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Energy Efficiency Maximization with SIC power aware Hybrid SDMA/NOMA scheme

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Abstract—As energy concerns grow with the rise of energy-constrained devices, it becomes imperative to design an energy-efficient and adaptive multiple access (MA) scheme, supported with accurate energy efficiency (EE) evaluation. Non-orthogonal multiple access (NOMA) enhances EE, yet downlink NOMA faces challenges in terms of computational complexity and power demands of successive interference cancellation (SIC), problematic particularly for energy-limited devices. Existing studies overlook the additional SIC power consumption at NOMA receivers, thus overestimating EE, and giving misleading insights for real system design. Besides the need for more accurate EE evaluation, an adaptive MA approach based on this additional power consumption is required. This paper proposes a SIC-power-aware adaptive SDMA/cooperative NOMA system. An optimization problem is formulated by optimizing MA mode decision, BS beamforming, power allocation factors, and strong user relaying power, to maximize the system EE. We decouple the problem into SDMA/NOMA selection and power allocation sub-problems, solved via a modified semi-orthogonal user selection (SUS) algorithm, successive convex approximation (SCA), difference-of-convex (DC) programming, and semidefinite programming (SDP) approaches. Numerical evaluation confirms the efficiency of the proposed scheme, compared to the baseline schemes.

Index Terms—Cooperative NOMA, SDMA, Energy Efficiency, SIC-power

I. INTRODUCTION

According to Cisco, the connected devices will surpass 75.4 billion devices, by 2025 [1]. This surge in connection density, as well as the emergent applications, invokes unprecedented demands of massive access, along with energy constraints in future generation networks, i.e., beyond 5G(B5G)/6G. Therefore, designing adaptive and energy-efficient multiple access (MA) techniques becomes critical for these networks. Non-orthogonal multiple access (NOMA) is a prominent technique suited to handle large-scale B5G networks and has proved its ability to provide high spectral and energy efficiency (EE) [2].

Specifically, power-domain NOMA enables superposing users' signals over the same time-frequency resources, using superposition coding and successive interference cancellation (SIC) techniques at the transmitter and receiver, respectively. To further improve the weak user's performance, cooperative NOMA (CNOMA) enables the strong user to act as a relay to assist the weak user [3]. Nevertheless, a pivotal concern in downlink NOMA is the receiver's capacity to handle the interference, via SIC. Despite being overlooked in the literature, SIC computational and power demands become challenging for energy-constrained users. Neglecting the additional SIC power in the power consumption model overestimates the theoretical evaluation of the EE, rendering significant gaps

between theoretical analysis and practical system design, and yielding misleading insights about the network lifetime.

In [4], authors were the first to study the impact of SIC-related power on the evaluation of EE, assuming static SIC power per each decoding stage for all users, regardless of their decoding rate. This assumption can not be accurate, as the decoding power scales with the decoding rate [5]. While the authors in [4] highlight the EE overestimation caused by neglecting SIC power, static SIC power assumptions further misrepresent this overestimation. To avoid misleading insights, accurate dynamic SIC power modeling is required. Moreover, while [4] was limited to highlighting the EE overestimation, it is required to leverage this insight for designing an adaptive MA scheme based on dynamic SIC power modeling. In a multi-antenna system, this can be a hybrid space division multiple access (SDMA)/NOMA scheme because, unlike NOMA, SDMA enables users to decode data by treating residual interference as noise, avoiding the need for SIC. In [6–8], the authors designed an adaptive MA scheme that incorporates the cost of each MA mode. For NOMA, this includes a SIC cost as the sum of a fixed part proportional to the NOMA cluster size, and a variable part proportional to the bit error rate as in [9]. The variable part arises from the increased complexity of SIC receivers due to error propagation. The adaptive scheme uses a utility function based on normalized sum throughput, with an additional penalty for MA mode costs. However, SIC power consumption is not considered, and the scheme is not designed from an energy efficiency perspective. In [10–12], the authors proposed a multi-dimensional MA scheme spanning OMA, NOMA, and SDMA, while considering costs for each MA mode. For NOMA, the SIC-related cost is quantified based on channel gain similarity between users, motivated by the fact that lower disparity requires more complexity for SIC decoding. However, in these studies, there is a lack of an adaptive MA mode selection approach from an EE perspective and with a decoding rate-dependent power consumption model.

To address the aforementioned gap, we propose a SIC-power-aware adaptive NOMA/SDMA scheme, with a rate-dependent SIC power modeling. To the best of our knowledge, this is the first work tackling this challenge. We formulate an energy efficiency maximization problem while considering the dynamic power consumption model accounting for SIC-related power. We aim to optimize the SDMA/NOMA decision for each user, base station (BS) beamforming, power allocation factor, and relaying power of strong users in NOMA case.

II. SYSTEM MODEL

Consider a downlink multiple-input-single output (MISO) hybrid SDMA/NOMA system with multi-antenna BS and a set of single-antenna users \mathcal{U} . The BS uses its N antennas

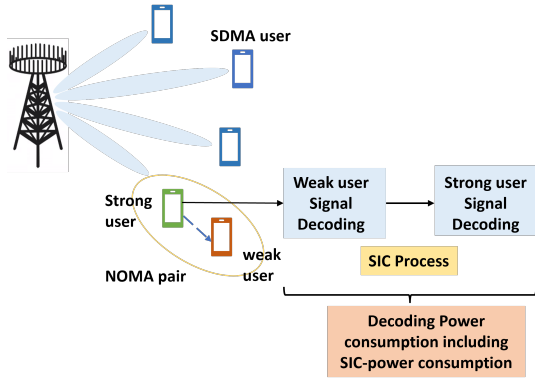


Fig. 1: Hybrid SDMA/NOMA System

to serve all users in the same frequency-time resource block. Some users are paired as NOMA pairs, and others as SDMA users. Each NOMA pair consists of a strong and a weak user. CNOMA is enabled to improve weak users' performance, with strong users acting as full-duplex relays [13]. A beamforming vector serves each NOMA pair, and a separate one for each SDMA user. We aim to design an adaptive approach that selects either SDMA or NOMA for each user based on the decoding power consumption, including additional SIC power consumed at each strong user in NOMA pairs. A binary decision variable $\zeta_k, \forall k \in \mathcal{K}$ models this decision as follows:

