Robust Energy-Efficient Resource Management, SIC Ordering, and Beamforming Design for MC MISO-NOMA Enabled 6G

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Abstract—This paper studies a novel approach for successive interference cancellation (SIC) ordering and beamforming in a multiple antennas non-orthogonal multiple access (NOMA) network with multi-carrier multi-user setup. To this end, we formulate a joint beamforming design, subcarrier allocation, user association, and SIC ordering algorithm to maximize the worst-case energy efficiency (EE). The formulated problem is a non-convex mixed integer non-linear programming (MINLP) which is generally difficult to solve. To handle it, we first adopt the linearization technique as well as relaxing the integer variables, and then we employ the Dinkelbach algorithm to convert it into a more mathematically tractable form. The adopted non-convex optimization problem is transformed into an equivalent rank-constrained semidefinite programming (SDP) and is solved by SDP relaxation and exploiting sequential fractional programming. Furthermore, to strike a balance between complexity and performance, a low complex approach based on alternative optimization is adopted. Numerical results unveil that the proposed SIC ordering method outperforms the conventional existing works addressed in the literature.

Index Terms—Multi carrier (MC), multiple input single output (MISO), non-orthogonal multiple access (NOMA), successive interference cancellation (SIC), beamforming, energy efficiency (EE).

I. INTRODUCTION

A. Motivations and State of the Art

In the recent decades, wireless communications have appealed to a growing number of customers, demanding high quality services, and ubiquitous connections. In order to fulfill these demands, the next generation of wireless networks, namely sixth-generation (6G), should be redesigned and exploit advanced technologies [1]. Regarding this, the network must be designed in such a way to dynamically change its architecture and the communications technologies. In such a flexible architecture, significant amount of signaling and computational resources are needed to optimally manage the network resources and enable to design the flexible resource sharing. Recently, various radio access network (RAN) architectures as distributed and centralized RAN (C-RAN) are developed to provide an efficient computational resource sharing and resource utilization [3]. To enable sustainable 6G networks, new emerging techniques such as new multiple access (MA) and multiple antennas systems (MAS) are needed to improve the network performance (e.g., energy efficiency (EE)) [5]. In this regard, non-orthogonal multiple access (NOMA) and multiple-input single-output (MISO) are promising approaches which can significantly improve EE and provide massive connectivity applications, i.e., Internet of Thing (IoT) compared to the orthogonal multiple access (OMA) and single antenna systems [6]–[9]. In fact, improving the EE, fairness, and flexibility in resource allocation have turned to apply NOMA systems as the main trend in the beyond current wireless network. The authors in [9] present a basic principle of NOMA in which they state a systematic comparison among the different NOMA techniques from the viewpoint of the EE and receiver complexity. In particular, NOMA utilizes power domain (PD-NOMA) based networks for MA as well as successive interference cancellation (SIC) which removes the undesired multiuser interference [10]. In NOMA, SIC ordering is one of the key challenges and it is critical for the performance of data transmission to handle the NOMA interference [11], [12]. However, the SIC ordering problem has not been addressed well, and there are open problems that need to be addressed properly [11], [12]. In fact, in most of the works, SIC ordering is considered based on the channel gain which is not practical and optimal due to necessity of full channel state information (CSI) [9], [13], [14], [16]–[18], [20], [25]. Besides, there is uncertainty in the CSI that cannot be applicable for multiple antennas systems.

1Recently, fifth generation of wireless networks is deployed and its evolution towards 6G has been started [2].
This paper proposes a worst-case SIC ordering, resource allocation policy, and beamforming design for multicarrier (MC) MISO-NOMA networks. We would like to see how much we can get performance gain in MAS for the SIC ordering as compared to OMA as well as traditional methods in which SIC ordering is based on the channel gains.

B. Related Works

In NOMA, the efficient allocation of scarce resources and SIC ordering are turned into a challenging necessity for improving users’ satisfaction [11]. There are some attempts to find proper resource allocation strategies which improves the overall performance of such networks [13]–[18]. For instance, the problem of power allocation and precoding design is proposed in [13] in which they employ single carrier multiple-input multiple-output (MIMO) NOMA systems. The authors in [14] propose an optimal resource allocation to maximize the system throughput for NOMA and full-duplex (FD) systems, respectively. However, the base station (BS) is equipped with a single antenna which cannot fully exploit the degrees of freedom of the network. The works in [19], [20], [22], [32] consider beamforming design for MISO-NOMA systems to optimize the performance and cost of the system. In particular, the authors in [19] propose a robust beamforming design for MISO-NOMA system to maximize the minimum data rate. In [20], beamforming design and subcarrier allocation for maximizing the total data rate are proposed where optimal and sub-optimal solutions are provided. The beamforming design for maximizing the minimum EE and proportional fairness are developed in [22] to strike a balance between the EE of the system and the fairness between users. Most of the previous works considered the fixed SIC ordering, in which the order of decoding at each receiver is determined according to the channel gains [13], [14], [16]–[18], [21]. In SIC, the users are ordered and each user can remove the interference from users determined by the ordering scheme. Although most of the works on the SIC ordering sort the users based on their channels, this is not a practical scenario and can not be guaranteed as well. Also, it should be noted that sorting users for SIC based on the channel gains is neither optimal nor practical scheme at all, especially in MAS due to unavailability of the full CSI [20]. To circumvent this problem, SIC ordering should be based on the network, channel gain, and the available resource conditions. The authors in [21] address this problem for single antenna BS and perfect CSI scenario which is not practical and appropriate for future networks due to considering single-antenna BS and also having perfect CSI channel.

Besides, EE is an important metric for wireless networks, especially for enabling green communication. New communication technologies are proposed to improve the system EE. In particular, various techniques are proposed which aim to enhance the network throughput while consuming less energy without sacrificing the quality of service (QoS). At the same time, EE maximization problems are indispensable in NOMA systems, to strike a good throughput-power trade-off and improve the system performance which is noticed as one of the key performance metrics in future wireless networks. However, there is a deficit of existing works on the literature considering the EE. For instance, in [23], EE maximization is studied to obtain an optimal power allocation based on the non-linear fractional programming method. Furthermore, in [24], a subchannel assignment and power allocation is investigated to maximize the EE in NOMA networks. However, in real scenarios assuming perfect CSI is not a valid assumption due to some issues like quantization and channel estimation errors as well as hardware limitations. In this regards the works in [19], [25]–[27] address the robust solution for imperfect CSI. In particular, in [19], [25], [27], robust designs for the MISO-NOMA systems are developed based on the bounded channel uncertainties. The joint user scheduling and power allocation are explored in [26] while considering imperfect CSI. User association in multi-cell NOMA systems is also challenging. Specifically, in addition to the NOMA interference caused by the co-channel interference, the interference between cells also needs to be taken into consideration [28], [29]. Nonetheless to the best of the authors knowledge, the problem of beamforming design and SIC ordering in a MC MISO-NOMA enabled C-RAN network while considering imperfect CSI has not been investigated yet. In [13], [14], [16]–[18], [21], the BS is equipped with single antenna while assuming perfect CSI. The works in [19], [25], [27] consider robust beamforming design while fixed SIC ordering. Furthermore, the authors in [28], [29] consider user association for the single antenna BS while SIC is based on the channel gains. In addition, in [21], the SIC ordering problem for single antenna BS and perfect CSI is considered. Consequently, user association policy and SIC ordering in a MISO-NOMA enabled C-RAN network with imperfect CSI are still open problems which have not been addressed yet.

C. Contributions and Research Outcomes

In this paper, we aim to bridge the above mentioned knowledge gap. In particular, we propose a joint beamforming design, subcarrier allocation, user association, and SIC ordering algorithm which maximizes the EE of the network under imperfect CSI. To this end, we formulate the problem of beamforming design and SIC ordering to maximize the worst-case system EE. In our method, SIC ordering is considered as an optimization variable while in more existing works, SIC ordering is fixed and depends on the channel gains. The optimization problem is a non-convex mixed integer non-linear programming which is very difficult to solve. To handle it, we employ majorization minimization (MM), abstract Lagrangian method, semi-definite relaxation (SDR) method, and sequential fractional programming to handle the beamforming design and integer variables. Our main contributions are summarized as follows:

- We propose a novel SIC ordering method for the downlink of a MC MISO NOMA. To this end, we formulate a novel optimization problem to maximize the EE by performing the subcarrier allocation, beamforming design, user association, and SIC ordering. In particular, we formulate a new problem to investigate how to order users to apply successful SIC based on the available resources. Also,
we derive the worst-case SIC ordering condition as an optimization constraint and then tackle its non-convexity.

- We study the practical imperfect CSI in C-RAN networks. In doing so, we consider the worst-case EE to provide a robust resource allocation algorithm.

- We propose a solution based on rank-constrained semidefinite programming (SDP) relaxation and exploiting sequential fractional programming. In particular, we adopt MM approach and penalty factor to make it mathematically tractable and then we adopt Dinkelbach algorithm. Moreover, we provide a low complexity iterative algorithm in which the scheduling variable, i.e., user association and subcarrier assignment, is obtained through the matching algorithm.

- Numerical results reveal that the proposed worst-case EE maximization and SIC ordering algorithm can alleviate negative effect of imperfect of CSI, SIC, and limited power and spectrum resources on the network performance. Also, the results showcase the superiority of the proposed algorithm compared to the other conventional schemes.

The rest of this paper is organized as follows. The system model and problem formulation is discussed in Section II. The solution algorithm and complexity analysis are presented in Section III. Finally, the simulation analysis and conclusions are provided in Sections IV and V, respectively.

Notations: Vector and matrix variables are indicated by bold lower-case and upper-case letters, respectively. $\| \|$ indicates the absolute value, $\| \|_2$ denotes the Euclidean norm ($l_2$ norm), and $A^H$ and $A^T$ indicate the conjugate transpose and transpose of matrix $A$, respectively. Also, $\text{Tr} [A]$ denotes the trace of matrix $A$ and $I_M$ denotes the $M \times M$ identity matrix. $\nabla_x g$ indicate the gradient vector of function $g(x)$. $S$ denotes the set $\{1, 2, \ldots , S\}$ and $|S| = S$ is the cardinality of set $S$. $S \setminus \{s\}$ discards the element $s$ from the set $S$. $C^{M \times 1}$ denotes the set of $M$-by-1 dimensional complex vectors, and operation $E \{ \cdot \}$ denotes the statistical expectation.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model Descriptions and Related Constraints

In this paper, we consider a downlink scenario for a C-RAN consisting of a set of $F$ active antenna units (AAUs) indexed by $f$, whose set is denoted by $F = \{1, \ldots , F\}$, where $f = 1$ is a high power AAU, and a base band unit (BBU). Let $P_{\text{max}}^f$ be the transmit power budget of AAU $f$. Each AAU is equipped with $M$ antennas, uses a set $N$ of $N$ shared subcarriers, is connected to the BBU with a limited bandwidth fronthaul/metro-edge link, and utilizes PD-NOMA to transmit data to single antenna end-users. In fact, we consider a MC MISO-NOMA communication network setup. We denote the set of all users as $K = \{1, \ldots , K\}$ which are randomly distributed with the uniform distribution inside the coverage/service area of the network [29], [32].

