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Spectral-Energy Efficiency Trade-off based Design for Hybrid TDMA-NOMA System

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***Abstract*—The combination of time division multiple access (TDMA) and non-orthogonal multiple access (NOMA), referred to as hybrid TDMA-NOMA system, is considered as a potential solution to meet the unprecedented requirements for future wireless networks. While recent resource allocation techniques aiming to individually maximize either spectral efficiency (SE) or energy efficiency (EE), this paper considers a SE-EE trade-off based technique for a hybrid TDMA-NOMA system. This design offers an additional degree of freedom in resource allocation. The proposed design is formulated as a multi-objective optimization (MOO) problem - a non-convex problem. The MOO framework is reformulated as a single-objective optimization (SOO) problem by combining the multi-objectives through a weighted-sum objective function. With this, each of the original objectives is assigned with a weight factor to reflect its importance in the design. Then, sequential convex approximation (SCA) and a second-order cone (SOC) approach are jointly utilized to deal with the non-convexity issues of the SOO problem. Simulation results reveal that the proposed trade-off based design strikes a good balance between the objective functions, while meeting the instantaneous requirements of the system.**

***Index Terms*—NOMA, TDMA, spectral efficiency (SE), energy efficiency (EE), multi-objective optimization (MOO).**

I. INTRODUCTION

Non-orthogonal multiple access (NOMA) is considered as a promising technique to meet the unprecedented requirements of beyond fifth-generation wireless networks [1]. The demanding requirements include higher spectral efficiency (SE) and energy efficiency (EE), as well as massive connectivity [2]. With power domain NOMA, multiple users are served simultaneously by utilizing power domain multiplexing. This can be achieved through employing a power-domain superposition coding at the transmitter [1]. At the receiver, the successive interference cancellation (SIC) technique is utilized at stronger users [1], [2]. However, as the number of users increases, the computational complexity of SIC becomes prohibitive in practical implementations. This might restrict the potential capabilities of employing NOMA in dense networks, in which SIC should be used to decode a large number of signals [6].

To deal with the challenges of using SIC in large networks, such as Internet-of-things (IoT), NOMA has been recently combined with other multiple access techniques. These include NOMA with multiple-antenna [7], [8], and conventional orthogonal multiple access (OMA) technology [2]. These strategic combinations facilitate the implementation of SIC in dense networks, and offer additional degrees of freedom. In a hybrid OMA-NOMA system, orthogonal domains along with power domain multiplexing are jointly utilized to serve more number of users, supporting the massive connectivity [2]. Specifically, in hybrid TDMA-NOMA systems, the available time for transmission is divided into several sub-time slots and each time slot is allocated to serve a group of users through power domain NOMA [12], [13].

To meet the requirements of future wireless networks, several resource allocation techniques have been proposed for hybrid TDMA-NOMA systems. Sum-rate maximization design (SE-Max) has been investigated in [3] and the work in [4] has considered the EE maximization (EE-Max) based resource allocation technique. The EE and SE are conflicting performance metrics. Optimizing SE degrades the overall EE, provided the available transmit power is more than the green power [5]. Similarly, EE maximization does not offer maximum SE.

An SE-EE trade-off based design has been proposed for a multiple-input single-output (MISO)-NOMA system in [6]. In [7], the SE-EE trade-off for the massive MIMO systems has been investigated through the particle swarm optimization algorithm. The EE-SE trade-off has been studied for the RIS-aided multi-user MIMO uplink system with the partial channel state information (CSI) in [8]. The solution to multi-objective optimization (MOO) problem can be achieved by converting it into a single-objective optimization (SOO) problem [9], [10].

Motivated by the importance of both SE and EE in future wireless networks, this paper considers a SE-EE trade-off based resource allocation technique for a hybrid TDMA-NOMA system. The hybrid TDMA-NOMA system with single-antenna has potential capabilities to achieve better performance and meet different requirements in specific scenarios compared to the conventional stand-alone NOMA or TDMA designs, including some practical applications, such as M2M communications [13], UAV communications [14], and IoT networks [15]. Unlike the existing stand-alone SE or EE resource allocation techniques in hybrid TDMA-NOMA system, the proposed design aims to strike a good balance between those performance metrics while fulfilling the requirements of future wireless networks. The SE-EE trade-off based design is formulated as a MOO problem, and the weighted sum utility function is utilized to reformulate the MOO framework as a SOO problem. Then, an iterative approach is proposed to solve the SOO problem.

