.

In this paper, the topic will discuss IRS assisted JP-COMP downlink transmission in a multiple-user MISO system and develop the problem of achieving energy efficiency in the cellular user scenario and provide an optimized solution. The structure of the rest paper is organized as follows. Chapter II will display the system model and indicates how to formulate the problem. Then providing the efficient algorithm in Chapter III. Chapter IV presents simulation results and evaluate the performance of the proposed designs. Finally, we conclude the paper in Chapter V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

This thesis considers an IRS-assisted JP-CoMP downlink transmission network composed of N BSs, one IRS and K cell-edge users, as shown in Figure 1. Compared with conventional systems [10], [22], all base stations in the JP-CoMP system can jointly transmit concurrently. In other words, each user data is available at all the involved base stations.

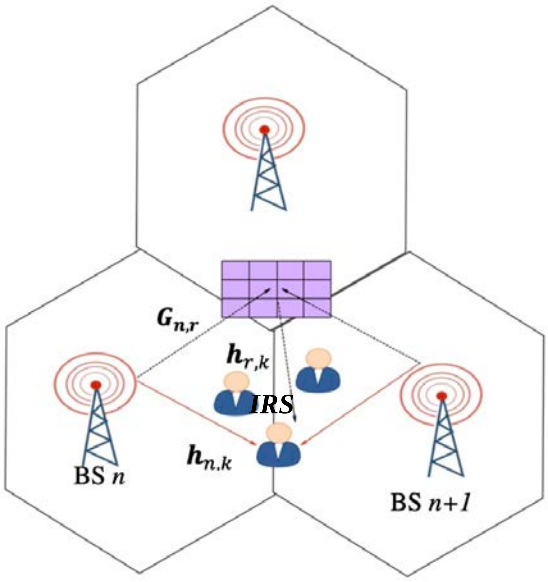

Fig. 1. IRS-assisted multi-user wireless network.

In this thesis, we assume that each base station has multiple transmit antennas ($N_t > 1$), each cell-edge user is equipped with one receive antenna ($N_r = 1$), the IRS is equipped with M reflecting elements. Variables N, K, and M represent the numbers of base stations, users, and the reflecting elements at the IRS, respectively. The delay between the direct link and reflected link is generally sufficiently small and can be ignored in the system model [12]. Then, let $\boldsymbol{h}_{n,k} \in C^{N_t \times 1}, \boldsymbol{G}_{n,r} \in C^{M \times N_t}, \boldsymbol{h}_{r,k} \in C^{M \times 1}$ represent the complex-valued equivalent baseband channel matrix of base station n to the kth user, base station n to the IRS, the IRS to the kth user, $\forall k \in K, \forall n \in N$, respectively.

Then, the equation of the transmitted signals from base station n, $n \in \{1, \ldots, N\}$, can be shown as below:

$$\boldsymbol{x}_n = \sum_{k=1}^{K} \boldsymbol{w}_{n,k} s_k, \qquad (1)$$

where $s_k \in C$ represents the complex-valued information data of user k, $\boldsymbol{w}_{n,k} \in C^{N_t}$ represents the emission beamforming matrix for user k adapted at BS n. It is assumed that CSI is fully known for all channel links, which can be achieved by some existing channel estimated methods [18], [26]. As shown in Figure 1, each user not only receives the desired signal from the N BSs, but also receives the signal reflected by the IRS. The received signal at user K can be expressed as:

$$\begin{aligned} y_k &= \sum_{n=1}^{N} \boldsymbol{h}_{n,k}^H x_n + \boldsymbol{h}_{r,k}^H \boldsymbol{\Phi} \sum_{n=1}^{N} \boldsymbol{G}_{n,r} x_n + n_k \\ &= \sum_{n=1}^{N} (\boldsymbol{h}_{n,k}^H + \boldsymbol{h}_{r,k}^H \boldsymbol{\Phi} \boldsymbol{G}_{\boldsymbol{n},\boldsymbol{r}}) \boldsymbol{w}_{n,k} s_k \\ &+ \sum_{n=1}^{N} \sum_{j \neq k}^{K} (\boldsymbol{h}_{n,k}^H + \boldsymbol{h}_{r,k}^H \boldsymbol{\Phi} \boldsymbol{G}_{\boldsymbol{n},\boldsymbol{r}}) \boldsymbol{w}_{n,j} s_j + n_k, \end{aligned} \qquad (2)$$

where $\boldsymbol{\Phi} = \mathrm{diag}(a_1 e^{j\theta_1}, \dots, a_M e^{j\theta_M})$ represents the phase shift matrix adapted in the IRS and we can set the amplitude $a_m = 1$ [8], [10]. $\theta_m \in [0,2\pi)$, $n_k \sim CN\ (0, \delta^2)$ denote phase shift of the m-th reflecting element and the additive white Gaussian noise at user k with noise variance $\delta^2 > 0$, respectively, $\forall m \in M, \forall k \in K$.

