Energy-Efficient Resource Scheduling for NOMA Systems With Imperfect Channel State Information

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***Abstract*—Non-orthogonal multiple access (NOMA) is considered as a promising technology for the fifth generation mobile communications. Energy-efficient resource allocation scheme is studied for a downlink NOMA wireless network, where multiple users can be multiplexed on the same subchannel by applying successive interference cancellation technique at the receivers. Most previous works focus on resource allocation for sum rate maximization with perfect channel state information (CSI) in NOMA systems. We formulate the energy-efficient resource allocation as a probabilistic mixed non-convex optimization problem by considering imperfect CSI. To solve this problem, we decouple it into user scheduling and power allocation sub-problems. We propose a low-complexity suboptimal user scheduling algorithm and a power allocation scheme to maximize the system energy efficiency under the maximum transmitted power limit, imperfect CSI and the outage probability constraints. Simulation results are provided to show that the proposed algorithms yield much improved energy efficiency performance over the conventional orthogonal frequency division multiple access scheme.**

I. Introduction

Orthogonal frequency division multiple access (OFDMA) has been widely adopted in the fourth generation (4G) mobile communication systems. However, in the next generation mobile communication systems, the demand for mobile traffic data volume is expected to be 1,000 times larger. As a result, non-orthogonal multiple access (NOMA) was proposed to meet overwhelming requirement of data rates [1]. By employing successive interference cancellation (SIC) technique, NOMA can achieve higher data rates than the traditional OFDMA system [2]. Therefore, NOMA is considered as a promising candidate for the fifth generation (5G) mobile communication systems [3].

Since the introduction of NOMA that shows user throughput improvement [1], NOMA has attracted much research attention. The resource allocation for NOMA systems was investigated in [4], [5]. In [4], a greedy subchannel and power allocation algorithm was proposed to maximize the data rate for OFDMA based NOMA systems. A cooperative NOMA transmission scheme with fixed choices of power allocation coefficients was presented in [5]. Moreover, the outage performance of NOMA systems was studied in [6], [7] for a cellular downlink scenario with randomly deployed mobile users. By assuming that randomly deployed users were uniformly distributed within a cell, the authors in [6] first derived the outage probability for downlink single-cell NOMA systems with perfect channel state information (CSI). In [7], the outage performance was further studied with the assumption of two types of partial CSI in the NOMA system. Recently, the energy consumption of wireless networks is rapidly increasing. Therefore, the improvement of energy efficiency is an important and practical consideration in wireless communication systems.

In [8], [9], an energy-efficient subchannel allocation algorithm was proposed for a simple downlink NOMA network with perfect CSI. However, perfect CSI is normally difficult to achieve in practice due to channel estimation errors, limited feedback and quantization errors [10]. In this paper, we focus on the energy-efficient resource allocation in a downlink NOMA network and use bits per Joule to measure the energy efficiency performance of the system. The resource allocation scheme is designed based on imperfect CSI. In this situation, the user data rate may not meet the minimum data rate requirement, determined by quality of service (QoS). Therefore, an outage probability requirement is considered for the resource allocation to maximize the system energy efficiency. By formulating user scheduling and power allocation as an energy efficiency optimization problem, a low-complexity suboptimal user scheduling scheme is proposed to achieve the maximum of the system energy efficiency. A gradient assisted binary search algorithm is utilized for the power allocation accross the subchannels to further maximize the energy efficiency of the system.

II. System Model and Problem Formulation

We consider a downlink single-cell NOMA network with one basestation (BS) and a number of paring users. The BS transmits its signals to M user equipments (UEs) through N subchannels (SCs). We denote m as the index for the mth mobile user where $m \in \{1, 2, \cdots, M\}$, and denote n as the index for the nth subchannel where $n \in \{1, 2, \cdots, N\}$. In this system model, the BS is located in the cell center and M users are uniformly distributed in a circular region. The total bandwidth of the system, BW, is equally divided into N subchannels where the bandwidth of each subchannel is $B_{sc} = BW/N$.