TABLE I: TABLE OF THE MAIN NOTATIONS

| Notation    | Description                                                                 |
|-------------|-----------------------------------------------------------------------------|
| $F / F / f$ | Set/number/index of all AAUs in the network                                  |
| $K / K / k$ | Set/number/index of all users in the network                                |
| $N / N / n$ | Set/number/index of the shared subcarriers in each AAU                      |
| $M / m$    | Number/index of antennas in each AAU                                        |
| $P_{\text{max}}^f$ | Maximum allowable transmit power of AAU $f$                               |
| $P_{\text{total}}$ | Total consumed power                                                          |
| $R_{\text{max}}$ | Maximum capacity of fronthaul link AAU $f$                                 |
| $b_{k,n,f}$ | Real channel coefficient between user $k$ and AAU $f$ on subcarrier $n$    |
| $\hat{b}_{k,n,f}$ | Estimated channel coefficient between user $k$ and AAU $f$ on subcarrier $n$ |
| $e_{k,n,f}$ | Channel estimation error for user $k$ and AAU $f$ on subcarrier $n$         |
| $\delta^f_{k,n}$ | Channel uncertainty radius for user $k$ and AAU $f$ on subcarrier $n$       |
| $L^f_{\text{n}}$ | Maximum reused number of each subcarrier $n$ at AAU $f$                    |
| $\sigma^2_{k,n,f}$ | Variance of noise at user $k$ on subcarrier $n$ from AAU $f$               |
| $s_{k,n,f}$ | Transmit signal at user $k$ on subcarrier $n$ from AAU $f$                 |
| $r^f_{k,n}$ | Achieved rate of user $k$ on subcarrier $n$ from AAU $f$                   |
| $p^f_{\text{n}}$ | Preprocessing weight of each fronthaul link of AAU $f$                     |
| $\beta$ | Drain efficiency of the power amplifier                                     |
| $\rho^f_{k,n}$ | Binary subcarrier assignment variables, equals to 1 means that user $k$ is scheduled to AAU $f$ and subcarrier $n$, otherwise, it is 0 |
| $\xi^k_{n}$ | Binary SIC ordering variable, which $\xi^k_{n} = 1$, if user $k$ decodes the signal of user $i$ on subcarrier $n$, else $\xi^k_{n} = 0$ |
| $w_{k,n,f}$ | Beamforming vector from AAU $f$ to user $k$ on subcarrier $n$               |

The considered system model is depicted in Fig. 1.
In addition, $s_{k,n}^f$ is the signal of user $k$ over subcarrier $n$ from AAU $f$, and $w_{k,n,f} = [w_{k,n,f}^m] \in \mathbb{C}^{M \times 1}$ is the vector of beamforming variables that is designed by AAU $f$ for user $k$ over subcarrier $n$. Let us define a joint subcarrier and user associations binary variable, $\delta_{k,n}^f$, if subcarrier $n$ is assigned to user $k$ that is served by $f$, $\delta_{k,n}^f = 1$, otherwise, $\delta_{k,n}^f = 0$. We introduce our scheduling policy in terms of subcarrier assignment technique and connectivity of users to AAUs as follows:

- **Subcarrier Assignment as Multiple Access Technique**: By exploiting NOMA, each subcarrier $n$ can be assigned to at most $L_n^f$ users in AAU $f$ which is ensured by

$$\sum_{k \in K} \delta_{k,n}^f \leq L_n^f, \forall n \in N, f \in F. \quad (1)$$

- **User Association as Connectivity Technique**: In general, user association refers to find an algorithm to assign users to the radio stations. We propose a novel user association policy where each user can be configured to receive its data on different subcarriers from different AAUs. We call it multi-connectivity technique which is different from the coordinated multipoint technologies\(^4\) [30]. Therefore, each user on each subcarrier can be connected to at most one AAU which is ensured by the following constraint:

$$\sum_{f \in F} \delta_{k,n}^f \leq 1, \forall n \in N, k \in K. \quad (2)$$

Let $h_{k,n,f} \in \mathbb{C}^{M \times 1}$ be the channel coefficient between user $k$ and AAU $f$ on subcarrier $n$. Following channel uncertainty, i.e., imperfect CSI model, we assume that the global CSI is not known because of estimation errors and/or feedback delays [19], [38]. Therefore, the real channel gain is given as follows [19]:

$$h_{k,n,f} = \tilde{h}_{k,n,f} + \epsilon_{k,n,f}, \forall k, n, f, \quad (3)$$

where $\tilde{h}_{k,n,f}$ denotes the estimated channel gain and $\epsilon_{k,n,f}$ indicates the error of estimation which lies in a bounded spherical set as given by $\|\epsilon_{k,n,f}\|^2 \leq \delta_{k,n}^f$, where $\delta_{k,n}^f$ is the channel uncertainty radius and is assumed to be a small constant [38], [46]. In the other words, we have $h_{k,n,f} \in \mathcal{H}_{k,n,f}$, where $\mathcal{H}_{k,n,f}$ is as follows:

$$\mathcal{H}_{k,n,f} \triangleq \left\{ \tilde{h}_{k,n,f} + \epsilon_{k,n,f} \mid \|\epsilon_{k,n,f}\|^2 \leq \delta_{k,n}^f \right\}. \quad (4)$$

The indispensable part of NOMA is the SIC algorithm which is applied in the receiver side to handle the NOMA interference. Since in NOMA, the SIC ordering has a key impact on the received signal to interference plus noise ratio (SINR), and the performance of NOMA for cell-edge or cell-central users [21], we devise a new SIC ordering method as follows:

2\(^2\)We assume its power is normalized to one, i.e., $\mathbb{E}\{|s_{k,n}^f|^2\} = 1$.

3\(^3\)Herein, we call it the scheduling variable.

4\(^4\)Because it does not require synchronization between different AAUs.

1) **Proposed SIC Ordering Algorithm**: In contrast to sorting users based on the channel condition to perform SIC, we introduce a new binary variable as $\xi_{k,n}^f$, where $\xi_{k,n}^f = 1$ if user $k$ decodes the signal of user $i$ on the assigned subcarrier $n$ (assuming both users $k$ and $i$ are multiplexed on subcarrier $n$), and otherwise, $\xi_{k,n}^f = 0$. Note that users $i$ and $k$ can be connected to different AAUs. It is worth noting that the traditional SIC ordering is based on the channel power gain, channel gain [6], [7], [14], and normalized noise power [45].

- **Worst-Case Data Rate**: The achievable rate of user $k$ on subcarrier $n$ and AAU $f$ with channel $h_{k,n,f}$ is obtained by (5) shown at the bottom of this page. The worst-case data rate of user $k$ over the uncertainty set can be formulated as

$$r_k = \sum_{f \in F} \sum_{n \in N} \min_{\hat{h}_{k,n,f} \in \tilde{H}_{k,n,f}} r_{k,n}^f, \forall k \in K. \quad (6)$$

- **Successful Decoding Constraints as SIC Constraints**: To ensure that user $k$ can successfully cancel the signal of user $i$, i.e., user $k$ is determined to perform SIC on subcarrier $n$ which means $\xi_{k,n}^f = 1$, we consider the following three constraints should be satisfied, simultaneously.

1) **SIC ordering variable can be 1, when both users $k$ and $i$ are multiplexed on subcarrier $n$ which is ensured by**

$$\xi_{k,n}^f \leq \sum_{f \in F} \sum_{n \in N} \rho_{k,n}^f \cdot \sum_{f \in F} \rho_{i,n}^f, \forall n \in N, i \neq k, i \in K. \quad (7)$$

2) **Ensuring that one of the user $k$ or user $i$ performs SIC over the multiplexed subcarrier $n$ by**

$$\xi_{k,n}^f + \xi_{i,n}^f \leq 1, \forall n \in N, k, i \in K, k \neq i. \quad (8)$$

3) **Successful decoding constraint, which ensures that signal of user $i$ (connected to $f$) on subcarrier $n$ is detected and cancelled by user $k$ (connected to $f$) in the worst condition (based on (5)), is given by (9) shown at the top of the next page. In (9), part A ensures the constraint holds for user $k$ that is determined to perform SIC to decode and remove user $i$’s signal where both of them are multiplexed on subcarrier $n$. Parts B and D assure that the constraint holds for the worst-case estimation of CSI. To be clear, assume an example where we have two parameters as $a \in [a_{\min}, a_{\max}]$ and $b \in [b_{\min}, b_{\max}]$, and to ensure an inequality $a \leq b$ for all/worst-cases, obviously, it occurs for $a_{\max} \leq b_{\min}$. Part C is the obtained rate of user $i$ and part E is the rate of user $i$ achieved by user $k$ [6], [7], [20]. It should be noted that (9) is sufficient (but not necessary) for SIC.

2) **Fronthaul Link Capacity Constraints**: Since the bandwidth of fronthaul links are limited, we introduce a new link capacity constraint as

$$\sum_{k \in K} \sum_{n \in N} r_{k,n}^f \leq R_{f_{\max}}^f, \forall f \in F, \quad (10)$$

$$r_{k,n}^f = \log_2 \left( 1 + \frac{\rho_{k,n}^f |h_{k,n,f}^w_{k,n,f}|^2}{\sum_{f \in F} \sum_{i \in K \setminus \{k\}} \rho_{i,n}^f \cdot (1 - \xi_{k,n}^f) \cdot |h_{k,n,f}^w_{i,n,f}|^2 + \sigma_{k,n}^2} \right), \quad (5)$$
where $\varphi$ and $R_{\text{max}}^f$, $\forall f \in \mathcal{F}$ are the preprocessing weight related to the fronthaul transmission technologies and maximum available transmission capacity of AAU $f$, respectively.

### B. Objective Function and Problem Formulation

In this section, the considered objective function and problem formulation are introduced.