- If $\zeta_k = 1$, then strong user $\text{CU}_{1,k}$ and weak user $\text{CU}_{2,k}$ form a CNOMA pair k . This means that $\text{CU}_{1,k}$ and $\text{CU}_{2,k}$ are served by a common beamforming vector $\mathbf{p}_{n,k}$.
- If $\zeta_k = 0$, then $\text{CU}_{1,k}$ will not implement SIC, thus $\text{CU}_{1,k}$ and $\text{CU}_{2,k}$ are SDMA users. Each is served by a separate beamforming vector, i.e., $\mathbf{p}_{s,1,k}$ and $\mathbf{p}_{s,2,k}$, respectively.

A. Signal Model and Rate Analysis

Denote by \mathcal{K}_n and \mathcal{K}_s , the set of NOMA pairs and SDMA users, with $\mathcal{K} = \mathcal{K}_n \cup \mathcal{K}_s$, where $|\mathcal{K}| = \frac{|\mathcal{U}|}{2}$. It is noteworthy that ζ_k will decide for each user to belong to either \mathcal{K}_n or \mathcal{K}_s . Let $\mathbf{p}_{n,k} \in \mathbb{C}^{N \times 1}$, the beamforming vector for each NOMA pair $k \in \mathcal{K}_n$, and $\mathbf{p}_{s,1,k'}, \mathbf{p}_{s,2,k'} \in \mathbb{C}^{N \times 1}$ for two SDMA users in $k' \in \mathcal{K}_s$. Thus, the transmitted BS signal can be as follows:

$$\tilde{\mathbf{x}} = \sum_{k \in \mathcal{K}_n} ((1 - \alpha_k) \mathbf{p}_{n,k} x_{1,k} + \alpha_k \mathbf{p}_{n,k} x_{2,k}) + \sum_{k' \in \mathcal{K}_s} (\mathbf{p}_{s,1,k'} x_{1,k'} + \mathbf{p}_{s,2,k'} x_{2,k'}), \quad (1)$$

where α_k denotes the power allocation factors for the weak user, in NOMA pair $k \in \mathcal{K}_n$. $x_{1,k}$ and $x_{2,k}$ denote the data of the strong and weak users, respectively.

The received signal at the strong user in NOMA pair $k \in \mathcal{K}_n$ can be formulated as $y_{1,k} = \mathbf{h}_{1,k}^H \tilde{\mathbf{x}} + h_{1,1} \sqrt{p_{r,k}} \hat{x}_{2,k} + \sum_{k' \in \mathcal{K} \setminus k} (h_{1,k',1,k} \sqrt{p_{r,k'}} \hat{x}_{2,k'}) + n$, where $\mathbf{h}_{u,k} \in \mathbb{C}^{N \times 1}$, $u \in \{1, 2\}$, is the BS-users channel gain, and n represents the additive white Gaussian noise (AWGN) with zero mean and variance σ^2 . The first term in $y_{1,k}$ denotes the received signal from the BS, and the second term denotes the self-interference (SI), with $h_{1,1}$, $p_{r,k}$, and $\hat{x}_{2,k}$ denote the SI channel gain, the strong user relaying power, and the decoded data of the weak user, respectively. The third term denotes the interference from strong users relaying in other NOMA pairs, where

$h_{1,k',u,k}, \forall u \in \{1, 2\}$ denotes the channel gain from the strong user in NOMA pair $k' \in \mathcal{K}_n$ to any other user.

The strong user in NOMA pair $k \in \mathcal{K}_n$, $\text{CU}_{1,k}$ applies SIC to decode $x_{2,k}$. The achievable rate to decode $x_{2,k}$ can be formulated as follows:

$$R_{1,2,k} = \log_2 \left(1 + \frac{\alpha_k |\mathbf{h}_{1,k}^H \mathbf{p}_{n,k}|^2}{(1 - \alpha_k) |\mathbf{h}_{1,k}^H \mathbf{p}_{n,k}|^2 + I_{\text{inter},1,k}^N + I_{SI,k} + I_{\text{coop},1,k}^N + \sigma^2} \right), \quad (2)$$

where the interference from BS transmission to other NOMA pairs and SDMA users, the SI, and the interference from relaying in other NOMA pairs can be given, respectively as

$$I_{\text{inter},u,k}^N = \sum_{k' \in \mathcal{K}_n \setminus k} |\mathbf{h}_{u,k}^H \mathbf{p}_{n,k'}|^2 + \sum_{k'' \in \mathcal{K}_s} (|\mathbf{h}_{u,k}^H \mathbf{p}_{s,1,k''}|^2 + |\mathbf{h}_{u,k}^H \mathbf{p}_{s,2,k''}|^2), \quad (3)$$

$$I_{SI,k} = |h_{1,1}|^2 p_{r,k}, \quad (4)$$

$$I_{\text{coop},u,k}^N = \sum_{k' \in \mathcal{K}_n \setminus k} |h_{1,k',u,k}|^2 p_{r,k'}, \quad u \in \{1, 2\}. \quad (5)$$

After canceling $x_{2,k}$ via SIC, the achievable rate for $\text{CU}_{1,k}$ to decode its data $x_{1,k}$ can be formulated as follows:

$$R_{1,k}^{\text{NOMA}} = \log_2 \left(1 + \frac{(1 - \alpha_k) |\mathbf{h}_{1,k}^H \mathbf{p}_{n,k}|^2}{I_{\text{inter},1,k}^N + I_{SI,k} + I_{\text{coop},1,k}^N + \sigma^2} \right). \quad (6)$$