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A. Signal and Channel Model

Assume that the feedback to the transmitter is instantaneous and error free in this system. That means the received CSI at the receiver can be known by the transmitter [11], [12]. By using the minimum mean square error channel estimation error model, we mathematically describe the small scale fading of the link between the BS and UE_m on the nth subchannel (SC_n) as

$$h_{m,n} = \hat{h}_{m,n} + e_{m,n} \tag{1}$$

where $h_{m,n}$ is the realistic Rayleigh fading channel gain on SC_n from the BS to UE_m. Here $h_{m,n} \sim \mathcal{CN}(0, \sigma_h^2)$ is a complex Gaussian distribution with mean zero and variance σ_h^2 where σ_h^2 captures both path-loss and shadowing effects. In (1), we denote $\hat{h}_{m,n} \sim \mathcal{CN}(0, \sigma_{\hat{h}}^2)$ as the estimate of $h_{m,n}$ and $e_{m,n} \sim \mathcal{CN}(0, \sigma_e^2)$ as the estimation error with $\sigma_{\hat{h}}^2 = \sigma_h^2 - \sigma_e^2$. We assume that $\hat{h}_{m,n}$ and $e_{m,n}$ are uncorrelated to each other.

Considering M_n users are multiplexed on SC_n, without loss of generality, we assume that the estimated channel gains in the cell are sorted as $|\hat{h}_{1,n}| > |\hat{h}_{2,n}| > \cdots > |\hat{h}_{M_n,n}|$. Therefore, the received signal at UE_m on SC_n is

$$y_{m,n} = \hat{h}_{m,n} \sum_{i=1}^{M_n} \sqrt{\beta_{i,n} p_n} s_i + e_{m,n} \sum_{i=1}^{M_n} \sqrt{\beta_{i,n} p_n} s_i + z_{m,n} \tag{2}$$

where s_i is the modulated symbol and $z_{m,n} \sim \mathcal{CN}\left(0, \sigma_n^2\right)$ is the additive white Gaussian noise (AWGN) with mean zero and variance σ_n^2. Let p_n be the power assigned to SC_n and denote $\beta_{m,n}$ as the power allocation factor for UE_m, with $\beta_{1,n} < \beta_{2,n} < \cdots < \beta_{M_n,n}$ and $\sum\limits_{i=1}^{M_n} \beta_{i,n} = 1$.

B. Outage Performance for the NOMA System

In the NOMA system, having SIC technology at the receiver, UE_m is required to detect message from User l ($m < l$) and remove the UE_l's message from its observation in a successive manner. Therefore, the outage event only occurs at UE_m when it is unable to decode the message from users $l \geq m$. Inspired by [6], the outage of UE_m on SC_n can be written by

$$\begin{aligned} \mathrm{P}_{m,n}^{out} =& \frac{M_n!}{(m-1)!(M_n-m)!} \sum_{r=0}^{m-1} \left(\begin{array}{c} m-1 \\ r \end{array} \right) (-1)^r \\ & \times \frac{\left(1 - \exp\left(-\frac{\xi_m^*(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2}\right)\right)^{M_n-m+r+1}}{M_n - m + r + 1} \end{aligned} \tag{3}$$

where $\rho = \frac{p_n}{\sigma_n^2}$, $\xi_m^* = \max\{\xi_{m+1}, \xi_{m+2}, \cdots, \xi_{M_n}\}$ and $\xi_l \triangleq \frac{\gamma_l}{\rho(\beta_l - \gamma_l \sum\limits_{i=1}^{l-1} \beta_i)}$ conditioned on $\beta_l > \gamma_l \sum\limits_{i=1}^{l-1} \beta_{i,n}$. Define $\tilde{R}_m$ as the minimum data rate of User m and $\gamma_m = 2^{\tilde{R}_m} - 1$. In a NOMA system with imperfect CSI, the communication fails when the user data rate is less than the minimum data rate QoS requirement. Therefore, the outage performance is a useful metric to evaluate whether the user can meet the QoS requirement.