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II. System Model And Problem Formulation

A. System Model

A downlink transmission of a multi-user single-input single-output hybrid TDMA-NOMA system is considered. In this hybrid system, a single-antenna base station (BS) communicates with K single-antenna users. The available time for transmission (T) is divided into a number of sub-time slots (t_i), $\forall i = 1, 2, 3, \cdots, C$, where C denotes the total number of sub-time slots, such that $T = \sum_{i=1}^{C} t$. Within a sub-time slot, K_i users are grouped into a cluster, and served based on NOMA approach. The $u_{j,i}$ represents the jth user at the ith sub-time slots, i.e., cluster. The number of users in the ith cluster (H_i) is denoted by K_i, $\forall i \in \mathcal{C} \triangleq \{1, 2, ..., C\}$.

The signal transmitted from the BS during t_i can be written as $x_i = \sum_{j=1}^{K_i} \tau_{j,i} s_{j,i}$, where $s_{j,i}$ and $\tau_{j,i}$ represent the message intended to $u_{j,i}$ and the corresponding power allocation, respectively. We assume that the signals are transmitted over a quasi-static flat Rayleigh fading channel and the BS has perfect CSI. The received signal at $u_{j,i}$ can be defined as

$$y_{j,i} = g_{j,i} x_i + n_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i \triangleq \{1, 2, ..., K_i\}, \quad (1)$$

where $g_{j,i}$ is the channel gain between the BS and $u_{j,i}$, and $n_{j,i} \sim \mathcal{CN}(0, \sigma_{j,i}^2)$ denotes the additive white Gaussian noise (AWGN) at the receiver. The corresponding channel gain is $|g_{j,i}|^2 = \frac{\beta}{(d_{j,i}/d_0)^\kappa}$ [16], where $d_{j,i}$ and d_0 are the distances between $u_{j,i}$ and the BS, and a reference distance in meters, respectively. The β and κ represent the signal attenuation and the path loss exponent at the reference distance, d_0, respectively. Note that users in the ith cluster, i.e., H_i, are served simultaneously using NOMA. Therefore, ordering users within a cluster is essential to determine the overall performance of the system. In this paper, the users at each cluster are ordered based on their channel gains [6], such that $|g_{1,i}|^2 \geq |g_{2,i}|^2 \geq ...|g_{K_i,i}|^2, \forall i \in \mathcal{C}$. The jth user at the ith cluster, i.e., $u_{j,i}$, should be able to decode and subtract the messages intended for weaker users, i.e., $s_{j+1,i}, \cdots, s_{K_i,i}$ prior to decoding its own message. Thus, the received signal at $u_{j,i}$ after performing SIC can be expressed as

$$y_{j,i}^{SIC} = g_{j,i} \tau_{j,i} s_{j,i} + g_{j,i} \sum_{s=1}^{j-1} \tau_{s,i} s_{s,i} + n_{j,i} \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i.$$

The signal-to-interference and noise ratio (SINR) at $u_{j,i}$ for decoding the messages intended to the weaker users $u_{d,i}, \forall d \in \{j+1, j+2, ..., K_i\}$ is given by

$$SINR_{j,i}^{d} = \frac{|g_{j,i}|^2 \tau_{d,i}^2}{|g_{j,i}|^2 \sum_{s=1}^{d-1} \tau_{s,i}^2 + \sigma_{j,i}^2}, \quad \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \quad (2)$$

Accordingly, the achieved rate at $u_{j,i}$ can be written as [11]:

$$R_{j,i} = B t_i \log_2(1 + SINR_{j,i}), \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \quad (3)$$

where

$$SINR_{j,i} = \min\{SINR_{j,i}^1, SINR_{j,i}^2, ..., SINR_{j,i}^j\}, \quad \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \quad (4)$$

Note that B is the available bandwidth. Thus, SE can be defined as $SE = \frac{\sum_{i=1}^{C} \sum_{j=1}^{K_i} R_{j,i}}{B}$. For notational simplicity, we assume that $B = 1$ throughout this paper. Therefore, both SE and sum-rate carry the same meaning throughout this work.