1) **Objective Function:** Considering the worst-case channel uncertainties, the main goal of the optimization problem is to maximize the worst-case global EE (GEE) of the system. GEE is defined as the ratio of the global achievable sum rate to the total consumed power [40], and the worst-case of GEE is obtained with considering the worst-case CSI in our model. To formulate the worst-case EE, we need the worst-case throughput of the system and the total consumed power. The total worst-case data rate can be calculated by

$$P_{\text{Total}}^{\text{Worst}} = \sum_{k \in \mathcal{K}} P_k.$$  \hfill (11)

The total power consumption of the system is obtained by [31]

$$P_{\text{Total}} = \sum_{f \in \mathcal{F}} \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \frac{1}{\beta} \|w_{k,n,f}\|_2^2 + P_{\text{Static}},$$

where $0 < \beta < 1$ is the drain efficiency of the power amplifier and $P_{\text{Static}}$ is the static term of power consumption which is obtained as $P_{\text{Static}} = \sum_{f \in \mathcal{F}} P_{\text{Static}}^f$, where $P_{\text{Static}}^f$ is the static term of power which is given by

$$P_{\text{Static}}^f = \begin{cases} P_{\text{Hardware}}^f & P_{TX}^f < P_{\text{max}}^f, \\ P_{\text{Sleep}}^f & P_{TX}^f = 0, \end{cases}$$

where $P_{\text{Sleep}}^f$ is the consumed power at BBU in the sleep mode of AAU $f$ and $P_{\text{Hardware}}^f = C_{\text{Circuit}} \times M$ is the power that is used by hardware at AAU $f$ in the transmission mode, and $C_{\text{Circuit}}$ is the consumed circuit power constant that is used for the signal processing functions at AAU which includes the power dissipation in the filtering, frequency synthesizer, digital-to-analog converter, etc. Therefore, the worst-case EE of the system is calculated by

$$P_{\text{EE}}^{\text{Worst}} = \frac{P_{\text{Total}}^{\text{Worst}}}{P_{\text{Total}}}.$$ \hfill (14)

where $P_{\text{Total}}^{\text{Worst}}$ and $P_{\text{Total}}$ are given by (11) and (12), respectively.

2) **Problem Formulation:** Based on these definitions and assumptions, our main aim is to maximize the worst case of EE considering beamforming and SIC ordering constraints. The optimization problem is mathematically formulated as follows:

$$\max_{W, \xi, \rho} \quad P_{\text{EE}}^{\text{Worst}}$$

s.t.  

$$C_1: \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} \rho_{k,n}^f |w_{k,n,f}|^2 \leq P_{\text{max}}^f, \forall f \in \mathcal{F},$$ \hfill (15a)

$$C_2: \sum_{k \in \mathcal{K}} \rho_{k,n}^f \leq L_n^f, \forall n \in \mathcal{N}, f \in \mathcal{F},$$ \hfill (15b)

$$C_3: \sum_{f \in \mathcal{F}} p_{k,n}^f \leq 1, \forall n \in \mathcal{N}, k \in \mathcal{K},$$ \hfill (15c)

$$C_4: \xi_{k,n}^f, \rho_{k,n}^f \in \{0, 1\}, \forall k \in \mathcal{K}, n \in \mathcal{N}, f \in \mathcal{F},$$ \hfill (15d)

$$W = [w_{k,n,f}], \rho = [\rho_{k,n}^f], \text{ and } \xi = [\xi_{k,n}^f].$$

Constraint (15b) indicates the maximum available power budget and constraint (15c) verifies that each subcarrier $n$ in each AAU $f$ can be utilized no more than $L_n^f$ times, recognized as NOMA constraint. Constraint (15d) ensures that each user on each subcarrier is served only by one AAU. Constraint (15e) is the NOMA constraint. Constraint (15f) indicates that for any two users only one of them can perform SIC on another one and (9) as shown at bottom of this page, ensures that user $k$ decodes the message of user $i$ on the assigned subcarrier $n$, successfully [6], [22]. Finally, constraint (10) is the link capacity restriction of fronthaul links.

### III. Proposed Solution Methods

The optimization problem in (15) is a non-convex mixed integer non-linear programming (MINLP) which is complicated to solve. We propose two different solution algorithms which are discussed in the following.

#### A. Algorithm 1: One Step Solution

In this section, we explain our proposed one-step solution, i.e., all variables are obtained without using alternating approach. First, let us define matrices $W_{k,n,f}$ and $H_{k,n,f}$ with size $M \times M$ as $W_{k,n,f} \triangleq w_{k,n,f} W_{k,n,f}$ and $H_{k,n,f} \triangleq h_{k,n,f} H_{k,n,f}$, respectively. To this end, we rewrite $|h_{k,n,f} w_{k,n,f}|^2$ as follows:

$$|h_{k,n,f} w_{k,n,f}|^2$$

$$= w_{k,n,f}^* (h_{k,n,f} + \epsilon_{k,n,f}) (h_{k,n,f} + \epsilon_{k,n,f}) w_{k,n,f}$$

$$= w_{k,n,f}^* (h_{k,n,f} + \Delta_{k,n,f}) w_{k,n,f}$$

$$= \text{Tr}[(H_{k,n,f} + \Delta_{k,n,f}) W_{k,n,f}],$$

$$\max_{A \in \mathcal{H}_{k,n,f}} \rho_{k,n}^f |h_{k,n,f} w_{k,n,f}|^2$$

$$\leq \xi_{k,n}^f \log_2 \left( 1 + \frac{\rho_{k,n}^f |h_{k,n,f} w_{k,n,f}|^2}{\sum_{f \in \mathcal{F}} \sum_{k \in \mathcal{K}} \rho_{k,n}^f (1 - \xi_{k,n}^f) |h_{k,n,f} w_{k,n,f}|^2 + \sigma_{k,n}^f} \right).$$

$$\min_{A \in \mathcal{H}_{k,n,f}} \rho_{k,n}^f |h_{k,n,f} w_{k,n,f}|^2$$ 

$$\leq \xi_{k,n}^f \log_2 \left( 1 + \frac{\rho_{k,n}^f |h_{k,n,f} w_{k,n,f}|^2}{\sum_{f \in \mathcal{F}} \sum_{k \in \mathcal{K}} \rho_{k,n}^f (1 - \xi_{k,n}^f) |h_{k,n,f} w_{k,n,f}|^2 + \sigma_{k,n}^f} \right).$$
where $\Delta_{k,n,f} = \mathbf{h}_{k,n,f}^\dagger e_{k,n,f}^\dagger f_{k,n,f} + e_{k,n,f}^\dagger f_{k,n,f} + e_{k,n,f}^\dagger i_{k,n,f}$ is a norm-bounded matrix which satisfies the following region:

$$
\|\Delta_{k,n,f}\| \leq \|\mathbf{h}_{k,n,f}\| e_{k,n,f}^\dagger f_{k,n,f} + e_{k,n,f}^\dagger f_{k,n,f} + \|e_{k,n,f}\| e_{k,n,f},
$$

$$+
\|e_{k,n,f}\| e_{k,n,f}.
$$

(17)

Therefore, equation (5) can be rewritten as (18) shown at the bottom of this page. Now, we aim at maximizing the worst-case data rate (18). Since the log function is a monotonically increasing function, the worst-case would be done over the SINR in (18). This can be obtained by minimizing (18) over $\Delta_{k,n,f}$ and $\Delta_{k,n,f'}$ where indexes $f$ and $f'$ can be the same, i.e., when we calculate the intra-cell interference. One conservative method to find the minimum of the SINR is minimizing the numerator and maximizing the denominator of SINR in (18) with respect to norm-bounded matrices [49]. Note that by this method, we provide a strictly bounded robust solution (SBRS) [49]. Motivated by this idea, the lower bound of SINR in (18) subject to (17) can be obtained by solving the following optimization problems:

$$
\min_{\|\Delta_{k,n,f}\| \leq e_{k,n,f}} \text{Tr}[(\mathbf{H}_{k,n,f} + \Delta_{k,n,f}) \mathbf{W}_{k,n,f}],
$$

(19)

$$
\max_{\|\Delta_{k,n,f'}\| \leq e_{k,n,f'}} \sum_{f \in F} \sum_{i \in K \setminus \{k\}} \text{Tr}[(\mathbf{H}_{k,n,f'} + \Delta_{k,n,f'}) \mathbf{W}_{i,n,f'}].
$$

(20)

Here, we apply the Lagrangian-based method to find the optimal solution of (19) and (20) for the given beamforming matrices [49].

**Proposition 1:** For the given $\mathbf{W}_{k,n,f}$, the minimum and maximum norm-bounded matrices of (19) and (20) given as follows, respectively, for all $k, i, n, f, f'$:

$$
\Delta_{k,n,f}^{\text{min}} = -e_{k,n,f} \mathbf{W}_{k,n,f}^\dagger \mathbf{W}_{k,n,f}, \quad \forall k, n, f,
$$

(21)

$$
\Delta_{k,n,f}^{\text{max}} = e_{k,n,f} \mathbf{W}_{i,n,f'}^\dagger \mathbf{W}_{i,n,f'}, \quad \forall k, i \in K, n, f, k \neq i.
$$

(22)

**Proof:** Please see Appendix A.

The update procedure in Dinkelbach algorithm is continued until the convergence condition is met. We call this method the exact worst-case of SINR. This method provides a numerical result which may not be as (30) shown at the bottom of the next page, where $\epsilon_{k,n,f}$ is the lower bound on the worst-case data rate. Therefore, the total data rate for the worst-case is given by

$$
R_{\text{total}}^{\text{West}} = \sum_{f \in F} \sum_{k \in K} \sum_{n \in K} \epsilon_{k,n,f}.
$$

(29)

Moreover, we restate the constraint (9) by using Proposition 1 as (30) shown at the bottom of the next page, which may not be

$$
\sum_{f \in F} \sum_{i \in K \setminus \{k\}} \rho_{f,i,n}^k (1 - \xi_{f,i,n}^k) \text{Tr}[(\mathbf{H}_{k,n,f'} + \Delta_{k,n,f'}) \mathbf{W}_{i,n,f'} + \sigma_{k,n,f}^2].
$$

(30)
tight. In (30), the left hand side is obtained for the maximum while the right hand side is obtained for the minimum. We also note that the term \( \{ \xi_{i,n} \cdot \rho_{i,n} \} \) in (28) is non-convex. To tackle this issue, we define a new variable as the multiplication of two binary variables \( x_{k,n}^{i,j} = \xi_{k,n} \cdot \rho_{i,n} \), which indicates the joint SIC ordering and scheduling variables. Then, we adopt a linearization technique and add the following constraints to the optimization problem [50], [51]:

\[
C_7 : s_{k,n}^{i,j} \geq x_{k,n}^{i,j}, \quad \forall k, i \in K, n \in N, f \in F, \quad (31)
\]

\[
C_8 : \rho_{i,n}^{j} \geq x_{k,n}^{i,j}, \quad \forall k, i \in K, n \in N, f \in F, \quad (32)
\]

\[
C_9 : \rho_{i,n}^{f} + \xi_{k,n}^{i,j} - 1 \leq x_{k,n}^{i,j}, \quad \forall k, i \in K, n \in N, f \in F. \quad (33)
\]