C. Optimization Problem Formulation

In this subsection, we formulate the energy-efficient user scheduling policy, $\mathcal{U} = \{UE_m, \forall m \in \{1, 2, \cdots, M\}\}$, and power allocation scheme, $\mathcal{P} = \{p_n > 0, \forall n \in \{1, 2, \cdots, N\}\}$, as an optimization problem in the NOMA system. Due to the decoding complexity of the receivers, we consider only two users multiplexed on one subchannel, with $|\hat{h}_{1,n}|^2 \geq |\hat{h}_{2,n}|^2$ corresponding to UE_1 and UE_2 on SC_n. The sum rate of the NOMA system can be described as

$$R(\mathcal{U}, \mathcal{P}) = \sum_{n=1}^{N} R_n(\mathcal{U}, \mathcal{P}) \tag{4}$$

where

$$\begin{aligned} R_n(\mathcal{U}, \mathcal{P}) =& B_{sc} \log_2 \left(1 + \frac{|\hat{h}_{1,n}|^2 \beta_{1,n} p_n}{\sigma_e^2 p_n + \sigma_n^2} \right) \\ & + B_{sc} \log_2 \left(1 + \frac{|\hat{h}_{2,n}|^2 \beta_{2,n} p_n}{|\hat{h}_{2,n}|^2 \beta_{1,n} p_n + \sigma_e^2 p_n + \sigma_n^2} \right). \end{aligned} \tag{5}$$

For energy-efficient communications, it is desirable to maximize the amount of transmitted data bits with a unit energy. The energy efficiency of the system can be expressed as

$$\eta_{EE}(\mathcal{U}, \mathcal{P}) = \frac{R(\mathcal{U}, \mathcal{P})}{P_T(\mathcal{U}, \mathcal{P}) + P_c} \tag{6}$$

where $P_T(\mathcal{U}, \mathcal{P}) = \sum\limits_{n=1}^{N} p_n$ is the transmitted power by the BS and P_c is the circuit power consumption of BS. The optimization problem can be formulated as

$$\max_{\mathcal{U}, \mathcal{P}} \quad \eta_{EE}(\mathcal{U}, \mathcal{P}) \tag{7}$$

$$\begin{aligned} \text{subject to } & C1: \mathrm{P}_{m,n}^{out} \leq \varepsilon_{out} \\ & C2: 0 \leq \beta_{m,n} \leq 1 \\ & C3: p_{m,n} \geq 0 \\ & C4: \sum_{n=1}^{N} p_n \leq P_{max} \end{aligned} \tag{8}$$

where ε_{out} is the outage probability requirement, and P_{max} is the maximum power constraint for the BS. As observed in (7), user scheduling and power allocation are coupled with each other. Thus, the optimization problem of (7) under the constraints in (8) is a constrained combinatorial non-convex optimization problem, and it is challenging to find the global optimal solution within polynomial time. To solve this problem efficiently, we divide it into two sub-problems: the user scheduling sub-problem and the power allocation sub-problem.

III. Energy-Efficient Resource Allocation Algorithms in the NOMA System

In this section, we first transform the probabilistic mixed non-convex optimization problem into a non-probabilistic optimization problem. Then we present a low-complexity suboptimal user scheduling algorithm and a power allocation scheme in the NOMA system.

A. Optimization Problem Transformation

Based on (3), the outage probability of UE_1 and UE_2 sharing SC_n can be respectively expressed as

$$\begin{aligned}\mathrm{P}_{1,n}^{out} =&F_{\left|\hat{h}_{1,n}\right|^2}(\xi_1^*(\rho\sigma_e^2+1)) \\ =&\left(1-\exp(-\frac{\xi_1^*(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2})\right)^2\end{aligned} \tag{9}$$

and

$$\begin{aligned}\mathrm{P}_{2,n}^{out} =&F_{\left|\hat{h}_{2,n}\right|^2}(\xi_2^*(\rho\sigma_e^2+1)) \\ =&2\left(1-\exp(-\frac{\xi_2^*(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2})\right) \\ &-\left(1-\exp(-\frac{\xi_2^*(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2})\right)^2\end{aligned} \tag{10}$$

