Energy-Efficient Configuration of Spatial and Frequency Resources in MIMO-OFDMA Systems

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***Abstract*—In this paper, we investigate adaptive configuration of spatial and frequency resources to maximize *energy efficiency* (EE) and reveal the relationship between the EE and the *spectral efficiency* (SE) in downlink *multiple-input-multiple-output* (MIMO) *orthogonal frequency division multiple access* (OFDMA) systems. We formulate the problem as minimizing the total power consumed at the base station under constraints on the ergodic capacities from multiple users, the total number of subcarriers, and the number of *radio frequency* (RF) chains. A three-step searching algorithm is developed to solve this problem. We then analyze the impact of spatial-frequency resources, overall SE requirement and user fairness on the SE-EE relationship. Analytical and simulation results show that increasing frequency resource is more efficient than increasing spatial resource to improve the SE-EE relationship as a whole. The EE increases with the SE when the frequency resource is not constrained to the maximum value, otherwise a tradeoff between the SE and the EE exists. Sacrificing the fairness among users in terms of ergodic capacities can enhance the SE-EE relationship. In general, the adaptive configuration of spatial and frequency resources outperforms the adaptive configuration of only spatial or frequency resource.**

***Index Terms*—Energy efficiency (EE), spectral efficiency (SE), multiple-input-multiple-output (MIMO), orthogonal frequency division multiple access (OFDMA).**

I. Introduction

VARIOUS techniques have been developed during the last two decades to improve *spectral efficiency* (SE), such as *multiple-input-multiple-output* (MIMO) and *orthogonal frequency division multiplexing* (OFDM). Meanwhile, energy-efficient design of wireless communication systems is attracting more and more attention since explosive growth of wireless service results in its increasing contribution to the worldwide carbon footprint [1]. Therefore, future wireless systems are expected to be designed in an energy-efficient way while guaranteeing the SE.

More spatial and frequency resources enhance the SE, but also bring higher circuit power consumption. Although MIMO needs less transmit power than *single-input-single-output* (SISO) to achieve the same channel capacity, it consumes more circuit power since more active transmit or receive *radio frequency* (RF) chains are used [2]. On the other hand, in MIMO-OFDM systems, spatial precoding and other baseband processing are carried out at each subcarrier and thus the circuit power consumption on processing increases with the total number of occupied subcarriers. Since signal processing becomes more complicated due to high requirement on the data rate and transmission reliability, we cannot neglect the circuit power consumed by the spatial and frequency resources when designing an energy-efficient MIMO-OFDM system.

There have been some preliminary results on saving energy by adaptively using the spatial and frequency resources. The *energy efficiency* (EE) of Alamouti diversity scheme has been discussed in [2]. It has been shown that for short-range transmission, *multiple-input-single-output* (MISO) transmission reduces the EE as compared with SISO transmission if adaptive modulation is not used. However, if modulation order is adaptively adjusted to balance the transmit and circuit power consumption, MISO systems always perform better. Spatial multiplexing, space-time coding, and single antenna transmission have been adaptively selected in [3] based on *channel state information* (CSI), and the EE improvement can be up to 30% compared with non-adaptive systems. Adaptive switching between MIMO and single-input-multiple-output modes has been addressed in [4] to save the energy in uplink cellular networks. In [5], the number of active RF chains has been optimized to maximize the EE given the minimum data rate. Dynamic spectrum management has been discussed in [6]. It is shown that the energy can be saved significantly by allocating active frequency band and assigning users among different cells. The relationship between the EE and bandwidth has been investigated in [7] and [8]. The EE is shown to increase with bandwidth if the circuit power consumption either is independent of or linearly increases with the bandwidth. Energy-efficient link adaptation for MIMO-OFDM systems has been studied in [9], where the number of active RF chains, the overall bandwidth, MIMO transmission modes are adjusted according to the data rate requirement and channel condition.

Priori work mainly focuses on single user systems. In downlink MIMO-*orthogonal frequency division multiple access* (OFDMA) networks, RF chains are shared by multiple users. In this scenario, switching on or off RF chains and allocating bandwidth are intertwined, which makes it complicated to investigate the EE. In this paper, we will study adaptive configuration of spatial and frequency resources to maximize

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the EE in downlink MIMO-OFDMA systems, and we will reveal the relationship between the SE and the EE. Different from optimizing the system bandwidth in [9], we will fix the system bandwidth and only adjust the total number of active subcarriers, which can avoid the variation of the sampling rate and is more practical.

The rest of this paper is organized as follows. We first present the system model and formulate the EE maximization problem in Section II. In Section III, we propose a three-step algorithm to find a suboptimal solution. Then we investigate the impact of overall SE requirement and the user fairness in terms of ergodic capacities on the EE in Section IV. The simulation results are provided in Section V and the paper is concluded in Section VI.

II. System Model and Problem Formulation

In this section, we first introduce the system model and then describe the power consumption at the *base station* (BS) based on the implementation structure. Next we provide the ergodic capacity for each user and formulate an optimization problem to maximize the EE.

A. System Model

Consider a downlink MIMO-OFDMA system with M users. N_t and N_r RF chains are respectively configured at the BS and each user. Overall K subcarriers are shared by multiple users without overlap. Since a large portion of power is consumed by the BS during downlink transmission [7], we concern about how to save energy at the BS side. Assume that n_t RF chains are active at the BS and k_i subcarriers are employed for user i. Then $1 \le n_t \le N_t$ and $\sum_{i=1}^{M} k_i \le K$. We will adjust n_t and $\{k_i\}_{i=1}^{M}$ based on the channel fading gains and user's data rate requirements.

A typical implementation structure of MIMO-OFDMA systems is shown in Fig. 1. The data first pass the channel coding and modulation unit and are mapped into complex symbols. After spatial processing in the MIMO unit, the signals are fed to n_t active RF chains. Each RF branch performs several OFDM operations, including *series to parallel converting* (S/P), *inverse fast fourier transform* (IFFT), and *parallel to series converting* (P/S). After digital processing, the analog signals generated by the *digital-to-analog converter* (D/A) are filtered and up-converted to a high frequency band. Finally, the signals are transmitted after the *power amplifiers* (PAs).

We assume that users undergo frequency-selective and spatially uncorrelated block fading channels, where different OFDM symbols suffer from independent channel fading. Denote $\mathbf{H}_{ij}$ as the spatial channel matrix from the BS to user i on subcarrier j. The elements of $\mathbf{H}_{ij}$ are independent and identically Gaussian distributed with zero mean and variance μ_i, where μ_i is the average channel gain from the BS to user i. We assume that the instantaneous CSI is unavailable and the average channel gains, $\{\mu_i\}_{i=1}^{M}$, are known at the BS. *Single-user MIMO* (SU-MIMO) transceivers, which achieve the MIMO capacity without *CSI at the transmitter* (CSIT), are applied. The power for each user is equally distributed over multiple subcarriers and RF chains. The noise at the receiver of each user is additive white Gaussian with zero mean and variance σ^2.

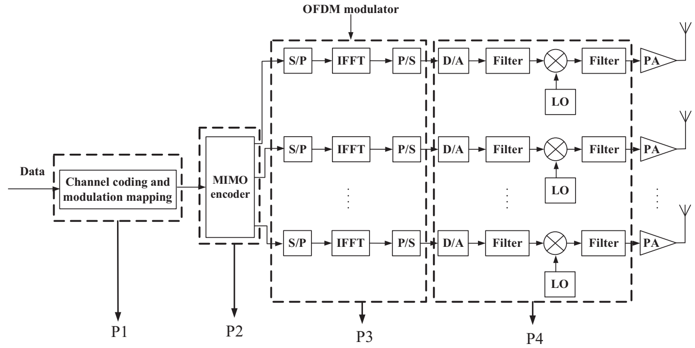

Fig. 1. Implementation structure of a MIMO-OFDMA system

TABLE I
Circuit Power consumptions of different components of BS in Fig. 1

Unit	Expression	Description
P1	$P_{c1}\sum_{i=1}^{M} C_i$	linearly increases with overall data rate [10], C_i is the data rate of user i and P_{c1} is a constant.
P2	$(\alpha n_t^2 + \beta n_t)P_{c2}\sum_{i=1}^{M} k_i$	linearly increases with overall number of used subcarriers.$(\alpha n_t^2 + \beta n_t)P_{c2}$ is the power consumed by matrix operations on each subcarrier [9]. α, β, and P_{c2} are constant.
P3	$n_t P_{c3}\sum_{i=1}^{M} k_i$	linearly increases with the number of used subcarriers and the number of active RF chains [9]. P_{c3} is a constant.
P4	$n_t P_{c4}$	linearly increases with the number of active RF chains [2]. P_{c4} is a constant.

B. Power Consumption at the BS

The total power consumed by the BS consists of the transmit power and circuit power and can be expressed as

$$P_{tot} = \frac{P_{tr}}{\rho} + P_{cc}, \tag{1}$$

where P_{tr} is the overall transmit power radiated to the air, P_{cc} is the circuit power, and ρ denotes the efficiency of the PA which is defined as the ratio of the output power of a PA to its input power.