Furthermore, in order to handle the non-convex integer variables in problem (15), we rewrite the constraint (15e) as the intersection of the following regions:

\[
C_{10} : 0 \leq \xi_{k,n}^{i,j} \leq 1, \quad C_{11} : \sum_{i,k \in K, n \in N} \left( \xi_{k,n}^{i,j} - (\xi_{k,n}^{i,j})^2 \right) \leq 0, \quad (34a)
\]

\[
C_{12} : 0 \leq \rho_{i,n}^{f} \leq 1, \quad C_{13} : \sum_{f \in F} \sum_{i,k \in K} \sum_{n \in N} \left( \rho_{k,n}^{f} - (\rho_{k,n}^{f})^2 \right) \leq 0, \quad (34b)
\]

\[
C_{14} : 0 \leq \rho_{i,n}^{f} \leq 1, \quad C_{15} : \sum_{f \in F} \sum_{i,k \in K} \sum_{n \in N} \left( x_{k,n}^{i,j} - (x_{k,n}^{i,j})^2 \right) \leq 0. \quad (34c)
\]

Now, we rewrite the optimization problem as:

\[
\max_{W, \xi, \rho} \eta_{\text{EE}}^\text{Worst} \quad \text{s.t. } C_1 : \sum_{k \in K, n \in N} \sum_{f \in F} \left( \rho_{k,n}^{f} \right) W_{k,n,f} \leq P_{\text{max}}^f, \quad (34d)
\]
\[
C_2 : \sum_{i,k \in K} \rho_{i,n}^{f} \leq L_{n}, \quad (34e)
\]

\[
\text{subject to } (2), (7), (8), (10), (30). \quad (34f)
\]

It can be concluded from the optimization problem (34), the product term of \( \rho_{k,n}^{f} W_{k,n,f} \) is an obstacle for solving the optimization problem. Let us define two new auxiliary variables as follows:

\[
\tilde{W}_{k,n,f} \triangleq \rho_{k,n}^{f} W_{k,n,f}, \quad W'_{i,k,n} \triangleq x_{k,n}^{i,j} W_{i,n,f}. \quad (35)
\]

Also, we employ the big-M method [14], [39] to circumvent this difficulty. In particular, we impose the following additional constraints to make it convex as follows:

\[
C_{16} : \tilde{W}_{k,n,f} \leq P_{\text{max}}^f I_{\text{P}} \rho_{k,n}^f, \quad (35)
\]
\[
C_{17} : \tilde{W}_{k,n,f} \leq W_{k,n,f}, \quad C_{18} : \tilde{W}_{k,n,f} \leq 0, \quad (36)
\]
\[
C_{19} : \tilde{W}_{k,n,f} \geq W_{k,n,f} - (1 - \rho_{k,n}^f) P_{\text{max}}^f I_{\text{M}}, \quad (37)
\]
\[
C_{20} : W'_{i,k,n} \leq P_{\text{max}}^f I_{\text{P}} x_{k,n}^{i,j}, \quad (38)
\]
\[
C_{21} : W'_{i,k,n} \leq W_{k,n,f}, \quad C_{22} : W'_{i,k,n} \leq 0, \quad (39)
\]
\[
C_{23} : W'_{i,k,n} \geq W_{k,n,f} - (1 - x_{k,n}^{i,j}) P_{\text{max}}^f I_{\text{M}}. \quad (40)
\]

The worst-case data rate (29) and constraint (30) are still non-convex. To handle these and facilitate the solution, (29) can be rewritten as

\[
R_{\text{Total}} = \log_2 \prod_{f \in F} \prod_{k \in K} \prod_{n \in N} \frac{\psi_{f,k,n}}{\phi_{f,k,n}}, \quad (41)
\]

where

\[
\psi_{f,k,n} = \frac{\text{Tr}[\hat{H}_{k,n,f} W_{k,n,f}]}{\rho_{k,n}^f} - e_{k,n}^f \left( A(W_{k,n,f}) \right) + \phi_{f,k,n},
\]

\[
\phi_{f,k,n} = \sum_{f \in F} \sum_{i \in K} \left( \text{Tr}[\hat{H}_{k,n,f} W_{i,n,f}] - \text{Tr}[\hat{H}_{k,n,f} W_{i,n,f}] \right)
\]

\[
+ e_{k,n}^f \left( A(W_{i,n,f}) - B(W_{i,n,f}) \right) + \sigma_{k,n}^2, \quad (42)
\]

where we define

\[
A(W_{k,n,f}) \triangleq \left\| \rho_{k,n}^f W_{k,n,f} \right\| = \left\| \tilde{W}_{k,n,f} \right\|, \quad (43)
\]

\[
\tilde{r}_{k,n}^f = \log_2 \left( 1 + \frac{\rho_{k,n}^f \left( \text{Tr}[\hat{H}_{k,n,f} W_{k,n,f}] - e_{k,n}^f \left\| W_{k,n,f} \right\| \right]}{\sum_{f \in F} \sum_{i \in K} \left( \rho_{i,n}^f (1 - \xi_{k,n}^{i,j}) \left( \text{Tr}[\hat{H}_{i,n,f} W_{i,n,f}] - e_{i,n}^f \left\| W_{i,n,f} \right\| \right) + \sigma_{i,n}^2 \right)} \right). \quad (28)
\]

\[
\log_2 \left( 1 + \frac{\xi_{k,n}^{i,j} \cdot \rho_{i,n}^f \left( \text{Tr}[\hat{H}_{k,n,f} W_{k,n,f}] - e_{k,n}^f \left\| W_{k,n,f} \right\| \right]}{\sum_{f \in F} \sum_{k \in K \setminus \{ k \}} \left( \rho_{k,n}^f (1 - \xi_{k,n}^{i,j}) \left( \text{Tr}[\hat{H}_{i,n,f} W_{i,n,f}] - e_{i,n}^f \left\| W_{i,n,f} \right\| \right) + \sigma_{i,n}^2 \right)} \right)
\]

\[
\leq \log_2 \left( 1 + \frac{\xi_{k,n}^{i,j} \cdot \rho_{i,n}^f \left( \text{Tr}[\hat{H}_{k,n,f} W_{k,n,f}] - e_{k,n}^f \left\| W_{k,n,f} \right\| \right]}{\sum_{f \in F} \sum_{k \in K \setminus \{ k \}} \left( \rho_{k,n}^f (1 - \xi_{k,n}^{i,j}) \left( \text{Tr}[\hat{H}_{i,n,f} W_{i,n,f}] - e_{i,n}^f \left\| W_{i,n,f} \right\| \right) + \sigma_{i,n}^2 \right)} \right). \quad (30)
\]
\[ B(W'_{i,k,n,f}) \triangleq \| x_{i,k,n,f} \| = \| W'_{i,k,n,f} \| . \] (44)

However, the total data rate (41) is still non-convex. Let us define
\[ \psi_{f,k,n} \triangleq \exp(a_{f,k,n}), \quad \phi_{f,k,n} \triangleq \exp(b_{f,k,n}), \] (45)
where \( a_{f,k,n} \) and \( b_{f,k,n} \) are slack variables. Moreover, the lower bound of slack variables have the following form [48]
\[ \exp(a_{f,k,n}) \geq \sigma_{k,n,f}^2, \quad \exp(b_{f,k,n}) \geq \sigma_{k,n,f}^2. \] (46)

Now, by substituting (45) into the objective function, we can obtain
\[ \max_{W,W',W,\xi,\rho,\lambda} \log_2 \prod_{f} \prod_{k} \prod_{n} \frac{\psi_{f,k,n}}{\phi_{f,k,n}} \frac{P_{\text{Total}}(W)}{P_{\text{Total}}(W')} = \max_{W,W',W,\xi,\rho,\lambda, a, b} \frac{\log_2 \prod_{f} \prod_{k} \prod_{n} \exp(a_{f,k,n} - b_{f,k,n})}{P_{\text{Total}}(W)} \sum_{f} \sum_{k} \sum_{n} (a_{f,k,n} - b_{f,k,n}) \log_2(e) \frac{P_{\text{Total}}(W)}{P_{\text{Total}}(W')}, \] where \( a = [a_{f,k,n}] \) and \( b = [b_{f,k,n}] \) are the collection vectors of slack variables. Also, \( P_{\text{Total}}(W) = \frac{1}{2} \text{Tr}[W_{k,n,f}] + P_{\text{Static}}. \) For notation simplicity, let define \( \Xi \triangleq [W', W, W, \xi, \rho, \lambda] \) as the collection of the optimization variables. It is worthwhile to mention that by this method, we can easily rewrite the non-convex constraint (10) as follows:
\[ \sum_{k} \sum_{n} \varphi_{f}(a_{f,k,n} - b_{f,k,n}) \leq R_{f}^{\text{max}}, \forall f \in F. \] (47)

Now, the optimization problem at hand can be mathematically formulated as
\[ \max_{\Xi} \sum_{f} \sum_{k} \sum_{n} (a_{f,k,n} - b_{f,k,n}) \log_2(e) + h(\xi, \rho, \lambda), \] \[ \text{s.t.} \quad C_1 : \sum_{k} \sum_{n} \text{Tr}[W_{k,n,f}] \leq P_{f}^{\text{max}}, \] \[ C_2 : \sum_{k} \rho_{k,n}^{f} \leq L_{n}^{f}, \] \[ C_3 : W_{k,n,f} \succeq 0, \] \[ C_4 : \text{Rank}(W_{k,n,f}) \leq 1, \] \[ \exp(a_{f,k,n}) \geq \sigma_{k,n,f}^2, \quad \exp(b_{f,k,n}) \geq \sigma_{k,n,f}^2, \] \[ a_{f,k,n} \geq b_{f,k,n}, \] \[ \psi_{f,k,n} \geq \exp(a_{f,k,n}), \quad \phi_{f,k,n} \leq \exp(b_{f,k,n}), \] \[ C_7 \sim C_{10}, C_{12}, C_{14}, C_{16} \sim C_{23}, \] \[ (2), (7), (8), (10), (30), \] (48a) \[ (48b) \] \[ (48c) \] \[ (48d) \] \[ (48e) \] \[ (48f) \] \[ (48g) \] \[ (48h) \] \[ (48i) \] \[ (48j) \] \[ (48k) \]
where \( h(\xi, \rho, \lambda) \triangleq -f(\xi, \rho, x, \lambda) + g(\xi, \rho, x, \lambda) \) is the penalty function. Furthermore, \( f(\xi, \rho, x, \lambda) \) and \( g(\xi, \rho, x, \lambda) \) are defined as
\[ f(\xi, \rho, x, \lambda) \triangleq \lambda \left( \sum_{i,k,n} \sum_{f} \sum_{k} \sum_{n} c_{i,n}^{k} + \sum_{f} \sum_{k} \sum_{n} \rho_{k,n}^{f} + \sum_{f} \sum_{k} \sum_{n} x_{i,n}^{k,f} \right), \] (49)
\[ g(\xi, \rho, x, \lambda) \triangleq \lambda \left( \sum_{i,k,n} \sum_{f} \sum_{k} \sum_{n} (c_{i,n}^{k})^2 \right), \] (50) respectively. It is worth mentioning that \( \lambda \) indicates a penalty factor to penalize the objective function for any \( c_{i,n}^{k}, \rho_{k,n}^{f}, \) and \( x_{i,n}^{k,f} \) which are not binary (i.e., their values are in [0,1]) [33]. However, the precise 0 and 1 are not always available. In this case, we round their values to the nearest integer values. The following proposition provides a mathematical analysis of the penalty factor.

