Energy-Efficient Resource Allocation for Downlink Non-Orthogonal Multiple Access (NOMA) Network

Fang Fang, Haijun Zhang, *Member, IEEE*, Julian Cheng, *Senior Member, IEEE*, Victor C.M. Leung, *Fellow, IEEE*

***Abstract*—Non-orthogonal multiple access (NOMA) is a promising technique for the fifth generation mobile communication due to its high spectral efficiency. By applying superposition coding and successive interference cancellation techniques at the receiver, multiple users can be multiplexed on the same subchannel in NOMA systems. Previous works focus on subchannel assignment and power allocation to achieve the maximization of sum rate; however, the energy-efficient resource allocation problem has not been well studied for NOMA systems. In this paper, we aim to optimize subchannel assignment and power allocation to maximize the energy efficiency for the downlink NOMA network. Assuming perfect knowledge of the channel state information at base station, we propose a low-complexity suboptimal algorithm which includes energy-efficient subchannel assignment and power proportional factors determination for subchannel multiplexed users. We also propose a novel power allocation across subchannels to further maximize energy efficiency. Since both optimization problems are non-convex, difference of convex programming is used to transform and approximate the original non-convex problems to convex optimization problems. Solutions to the resulting optimization problems can be obtained by solving the convex sub-problems iteratively. Simulation results show that the NOMA system equipped with the proposed algorithms yields much better sum rate and energy efficiency performance than the conventional orthogonal frequency division multiple access scheme.**

***Index Terms*—Difference of convex, energy efficiency, non-orthogonal multiple access, orthogonal frequency division multiple access, resource allocation, successive interference cancellation.**

I. Introduction

In the fourth generation mobile communication systems such as long-term evolution (LTE) and LTE-Advanced [1], orthogonal frequency division multiple access (OFDMA) has been widely adopted to achieve higher data rate. The demand for mobile traffic data volume is expected to be 500-1,000 times larger in 2020 than that in 2010 [2]. To further meet overwhelming requirement of data rates, various new techniques have been proposed in recent years, and these techniques include interleave division multiple access [3], low density spreading [4], and non-orthogonal multiple access (NOMA) [5]. Among them, NOMA takes advantage of spectrum efficiency by allowing multiple users to occupy the same subchannel. By applying successive interference cancellation (SIC) in NOMA systems, superposition coded signal can be correctly decoded and demodulated at the receiver [6]–[9]. Therefore, NOMA has been well considered as a promising candidate for the next generation mobile communication systems.

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A. Related Works and Motivation

Since the basic concept of NOMA was introduced and the cell-edge user throughput performance improvement was presented in [10], NOMA has attracted much research attention. The NOMA system has also been envisioned as a key technology in the fifth generation mobile communication systems [11]. In [12], the author discussed an application of combining NOMA with multiple-input multiple-output (MIMO) technologies. Various aspects of resource allocation have been investigated in NOMA systems [13]–[16]. By using fractional transmit power allocation (FTPA) among users and equal power allocation across subchannels, the authors in [13] compared system-level performance of the NOMA system with the OFDMA system and showed that the overall cell throughput, cell-edge user throughput, and the degree of proportional fairness of NOMA are all superior to those of OFDMA scheme. In [14], the same authors also showed that NOMA still achieves higher gains than OFDMA scheme even with the error propagation in SIC. Though it is simple to implement, FTPA fails to optimally allocate power among multiplexed users on each subchannel. In [15], a new power allocation scheme based on water filling was proposed to achieve high spectral efficiency. The authors in [16] proposed cooperative relay system based on NOMA and showed the improvement of the spectral efficiency. A greedy subchannel and power allocation algorithm was proposed for the NOMA system in [17], and a cooperative NOMA transmission scheme, where some users have prior information of the other users' message, was proposed to improve spectrum efficiency in [18]. The multiple-input and multiple-output (MIMO) NOMA design for small packet transmission and the multi-user detection for uplink grant-free NOMA systems were investigated in [19] and [20], respectively. The energy-efficient power allocation was investigated for MIMO NOMA systems in [21]. In this work, using statistical channel state information at the transmitter, the authors proposed a near optimal power allocation scheme to maximize the system energy efficiency.

Although several recent works have been considered for subchannel and power allocation in NOMA systems [10], [13], [14], these papers mainly focused on sum rate maximization. However, with the exponential growth of wireless data traffic, energy consumption of wireless networks has been rapidly increasing. Therefore, saving transmit energy for a block of bits is an important and practical consideration. To the best of the authors' knowledge, the resource allocation problem that maximizes the system energy efficiency has not been well studied for the NOMA systems.

B. Contributions

In this paper, we consider a downlink NOMA wireless network where the base station (BS) assigns subchannels to multiple users, allocates different powers among users who share the same subchannel, and allocates the power across subchannels. Assuming the BS knows perfect channel state information, we investigate the energy-efficient subchannel assignment and power allocation algorithms for the NOMA systems with the constraints of maximum BS transmit power and the maximum number of users allocated on the same subchannel. The main contributions of this paper are summarized as follows.

- We focus on the energy efficiency aspect of resource allocation in a downlink NOMA network and use bits per Joule to measure the system energy efficiency performance [22]. We formulate the subchannel assignment and power allocation problem for the downlink NOMA network as an energy efficiency optimization problem, which is an NP-hard. To obtain an energy-efficient resource allocation scheme, we decouple subchannel assignment and subchannel power allocation from each other. A maximum BS transmit power is provided. The maximum number of users can be multiplexed on the same subchannel is limited to two in order to reduce the computing complexity of the SIC receiver. As a result, the proposed resource allocation algorithms are only valid for the two user case.
- For subchannel assignment, we first assume equal power allocation across subchannels, then we formulate the subchannel assignment as a two-sided matching problem between the subchannels and the users. To maximize the energy efficiency of the NOMA system, we propose a low-complexity suboptimal matching scheme for subchannel assignment (SOMSA). The complexity of the SOMSA is compared to the optimal solution obtained through exhaustive searching.
- Based on the proposed subchannel assignment scheme, the power allocation across subchannels is formulated as a difference of two convex functions (DC). Since the problem is non-convex, in order to use the DC programming approach to obtain its suboptimal solution, we prove the convexity of the sub-functions in the objective function. A convex approximation expression is found by exploiting the structure of DC programming problem. Due to the considerable computing complexity of the global optimal solution, we propose a suboptimal approach to obtain an energy-efficient power allocation scheme by iteratively solving the convex sub-problems.

The proposed algorithms are evaluated by extensive simulations. Numerical results show that the NOMA system with proposed subchannel assignment and power allocation algorithms outperforms the OFDMA system in terms of sum rate and energy efficiency. We further show that the performance of the power allocation among multiplexed users is better than both equal power allocation and the FTPA scheme.

C. Paper Organization

The rest of the paper is organized as follows. Section II presents the NOMA system model and formulates the optimization problem. In Section III, we propose a two-sided matching algorithm for subchannel assignment and determine the power proportional factors for multiplexed users. Section IV introduces the DC programming approach, and a sub-optimal power allocation scheme is proposed to maximize the system energy efficiency. Performance of the proposed algorithms is evaluated in Section V by simulations. Finally, Section VI concludes the paper.