The transmit power that is radiated to the air is contributed by all users. Denote P_i as the power per subcarrier at each RF chain for user i and then P_{tr} can be written as

$$P_{tr} = n_t \sum_{i=1}^{M} k_i P_i. \tag{2}$$

Besides a fixed circuit power consumption to maintain operations of the BS, circuit power consumptions from different components depend on different system parameters. For example, circuit power consumption from the channel coding and modulation mapping unit is proportional to the overall data rate [10]. The specific circuit power consumptions for different components are described in Table I. Based on the circuit power consumption models, the overall circuit power consumption at the BS can be written as follows,

$$\begin{aligned}P_{cc} =& P_{c1}\sum_{i=1}^{M} C_i + (\alpha n_t^2 + \beta n_t)P_{c2}\sum_{i=1}^{M} k_i + n_t P_{c3}\sum_{i=1}^{M} k_i \\ &+ n_t P_{c4} + P_{c5} \\ =& P_{c1}\sum_{i=1}^{M} C_i + \sum_{i=1}^{M} k_i g(n_t) + n_t P_{c4} + P_{c5},\end{aligned} \tag{3}$$

where $g(n_t) \triangleq \alpha P_{c2} n_t^2 + (\beta P_{c2} + P_{c3})n_t$, C_i denotes the data rate of user i, and P_{c5} is the fixed circuit power.

Substituting (2) and (3) into (1), the total power consumption at the BS can be finally expressed as

$$P_{tot} = \sum_{i=1}^{M} k_i \left[\frac{n_t P_i}{\rho} + g(n_t)\right] + P_{c1}\sum_{i=1}^{M} C_i + n_t P_{c4} + P_{c5}. \tag{4}$$

C. Ergodic Capacity for Each User

When the CSIT is not known at the BS and different OFDM symbols suffer from independent channel fading, the maximum achievable data date is equal to the ergodic capacity [11]. We assume that the transceiver that can achieve the channel capacity is applied and thus the data rate is the maximum value. Therefore, we will use the ergodic capacity instead of the data rate to avoid confusing from now on. For the SU-MIMO scheme, the ergodic capacity of user i can be expressed as [12]

$$\begin{aligned}C_i =& \Delta f \sum_{j=1}^{k_i} \mathbb{E}\left[\log_2 \det\left(\mathbf{I}_{N_r} + \frac{P_i}{\sigma^2}\mathbf{H}_{ij}\mathbf{H}_{ij}^H\right)\right] \\ =& \Delta f \sum_{j=1}^{k_i} \mathbb{E}\left[\log_2 \det\left(\mathbf{I}_{N_r} + \frac{\mu_i P_i}{\sigma^2}\frac{1}{\sqrt{\mu_i}}\mathbf{H}_{ij}\frac{1}{\sqrt{\mu_i}}\mathbf{H}_{ij}^H\right)\right] \\ =& \Delta f \sum_{j=1}^{k_i} \mathbb{E}\left[\log_2 \det\left(\mathbf{I}_{N_r} + \omega_i P_i \tilde{\mathbf{H}}_{ij}\tilde{\mathbf{H}}_{ij}^H\right)\right],\end{aligned} \tag{5}$$

where Δf denotes the subcarrier spacing, $\mathbf{I}_{N_r}$ denotes an $N_r \times N_r$ identity matrix, $\mathbb{E}[\cdot]$ denotes expectation operation over small scale fading, $\omega_i \triangleq \frac{\mu_i}{\sigma^2}$ represents the average channel gain from the BS to user i normalized by the noise power, and $\tilde{\mathbf{H}}_{ij} \triangleq \frac{1}{\sqrt{\mu_i}}\mathbf{H}_{ij}$ is the normalized channel matrix.

According to [12], the ergodic capacity in (5) can be calculated as follows,

$$\begin{aligned}C_i &= \Delta f \sum_{j=1}^{k_i} m \int_0^\infty \log_2(1 + \omega_i P_i x) p_{\mathbf{x}}(x)\mathrm{d}x \\ &= \Delta f k_i m \int_0^\infty \log_2(1 + \omega_i P_i x) p_{\mathbf{x}}(x)\mathrm{d}x,\end{aligned} \tag{6}$$

where $m \triangleq \min\{n_t, N_r\}$ and $p_{\mathbf{x}}(x)$ is the probability density function of all nonzero eigenvalues of $\tilde{\mathbf{H}}_{ij}\tilde{\mathbf{H}}_{ij}^H$, whose expression can be found in [12].

Denote

$$f(n_t, \omega_i P_i) = \Delta f m \int_0^\infty \log_2(1 + \omega_i P_i x) p_{\mathbf{x}}(x)\mathrm{d}x,$$

then we rewrite the ergodic capacity as

$$C_i = k_i f(n_t, \omega_i P_i). \tag{7}$$

D. Energy Efficiency Optimization

The EE in downlink transmission is defined as the overall average number of bits transmitted from the BS per unit energy [13], and is equal to the sum of capacities of multiple users per unit power. From the total power consumption in (4), we can obtain the EE of the downlink MIMO-OFDMA network as

$$\eta = \frac{\sum_{i=1}^{M} C_i}{\sum_{i=1}^{M} k_i \left[\frac{n_t P_i}{\rho} + g(n_t)\right] + P_{c1}\sum_{i=1}^{M} C_i + n_t P_{c4} + P_{c5}}. \tag{8}$$

The SE in downlink transmission, which is defined as the sum capacity per unit bandwidth, depends on the capacities of multiple users. To study the SE-EE relationship, we formulate a problem to maximize the EE under constraints on the capacities from multiple users.

When the capacities of multiple users are given, maximizing the EE is equivalent to minimizing the total power consumption. Considering the constraints on the total number of subcarriers and the number of active RF chains, the optimization problem can be formulated as follows,

$$\min_{n_t, \mathbf{K}, \mathbf{P}} \quad \sum_{i=1}^{M} k_i \left[\frac{n_t P_i}{\rho} + g(n_t)\right] + P_{c1}\sum_{i=1}^{M} C_i + n_t P_{c4} + P_{c5} \tag{9}$$

$$\text{s. t.} \quad k_i f(n_t, \omega_i P_i) = C_i, \qquad i = 1, 2, \cdots, M, \tag{9a}$$

$$\sum_{i=1}^{M} k_i \le K, \tag{9b}$$

$$1 \le n_t \le N_t, \tag{9c}$$

$$k_i > 0, \qquad P_i > 0, \qquad i = 1, 2, \cdots, M, \tag{9d}$$

where $\mathbf{K} \triangleq \{k_i\}_{i=1}^M$ denotes the set of numbers of subcarriers and $\mathbf{P} \triangleq \{P_i\}_{i=1}^M$ denotes the set of transmit powers. We will optimize the number of active RF chains, n_t, the number of subcarriers used by each user, $\{k_i\}_{i=1}^M$, and the transmit power for each user, $\{P_i\}_{i=1}^M$, to find the maximum EE.

III. Three-Step Searching Algorithm

Problem (9) is a mixed integer programming since both integer variables, n_t and $\{k_i\}_{i=1}^M$, and continuous variables, $\{P_i\}_{i=1}^M$, are included. Because the maximum number of subcarriers, K, is usually very large in MIMO-OFDMA systems, the number of possible integer values for $\{k_i\}_{i=1}^M$ is huge and finding the optimal values by exhaustive searching is complexity-prohibitive. Moreover, $f(n_t, \omega_i P_i)$ is a very complicated function of n_t [12], which makes it difficult to find the optimal n_t. In this section, we develop a three-step searching algorithm to obtain a solution with acceptable complexity. We first relax the numbers of subcarriers as continuous variables and find the optimal continuous solutions for $\{k_i\}_{i=1}^M$ and $\{P_i\}_{i=1}^M$ with a given n_t. Then we propose a searching algorithm to find the optimal n_t with minimum power consumption. Finally, we discretize the number of subcarriers used by each user. Note that only the discretization step will cause the performance loss.