To align with the fundamental concepts of NOMA, the weaker users in the clusters should be allocated higher power levels compared to those with stronger channel gains. This can be ensured through imposing the following constraint [11]:

$$\tau_{K,i}^2 \geq \tau_{K-1,i}^2 \geq ... \geq \tau_{1,i}^2, \forall i \in \mathcal{C}. \quad (5)$$

The total transmit power at the BS, P_t, should be less than the available power budget, P^{max}. This constraint can be mathematically expressed as

$$P_t = \sum_{i=1}^{C} \sum_{j=1}^{K_i} \tau_{j,i}^2 \leq P^{max}. \quad (6)$$

The power consumption at the BS should take into account the transmit power, i.e., P_t, along with total power losses at the BS (P_{loss}) [4]. Therefore, the total power consumption at the BS can be defined as $P_{total} = \frac{1}{\omega} P_t + P_{loss}$ [10], [17], where $\omega \in [0, 1]$ is the efficiency of the power amplifier [8].

Note that the overall EE and global EE (GEE) carry the same meaning. The overall EE of the system can be defined as

$$GEE = \frac{\sum_{i=1}^{C} \sum_{j=1}^{K_i} R_{j,i}}{P_{total}}. \quad (7)$$

It is obvious that GEE and SE are conflicting performance metrics, and they have been considered in isolation in the previous works. For example, the GEE maximization (GEE-Max) design has been proposed in [17], [4] without considering SE. For ease of access, the GEE-Max resource allocation technique for the hybrid TDMA-NOMA is defined here as follows [6]:

$$\textbf{(P1)}: \quad \max_{\tau_{j,i}, t_i} \quad \frac{\sum_{i=1}^{C} \sum_{j=1}^{K_i} t_i \log_2(1 + SINR_{j,i})}{\frac{1}{\omega} \sum_{i=1}^{C} \sum_{j=1}^{K_i} \tau_{j,i}^2 + P_{loss}} \quad (8)$$

$$\text{s.t.} \quad \sum_{i=1}^{C} t_i \leq T, \quad (9)$$

$$(5), (6), R_{j,i} \geq R_{j,i}^{min}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \quad (10)$$

Note that $R_{j,i}^{min}$ is the minimum rate requirement for user $u_{j,i}$, and (9) ensures that the total allocated time does not exceed the available transmission time T. Furthermore, (5) facilitates the successful implementation of SIC at stronger users [11].

With the total power and time constraints, the SE-Max resource allocation technique for the hybrid TDMA-NOMA can be formulated as

$$\textbf{(P2)}: \max_{\tau_{j,i}, t_i} \sum_{i=1}^{C} \sum_{j=1}^{K_i} R_{j,i} \quad \text{s.t.} \quad (9), (5), (6). \quad (11)$$

Note that the objective functions of **P1** and **P2** are conflicting in nature. In particular, maximizing the sum rate in **P1** might degrade the GEE of the system. Similarly, maximizing GEE through solving **P2** has a negative impact on the achieved sum-rate. To overcome this conflicting issue and to align with different requirements of both users and service providers, we propose an SE-EE trade-off based design in the following subsection.

B. Problem Formulation

We formulate the SE-EE trade-off based design for the hybrid TDMA-NOMA system. The objective function of this MOO design consists of the conflicting performance metrics, i.e., SE and GEE. For simplicity, we represent SE and GEE by the functions $f_1(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$ and $f_2(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$, respectively. In fact, the objective function of this trade-off based design can be defined as a vector $\mathbf{f}$, with the elements of both performance metrics f_1 and f_2. Accordingly, the proposed trade-off based design can be formulated as

$$\textbf{(P3)}: \max_{\tau_{j,i},t_i} \mathbf{f}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \quad \text{s.t.} \quad (9),(5),(6),(10),$$

where

$$\begin{aligned}&\mathbf{f}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})\\ &=[f_1(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}), f_2(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})].\end{aligned} \quad (12)$$

There are several challenges associated in solving **P3**. Firstly, it is essential to identify the users that have to be grouped and served at each sub-time slot as different solutions can be obtained with different grouping strategies. Secondly, once the grouping strategy is determined, a feasibility check has to be carried out prior to solving the problem. This is due to the fact that the minimum rate constraints in **P3** cannot be satisfied for some power budget at BS. Finally, given a multi-objective function in **P3**, the conventional approaches cannot be directly employed to determine its feasible solution. Thus, we propose a solution approach to address all of these issues in the following section.

III. Proposed Methodology

The solution of the original problem **P3** depends on the selected users for each cluster. Hence, it is important to determine an appropriate grouping strategy in the considered hybrid TDMA-NOMA system. The optimal grouping strategy can be only determined through exhaustive search [24], which has a high computational complexity. To reduce the computational complexity, different sub-optimal grouping strategies have been considered in the literatures [22], [23].