D. Notation

The following notation is adopted in the rest of the paper. Lowercase and uppercase bold fonts denote vectors and matrices, respectively. Inequalities between vectors are component-wise inequalities. The transpose and the conjugate (Hermitian) transpose operations are denoted by $(\cdot)^T$ and $(\cdot)^H$, respectively. $\|\cdot\|_1$ is the l_1 (Euclidean) vector norms [23]. The gradient of $f(\boldsymbol{x})$ at point $\boldsymbol{x_0}$ is denoted by $\nabla f(\boldsymbol{x_0})$.

II. System Model and Problem Formulation

A. System Model

Figure 1 shows a downlink NOMA network. A BS transmits its signals to M user terminals (UTs) through N subchannels, and SIC is employed at the receiver of UTs. We denote m as index for the mth mobile user where $m \in \{1, 2, \cdots, M\}$ and denote n as index for the nth subchannel where $n \in \{1, 2, \cdots, N\}$. In the cell, M users are uniformly distributed in a circular region with radius R. The total bandwidth of the system, BW, is equally divided into N subchannels where the bandwidth of each subchannel is $B_{sc} = BW/N$. Let $M_n \in \{M_1, M_2, \cdots, M_N\}$ be the number of users allocated on the subchannel n (SC_n) and the power allocated to the lth user on SC_n is denoted by $p_{l,n}$. Then the subchannel and BS power constraints are given by $\sum\limits_{i=1}^{M_n} p_{i,n} = p_n$ and $\sum\limits_{n=1}^{N} p_n = P_s$, where p_n and P_s are, respectively, the allocated power on SC_n and the total transmitted power of the BS. In NOMA systems, we assume that the BS has full knowledge of the channel state information. According to the NOMA protocol [10], multiple users can be allocated to the same subchannel with SIC technique. A block fading channel is considered in the system model, where the channel fading of each subchannel remains the same, but it varies independently across different subchannels. Based on the parameters and constraints of the system, the BS needs to assign multiple users (with different power levels) to different subchannels and allocate different powers across subchannels. Considering

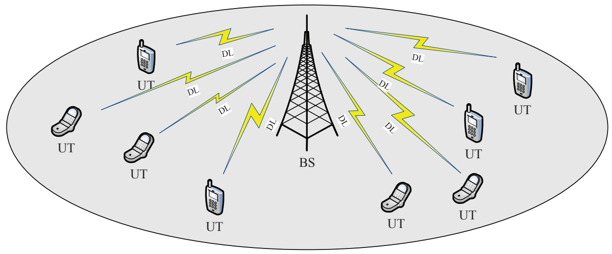

Fig. 1. System model of cognitive heterogeneous small cell networks.

M_n users are allocated on SC_n, the symbol transmitted by the BS on each subchannel SC_n can be expressed as

$$x_n = \sum_{i=1}^{M_n} \sqrt{p_{i,n}} s_i \tag{1}$$

where s_i is the modulated symbol of the ith user on SC_n, which is denoted by $UT_{i,n}$[1]. The received signal at the lth user on SC_n is

$$\begin{aligned} y_{l,n} &= h_{l,n} x_n + z_{l,n} \\ &= \sqrt{p_{l,n}} h_{l,n} s_l + \sum_{i=1, i\neq l}^{M_n} \sqrt{p_{i,n}} h_{l,n} s_i + z_{l,n} \end{aligned} \tag{2}$$

where $h_{l,n} = g_{l,n} \cdot PL^{-1}(d)$ is the coefficient of SC_n from the BS to $UT_{l,n}$, and where $g_{l,n}$ is assumed to have Rayleigh fading channel gain, and $PL^{-1}(d)$ is the path loss function between the BS and $UT_{l,n}$ at distance d. The impact of users' channel conditions on the performance gain of NOMA over OFDMA was studied in [24]. In this work, the authors presented that the performance gain of the NOMA over OFDMA will increase when the difference of channel gain of users becomes larger. The authors in [25] showed that the distances between BS and UTs will affect the performance of the NOMA system. In this paper, we assume these distances of different users are known by BS. Let $z_{l,n} \sim \mathcal{CN}\left(0, \sigma_n^2\right)$ be the additive white Gaussian noise (AWGN) with zero mean and variance σ_n^2. In a downlink NOMA network, each subchannel can be shared by multiple users. Each user on SC_n receives its signals as well as interference signals from the other users on the same subchannel. Therefore, without SIC at receiver, the received signal-to-interference-plus-noise ratio (SINR) of the lth user on the SC_n is written by

$$\begin{aligned} SINR_{l,n} &= \frac{p_{l,n} |h_{l,n}|^2}{\sigma_n^2 + \sum\limits_{i=1, i\neq l}^{M_n} p_{i,n} |h_{l,n}|^2} \\ &= \frac{p_{l,n} H_{l,n}}{1 + \sum\limits_{i=1, i\neq l}^{M_n} p_{i,n} H_{l,n}} \end{aligned} \tag{3}$$

where $\sigma_n^2 = E[|z_{l,n}|^2]$ is the noise power on SC_n and $H_{l,n} \triangleq |h_{l,n}|^2 / \sigma_n^2$ represents the channel response normalized by noise (CRNN) of the lth user on SC_n.

[1]Without causing notational confusion, $UT_{i,n}$ denotes the ith user on SC_n, while UT_m denotes the mth user in the whole cell, where $m \in \{1, 2, \cdots, M\}$.

Based on the Shannon's capacity formula, the sum rate of SC_n is given by

$$\begin{aligned} R_n &= B_{sc} \sum_{l=1}^{M_n} \log_2 \left(1 + SINR_{l,n}\right) \\ &= B_{sc} \sum_{l=1}^{M_n} \log_2 \left(1 + \frac{p_{l,n} H_{l,n}}{1 + I_{l,n}}\right) \end{aligned} \tag{4}$$

where $I_{l,n}$ is the interference that $UT_{l,n}$ receives from the other users on the SC_n, which can be expressed as

$$I_{l,n} = \sum_{i=1, i\neq l}^{M_n} p_{i,n} H_{l,n}. \tag{5}$$

In NOMA systems, the SIC process is implemented at UT receiver to reduce the interference from the other users on the same subchannel. The optimal decoding order for SIC is the increasing order of CRNNs. Based on this order, any user can successfully and correctly decode the signals of the other users with smaller CRNN values. Thus, the interference from the users having poorer channel condition can be cancelled and removed by the user who has better channel condition. In order to maximize the sum rate of SC_n, NOMA protocol allocates higher power to the users with lower CRNN [10], i.e., for two users $UT_{i,n}$ and $UT_{j,n}$ sharing the same SC_n with CRNNs $|H_{i,n}| \geq |H_{j,n}|$, we always set $p_{i,n} \leq p_{j,n}$ to achieve user fairness. This assumption is widely used in the NOMA scheme [13], [14]. Consider that M_n users are allocated on SC_n with CRNNs order

$$|H_{1,n}| \geq |H_{2,n}| \geq \cdots \geq |H_{l,n}| \geq |H_{l+1,n}| \geq \cdots \geq |H_{M_n,n}|. \tag{6}$$

According to the optimal SIC decoding order, User l can successfully decode and remove the interference symbols from users $i > l$. However, the interference symbol from User i ($i < l$) cannot be removed and will be treated as noise by User l. Therefore, the SINR of User l with SIC at receiver can be written as

$$\widetilde{SINR}_{l,n} = \frac{p_{l,n} H_{l,n}}{1 + \sum\limits_{i=1}^{l-1} p_{i,n} H_{l,n}}. \tag{7}$$