A. Solution of Continuous Numbers of Subcarriers Given the Number of Active RF Chains

When the numbers of subcarriers occupied by multiple users, $\{k_i\}_{i=1}^M$, are relaxed as continuous variables, they can be expressed as functions of $\{P_i\}_{i=1}^M$ from constraint $(9a)$ as

$$k_i = C_i/f(n_t, \omega_i P_i), \qquad i = 1, 2, \cdots, M. \tag{10}$$

Substituting (10) into problem (9) and considering that constraint $(9c)$ can be discarded automatically for a given n_t, we can obtain a new optimization problem as follows,

$$\min_{\mathbf{P}} \quad \sum_{i=1}^{M} \frac{C_i\left[\frac{n_t P_i}{\rho} + g(n_t)\right]}{f(n_t, \omega_i P_i)} + P_{c1}\sum_{i=1}^{M} C_i + n_t P_{c4} + P_{c5} \tag{11}$$

$$\text{s. t.} \quad \sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_i)} \le K, \tag{11a}$$

$$P_i > 0, \qquad i = 1, 2, \cdots, M. \tag{11b}$$

The Lagrange function of this problem can be written as

$$L\left(\{P_i\}_{i=1}^M, \lambda, \{\xi_i\}_{i=1}^M\right) = \Phi(n_t, \mathbf{P}) + \lambda\left(\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_i)} - K\right) - \sum_{i=1}^{M} \xi_i P_i, \tag{12}$$

where $\Phi(n_t, \mathbf{P})$ denotes the objective function of problem (11), and λ and $\{\xi_i\}_{i=1}^M$ represent Lagrange multipliers for constraints $(11a)$ and $(11b)$, respectively. The *Karush-Kuhn-Tucker* (KKT) conditions of problem (11) can be expressed as follows,

$$n_t f(n_t, \omega_i P_i) - \omega_i\left[n_t P_i + \rho(g(n_t) + \lambda)\right] f'(n_t, \omega_i P_i) = 0 \quad i = 1, 2, \cdots, M, \tag{13a}$$

$$\lambda \ge 0, \quad \sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_i)} \le K, \tag{13b}$$

$$\lambda\left(\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_i)} - K\right) = 0, \tag{13c}$$

$$P_i > 0, \quad i = 1, 2, \cdots, M, \tag{13d}$$

$$\xi_i \ge 0, \text{ and } \xi_i P_i = 0, \quad i = 1, 2, \cdots, M, \tag{13e}$$

where the left hand side of $(13a)$ is the partial derivative of Lagrange function (12) with respect to P_i and $f'(n_t, \omega_i P_i) \triangleq \frac{\partial f(n_t, \gamma)}{\partial \gamma}|_{\gamma = \omega_i P_i}$.

Because the equality is only included in constraint $(11a)$, according to *linear independence constraint qualification* (LICQ) [14], the KKT conditions are necessary to achieve the global optimum of problem (11).

From complementary slackness condition, $\xi_i P_i = 0$ and condition $(13d)$, $P_i > 0$, we can obtain that $\xi_i = 0$. In the following, we find $\{P_i\}_{i=1}^M$ and λ that satisfy KKT conditions in two steps. We first obtain the solutions for equations $(13a)$ and $(13c)$ and then judge whether they satisfy inequalities $(13b)$ and $(13d)$.

It is proved in Appendix A that P_i which satisfies equation $(13a)$ is a monotonically increasing function with λ. Denoting $P_i = \theta_i(\lambda)$ and substituting it into $(13c)$, we have

$$\lambda\left(\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(\lambda))} - K\right) = 0. \tag{14}$$

Then we can find two solutions of λ that satisfy $(13a)$ and $(13c)$: $\lambda_1 = 0$ and λ_2 satisfies

$$\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(\lambda))} = K. \tag{15}$$

Next we judge whether λ_1 and λ_2 satisfy $(13b)$ and $(13d)$. When $\lambda = 0$, the term inside the bracket in (14) is not necessary to be equal to zero, which means the required total number of subcarriers does not need to be K. Based on this observation, we discuss the feasibility of λ_1 and λ_2 in the following two cases.

C 1. When $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(0))} \le K$, i.e., the total number of used subcarriers when $\lambda = 0$ is less than or equal to the maximum number, $\lambda_1 = 0$ satisfies $(13b)$ obviously. It is readily derived that $\lambda = -g(n_t)$ when $P_i = 0$. Therefore, $P_i > 0$ holds automatically when $\lambda = 0$ based on the monotonically increasing relationship between λ and P_i. Therefore, KKT condition $(13d)$ is satisfied. $\lambda_1 = 0$ is the solution of KKT conditions (13). Because $P_i = \theta_i(\lambda)$ is a monotonically increasing function of λ and $f(n_t, \omega_i P_i)$ is a monotonically increasing function of P_i, $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(\lambda))}$ decreases with λ due to the composition rule of monotonic function. Then, λ_2 that satisfies (15) is less than zero since $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(0))} \le K$. Therefore, condition $\lambda \ge 0$ is not satisfied for λ_2 and λ_2 is not a solution of the KKT conditions.

C 2. When $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(0))} > K$, $\lambda_1 = 0$ is not a solution of KKT conditions (13) since the second inequality in KKT condition $(13b)$ is not satisfied. From $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(0))} > K$ and $\lim_{\lambda \to \infty} \sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(\lambda))} = 0 < K$, we can conclude that λ_2 which satisfies (15) is greater than zero since $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i \theta_i(\lambda))}$ decreases with λ. Therefore, KKT condition $(13b)$ is satisfied. According to the monotonically increasing relationship between P_i and λ, we have $P_i = \theta_i(\lambda_2) > 0$ and thus KKT condition $(13d)$ is satisfied. Consequently, λ_2 is the solution of the KKT conditions.

From the above analysis, we can observe that there exists only one solution of λ in both cases. Since these two cases are disjoint, a unique solution of λ exists for KKT conditions (13). Due to the monotonically increasing relationship between P_i and λ, the solution of P_i is also unique for KKT conditions. Consequently, we obtain an optimal solution for the problem (11).

Note that due to the complicated relationship between λ and P_i as shown in $(13a)$, the closed-form expression of $P_i = \theta_i(\lambda)$ cannot be obtained. We use bisection searching algorithm to numerically find P_i for a given λ since P_i monotonically increases with λ [13], which is described in Table II*. In this algorithm, we first determine the interval that includes P_i which satisfies $(13a)$. Then we shorten the interval by half iteratively until the interval length is smaller than the required accuracy of P_i.

The specific procedure to find the optimal solution for problem (11), $\{P_i^c\}_{i=1}^M$, is summarized in Table III, which is

*Variables in expressions f and f' in this table are ignored for simplicity.

TABLE II
BISECTION SEARCHING ALGORITHM TO SOLVE $P_i = \theta_i(\lambda)$

Input: number of active RF chains at the BS and user sides, n_t and N_r, λ, and constants $\nu_1 > 0$, $\delta_1 > 1$, and $\epsilon_1 > 0$.
Output: power values, $\{P_i\}_{i=1}^M$, which satisfy $(13a)$, i.e., $P_i = \theta_i(\lambda), \quad i = 1, \cdots, M$

1. Set $P_{i,l} = 0$.
2. Initialize $P_{i,temp} = \nu_1$.
3. **while** $n_t f - \omega_i \left[n_t P_{i,temp} + \rho(g(n_t) + \lambda)\right] f' \leq 0$
4. $\quad$ $P_{i,temp} = \delta_1 P_{i,temp}$.
5. **end**
6. $P_{i,r} = P_{i,temp}$.
7. **while** $(P_{i,r} - P_{i,l}) > \epsilon_1$
8. $\quad$ $P_{i,temp} = (P_{i,l} + P_{i,r})/2$
9. $\quad$ **if** $n_t f - \omega_i \left[n_t P_{i,temp} + \rho(g(n_t) + \lambda)\right] f' < 0$,
10. $\quad\quad$ $P_{i,l} = P_{i,temp}$;
11. $\quad$ **else**
12. $\quad\quad$ $P_{i,r} = P_{i,temp}$;
13. $\quad$ **end**
14. **end**
15. $P_i = P_{i,temp}$.

mainly from the discussion on the above two cases. We first check whether the solution when $\lambda = 0$ satisfies the constraint on the total number of subcarriers in $(11a)$. If constraint $(11a)$ holds, it is the optimal solution for problem (11). Otherwise, we search the optimal nonzero λ and the optimal P_i by the bisection searching algorithm.

Substituting the optimal transmit power, $\{P_i^c\}_{i=1}^M$, into (10), we can obtain the optimal continuous values of the numbers of subcarriers for multiple users.

B. Find the Optimal Number of Active RF Chains

When the maximum number of RF chains at the BS, N_t, is small, we can compute the EE for each possible value of n_t in the interval $[1, N_t]$ and find the one with the maximum EE. When N_t is large, this leads to high computational complexity, which may cause considerable extra energy consumption. In the sequel, we develop a searching algorithm to find the optimal number of active RF chains for the case with a large N_t.

Before introducing the method to optimize n_t, we first present the properties of the objective function of problem (11) in Theorem 1, which is proved in Appendix B.

Theorem 1. *When the circuit power consumption is zero, the minimum value of the objective function of problem* (11) *does not depend on the number of active RF chains. When the circuit power consumption is not zero, the minimum value of the objective function of problem* (11) *increases with the number of active RF chains.*

Denote the minimum value of the objective function of problem (11) for a given n_t as $P_{tot}^{\dagger}(n_t)$ and the optimal value of problem (11) for a given n_t as $P_{tot}^{\star}(n_t)$, respectively. Since the optimal total power consumption, $P_{tot}^{\star}(n_t)$, is found by minimizing the objective function under some constraints, we know that

$$P_{tot}^{\dagger}(n_t) \leq P_{tot}^{\star}(n_t). \tag{16}$$

TABLE III
ALGORITHM FOR SOLVING KKT CONDITIONS (13)

Input: number of active RF chains at the BS and user sides, n_t and N_r, and constants $\nu_2 > 0$, $\delta_2 > 1$, and $\epsilon_2 > 0$.
Output: optimal power values for multiple users, $\{P_i^c\}_{i=1}^M$.