**Proposition 2:** For sufficiently large value of \( \lambda, \) we have \( \min_{\lambda} \max_{\psi, \rho, x, \lambda} \mathcal{L}(\psi, \rho, x) = \max_{\psi, \rho, x} \mathcal{L}(\psi, \rho, x). \) In other words, the optimization problem (34) is equivalent to (48) where both problems obtain the same values.

**Proof:** See Appendix B.

Problem (48) is non-convex due to the constraints (48i) and (30) and \( g(\xi, \rho, x, \lambda) \) in the objective function. In order to convert it into a convex one, we employ MM approach where a surrogate function is approximated by the first order Taylor approximation. Therefore, we use the following inequalities:
\[ g(\xi, \rho, x, \lambda) \leq g(\xi^{t-1}, \rho^{t-1}, x^{t-1}, \lambda) \] \[ + \nabla g^{T}(\xi^{t-1}, \rho^{t-1}, x^{t-1}, \lambda)(\xi - \xi^{t-1}) \] \[ + \nabla ho^{t} g^{T}(\xi^{t-1}, \rho^{t-1}, x^{t-1}, \lambda)(\rho^{t-1} - \rho^{t-1}) \] \[ + \nabla x g^{T}(\xi^{t-1}, \rho^{t-1}, x^{t-1}, \lambda)(x - x^{t-1}) \] \[ \triangleq \tilde{g}(\xi, \rho, x, \lambda), \] (51)
\[ A(W_{k,n,f}) \leq A(W_{k,n,f})^{t-1} + \text{Tr} \left( \nabla W_{k,n,f} A(W_{k,n,f})^{t-1} \right) \] \[ - A(W_{k,n,f})^{t-1} \] \[ \triangleq \tilde{A}(W_{k,n,f}), \] (52)
\[ B(W'_{i,k,n,f}) \leq B(W'_{i,k,n,f})^{t-1} + \text{Tr} \left( \nabla W'_{i,k,n,f} B(W'_{i,k,n,f})^{t-1} \right) \] \[ - B(W'_{i,k,n,f})^{t-1} \] \[ \triangleq \tilde{B}(W'_{i,k,n,f}), \] (53)
\[ \text{Note that } \mathcal{L}(\psi, \rho, x) \text{ is the objective function in (34).} \]
\[ \phi_{f,k,n} \leq \exp\left(\beta_{f,k,n}^{-1}(\beta_{f,k,n} - \beta_{f,k,n}^{-1} + 1)\right) \triangleq \tilde{\phi}_{f,k,n}. \]  

(54)

It should be noted that the right hand sides of (51)-(53) are affine functions. Now the main challenge in problem (48) is the non-convex constraint (30), i.e., SIC ordering constraint. Next, we handle this constraint similar to the objective function.

To this end, first, we rewrite (30) as (55) shown at the bottom of this page, by replacing the previously defined auxiliary variables \( x_{i,k,n} = e_{i,n}, \rho_{k,n} f_{i,k,n}, W_{k,n,f} = \rho_{k,n} W_{k,n,f}, W'_{i,k,n,f} = x_{i,k,n} W_{i,n,f} \), (43), and (44). Now, we can rewrite (55) as follows:

\[
\log_2 \left( \frac{D_{i,k,n,f}}{E_{i,k,n,f}} \right) - \log_2 \left( \frac{F_{i,k,n,f}}{G_{i,k,n,f}} \right) \leq 0, \tag{56}
\]

where

\[
E_{i,n,f} = \sum_{f \in F} \sum_{k' \in K \setminus\{i\}} \left\{ \text{Tr}[\tilde{H}_{i,n,f} W'_{k',n,f}] - e_{i,n} A(W'_{k',n,f}) \right\} + \sigma_{i,n}^2,
\]

(57)

\[
D_{i,k,n,f} = \text{Tr}[\tilde{H}_{i,n,f} W'_{i,k,n,f}] + e_{i,n} B(W'_{i,k,n,f}) + E_{i,n,f},
\]

(58)

\[
G_{i,k,n,f} = \sum_{f \in F} \sum_{k' \in K \setminus\{i\}} \text{Tr}[\tilde{H}_{k,n,f} W'_{k',n,f}] + e_{i,n} A(W'_{k',n,f}) \]

\[
\text{where } E_{i,n,f} = \sum_{f \in F} \sum_{k' \in K \setminus\{i\}} \left\{ \text{Tr}[\tilde{H}_{i,n,f} W'_{k',n,f}] - e_{i,n} A(W'_{k',n,f}) \right\} + \sigma_{i,n}^2.
\]

(59)

\[
F_{i,k,n,f} = G_{i,k,n,f} + \text{Tr}[\tilde{H}_{k,n,f} W'_{i,k,n,f}],
\]

(60)

Hereafter, we drop the subscripts of \( E_{i,n,f}, D_{i,k,n,f}, G_{i,k,n,f}, \) and \( F_{i,k,n,f} \) for the notation simplicity and denote them by \( \tilde{E}, \tilde{D}, \tilde{G}, \) and \( \tilde{F} \), respectively.

After this, similar to (45), we obtain

\[
0 \geq \log_2 \left( \frac{D}{E} \right) - \log_2 \left( \frac{F}{G} \right),
\]

(61)

\[
= \log_2(\exp(d - e)) - \log_2(\exp(f - g)),
\]

(62)

\[
= \log_2(e \times (d - e - (f - g)),
\]

which has a linear form. For these auxiliary variables, we have the following constraints:

\[
d \geq e, \ f \geq g, \ D \geq \exp(d), \ E \leq \exp(e), \ F \geq \exp(f), \ G \leq \exp(g).
\]

(63)

Constraint (63) is non-convex due to the form of \( \tilde{E}, \tilde{G}, \) and constraints \( \tilde{E} \leq \exp(e) \) and \( \tilde{G} \leq \exp(g) \). However, by replacing \( A(\cdot) \) and \( B(\cdot) \) with their linear approximations defined in (52) and (53), \( \tilde{E} \) and \( \tilde{G} \) would become affine functions denoted by \( \tilde{E} \) and \( \tilde{G} \), respectively. Finally, by employing a Taylor series expansion of \( \exp(e) \) and \( \exp(g) \), the constraints \( \tilde{E} \leq \exp(e) \) and \( \tilde{G} \leq \exp(g) \) can be transformed by

\[
\tilde{E} \leq \exp(e) - \delta e + 1,
\]

(64)

\[
\tilde{G} \leq \exp(g) - \delta g + 1,
\]

(65)

Recall that for notation simplicity, we removed the subscripts of \( d, e, f, \) and \( g \). As for the final step, we have to tackle non-convex constraint (7). To this end, we first handle the right hand side of (7), i.e., \( \epsilon_{k,n} \leq \sum_{f \in F} \rho_{k,n} f_{i,k,n} \), \( \forall k \neq i \), by using the MM approach to obtain a convex form that is inspired from [37]. It is straightforward to show that

\[
z_1 z_2 = \frac{1}{2} [(z_1 + z_2)^2 - (z_1)^2 - (z_2)^2],
\]

where \( z_2 = y_{i,n} \neq \sum_{f \in F} \rho_{k,n} f_{i,k,n} \) to transform (7) into a convex one. Now, we rewrite the constraint in (7) as follows:

\[
2 \epsilon_{k,n} \leq (z_{k,n} + y_{i,n})^2 - (z_{k,n})^2, \forall k, i \in K, k \neq i.
\]

The above constraint is non-convex.

Similarly, we adopt Taylor approximation for \( Q_{k,n}^i Z_{k,n} \) to obtain a convex constraint. Therefore, after employing Taylor approximation this constraint can be written as follows:

\[
2 \epsilon_{k,n} \leq \left( z_{k,n} + y_{i,n} \right)^2 - \tilde{Q}_{k,n}^i, \forall k, i \in K, k \neq i,
\]

(66)

where \( \tilde{Q}_{k,n}^i \) is the first order Taylor approximation for \( Q_{k,n}^i \).

We further use the following theorem which is related to the non-linear fractional programming.

**Definition 1:** A generalized fractional problem is defined as:

\[
\max \ x \ \min_{k=1,\ldots,K} \ f_k(x), \ s.t. \ x \in D.
\]

(67)
Proposition 3: The optimal vector $x^*$ for solution of (67) can be achieved if and only if [35]

$$\begin{align}
x^* &= \text{argmax}_{x \in \mathcal{D}} \left\{ \min_{k = 1, \ldots, K} \left[ f_k(x) - \alpha^* g_k(x) \right] \right\},
\end{align}$$

(68)

where $\alpha^*$ is obtained via the following problem:

$$F(\alpha) = \max_{x \in \mathcal{D}} \min_{k = 1, \ldots, K} \left[ f_k(x) - \alpha g_k(x) \right] = 0. \quad (69)$$

By using Proposition 3, the optimal value of the EE is given by

$$q^* = \frac{\log_2(e) \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n})}{P_{\text{Total}}(W^*)} = \max_{w} \frac{\log_2(e) \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n})}{P_{\text{Total}}(w)}. \quad (70)$$

As a result, the maximum EE, $q^*$ can be achieved if and only if

$$\max_{\Xi} \frac{\log_2(e) \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n}) - q^* P_{\text{Total}}(\Xi)}{P_{\text{Total}}(\Xi)} = 0. \quad (71)$$

Based on the previous steps and defining $\Xi' \triangleq [\Xi, d, e, f, g]$, we solve the following problem instead of dealing with fractional programming in (48)

$$\max_{\Xi} \frac{\log_2(e) \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n}) - q^* P_{\text{Total}}(\Xi)}{P_{\text{Total}}(\Xi)} - q^* P_{\text{Total}}(\Xi) = -f(\xi, \rho, x, \lambda) + \tilde{g}(\xi, \rho, x, \lambda) \quad (72a)$$

s.t.

$$\psi_{f,k,n} \geq \exp(a_{f,k,n}), \quad (72b)$$

$$C_7 - C_{10}, C_{12}, C_{14}, C_{16} - C_{23}, \quad (72c)$$

(2), (8), (47), (65), (46), (66), (48h). \quad (72d)

Notice that, (72) is an standard SDP programming which can be solved optimally by using an off-the-shelf optimization tool, e.g., CVX. Denote by $W^*_{k,n,f}, \forall k, n, f$, the optimal value of variable $W_{k,n,f}$ in the solution of (72). If $W^*_{k,n,f}$ satisfies the rank-one constraint, i.e., Rank($W^*_{k,n,f}$) = 1, the optimal solution $W^*_{k,n,f}$ can be obtained by using the eigenvalue decomposition (EVD) of $W^*_{k,n,f}$. As for the final step, we employ SDP relaxation by removing constraint $C4$. The problem (72) may not yield a rank-one solution. Thus, we propose a penalty function to the objective function to penalize it [48], [53]. To this end, first, we introduce the following proposition.