where $F_{\left|\hat{h}_{m,n}\right|^2}(\cdot)$ is the cumulative density functions (CDF) of the unordered channel coefficient $|\hat{h}_{m,n}|^2$. The probabilistic constraint $C1$ in (7) can be written by

$$C1:\mathrm{P}_{m,n}^{out}\le\varepsilon_{out}\Rightarrow\left\{\begin{array}{l}F_{\left|\hat{h}_{1,n}\right|^2}(\xi_1^*(\rho\sigma_e^2+1))\le\varepsilon_{out}\\ F_{\left|\hat{h}_{2,n}\right|^2}(\xi_2^*(\rho\sigma_e^2+1))\le\varepsilon_{out}\end{array}\right. \tag{11}$$

where $\xi_1^*=\max\{\xi_1\}=\xi_1=\frac{\gamma_l}{\rho(\beta_{1,n})}$, $\xi_2^*=\max\{\xi_1,\xi_2\}=\xi_2=\frac{\gamma_l}{\rho(\beta_{2,n}-\gamma_l\beta_{1,n})}$, $l\ge 1$. Define $F^{-1}_{\left|\hat{h}_{m,n}\right|^2}(\cdot)$ as the inverse CDF of $|\hat{h}_{m,n}|^2$. Therefore, the constraint $C1$ can be converted to

$$\left\{\begin{array}{c}\frac{\gamma_1}{\rho\beta_{1,n}}\frac{(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2}\le F^{-1}_{\left|\hat{h}_{1,n}\right|^2}(\varepsilon_{out})\\ \frac{\gamma_2}{\rho(\beta_{2,n}-\gamma_2\beta_{1,n})}\frac{(\rho\sigma_e^2+1)}{\sigma_{\hat{h}}^2}\le F^{-1}_{\left|\hat{h}_{2,n}\right|^2}(\varepsilon_{out})\end{array}\right. \tag{12}$$

where

$$\begin{aligned}F^{-1}_{\left|\hat{h}_{1,n}\right|^2}(\varepsilon_{out})=-\sigma_{\hat{h}}^2\log(1-\sqrt{\varepsilon_{out}})\\ F^{-1}_{\left|\hat{h}_{2,n}\right|^2}(\varepsilon_{out})=-\sigma_{\hat{h}}^2\log(\sqrt{1-\varepsilon_{out}}).\end{aligned} \tag{13}$$

Therefore, the power allocation factor range of the two users can be determined by (12) and (13).

B. User Scheduling Algorithm

The user scheduling algorithm starts with assigning equal power allocation across subchannels $p_n=P_{\max}/N$. The optimal solution of user scheduling is difficult to obtain in practice as it requires to search all the possible combinations of every two users in the system. Thus, we propose a low-complexity suboptimal user scheduling algorithm. In this user scheduling algorithm, the power allocation factor $\beta_{m,n}$ among the multiplexed users sharing the same subchannel is determined to maximize the system energy efficiency.

Algorithm 1 describes the proposed suboptimal user scheduling process. We denote $\mathbb{U}_{UnAll}$ as a set of users who have not been allocated on any subchannel, and denote $\mathbb{SC}_{UnAll}$ as a set of subchannels where no users have been