1. Find $P_{i,0}$ that satisfies $(13a)$ when $\lambda = 0$ by using the bisection searching algorithm in Table II.
2. **if** $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_{i,0})} \leq K$
3. $\quad$ $P_i^c = P_{i,0}$;
4. **else**
5. $\quad$ Set $\lambda_l = 0$ since $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_{i,0})} > K$
6. $\quad$ Initialize $\lambda_{temp} = \nu_2$.
7. $\quad$ Calculate $P_{i,temp}$ that satisfies $(13a)$ when $\lambda = \lambda_{temp}$ by the algorithm in Table II.
8. $\quad$ **while** $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_{i,temp})} \geq K$
9. $\quad\quad$ $\lambda_{temp} = \delta_2 \lambda_{temp}$ and calculate $P_{i,temp}$ that satisfies $(13a)$ when $\lambda = \lambda_{temp}$ by using the algorithm in Table II.
10. $\quad$ **end**
11. $\quad$ $\lambda_r = \lambda_{temp}$.
12. $\quad$ **while** $(\lambda_r - \lambda_l) > \epsilon_2$
13. $\quad\quad$ $\lambda_{temp} = (\lambda_l + \lambda_r)/2$ and calculate $P_{i,temp} = \theta_i(\lambda_{temp})$by using the algorithm in Table II.
14. $\quad\quad$ **if** $\sum_{i=1}^{M} \frac{C_i}{f(n_t, \omega_i P_{i,temp})} > K$,
15. $\quad\quad\quad$ $\lambda_l = \lambda_{temp}$;
16. $\quad\quad$ **else**
17. $\quad\quad\quad$ $\lambda_r = \lambda_{temp}$;
18. $\quad\quad$ **end**
19. $\quad$ **end**
20. $\quad$ $P_i^c = P_{i,temp}$.
21. **end**

Moreover, if the equality in constraint $(11a)$ does not hold at the optimal point when $n_t = n_0$, we have

$$P_{tot}^{\star}(n_0) = P_{tot}^{\dagger}(n_0). \tag{17}$$

According to Theorem 1, we know that for any $n_t > n_0$,

$$P_{tot}^{\dagger}(n_0) \leq P_{tot}^{\dagger}(n_t). \tag{18}$$

From (16), (17), and (18), we can conclude that

$$P_{tot}^{\star}(n_0) \leq P_{tot}^{\star}(n_t). \tag{19}$$

This conclusion implies that once we find the value of n_0, the optimal number of active RF chains to achieve the minimum power consumption over all possible values of n_t lies in the interval $[1, n_0]$. Consequently, we can first serially search n_0 from $n_t = 1$, then compute the total power consumption for each n_t in the interval $[1, n_0]$ and finally find the optimal number of active RF chains with minimal power consumption. When n_0 is much less than N_t, for example, when the capacity requirements of multiple users are very low, the complexity to find the optimal number can be dramatically reduced.

C. Discretization of the Continuous Numbers of Subcarriers

The continuous values of the subcarrier's numbers for multiple users need to be discretized for practical application. We discretize the numbers in two steps, which is summarized in Table IV. We first ensure that the total number of subcarriers occupied by multiple users is an integer that is nearest to the sum of the continuous numbers of subcarriers and its value is shown in (23). Then, we discretize the number of subcarriers for each user. We initially assign user i with the integer part of the continuous number of subcarriers as shown in line 2 of Table IV. Then the remaining subcarriers is allocated one by one to a user with the largest gap from its expected capacity as in lines 3-7 of this table.

After discretizing the number of subcarriers for each user, the transmit power $\{P_i^c\}_{i=1}^M$ may not satisfy the capacity requirements any more. According to (10), the final optimal transmit power values, $\{P_i^o\}_{i=1}^M$, should be

$$k_i^o f\left(n_t, \omega_i P_i^o\right) = C_i, \qquad i = 1, 2, \cdots, M. \tag{20}$$

Since $f\left(n_t, \omega_i P_i\right)$ is a monotonically increasing function with respect to P_i, P_i^o can be found numerically by the bisection searching algorithm [13].

TABLE IV
ALGORITHM FOR DISCRETIZING THE NUMBER OF SUBCARRIERS

Input: $\{k_i^c\}_{i=1}^M$, n_t, and $\{P_i^c\}_{i=1}^M$.
Output: the numbers of subcarriers for multiple users, $\{k_i^\star\}_{i=1}^M$.
1. Set the total number of used subcarriers to be
$$K_d = \left\lfloor \sum_{i=1}^M k_i^c \right\rfloor + \left\lfloor 2 * \left(\sum_{i=1}^M k_i^c - \left\lfloor \sum_{i=1}^M k_i^c \right\rfloor \right) \right\rfloor. \tag{23}$$
2. Initialize $k_i = \lfloor k_i^c \rfloor$, and $\Delta K = K_d - \sum_{i=1}^M \lfloor k_i^c \rfloor$.
3. **while** $\Delta K > 0$
4. Calculate the capacity gaps from the expected ergodic capacity as follows,
$$\chi_i \triangleq C_i - k_i f\left(n_t, \omega_i P_i^c\right). \tag{24}$$
5. $i_0 = \arg\max\{\chi_1, \cdots, \chi_M\}$ and $k_{i_0} = k_{i_0} + 1$.
6. $\Delta K = \Delta K - 1$.
7. **end**
8. **return** $k_i^* = k_i$.

IV. Impact of SE Requirement and Capacity Fairness among Users on EE

In the downlink network, data streams are transmitted to multiple users and thus both the downlink SE and the fairness among users affect the EE. Since it is very hard to analyze the impact when the numbers of subcarriers occupied by multiple users, $\{k_i\}_{i=1}^M$, are discrete variables, we relax them as continuous variables as in Section III.A.

Consider the sum capacity and capacity ratios as follows,

$$C_{tot} \triangleq \sum_{i=1}^M C_i, \quad \text{and} \quad \pi_i \triangleq \frac{C_i}{\sum\limits_{i=1}^M C_i}, \quad i = 1, \cdots, M. \tag{21}$$

Since the downlink SE is the ratio of the sum capacity to the system bandwidth, and the bandwidth is fixed, the impact of the SE requirement can be found by studying the relationship between C_{tot} and the EE. After substituting (21) into the objective function of problem (11), the optimal EE for a given n_t can be expressed as

$$\eta^\star(n_t) = \frac{C_{tot}}{\sum\limits_{i=1}^M \frac{C_{tot}\pi_i\left[n_t P_i^\star(n_t)/\rho + g(n_t)\right]}{f\left(n_t, \omega_i P_i^\star(n_t)\right)} + P_{c1}C_{tot} + n_t P_{c4} + P_{c5}}, \tag{22}$$

where $\{P_i^\star(n_t)\}_{i=1}^M$ is the optimal solution of problem (11) for a given n_t. The capacity ratios, $\{\pi_i\}_{i=1}^M$, reflect the fairness among users. In the following, we will investigate the impact of sum capacity and capacity ratios on the EE, respectively.

A. Impact of the SE Requirement

Similar to finding the solution of Lagrange multiplier for KKT conditions (13) in Section III, we investigate the impact of the SE in two cases. To simplify the following description, we denote the solution of Lagrange multiplier as $\lambda^\star$.

C 1. When $\sum_{i=1}^M \frac{C_i}{f(n_t, \omega_i \theta_i(0))} \le K$, i.e. $\sum_{i=1}^M \frac{C_{tot}\pi_i}{f(n_t, \omega_i \theta_i(0))} \le K$, we know from Section III A that $\lambda^\star$ is zero. Then KKT condition $(13a)$ becomes

$$n_t f\left(n_t, \omega_i P_i\right) - \omega_i\left[n_t P_i + \rho g(n_t)\right] f^{'}\left(n_t, \omega_i P_i\right) = 0. \tag{25}$$

It can be observed that the optimal power for user i, $P_i^\star(n_t)$, which is solved from (25) is independent of C_i and thus is not changed with the total data rate C_{tot}. When both the numerator and denominator of the EE expression in (22) are divided by C_{tot}, we can easily obtain that the optimal EE increases with C_{tot}.