The received signal at the weak user $\text{CU}_{2,k}$ in NOMA pair $k \in \mathcal{K}_n$ can be given as follows $y_{2,k} = \mathbf{h}_{2,k}^H \tilde{\mathbf{x}} + h_{1,2,k} \sqrt{p_{r,k}} x_{2,k} + \sum_{k' \in \mathcal{K}_n \setminus k} (h_{1,k',2,k} \sqrt{p_{r,k'}} \hat{x}_{2,k'}) + n$. The first term denotes the BS signal, the second term denotes the relayed signal from $\text{CU}_{1,k}$, and the third term denotes the interference from strong users relaying in other NOMA pairs. $\text{CU}_{2,k}$ does not apply SIC, and directly decodes $x_{2,k}$, while treating interference as noise. Assuming BS and relaying signals are resolvable at $\text{CU}_{2,k}$, they are co-phased and merged using the maximal ratio combining (MRC) technique. The achievable rate to decode $x_{2,k}$ at $\text{CU}_{2,k}$ is $R_{\text{MRC},k} = \log_2(1 + \gamma_{\text{mrc}})$, where $\gamma_{\text{mrc}} = \gamma_{2,2,k} + \gamma_{2,1,k}$ with $\gamma_{2,2,k} = \frac{\alpha_k |\mathbf{h}_{2,k}^H \mathbf{p}_{n,k}|^2}{(1 - \alpha_k) |\mathbf{h}_{2,k}^H \mathbf{p}_{n,k}|^2 + I_{\text{inter},2,k}^N + I_{\text{coop},2,k}^N + \sigma^2}$, and $\gamma_{2,1,k} = \frac{|h_{1,2,k}|^2 p_{r,k}}{I_{\text{inter},2,k}^N + I_{\text{coop},2,k}^N + \sigma^2}$.

Due to the decoding success constraint where rate of decoding $x_{2,k}$ at $\text{CU}_{1,k}$ should be greater than rate of decoding $x_{2,k}$ at $\text{CU}_{2,k}$; thus the achievable rate to decode $x_{2,k}$ at $\text{CU}_{2,k}$ is limited by $R_{1,2,k}$, as follows $R_{2,k}^{\text{NOMA}} = \min(R_{\text{MRC},k}, R_{1,2,k})$.

Now, moving to the SDMA users set \mathcal{K}_s . The achievable rates to decode $x_{1,k}$ at $\text{CU}_{1,k}$ and $x_{2,k}$ at $\text{CU}_{2,k}$, where $k \in \mathcal{K}_s$ can be formulated, respectively, as follows:

$$R_{1,k}^{\text{SDMA}} = \log_2 \left(1 + \frac{|\mathbf{h}_{1,k}^H \mathbf{p}_{s,1,k}|^2}{|\mathbf{h}_{1,k}^H \mathbf{p}_{s,2,k}|^2 + I_{1,k}^S + I_{\text{coop},1,k}^S + \sigma^2} \right), \quad (7)$$

$$R_{2,k}^{\text{SDMA}} = \log_2 \left(1 + \frac{|\mathbf{h}_{2,k}^H \mathbf{p}_{s,2,k}|^2}{|\mathbf{h}_{2,k}^H \mathbf{p}_{s,1,k}|^2 + I_{2,k}^S + I_{\text{coop},2,k}^S + \sigma^2} \right), \quad (8)$$

where $I_{u,k}^S = \sum_{k' \in \mathcal{K}_s \setminus k} |\mathbf{h}_{u,k}^H \mathbf{p}_{s,u,k'}|^2 + \sum_{k'' \in \mathcal{K}_n} |\mathbf{h}_{u,k}^H \mathbf{p}_{n,k''}|^2$, and $I_{\text{coop},u,k}^S = \sum_{k'' \in \mathcal{K}_n} |h_{1,k'',u,k}|^2 p_{r,k''}$ are the interference from BS transmissions to other SDMA users and NOMA pairs, and the interference from relaying in NOMA pairs,

respectively. Therefore, the achievable rates for all strong and weak users in \mathcal{K} can be formulated, respectively, as:

$$R_{1,k} = \zeta_k R_{1,k}^{\text{NOMA}} + (1 - \zeta_k) R_{1,k}^{\text{SDMA}}, \quad (9)$$

$$R_{2,k} = \zeta_k R_{2,k}^{\text{NOMA}} + (1 - \zeta_k) R_{2,k}^{\text{SDMA}}. \quad (10)$$

B. Power Consumption Model

The proposed power consumption model for the hybrid SDMA/NOMA system can be given as

$$P_{\text{total}} = \sum_{k \in \mathcal{K}} \left(\zeta_k \mathbf{p}_{n,k}^H \mathbf{p}_{n,k} + (1 - \zeta_k) (\mathbf{p}_{s,1,k}^H \mathbf{p}_{s,1,k} + \mathbf{p}_{s,2,k}^H \mathbf{p}_{s,2,k}) + \zeta_k p_{r,k} + w_d (\zeta_k R_{1,2,k} + R_{1,k} + R_{2,k}) \right). \quad (11)$$

The first two terms represent the BS transmit power, and the third term represents the strong users relaying power in NOMA pairs. The last term represents the decoding power, including the SIC power, which is modeled based on w_d , i.e., a rate-dependent factor in Watt/bps/Hz.