For notational simplicity, we define $\overline{\boldsymbol{h}}_{n,k} = \boldsymbol{h}_{n,k} + \boldsymbol{h}_{r,k} \boldsymbol{\Phi} \boldsymbol{G}_{n,r}$ and $\overline{\boldsymbol{h}}_k = [\boldsymbol{h}_{1,k}, \dots . \boldsymbol{h}_{n,k}]$ and $\boldsymbol{W}_k = [\boldsymbol{w}_{1,k}^T, \dots . , \boldsymbol{w}_{n,k}^T]^T$. Equation (2) can be rewritten as:

$$y_k = \bar{\boldsymbol{h}}_k^H \boldsymbol{W}_k s_k + \bar{\boldsymbol{h}}_k^H \sum_{j\neq k}^{K} \boldsymbol{W}_j s_j + n_{k.} \quad (3)$$

The signal-to-interference-plus-noise ratio received at user k is defined as follow:

$$\gamma_k = SINR_k = \frac{\left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2}{\sum_{n=1}^{N}\sum_{j\neq k}^{K} |(\boldsymbol{h}_{n,k}{}^H + \boldsymbol{h}_{r,k}{}^H \boldsymbol{\Phi} \boldsymbol{G}_{n,r})\boldsymbol{W}_{n,j}|^2 + \delta^2}$$
$$= \frac{\left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2}{\sum_{j\neq k}^{k}\left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2 + \delta^2}. \quad (4)$$

The achievable rate at user k can be defined as follow [23], [42]:

$$R_k = \ log_2(1+\gamma_k). \quad (5)$$

Then, the total sum rate of the system is written as:

$$R = \sum_{k=1}^{K} R_k = \sum_{k=1}^{K} log_2(I + \gamma_k). \quad (6)$$

B. Design Problem Formulation

In this system, our goal is to maximize the system energy efficiency, which is defined as the ratio of the total rate of the system to the total power consumption. Considering the minimum required data rate constraint and the total transmitted power budget, the energy efficiency maximization problem can be expressed as:

$$P1: \qquad \text{maximize}_{\boldsymbol{w}_{n,k},\boldsymbol{\Phi}} \frac{R}{\sum_{n=1}^{N}\sum_{k=1}^{K}\left|\left|\boldsymbol{w}_{n,k}\right|\right|^2 + P_c}$$

s.t

$$\text{C1:} \sum_{k=1}^{K}\left|\left|\boldsymbol{w}_{n,k}\right|\right|^2 \leq P_{max}, \forall n \epsilon N, \quad (7.1)$$

$$\text{C2: } R_k \geq R_{k,min}, \forall k \epsilon K, \quad (7.2)$$

$$\text{C3: } 0 \leq \theta_m \leq 2\pi, \ \forall m \epsilon M. \quad (7.3)$$

Constraint 1 limits the total transmit power per base station since the transmission power should be less than the total power budget maximation P_{max}. Constraint 2 imposes the minimum requirement of data rate at the receiver side denoting the QoS for each user [4]. Constraints 3 specifies the range of phase shift at the IRS.

Even though constraint 1 is convex and constraint 3 is an affine function with respect to θ_m, obtaining the globally optimal solution of problem P1 is challenging due to its non-convexity (i.e, R_k is not jointly concave with respect to $\boldsymbol{w}_{n,k}, \boldsymbol{\Phi}$), since both of the objective function and constraint 2 are not convex functions. In particular, variables $\boldsymbol{w}_{n,k}$ *and* $\boldsymbol{\Phi}$ are coupled affecting the development of solution.

III. ALTERNATING OPTIMIZATION SOLUTION

A. Algorithm Design

Solving P1 optimally is intractable due to the non-convex feature. As a compromise approach, in this section, we propose an alternating optimization-based algorithm [22], [15] to deal with coupled variables $\boldsymbol{w}_{n,k}$ *and* $\boldsymbol{\Phi}$. Specifically, we can divide problem P1 into the beamforming optimization and the phase shift optimization subproblems respectively, and then solve these two subproblems alternatingly. For subproblem 1, in particular, $\boldsymbol{w}_{\boldsymbol{n},\boldsymbol{k}}$ can be optimized by employing successive convex approximation (SCA) [3], [8] and the Dinkelback's method [2], [53]. As for subproblem 2, $\mathbf{\Phi}$ is optimized by SCA and semi-definite relaxation [11]-[15]. Overall, the designed algorithm can obtain a suboptimal solution of the P1 effectively and the overall algorithm is summarized in Figure 2. In the following, we will discuss the detailed solutions for each subproblem.

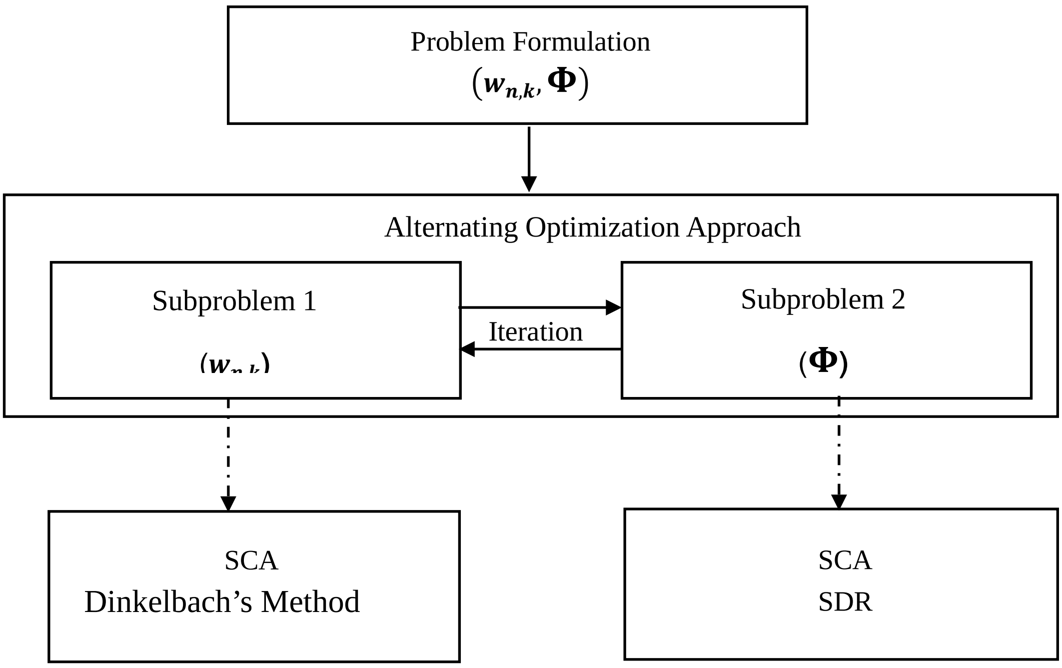

Fig. 2. A flow chart of the proposed iterative algorithm.