A. Feasibility Analysis

With the grouping strategy, we now investigate the feasibility of **P3**. Note that **P3** might turn out to be infeasible due to the limited total power constraint in (6). Therefore, it is important to firstly examine the required minimum transmit power to fulfill these minimum rate constraints. It can be evaluated by solving the following problem:

$$\textbf{(P-Min)}: \quad P^{min} = \min_{\tau_{j,i},t_i} \sum_{i=1}^{C}\sum_{j=1}^{K_i}\tau_{j,i}^2 \quad (13)$$
$$\text{s.t.}(9),(5), SINR_{j,i} \geq 2^{\frac{R_{j,i}^{min}}{t_i}}-1, \forall i\in\mathcal{C}, \forall j \in \mathcal{K}_i,$$

where P^{min} is the minimum total transmit power required to meet the minimum rate requirements. The **P3** is feasible, and thus worthy to solve if $P^{min} \geq P^{max}$. When $P^{min} < P^{max}$, **P3** turns out to be infeasible. In this paper, it is assumed that an alternative SE-Max design is considered if **P3** is infeasible.

B. The Proposed Algorithm

Given that **P3** is feasible, we propose an approach to solve this MOO problem. Note that no single unique optimal solution exists to simultaneously optimize both $f_1(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$ and $f_2(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$. Therefore, we aim to determine the set of the best trade-off solutions, referred to as the Pareto-optimal solutions [18]. A feasible solution $\{\tau_{j,i}^*, t_i^*\}$ is considered to be a Perto-optimal solution if no other solution exists such that $f(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \preceq f(\{\tau_{j,i}^*\},\{t_i^*\}_{i=1}^{C}{}_{j=1}^{K_i})$ [19]. To determine the Pareto-optimal solution, the multi-objective function should be firstly replaced with a single-objective function [18], [19]. In this work, we select the weighted-sum utility function to determine the Pareto-optimal solution [19]. A weight factor $\alpha_i \in [0,1]$ is assigned to the ith objective function to reflect its relative importance on the overall design, and the sum of both weighted functions is considered. The SOO framework to represent **P3** can be formulated as

$$\textbf{(P4)}: \quad \max_{\tau_{j,i},t_i} \quad \sum_{l=1}^{2}\alpha_l f_l^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \quad (14)$$
$$\text{s.t.} \quad (9),(5),(6),(10), \quad (15)$$

where $f_1^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$ and $f_2^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$ are the normalized versions of $f_1(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$ and $f_2(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})$, respectively. These can be expressed as

$$f_1^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) = \frac{f_1(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})}{f_1^*}, \quad (16a)$$

$$f_2^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) = \frac{f_2(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i})}{f_2^*}, \quad (16b)$$

where f_1^* and f_2^* are the maximum values of SE and GEE, respectively. With such a normalization, a non-dimensional objective function with an unity upper bound is obtained. For simplicity, let $\alpha_2 = \alpha$ and $\alpha_1 = 1-\alpha$. Note that **P4** is non-convex problem. Therefore, we exploit the SCA technique to deal with its non-convexity issue.

C. Sequential Convex Approximation (SCA)

The SCA technique is a local optimization method for evaluating the solutions of non-convex problems, and it has been utilized to obtain the solutions for several optimization frameworks in wireless communications [6], [20]. We start with the objective function by introducing two slack variables γ_1 and γ_2 such that

$$(1-\alpha)f_1^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \geq \gamma_1, \quad (17a)$$

$$\alpha f_2^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \geq \gamma_2. \quad (17b)$$

With γ_1 and γ_2, **P4** can be equivalently written as

$$\textbf{(P5)}: \quad \max_{\tau_{j,i},t_i,\gamma_1,\gamma_2} \gamma_1+\gamma_2 \quad (18)$$
$$\text{s.t.} \quad (9),(5),(6),(10), \quad (19)$$
$$(1-\alpha)f_1^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \geq \gamma_1, \quad (20)$$
$$\alpha f_2^{Norm}(\{\tau_{j,i}\},\{t_i\}_{i=1}^{C}{}_{j=1}^{K_i}) \geq \gamma_2. \quad (21)$$

Note that the objective function in **P5** is linear in terms of γ_1 and γ_2. However, the non-convex constraints in (20) and (21) are introduced to **P5**. We exploit the SCA to approximate the non-convex terms.