Algorithm 1 Low-Complexity User Scheduling Algorithm

Construct the estimate channel gain $\mathbb{H}\triangleq[|\hat{h}_{m,n}|]_{M\times N}$.
Initialize the sets $\mathbb{U}_{UnAll}$ and $\mathbb{SC}_{UnAll}$ to record the unallocated users and unallocated subchannels in the system.
Initialize the lists for all the subchannels $S_{Allocated}(n)$ to record the allocated users on SC_n, $\forall n\in\{1,2,\cdots,N\}$.
Initialize the lists for all the subchannels $EE(n)$ to record the energy efficiency of SC_n.
while $\mathbb{SC}_{UnAll}\neq\emptyset$ **do**
  Find the maximum value $|\hat{h}_{m,n}|$ in $\mathbb{H}$, and assign the user m onto the subchannel n,
$$|\hat{h}_{m,n}|=\arg\max_{m\in_{UnAl},n\in\mathbb{H}_{UnAl}}(\mathbb{H})$$
  $\mathbb{U}_{UnAll}$=$\mathbb{U}_{UnAll}\backslash UE_m$.
  $EE_{n,possible}$=$\emptyset$.
  $EE_{n,i}$=$\emptyset$.
  for each user in $\mathbb{SC}_{UnAll}$ **do**
    a) Find power allocation factor $\beta_{m,n}$ for UE_m and UE_i by exhaustive searching in Section III.
    b) Calculate the energy efficiency EE_n of these two users on SC_n.
    c) $EE_{n\_possible}\leftarrow EE_{n,i}$.
  end for
  $EE(n)=\max_{UE_i,i\in\mathbb{U}_{UnAl}}(EE_{n\_possible})$.
  $\mathbb{SC}_{UnAll}$=$\mathbb{SC}_{UnAll}\backslash SC_n$.
  $\mathbb{U}_{UnAll}$=$\mathbb{U}_{UnAll}\backslash UE_i$.
  Let the mth and ith row's elements in $\mathbb{H}$ be zeros.
  Let the nth column's elements in $\mathbb{H}$ be zeros.
end while

allocated. First, $\mathbb{U}_{UnAll}$ is initialized to record the users who have not been allocated on any subchannel, and $\mathbb{SC}_{UnAll}$ is initialized to record the subchannels where no user has been allocated. In the allocating procedure, we first find the user who has the maximum channel gain and allocate it to the corresponding subchannel. On this subchannel, the second user should be selected from the remaining unallocated users in $\mathbb{U}_{UnAll}$. The users who are chosen to multiplex on this subchannel must have the maximum energy efficiency. This process terminates if there is no user left to be allocated.

1) Complexity Analysis: For a given power allocation scheme, the optimal user scheduling algorithm can only be obtained through exhaustive search. The time complexity of exhaustive searching is $O(\frac{(2N)!}{2^N})$. The complexity of the proposed algorithm is $O(2N^2)$. Taking natural logarithm of the complexity, $O(\ln N)<O(N\ln N)$. Therefore, the complexity of the proposed algorithm is much less than the optimal user scheduling scheme.

2) Power Allocation Factors Determination: In the step of determining power allocation factor $\beta_{m,n}$, the optimal value can be found through an exhaustive search for all the values in $[0,1]$.

IV. Energy-Efficient Power allocation for subchannels

In Algorithm 1, it is required to determine the power proportional factor $\beta_{m,n}$ for subchannel multiplexing users. In this section, given the user scheduling scheme, a novel power allocation for subchannels algorithm is proposed to replace the equal power allocation scheme.

A. Energy-Efficient Power Allocation Scheme

Given the user scheduling and power allocation factors by Algorithm 1, the optimization problem can be rewritten by

$$\max_{\mathbf{P}\succ 0} \quad \eta_{EE}(\mathbf{P}) = \frac{\sum\limits_{n=1}^{N} R_n}{\sum\limits_{n=1}^{N} p_n + P_c} \tag{14}$$

$$\text{subject to :} \quad \sum_{n=1}^{N} p_n \leq P_{max} \tag{15}$$

where $\mathbf{P} = [p_1, p_2, \cdots, p_n, \cdots, p_N]^T$ represents the assigned powers on the subchannels, $(\cdot)^T$ is denoted as the transpose, and $\mathbf{P} \succ 0$ means all elements of $\mathbf{P}$ are positive. However, the utility function in (14) is a nonlinear function respect to the transmission power $\mathbf{P}$. It is difficult to solve (14) with the constraint (15). Therefore, to reduce the computation complexity, we utilize the gradient assisted binary search algorithm to achieve the energy-efficient power allocation [13], [14]. Before describing the algorithm, we first prove that (14) is a quasi-concave function by using Proposition 1 and Proposition 2 as follows.

Proposition 1: If $R(\mathbf{P})$ is strictly concave in $\mathbf{P}$, $\eta_{EE}(\mathbf{P})$ is strictly quasi-concave.