Then the data rate of the lth user on SC_n can be expressed as

$$R_{l,n}\left(p_{l,n}\right) = B_{sc} \log_2 \left(1 + \frac{p_{l,n} H_{l,n}}{1 + \sum\limits_{i=1}^{l-1} p_{i,n} H_{l,n}}\right). \tag{8}$$

Therefore, the overall sum rate of NOMA systems can be written as

$$R = \sum_{n=1}^{N} \sum_{l=1}^{M_n} R_{l,n}\left(p_{l,n}\right) = \sum_{n=1}^{N} R_n\left(p_n\right). \tag{9}$$

B. Problem Formulation

In this subsection, we formulate the energy-efficient subchannel assignment and power allocation as an optimization problem. For energy-efficient communication, it is desirable to maximize the amount of transmitted data bits with a unit energy, which can be measured by energy efficiency. For each subchannel in the NOMA system, given assigned power p_n on SC_n and additional circuit power consumption p_c, the energy efficiency over SC_n is defined as

$$E_n = \frac{R_n}{p_c + p_n}. \tag{10}$$

Then the overall energy efficiency of the system can be given by

$$E = \sum_{n=1}^{N} E_n. \tag{11}$$

For the downlink NOMA network, SIC technique is well investigated in [6], [9]. The implementation complexity of SIC at the receiver increases with the maximum number of the users allocated on the same subchannel. In order to keep the receiver complexity comparatively low, we consider the simple case where only two users can be allocated on the same subchannel. This assumption is important because it also restricts the error propagation. In this case, given that the two users sharing SC_n with CRNNs $|H_{1,n}| \geq |H_{2,n}|$, the sum rate of SC_n can be expressed as

$$\begin{aligned} R_n\left(p_n\right) = & W_{1,n}\log_2\left(1 + \beta_n p_n H_{1,n}\right) \\ & + W_{2,n}\log_2\left(1 + \frac{\left(1-\beta_n\right)p_n H_{2,n}}{1 + \beta_n p_n H_{2,n}}\right) \end{aligned} \tag{12}$$

where β_n is the power proportional factor for the two users on SC_n. Generally, β_n is used for the user who performs SIC on SC_n and $\beta_n \in (0,1)$. The optimal power proportional factor can be decided within our proposed subchannel assignment scheme. In (12), $W_{i,n}$ represents the weighted bandwidth of the ith user. To obtain an energy-efficient resource allocation scheme for this system, we formulate the energy efficiency optimization problem as

$$\max_{p_n > 0} \sum_{n=1}^{N} \frac{R_n\left(p_n\right)}{p_c + p_n} \tag{13}$$

$$\begin{aligned} \text{subject to } & C1 : R_{l,n}(p_n) \geq R_{min} \\ & C2 : \sum_{n=1}^{N} p_n = P_s \end{aligned} \tag{14}$$

where $C1$ guarantees user minimum data rate constraint and R_{min} is denoted as minimum data rate determined by quality of service (QoS) requirement. The constraint $C2$ ensures the maximum BS power constraint. Since this optimization problem is non-convex and NP-hard, it is challenging to find the global optimal solution within polynomial time. To solve this problem efficiently, we will treat subchannel assignment and subchannel power allocation separately. Assuming equal power is allocated to the subchannels, we first match subchannels to multiple users to maximize the energy efficiency and find proportional factor for multiplexed users on each subchannel. Based on the efficient subchannel assignment, we then focus on the energy-efficient power allocation across subchannels within the constraint of total transmit power of BS.

III. Energy-Efficient Subchannel Matching for NOMA Systems

In this section, we investigate the energy-efficient matching algorithm for subchannel assignment in the NOMA network. For the optimization problem (13), it can be shown that the subchannel assignment and power allocation for subchannels are coupled with each other in terms of energy efficiency. Due to the considerable complexity of global optimum solution, we decouple subchannel assignment and power allocation to obtain a suboptimal solution. We first propose a greedy subchannel-user matching algorithm by assuming equal power is allocated on each subchannel, in which each power proportional factor β_n is also determined to allocate different powers to the multiplexed users on the same subchannel. We define the parameter β_n as the proportional factor of assigned power to the user who performs SIC on SC_n. By decomposing the objective function into difference of convex functions, the suboptimal matching scheme for subchannel assignment is decided by a DC programming approach.

A. Subchannel Matching Problem Formulation

To describe the dynamic matching between the users and the subchannels, we consider subchannel assignment as a two-sided matching process between the set of M users and the set of N subchannels. Considering only two users can be multiplexed on the same subchannel due to the complexity of decoding, following [10] we assume $M = 2N$. We say UT_m and SC_n are matched with each other if UT_m is allocated on SC_n. Based on the perfect channel state information, the preference lists of the users and subchannels can be denoted by

$$\begin{aligned} PF\_UT &= \left[PF\_UT(1), \cdots, PF\_UT(m), \cdots, PF\_UT(M)\right]^T \\ PF\_SC &= \left[PF\_SC(1), \cdots, PF\_SC(n), \cdots, PF\_SC(N)\right]^T \end{aligned} \tag{15}$$

where $PF\_UT(m)$ and $PF\_SC(n)$ are the preference lists of UT_m and SC_n, respectively. We say UT_m prefers SC_i to SC_j if UT_m has higher channel gain on SC_i than that on SC_j, and it can be expressed as

$$SC_i\left(m\right) \succ SC_j\left(m\right). \tag{16}$$

For an example, we consider four users and two subchannels with channel gain matrix

$$H = \begin{bmatrix} 0.197 & 0.778 \\ 0.437 & 0.143 \\ 0.322 & 0.545 \\ 0.272 & 0.478 \end{bmatrix}$$

where row index denotes the users and column index denotes the subchannels. Therefore, we have preference list of the users as

$$PF\_UT(1) = \left[\begin{array}{cc} 2 & 1 \end{array}\right]^T$$
$$PF\_UT(2) = \left[\begin{array}{cc} 1 & 2 \end{array}\right]^T$$
$$PF\_UT(3) = \left[\begin{array}{cc} 2 & 1 \end{array}\right]^T$$
$$PF\_UT(4) = \left[\begin{array}{cc} 2 & 1 \end{array}\right]^T$$

and preference list of the subchannels as

$$PF\_SC(1) = \left[\begin{array}{cccc} 2 & 3 & 4 & 1 \end{array}\right]^T$$
$$PF\_SC(2) = \left[\begin{array}{cccc} 1 & 3 & 4 & 2 \end{array}\right]^T.$$

We say SC_n prefers user set q_m to user set q_n (q_n, q_m is denoted as subsets of $\{1, 2, \cdots, M\}$) if the users in set q_m can provide higher energy efficiency than users in set q_n on SC_n, and we represent this scenario as

$$E_n\left(q_m\right) > E_n\left(q_n\right), q_m, q_n \subset \left\{UT_1, UT_2, \cdots, UT_{M_n}\right\}. \tag{17}$$

Matching theory has been studied in [26], [27], where various properties and types of preferences have been discussed. Based on the preference lists of users and subchannels, the subchannel assignment problem is formulated as a two-sided matching problem [26], [27].

