Energy and Spectral Efficiency Tradeoff with User Association and Power Coordination in Massive MIMO Enabled HetNets

Yuanyuan Hao, Qiang Ni, Hai Li, and Shujuan Hou

***Abstract*—In this paper, we investigate the tradeoff between energy efficiency (EE) and spectral efficiency (SE) while ensuring proportional rate fairness in massive multiple-input-multiple-output enabled heterogenous networks, where user association and power coordination are jointly considered. It is first formulated as a multi-objective optimization problem, and then transformed into a single-objective optimization problem. To solve this mixed-integer non-convex problem, an effective algorithm is developed, where the original problem is separated into *lower level* power coordination problem and *master* user association problem. Simulation results verify that our proposed algorithm can significantly improve the performance of EE-SE tradeoff and obtain higher rate fairness compared to other algorithms.**

***Index Terms*—Energy efficiency, spectral efficiency, massive MIMO, HetNets, user association, power coordination.**

I. Introduction

MASSIVE multiple-input-multiple-output (MIMO) and dense heterogenous networks (HetNets) can significantly improve energy efficiency (EE), spectral efficiency (SE), which are recognized as promising technologies in the future fifth-generation (5G) cellular networks. Meanwhile, green communication has caught substantial attentions due to steadily rising energy costs and environmental concerns. Therefore, increasing EE has become an essential issue in 5G networks [1].

Energy-efficient resource allocation in HetNets has been considered extensively in the literature [2]. However, the research on energy-efficient massive MIMO enabled HetNets is still limited. The authors in [3] analyze the effect of massive MIMO on the SE and EE of K-tier HetNets. In [4], the network EE is maximized, but only the user association is optimized and the transmit power of each base station (BS) is fixed. Although EE is the major design metric for green communications, optimal EE and SE are not always achievable simultaneously and often conflict with each other [5], [6]. The EE-SE tradeoff in HetNets is studied in [7], while the power coordination is optimized with predefined user association.

In this letter, we comprehensively consider the joint user association and power coordination optimization problem in massive MIMO enabled HetNets to investigate the EE-SE tradeoff with proportional rate fairness. To the best of our knowledge, this issue has not been studied in the existing literature. We first formulate it as a multi-objective optimization (MOO) problem, and then transform it into a single-objective optimization (SOO) problem. To solve this mixed-integer non-convex problem, we employ the primal decomposition approach to divide it into *lower level* power coordination problem and *master* user association problem, which are further solved by sequential convex programming algorithm and Lagrangian dual decomposition (LDD) method, respectively. Simulation results provide insights on the EE-SE tradeoff and rate fairness among users, and demonstrate that our proposed algorithm can achieve better EE and SE performance while ensuring higher rate fairness compared to other algorithms.

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II. System Model

Consider a two-tier HetNet composed of a macro BS (MBS) equipped with a large-scale array of M antennas, $J-1$ single-antenna pico BSs (PBS), and K single-antenna users. Let $j \in \{1, 2, \cdots, J\}$ be the index of BSs, where $j = 1$ denotes the MBS, and the others are PBSs. Besides, all BSs share the same frequency band, and each user can be only associated with one BS at any time. Equal resource sharing is also assumed for users associated with the same BS. $\mathbf{x} = [x_{jk}]$ is then introduced to describe the user association, where $x_{jk} = 1$ if user k is associated with BS j, and $x_{jk} = 0$, otherwise. We also define $\mathbf{p} = [p_1, p_2, \cdots p_J]$ as the transmit power vector of all BSs.

We assume that the massive MIMO MBS can transmit at most N ($N \ll M$) downlink data streams simultaneously over the same frequency band, and zero-forcing beamforming is used for the massive MIMO downlink transmission. Thus, the achievable downlink data rate of user k associated with MBS is approximated as [8]

$$r_{jk} = \frac{N}{k_j}\log_2\left(1+\frac{M-N+1}{N}\cdot\frac{p_j h_{jk}}{\sum\limits_{i\neq 1} p_i h_{ik}+\sigma_k^2}\right),\ j=1, \tag{1}$$

where $k_j = \sum\limits_k x_{jk}$ denotes the number of users associated with BS j, h_{jk} represents the channel gain, and σ_k^2 is the noise power. Note that there is no small-scale fading in (1), which is proven to be accurate [8].