Proposition 4: The inequality $||Y||_2 \geq \max_i \sigma_i$ holds for any given $Y \in \mathbb{H}^{m \times n}$, $m, n \in \mathbb{N}$, where $\sigma_i$ is the $i$-th eigenvalue of $Y$. The equality holds if and only if $Y$ is rank-one.

Inspired by Proposition 4, the equivalent form of the rank-one constraint $C4$ can be written as $\omega_{k,n,f} \triangleq ||W_{k,n,f}|| < ||W_{k,n,f}||_2 \leq 0, \forall k, n, f$. Hence, we use the penalty-based approach by integrating such a constraint into the objective function. By introducing $\mu > 1$ as a penalty factor, the objective function, by dropping the constant term $\log_2(e)$, can be rewritten as follows:

$$\sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n}) - q \cdot P_{\text{Total}} - f(\xi, \rho, x, \lambda) + \tilde{g}(\xi, \rho, x, \lambda) - \mu \times \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} \omega_{k,n,f} \quad (73)$$

For a sufficiently large value of $\mu$, maximizing (73) under the constraints of (72) yields a rank-one solution by ensuring a small value of $\omega_{k,n,f}$ [48], [53]. However, (73) is still a non-convex function over $W_{k,n,f}$. Hence, we rewrite $\omega_{k,n,f}$ as follows:

$$\omega_{k,n,f} = ||W_{k,n,f}||_2 - \tilde{A}(W_{k,n,f}), \forall k, n, f, \quad (74)$$

where $\tilde{A}(W_{k,n,f})$ is obtained by (52). The above equation is updated iteratively with iteration number $t$. We also update the penalty factor in each iteration as $\alpha^*(t+1) = \alpha^*(t)$, where $\alpha > 1$ is a constant. Nevertheless, the returned solution may not be rank-one. In such cases, the Gaussian randomization method is exploited to obtain a feasible solution. Consequently, the optimization problem (72) can be written with same constraints by considering the following objective function:

$$\sum_{f \in F} \sum_{k \in K} \sum_{n \in N} (a_{f,k,n} - b^*_{f,k,n}) - q \cdot P_{\text{Total}}(W) - f(\xi, \rho, x, \lambda) + \tilde{g}(\xi, \rho, x, \lambda) - \mu \times \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} \omega_{k,n,f}$$

$$\text{Term 1}$$

$$\text{Term 2}$$

(75)

where “Term 1” of the penalty function is to penalties of the relaxed binary variables and “Term 2” is for rank-one solution discussed above. It is worth mentioning that the final optimization problem is an standard SDP programming which can be solved optimally using CVX. Therefore, an iterative algorithm can be employed to tighten the obtained upper bound of (75) in iteration $t$ is used as an approximation point for the next iteration ($t+1$) [20], [33]. The main steps of the proposed solution algorithm are listed in Algorithm 1. Next, we discuss the initialization algorithm and optimally of the proposed solution.

1) Initialization Algorithm: Due to the existence of Taylor approximations, we should determine the initial feasible values for relevant variables. The initial point for the relaxed variables denoted by $\rho^0 = [\rho_{k,n,f}^f]$, $\xi^0 = [\xi_{k,n,f}^f]$, $X^0 = [x_{k,n,f}^{f,0}]$, beam-forming variables, i.e., $W^0$, $W^0$, and $W^0$ (subscripts are removed for simplicity), and auxiliary variables, i.e., $b^0 = [b_{k,n,f}^f]$, $e^0 = [e_{i,n,f}^f]$, and $g^0 = [g_{i,k,n,f}^f]$. We randomly generated $\rho^0$, $\xi^0$, and $X^0$ between zero and one. For beamforming variable, it should satisfy the power budget constraint. Therefore, we set $w^0_0 = \sqrt{P_{\text{Max}}/M_{\text{AAU}}} \cdot r_{M \times 1}$, where $P_{\text{Max}}$ denotes the power budget of the macro AAU, $M$ is the number of antennas, and $r_{M \times 1}$ is the vector with size $M \times 1$ and random elements between zero and one. Now, according to the previous definitions, we can set $W_{k,n,f}^0 = w_0^0(\mathbf{w})^0$, $W_{k,n,f}^0 = x_{i,n}^{k,f,0} W_{k,n,f}^0$, and $W_{k,n,f}^0 = P_{f,n}^{f,0} W_{k,n,f}^0, \forall f, i, n$. The
Algorithm 1: Proposed Iterative Algorithm

Require \( q_0 = 0, \ t = 0, \ \epsilon > 0, \) initialize feasible points as described in Section III-A1

1: \( q_t : \) Dinkelbach parameter
2: \( t : \) Iteration index
3: \( \epsilon : \) The maximum tolerance

4: while \( q_t - q_{t-1} > \epsilon \) do
5: Obtain resource allocation policy through solving problem (72)
6: Set \( t = t + 1 \)
7: Set \( q^* = \max_{\Xi} \left( \log_{1+e}(e) \sum_{f \in \mathcal{F}} \sum_{k \in \mathcal{K}} \sum_{n \in \mathcal{N}} (a^t_{i,k,n,n} - b^t_{f,k,n}) = \frac{L_i}{W} \ln(\rho_k + \sigma_b^2) \right) \)
8: end while
9: Set \( \{ W^t, W^t, G^t, \forall f, k, n, t \} \)
10: return

feasible points for the auxiliary variables can be set as follows:

\[
b^0_{f,k,n} = \phi^0_{f,k,n} = \ln \left( \sum_{f' \in \mathcal{F}} \sum_{i \in \mathcal{K}} \text{Tr}[H_{i,n,f} W^0_{i,n,f}] - \text{Tr}[H_{k,n,f} W^0_{i,n,f}] \right)
+ c^t_{k,n} \left( A(W^t_{i,n,f}) - B(W^t_{i,n,f}) \right) + \sigma_b^2_{i,k,n,f}.
\]

Similarly, the feasible points of the auxiliary variables for handling of the SIC ordering constraint (55) are obtained by

\[
i_{i,n,f}^0 \triangleq \ln(c^0_{i,n,f}), \forall i, n, f
\]

\[
g^0_{i,n,f} \triangleq \ln(g^0_{i,n,f}),
\]

where \( c^0_{i,n,f} \) and \( g^0_{i,n,f} \) are obtained by (57) and (59), respectively, with replacing the above initial values. However, the randomly generated values may not be a feasible solution. In such cases, we generate a new one, until we find a feasible point. It is worthwhile mentioning that this method may not be efficient, especially, when we have more constraints and high dimensional variables. For such cases, the initialization algorithm proposed in [53] can be utilized. Further, sometimes for a given resources, e.g., power budget, the problem may not be feasible. In this case, the elasticization method can be used [55].

Now, we discuss the optimality of the proposed algorithm. In general, we adopted three techniques as follows: 1) the Majorization-Minimization technique for approximating the non-convex term, 2) fractional programming theory via Dinkelbach method to transform the problem into a subtractive form, and 3) penalty function for handling the rank-one constraint and penalize the objective function when the relaxed variables (scheduling variables) are not binary. Therefore, the performance of algorithm is affected by the performance of these techniques in general which is discussed as follows:

1) MM: For solving problem (49), we adopted MM technique where a surrogate function is approximated to obtain a convex optimization problem. In MM approach the iteration starts from a feasible initial point and iteratively solves the optimization problem and obtains a locally optimal solution eventually and the MM approach generates a sequence of improved feasible solutions, which will finally converges to a sub-optimal point [57].

2) Dinkelbach algorithm: For solving the fractional programming, we adopt Dinkelbach algorithm to transform the fractional programming into a sub-tractive form. Note that Dinkelbach algorithm obtains the optimal solution for the concave-convex function. It can be seen that, optimization problem (73) is a convex problem and the Dinkelbach approach can obtain the optimal solution for this problem [56].

3) Penalty function: For obtaining the rank-one solution as well as obtaining the binary values, we adopted a penalty method to penalize the objective function. In fact, it has been proved (see Appendix B) that for sufficiently large values of penalty factor the rank-one solution as well as integer values can be obtained [14], [48].

In conclusion, by using the aforementioned methods the final solution reaches to a stationary point satisfying the KKT conditions.

B. Low Complexity Algorithm Design

It can be perceived that Algorithm 1 achieves a close to optimal solution. However, it may not suitable for large scale resource allocation with limited computational complexity. Now, we aim at designing a low complexity algorithm for improving the practicality of Algorithm 1. The proposed low-complexity algorithm is based on the heuristic solution known as two-step iterative approach. In particular, the original problem is decomposed into two sub-problems, namely: 1) scheduling (i.e., joint user association and subcarrier allocation) and 2) beamforming design and SIC ordering. Each subproblem can be solved while fixing the variables of other problems. The iterative procedure is adopted to find the scheduling, beamforming design, and SIC ordering.

1) Solution of the Scheduling Subproblem: By assuming fixed beamforming design and SIC ordering parameters, the scheduling sub-problem is formulated as follows:

\[
\max_{\rho} \eta_{\text{WEE}}
\]

s.t. \( C_2 : \sum_{k \in \mathcal{K}} \rho_{k,n} \leq L_n, \forall n \in \mathcal{N}, f \in \mathcal{F}, \)

\( C_4 : \rho_{k,n}^t \in \{ 0, 1 \}, \forall k \in \mathcal{K}, n \in \mathcal{N}, \forall f \in \mathcal{F}, \quad (79c) \)

(2), (66), (8), (65).

Problem (79) is integer non-linear programming. To solve it, we propose a low-complex modified two-sided many-to-many matching algorithm [21]. As stated before, the scheduling variable determines both AAU selection and subcarrier assignment. To complete it, we propose two-stage matching algorithm [21], [42], [43], [47]. In the proposed matching algorithm, in the first stage, we match users to the AAUs (“AAU selection”)
and in the second stage, we match users of each AAUs to the subcarriers ("subcarrier assignment"). In so doing, each user $k \in K$ constructs its own preference list of AAUs denoted by $L^A_{k} = \{l_k, f\}, \forall k, f$, based on the path loss, i.e., the nearest AAU has the maximum preference and is the first in list $L^A_{k}$. All paired users of each AAU $f$ is indicated by $K_f$ which is the output of the first stage of matching process. After that each user in $K_f$ regenerates the preference list with respect to the each subcarrier $n$ based on the $|h|^{\alpha}_{k,n,f}w_{k,n,f}$, $h_{k,n,f} \in H_{k,n,f}, \forall k \in K_f$ as a matching criteria. After that, the second stage of matching process is started to assign subcarriers to users in each AAU.