Definition 1: *(Two-sided Matching)* Consider users and subchannels as two disjoint sets, $\boldsymbol{M} = \{1, 2, \cdots, M\}$ and $\boldsymbol{N} = \{1, 2, \cdots, N\}$. A two-to-one, two-sided matching $\mathcal{M}$ is a mapping from all the subsets of users $\boldsymbol{M}$ into the subchannel set $\boldsymbol{N}$ satisfying $UT_m \in \boldsymbol{M}$ and $SC_n \in \boldsymbol{N}$

1) $\mathcal{M}(UT_m) \in \boldsymbol{N}$.
2) $\mathcal{M}^{-1}(SC_n) \subseteq \boldsymbol{M}$.
3) $|\mathcal{M}(UT_m)| = 1$, $|\mathcal{M}^{-1}(SC_n)| = 2$.
4) $SC_n \in \mathcal{M}(UT_m) \Leftrightarrow UT_m \in \mathcal{M}^{-1}(SC_n)$.

Condition 1) states that each user matches with one subchannel, and Condition 2) represents each subchannel can be matched with a subset of users. Condition 3) states that the number of users can be allocated on each subchannel is limited to two. Condition 4) means UT_m and SC_n are matched with each other.

Definition 2: *(Preferred Matched Pair)* Given a matching $\mathcal{M}$ that $UT_m \notin \mathcal{M}^{-1}(SC_n)$ and $SC_n \notin \mathcal{M}(UT_m)$. If $E_n\left(S_{new}\right) > E_n\left(\mathcal{M}^{-1}(SC_n)\right)$ where $S_{new} \subseteq \{UT_m\} \cup S$ and $S = \mathcal{M}^{-1}(SC_n)$, where S is the user set has been assigned to SC_n, S_{new} becomes the preferred users set for subchannel n and $(UT_m,\ SC_n)$ is a preferred matched pair. Based on the above definition, we will describe in Section III.B the matching action between the users and the subchannels. If each subchannel has to select the best subset of users to allocate, it will cause considerable complexity especially when the number of users is large. Because the optimal solution requires to search all the possible combinations of the users to maximize energy efficiency. To reduce the complexity, a suboptimal matching algorithm is proposed for subchannel assignment as follows.

B. Suboptimal Matching for Subchannel Assignment Algorithm in NOMA

In this section, we propose a suboptimal matching algorithm for subchannel assignment. The main idea of this matching model is that each user sends the matching request to its most preferred subchannel according to its preference list. But this preferred subchannel has the right to accept or reject the user according to energy efficiency that the all users can provide on this subchannel. Based on the equal power allocation across subchannels, the user selection algorithm is a process of finding the preferred matching pair for each user and subchannel.

Algorithm 1 Suboptimal Matching for Subchannel Assignment

Initialize the matched list $S_{Match}(n)$ to record users matched on SC_n for all the subchannels $\forall n \in \{1, 2, \cdots, N\}$.
Initialize preference lists $PF\_UT\left(m\right)$ and $PF\_SC\left(n\right)$ for all the users $\forall m \in \{1, 2, \cdots, M\}$ and all the subchannels $\forall n \in \{1, 2, \cdots, N\}$ according to CRNNs.
Initialize the set of unmatched users $S_{UnMatch}$ to record users who has not been allocated to any subchannel.
while $\{S_{UnMatch}\}$ is not empty **do**
  for $m = 1$ to M **do**
    Each user sends matching request to its most preferred subchannel $\hat{n}$ according to $PL\_UT\left(m\right)$.
    if $|S_{Match}\left(\hat{n}\right)| < 2$ **then**
      Sub-channel $\hat{n}$ adds user m to $S_{Match}\left(\hat{n}\right)$, and removes user m from $\{S_{UnMatch}\}$
    end if
    if $|S_{Match}\left(\hat{n}\right)| = 2$ **then**
      a) Find power proportional factor β_n for every two users in S_{q_m}, $S_{q_m} \subset \{S_{match}(\hat{n}), m\}$ by using (18), or exhaustive search method or DC programming algorithm in Section IV.
      b) Subchannel $\hat{n}$ selects a set of 2 users S_{q_m} satisfying maximum energy efficiency $E_{\hat{n}}(q_m) \geq E_{\hat{n}}(q_n), q_m, q_n \subset \{S_{match}(\hat{n}), m\}$.
      c) Subchannel $\hat{n}$ sets $S_{match}(\hat{n}) = q_m$, and rejects other users. Remove the allocated users from $\{S_{UnMatch}\}$, add the unallocated user to $\{S_{UnMatch}\}$.
      d) The rejected user removes subchannel from their preference lists.
    end if
  end for
end while

1) SOMSA Algorithm Description: Algorithm 1 describes the proposed SOMSA scheme to maximize the system energy efficiency. This algorithm includes initialization and matching procedures. In the initialization step, preferences lists of subchannels and users are decided according to the channel state information, and $S_{Match}(n)$, $\forall n \in \{1, 2, \cdots, N\}$ and $S_{UnMatch}$ are initialized to record the allocated users on SC_n and unallocated users of the system, respectively. In the matching procedure, at each round, each user sends the matching request to its most preferred subchannel. According to the preferred list of each user ($PF\_UT(m)$, $\forall m \in \{1, 2, \cdots, M\}$) which is a list of subchannels ordered by decreasing channel gains, the mth user will find the first nonzero entry in $PF\_UT(m)$ and send matching request to the corresponding subchannel. The subchannel accepts the user directly if the number of allocated users on this subchannel is less than two. When the number of the allocated users equals to two, only the subset of users that can provide higher energy efficiency will be accepted or it will be rejected. This matching process will terminate when there is no user left to be matched. After that, the allocated user and the corresponding subchannels in the preference list are set to zero. The proposed SOMSA converges to a stable matching after a limited number of iterations [27].

2) Complexity Analysis: The optimal subchannel assignment scheme can only be obtained by searching over all possible combinations of users and selecting one that maximizes the system energy efficiency. If we have M users and N subchannels $(M = 2N)$. The scheduler needs to search $\begin{pmatrix} 2N \\ 2 \end{pmatrix} \begin{pmatrix} 2N-2 \\ 2 \end{pmatrix} \cdots \begin{pmatrix} 2 \\ 2 \end{pmatrix} = \frac{(2N)!}{2^N}$ combinations. The time complexity of exhaustive searching is $O(\frac{(2N)!}{2^N})$. In order to compare the complexity of different algorithms, we take natural logarithm of the complexity. The logarithm complexity is $O(\ln((2N)!) - N) = O(\ln((2N)!))$. By using the Stirling's formula, $\ln(n!) = n \ln n - n + O(\ln(n))$, the logarithm complexity of the exhaustive searching can be written by $O(N \ln N)$. In the SOMSA algorithm, the complexity of the worst case is $O(N^2)$. Taking natural logarithm of the complexity, the logarithm complexity is $O(\ln N)$. Since $O(\ln N) < O(N \ln N)$ and actual complexity of SOMSA is much less than the complexity of the worst case, the complexity of SOMSA algorithm is much less than the optimal subchannel assignment scheme. It can be shown that for a small number of users $(M = 4)$, the SOMSA will yield the identical results from the exhaustive search.