Firstly, the constraint in (20) can be rewritten as

$$\sum_{i=1}^{C}\sum_{j=1}^{K_i} t_i \log_2(1+SINR_{j,i}) \geq \frac{f_1^*}{1-\alpha}\gamma_1. \tag{22}$$

We deal with the non-convexity of (22) by introducing slack variables $z_{j,i}$ and $\chi_{j,i}$, such that

$$(1+SINR_{j,i}) \geq z_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1,...,K_i\}, \tag{23a}$$

$$\log_2(1+SINR_{j,i}) \geq \chi_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \tag{23b}$$

$$z_{j,i} \geq 2^{\chi_{j,i}}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \tag{23c}$$

$$\sum_{i=1}^{C}\sum_{j=1}^{K_i} t_i \chi_{j,i} \geq \frac{f_1^*}{1-\alpha}\gamma_1, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \tag{23d}$$

Note that the constraint in (23c) is convex while the others are not. To overcome the non-convexity issues of (23a), we introduce another slack variable $\xi_{j,i}$, such that (23a) can be rewritten as

$$\frac{|g_{j,i}|^2\tau_{d,i}^2}{|g_{j,i}|^2\sum_{s=1}^{d-1}\tau_{s,i}^2+\sigma_{j,i}^2} \geq \frac{(z_{j,i}-1)\xi_{j,i}^2}{\xi_{j,i}^2},$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \tag{24}$$

Furthermore, the constraint in (24) can now be decomposed into two constraints as follows:

$$|g_{j,i}|^2\tau_{d,i}^2 \geq (z_{j,i}-1)\xi_{j,i}^2,$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}, \tag{25a}$$

$$|g_{j,i}|^2\sum_{s=1}^{d-1}\tau_{s,i}^2+\sigma_{j,i}^2 \leq \xi_{j,i}^2,$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \tag{25b}$$

Then, the first-order Taylor series expansion is exploited to approximate both sides of (25a) with their corresponding linear approximations, such that

$$|g_{j,i}|^2\left({\tau_{d,i}^2}^{(n)}+2\tau_{d,i}^{(n)}(\tau_{d,i}-\tau_{d,i}^{(n)})\right) \geq {\xi_{j,i}^2}^{(n)}\left(z_{j,i}^{(n)}-1\right)$$
$$+2\left(z_{j,i}^{(n)}-1\right)\xi_{j,i}^{(n)}\left(\xi_{j,i}-{\xi_{j,i}}^{(n)}\right)+{\xi_{j,i}^2}^{(n)}\left(z_{j,i}-{z_{j,i}}^{(n)}\right),$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}, \tag{26}$$

where $\tau_{d,i}^{(n)}$, ${\xi_{j,i}}^{(n)}$ and $z_{j,i}^{(n)}$ represent the approximations of $\tau_{d,i}$, $\xi_{j,i}$ and $z_{j,i}$ at the nth iteration, respectively. Note that both sides of (26) are now linear in terms of $\tau_{d,i}$, $\xi_{j,i}$, and $z_{j,i}$. Furthermore, the constraint in (25b) can be rewritten as the following SOC constraint:

$$\| |g_{j,i}|\tau_{1,i}, |g_{j,i}|\tau_{2,i}, ..., |g_{j,i}|\tau_{d-1,i}, \sigma_{j,i} \| \leq \xi_{j,i},$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}, \tag{27}$$

where $||\cdot||$ denotes the Euclidean norm of a vector. With these approximations, (23a) can now be approximated as the convex constraints in (26) and (27).

Next, we address the non-convexity issue of the constraint in (23d). This can be dealt by incorporating a new slack variable $\nu_{j,i}$, such that

$$t_i\chi_{j,i} \geq \nu_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \tag{28a}$$

$$\sum_{i=1}^{C}\sum_{j=1}^{K_i}\nu_{j,i} \geq \frac{f_1^*}{1-\alpha}\gamma_1, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \tag{28b}$$

To tackle the non-convexity issue of (28a), we incorporate non negative $t_i^2+\chi_{j,i}^2$ to the both sides of inequality (28a) without affecting the original inequality. This constraint can be now formulated as the following SOC constraint:

$$t_i+\chi_{j,i} \geq \left\| \begin{matrix} 2\sqrt{\nu_{j,i}} \\ t_i-\chi_{j,i} \end{matrix} \right\|_2, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \tag{29}$$