III. PROBLEM FORMULATION

We aim to maximize the overall EE by optimizing the BS beamforming $\mathbf{p}_{n,k} \in \mathbb{C}^{N \times 1}$, $\mathbf{p}_{s,1,k}$ and $\mathbf{p}_{s,2,k} \in \mathbb{C}^{N \times 1}$, $\forall k \in \mathcal{K}$, the strong user relaying power and power allocation factor, $p_{r,k} \in \mathbb{R}$, $\alpha_k \in \mathbb{R}$, respectively, and the SDMA/NOMA decision $\zeta_k \in \{0, 1\}$, $\forall k \in \mathcal{K}$. The overall EE can be formulated as follows:

$$\text{EE} = \frac{\sum_{k \in \mathcal{K}} (R_{1,k} + R_{2,k})}{P_{\text{total}}}. \quad (12)$$

Hence, our optimization problem can be formulated as follows:

$$\mathbf{P1} \max_{\mathcal{V}_1} \quad \text{EE} \quad (13a)$$

$$\text{subject to} \quad \mathbf{C}_1 : \zeta_k \in \{0, 1\}, \forall k \in \mathcal{K}, \quad (13b)$$

$$\mathbf{C}_2 : \mathbf{p}_k^H \mathbf{p}_k \leq \zeta_k P_{BS}, \forall k \in \mathcal{K}, \quad (13c)$$

$$\mathbf{C}_3 : \mathbf{p}_{s,1,k}^H \mathbf{p}_{s,1,k} \leq (1 - \zeta_k) P_{BS}, \forall k \in \mathcal{K} \quad (13d)$$

$$\mathbf{C}_4 : \mathbf{p}_{s,2,k}^H \mathbf{p}_{s,2,k} \leq (1 - \zeta_k) P_{BS}, \forall k \in \mathcal{K}, \quad (13e)$$

$$\mathbf{C}_5 : \sum_{k \in \mathcal{K}} \zeta_k \mathbf{p}_{n,k}^H \mathbf{p}_{n,k} + (1 - \zeta_k) \left(\mathbf{p}_{s,1,k}^H \mathbf{p}_{s,1,k} + \mathbf{p}_{s,2,k}^H \mathbf{p}_{s,2,k} \right) \leq P_{BS}, \quad (13f)$$

$$\mathbf{C}_6 : p_{r,k} \leq \zeta_k P_{r,\max}, \forall k \in \mathcal{K}, \quad (13g)$$

$$\mathbf{C}_7 : \alpha_k \geq 0.5, \forall k \in \mathcal{K}, \quad (13h)$$

$$\mathbf{C}_8 : R_{u,k} \geq R_{\min}, \forall k \in \mathcal{K}, \forall u \in \{1, 2\}, \quad (13i)$$

where $\mathcal{V}_1 = \{\mathbf{p}_{n,k}, \mathbf{p}_{s,1,k}, \mathbf{p}_{s,2,k}, p_{r,k}, \zeta_k, \forall k \in \mathcal{K}\}$. P_{BS} , $P_{r,\max}$, and R_{\min} represent the BS power budget, the relaying power budget of each strong user, and the minimum rate requirement, respectively. Constraint \mathbf{C}_1 represents the binary SDMA/NOMA decision, and \mathbf{C}_2 , \mathbf{C}_3 , \mathbf{C}_4 and \mathbf{C}_5 represent the BS power budget. \mathbf{C}_6 represents the relaying power constraint at strong users. \mathbf{C}_7 represents the constraint on the power allocation between users of NOMA pair k , and \mathbf{C}_8 represents the minimum rate requirements.

$\mathbf{P1}$ is challenging to be solved with standard optimization solvers due to non-convex constraints and objective function. Motivated by this, successive convex approximation (SCA) will be used to transform the problem into tractable versions.

IV. PROPOSED SOLUTION

We decouple the problem into SDMA/NOMA decision sub-problem (i.e., ζ) and power allocation sub-problem. We solve the first sub-problem using the semi-orthogonal user selection (SUS) algorithm in **Algorithm 1**, then SCA, difference-of-convex (DC) programming and semi-definite program (SDP) approaches are used for the second sub-problem.

For the first sub-problem, we propose the modified SUS algorithm based on that in [14] to select semi-orthogonal strong users based on channel correlation factor θ . This aims to reduce the inter-cluster interference between NOMA pairs. **Algorithm 1** starts by selecting only one strong user. A weak user is then selected to be paired with it as a NOMA pair, via exhaustive search or a pairing approach as matching theory. All other users will be SDMA users. In the next iteration, only two strong users are selected, and two weak users will be paired with them as NOMA pairs, while all other users are SDMA users. This process continues until all users are paired as NOMA pairs. These iterations generate $\frac{|\mathcal{U}|}{2}$ possibilities of SDMA/NOMA decision. We add the possibility that all users are in SDMA mode. These possibilities are fed to the next sub-problem, to identify the one that maximizes EE. Now based on **Algorithm 1** output ζ^* , we have \mathcal{K}_n and \mathcal{K}_s . The second sub-problem is then formulated as follows:

$$\mathbf{P2} \max_{\mathcal{V}_1 \setminus \zeta} \quad \text{EE}(\zeta^*), \quad (14a)$$

$$\text{subject to} \quad (12f)-(12i). \quad (14b)$$

We start by the objective function in $\mathbf{P2}$. We introduce the slack variables, \mathbf{r} , and ρ , in the numerator and denominator, respectively. We add the related constraints. The objective is now denoted $\frac{F(\mathbf{r})}{\rho}$, where $F(\mathbf{r})$ is given as follows:

$$F(\mathbf{r}) = \sum_{k \in \mathcal{K}_n} (r_{1,k}^N + r_{2,k}^N) + \sum_{k' \in \mathcal{K}_s} (r_{1,k'}^S + r_{2,k'}^S). \quad (15)$$

We introduce slack variable t , and following semidefinite relaxation (SDR) approach, we replace the beamforming vectors, $\mathbf{p}_{n,k}$, $\mathbf{p}_{s,1,k}$, and $\mathbf{p}_{s,2,k}$, and channel coefficients with positive semidefinite (PSD) matrices such as, $\mathbf{H}_{u,k} = \mathbf{h}_{u,k} \mathbf{h}_{u,k}^H$, $\forall k \in \mathcal{K}$, $\mathbf{P}_{n,k} = \mathbf{p}_{n,k} \mathbf{p}_{n,k}^H$, $\forall k \in \mathcal{K}_n$, and $\mathbf{P}_{s,u,k} = \mathbf{p}_{s,u,k} \mathbf{p}_{s,u,k}^H$, $\forall k \in \mathcal{K}_s$, $u = \{1, 2\}$. Thus, $\mathbf{P2}$ can be formulated as follows:

$$\mathbf{P3} \max_{\mathcal{V}_3} \quad t, \quad (16a)$$

$$\text{subject to} \quad F(\mathbf{r}) \geq w^2, \quad (16b)$$

$$P_{\text{total}} \leq \rho, \quad (16c)$$

$$\frac{w^2}{\rho} \geq t, \quad (16d)$$

$$\log_2(1 + s_{1,k}^N) \geq r_{1,k}^N, \quad (16e)$$

$$\log_2(1 + s_{1,2,k}^N) \geq r_{2,k}^N, \quad (16f)$$

$$\log_2(1 + s_{\text{mrc},k}^N) \geq r_{2,k}^N, \quad (16g)$$

$$\log_2(1 + s_{1,k}^S) \geq r_{1,k}^S, \quad (16h)$$

$$\log_2(1 + s_{2,k}^S) \geq r_{2,k}^S, \quad (16i)$$

$$s_{2,1,k} + s_{2,2,k} \geq s_{\text{mrc},k}, \forall k \in \mathcal{K}_n \quad (16j)$$

$$\gamma_{1,k}^N \geq s_{1,k}^N, \forall k \in \mathcal{K}_n, \quad (16k)$$

$$\gamma_{1,2,k} \geq s_{1,2,k}, \forall k \in \mathcal{K}_n \quad (16l)$$

$$\gamma_{2,2,k} \geq s_{1,2,k}, \forall k \in \mathcal{K}_n \quad (16m)$$

$$\gamma_{2,1,k} \geq s_{2,1,k}, \forall k \in \mathcal{K}_n \quad (16n)$$

$$\gamma_{1,k}^S \geq s_{1,k}^S, \forall k \in \mathcal{K}_s, \quad (16o)$$

$$\gamma_{2,k}^S \geq s_{2,k}^S, \forall k \in \mathcal{K}_s, \quad (16p)$$

$$\sum_{k \in \mathcal{K}_n} Tr(\mathbf{P}_{n,k}) + \sum_{k' \in \mathcal{K}_s} \left(Tr(\mathbf{P}_{s,1,k'}) + Tr(\mathbf{P}_{s,2,k'}) \right) \leq P_{BS}, \quad (16q)$$

$$p_{r,k} \leq P_{r,max}, \forall k \in \mathcal{K}_n, \quad (16r)$$

$$\alpha_k \geq 0.5, \forall k \in \mathcal{K}_n, \quad (16s)$$

$$r_{u,k}^N \geq R_{min}, \forall k \in \mathcal{K}_n, \forall u \in \{1, 2\}, \quad (16t)$$

$$r_{u,k}^S \geq R_{min}, \forall k \in \mathcal{K}_s, \forall u \in \{1, 2\}, \quad (16u)$$

$$r_{1,2,k} \geq R_{min}, \forall k \in \mathcal{K}_n, \quad (16v)$$

$$\text{rank}(\mathbf{P}_{n,k}) = 1, \forall k \in \mathcal{K}_n, \quad (16w)$$

$$\text{rank}(\mathbf{P}_{s,u,k}) = 1, \forall k \in \mathcal{K}_s, \forall u \in \{1, 2\}. \quad (16x)$$

where $\mathcal{V}_3 = \{\mathbf{P}_n, \mathbf{P}_{s,1}, \mathbf{P}_{s,2}, \mathbf{p}_r, \alpha, \omega, \rho, t, \mathbf{r}^N, \mathbf{r}^S, \mathbf{s}^N, \mathbf{s}^S\}$ is the set of slack variables, where $\mathbf{P}_n = \{\mathbf{P}_{n,k}, \forall k \in \mathcal{K}_n\}$, where the PSD matrix $\mathbf{P}_{n,k} = \mathbf{p}_{n,k} \mathbf{P}_{n,k}^H$. Similarly, $\mathbf{P}_{s,1} = \{\mathbf{P}_{s,1,k}, \forall k \in \mathcal{K}_s\}$, where a PSD matrix $\mathbf{P}_{s,1,k} = \mathbf{p}_{s,1,k} \mathbf{P}_{s,1,k}^H$, and $\mathbf{P}_{s,2} = \{\mathbf{P}_{s,2,k}, \forall k \in \mathcal{K}_s\}$, where a PSD matrix $\mathbf{P}_{s,2,k} = \mathbf{p}_{s,2,k} \mathbf{P}_{s,2,k}^H$. Also, $\mathbf{p}_r = \{p_{r,k}, \forall k \in \mathcal{K}_n\}$, and $\alpha = \{\alpha_k, \forall k \in \mathcal{K}_n\}$. Then, $\mathbf{r}^N = \{r_{u,k}^N, r_{1,2,k}, \forall k \in \mathcal{K}_n, u \in \{1, 2\}\}$, $\mathbf{r}^S = \{r_{u,k}^S, \forall k \in \mathcal{K}_s, u \in \{1, 2\}\}$. Finally, $\mathbf{s}^N = \{s_{u,k}^N, s_{1,2,k}, s_{mrc,k}, s_{2,2,k}, s_{2,1,k}, \forall k \in \mathcal{K}_n, \forall u \in \{1, 2\}\}$, and $\mathbf{s}^S = \{s_{u,k}^S, \forall k \in \mathcal{K}_s, \forall u \in \{1, 2\}\}$. $\gamma_{1,2,k}$, $\gamma_{1,k}^N$, $\gamma_{1,k}^S$ and $\gamma_{2,k}^S$ are the SINR in the throughput equations (2), (6), (7), and (8), respectively. We first move to the rank-one constraints (15w)-