For users associated with the same PBS, the achievable downlink rate of user k associated with PBS j is

$$r_{jk} = \frac{1}{k_j}\log_2\left(1+\frac{p_j h_{jk}}{\sum\limits_{i\neq j} p_i h_{ik}+\sigma_k^2}\right),\ j>1. \tag{2}$$

On the other hand, the total power consumption of the MBS can be expressed as [9] $P_j = \frac{p_j}{\varepsilon_j} + M\rho + \xi_j,\ j = 1$, where ε_j denotes the power amplifier efficiency, ρ describes the circuit power per antenna, and ξ_j represents the static circuit power term independent of the antenna number. In contrast, the power consumption of single-antenna PBS j is given by $P_j = \frac{p_j}{\varepsilon_j} + \xi_j, j > 1$. Thus, the network total power consumption can be calculated as

$$P_{\rm tot} = \sum_j P_j = M\rho + \sum_j (p_j/\varepsilon_j + \xi_j). \tag{3}$$

III. Problem Formulation

To study the EE-SE tradeoff while ensuring proportional rate fairness, we formulate the joint user association and power coordination problem as a MOO problem

$$\begin{aligned}
&\max_{\mathbf{x},\mathbf{p},\mathbf{k}} \ \sum_j \sum_k x_{jk} \ln(r_{jk}), && \text{(4a)}\\
&\max_{\mathbf{x},\mathbf{p},\mathbf{k}} \ -P_{\rm tot}, && \text{(4b)}\\
\text{s.t.}\ & \text{C1}: p_j \le p_{j,\max},\ \forall j, && \text{(4c)}\\
& \text{C2}: x_{jk} \in \{0,1\},\ \forall j,k, && \text{(4d)}\\
& \text{C3}: \sum_j x_{jk} = 1,\ \forall k, && \text{(4e)}\\
& \text{C4}: \sum_k x_{jk} = k_j,\ \forall j, && \text{(4f)}\\
& \text{C5}: \sum_j k_j = K, && \text{(4g)}
\end{aligned}$$

where $p_{j,\max}$ is the maximum transmit power of BS j. Note that here we keep k_j as an optimization variable for convenience in subsequent analysis.

It can be observed that problem (4) is a mixed-integer and non-convex problem, and finding its global optimum is quite difficult. We first employ weighted sum method [10] to transfer problem (4) into a SOO problem. Although this method does not guarantee to find the whole Pareto front due to the non-concavity of rate function [11], we aim at finding a practical algorithm to obtain the local optimum of user association and power coordination, and it still provides many options to achieve various levels of EE-SE tradeoff. To ensure the consistent comparison, the objectives are first normalized as

$$\begin{aligned}
&\max_{\mathbf{x},\mathbf{p},\mathbf{k}} \ \frac{\sum_j \sum_k x_{jk} \ln(r_{jk}) - U_{\min}}{U_{\max} - U_{\min}}, && \text{(5a)}\\
&\max_{\mathbf{x},\mathbf{p},\mathbf{k}} \ -P_{\rm tot}/P_{\max}, && \text{(5b)}
\end{aligned}$$

where $U_{\max}$ and $U_{\min}$ are the maximum and minimum sum utility, and $P_{\max}$ denotes the maximum total power consumption. Specifically,

$$P_{\max} = M\rho + \sum_j (p_{j,\max}/\varepsilon_j + \xi_j), \tag{6a}$$

$$U_{\max} = \max_{\mathbf{x},\mathbf{p},\mathbf{k}} \sum_j \sum_k x_{jk} \ln(\tilde{r}_{jk}), \quad U_{\min} = K \ln(\delta), \tag{6b}$$

where $\tilde{r}_{jk}$ is obtained by omitting the interference from other BSs, and $\delta > 0$ is a predefined, sufficiently small value. Note that $U_{\max}$ must be maximized at the maximum transmit power, and thus we can employ the LDD method presented in Section IV to find its user association solution.