C. Power Allocation Between Multiplexed Users on Each Subchannel

In Algorithm 1, it is required to determine the power proportional factor β_n for every two subchannel users. In this section, we will first review the existing fractional transmit power allocation scheme and exhaustive searching method. Then we will introduce a new energy-efficient power allocation algorithm based on DC programming in Section IV.B. It will be shown in Section V that the new algorithm can result in improved energy efficiency.

1) Fractional transmit power allocation: According to the SINR expression in (7), the transmit power allocation to one user affects the achievable sum rate as well as the energy efficiency on each subchanel. Due to its low computational complexity, FTPA is widely adopted in OFDMA systems and NOMA systems [9], [10]. In the FTPA scheme, the transmit power of UT_m on SC_n is allocated according to the channel gains of all the multiplexed users on SC_n, which is given as

$$p_{l,n} = p_n \frac{(H_{l,n})^{-\alpha}}{\sum\limits_{i=1}^{M_n} (H_{i,n})^{-\alpha}} \tag{18}$$

where $\alpha \, (0 \leq \alpha \leq 1)$ is a decay factor. In the case $\alpha = 0$, it corresponds to equal power allocation among the allocated users. From (18), it is clear that when α increases, more power is allocated to the user with poorer CRNN. Note that the same decay factor should be applied to all subchannels and transmission times.

2) Exhaustive searching method: In finding power proportional factor β_n, the method of exhaustion also can be exploited for $\beta_n \in (0, 1)$. The optimal value can be found through searching all β_n values in $(0, 1)$ with a sufficiently small step size. Therefore, the optimal power proportional factors for the multiplexed users can be obtained. However, the computational complexity of the exhaustion method is much higher than FTPA. Therefore, in the following, we consider a suboptimal but efficient DC programming to allocate power among multiple users to maximize the energy efficiency.

IV. Energy-Efficient Power Allocation across Subchannels for NOMA systems

As mentioned in Section III, equal power allocation is assumed across subchannels in SOMSA. In order to further improve the energy efficiency of the NOMA system, we consider obtaining the energy-efficient subchannel power allocation instead of equal power allocation. In this section, we introduce DC programming approach and discuss its application in finding power proportional factors as well as power allocation across subchannels.

A. DC Programming

DC programming approach has been studied recently to solve non-convex optimization problems [28]. It is shown that DC programming can be applied if the objective function can be written as a minimization of a difference of two convex functions, which is represented as

$$\min_{\boldsymbol{x} \in \chi} q(\boldsymbol{x}) = f(\boldsymbol{x}) - g(\boldsymbol{x}) \tag{19}$$

where $\boldsymbol{x} = [x_1, x_2, \cdots x_L]^T$ and χ is the convex set; $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ are continuous, convex or quasi-convex [28]. In general, the problem defined (19) is non-convex. However, it can be solved sub-optimally by using Algorithm 2. The key idea of Algorithm 2 is to convert a non-convex problem to convex sub-problems by using successive convex approximations. In this algorithm, ε is the difference tolerance and the term $-g(\boldsymbol{x})$ in the objective function (19) is replaced by $-g\left(\boldsymbol{x}^{(k)}\right) - \nabla g^T\left(\boldsymbol{x}^{(k)}\right)\left(\boldsymbol{x} - \boldsymbol{x}^{(k)}\right)$ in (20). The convex optimization problem in (20) can be solved by using standard algorithms from convex optimization theory [29]–[31], i.e., interior point method and sequential quadratic programming. In this paper, sequential quadratic programming is used in the simulations.

The convergence of Algorithm 2 can be easily proved by

$$q\left(\boldsymbol{x}^{(k)}\right) = \hat{q}^{(k)}\left(\boldsymbol{x}^{(k)}\right) \geq \hat{q}^{(k)}\left(\boldsymbol{x}^{(k+1)}\right) \geq q\left(\boldsymbol{x}^{(k+1)}\right) \tag{22}$$

where $q\left(\boldsymbol{x}^{(k)}\right) = \hat{q}^{(k)}\left(\boldsymbol{x}^{(k)}\right)$ is the kth iteration step, and $\hat{q}^{(k)}\left(\boldsymbol{x}^{(k)}\right) \geq \hat{q}^{(k)}\left(\boldsymbol{x}^{(k+1)}\right)$ can be obtained by (21). Therefore, $q\left(\boldsymbol{x}^{(k)}\right)$ monotonically decreases when k increases. Under an additional assumption that $f(\boldsymbol{x})$ and $g(\boldsymbol{x})$ are

Algorithm 2 Iterative, Suboptimal Solution for DC Problems [29]

1: Initialize $\boldsymbol{x}^{(0)}$, set iteration number $k=0$.
2: **while** $\left|q\left(\boldsymbol{x}^{(k+1)}\right)-q\left(\boldsymbol{x}^{(k)}\right)\right|>\varepsilon$ **do**
3: Define convex approximation of $q^{(k)}\left(\boldsymbol{x}\right)$ as

$$\hat{q}^{(k)}\left(\boldsymbol{x}\right)=f\left(\boldsymbol{x}\right)-g\left(\boldsymbol{x}^{(k)}\right)-\nabla g^{T}\left(\boldsymbol{x}^{(k)}\right)\left(\boldsymbol{x}-\boldsymbol{x}^{(k)}\right) \quad (20)$$

4: Solve the convex problem

$$\boldsymbol{x}^{(k+1)}=\underset{\boldsymbol{x}\in\chi}{\arg\min}\,\hat{q}^{(k)}\left(\boldsymbol{x}\right) \quad (21)$$

5: $k\leftarrow k+1$
6: **end while**

continuous and differentiable on the constraint set. In this case, Algorithm 2 always returns a stationary point of $q\left(\boldsymbol{x}\right)$, which may not be the global optimal solution [28].

B. DC Programming to Obtain Power Proportional Factor β_n

Considering two users UT_1 and UT_2 that are to be multiplexed over SC_n with CRNNs $H_{1,n}\geq H_{2,n}$ and weighted bandwidths $W_{1,n},\ W_{2,n}$. According to the principle of SIC decoding sequences, UT_1 can cancel the interfering power term of UT_2, whereas UT_2 treats the symbol power UT_1 as noise. The problem of finding β_n to maximize energy efficiency of SC_n can be formulated as

$$\begin{aligned}\max_{\beta_n\in(0,1)}\ &\frac{W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right)}{p_c+p_n}\\&+\frac{W_{2,n}\log_2\left(1+\frac{(1-\beta_n)p_nH_{2,n}}{1+\beta_np_nH_{2,n}}\right)}{p_c+p_n}\end{aligned} \quad (23)$$

which can be rewritten as

$$\max_{\beta_n\in(0,1)}\frac{W_{1,n}\log_2\left(1+\beta_np_nH_{1,n}\right)+W_{2,n}\log_2\left(\frac{1+p_nH_{2,n}}{1+\beta_np_nH_{2,n}}\right)}{p_c+p_n}. \quad (24)$$

In order to use the DC programming approach, we can convert (24) to DC representation

$$\begin{aligned}\min_{\beta_n\in(0,1)}\ &-\frac{W_{1,n}\log_2\left(1+\beta_np_nH_{1,n}\right)}{p_c+p_n}\\&-\frac{W_{2,n}\log_2\left(\frac{1+p_nH_{2,n}}{1+\beta_np_nH_{2,n}}\right)}{p_c+p_n}\end{aligned} \quad (25)$$

or

$$\min_{\beta_n\in(0,1)}\left(f\left(\beta_n\right)-g\left(\beta_n\right)\right) \quad (26)$$

where $f\left(\beta_n\right)=-\frac{W_{1,n}\log_2(1+\beta_np_nH_{1,n})}{p_c+p_n}$ and $g\left(\beta_n\right)=\frac{W_{2,n}\log_2\left(\frac{1+p_nH_{2,n}}{1+\beta_np_nH_{2,n}}\right)}{p_c+p_n}$, and both terms are convex functions with respect to β_n because $\nabla^2 f\left(\beta_n\right)>0$ and $\nabla^2 g\left(\beta_n\right)>0$. Therefore, the DC programming approach can be used to find β_n by replacing $\boldsymbol{x}$ with β_n in Algorithm 2.