To this end, the non-convex constraint in (20) is replaced with the following convex constraints:

$$(20) \Leftrightarrow (26), (27), (23c), (29), (28b).$$

Similarly, the non-convexity of the constraint in (21) is tackled by introducing a new slack variable b such that

$$\frac{\sum_{i=1}^{C}\sum_{j=1}^{K_i} t_i\log_2(1+SINR_{j,i})}{\frac{1}{\omega}\sum_{i=1}^{C}\sum_{j=1}^{K_i}\tau_{j,i}^2+P_{loss}} \geq \frac{\gamma_2 f_2^* b^2}{\alpha b^2}. \tag{30}$$

The constraint in (30) can be split into the following two constraints:

$$\sum_{i=1}^{C}\sum_{j=1}^{K_i} t_i\log_2(1+SINR_{j,i}) \geq \frac{f_2^*}{\alpha}\gamma_2 b^2, \tag{31}$$

$$b^2 \geq \frac{1}{\omega}\sum_{i=1}^{C}\sum_{j=1}^{K_i}\tau_{j,i}^2+P_{loss}. \tag{32}$$

To handle the non-convexity issue of (31), we exploit the same approaches that were used for constraint in (20). We introduce a set of new slack variables $\varpi_{j,i}$, $\epsilon_{j,i}$, $\delta_{j,i}$ and $\beta_{j,i}$, such that

$$(1+SINR_{j,i}) \geq \epsilon_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1,...,K_i\}, \tag{33a}$$

$$\epsilon_{j,i} \geq 2^{\varpi_{j,i}}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \tag{33b}$$

$$\sum_{i=1}^{C}\sum_{j=1}^{K_i} t_i\varpi_{j,i} \geq \frac{f_2^*}{\alpha}\gamma_2 b^2, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \tag{33c}$$

The constraint in (33a) can be written as

$$\frac{|g_{j,i}|^2\tau_{d,i}^2}{|g_{j,i}|^2\sum_{s=1}^{d-1}\tau_{s,i}^2+\sigma_{j,i}^2} \geq \frac{(\epsilon_{j,i}-1)\delta_{j,i}^2}{\delta_{j,i}^2}. \tag{34}$$

Following a similar approach,

$$|g_{j,i}|^2\tau_{d,i}^2 \geq (\epsilon_{j,i}-1)\delta_{j,i}^2,$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}, \tag{35a}$$

$$|g_{j,i}|^2\sum_{s=1}^{d-1}\tau_{s,i}^2+\sigma_{j,i}^2 \leq \delta_{j,i}^2,$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \tag{35b}$$

The inequalities in (35) can now be approximated with linear function using the first-order Taylor series approximation as

$$|g_{j,i}|^2 \left({\tau_{d,i}^2}^{(n)} + 2\tau_{d,i}^{(n)}(\tau_{d,i} - \tau_{d,i}^{(n)}) \right) \geq {\delta_{j,i}^2}^{(n)} \left(\epsilon_{j,i}^{(n)} - 1 \right)$$
$$+ 2\left(\epsilon_{j,i}^{(n)} - 1 \right) \delta_{j,i}^{(n)} \left(\delta_{j,i} - {\delta_{j,i}}^{(n)} \right) + {\delta_{j,i}^2}^{(n)} \left(\epsilon_{j,i} - {\epsilon_{j,i}}^{(n)} \right),$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}, \quad (36a)$$

$$\| |g_{j,i}|\tau_{1,i}, |g_{j,i}|\tau_{2,i}, ..., |g_{j,i}|\tau_{d-1,i}, \sigma_{j,i} \| \leq \delta_{j,i},$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \quad (36b)$$

The constraint in (33c) can be reformulated with the following convex constraints:

$$t_i \varpi_{j,i} \geq \beta_{j,i}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \quad (37a)$$

$$t_i + \varpi_{j,i} \geq \left\| \begin{matrix} 2\sqrt{\beta_{j,i}} \\ t_i - \varpi_{j,i} \end{matrix} \right\|_2, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \quad (37b)$$

$$\sum_{i=1}^{C} \sum_{j=1}^{K_i} \beta_{j,i} \geq \frac{f_2^*}{\alpha} \gamma_2 b^2, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \quad (37c)$$

$$\sum_{i=1}^{C} \sum_{j=1}^{K_i} \beta_{j,i} \geq \frac{f_2^*}{\alpha} (b^{2(n)} {\gamma_2}^{(n)} + 2{\gamma_2}^{(n)} b^{(n)} (b - b^{(n)})$$
$$+ b^{2(n)} (\gamma_2 - {\gamma_2}^{(n)})), \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \quad (37d)$$