C 2. When $\sum_{i=1}^M \frac{C_i}{f(n_t, \omega_i \theta_i(0))} > K$, the Lagrange multiplier, $\lambda^\star$, satisfies

$$\sum_{i=1}^M \frac{C_{tot}\pi_i}{f\left(n_t, \omega_i \theta_i(\lambda^\star)\right)} = K. \tag{26}$$

Due to the complicated relationship among C_{tot}, $\lambda^\star$, and $P_i^\star(n_t)$ shown in $(13a)$ and (26), it is difficult to study the impact of the SE on the EE in this case. Instead, we investigate an extreme scenario when the sum capacity goes to infinity. When $C_{tot} \to \infty$, we can easily find from (26) that $\sum_{i=1}^M \frac{\pi_i}{f(n_t, \omega_i \theta_i(\lambda^\star))} \to 0$. Therefore, $P_i^\star(n_t) \triangleq \theta_i(\lambda^\star)$ approaches infinity. Then the optimal EE in this extreme scenario can be derived as follows,

$$\lim_{C_{tot}\to\infty} \eta^\star(n_t) = \lim_{C_{tot}\to\infty} \frac{1}{\sum\limits_{i=1}^M \frac{\pi_i\left[n_t P_i^\star(n_t)/\rho + g(n_t)\right]}{f\left(n_t, \omega_i P_i^\star(n_t)\right)} + P_{c1} + \frac{n_t P_{c4} + P_{c5}}{C_{tot}}}$$

$$= \frac{1}{\sum_{i=1}^{M} \lim_{P_i^\star(n_t)\to\infty} \frac{\pi_i\left[n_t P_i^\star(n_t)/\rho + g(n_t)\right]}{f\left(n_t,\omega_i P_i^\star(n_t)\right)} + P_{c1}} = 0. \tag{27}$$

From the result that the optimal EE is zero when the sum of data rates goes to infinity, it can be implied that a tradeoff between the SE and the EE exists when $C_{tot} > \frac{K}{\sum_{i=1}^{M}\pi_i/f(n_t,\omega_i\theta_i(0))}$.

In summary, the above discussion reveals that when the SE is low enough such that $C_{tot} \le \frac{K}{\sum_{i=1}^{M}\pi_i/f(n_t,\omega_i\theta_i(0))}$, i.e., the total number of subcarriers used by all users is not constrained to the maximum number when $\lambda^\star = 0$, the optimal EE increases with the SE. When the SE is so large that $C_{tot} > \frac{K}{\sum_{i=1}^{M}\pi_i/f(n_t,\omega_i\theta_i(0))}$, there exists a tradeoff between the SE and the EE.

B. Impact of Capacity Fairness among Users

Substituting $\{C_i\}_{i=1}^M$ by C_{tot} and $\{\pi_i\}_{i=1}^M$, problem (11) is formulated as a linear program with respect to $\{\pi_i\}_{i=1}^M$. According to the simplex method of linear programming [15], the optimal solution is achieved only when at most two elements of $\{\pi_i\}_{i=1}^M$ are nonzero. Without loss of generality, we assume that π_j and π_k are nonzero. Then problem (11) is reformulated as

$$\min_{\mathbf{P}} \quad C_{tot}\left\{\frac{\pi_j\left[\frac{n_t P_j^r}{\rho\omega_j}+g(n_t)\right]}{f\left(n_t,P_j^r\right)} + \frac{\pi_k\left[\frac{n_t P_k^r}{\rho\omega_k}+g(n_t)\right]}{f\left(n_t,P_k^r\right)}\right\} + P_{c1}C_{tot} + n_t P_{c4} + P_{c5} \tag{28}$$

$$\text{s. t.} \quad C_{tot}\left[\frac{\pi_j}{f\left(n_t,P_j^r\right)} + \frac{\pi_k}{f\left(n_t,P_k^r\right)}\right] \le K, \tag{28a}$$

$$P_j^r > 0, \quad P_k^r > 0, \tag{28b}$$

where $P_i^r \triangleq \omega_i P_i$ denotes the received SNR of user i.

When the values of π_j, π_k, P_j^r, and P_k^r are given, the value of the objective function of problem (28) decreases with ω_j and ω_k. Therefore, choosing the maximum two values from $\{\omega_i\}_{i=1}^M$, i.e., selecting two users with maximum channel gains to transmit data, will minimize the total power consumption. Assume that ω_1 and ω_2 are the maximum two channel gains. We can further show that the maximal EE is achieved when $\pi_1 = 1$ in the following two extreme cases.

C 1. When $C_{tot} \to 0$, the equality in constraint $(28a)$ does not hold when the minimum value of problem (28) is achieved, we know from $(13c)$ that the solution of Lagrange multiplier, $\lambda^\star$, is zero. Then according to KKT condition $(13a)$, we can express the optimal values of transmit power, $P_1^\star(n_t)$ and $P_2^\star(n_t)$ as

$$P_i^\star(n_t) = \frac{f\left(n_t,\omega_i P_i^\star(n_t)\right)}{\omega_i f'(n_t,\omega_i P_i^\star(n_t))} - \frac{\rho}{n_t}g(n_t), \quad i=1,2. \tag{29}$$

After substituting it into (22), we have

$$\eta^\star(n_t) = \frac{C_{tot}}{\sum_{i=1}^{2}\frac{C_{tot}\pi_i n_t}{\rho\omega_i f'(n_t,\omega_i P_i^\star(n_t))} + P_{c1}C_{tot} + n_t P_{c4} + P_{c5}}. \tag{30}$$

It is proved in Appendix C that the term $\omega_i f'(n_t,\omega_i P_i^\star(n_t))$ increases with ω_i. Then we can obtain $\frac{n_t}{\rho\omega_1 f'(n_t,\omega_1 P_1^\star(n_t))} < \frac{n_t}{\rho\omega_2 f'(n_t,\omega_2 P_2^\star(n_t))}$. Furthermore,

$$\eta^\star(n_t) \le \frac{C_{tot}}{\frac{n_t C_{tot}}{\rho\omega_1 f'(n_t,\omega_1 P_1^\star(n_t))} + P_{c1}C_{tot} + n_t P_{c4} + P_{c5}}, \tag{31}$$

where the equality holds when $\pi_1 = 1$.

C 2. When $C_{tot} \to \infty$, the equality in constraint $(28a)$ holds when the minimum value of problem (28) is achieved. The optimal transmit power satisfies

$$C_{tot}\left[\frac{\pi_1}{f\left(n_t,\omega_1 P_1^\star(n_t)\right)} + \frac{\pi_2}{f\left(n_t,\omega_2 P_2^\star(n_t)\right)}\right] = K. \tag{32}$$

Substituting (32) into (22), the optimal EE becomes

$$\eta^\star(n_t) = \frac{C_{tot}}{\sum_{i=1}^{2}\frac{C_{tot}n_t\pi_i P_i^\star(n_t)}{\rho f\left(n_t,\omega_i P_i^\star(n_t)\right)} + Kg(n_t) + P_{c1}C_{tot} + n_t P_{c4} + P_{c5}}. \tag{33}$$

Since $P_i^\star(n_t) \to \infty$ when $C_{tot} \to \infty$, $f(n_t,\omega_i P_i^\star(n_t))$ can be approximated as follows,

$$f\left(n_t,\omega_i P_i^\star(n_t)\right) \approx \Delta f m \int_0^\infty \log_2(\omega_i P_i^\star(n_t)x)p_{\mathbf{x}}(x)\mathrm{d}x = \Delta f m\left(\log_2(\omega_i P_i^\star(n_t)) + \int_0^\infty \log_2 x p_{\mathbf{x}}(x)\mathrm{d}x\right). \tag{34}$$

Using this approximation, we prove in Appendix D that $\frac{\pi_i P_i^\star(n_t)}{f\left(n_t,\omega_i P_i^\star(n_t)\right)}$ decreases with ω_i. Consequently, the optimal EE satisfies

$$\eta^\star(n_t) \le \frac{C_{tot}}{\frac{C_{tot}n_t P_1^\star(n_t)}{\rho f\left(n_t,\omega_i P_i^\star(n_t)\right)} + Kg(n_t) + P_{c1}C_{tot} + n_t P_{c4} + P_{c5}},$$

where the equality holds when $\pi_1 = 1$.

We have shown from the above analysis that the optimal EE is maximized when all data are transmitted by at most two users with the maximum channel gains in general cases. For two extreme cases, it is concluded that the optimal EE is maximized when all data are transmitted to one user with the maximum channel gain. These results imply that sacrificing the fairness among users can gain better performance.