C. Subchannel Power Allocation by DC Programming

Given the subchannel-user matching scheme and power proportional factors on different subchannels by Algorithm 1, the optimization problem in (13) can rewritten as

$$\max_{p_n\geq 0}\sum_{n=1}^{N}\left\{\frac{W_{1,n}\log_2\left(1+\beta_np_nH_{1,n}\right)}{p_c+p_n}+\frac{W_{2,n}\log_2\left(\frac{1+p_nH_{2,n}}{1+\beta_np_nH_{2,n}}\right)}{p_c+p_n}\right\} \quad (27)$$

$$\begin{aligned}\text{subject to } &C1: R_{l,n}(p_n)\geq R_{min}\\&C2:\sum_{n=1}^{N}p_n=P_s\end{aligned} \quad (28)$$

where $R_{l,n}(p_{l,n})$ is defined in (8). Since $R_{l,n}(p_{l,n})$ is a linear function respect to assigned power p_n on SC_n. The constraint $C1$ can be converted to $p_n>p_{n,min}$, where $p_{n,min}$ is the minimum assigned power on SC_n determined by R_{min}. Condition $C2$ in (28) guarantees BS power constraint. Note that the optimization problem in (27) is non-convex with respect to p_n. However, the representation of (27) is similar to the DC problem representation. Thus (27) can be rewritten as (29) and (30) at the top of next page. Where $\mathbf{P}=\left[p_1,p_2,\cdots,p_n,\cdots,p_N\right]^T$ represents the allocated powers on the subchannels. Problem (27) can be written as

$$\min_{\mathbf{P}\succ\mathbf{0}}Q\left(\mathbf{P}\right)=\min_{\mathbf{P}\succ\mathbf{0}}F\left(\mathbf{P}\right)-G\left(\mathbf{P}\right)$$

$$\begin{aligned}\text{subject to } &C1:\mathbf{P}\succ\mathbf{P}_{min}\\&C2:\left\|\mathbf{P}\right\|_1=P_s\end{aligned} \quad (31)$$

where $\mathbf{P}_{min}=\left[p_{1,min},p_{2,min},\cdots,p_{n,min},\cdots,p_{N,min}\right]^T$ and $\mathbf{P}\succ\mathbf{P}_{min}$ means all the elements in $\mathbf{P}$ are larger than the corresponding elements in $\mathbf{P}_{min}$, $p_n>p_{n,min}$. Proposition 1 on the next page proves convexity of $F\left(\mathbf{P}\right)$ and $G\left(\mathbf{P}\right)$, Therefore, the DC programming approach can be applied to realize energy-efficient power allocation using Algorithm 3 on the next page. Once the power allocation over subchannels is obtained, we replace the equal power allocation with our new power allocation scheme to achieve higher energy efficiency of the system.

Algorithm 3 DC Programming Algorithm for Power Allocation across Subchannels

1: Initialize $\mathbf{P}^{(0)}$, set iteration number $k=0$. The Objective function $Q\left(\mathbf{P}\right)$, convex functions $F\left(\mathbf{P}\right)$ and $G\left(\mathbf{P}\right)$.
2: **while** $\left|Q\left(\mathbf{P}^{(K+1)}\right)-Q\left(\mathbf{P}^{(k)}\right)\right|>\varepsilon$ **do**
3: Define convex approximation of $G^{(k)}\left(\mathbf{P}\right)$ at $\mathbf{P}^{(k)}$ as

$$Q^{(k)}\left(\mathbf{P}\right)=F\left(\mathbf{P}\right)-G\left(\mathbf{P}^{(k)}\right)-\nabla G^{T}\left(\mathbf{P}^{(k)}\right)\left(\mathbf{P}-\mathbf{P}^{(k)}\right) \quad (32)$$

4: Solve the convex problem

$$\mathbf{P}^{(k)}=\underset{p_n\geq p_{n,min},\ \left\|\mathbf{P}\right\|_1=\mathrm{P}_s}{\arg\min}Q^{(k)}\left(\mathbf{P}\right) \quad (33)$$

5: $k\leftarrow k+1$
6: **end while**

$$\min_{p_n \geq 0} -\sum_{n=1}^{N} \left\{ \frac{W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right)}{p_c+p_n} + \frac{W_{2,n}\log_2\left(\frac{1+p_n H_{2,n}}{1+\beta_n p_n H_{2,n}}\right)}{p_c+p_n} \right\}$$
$$\min_{p_n \geq 0} \left\{ -\sum_{n=1}^{N} \frac{W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right)}{p_c+p_n} - \sum_{n=1}^{N} \frac{W_{2,n}\log_2\left(1+p_n H_{2,n}\right)}{p_c+p_n} + \sum_{n=1}^{N} \left(\frac{W_{2,n}\log_2\left(1+\beta_n p_n H_{2,n}\right)}{p_c+p_n} \right) \right\}. \tag{29}$$

Let

$$F\left(\mathbf{P}\right) = -\sum_{n=1}^{N} \frac{W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right)}{p_c+p_n} - \sum_{n=1}^{N} \frac{W_{2,n}\log_2\left(1+p_n H_{2,n}\right)}{p_c+p_n}$$
$$G\left(\mathbf{P}\right) = -\sum_{n=1}^{N} \left(\frac{W_{2,n}\log_2\left(1+\beta_n p_n H_{2,n}\right)}{p_c+p_n} \right). \tag{30}$$

$$\nabla G\left(\mathbf{P}^{(k)}\right) = \sum_{n=1}^{N} \frac{W_{1,n}\log_2\left(1+\beta_n p_n H_{2,n}\right) - \left(p_c+p_n\right)\frac{\beta_n H_{2,n}}{\left(1+\beta_n p_n H_{2,n}\right)\ln 2}}{\left(p_c+p_n\right)^2}. \tag{34}$$

In Algorithm 3, $\nabla G\left(\mathbf{P}^{(k)}\right)$ is the gradient of $G(\mathbf{P})$ at the point $\mathbf{P}^{(k)}$ and it is calculated by (34) at the top of this page. Since (32) and the power domain are convex, problem (33) can be solved by either the interior point method or the sequential quadratic programming. In order to use the DC programming approach, the quasi-convexity of $F\left(\mathbf{P}\right)$ and $G\left(\mathbf{P}\right)$ needs to be established. It is easy to show that $f\left(\mathbf{P}\right) = -\sum_{n=1}^{N} W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right) - \sum_{n=1}^{N} W_{2,n}\log_2\left(1+p_n H_{2,n}\right)$ and $g\left(\mathbf{P}\right) = -\sum_{n=1}^{N} W_{2,n}\log_2\left(1+\beta_n p_n H_{2,n}\right)$ are convex since $\nabla^2 f\left(\mathbf{P}\right)$ and $\nabla^2 g\left(\mathbf{P}\right)$ are positive semi-definite matrices.