The SOO problem is then obtained from (5) via weighted sum method [10] as the following

$$\begin{aligned}
&\max_{\mathbf{x},\mathbf{p},\mathbf{k}} \ w\frac{\sum_j \sum_k x_{jk} \ln(r_{jk}) - U_{\min}}{U_{\max} - U_{\min}} - (1-w)\frac{P_{\rm tot}}{P_{\max}},\\
&\text{s.t.}\ \ (4c) - (4g),
\end{aligned} \tag{7}$$

where $w \in [0,1]$ is the weighting parameter. As stated in [11], the EE-SE tradeoff is achieved when $w_{\rm EE} \le w \le 1$, where $w_{\rm EE}$ corresponds to the point of the maximum EE.

IV. Proposed Algorithm

To solve (7), we need to do the following: select one BS for each user and ascertain the transmit power of each BS. We first employ the primal decomposition method to separate (7) into the following two levels of optimization. By fixing user association matrix $\mathbf{x}$, the original problem can be transformed into the equivalent *lower level power coordination problem* as

$$\begin{aligned}
&\max_{\mathbf{p}} \ \mathrm{f}(\mathbf{p}) = \frac{w\sum_j \sum_k x_{jk} \ln(c_{jk})}{U_{\max} - U_{\min}} - \frac{(1-w)\sum_j p_j/\varepsilon_j}{P_{\max}},\\
&\text{s.t.}\ (4c),
\end{aligned} \tag{8}$$

where $c_{jk} = r_{jk} \cdot k_j$. At the higher level when the transmit power vector $\mathbf{p}$ is fixed, we can obtain the *master user association problem* as

$$\begin{aligned}
&\max_{\mathbf{x},\mathbf{k}} \ \mathrm{g}(\mathbf{x},\mathbf{k}) = \sum_j \sum_k x_{jk} \ln(c_{jk}) - \sum_j k_j \ln(k_j),\\
&\text{s.t.}\ \ (4d)\text{–}(4g).
\end{aligned} \tag{9}$$

Note that constant terms are omitted here for simplicity.

A. Lower Level Problem: Power Coordination

As mentioned before, the power coordination problem (8) is a non-convex problem, and therefore finding its global optimum with affordable complexity is rather difficult. Alternatively, we employ sequential convex programming [12], i.e., finding local optimum of (8) by solving a sequence of easier problems, which helps to develop a low-complexity algorithm guaranteed to converge to a first-order optimal solution of (8).

We adopt the lower bound of the logarithmic function [13], i.e., $\log_2(1+\gamma) \ge \alpha \log_2 \gamma + \beta$, where $\alpha = \frac{\gamma'}{1+\gamma'}$, and $\beta = \log_2(1+\gamma') - \frac{\gamma'}{1+\gamma'}\log_2\gamma'$. Note that when $\gamma = \gamma'$, the above equality holds. Thus, by adopting the transformation $q_j = \log_2 p_j, \forall j$, $\mathrm{f}(\mathbf{p})$ in (8) can be lower-bounded by

$$\mathrm{f}(\mathbf{p}) \ge \frac{w\sum_j \sum_k x_{jk} \ln(\tilde{c}_{jk}(\mathbf{q}))}{U_{\max} - U_{\min}} - \frac{(1-w)\sum_j \frac{2^{q_j}}{\varepsilon_j}}{P_{\max}} = \tilde{\mathrm{f}}(\mathbf{q}), \tag{10}$$

where $\tilde{c}_{jk}(\mathbf{q}) = \alpha_{jk}\log_2(\mathrm{SINR}_{jk}(\mathbf{q})) + \beta_{jk}$, and α_{jk} and β_{jk} are calculated according to a given approximate SINR value $\tilde{\gamma}_{jk}$. Since $\tilde{\mathrm{f}}(\mathbf{q})$ is a concave function over $\mathbf{q}$ due to the convexity of the log-sum-exp function [14], problem (8) can be solved via the standard convex optimization problem

$$\begin{aligned}
&\max_{\mathbf{q}} \ \tilde{\mathrm{f}}(\mathbf{q}), && \text{(11a)}\\
&\text{s.t.}\ \ 2^{q_j} \le p_{j,\max},\ \forall j, && \text{(11b)}
\end{aligned}$$

which can be solved by the interior-point method [14]. To tighten the lower bound in (10), it is natural to update