B. Subproblem1: Beamforming Optimization

For a given phase shift $\mathbf{\Phi}$, the objective function is to maximize the energy efficiency with respect to variable $\boldsymbol{w}_{n,k}$ leading to subproblem 1. Considering the constraints and limitations established in the system model section, the resource allocation is developed as following:

- Firstly, we rewrite the total sum rate R as follow:

$$R = \sum_{k=1}^{K} log_2(I + \gamma_k) = \sum_{k=1}^{K} log_2\left(1 + \frac{\left|\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2}{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2}\right)$$

$$= \sum_{k=1}^{K} log_2\left(\frac{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2}{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2} + \frac{\left|\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2}{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2}\right)$$

$$= \sum_{k=1}^{K} log_2\left(\frac{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2 + \left|\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2}{\sum_{j\neq k}^{K} |\,\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2}\right)$$

$$= \sum_{k=1}^{K}\left[\underbrace{log_2\left(\sum_{j\neq k}^{K} |\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2 + \left|\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_k\right|^2\right)}_{\text{Concave Function}} - \underbrace{log_2\left(\sum_{j\neq k}^{K} |\overline{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j|^2 + \delta^2\right)}_{\text{Concave Function}}\right]. \quad (8)$$

In particular, (8) is a difference between two log functions facilitating the following design of resource allocation in the later section.

- Secondly: In order to maximize the energy efficiency, we can rewrite the total sum rate R and the data rate at user k, R_k, by introducing auxiliary optimization variables τ_k *and* β_k:

$$R = \sum_{k=1}^{K} log_2\left(1 + \frac{\tau_k}{\beta_k}\right) = \sum_{k=1}^{K} log_2(\ \beta_k + \tau_k) - log_2(\beta_k), \quad (9)$$

$$R_k = log_2(\beta_k + \tau_k) - log_2(\beta_k). \quad (10)$$

- Then the optimization subproblem 1 can be equivalently written as

$$P1: \underset{\boldsymbol{W}_k,\tau_k,\beta_k}{\text{maximize}} \frac{\sum_{k=1}^{K} log_2(\beta_k + \tau_k) - log_2(\beta_k)}{\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c}$$

s.t. C1: $\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) \leq P_{max}$, (11.1)

C2: $log_2(\beta_k + \tau_k) - log_2(\beta_k) \geq R_{k,min}, \forall k \epsilon K$, (11.2)

C3: $\tau_k \leq Tr\left(\boldsymbol{W}_k \bar{\boldsymbol{h}}_k \bar{\boldsymbol{h}}_k^{\ H}\right), \forall k \epsilon K$, (11.3)

C4: $\beta_k \geq \sum_{j\neq k}^{k} \left|\bar{\boldsymbol{h}}_k^{\ H} \boldsymbol{W}_j\right|^2 + \delta^2, \forall k$, (11.4)

C5: $Rank(\boldsymbol{W_k}) \leq 1, \forall k \epsilon K$, (11.5)

C6: $\boldsymbol{W_k} \succcurlyeq 0$. (11.6)

- Then, to address the non-convex of the numerator in the objection function, we adopt the iterative SCA method [20]. To start with, we establish an upper bound:

$$log_2(\beta_k) \leq C^{(t)}. \tag{12}$$

The upper bound can be obtained through the theorem of Taylor's expansion [10]: if the function $f(x)$ is second-order differentiable near the point x_0, we can get as follow:

$$\text{If } f''(x) \leq 0, \ f(x) \leq f(x_0) + f'(x_0)(x - x_0). \tag{13}$$

Note: the equality holds when x is equal to x_0.

Let $f(x) = log_2(\beta_k)$,

The first-order and second-order Taylor expansion can be expressed as follow:

$$f'(x) = \frac{1}{\beta_k In(2)}, \tag{14}$$

$$f''(x) = -\frac{1}{{\beta_k}^2 In(2)} < 0. \tag{15}$$

Accordingly, performing the first-order Taylor approximation, we obtain following:

$$log_2(\beta_k) \leq \ log_2({\beta_k}^{(t)}) + \frac{1}{{\beta_k}^{(t)} \ln(2)}\left(\beta_k - {\beta_k}^{(t)}\right) = C^{(t)}. \tag{16}$$

where the equality holds when β_k is equal to ${\beta_k}^{(t)}$. $C^{(t)}$ is the Taylor series of $log_2(\beta_k)$ in the t-th iteration. ${\beta_k}^{(t)}$ is the value of the variable β_k after the t-th iteration in the proposed SCA-based algorithm.