Proposition 1: If $-f_1\left(p_n\right) = W_{1,n}\log_2\left(1+\beta_n p_n H_{1,n}\right) + W_{2,n}\log_2\left(1+p_n H_{2,n}\right)$ and $-g_1\left(p_n\right) = W_{2,n}\log_2\left(1+\beta_n p_n H_{2,n}\right)$ are strictly concave in p_n, $-F_1\left(p_n\right) = \frac{-f_1\left(p_n\right)}{p_c+p_n}$ and $-G_1\left(p_n\right) = \frac{-g_1\left(p_n\right)}{p_c+p_n}$ are quasi-concave with constant p_c. Inspired by [32], we can prove Proposition 1 as follows.

Proof: Denote the α-sublevel sets of function $-F_1\left(p_n\right)$ as

$$S_\alpha = \left\{ p_n > 0 \middle| -F_1\left(p_n\right) \geq \alpha \right\}. \tag{35}$$

Based on the Proposition 1, $-F_1\left(p_n\right)$ is strictly quasi-concave if and only if S_α is strictly convex for any α. In this case, when $\alpha < 0$, there are no points satisfying $-F_1\left(p_n\right) = \alpha$. Therefore, S_α is strictly convex when $\alpha \leq 0$. When $\alpha > 0$, we can rewrite S_α as $S_\alpha = \left\{ p_n > 0 \middle| \alpha\left(p_c+p_n\right) + f_1\left(p_n\right) \leq 0 \right\}$. Since $f\left(p_n\right)$ is strictly convex in p_n, S_α is therefore also strictly convex. Hence, $-F_1\left(p_n\right)$ and $-G_1\left(p_n\right)$ are strictly quasi-concave. Therefore, $F_1\left(p_n\right)$ and $G_1\left(p_n\right)$ are quasi-convex. As a result, $F\left(\mathbf{P}\right)$ and $G\left(\mathbf{P}\right)$ are quasi-convex. ■

V. Simulation Results and Discussion

In this section, simulation results are presented to evaluate the performance of the proposed resource allocation algorithms for NOMA systems through extensive Monte Carlo simulations. In the simulations, we consider one base station located in the cell center and the user terminals are uniformly distributed in a circular range with radius of 500 m. We set the minimum distance between users to be 40 m, and the minimum distance from users to BS is 50 m. The bandwidth is 5 MHz. Let M users be randomly distributed in the cell. In NOMA systems, to reduce demodulating complexity of the SIC receiver, we consider each subchannel is only allocated with two users. In OFDMA schemes, each user can only be assigned to one subchannel. In the simulations, we compare the performance of NOMA systems with OFDMA systems, both with resource allocation algorithms. For the subchannel power allocation, we compare our proposed suboptimal algorithm with equal power allocation scheme based on our proposed subchannel assignment scheme. FTPA for multiplexed users on subchannel is also compared with our proposed algorithms. In our simulations, we set BS peak power, P_s, to be 41 dBm and circuit power consumption $p_c = 1$ W [33]. The maximum number of users is 60 and $\sigma_n^2 = \frac{BW}{N} N_0$, where $N_0 = -174$ dBm/Hz is the AWGN power spectral density. For simplicity, we consider each user has the same weighted bandwidth ($W_{1,n} = W_{2,n} = BW/N$). In the simulations, we set the value of α as 0.4 [13].

In Fig. 2, the performance of total sum rate is evaluated with the number of users M (M varies from 10 to 60). We set difference tolerance $\varepsilon = 0.01$, and the bandwidth is limited to 5 MHz. It is shown that the total sum rate increases when the number of the users grows. As the number of users grows larger, the sum rate continues to increase, but the rate of growth becomes slower, as expected from the Shannon's formula in calculating the sum rate. From Fig. 2, we observe that the

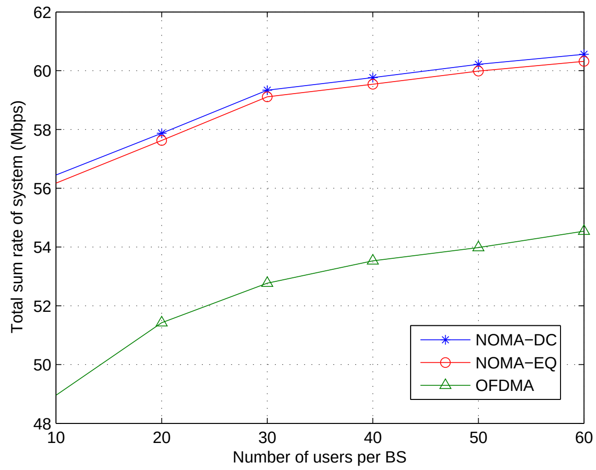

Fig. 2. Sum rate of the system versus different number of users.

performance of NOMA system with the proposed resource allocation algorithms, including subchannel assignment and power allocation, is much better than the OFDMA scheme. For example, when the number of users is 30, the sum rate of the proposed algorithm (NOMA-DC) [2] is 12.5% more than that of OFDMA scheme, and the sum rate of equal power allocation (NOMA-EQ) is 11.9% more than that of OFDMA scheme. That is because in OFDMA scheme, one subchannel can only be used by one user. As a result, BS cannot fully use the spectrum resources. For different subchannel power allocation schemes, the sum rate of NOMA-DC is higher than that of NOMA-EQ. Figure 3 shows the energy efficiency versus the number of users with the same constraints of Fig. 2. It can be observed that the energy efficiency also increases when the number of users grows. The trend of curve is similar to the sum rate curves due to the energy efficiency expression. From this figure, the performance of our proposed subchannels and power allocation is much more energy-efficient than the OFDMA scheme. Our proposed subchannel power allocation

[2]NOMA-DC uses DC programming to allocate power across subchannels.

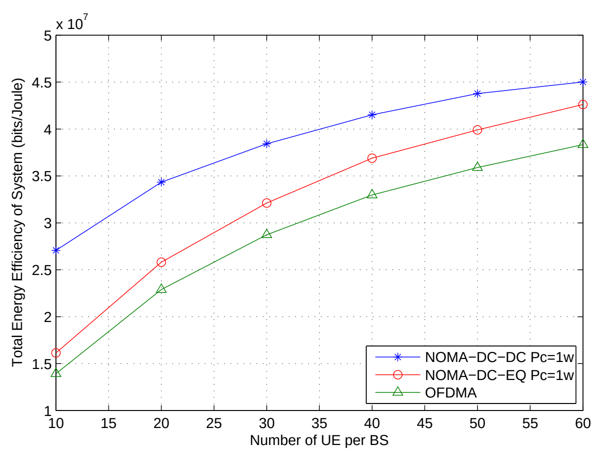

Fig. 3. Energy efficiency of the system versus different number of users.

through the DC programming achieves better performance than the equal power allocation. When the number of users is 30, the energy efficiency of NOMA-DC is 33% more than that of the OFDMA scheme and 19% more than NOMA-EQ. In Fig. 4, the performance of total sum rate versus BS power