Following a similar approach in (25b), the constraint in (32) can be cast as the following SOC constraint:

$$b \geq \frac{1}{\omega} \left\| \left[\tau_{1,i}, \tau_{2,i}, ..., \tau_{d-1,i}, \sqrt{P_{loss}} \right]^T \right\|_2,$$
$$\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i, \forall d \in \{j+1, j+2, ..., K_i\}. \quad (38)$$

To this end, the non-convex constraint in (21) is replaced with the following convex constraints:

$$(21) \Leftrightarrow (36a), (36b), (33b), (37b), (37d), (38).$$

The non-convexity issue of (5) can be dealt by approximating each non-convex term of the inequality by a lower bounded convex term using the first-order Taylor series. Each term in (5) can be written as

$$\tau_{K,i}^2 \geq {\tau_{K,i}^2}^{(n)} + 2{\tau_{K,i}}^{(n)} (\tau_{K,i} - {\tau_{K,i}}^{(n)}), \forall i \in \mathcal{C}. \quad (39)$$

Finally, the minimum rate constraints in (10) can be formulated as the following convex constraints:

$$\nu_{j,i} \geq R_{j,i}^{min}, \forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i. \quad (40)$$

With the above approximations, **P3** can be equivalently written as the following approximated convex one:

$$\textbf{(P6)}: \max_{\Gamma} \quad \gamma_1 + \gamma_2 \quad (41)$$
$$\text{s.t.} \quad (9), (6), (39), (40), \quad (42)$$
$$(26), (27), (23c), (29), (28b), \quad (43)$$
$$(36a), (36b), (33b), (37b), (37d), (38), \quad (44)$$

where Γ consists of all the optimization parameters, such that $\Gamma = \{\tau_{j,i}, t_i, \gamma_1, \gamma_2, \beta_{j,i}, \chi_{j,i}, \xi_{j,i}, z_{j,i}, \nu_{j,i}, \epsilon_{j,i}, \varpi_{j,i}, \delta_{j,i}, b\}$, $\forall i \in \mathcal{C}, \forall j \in \mathcal{K}_i$. In fact, the solution to **P3** can be obtained by iteratively solving **P6**. With this iterative algorithm, the initial value of $\Gamma^{(0)}$ needs to be carefully selected as it plays a crucial role in determining the solution. Therefore, we discuss a simplified approach to select these initial values. Firstly, an appropriate initial power allocation and time slots are selected to fulfill all the constraints of **P6**. Then, the corresponding slack variables can be evaluated based on the initial power allocation and time slots. Note that the iterative process is continued until the required accuracy.

TABLE I
PARAMETER VALUES USED IN THE SIMULATIONS

Simulation Parameter	Value(s)
Number of users (K)	10
Number of users in each cluster (K_i)	2
Distances of users (m)	$1.0 \leq d_{j,i} \leq 10.0$
Pass loss exponent(κ)	2
Noise variance of users ($\sigma_{j,i}^2$)	0.01
Power amplifier efficiency (ω)	0.35
Threshold of algorithm	0.01
Bandwith B (MHz)	1

IV. Simulation Results

In this section, we provide simulation results to demonstrate the effectiveness of the proposed SE-EE trade-off based design for the hybrid TDMA-NOMA system. For the grouping strategy, we consider clusters with two users in each cluster, i.e., $K_i = 2$. Clusters with two users have been considered due to practical implementation challenges, including high computational complexity and error propagations in SIC. However, the analysis provided in this work is applicable to clusters with any number of users. Motivated by the fact that SIC can be successfully implemented when the difference of the channel gains is high, we group users with higher difference in their channel gains. Based on this grouping strategy, the clusters for the considered system can be presented as $(\{u_{1,1}, u_{2,1}\}, \{u_{1,2}, u_{2,2}\}, ...\{u_{1,C}, u_{2,C}\}) \equiv \left(\{u_1, u_K\}, \{u_2, u_{K-1}\}, ...\{u_{\frac{K}{2}}, u_{\frac{K}{2}+1}\}\right)$, where u_1 and u_K are the strongest and the weakest users, respectively. Table I provides simulation parameters [11], [20]. Similar to the works in the literature [11], [21], a pico-cell is considered in this simulation.