- Then, replacing $log_2(\beta_k)$ by its affine upper bound, subproblem 1 optimization can becomes:

$$P1: \quad \underset{W_k, \tau_k, \beta_k}{\text{maximize}} \frac{\sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)}}{\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c}$$

s.t. C1: $\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) \leq \ P_{max}$, (17.1)

C2: $log_2(\beta_k + \tau_k) - C^{(t)} \geq R_{k,min}, \forall k \epsilon K,$ (17.2)

C3: $\tau_k \leq Tr\ (\boldsymbol{W}_k \bar{\boldsymbol{h}}_k {\bar{\boldsymbol{h}}_k}^{H})\ , \forall k \epsilon K,$ (17.3)

C4: $\beta_k \geq \sum_{j\neq k}^{k} \left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j\right|^2 + \delta^2, \forall k\epsilon K,$ (17.4)

C5: $Rank(\boldsymbol{W}_k) \leq 1, \forall k\epsilon K,$ (17.5)

C6: $\boldsymbol{W_k} \succcurlyeq 0.$ (17.6)

The constraint C5 is imposed to guarantee that $\boldsymbol{W} = \boldsymbol{w}_{n,k}\boldsymbol{w}_{n,k}{}^H$ holds after optimization.

- Then subproblem 1 can be solved through Dinkelbach's method $(F(q_k) = \max\{N(x) - q_k D(x) | x \in S\})$, a kind of fractional programming, which uses an iterative method to solve the equivalent parameter programming of problems. The main advantage of Dinkelbach's method is effectively reducing the computational complexity which is unavoidable in traditional fractional programming [28]. Hence, objective function can be written in the follow form:

$$P1: \quad \underset{\boldsymbol{W}_k, \tau_k, \beta_k}{\text{maximize}} \frac{\sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)}}{\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c}$$

$\Leftrightarrow$ $\text{maximize}_{\boldsymbol{W}_k, \tau_k, \beta_k} \sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)} - q^{*l}[\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c]$ (18)

The optimization iteration algorithm used in Dinkelbach's method allows to find maximum feasible q through repetition solving $F(q_k)$, until $F(q_k)$ closes to the pre-set tolerance value.

The algorithm based on SCA and Dinkelbach's method as shown below:

Algorithm 1 Successive Convex Approximation and Dinkelbach-Based Algorithm

1. **Initialization:** Set $\mathbf{\Phi} = \mathbf{\Phi}_0$, outer iteration index $t = 1, C$.

2. **Repeat**

3. **Beamforming Optimization:** Initialize inner iteration index $l = 1$, β_k^t , τ_k^t. Solve the objective function (11) for given β_k^t, and store the intermediate solution β_k, store $C^{(t)}$.

4. **Repeat**

5. Initialize q^l, finding maximal q^l by solving objective equation (18) with Dinkelbach'method.

6. Set $l = l + 1$.

7. **Until** $F(q_k)^l$ approaches the pre-set tolerance value.

8. Set $t = t + 1 \; and \; \beta_k^t = \beta_k, C = C^{(t)}$.

9. **Until** convergence.

10. set ${\beta_k}^* = {\beta_k}^t$

- By applying the Dinkelbach's algorithm, a more efficient design is established by using the semidefinite programming relaxation method. First of all, reversing the maximization function P1 into minimization form as follows to meet the standard form of Lagrangian dual problem.

$$P1: \underset{\boldsymbol{W}_k, \tau_k, \beta_k}{minimize} - \sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)} \; + q^l \left[\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c \right]$$

s.t. C1: $\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) - P_{max} \leq 0,$ （19.1）

C2: $log_2(\beta_k + \tau_k) - C^{(t)} - R_{k,min} \geq 0, \forall k \epsilon K.$ （19.2）

C3: $Tr\left(\boldsymbol{W}_k \bar{\boldsymbol{h}}_k {\bar{\boldsymbol{h}}_k}^H\right) - \tau_k \geq 0, \forall k \epsilon K.$ （19.3）

C4: $\beta_k \geq \sum_{j \neq k}^{k} \left| {\bar{\boldsymbol{h}}_k}^H \boldsymbol{W}_j \right|^2 + \delta^2, \forall k.$ (19.4)

C5: $Rank(\boldsymbol{W}_k) \leq 1, \forall k \epsilon K.$ （19.5）

- Constraint 5 can be removed by proving the tightness of the SDP relaxation, which could be achieved by the following theorem 1:

The rank of optimal beamforming matrix $\boldsymbol{W}_k$ is less than or equal to one if channels are statistically independent and the objective function is feasible [28]. As long as the condition in Theorem 1 is satisfied, the dual problem of the objective function (19) satisfies the Karush-Kuhn-Tucker condition and the Slater condition. Thus, the semidefinite programming relaxation is tight and the beamforming matrix $\boldsymbol{W}$ is optimal to maximize the energy efficiency.

$$P1: \underset{\boldsymbol{W}_k,\tau_k,\beta_k}{minimize} - \sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)} \; + q^l \left[\sum_{n=1}^{N} \sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c \right]$$

s.t. $\quad$ C1: $\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) - P_{max} \leq 0,$ (20.1)

C2: $log_2(\beta_k + \tau_k) - C^{(t)} - R_{k,min} \geq 0, \forall k \epsilon K.$ (20.2)

C3: $Tr\left(\boldsymbol{W}_k \bar{\boldsymbol{h}}_k \bar{\boldsymbol{h}}_k{}^H\right) - \tau_k \geq 0$. (20.3)

C4: $\beta_k \geq \sum_{j \neq k}^{k} \left| \bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j \right|^2 + \delta^2, \forall k.$ (20.4)

Proof: Please refer to Appendix.