Algorithm 1 Sequential convex programming algorithm

1. Initialize $n=0$, $flag\_p=1$, and $p_j^0=p_{j,\max}$, $\forall j$.
2. Calculate the SINR $\tilde{\gamma}_{jk}^0$.
3. **while** $flag\_p>0.01$**, do**
4. $n=n+1$;
5. Calculate α_{jk}^{n-1} and β_{jk}^{n-1} according to $\tilde{\gamma}_{jk}^{n-1}$, $\forall j,k$;
6. Solve problem (11) with α_{jk}^{n-1} and β_{jk}^{n-1}, and
7. obtain the global optimum $\mathbf{q}^n$;
8. Update $p_j^n=2^{q_j^n}$, and SINR $\tilde{\gamma}_{jk}^n$ with $\mathbf{p}^n$, $\forall j,k$;
9. Calculate $\Delta\tilde{\gamma}_{jk}^n=\left|\left(\tilde{\gamma}_{jk}^n-\tilde{\gamma}_{jk}^{n-1}\right)\big/\tilde{\gamma}_{jk}^{n-1}\right|$, $\forall j,k$;
10. Calculate $flag\_p=\max\limits_{j,k}\left\{\Delta\tilde{\gamma}_{jk}^n\right\}$.
11. **end while**

α_{jk} and β_{jk} in iterative manner with the updated SINR $\tilde{\gamma}_{jk}=\mathrm{SINR}_{jk}\left(\mathbf{q}^*\right)$ and solving (11) until convergence. The procedure is summarized in **Algorithm 1**, and the following proposition further illustrates its convergence and optimality.

Proposition 1: Algorithm 1 monotonically increases the value of $\mathrm{f}\left(\mathbf{p}\right)$ at every iteration, and finally converges to a point which satisfies the KKT conditions of problem (8).

Note that the proof of Proposition 1 can be found in [12].

B. Master Problem: User Association

Defining dual variables $\boldsymbol{\lambda}=[\lambda_1,\lambda_2,\cdots,\lambda_J]$ for the constraint (4f), and μ for (4g), the Lagrange function of (9) is

$$\begin{aligned}\mathrm{L}\left(\mathbf{x},\mathbf{k},\boldsymbol{\lambda},\mu\right)&=\sum_j\sum_k x_{jk}\ln\left(c_{jk}\right)-\sum_j k_j\ln\left(k_j\right)\\&+\sum_j\lambda_j\left(k_j-\sum_k x_{ij}\right)+\mu\left(\sum_j k_j-K\right).\end{aligned}\tag{12}$$

Thus, the dual function $\mathrm{h}\left(\boldsymbol{\lambda}\right)$ can be represented as

$$\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)=\begin{cases}\max\limits_{\mathbf{x},\mathbf{k}}\mathrm{L}\left(\mathbf{x},\mathbf{k},\boldsymbol{\lambda},\mu\right),\\ \text{s.t. }(4\text{d})-(4\text{e}),\end{cases}\tag{13}$$

which can be divided into

$$\begin{aligned}&\mathrm{h}_1\left(\boldsymbol{\lambda}\right)=\max_{\mathbf{x}}\sum_k\left(\sum_j x_{jk}\left(\ln\left(c_{jk}\right)-\lambda_j\right)\right),\\&\text{s.t. }(4\text{d})-(4\text{e}),\end{aligned}\tag{14}$$

and

$$\mathrm{h}_2\left(\boldsymbol{\lambda},\mu\right)=\max_{\mathbf{k}}\sum_j k_j\left(\lambda_j+\mu-\ln\left(k_j\right)\right).\tag{15}$$

Observing (14), the optimal user association is

$$x_{jk}^*=\begin{cases}1, & j=\arg\max\limits_i\ln\left(c_{ik}\right)-\lambda_i,\\ 0, & \text{otherwise.}\end{cases}\tag{16}$$

On the other hand, the optimal k_j^* can be obtained by setting $\frac{\partial\sum_j k_j\left(\lambda_j+\mu-\ln(k_j)\right)}{\partial k_j}=0$, which is calculated as $k_j^*=e^{\lambda_j+\mu-1}$. Thus, the dual function can be expressed as

$$\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)=\sum_k\max_j\left(\ln\left(c_{jk}\right)-\lambda_j\right)+\sum_j e^{\lambda_j+\mu-1}-\mu K.\tag{17}$$