Inspired by [15], we can prove Proposition 1 as follows.

Proof: Denote the upper contour sets of $\eta_{EE}(\mathbf{P})$ as

$$S_\alpha = \{\mathbf{P} \succ 0 | \eta_{EE}(\mathbf{P}) \geq \alpha\}. \tag{16}$$

According to a proposition in [16], $\eta_{EE}(\mathbf{P})$ is strictly quasi-concave if and only if S_α is strictly convex for any real number α. When $\alpha < 0$, there are no points satisfying $\eta_{EE}(\mathbf{P}) = \alpha$. When $\alpha = 0$, only $\mathbf{0}$ is on the contour $\eta_{EE}(\mathbf{0}) = \alpha$. When $\alpha > 0$, $S_\alpha = \{\mathbf{P} \succ 0 | \alpha P_c + \alpha P_T(\mathbf{P}) - R(\mathbf{P}) \leq 0\}$. Since $P_T(\mathbf{P})$ is strictly convex in $\mathbf{P}$ and $R(\mathbf{P})$ is concave, which is to be proved by Proposition 2. Therefore, we prove the strict quasi-concavity of $\eta_{EE}(\mathbf{P})$.

Proposition 2: $R_n(p_n) = \log_2(g_1(p_n)) + \log_2(g_2(p_n))$ is concave if g_1 and g_2 are concave and positive, where $g_1(p_n) = 1 + \frac{|\hat{h}_{1,n}|^2 \beta_{1,n} p_n}{\sigma_e^2 p_n + \sigma_n^2}$ and $g_2(p_n) = 1 + \frac{|\hat{h}_{2,n}|^2 \beta_{2,n} p_n}{\Omega_{m,n}}$ with $\Omega_{m,n} = |\hat{h}_{2,n}|^2 \beta_{1,n} p_n + \sigma_e^2 p_n + \sigma_n^2$. *Proof*: Since

$$\begin{aligned} \frac{\partial^2 g_1}{\partial p_n^2} &= \frac{-|\hat{h}_{1,n}|^2 \beta_{1,n} \sigma_n^2}{(\sigma_e^2 p_n + \sigma_n^2)^4} < 0, \\ \frac{\partial^2 g_2}{\partial p_n^2} &= \frac{-|\hat{h}_{2,n}|^2 \beta_{2,n} \sigma_n^2 2\Omega_{m,n} \left(|\hat{h}_{2,n}|^2 \beta_{1,n} + \sigma_e^2\right)}{\Omega_{m,n}^4} < 0 \end{aligned} \tag{17}$$

and $g_1 > 0, g_2 > 0$. $g_1(p_n)$ and $g_2(p_n)$ are concave functions. As a result, $R(\mathbf{P})$ is concave.

After we prove the quasi-concavity of problem (14), the gradient assisted binary search algorithm (GABS) can be used for power allocation as shown in Algorithm 2. The GABS algorithm is specifically described in [13]. $[\mathbf{P}]^+$ sets the negative elements in vector $\mathbf{P}$ to be zero.

Algorithm 2 Power Allocation Based on Gradient Assisted Binary Search Algorithm

```
Initialization P^(0) and tolerance ε.
Optimization power allocation vector P. Let P = P_o.
Repeat
    use GABS to find the optimal step size t*
        P^1 = [P^0 + t* ∇η_EE(P^0)]^+
        if η_EE(P^1) − η_EE(P^0) < ε
            Return P^1.
        else
            P^0 = P^1.
        end
```

