

Maximizing Energy Efficiency in Heterogeneous Cellular Network with Massive MIMO and Small Cells

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Abstract—With the rapid development of wireless cellular network, massive multiple input and multiple output (MIMO) and Small Cells (SCs) are both suitable candidates for the future fifth generation (5G) networks. Energy Efficiency (EE) has become increasingly concerned along with the two power-hungry candidates. This paper herein analyzed the energy efficiency of heterogeneous cellular network with massive MIMO and SCs. We maximized the EE by assigning the antennas of macro base station and SCs. We studied the relationship among the macro base station antennas, SCs and users by simulation and curve-fitting. Due to the fact that the Minimum Mean Square Error (MMSE) algorithm has better performance than the convex operation for total power minimization, we chose the MMSE algorithm to acquire the maximum energy efficiency with different amount of macro base station antennas, SCs and users. From the numerous simulation results, it can be seen that the number of antennas in the macro base station, the number of SCs and the user numbers have linear relationship when EE reaches the maximum value.

Index Terms—Massive MIMO, small cells, energy efficient, curve-fitting, 5G

I. INTRODUCTION

By 2020, the capacity of the cellular networks might be thousands times larger than the current commercial cellular systems in amazing fifth generation (5G) network [1]. There are lots of candidates to satisfy the proposed targets of 5G, such as Small Cells (SCs) and massive Multiple Input and Multiple Output (MIMO) [2], [3].

To address the capacity requirement of the radio access network, network densification and spectrum extension are inevitable trends. Massive MIMO and SCs are the main patterns of network densification. On one hand, the energy consumption increases exponentially since massive MIMO and SCs are both energy thrifless, so Energy Efficiency (EE) has become increasingly concerned [4]. On the other hand, both massive MIMO and SCs are expected to achieve high EE in the high throughput cellular networks if an appropriate structure is designed [5]. Massive MIMO base station can offer huge spatial degree of freedom due to unconventionally massive number of antennas, which is conducive to signal

gains and resilient to imperfect channel knowledge with small inter-user interference. Thus, massive MIMO is widely considered as a key enabler for filling the capacity gap towards the 5G network [6]. In [7], [8], the authors analyzed the hardware-constrained base stations with low-cost antenna elements in practical deployment of massive MIMO, and derived a closed form scaling law to show how fast the imperfections increase with the number of antennas at the base station.

As we know, SCs are efficient methods to provide local capacity enhancements. In [9], the authors highlighted the capacity and energy consumption of small cells, and proposed a sleep mode scheme that switches off some SCs when the traffic was low. Simulation results show that SCs are a good choice for network densification because they can achieve higher network capacities with better EE. Unfortunately, SCs cannot replace macro cells, which ensure area coverage and support high-speed mobile terminals. Hence, a two-tier architecture for cellular systems naturally emerged. It proposed the challenge of how SCs and macro cells can coexist [10].

Since massive MIMO and SCs are destined to meet each other in future network to densify the topology of network, in [11] the authors analyzed the combination of the two densification approaches. And then maximized the energy efficiency by minimizing the total power consumption without satisfying Quality of Service (QoS) constraints. In order to get the maximal energy efficiency in the massive MIMO network, in [12], the authors obtained the optimal number of antennas, active users, and transmit power theoretically. Numerical and analytical results show that the maximal EE was achieved wherein the number of antennas were deployed to serve the same magnitude of users. In [13], the authors considered a two-tier Orthogonal Frequency Division Multiple Access (OFDMA) based heterogeneous network and transformed the multi objective optimization problem of simultaneously maximizing EE and Spectrum Efficiency (SE) into an EE-SE tradeoff single objective optimization problem. The problem was solved by power allocation and user association scheme in which each user can only be associated with one BS. Different from [13], authors in [14] proposed a low-complexity joint subcarrier and power allocation algorithm to maximize

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EE with QoS constrained in multi-user multi-carrier OFDMA systems by Maclaurin series expansions technique with the tractable upper bound of truncation error. Different from [13] and [14], this paper maximized EE in heterogeneous cellular network with massive MIMO and small cells from the perspective of antenna deployment.