Fig. 1 presents the achieved SE and EE with different weight factors α. As seen in Fig. 1, both SE and EE remain the same when the weight factor α is small. Then, with increasing α, the SE decreases whereas the EE increases. This is due to the fact that more resources are allocated for maximizing EE as the weight factor α increases. With an appropriate weight factor α, the BS has the flexibility to achieve different performance trade-off according to the requirements of the systems. Furthermore, Fig. 1 shows the achieved EE and SE for the proposed design against α with 10 and 30 meters radii around the BS. As expected, with the 30 meters radius, both the achieved EE and SE decrease compared to those achieved with 10 meter radius.

Fig. 2 and Fig. 3 depict the achieved SE and EE performance versus P^{max} with different α, respectively. It can be observed that the achieved SE first increases until reaching a certain value, and it then remains constant. Similarly, the performance of EE first increases until reaching the maximum value, however, it then decreases as the transmit power increases. The proposed SE-EE trade-off based design becomes the conventional SE and EE designs with α = 0 and 1, respectively.

Finally, the SE-EE performance trade-off is illustrated in Fig. 4 with the set of Pareto-optimal solutions for the original optimization problem. Note that each point on this curve

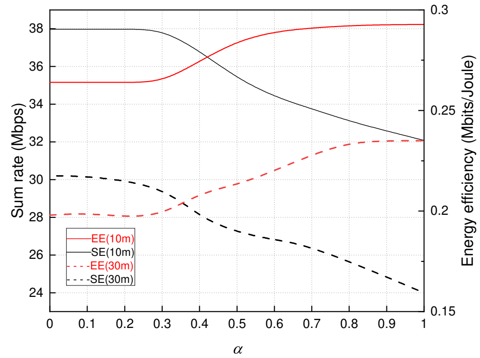

Fig. 1. Achieved SE and EE with different weight factors.

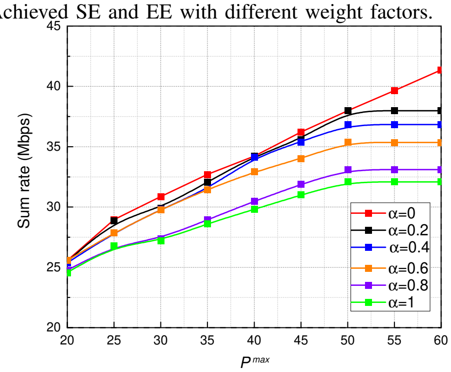

Fig. 2. The achieved SE performance versus P^{max} with different α.

represents a Pareto-optimal solution for a particular α, based on sum rate and EE performance. In other words, no other solution exists to simultaneously improve both the SE and GEE objective functions.

V. Conclusion

In this paper, we have investigated the SE-EE trade-off based resource allocation technique for a hybrid TDMA-NOMA system. The original problem has been formulated as a MOO problem with the conflicting objective functions SE and EE. Then, a weighted-sum approach has been utilized to convert the MOO framework into a SOO problem, and

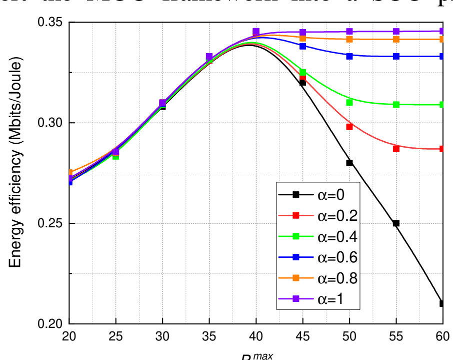

Fig. 3. The achieved EE performance versus P^{max} with different α.

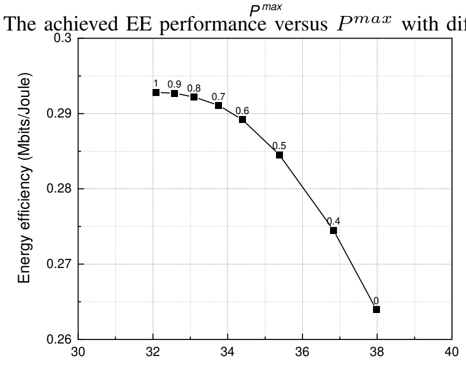

Fig. 4. A set of Pareto-optimal solutions of the proposed design.

thus to obtain the Pareto-optimal solutions. However, the SOO problem has turned out to be a non-convex problem. Therefore, an iterative algorithm has been developed to deal with the non-convexity issues. Simulation results have demonstrated that the proposed SE-EE trade-off based design has the flexibility to strike a good balance between the conflicting metrics SE and EE compared to the conventional SE and EE designs. To deal with the channel uncertainties, a robust design needs to be considered, which is an interesting future direction to extend our work.

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