V. Simulation Results

In this section, simulation results are presented to evaluate the performance of the proposed resource allocation scheme for the NOMA system. In the simulations, we consider one basestation located in the cell center and M UEs are uniformly distributed in the circular range. Denote the bandwidth of the system as 5 MHz and the small-scale fading gain as Rayleigh distributed with $\sigma_n^2 = 1$. In NOMA systems, to reduce demodulation complexity of the SIC receiver, each subchannel is shared by two users. In OFDMA systems, each user can only be assigned to one subchannel. In the simulations, we compare our proposed resource allocation scheme for NOMA systems with a conventional OFDMA system. Since the algorithm has been designed based on imperfect CSI, the energy efficiency performance of the system with different channel estimation error variance σ_e^2 is shown in Fig. 2. For our simulations, we set BS peak power P_{max} to 1 W and circuit power consumption $P_c = 0.1$ W. The maximum number of users is 60 and $\sigma_n^2 = \frac{B}{N} N_0$, where $N_0 = -174$ dBm/Hz is the AWGN power spectral density. The minimum data rate QoS requirements of UE_1 and UE_2 are $\tilde{R}_1 = \tilde{R}_2 = 0.5$ bits/s/Hz.

In Fig. 1, performance of energy efficiency is evaluated versus the number of users M. In the simulation environment, we set the channel estimation error variance as $\sigma_e^2 = 0.005$ and the outage probability ε_{out} as 0.01. It is shown that the system energy efficiency increases when the number of users grows. As the number of users grows, the energy efficiency continues to increase, but the rate of growth becomes slower. The performance of our proposed resource scheduling scheme for the NOMA system achieves higher energy efficiency than the OFDMA scheme as well as the NOMA system with the equal power allocation (NOMA-EQ) scheme. For example, when the number of users is 20, the energy efficiency of

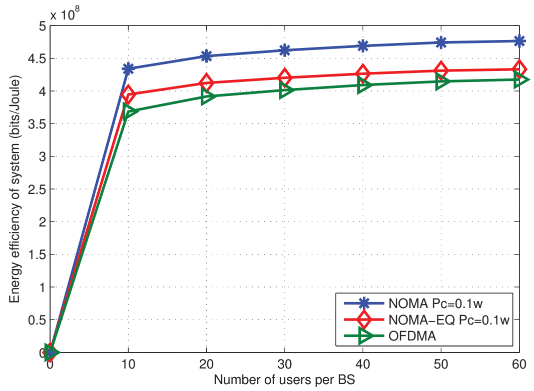

Fig. 1. Energy efficiency performance comparison with existing schemes.

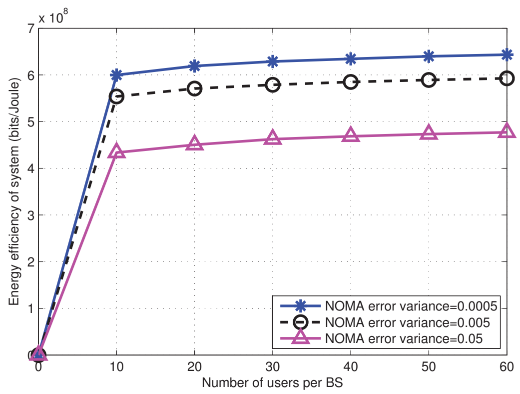

Fig. 2. Energy efficiency of proposed resource allocation scheme with different σ_e^2 values.

proposed resource allocation scheme for the NOMA system is 21% more than that of the OFDMA scheme, and is 12% more than that of the NOMA-EQ scheme.

In Fig. 2, the energy efficiency of the NOMA system with different estimation error variances is presented versus the number of users M. As observed in Fig. 3, the energy efficiency of the system deteriorates when the error variances increases. When the number of users is 30, the energy efficiency of the proposed resource allocation scheme with $\sigma_e^2 = 0.0005$ is 5% more than that with $\sigma_e^2 = 0.005$ and is 44% more than that with $\sigma_e^2 = 0.05$. Thus, as expected, the channel estimation error can degrade the energy efficiency performance.

VI. Conclusion

We studied the resource allocation in the NOMA system by considering imperfect CSI. By formulating the resource allocation as a probabilistic mixed non-convex optimization problem, a low-complexity suboptimal user scheduling algorithm was proposed to maximize the system energy efficiency. Given the user scheduling scheme, we presented an energy-efficient power allocation scheme. The performance of the proposed resource allocation scheme was compared with that of the conventional OFDMA system. It was shown that the energy efficiency of the NOMA system was higher than the OFDMA scheme, and the energy efficiency of the NOMA system deteriorates when the channel estimation error is increased.

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