V. Simulation Results

In this section, we first study the impact of the SE, the fairness among users, and the spatial- frequency resources on the EE. Then we show the impact of the maximum amount of spatial and frequency resources on the relationship between the SE and the EE. Finally, we demonstrate the performance gain of jointly configuring spatial-frequency resources over those only adaptively configuring spatial or frequency resource. Main system parameters in the simulation are similar

TABLE V
LIST OF SIMULATION PARAMETERS

Subcarrier spacing, Δf	15 kHz
Maximum number of subcarriers, K	512, 768, 1024
Number of RF chains at the BS, N_t	2, 4, 8
Number of RF chains at each user, N_r	4
Power spectral density of noise	-174 dBm/Hz
Noise amplifier gain	7 dBi
Minimum distance from BS to users	35 m
Path loss (dB)	35 + 38 $\log_{10} d$
Efficiency of power amplifier, ρ	38%
P_{c1}	0.01 μW
αP_{c2}	20 mW
$\beta P_{c2} + P_{c3}$	20 mW
P_{c4}	1000 mW
P_{c5}	10000 mW

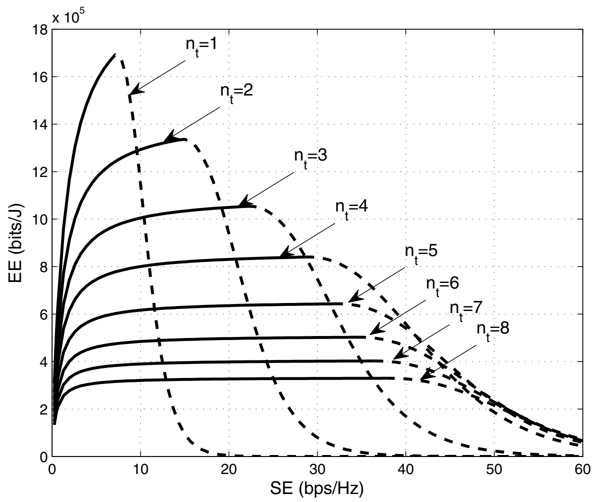

Fig. 2. EE vs. SE when the sum capacity is uniformly distributed among 8 users, $K = 1024$, and $N_t = 8$.

to those in [9] and are listed in Table V. Since the configuration of spatial and frequency resources depends on the channel gains of multiple users, we fix user locations to study the impact of the SE and the fairness among users. The distances of 8 users from the BS are set to 60 m,80 m,100 m,120 m,140 m,160 m,180 m, and 200 m, respectively.

Figure 2 shows the EEs achieved by the algorithm in Section IV.A versus the SE with different numbers of active RF chains at the BS. We can divide the SE region into two parts based on whether the total number of used subcarriers is constrained to the maximum value when the optimum of (11) is achieved. Solid curves represent the unconstrained regions while dash curves represent the constrained regions. We can see that the optimal EE increases with the SE in the unconstrained regions while there exists a tradeoff between the SE and the EE in the constrained regions. We can further observe that in the unconstrained regions, the EE decreases with the number of active RF chains, which is consistent with Theorem 1.

When we select the maximum value from all the EEs under different numbers of active RF chains, we can obtain the maximum EE by optimizing the number of active RF chains. We plot the optimal number of active RF chains and the sum of optimal numbers of used subcarriers in Fig. 3. We can see that both the amount of used spatial resource and that of

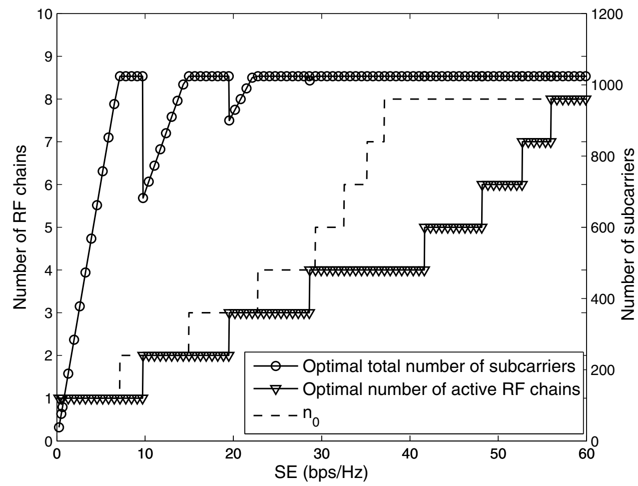

Fig. 3. Optimal number of active RF chains and optimal total number of subcarriers vs. SE when the sum capacity is uniformly distributed among 8 users, $K = 1024$, and $N_t = 8$.

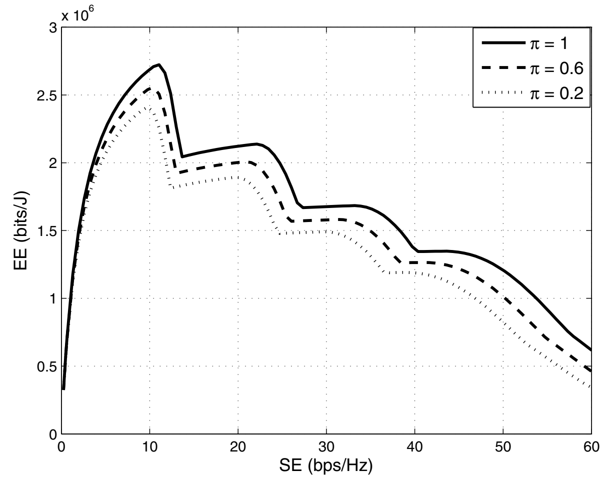

Fig. 4. EE vs. SE under different capacity ratios when $K = 1024$ and $N_t = 8$.

frequency resource increase with the SE. We can also observe that the optimal number of active RF chains increases only when the the sum of optimal numbers of used subcarriers is constrained to the maximum value, K. This phenomenon implies that frequency resource is more beneficial to increase the EE than spatial resource in MIMO-OFDMA systems. We also plot n_0 which is mentioned in Section III.B versus the SE. We can see that the value of n_0 increases with the SE and is much smaller than N_t in the low SE region. Therefore, the complexity to find the optimal number of active RF chains can be greatly reduced by the serial searching method in the low SE region.

In Fig. 4 and Fig. 5, we demonstrate the impact of fairness among users on the EE and the required optimal spatial and frequency resources, respectively. Because we have proved in Section IV.B that the optimal EE is maximized when all data are transmitted to at most two users with the maximum channel gains. We only consider the case when the sum capacity is only allocated to the users which are 60 m and 80 m away from the BS. Denote π as the capacity ratio for the user 60 m away from the BS. Fig. 4 shows that the EE

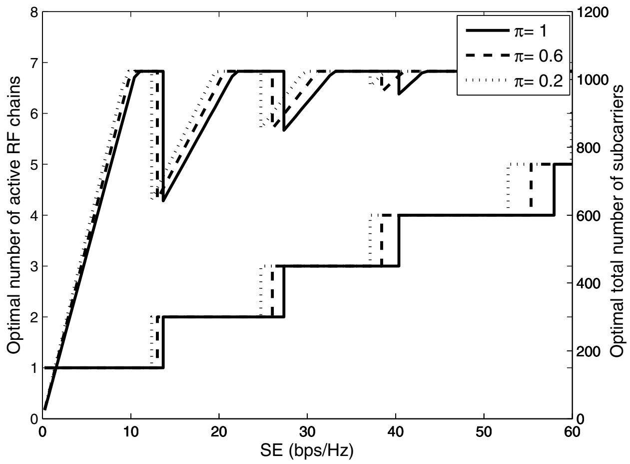

Fig. 5. Optimal number of active RF chains and optimal total number of subcarriers vs. SE under different capacity ratios when $K = 1024$ and $N_t = 8$.

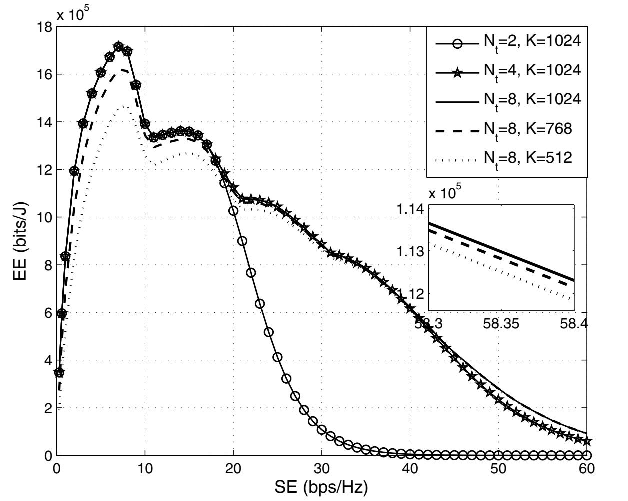

Fig. 6. Impact of the maximum number of subcarrier, K, and that of RF chains, N_t, on the relationship between the EE and the SE.

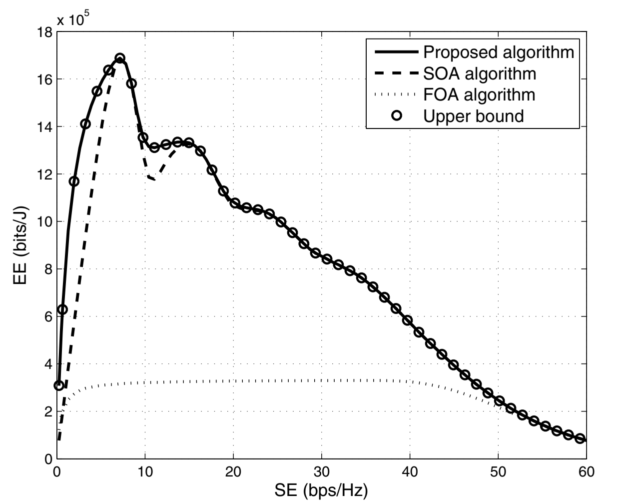

Fig. 7. Comparison of the performance of different resource configuration schemes when $K = 1024$ and $N_t = 8$.

increases with π, which implies that transmitting more data by the user with highest channel gain improves the relationship between the SE and the EE as a whole. This allows us to extend the conclusion in the extreme two cases in Section IV.B to general cases. From Fig. 5, we can see that both the optimal number of active RF chains and the sum of the optimal numbers of subcarriers decrease with π, which means that transmitting more data by the user with higher channel gain can also reduce the required resources.