C. Subproblem2: Phase Shift Optimization

In this section, we focus on the phase optimization. In this work, given by the transmit beamforming vectors $\{\boldsymbol{w}_{n,k}\}$ obtained from the beamforming optimization, the energy efficiency maximization P1 can be reduced to a sum-rate maximization problem shown in following:

$$\max_{\boldsymbol{\Phi}} R$$

s.t. $$R_k \geq R_{k,min} \quad (21)$$

$$0 \leq \theta_m \leq 2\pi,\ m = 1, \dots M \quad (22)$$

In this section, we focus on the phase optimization. In this work, given by the transmit beamforming vectors $\{\boldsymbol{w}_{n,k}\}$ obtained from the beamforming optimization, the energy efficiency maximization P1 can be reduced to a sum-rate maximization problem as shown in following:

$$\max_{\boldsymbol{\Phi}} \ \sum_{k=1}^{K} R_k$$

s.t. C1: $$R_k \geq R_{k,min} \quad (23.1)$$

C2: $$0 \leq \theta_m \leq 2\pi,\ m = 1, \dots M \quad (23.2)$$

Firstly, rewriting the total sum rate equation following (8):

$$R = \sum_{k=1}^{K}\left[log_2\left(\sum_{j\neq k}^{K}\left|\overline{\boldsymbol{h}}_k{}^H\boldsymbol{W}_j\right|^2 + \delta^2 + \left|\overline{\boldsymbol{h}}_k{}^H\boldsymbol{W}_k\right|^2\right) - log_2\left(\sum_{j\neq k}^{K}\left|\overline{\boldsymbol{h}}_k{}^H\boldsymbol{W}_j\right|^2 + \delta^2\right)\right]$$
$$= log_2(\beta_k + \tau_k) - log_2(\beta_k).$$

After adopting SCA method, the process has been shown in beamforming optimization, then we get:

$$P1\text{: maximize}_{\boldsymbol{\Phi}} \sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)}$$

s.t. C1: $$log_2(\beta_k + \tau_k) - log_2(\beta_k) \geq R_{k,min}, \forall k \epsilon K, \quad (24.1)$$

C2: $$0 \leq \theta_m \leq 2\pi,\ m = 1, \dots M \quad (24.2)$$

Then, we can formulate P1 into maximizing $\beta_k + \tau_k$, where $\beta_k = \sum_{j\neq k}^{K} \left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{w}_j\right|^2 + \delta^2$, $\tau_k = |\bar{\boldsymbol{h}}_k{}^H \boldsymbol{w}_k|^2$. For achieving this, the channel gain can be rewrite into a more tractable form as following:

$$\bar{\boldsymbol{h}}_{n,k}{}^H = \boldsymbol{h}_{n,k}{}^H + \boldsymbol{h}_{r,k}{}^H \boldsymbol{\Phi} \boldsymbol{G}_{n,r} = \tilde{\boldsymbol{v}}^H \boldsymbol{G}_{n,k}, \tag{24.3}$$

where $\tilde{\boldsymbol{v}} = [\boldsymbol{v}, 1]^H, \boldsymbol{G}_{n,k} = \left[diag\left(\boldsymbol{h}_{n,k}{}^H\right); \boldsymbol{h}_{r,k}{}^H \boldsymbol{\Phi} \boldsymbol{G}_{n,r}\right]$ $and\ v = \left[e^{j\theta_1}, \dots e^{j\theta_N}\right]$. Hence, we have $\bar{\boldsymbol{h}}_{n,k}{}^H \boldsymbol{w}_{n,k} \boldsymbol{w}_{n,k}^H \ \bar{\boldsymbol{h}}_{n,k} = \tilde{\boldsymbol{v}}^H \boldsymbol{G}_{n,k} \boldsymbol{w}_{n,k} \boldsymbol{w}_{n,k}^H \boldsymbol{G}_{n,k}{}^H \tilde{\boldsymbol{v}} = \tilde{\boldsymbol{v}}^H \boldsymbol{x}_{n,k} \boldsymbol{x}_{n,k}{}^H \boldsymbol{v} = Tr\left(\boldsymbol{X}_{n,k} \widetilde{\boldsymbol{V}}\right)$, where $\boldsymbol{x}_{n,k} = \boldsymbol{G}_{n,k} \boldsymbol{w}_{n,k}$. Since we have $\bar{\boldsymbol{h}}_k = \left[\boldsymbol{h}_{1,k}, \dots . \boldsymbol{h}_{n,k}\right]$, then, we can obtain $\sum_{n=1}^{N} Tr\left(\boldsymbol{X}_{n,k} \widetilde{\boldsymbol{V}}\right) = Tr\left(\boldsymbol{X}_k \widetilde{\boldsymbol{V}}\right)$. Thus, according to the SDR technique [25], and omitting the rank-one constraint the problem can be reformulated as:

$$P1: \underset{\widetilde{\boldsymbol{V}}}{\text{Maximize}}\ Tr\left(\boldsymbol{X}_k \widetilde{\boldsymbol{V}}\right)$$

$$R_{k,min}[\delta^2 + \sum_{j\neq k}^{K} Tr\left(\boldsymbol{X}_{n,j} \widetilde{\boldsymbol{V}}\right)] - Tr\left(\boldsymbol{X}_k \widetilde{\boldsymbol{V}}\right) \leq 0. \tag{25.1}$$

$$0 \leq |v_n|^2 \leq 1, n = 1, \dots N \tag{25.2}$$

$$\widetilde{\boldsymbol{V}} \succcurlyeq 0. \tag{25.3}$$

where v_n is the diagonal elements of $\widetilde{\boldsymbol{V}}$. Now, reforming problem is a standard semidefinite programming and can be solved by optimization solvers like CVX. Then we apply the eigenvalue decomposition (EVD) as $\widetilde{\boldsymbol{V}} = \boldsymbol{U \Lambda U}^H$ to obtain the solution, where $\boldsymbol{U} = [e_{1,\dots} e_n]$ is a unitary matrix and $\boldsymbol{\Lambda} = \text{diag}(\lambda_1, \dots \lambda_N)$ is a diagonal matrix.