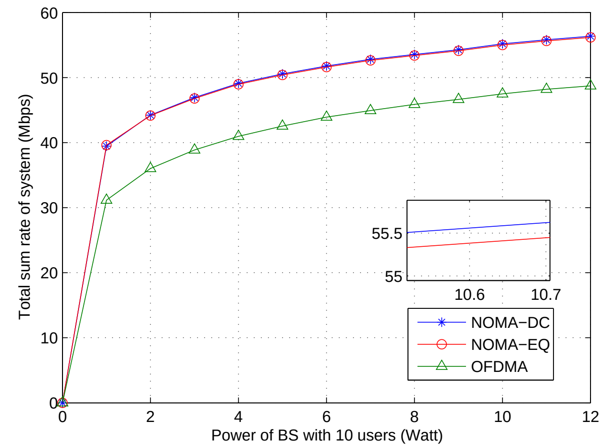

Fig. 4. Sum rate of the system versus BS power.

with a fixed circuit power of $p_c = 1$ W, the total number of users $M = 10$, and the BS power is from 1 W to 12 W. In Fig. 4, the sum rate of the system increases as the BS power grows. In NOMA systems, our proposed algorithm using DC for subchannel power allocation performs better than equal power allocation. Both algorithms outperforms the OFDMA system. Figure 5 illustrates the total energy efficiency versus BS power

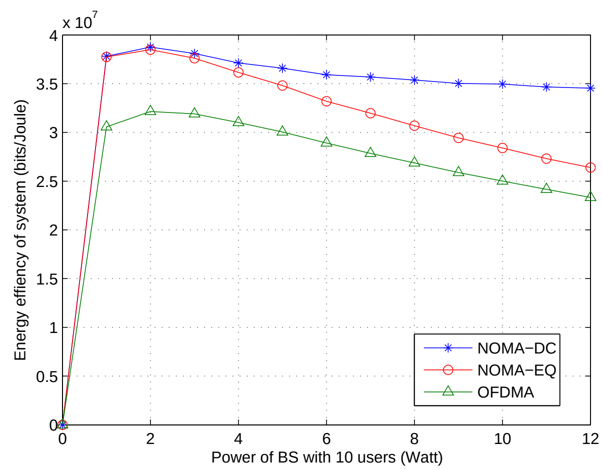

Fig. 5. Energy efficiency of the system versus BS power.

with the fixed circuit power of $p_c = 1$ W, and the number of users is $M = 10$, and the BS power ranges from 1 W to 12 W. It shows that the total energy efficiency first increases from 0 when BS transmit power increases. After the power reaches a certain level, the total energy efficiency begins to decreases. That is because there is a tradeoff between transmission capacity and power consumption for the energy-efficient power allocation. From Fig. 5, it is seen that NOMA-DC can achieve better performance than NOMA-EQ and OFDMA schemes.

For larger BS power levels, NOMA-DC achieves much better performance than NOMA-EQ and OFDMA.

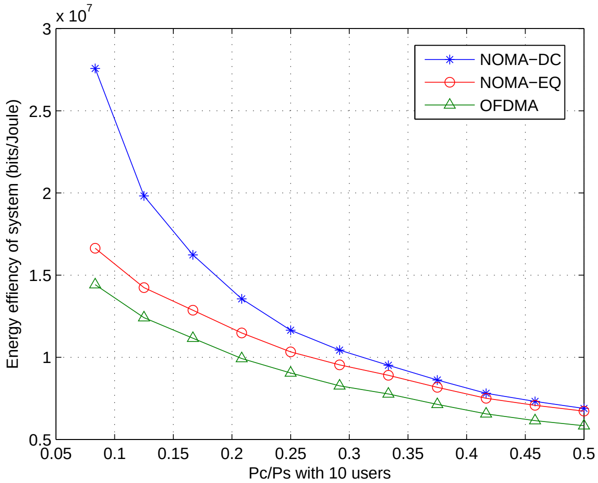

Fig. 6. Energy efficiency of the system versus Pc/BS power.

Figure 6 shows the total energy efficiency versus circuit power to BS power ratio p_c/P_s. The system energy efficiency decreases when the ratio p_c/P_s increases. With the fixed BS power of 12 W, the system performs less energy-efficient when the circuit power increases. According to the definition of energy efficiency, its value will become smaller when p_c increases. However, the NOMA system equipped with the proposed resource allocation algorithms still outperforms the OFDMA system. In Fig. 7, FTPA among multiplexed users with equal subchannel power scheme is compared with the NOMA-DC, NOMA-EQ and OFDMA schemes. Fig. 7 shows that the energy efficiency increases as the number of users grows. NOMA-DC-DC[3] performs the best among those schemes. When user number is 20, the energy efficiency of NOMA-DC-DC is 35% more than that of the OFDMA scheme and 30% more than NOMA-FTPA-EQ[4]. NOMA-DC-EQ[5]achieves 12% more than OFDMA schemes in terms of energy efficiency.

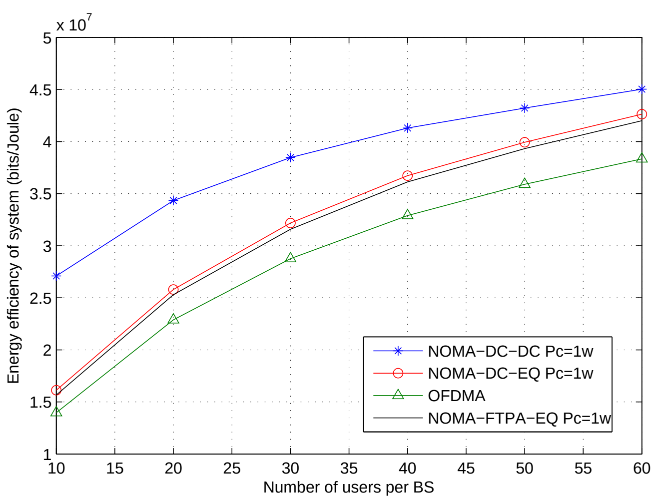

Fig. 7. Energy efficiency of the system versus different number of users.

VI. Conclusion

By assigning only two users to the same subchannel, we proposed energy-efficient resource allocation algorithms for a downlink NOMA wireless network. These algorithms include subchannel assignment, power proportional factors determination for multiplexed users and power allocation across subchannels. By formulating subchannel assignment problem as a two-sided matching problem, we proposed the SOMSA algorithm to maximize the system energy efficiency. Power proportional factors for the multiplexed users on each subchannel are determined by SOMSA. In the power allocation across subchannels scheme, since the objective function is non-convex, DC programming was utilized to approximate the non-convex optimization problem into the convex sub-problem. Therefore, a suboptimal power allocation across subchannels was obtained by solving the convex sub-problems iteratively. Based on the resource scheduling from proposed SOMSA algorithm, further improvement in the system energy efficiency was achieved by the proposed subchannel power allocation scheme. Through extensive simulations, the performance of the proposed algorithms for resource allocation was compared with the OFDMA system. It was shown that the total sum rate and energy efficiency of NOMA system are much higher than the OFDMA scheme. The proposed power allocation for subchannel users outperforms the FTPA scheme. Moreover, the proposed subchannel power allocation achieves better performance than the equal power allocation scheme.

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[5]NOMA-DC-DC uses DC programming approach to determine the power proportional factors and equal power allocation acrose the subchannels.

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