Motivated by the analytical analysis and numerical results in [12], this paper herein analyzes the EE of the network with massive MIMO and SCs by assigning the antennas in macro base station and small cells. Different from [12], we try to enhance EE through appropriate network structure and practical algorithms. We apply the realistic power consumption proposed in [12], and consider an accurate downlink channel model with Rayleigh small-scale fading distribution, path loss, shadowing, penetration loss and especially the antenna correlation loss. Then we figure out the relationship among the number of macro BS antennas, small cells and users by simulation and curve-fitting. In order to seek for the maximum energy efficiency, several existing algorithms are compared. The simulation results show that Minimum Mean Square Error (MMSE) algorithm for sum rate maximization outperforms complex convex operation for total power minimization. According to the simulation results, interestingly, the antennas number in macro base station, the number of small cells and the number of users turn out to be linear restriction corresponding to the maximum EE. Future work for theoretical support is worth researching.

The remainder of this paper is organized as follows. In Section II, we introduce the system model, which is a heterogeneous network with massive MIMO and SCs. In Section III, we formulate the problem and describe the algorithms. In Section IV, simulations results and analysis are given for the proposed scheme and followed by the concluding remarks in Section V.

II. SYSTEM MODEL

In this paper, we consider the single-cell downlink heterogeneous network system with massive MIMO and several SCs, which is illustrated in Fig. 1. In this scenario, the macro base station is equipped with N_{BS} antennas and $K_t - 1$ SCs are equipped with N_{SCA} antennas. There are K_t ($K_t \geq 1$) access points in this cell include macro base station ($K_t = 1$ indicates that there is only one macro base station in the cell). There are K_r single antenna users randomly distributed in this cell. It is known as massive MIMO if $N_{BS} \gg K_r$. However, as proved in [11], we can regard $N_{BS} \geq K_r$ as the condition of “massive”. It means that N_{BS} and K_r can be of the same order of magnitudes.

TDD protocol is regarded as a key enabler for exploiting channel reciprocity to estimate channels without additional overhead [15]. We assume that the access points and users are perfectly synchronized and coordinated with the time division duplex protocol. In

this paper, the channel state information is assumed to be perfectly known at each base station.

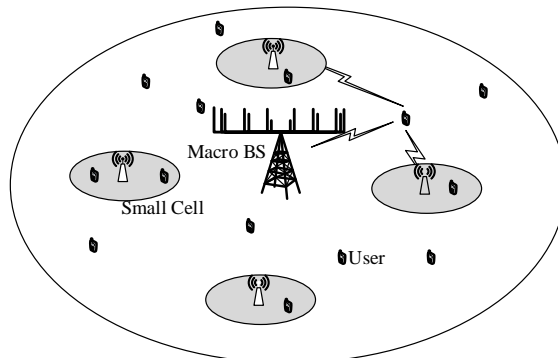


Fig. 1 Illustration of a downlink heterogeneous network with massive MIMO and SCs.

A. Channel Model

The channels between users and access points are considered as block flat-fading. Each channel is equivalent to the combination of small scale fading and large scale fading. We consider Rayleigh fading distribution as small scale fading. The large scale fading include path loss, shadowing, penetration loss and the antenna correlation loss in massive MIMO base station.

Let M denotes the total antennas of all access points, where $M = N_{BS} + (K_t - 1) \times N_{SCA}$. So the channel can be expressed as $\mathbf{H} \in \mathbb{C}^{M \times K}$, where $H_{j,k}$ denotes the channel between antenna j and user k , j denotes the antenna of n -th access point. When $K_t > 1$, we have $N_{BS} + n \times N_{SCA} \leq j \leq N_{BS} + (n+1) \times N_{SCA}$; and when $K_t = 1$, $1 \leq j \leq N_{BS}$.

TABLE I: PART OF CHANNEL PARAMETERS

| Parameters | Macro | Small Cell |
|------------------|-----------------------|---------------------|
| Tx power | 46dBm | 30dBm |
| Path Loss | $128.1 + 37.6 \log d$ | $147 + 36.7 \log d$ |
| Shadowing Factor | 8dB | 10dB |
| Radius | 500m | 50m |
| Penetration Loss | 20dB | 20dB |
| Thermal Noise | -174dBm/Hz | -174dBm/Hz |
| ρ_j | 2.577 | 19.25 |
| η_j | 189mW | 5.6mW |

For macro base station and each small cell, we consider the Rayleigh small-scale fading distribution with path loss, shadowing and penetration loss in the channel. All of those parameters can be found in scenario 2 in the reference [16]. To ensure the practicality, the channel models are generated based on the channel coefficient generation procedure in [17]. The accurate channel models are considered so that we can investigate this project mainly by simulation and curve-fitting. The main parameters for simulation are given in Table I, where $d(km)$ is the distance between users and access points, ρ_j and η_j will introduce in section II-B. More detailed information please refer to [17].