In the following simulation, we consider that 8 users are uniformly distributed within a circle with radius of 200 m and the required sum capacity is randomly allocated to multiple users. Fig. 6 shows the impact of the maximum amount of spatial and frequency resources on the SE-EE relationship. We can see that the relationship can be improved as a whole by increasing the overall frequency resource while increasing the overall spatial resource can only increase the relationship in the high SE region. This also infers that the frequency resource is more efficient than the spatial resource to improve the SE-EE relationship.

Figure 7 shows the benefit of adaptive configuration of both spatial and frequency resources. We compare the EE of the proposed algorithm with *spatial-only adaptation* (SOA) and *frequency-only adaptation* (FOA). For the SOA, the total number of used subcarriers is set to be the maximum number, K. For the FOA, the number of active RF chains at the BS is set to be the maximum value, N_t. As shown in the figure, the *spatial-frequency-adaptation* outperforms both SOA and FOA and its performance is overlapped with its upper bound which is obtained by relaxing the numbers of subcarriers used by 8 users as continuous variables. This means that the proposed algorithm is near-optimal. In most of the SE region, the SOA outperforms the FOA.

VI. Conclusion

In this paper, we have studied the configuration of spatial and frequency resources from the perspective of maximizing the EE for downlink MIMO-OFDMA systems when channel information is not available at the BS. We first formulated an optimization problem to minimize the total power including transmit power and circuit power consumption at the BS with ergodic capacity requirements from multiple users. Then we developed a three-step searching algorithm, which first found the continuous variable solution for the number of subcarriers occupied by each user based on the KKT conditions, then optimized the number of active RF chains, and finally discretized the number of subcarriers for each user with the optimal number of active RF chains. We investigated the impact of the SE and the user fairness on the optimal EE. It is shown that a tradeoff between the SE and the EE exists when the total number of active subcarriers is restricted to a maximum value. The optimal number of active RF chains increases only when the total number of used subcarriers cannot be increased, which means that frequency resource is more efficient than spatial resource on improving the EE. Moreover, increasing the amount of frequency resource can improve the SE-EE relationship as a whole while increasing the amount of spatial resource can only gain the enhancement in the high SE region. Transmitting more data by users with larger channel gains can obtain better SE-EE relationship, which implies a tradeoff between the capacity fairness among users and the EE. The proposed spatial-frequency resource adaptive configuration outperforms both the spatial-only-adaptation and the frequency-only-adaptation.

APPENDIX A
PROOF OF MONOTONICALLY INCREASING OF THE OPTIMAL P_i WITH λ

According to $(13a)$, λ can be expressed as

$$\lambda = \frac{n_t}{\rho}\left(\frac{f\left(n_t, \omega_i P_i\right)}{\omega_i f'\left(n_t, \omega_i P_i\right)} - P_i\right) - g(n_t).$$

Then we can obtain the derivative of λ on P_i as

$$\frac{d\lambda}{dP_i} = -\frac{n_t f\left(n_t, \omega_i P_i\right) f''\left(n_t, \omega_i P_i\right)}{\rho(f'\left(n_t, \omega_i P_i\right))^2},$$

where $f''\left(n_t, \omega_i P_i\right) \triangleq \frac{\partial^2 f(n_t,\gamma)}{\partial \gamma^2}|_{\gamma=\omega_i P_i}$. Because $f(n_t, \omega_i P_i)$ is a concave function with respect to P_i as shown in the expression under (7), we have $f''\left(n_t, \omega_i P_i\right) < 0$. Consequently we can conclude $\frac{d\lambda}{dP_i} > 0$ and thus λ is a monotonically increasing function of P_i.

APPENDIX B
PROOF OF THEOREM 1

When the circuit power is zero, the objective function of problem (11) becomes

$$P_{tot} = \sum_{i=1}^{M} \frac{C_i n_t P_i}{\rho f\left(n_t, \omega_i P_i\right)}. \tag{35}$$

Differentiating P_{tot} with respect to P_i, we can obtain

$$\frac{\partial P_{tot}}{\partial P_i} = \frac{C_i n_t}{\rho} \frac{f\left(n_t, \omega_i P_i\right) - \omega_i P_i f'\left(n_t, \omega_i P_i\right)}{f^2\left(n_t, \omega_i P_i\right)}. \tag{36}$$

Since $f\left(n_t, \omega_i P_i\right) \triangleq \Delta f m \int_0^{\infty} \log_2(1+\omega_i P_i x) p_{\mathbf{x}}(x) \mathrm{d}x$, which is a strict concave function with respect to $\omega_i P_i$ and $f\left(n_t, 0\right) = 0$, we have

$$f\left(n_t, \omega_i P_i\right) - \omega_i P_i f'\left(n_t, \omega_i P_i\right) > 0. \tag{37}$$

Substituting (37) into (36), we can obtain that $\frac{\partial P_{tot}}{\partial P_i} > 0$, which means that the total power consumption increases with P_i. Therefore, the minimum power consumption is achieved when $P_i = 0$ and its value is

$$P_{tot}^{min} = \sum_{i=1}^{M} \left.\frac{C_i n_t P_i}{\rho f\left(n_t, \omega_i P_i\right)}\right|_{P_i=0}. \tag{38}$$

According to L′Hôpital′s rule, we can further derive

$$P_{tot}^{min} = \sum_{i=1}^{M} \frac{C_i n_t}{\rho \left.\frac{\partial f(n_t, \omega_i P_i)}{\partial P_i}\right|_{P_i=0}}. \tag{39}$$

Based on the expression of $f\left(n_t, \omega_i P_i\right)$, we can easily find its derivative at $P_i = 0$ as follows,

$$\left.\frac{\partial f\left(n_t, \omega_i P_i\right)}{\partial P_i}\right|_{P_i=0} = \frac{\Delta f m \omega_i}{\ln 2} \int_0^{\infty} x p_{\mathbf{x}}(x) \mathrm{d}x = \frac{\Delta f \omega_i N_r n_t}{\ln 2}. \tag{40}$$

Substituting (40) into (39), we can finally obtain the minimum power consumption as

$$P_{tot}^{min} = \frac{\ln 2}{\rho \Delta f N_r} \cdot \sum_{i=1}^{M} \frac{C_i}{\omega_i}. \tag{41}$$

We can see from (41) that when the circuit overhead is zero, the minimum power consumption is independent of the number of transmit antennas.

When the circuit power is not zero, we prove the theorem by first studying the property of $f\left(n_t, \omega_i P_i\right)$.

According to (5), the matrix form of $f\left(n_t, \omega_i P_i\right)$ is

$$f\left(n_t, \omega_i P_i\right) = \Delta f \mathbb{E}[\log_2 \det(\mathbf{I}_{N_r} + \omega_i P_i \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H)], \tag{42}$$

where $\mathbf{H}_{n_t}$ denotes an $N_r \times n_t$ matrix whose elements are subject to Gaussian distribution with zero mean and unit variance. To simplify the following expressions, we denote $\gamma = \omega_i P_i$. We first study some properties of $f(n_t, \gamma)$. From (42), we can derive $f\left(n_t+1, \gamma\right)$ as follows,

$$\begin{aligned} f\left(n_t+1, \gamma\right) &= \Delta f \mathbb{E}[\log_2 \det(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t+1} \mathbf{H}_{n_t+1}^H)] \\ &= \Delta f \mathbb{E}\left[\log_2 \det(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H + \gamma \mathbf{h}\mathbf{h}^H)\right], \end{aligned}$$

where the matrix partition, $\mathbf{H}_{n_t+1} = \left[\begin{array}{cc} \mathbf{H}_{n_t} & \mathbf{h} \end{array}\right]$, is used. Then we can obtain

$$\begin{aligned} &\frac{f\left(n_t, \gamma\right) - f\left(n_t+1, \gamma\right)}{\Delta f} \\ &= \mathbb{E}[\log_2 \det\left((\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H)\right)] - \\ &\quad \mathbb{E}\left[\log_2 \det(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H + \gamma \mathbf{h}\mathbf{h}^H)\right] \\ &= -\mathbb{E}\left[\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h}\right)\right], \end{aligned} \tag{43}$$

where the matrix inverse lemma is used. Similarly, we can derive

$$\begin{aligned} &\frac{f\left(n_t+1, \gamma\right) - f\left(n_t+2, \gamma\right)}{\Delta f} \\ &= -\mathbb{E}\left[\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t+1} \mathbf{H}_{n_t+1}^H\right)^{-1} \mathbf{h}\right)\right] \\ &= -\mathbb{E}\left[\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma(\mathbf{H}_{n_t} \mathbf{H}_{n_t}^H + \mathbf{h}_1 \mathbf{h}_1^H)\right)^{-1} \mathbf{h}\right)\right] \\ &= -\mathbb{E}\left[\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h} - \gamma \mathbf{h}^H \mathbf{A} \mathbf{h}\right)\right], \end{aligned}$$

where $\mathbf{H}_{n_t+1} = \left[\begin{array}{cc} \mathbf{H}_{n_t} & \mathbf{h}_1 \end{array}\right]$ is used and $\mathbf{A} \triangleq \frac{\left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h}_1 \mathbf{h}_1^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1}}{\left(\frac{1}{\gamma} + \mathbf{h}_1^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h}_1\right)}$.