**Proposition 5:** Each stage of the adopted matching algorithm after a few numbers of iterations will be a two-sided exchange-stable matching. Therefore, the devised two-stage matching algorithm is an stable matching algorithm.

**Proof:** Please see [Proposition 1, [21]]. □

2) Beamforming Design and SIC Ordering Subproblems:

For the given scheduling, we aim to solve the problem of beamforming design and SIC ordering. To this end, we first define a new variable as $\tilde{W}_{i,k,n,f} \triangleq \frac{c_k}{\alpha_i,n}W_{k,n,f}$. In a similar manner, we adopt the same approach for obtaining the beamforming design as well as SIC ordering. Consequently, the problem at hand can be written mathematically as

$$\max_{\tilde{W},W,\xi,a,b} \sum_{f \in F} \sum_{k \in K} \sum_{n \in N}(a_{f,k,n} - b_{f,k,n}) \log_2(e) - q \cdot P_{\text{Total}}(\tilde{W})$$

$$- f(\xi, \lambda) + \tilde{g}(\xi, \lambda) - \mu \sum_{f \in F} \sum_{k \in K} \sum_{n \in N} \tilde{w}_{k,n,f}$$

s.t. $C_1 : \sum_{k \in K} \sum_{n \in K} \text{Tr}[\tilde{p}_{f,n}^{f,k,n}W_{k,n,f}] \leq P^f_{\text{max}}$, $\forall f \in F$, (80a)

$$C_2 : W_{k,n,f} \geq 0,$$ (80b)

$$C_3 : \exp(a_{f,k,n}) \geq \sigma_{k,n,f}^2, \exp(b_{f,k,n}) \geq \sigma_{k,n,f}^2,$$ (80c)

$$C_4 : a_{f,k,n} \geq b_{f,k,n},$$ (80d)

$$C_5 : \psi_{f,k,n} \geq \exp(a_{f,k,n}), \phi_{f,k,n} \leq \exp(b_{f,k,n}).$$ (80e)

$$C_6 : \tilde{W}_{i,k,n,f} \preceq P^f_{\text{max}} I_M \xi_{i,n}^k,$$ (80f)

$$C_7 : \tilde{W}_{i,k,n,f} \preceq W_{k,n,f},$$ (80g)

$$C_8 : \tilde{W}_{i,k,n,f} \preceq W_{k,n,f} - (1 - \xi_{i,n}^k)P^f_{\text{max}} I_M,$$ (80h)

$$C_9 : \tilde{W}_{i,k,n,f} \geq 0,$$ (80i)

$$C_{10} : 0 \leq \xi_{i,n}^k \leq 1,$$ (80j)

(8), (47), (65), (66), (80k)

(80l)

where $W$ stands for all of $W_{i,k,n,f}, \forall k, i, n, f, i \neq k$. This problem is convex and can be solved via efficient convex programming libraries like CVX.

### C. Complexity Analysis of the Solution Algorithms

This section provides the complexity analysis and the comparison of the proposed solution algorithms. In the first algorithm, i.e., Algorithm 1, we solve the original problem in one step as the form of (72) via CVX. In this problem, there are totally $7KNF + 5 K^2NF$ variables and $10KNF + 8 K^2NF + 4 K^2NF^2 + F + 2KN + 4KNF^2$ convex and affine constraints. Note that the term $K^2$ instead of $K$ is from considering the SIC ordering variable and the resulting constraints. Thus, the complexity of the algorithm per iteration is $O((7KNF + 5 K^2NF)^3(10KNF + 8 K^2NF + 4 K^2NF^2 + F + 2KN + 4KNF^2))$. Therefore, by considering $K > F$ and $N > F$, which is logical for practical setting, and for sufficiently large values of $K$ and $N$, the overall order of the complexity of our first algorithm can be calculated by $O(K^2NF)^3$. In the second algorithm, we applied the alternating approach. Based on this, the overall complexity is a linear combination of the complexity of solution of each sub-problem. The solution of the first sub-problem is a matching algorithm whose complexity is a linear function of the number of the subcarriers, users, and AAUs, i.e., $O(K \times N \times F)$. For the second sub-problem (80), we also applied a similar approach as the first algorithm, but the number and dimension of variables as well as constraints are considerably reduced. Problem (80) includes $4KNF + 3 K^2NF$ variables and $7KNF + 5 K^2NF^2 + 2F$ convex and affine constraints. Based on the solution algorithm of (80), the computational complexity per iteration is $O((4KNF + 3 K^2NF)^3(7KNF + 5 K^2NF^2 + 2F))$. Thus, the overall complexity is $O(K^2NF)^3$. As a result, both of the proposed algorithms have a polynomial order of complexity, whereas the overall complexity of an exhaustive method is exponential over the number of constraints and search variables.

### IV. NUMERICAL EVALUATION

This section presents numerical results to assess and compare the designed SIC ordering and beamforming scheme under various configurations which makes comparisons with conventional ones. We provide numerical results regarding to different metrics such as energy efficiency and utilized power under variation of different parameters.

#### A. Simulation Setup

We consider a C-RAN network such that a high power AAU is located at the center of a service coverage area with 500 m radius, and 3 low power AAUs with a circular coverage area with 20 m radius which are randomly located [41]. Also, the number of total users is $K = 8$ and the number of antennas for each AAU is $M = 3$ [27], [38]. Unless otherwise stated, the simulation results are based on values of the parameters which are listed in Table II. Moreover, the small-scale fading of the channels is assumed to be Rayleigh fading and the large-scale fading effect is denoted by $d_{k,f}$ to incorporate the path-loss effects, where $d_{k,f}$ is the distance between user $k$ and AAU $f$ measured in meters, and $\alpha = 3$ is the path-loss exponent [27].
TABLE II  
MAIN PARAMETERS VALUES FOR NETWORK SETUP

| Parameter                  | Value(s)      |
|----------------------------|---------------|
| Size of AAO, Small AAO     | 8/7/6/5/4     |
| Power budget of AAO, Max, AAO | 30/40 dBm   |
| $\sigma_{k,n}^2 / \sigma_{l,n}^2$ | -174 dBm/0.001 |

**B. Results Discussions**

In this subsection, we discuss about the simulation results achieved for the following main scenarios:

1) **Proposed near-optimal solution and SIC ordering method (Proposed algorithm)**
2) **Proposed two-step solution and SIC ordering as a baseline (Baseline 1):** In this baseline, the main problem is solved iteratively in which the scheduling variable is obtained by the devised matching algorithm.
3) **SIC ordering based on channel gains as a baseline (Baseline 2):** In this baseline, the decoding of users is based on the absolute value of channel gains as considered in [9], [13], [14], [16]–[18], [20], [25]. Note that in this algorithm, SIC constraints lead to the lower achievable rates.

All the above scenarios are investigated under different system parameters which are discussed in the following. First, we investigate the effect of variation of power budget on the EE of the network for different number of AAUs in Fig. 2. In this figure, we change the power budget values from 20 dBm to 47 dBm and also we observe that the EE first increases and then is saturated when the transmit power is larger than 35 dBm, i.e., $P_{\text{max}}^f = 35$ dBm. This is because of exploiting power control via designing beamforming for all schemes, and also we can deduce that the beamforming works well to improve EE up to the maximum point. Besides, we observe that the performance of our proposed SIC ordering and beamforming algorithm in terms of EE significantly outperforms the other baselines. The main reason behind this achievement is that the proposed SIC ordering algorithm is performed via optimizing the SIC ordering variable which is exploited to handle the intra-cell and inter-cell interference to maximize EE. We also observe that our proposed algorithm has a better performance as compared to baseline 1 due to performing resource allocation design and SIC ordering jointly in a one-step optimization problem. While, in baseline 2, SIC ordering is based on the absolute value of the channel gains. However, SIC ordering in baseline 2 is applicable with an acceptable performance guarantee for single antenna systems and cannot be applied for MISO NOMA systems, efficiently. Also, this figure investigates the effect of AAUs on the EE of the system. It is evident that our proposed algorithm outperforms other baseline schemes due to performing joint user association and subcarrier allocation which improves significantly the performance of the system.

In Fig. 3, we study the effect of the number of subcarriers and also the performance of NOMA as compared to the conventional OMA on the baseline schemes. It is observed that the improvement of the proposed algorithm compared to the baselines is sustainable. This improvement is achieved not only in the NOMA-based systems but also in the OMA-based systems. Note that in OMA, there is no intra-cell interference due to orthogonality in the utilization of the subcarriers. Besides, our proposed SIC ordering controls the inter-cell interference. Thus, our designed SIC ordering and beamforming are applicable not only for NOMA but also for any co-channel interference suffered communication networks without any need on the CSI of these channels. Consequently, the improvement of EE in NOMA is more than OMA. Also we can conclude that the performance of NOMA is much better than that of OMA due to exploiting each subcarrier more than one in the network.

In Fig. 4, we evaluate the EE of the considered schemes while considering the effect of the number of antennas in each AAO for different circuit power values. As can be seen from this figure, EE increases as the number of antennas increases due to the array giants and spatial diversity, and then drops after certain value for the number of antennas, i.e., $M > 7$. This is because that employing more antenna enables high degrees of freedom in the spatial diversity gain which turns on improving SE while exceeding power consumption, specifically hardware power consumption which linearly increases as $M$ increases due to activating RF chain per each antenna. While the SE is changed slowly with respect to the value of $M$ which turns a
strive a balance between SE and power consumption which leads to trade-off between SE and EE. Further, for the higher values of circuit power, the maximum value of EE is obtained for a lower number of $M$. This is because that system’s aggregated power consumption has a greater impact on improving system’s EE than maximizing the SE as SE commensurates to log-function. The interesting results from this evaluation can be explained as two folds: First, we need an appropriate beamforming design for massive antennas communication systems and second there is a need for designing an efficient antenna selection algorithm to select appropriate antennas and then doing precoding, especially for massive MIMO mmWave 6G networks. Also, this figure reveals the performance of our SIC ordering algorithm for massive antennas networks. In our future work, we will propose an appropriate antenna selection (finding optimum $M$) as well as beamforming design for massive mmWave networks.