The algorithm for solving phase shift optimization as shown below:

Algorithm 3 - Obtain the optimal phase shift

1. Initialize beamforming values of $\boldsymbol{w}_{n,k}$.
2. **Repeat**：Solving the SDR Problem (22) by CVX to obtain $\widetilde{\boldsymbol{V}}$.
3. Obtain $\widetilde{\boldsymbol{v}}$ by applying EVD.
4. Update $\overline{\boldsymbol{h}}_{n,k}$ through formula (21.3).
5. Update $\boldsymbol{w}_{n,k}$ **through beamforming optimization.**
6. Until: The value of objective function in Problem (22) converges.

IV. SIMULATION RESULTS

In this section, we investigate the system performance of the proposed resource allocation scheme via simulations. Note that there are two cells in the simulation system, the distance we set between inter-sites is 150 meters. The path loss exponents of the BS-IRS, IRS-users are 2 and 3.6 respectively due to large scale fading and there are k-users randomly distributed within in JP-CoMP system cell, the carrier frequency is 2.1GHz. In this case, we optimized beamforming $\boldsymbol{w}_{\boldsymbol{k}}$ and phase shift $\boldsymbol{\Phi}$ jointly and denotes the relationship between the IRS reflecting elements and average energy efficiency, maximum transmit power per BS and average energy efficiency respectively and numerical results show how the proposed resource allocation scheme deployed in IRS affects energy efficiency.

Moreover, the results obtained in this section have demonstrated that IRS can enhance the performance of system.

From the beginning, we set $P_{max} = 28dBm,$ k=5 users and the number of transmitting antennas is 3,6 and 9 respectively. Then, the relationship between the number of IRS reflecting elements and average energy efficiency could be obtained in Figure 3. As expected, it is clearly illustrated that increasing the number of IRS elements and can improve energy efficiency, it can be seen from the expression of Mbits/Joule that the more reflected elements, the more bits per joule can be achieved on average. There is no doubt that the more IRS reflecting elements there are, the better system performance is going to be. In fact, by jointly optimizing $\boldsymbol{\Phi}$ and $\boldsymbol{w_k}$, the scheme can simultaneously provide users with a more favorable radio propagation environment. Besides, we can observe from Figure 3 that in a given number of IRS reflecting elements, if we focus on the number of IRS elements at 60, the more transmitting antennas, the better system capacity will be multiplied.

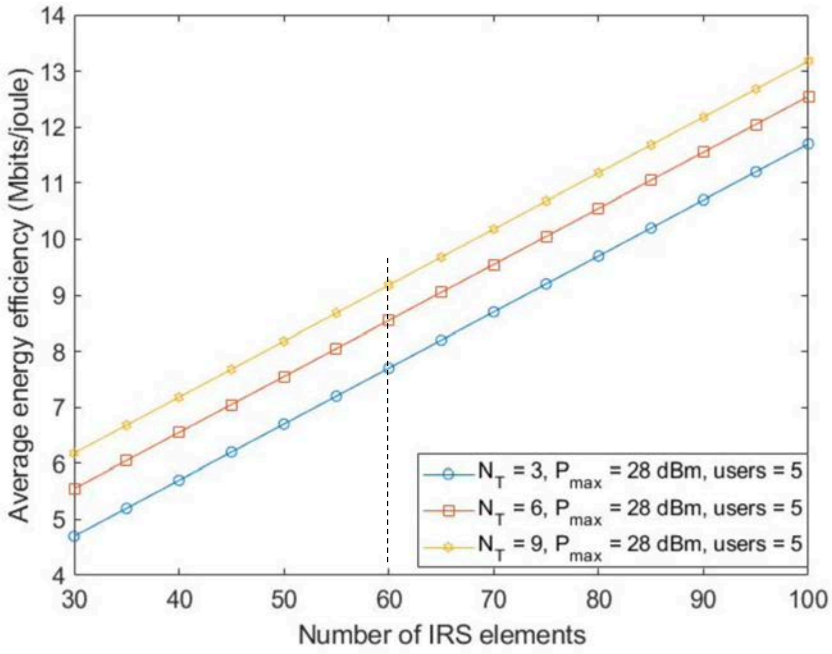

Figure. 3 Number of IRS elements VS Average energy efficiency.

In Figure 4, we set the number of users and IRS elements to 5 and 20, respectively and the number of transmitter antenna is 3,6,9, respectively. Then, we observe that the system energy efficiency first increases band then saturates by the proposed scheme as maximum transmit power increases, since it is understandable that a larger transmit power can obtain a higher energy efficiency, but it will reach a peak when the transmission power increases to 38dBm with continuous increase. Therefore, the energy efficiency will reach the saturation point when the transmit power continues to increase. In addition, it can also be concluded in Figure 4 that in a certain number of maximum transmit power per BS, the more transmitting antennas, the higher the energy efficiency, which is a common feature of the two simulation results, however, in reality circumstance, the cost of system implementation should be considered.