It is easy to show that $\mathbf{A}$ is a positive semi-definite matrix. Then we have

$$\begin{aligned} &\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h}\right) \geq \\ &\log_2\left(1 + \gamma \mathbf{h}^H \left(\mathbf{I}_{N_r} + \gamma \mathbf{H}_{n_t} \mathbf{H}_{n_t}^H\right)^{-1} \mathbf{h} - \gamma \mathbf{h}^H \mathbf{A} \mathbf{h}\right). \end{aligned}$$

Since $\mathbf{H}_{n_t}$, $\mathbf{h}_1$ and $\mathbf{h}$ are mutually independent, the equality dose not hold for all the possible values of $\mathbf{H}_{n_t}$, $\mathbf{h}_1$ and $\mathbf{h}$. Consequently, we can obtain

$$f(n_t{+}2, \gamma) - f(n_t{+}1, \gamma) < f(n_t{+}1, \gamma) - f(n_t, \gamma),\ n_t = 1, \cdots. \tag{44}$$

In addition, we can easily prove from (43) that $f(2, \gamma) - f(1, \gamma) < f(1, \gamma)$. Defining $f(0, \gamma) = 0$, (44) also holds when $n_t = 0$. Based on this result, we derive the following inequality as

$$\begin{aligned} f(n_t+1, \gamma) - f(n_t, \gamma) &< \frac{1}{n_t} \sum_{i=1}^{n_t} \left(f(i, \gamma) - f(i-1, \gamma)\right) \\ &= \frac{f(n_t, \gamma)}{n_t}. \end{aligned}$$

Finally, we have

$$\frac{f(n_t+1,\gamma)}{n_t+1} < \frac{f(n_t,\gamma)}{n_t}. \tag{45}$$

Meanwhile, the objective function of problem (11) can be rewritten as

$$\begin{aligned}\Phi(n_t,\mathbf{P}) =& \sum_{i=1}^{M} \frac{C_i\left[P_i/\rho + g(n_t)/n_t\right]}{f\left(n_t,\omega_i P_i\right)/n_t} + P_{c1}\sum_{i=1}^{M} C_i \\ &+ n_t P_{c4} + P_{c5}.\end{aligned} \tag{46}$$

We know from the expression of $g(n_t)$ that $g(n_t)/n_t$ increases with n_t when $g(n_t) \neq 0$. Moreover, $f\left(n_t,\omega_i P_i\right)/n_t$ decreases with n_t as shown in (45). Therefore, $\Phi(n_t,\mathbf{P})$ increases with n_t, i.e.,

$$\Phi(n_t,\mathbf{P}) < \Phi(n_t+1,\mathbf{P}). \tag{47}$$

Finally we have

$$\min_{\mathbf{P}}\{\Phi(n_t,\mathbf{P})\} < \min_{\mathbf{P}}\{\Phi(n_t+1,\mathbf{P})\}. \tag{48}$$

Consequently, the minimum value of the objective function in problem (11) increases with n_t when the circuit power related to RF chains is not zero.

Appendix C
Proof of the Increasing of $\omega_i f^{'}(n_t,\omega_i P_i)$ with ω_i

We can define an implicit function from KKT condition $(13a)$ as follows,

$$F(\omega_i,P_i) \triangleq n_t f_i - \omega_i\left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i^{'}, \tag{49}$$

where notations, $f_i \triangleq f\left(n_t,\omega_i P_i\right)$ and $f_i^{'} \triangleq f^{'}\left(n_t,\omega_i P_i\right)$ are used to simplify the expression.

According to the implicit function theorem, P_i can be expressed as a function of ω_i from KKT condition, $F(\omega_i,P_i) = 0$, and its derivative with respect to ω_i can be calculated as

$$\begin{aligned}\frac{\mathrm{d}P_i}{\mathrm{d}\omega_i} &= -\frac{F^{'}_{\omega_i}}{F^{'}_{P_i}} \\ &= -\frac{\rho(g(n_t)+\lambda)f_i^{'} + \left[n_t P_i + \rho(g(n_t)+\lambda)\right]\omega_i P_i f_i^{''}}{\omega_i^2\left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i^{''}},\end{aligned} \tag{50}$$

where $f_i^{''} \triangleq f^{''}\left(n_t,\omega_i P_i\right)$ is used to simplify the expression.

Then the derivative of $\omega_i f_i^{'}$ with respect to ω_i can be derived as follows,

$$\begin{aligned}\frac{\mathrm{d}(\omega_i f_i^{'})}{\mathrm{d}\omega_i} &= f_i^{'} + \omega_i f_i^{''}\left(P_i + \omega_i\frac{dP_i}{d\omega_i}\right) \\ &= f_i^{'} - \omega_i f_i^{''}\frac{\rho(g(n_t)+\lambda)f_i^{'}}{\omega_i\left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i^{''}} \\ &= \frac{n_t P_i f_i^{'}}{n_t P_i + \rho(g(n_t)+\lambda)},\end{aligned} \tag{51}$$

where (50) is used. We know that $f_i^{'} > 0$ because f_i is a monotonically increasing function of P_i. Therefore, $\frac{\mathrm{d}(\omega_i f_i^{'})}{\mathrm{d}\omega_i} > 0$, which means that $\omega_i f_i^{'}$ is a monotonically increasing function of ω_i.

Appendix D
Proof of the Decreasing of $\frac{P_i^\star(n_t)}{f\left(n_t,\omega_i P_i^\star(n_t)\right)}$ with ω_i

From KKT condition $(13a)$, P_i can be expressed as a function of ω_i and its derivative is shown in (50). Denoting $y(\omega_i) = \frac{P_i}{f_i}$, we can find the derivative of $y(\omega_i)$ with respect to ω_i as shown on the top of this page.

Due to the concavity of f_i, we know $f_i^{''} < 0$. Therefore, we can obtain

$$\frac{\mathrm{d}y(\omega_i)}{\mathrm{d}\omega_i} < \frac{\rho(g(n_t)+\lambda)\left(\omega_i P_i f_i^{'2} - f_i^{'} f_i - \omega_i P_i f_i^{''} f_i\right)}{\omega_i^2\left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i^{''} f_i^2}. \tag{52}$$

Based on the approximation of $f\left(n_t,\omega_i P_i^\star(n_t)\right)$ in (34), we have

$$\omega_i P_i f_i^{'2} - f_i^{'} f_i - \omega_i P_i f_i^{''} f_i = \omega_i P_i f_i^{'2}.$$

Substituting it into (52), we have

$$\frac{\mathrm{d}y(\omega_i)}{\mathrm{d}\omega_i} < \frac{\rho(g(n_t)+\lambda)\omega_i P_i f_i^{'2}}{\omega_i^2\left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i^{''} f_i^2}. \tag{53}$$

Because $f_i^{''} < 0$, we can conclude that $\frac{\mathrm{d}y(\omega_i)}{\mathrm{d}\omega_i} < 0$ and $\frac{P_i^\star(n_t)}{f\left(n_t,\omega_i P_i^\star(n_t)\right)}$ decreases with ω_i.

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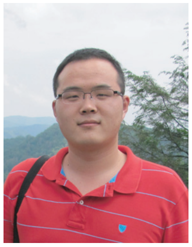
$$\frac{\mathrm{d}y(\omega_i)}{\mathrm{d}\omega_i} = \frac{\frac{\mathrm{d}P_i}{\mathrm{d}\omega_i} f_i - P_i f_i'\left(P_i + \omega_i \frac{\mathrm{d}P_i}{\mathrm{d}\omega_i}\right)}{f_i^2} = \frac{\omega_i P_i \rho(g(n_t)+\lambda) f_i'^2 - \rho(g(n_t)+\lambda) f_i' f_i - \left[n_t P_i + \rho(g(n_t)+\lambda)\right] \omega_i P_i f_i'' f_i}{\omega_i^2 \left[n_t P_i + \rho(g(n_t)+\lambda)\right] f_i'' f_i^2}.$$



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