Algorithm 1: Modified SUS algorithm

Input : $\mathbf{h}, \theta, \mathcal{U}_0 = \mathcal{U}$, set of strong users $\mathcal{U}_1 = \phi$
while $j \leq |\mathcal{U}|$ and $\mathcal{U}_0 \neq \phi$ **do**
 foreach $u \in \mathcal{U}_0$ **do**
 $g_u = h_u - \sum_{j'=1}^{j-1} \frac{h_j g_{j'}}{\|g_{j'}\|^2} g_{j'}$
 Select $j^* = \text{argmax}_{u \in \mathcal{U}_0} g_u$
 $\mathcal{U}_1 \leftarrow \mathcal{U}_1 \cup j^*$
 $\mathcal{U}_0 \leftarrow \{u | u \in \mathcal{U}_0, u \neq j^*, \frac{h_u g_j^*}{\|h_u\| \|g_j^*\|} \leq \theta\}$
 for $i = 1$ to $\frac{|\mathcal{U}|}{2}$ **do**
 if $|\mathcal{U}_1| == i$ **then break**
 end
 $j \leftarrow j + 1$
 end
end
Output : \mathcal{U}_1, ζ^*

(15x). SDR is a common approach to handle the rank-one constraint, simply by removing (15w)-(15x), which turns the problem SDP. However, in large-scale problems, SDR is less probably to obtain a rank-one solution. Instead, we replace this constraint with DC representation as follows:

$$\begin{aligned} \mathcal{A}(\mathbf{P}_{n,k}) &= 0, k \in \mathcal{K}_n, \\ \mathcal{B}(\mathbf{P}_{s,u,k}) &= 0, \forall u \in \{1, 2\}, k \in \mathcal{K}_s, \end{aligned} \quad (17)$$

where $\mathcal{A}(\mathbf{P}_{n,k}) = \|\mathbf{P}_{n,k}\|_* - \|\mathbf{P}_{n,k}\|_2$, and $\mathcal{B}(\mathbf{P}_{s,u,k}) = \|\mathbf{P}_{s,u,k}\|_* - \|\mathbf{P}_{s,u,k}\|_2$. This DC representation is justified by the fact that any PSD matrix $\mathbf{X} \in \mathbb{C}^{(A \times A)}$, rank-one constraint implies that $\sigma_1(\mathbf{X}) \geq 0$ and $\sigma_a(\mathbf{X}) = 0, \forall a \in [2, A]$, where σ_a denotes the largest a -th eigen value of \mathbf{X} . So since $\mathbf{P}_{n,k}, \forall k \in \mathcal{K}_n$, and $\mathbf{P}_{s,u,k}, \forall u \in \{1, 2\}, k \in \mathcal{K}_s$, are PSD matrices, the rank-one constraint can be formulated by the difference between their nuclear and spectral norms as in (17).

The DC representation in (17) can be added to the objective function in **P3** as a penalty term with penalty factor η . So, **P3** can be equivalently reformulated as follows:

$$\begin{aligned} \mathbf{P4} \max_{\mathcal{V}_3} \quad & t - \eta \left(\sum_{k \in \mathcal{K}_n} \mathcal{A}(\mathbf{P}_{n,k}) + \sum_{k \in \mathcal{K}_n} \sum_{u \in \{1, 2\}} \mathcal{B}(\mathbf{P}_{s,u,k}) \right), \\ \text{subject to} \quad & (15b) - (15v). \end{aligned} \quad (18a) \quad (18b)$$

where η is a penalty factor that forces the rank-one constraint. Thus, a rank-one solution can be obtained, when the penalty term reaches zero. We can initialize the penalty coefficient λ with a small value and gradually increase it until the penalty term reaches zero as follows: $\eta = \lambda \eta$, where $\lambda > 1$. The objective function is still non-convex. We linearize the second term of \mathcal{A} and \mathcal{B} . So, **P4** can be reformulated as follows:

$$\begin{aligned} \mathbf{P5} \max_{\mathcal{V}_3} \quad & t - \left(\sum_{k \in \mathcal{K}_n} \bar{\mathcal{A}}(\mathbf{P}_{n,k}) + \sum_{k \in \mathcal{K}_s} \sum_{u \in \{1, 2\}} \bar{\mathcal{B}}(\mathbf{P}_{s,u,k}) \right), \\ \text{subject to} \quad & (15b) - (15v). \end{aligned} \quad (19a) \quad (19b)$$

where

$$\bar{\mathcal{A}}(\mathbf{P}_{n,k}) = \left(\|\mathbf{P}_{n,k}\|_* - \left\langle \delta_{\mathbf{P}_{n,k}^{(n)}} \|\mathbf{P}_{n,k}^{(n)}\|, \mathbf{P}_{n,k} \right\rangle \right), \quad (20)$$

$$\bar{\mathcal{B}}(\mathbf{P}_{s,u,k}) = \left(\|\mathbf{P}_{s,u,k}\|_* - \left\langle \delta_{\mathbf{P}_{s,u,k}^{(n)}} \|\mathbf{P}_{s,u,k}^{(n)}\|, \mathbf{P}_{s,u,k} \right\rangle \right), \quad (21)$$

where $\mathbf{X}^{(n)}$ is the solution obtained at the n th iteration, $\delta_{\mathbf{X}^{(n)}} \|\mathbf{X}^{(n)}\|$ is the subgradient of $\|\mathbf{X}\|$ with respect to \mathbf{X} at $\mathbf{X}^{(n)}$, for any PSD matrix $\mathbf{X} \in \mathbb{C}^{(A \times A)}$, and $\langle \cdot, \cdot \rangle$ denotes the inner product. $\delta_{\mathbf{X}^{(n)}} \|\mathbf{X}^{(n)}\|$ can be written as $a_i a^H$, where a_i is the normalized eigenvector corresponding to the maximum eigenvalue of matrix $\mathbf{X}^{(n)}$. Now, the objective function is convex, we move to the constraints. The constraints (15b)-(15c), (15e)-(15j), and (15q)-(15v) are convex. For (15d), the non-convexity lies in the left-hand side. We use its first-order Taylor series approximation $G_1(w, \rho)$ as follows:

$$\bar{G}_1(w, \rho) = 2 \frac{(w^{(n)})}{\rho} w - \left(\frac{w^{(n)}}{\rho^{(n)}} \right)^2 \rho, \quad (22)$$

where $w^{(n)}$ and $\rho^{(n)}$ are w and ρ at the SCA n th iteration. We move to constraints (15k)-(15p). For (15k), we introduce two slack variables c_1 and β_1 , and it is transformed as follows:

$$\frac{c_1^2}{\beta_1} \geq s_{1,k}^N, \quad (23)$$

$$(1 - \alpha_k) \text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{n,k}) \geq c_1^2, \quad (24)$$

$$I_{inter,1,k}^N + I_{SI,k} + I_{coop,1,k} \leq \beta_1, \quad (25)$$

where

$$\begin{aligned} I_{inter,u,k}^N &= \sum_{k' \in \mathcal{K}_n \setminus k} \text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{n,k'}) \\ &+ \sum_{k'' \in \mathcal{K}_s} \left(\text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{s,1,k''}) + \text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{s,2,k''}) \right), \end{aligned} \quad (26)$$

$$I_{SI,k} = |h_{1,1}|^2 p_{r,k}, \quad (27)$$

$$I_{coop,u,k} = \sum_{k'' \in \mathcal{K}_n} |\mathbf{h}_{1,k'',u,k}|^2 p_{r,k''}, u = \{1, 2\}. \quad (28)$$

Constraint (22) is treated similar to (15d). Constraint (23) is a quadratic conic convex constraint, and (24) is convex. Now, we move to constraint (15l), we introduce two slack variables c_2 and β_2 , and it is transformed to the following constraints:

$$\frac{c_2^2}{\beta_2} \geq s_{1,2,k}, \quad (29)$$

$$\alpha_k \text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{n,k}) \geq c_2^2, \quad (30)$$

$$d_1 + I_{inter,1,k}^N + I_{SI,k} + I_{coop,1,k} \leq \beta_2, \quad (31)$$

$$(1 - \alpha_k) \text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{n,k}) \leq d_1. \quad (32)$$

Constraint (28) is treated as (15d). Constraint (29) is a quadratic conic convex constraint, and (30) is convex. The non-convexity in (31) lies in the variables multiplication in the left-hand side. We can transform it as follows:

$$\begin{aligned} & \frac{1}{4} \left((1 - \alpha_k) + \text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{n,k}) \right)^2 - d_1 + \\ & \frac{1}{4} \left((1 - \alpha_k) - \text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{n,k}) \right)^2 \leq 0. \end{aligned} \quad (33)$$

We can see that it is a DC term, so we use first-order Taylor series approximation for the third term.

Now, we move to the constraint (15m). We introduce the slack variables c_3 and β_3 such that it is transformed as follows:

$$\frac{c_3^2}{\beta_3} \geq s_{2,2,k}, \quad (34)$$

$$\alpha_k \text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{n,k}) \geq c_3^2, \quad (35)$$

$$d_2 + I_{inter,2,k}^N + I_{coop,2,k} \leq \beta_3, \quad (36)$$

$$(1 - \alpha_k) \text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{n,k}) \leq d_2. \quad (37)$$

Constraint (33) is treated similar to (15d), constraint (34) is a quadratic conic convex constraint, and constraint (35) is convex. Constraint (36) is treated similar to (31).

Now, we move to the constraint (15n). We introduce the slack variable β_4 such that it is transformed as follows:

$$\frac{|h_{1,2,k}|^2 p_{r,k}}{\beta_4} \geq s_{2,1,k}, \quad (38)$$

$$I_{inter,2,k}^N + I_{coop,2,k} \leq \beta_4. \quad (39)$$

We deal with constraint (37) by first-order Taylor series approximation of the left-hand side $G_2(p_{r,k}, \beta_4)$ as follows:

$$\bar{G}_2(p_{r,k}, \beta_4) = |h_{1,2,k}|^2 \left(\frac{p_{r,k}^{(n)}}{\beta_4^{(n)}} + \frac{(p_{r,k} - p_{r,k}^{(n)})}{\beta_4^{(n)}} - \frac{(\beta_4 - \beta_4^{(n)})}{(\beta_4^{(n)})^2} p_{r,k} \right). \quad (40)$$

Now, we introduce the slack variables β_5 and β_6 to deal with constraints (15o) and (15p), respectively. They are transformed into (40)-(41) and (42)-(43)), respectively, as follows:

$$\frac{\text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{s,1,k})}{\beta_5} \geq s_{1,k}^S, \forall k \in \mathcal{K}_s, \quad (41)$$

$$\text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{s,2,k}) + I_{inter,1,k}^S + I_{coop,1,k}^S \leq \beta_5, \quad (42)$$

$$\frac{\text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{s,2,k})}{\beta_6} \geq s_{2,k}^S, \forall k \in \mathcal{K}_s, \quad (43)$$

$$\text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{s,1,k}) + I_{inter,2,k}^S + I_{coop,2,k}^S \leq \beta_6, \quad (44)$$

where

$$\begin{aligned} I_{inter,u,k}^S &= \sum_{k' \in \mathcal{K}_s \setminus k} \left(\text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{s,1,k'}) + \right. \\ & \left. \text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{s,2,k'}) \right) + \sum_{k'' \in \mathcal{K}_n} \text{Tr}(\mathbf{H}_{u,k} \mathbf{P}_{n,k''}), \forall k \in \mathcal{K}_s, u \in \{1, 2\} \end{aligned} \quad (45)$$

$$I_{coop,u,k}^S = \sum_{k'' \in \mathcal{K}_n} |h_{1,k'',u,k}|^2 p_{r,k''}, \forall k \in \mathcal{K}_s. \quad (46)$$

Constraints (41) and (43) are convex. To convexify (40) and (42), we use Taylor series approximations for their left-hand sides given in (46) and (47), respectively. Now the problem is convex, and can be solved with a convex optimization solver.