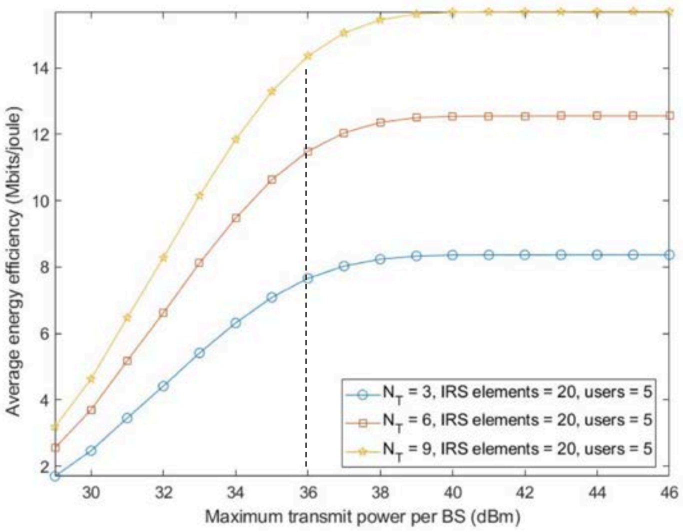

Fig. 4 Maximum transmit power per BS VS Average energy efficiency.

V. Conclusion

In this paper, we proposed an effective approach to improve the energy efficiency for the IRS aided JP-CoMP network. Specifically, beamforming and phase shift were alternately optimized to achieve the maximum system energy efficiency. Given the fixed phase shift, the beamforming was optimized by introducing some auxiliary variables and applying SCA. Moreover, we used a lower bound and SDR to optimize the phase shift. Compared with the conventional system and random phase scheme, the proposed algorithm can achieve higher energy efficiency than the benchmarks. The proposed scheme can also be extended to the multi-user case but with a different phase optimization scheme.

A. Conclusion based on current work

This semester concentrates on achieving the energy efficiency in IRS-assisted wireless communication, then doing the problem formulated and providing an appropriate method to solve the non-convex mathematical equations. In the process, the main difficulties were formulating mathematical equations, understanding the meaning of each expression. By reviewing tons of literatures and receiving help from professor, I finally found the efficiency way to solve the original problem.

C. Future work

IRS is a revolutionary new technology that significantly improves the performance of wireless communication networks by intelligently refactoring the wireless transmission environment through a plane consisting of a large number of low-cost passive reflection units. While 5G physical layer technology is usually able to adapt to changes in the wireless environment, the propagation of signals is inherently random and largely uncontrollable. The intelligent reflective surface can control the reflection by software to reconstruct the wireless propagation environment. Specifically, low-cost passive reflection units deployed in

IRS can independently change the amplitude and or phase of the incident signal, enabling synergistically fine-grained three-dimensional beamforming. IRS modifies the wireless channel through controlled reflection, providing a new degree of freedom for wireless communications and paving the way for intelligent programmable wireless environments that are in stark contrast to existing transmitter/receiver wireless link configurations. In the future 6G Internet of Things, a large number of intelligent reflective surfaces can be arranged, such as glass can be arranged in high-rise buildings. The intelligent reflective surface can effectively control the reflection phase coefficient of each reflective element, so that the propagation mode of incident signal can be changed, so that the useful signal is strengthened in the correct direction at the receiver, and the useless interference signal is eliminated in the reverse direction at the receiver end. This will effectively improve the strength of the signals sent by the Internet of Things devices at the base station, suppress the interference of other users, and then enable the Internet of things devices to transmit useful information to the base station with the lowest possible energy consumption. Therefore, intelligent reflective surfaces have broad application prospects in the future 6G Internet of Things.

Although the theoretical result obtained in the previous section is that the more transmitting antennas, the better the system capacity we have, considering the cost of system implementation, in the actual network deployment, the number of transmitting antennas will not be blindly pursued. Then, creating an efficient, low-cost network environment in the actual operating environment is very worth exploring. Apart from achieving energy efficiency, it's also worth exploring issues about IRS security in different systems like MIMO, NOMA, etc. simultaneously.

The future work will mainly focus on security scope, discuss how the IRS affects kinds of wireless communication system security while ensuring that the efficiency of the system is improved. In other words, the efficiency of safety is improved. Comparing the security in different wireless systems to see if any particular system achieves higher security under the same conditions.

APPENDIX

As derived above, we express a given difficult optimization problem as a rank constrained SDR. Then, the rank constraint is removed to obtain an SDP.

If $\boldsymbol{W}_k \geq 0 \; and \; Rank(\boldsymbol{W}_k) = R$, then we can decompose it as follow [31]:

$$\boldsymbol{W}_k = \sum_{i=1}^{R} \alpha_i \varphi_i \varphi_i^H \geq 0 \tag{21}$$

The above equation denotes the eigen-decomposition of $\boldsymbol{W}_k$, and $\alpha_1 \geq \alpha_2 \geq \cdots \geq \alpha_R > 0$ are the eigenvalues and $\varphi_1, \ldots, \varphi_R \in R^n$ are the respective eigenvectors. When R=1, $\boldsymbol{W}_k$ is feasible for all constraints, therefore, Slater's constraint is satisfied, and strong duality is guaranteed.