Algorithm 2 Joint User Association and Power Coordination

1. For any given weighting parameter w,
2. Initialize $l=0$, $flag=1$, and $p_j^0=p_{j,\max}$.
3. **while** $flag>0.01$**, do**
4. $l=l+1$;
5. Calculate $\mathbf{x}^l$ via (16) with $\mathbf{p}^{l-1}$;
6. Calculate $\mathbf{p}^l$ by adopting Algorithm 1 with $\mathbf{x}^l$.
7. Calculate $flag=\max\limits_{j,k}\left|x_{jk}^l-x_{jk}^{l-1}\right|$.
8. **end while**

Finally, problem (9) can be solved via the dual problem $\min\limits_{\boldsymbol{\lambda}\geq 0,\mu\geq 0}\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)$ by adopting subgradient method [15]. Since the user association variable x_{jk} is discrete in nature, there may be a non-zero duality gap. Nevertheless, the optimum of dual problem often results in good solutions [4] and the following proposition proves that the duality gap is bounded.

Proposition 2: For problem (9), the duality gap between the objective $\mathrm{g}\left(\mathbf{x},\mathbf{k}\right)$ obtained via subgradient method and the global optimum is bounded by $\sum\limits_j k_j\ln\left(k_j/e^{\lambda_j+\mu-1}\right)$.

Proof: Suppose that $\left(\boldsymbol{\lambda},\mu\right)$ are the optimized dual variables at convergence of subgradient method, and $\left(\mathbf{x},\mathbf{k}\right)$ is the corresponding solution obtained according to (16) and $k_j=\sum\limits_k x_{jk}$. Thus, we have

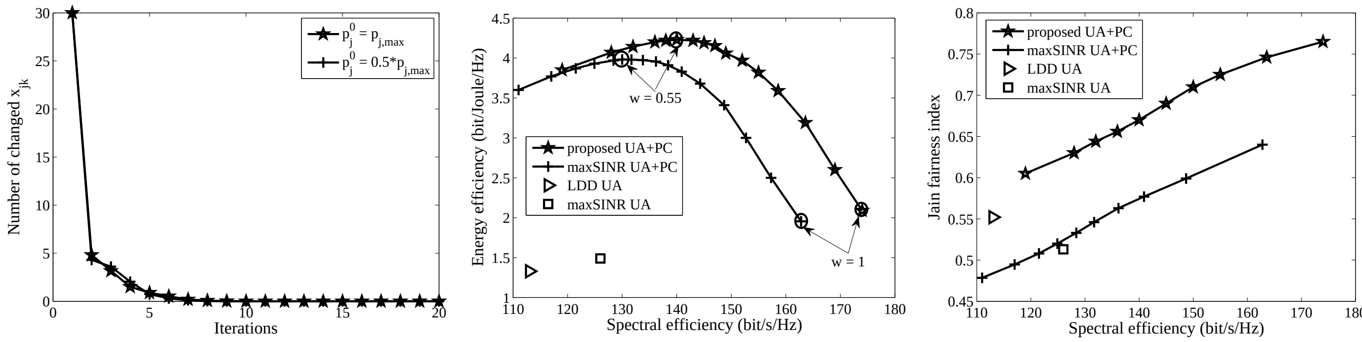
$$\begin{aligned}\mathrm{g}\left(\mathbf{x},\mathbf{k}\right)&=\sum_j\sum_k x_{jk}\ln\left(c_{jk}\right)-\sum_j k_j\ln\left(e^{\lambda_j+\mu-1}\right)-\Theta\\&\overset{(a)}{=}\sum_k\max_j\left(\ln\left(c_{jk}\right)-\lambda_j\right)+\left(1-\mu\right)K-\Theta\\&\overset{(b)}{=}\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)-\Theta,\end{aligned}\tag{18}$$

where $\Theta=\sum\limits_j k_j\ln\left(k_j/e^{\lambda_j+\mu-1}\right)$. Note that the equality (a) is derived from (16), and (b) is due to the optimality condition for μ: since $\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)$ is a convex function over μ, the optimal μ satisfies $\partial\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)/\partial\mu=\sum\limits_j e^{\lambda_j+\mu-1}-K=0$. Now, assume that $\left(\mathbf{x}^*,\mathbf{k}^*\right)$ is the global optimal solution for problem (9). Because of the weak duality, $\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)\geq\mathrm{g}\left(\mathbf{x}^*,\mathbf{k}^*\right)$ always holds. Thus, we prove that $\mathrm{g}\left(\mathbf{x},\mathbf{k}\right)\geq\mathrm{g}\left(\mathbf{x}^*,\mathbf{k}^*\right)-\sum\limits_j k_j\ln\left(k_j/e^{\lambda_j+\mu-1}\right)$. ■