Fig. 5 illustrates the impact of channel estimation error on the EE for different values of the power budget. As can be seen, the relation between the error bound and the system EE is indirect. Also, the upper bound is obtained for the perfect CSI setting.\footnote{It is worthwhile to note that the zero error is equivalent to the perfect CSI in which the complete information of channels of users is available in the BBU side.} It is seen that with increasing the error bound, our algorithm has a vigorous capability for deducting the impact of the imperfect CSI. It can be also observe that the performance gap with respect to the baseline schemes becomes significantly large. This is because of the existing indirect efficacy of the error bound on the performance of the SIC ordering based on the channel gains. It is worthwhile to note that performing SIC based on the channel gains needs full CSI which is not practical in the real wireless communication networks. Furthermore, more power consumption is needed for large values of the error bound to reach the same SE which makes the reduction on EE with increasing the error bound. In other words, for a fixed value of consumed power, the SE tends to low values for the higher error bounds which results in the EE reduction. Moreover, we study the behavior of EE achieved via the scenarios with respect to the number of users and maximum reuse number of each subcarrier in each AAU which is plotted in Fig. 6. Note that when the reuse number is 1, the considered network operates as OMA while for values of 2 and 3, the network operates as NOMA. From this figure, it can be observed that the EE grows with the number of users and reuse factor of NOMA because of multi user diversity. In addition, for the higher number of reuse factors in NOMA, the improvement on the EE is low. The reason behind this trend is that the high reuse factors in NOMA boosts the denominator of the system throughput due to incorporating intra-cell interference in the data rate which results in an exceeding power consumption and consequently degrading the EE of the system. Furthermore, we can declare that for the high reuse factor, it is better to adopt clustering, i.e., user pairing methods, especially for the large number of users (e.g., massive connections).

Finally, we investigate the performance gap between the exactly robust solution denoted by ExRS (approach in Remark 2) and strictly bounded robust solution denoted by SBRs, and the behavior of the introduced penalty function in (75). For the first, Fig. 7 shows the performance comparison between ExRS and SBRs under variation of the channel estimation error bound for different power budget for macro AAU denoted by $P_{max}^{1}$. As can be seen from the figure, for low power budget and small values of the error the performance of ExRS and SBRs are close to each other. Moreover, the effect of penalty factors
on the penalty function is examined in Fig. 8. In this figure, \( P_{\text{max}}^1 = 35 \, \text{dBm} \), \( K = 8 \), \( N = 5 \), \( \lambda = \mu \), and both axes are plotted in the Logarithmic scale. Note that in “Without Round,” the obtained result is the total penalty function defined in (75) (“Term 1+Term 2”), and in “With Round,” the penalty function is only the penalty term for the rank-one (“Term 2” in (75)) due to \( h(\xi, \rho, x, \lambda) = 0 \). Fig. 8 shows that the penalty function values are close to 0, for the sufficiently large value of penalty factors, e.g., \( 10^5 \), ensures achieving a rank-one solution. Thus, the relaxed binary variables converges to binary ones.

V. CONCLUSION

In this paper, we proposed a novel SIC ordering and also provided a robust and efficient algorithm for resource allocation and beamforming design for C-RAN assisted MC NOMA networks with imperfect CSI. In particular, we formulated the worst-case EE by optimizing the SIC ordering, beamforming, and scheduling variables. Although, the underlying optimization problem is non-convex which is in the form of MINLP, we adopted majorization-minimization and penalty factor methods to convert it into the convex one. Furthermore, we provided a low complexity algorithm based on two-step iterative solution to strike the balance between the complexity and performance gain.

Extensive simulations were provided to assess the performance of the proposed algorithms. Moreover, simulation results unveil the superiority of the proposed algorithm as compared to the baseline schemes.

The SIC ordering algorithm in NOMA-based communications has not been well addressed, especially restraining the inter-cell interference, and it would be a critical issue and pivotal impact on the performance of co-channel interference communication networks. In order to broaden a new horizon that is inferred from the results for the future of massive antennas and high energy efficiency that necessitates the ubiquitous 6G, it is crucial to design efficient antenna selection, clustered beamforming, channel estimation, and spectrum management algorithms in a future wireless networks.

APPENDIX

A. Proof of Proposition 1

The proof includes two parts: 1) minimization and 2) maximization which are discussed as follows.

Proof of minimization: Using an arbitrary positive multiplier \( \phi \geq 0 \), the Lagrangian function of (19) can be written as

\[
\mathcal{L}(\Delta, \phi) = \text{Tr}([\bar{H}_{k,n,f} + \Delta_{k,n,f}]W_{k,n,f}) + \phi(\text{Tr} [\Delta_{k,n,f}W_{k,n,f}^1] - e_{k,n,f}). \tag{81}
\]

Setting the derivative of the Lagrangian with respect to \( \Delta_{k,n,f} \) to zero, we have:

\[
\nabla_{\Delta_{k,n,f}} \mathcal{L}(\Delta_{k,n,f}, \phi) = W_{k,n,f}^1 + \phi \Delta_{k,n,f} = 0. \tag{82}
\]

The optimal value of \( \Delta_{k,n,f} \) is denoted by \( \Delta^*_{k,n,f} \) which can be obtained as \( \Delta^*_{k,n,f} = -\frac{1}{\phi} W_{k,n,f}^1 \). We also differentiate the Lagrangian function with respect to \( \phi \) and equates it to zero as \( \nabla_{\phi} \mathcal{L}(\Delta_{k,n,f}, \phi) = 0 \), where the optimal solution for \( \phi \) is given by \( \phi^* = \frac{1}{e_{k,n,f}} \left\| W_{k,n,f}^1 \right\| \). By substituting the optimal value of \( \phi \), i.e., \( \phi^* \), we conclude that

\[
\Delta_{k,n,f} \min = -e_{k,n,f} \frac{W_{k,n,f}^1}{\left\| W_{k,n,f}^1 \right\|}. \tag{83}
\]

Hessian of the Lagrangian function verifies the obtained solution is minimum. To this end, we need to check the second derivative at the optimal point that should be positive semi-definite, i.e., [54]

\[
\nabla^2_{\Delta^*_{k,n,f}} \mathcal{L}(\Delta^*_{k,n,f}, \phi^*) = \frac{\text{vec}(I_M) \text{vec}(I_M)^T}{e_{k,n,f}} \geq 0. \tag{84}
\]

Proof of maximization: The Lagrangian of (20) is given by

\[
\mathcal{L}(\Delta_{k,n,f}, \phi) = \text{Tr}([\bar{H}_{k,n,f} + \Delta_{k,n,f}]W_{i,n,f}) - \phi(\text{Tr} [\Delta_{k,n,f}W_{k,n,f}^1] - e_{k,n,f}). \tag{86}
\]

By differentiating above function with respect to \( \Delta_{k,n,f} \) and setting the derivative to zero, we have:

\[
\nabla_{\Delta_{k,n,f}} \mathcal{L}(\Delta_{k,n,f}, \phi) = W_{i,n,f}^1 - \phi \Delta_{k,n,f} = 0. \tag{87}
\]
We will found that \( \Delta_{k,n,f}^* = \frac{1}{\phi} W_{k,n,f}^\dagger \). Following the same steps for eliminating the role of \( \phi \), we obtain that

\[
\Delta_{k,n,f}^{\prime \text{max}} = c_{k,n,f} W_{k,n,f}^\dagger / \| W_{k,n,f}^\dagger \|. 
\]  
(88)

Hessian of the Lagrangian function verifies that the obtained solution is maximum. Hence, we check the second derivative at the optimal point that should be negative semi-definite, i.e., [54]

\[
\nabla^2 \Delta_{k,n,f} \mathcal{L}(\Delta_{k,n,f}^*, \phi^*) = - || W_{k,n,f}^\dagger || \left( \text{vec}\{ M \} \text{vec}\{ M^\dagger \} \right)^T \leq 0.
\]  
(89)

**B. Proof of Proposition 2**

We aim to prove this proposition by using the abstract Lagrangian duality. The primal problem of (34) can be written as

\[ p^* = \max_{W, \xi, \rho, \phi} \mathcal{L}(\xi, \rho, x), \]

where the dual problem of (48a) is given by:

\[ d^* = \min_{\lambda} \max_{W, \xi, \rho, x} \mathcal{L}(\xi, \rho, x). \]  
(90)

For simplicity, we also define:

\[ \mu(\lambda) \triangleq \max_{W, \xi, \rho, x} \mathcal{L}(\xi, \rho, x). \]  
(91)

Based on the weak duality theorem, we have:

\[ p^* \leq d^* = \min_{\lambda \geq 0} \mu(\lambda). \]  
(92)

It should be noted that for the feasible set, we have 2 cases as follows:

**Case 1:** One can easily verify that at the optimal point, we have

\[
\mathcal{R}_1 = \sum_{i,k \in K} \sum_{n \in N} \left( x_{i,n}^k - x_{i,n}^k \right)^2 = 0,
\]  
(93)

\[
\mathcal{R}_2 = \sum_{j \in P} \sum_{k \in K} \sum_{n \in N} \left( \rho_{j,n}^k - \rho_{j,n}^k \right)^2 = 0,
\]  
(94)

\[
\mathcal{R}_3 = \sum_{j \in P} \sum_{i,k \in K} \sum_{n \in N} \left( x_{i,n}^k - x_{i,n}^k \right)^2 = 0.
\]  
(95)

As a result, \( d^* \) is also a feasible solution of (34). Subsequently, substituting the optimal value of \( \lambda \), i.e., \( \lambda^* \), into the optimization problem (34) yields

\[ d^* = \mu(\lambda^*) = \max_{W, \xi, \rho, x} \mathcal{L}(\xi, \rho, x) = p^*. \]  
(96)

Moreover, referring to Lagrangian function in the region

\[ \xi, \rho, x, \mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3, \]

function \( \mu(\lambda) \) is a monotonically decreasing function with respect to \( \lambda \). On the other hand, it is argued that \( d^* = \min_{\lambda \geq 0} \mu(\lambda) \), so we have

\[ \mu(\lambda) = d^*, \forall \lambda \geq \lambda^*. \]  
(97)

This means that for any value of \( \lambda \geq \lambda^* \), the solution of Lagrangian function yields the optimal solution of (34).

**Case 2:** The second case occurs when some of integer variables take some values between 0 and 1, causing

\[ \mathcal{R}_1 > 0, \mathcal{R}_2 > 0, \mathcal{R}_3 > 0. \]  
(98)

Referring to the Lagrangian function and (91), at the optimal point, \( \mu(\lambda^*) \) tends to \( -\infty \). However, this can not happen as it contradicts with primal solution stating that \( \mu(\lambda^*) \) is limited from below by the solution of (34) which is always greater than zero. Thus, at the optimal point, we have, \( \mathcal{R}_1 = 0, \mathcal{R}_2 = 0, \) and \( \mathcal{R}_3 = 0. \)

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