In order to prove the SDR is tight, Karush-Kuhn-Tucker KKT conditions [39] can be analyzed. Firstly, the Lagrangian function can be derived as follows:

$$L(\boldsymbol{W}, \lambda_1, \lambda_2, \lambda_3, \lambda_4) = -\sum_{k=1}^{K} log_2(\beta_k + \tau_k) - C^{(t)} + q^l[\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) + P_c] + \lambda_1(\sum_{k=1}^{K} Tr(\boldsymbol{W}_k) - P_{max}) + \lambda_2\left(R_{k,min} - log_2(\beta_k + \tau_k) - C^{(t)}\right) + \lambda_3\left(\tau_k - Tr\left(\boldsymbol{W}_k \bar{\boldsymbol{h}}_k \bar{\boldsymbol{h}}_k{}^H\right)\right) + \lambda_4(\sum_{j\neq k}^{k} \left|\bar{\boldsymbol{h}}_k{}^H \boldsymbol{W}_j\right|^2 + \delta^2 - \beta_k) - Tr(\boldsymbol{YW}). \tag{22}$$

where, $\boldsymbol{Y} \succcurlyeq 0$ and $\lambda_1, \lambda_{2,}\lambda_3, \lambda_4 > 0$ are the dual variables corresponding to the constraint conditions C5, C1, C2, C3 and C4 of the optimization problem respectively. The Lagrangian function derived above is used to solve the duality problem of the objective function. Then, the dual problem can be written as:

$$\max_{\boldsymbol{Y},,\lambda_1,\lambda_{2,}\lambda_3,\lambda_4} \inf_{\boldsymbol{W}} L.$$

We now focus on the Karush-Kuhn-Tucker (KKT) conditions and its theoretical proof relating to the structure of matrix $\boldsymbol{W}$. We can obtain the value of $\boldsymbol{Y}$ when the gradient of the Lagrange function is zero by taking the derivative of the Lagrange function with respect to $\boldsymbol{W}$:

$$\frac{\partial L}{\partial \boldsymbol{W}} = q^l \boldsymbol{I} + \lambda_1 \boldsymbol{I} - \lambda_3 \overline{\boldsymbol{h}}_k \overline{\boldsymbol{h}}_k{}^H + \lambda_4 \overline{\boldsymbol{h}}_k \overline{\boldsymbol{h}}_k{}^H - \boldsymbol{Y}, \tag{23}$$

$$\boldsymbol{Y} = q^l \boldsymbol{I} + \lambda_1 \boldsymbol{I} - \lambda_3 \overline{\boldsymbol{h}}_k \overline{\boldsymbol{h}}_k{}^H + \lambda_4 \overline{\boldsymbol{h}}_k \overline{\boldsymbol{h}}_k{}^H. \tag{24}$$

where $\boldsymbol{I}$ is an identity matrix.

From the perspective of complementary slackness of KKT conditions, which explains that the corresponding original constraint must be an equality if a dual variable is greater than zero, and vice versa [28]. Since $\boldsymbol{Y}$ is positive semidefinite expressed by: $\boldsymbol{Y} \succcurlyeq 0$ and $\lambda_1, \lambda_3, \lambda_4 > 0$, we can get:

$$\boldsymbol{Y}\boldsymbol{W} = \boldsymbol{0}.$$

Rewriting the equation (24) by introducing matrices $\boldsymbol{A}$ and $\boldsymbol{H}$ with same dimensions:

$$\boldsymbol{Y} = \boldsymbol{A} - \boldsymbol{H}, \tag{25}$$

where $\boldsymbol{A} = q^l \boldsymbol{I} + \lambda_1 \boldsymbol{I}, \boldsymbol{H} = \lambda_3 \bar{\boldsymbol{h}}_k \bar{\boldsymbol{h}}_k^H - \lambda_4 \bar{\boldsymbol{h}}_k \bar{\boldsymbol{h}}_k^H$. Assuming $\boldsymbol{A}$ is a positive semi-definite matrix, for any $\boldsymbol{v} \neq 0, \boldsymbol{v}^H A \boldsymbol{v} \geq 0$. Letting $\boldsymbol{V} = \boldsymbol{v}^H \boldsymbol{v}$ and multiplying the equation (25) by a matrix $\boldsymbol{V}$ and applying the trace operation on both sides, we can get:

$$\begin{aligned}\mathrm{Tr}(\boldsymbol{YV}) &= \mathrm{Tr}(\boldsymbol{AV}) - \mathrm{Tr}(\boldsymbol{HV}) \\ &= -Tr(\boldsymbol{HV}).\end{aligned} \tag{26}$$

Since, $Tr(\boldsymbol{HV})$ is larger than zero, $\mathrm{Tr}(\boldsymbol{YV})$ is greater than or equal to zero, there's a contradiction on both sides of the equation, and in order to maintain this equation, matrix $\boldsymbol{A}$ should be a positive definite matrix with full-rank ($\boldsymbol{A} > 0$), Rank $(\boldsymbol{A}) = N_t$.

Applying the basic principle of rank inequality to find the rank of ($\boldsymbol{Y}$) [29], the sum of the rank of the individual matrix $\boldsymbol{A}$ and $\boldsymbol{B}$ with same dimensions is greater than the rank of the matrix $\boldsymbol{A} + \boldsymbol{B}$. It can be expressed as: $Rank(\boldsymbol{A}+\boldsymbol{B}) \leq Rank(\boldsymbol{A}) + Rank(\boldsymbol{B})$ [30]. Hence, we have:

$$Rank(\boldsymbol{A}) \leq Rank(\boldsymbol{A}+\boldsymbol{B}) + Rank(-\boldsymbol{B}).$$

$$Rank(\boldsymbol{Y}) = Rank(-\boldsymbol{Y})$$

$$= Rank(-\boldsymbol{A} + \boldsymbol{H}) \geq Rank(-\boldsymbol{A}) -$$

$$Rank(\boldsymbol{H}) \geq N_t - 1. \quad (27)$$

Accordingly, the columns of $\boldsymbol{W}$ are members of the null space of $\boldsymbol{Y}$, then we can conclude that $Rank(\boldsymbol{W}) \leq 1$.

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