The iterative joint user association and power coordination algorithm is summarized in **Algorithm 2**, which only requires polynomial complexity: the power coordination solution can be found by solving a series of standard convex optimization problems with polynomial complexity; the complexity of the user association problem is $\mathcal{O}\left(JK\right)$ at each inner iteration, and the complexity of outer Lagrangian dual variable update based on sub-gradient method is a polynomial function of the dual problem dimension [15], i.e., $J+1$ for $\mathrm{h}\left(\boldsymbol{\lambda},\mu\right)$.

V. Simulation Results

We consider a cell in a two-tier HetNet with one macro BS, three pico-BSs, and 30 users. The pathloss (dB) between BS and user is modelled as $128.1+37.6\log_{10}d$ (km), and the shadow fading is log-normal distributed as $\left(0,\vartheta^2\right)$, where $\vartheta=8$dB. The power spectral density of noise is -174 dBm/Hz, and



(a) (b) (c)

Fig. 1. (a) The convergence procedure of the proposed algorithm. (b) Energy efficiency *vs.* spectral efficiency. (c) Jain's fairness index *vs.* spectral efficiency.

TABLE I
SIMULATION PARAMETERS

Parameters	Default value	Parameters	Default value
Cell radius	500 m	Bandwidth	10 MHz
M	100	N	10
$p_{1,\max}$	43 dBm	$p_{j,\max}, j > 1$	23 dBm
$\varepsilon_j, \forall j$	0.38	ρ	0.02 W
ξ_1	10 W	$\xi_j, j > 1$	0.2 W

the other simulation parameters are shown in Table I. We first present the convergence procedure of our proposed algorithm in Fig. 1(a), which shows that the number of changed x_{jk} ($\forall j, k$) between two iterations plummets to zero within about 8 iterations, indicating that the proposed algorithm can converge quickly within a few iterations.

Then, we compare our algorithm 'proposed UA+PC' with three algorithms: 'LDD UA' is the proposed LDD method for user association with the fixed maximum transmit power of each BS; 'maxSINR UA' means that each user chooses the BS with the highest SINR, where the transmit power is also fixed; 'maxSINR UA+PC' further includes power coordination by adopting our proposed Algorithm 1.

By adjusting the weighting parameter w, the EE-SE tradeoff for different algorithms is presented in Fig. 1(b). For our proposed algorithm and 'maxSINR UA+PC', with the growing of SE (w), EE first increases to the maximum point and then decreases to a low level. Therefore, the EE-SE tradeoff can be achieved with a specific range of $0.55 \leq w \leq 1$ for the given the simulation parameters. Besides, for a given SE, our proposed algorithm can achieve a higher EE compared to 'maxSINR UA+PC'. In contrast, since the transmit power of each BS is fixed for 'LDD UA' and 'maxSINR UA', their performances are represented by single points, whose corresponding SE and EE are much lower than those achieved by our proposed algorithm and 'maxSINR UA+PC'.

Fig. 1(c) finally provides insights on the rate fairness performance for different algorithms. For a given SE, our proposed algorithm can achieve higher rate fairness than the other algorithms. For algorithms without power coordination, it is reasonable to see that 'LDD UA' achieves better rate fairness than 'maxSINR' because of its logarithmic objective, while the price to pay is the loss of SE.

VI. CONCLUSION

In this paper, we investigated the tradeoff between EE and SE in massive MIMO enabled HetNets, and proposed an efficient algorithm for joint optimization of user association and power coordination, which only requires polynomial computational complexity. Simulation results provided insights on the EE-SE tradeoff and rate fairness among users, and demonstrated the effectiveness of our proposed algorithm in comparison with other algorithms.

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