V. NUMERICAL RESULTS

In this section, we evaluate the performance of our adaptive MA approach in a single cell with N-antennas BS and single-antenna users. The SI channel is modeled as a random Gaussian variable with zero mean and variance Γ_{SI} . We use both large-scale and small-scale fading to model the channel gains. For small-scale fading, Rayleigh fading with zero mean and unit variance, and for large-scale fading, path loss model $\text{PL}(\text{distance}) = \text{distance}^{-\xi}$, with $\xi = 2$, are considered [15]. Unless otherwise stated, we use the following parameters, $P_{BS} = 38$ dBm, $P_{r,\max} = 20$ dBm, $w_d = 0.1$ watt/bps/Hz, $|\mathcal{U}| = 4$, $\sigma^2 = -174$ dBm/Hz. We compare the performance of our hybrid NOMA/SDMA scheme with **NOMA** and **SDMA**, and also with **fixed power consumption model** (i.e., $w_d = 0$). We average our results on 50 channel realizations.

First, we compare our SCA approximation solution with the optimal solution obtained by off-the-shelf optimization solver, `fmincon`, in Fig. (2(a)). We compare in terms of energy efficiency as the number of BS antennas varies. We can see our proposed SCA approximation is close to the optimal solution by approximately 3%. In Figure (2 (b)), we compare our objective function between the proposed SDMA/NOMA mode, NOMA, and SDMA modes versus R_{min} . The energy efficiency of all MA modes decreases with the increase of R_{min} , since the BS must allocate higher power for users to satisfy R_{min} . We can see that at different R_{min} values, the proposed scheme outperforms the other two modes. At low throughput requirements, the adaptive mode is equal to the NOMA mode. Explicitly, the SDMA/NOMA decision is optimized as all users are addressed by NOMA, i.e., $\zeta_k = 1, \forall k \in \mathcal{K}$. The adaptive mode clearly outperforms the SDMA mode. For instance, at $R_{min} = 1$ bps/Hz, the gain is approximately 36%. The gain over NOMA is approximately 11% at $R_{min} = 8$ bps/Hz.

In Figure (2(c)), we compare the energy efficiency between our proposed power consumption model, and the widely used model that overlooks the SIC-related power, versus the decoding power factor w_d . We vary w_d in a non-linear way to cover a larger interval, specifically because the decoding power is given different values in the literature. We can see

$$\bar{C}_3(\mathbf{P}_{s,1,k}, \beta_5, \mathbf{P}_{s,1,k}^{(n)}, \beta_5^{(n)}) = \frac{\text{Re}(\text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{s,1,k}))}{\beta_5^{(n)}} + \frac{\text{Re}(\text{Tr}(\mathbf{H}_{1,k}(\mathbf{P}_{s,1,k} - \mathbf{P}_{s,1,k}^{(n)}))}{\beta_5^{(n)}} - \frac{\text{Re}(\text{Tr}(\mathbf{H}_{1,k} \mathbf{P}_{s,1,k}^{(n)}))}{(\beta_5^{(n)})^2} (\beta_5 - \beta_5^{(n)}) \quad (47)$$

$$\bar{C}_4(\mathbf{P}_{s,2,k}, \beta_6, \mathbf{P}_{s,2,k}^{(n)}, \beta_6^{(n)}) = \frac{\text{Re}(\text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{s,2,k}))}{\beta_6^{(n)}} + \frac{\text{Re}(\text{Tr}(\mathbf{H}_{2,k}(\mathbf{P}_{s,2,k} - \mathbf{P}_{s,2,k}^{(n)}))}{\beta_6^{(n)}} - \frac{\text{Re}(\text{Tr}(\mathbf{H}_{2,k} \mathbf{P}_{s,2,k}^{(n)}))}{(\beta_6^{(n)})^2} (\beta_6 - \beta_6^{(n)}) \quad (48)$$

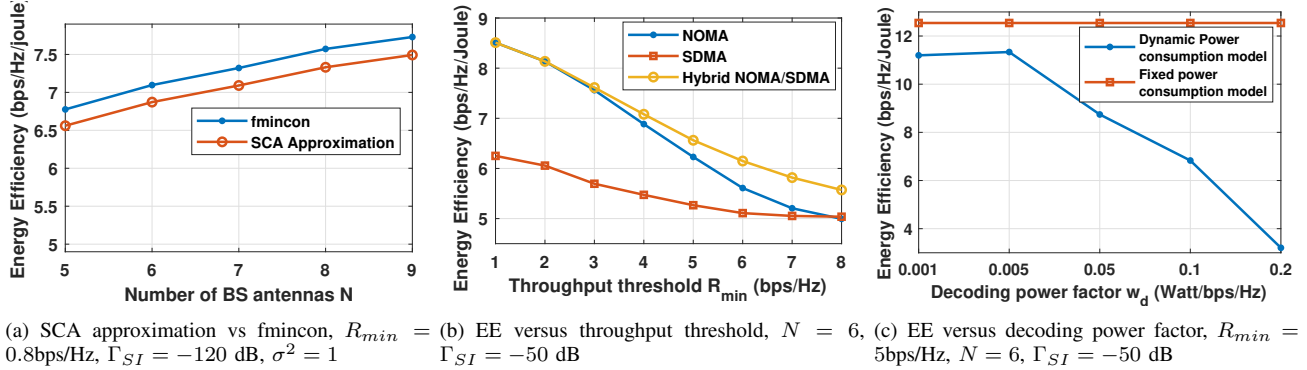


Fig. 2: Numerical results for the model under different parameters.

that the gap increases significantly with w_d . For example, at $w_d = 0.05$, EE of the fixed model is higher by approximately 50%, and this gap can increase up to around 4 times (i.e., 400%). It is clear that the model that overlooks the decoding power yields a significant overestimation of the energy efficiency.

VI. CONCLUSION

This paper proposes a SIC-power aware adaptive SDMA/NOMA scheme based on a more accurate power consumption model. The proposed power consumption model includes a rate-dependent decoding power, particularly the additional SIC power. The optimization problem aimed at maximizing the EE by optimizing a NOMA/SDMA decision, BS beamforming, BS power allocation factor, and strong user relaying power. Numerical evaluations show that the proposed approach is an adaptive approach that selects the MA mode, based on the system requirements. Also, it is shown to avoid significant overestimation in the EE, avoiding misleading insights built upon the theoretical analysis. As a future work, we aim to solve the problem using a machine learning approach to enhance scalability.

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