Antenna correlation of macro base station is introduced in [18]. We introduce the model used in the simulation briefly here. The antenna correlation matrix of an uniform linear array can be expressed as $\mathbf{R}=[\mathbf{A} \ \mathbf{0}]$ and \mathbf{A} is given by

$$\mathbf{A} = [a(\theta_1) \dots a(\theta_p)] \in \mathbb{C}^{N_{BS} \times P} \quad (1)$$

where $a(\theta)$ stands for steering vectors and is given by

$$a(\theta) = 1/\sqrt{P} \cdot [1, e^{-i2\pi\omega\sin(\theta)}, \dots, e^{-i2\pi\omega(N-1)\sin(\theta)}]^T \quad (2)$$

where ω is the antenna spacing in multiples of the wavelength, $\theta(p) = -\pi/2 + (p-1)\pi/P$ with $p=1, \dots, P$ and $P=N_{BS}/2$ is the number of dimensions. $1/N \times \text{tr}(\mathbf{A}\mathbf{A}^H) = \mathbf{1}$ to ensure that the ultimately achievable rate under this channel model is equal to that of the previous channel model without antenna correlation.

B. Energy Efficiency

We assume that the channel matrix \mathbf{H} presented before is perfectly known at transmitters and receivers by channel estimation. So the received signal of user k is

$$\mathbf{y}_k = \sum_{j=1}^M \mathbf{H}_{k,j}^H \mathbf{x}_j + n_k \quad (3)$$

where the noise vector $n_k \sim N_C(0, \sigma^2)$ denotes the independent additive white Gaussian noise with zero mean and σ^2 variance (mW). \mathbf{x}_j is the transmit data of antenna j , denoted as

$$\mathbf{x}_j = \sum_{k=1}^K w_{j,k} x_{j,k} \quad (4)$$

where $x_{j,k}$ is the data transmitted from antenna j to user k , and \mathbf{W} indicates the beamforming matrix.

The SINR of user k can be formulated as

$$\gamma_k = \frac{S_k}{I_k + \sigma^2} = \frac{\sum_{j=1}^M |h_{k,j}^H w_{k,j}|^2}{\sum_{i=1, i \neq k}^K \left(\sum_{j=1}^M |h_{k,j}^H w_{i,j}|^2 \right) + \sigma_k^2} \quad (5)$$

where S_k and I_k stand for the useful signal and the interference signal, respectively. Furthermore, the rate of user k is

$$R_k = \log_2(1 + \gamma_k) \quad (6)$$

The realistic power model which formulates the energy consumption as the dynamic power P_d and the static power P_s is used in this paper. The dynamic power denotes the beamforming consumption which fluctuates with beamforming. The static power denotes the total power consumed by different analog components and digital signal processing [10]. The dynamic power and static power can be calculated by

$$P_d = \sum_{j=1}^M \rho_j \sum_{k=1}^K \|w_{k,j}\|^2, \quad (7)$$

$$P_s = \frac{\eta_0}{C} \times N_{BS} + \sum_{j=1}^{K_r} \frac{\eta_j}{C} \times N_{sca}$$

where $w_{k,j}$ is the aggregation of all antenna including all SCs, $\rho_j \geq 1$ accounting for the efficiency of the power amplifier of each transmitter antenna, η_1 and $\eta_j (j>1)$ model the circuit power dissipation of macro base station and each SC, respectively. These parameters are listed in Table I.

We define EE (Mbit/Joule) as

$$EE = \frac{E[R_k]}{P_d + P_s} \quad (8)$$

where $E[\cdot]$ means the expectation operation, P_d and P_s can be calculated by Eq. (7).

III. PROBLEM FORMULATION AND ALGORITHM DESCRIPTION

In this work, we try to maximize the energy efficiency in the heterogenous network system, and seek for the relationship of the three parameters: the antenna number in macro base station, the number of SCs, and the number of users. Due to the complex channel information and high complicated computing process, it's difficult to figure out a closed form expression of EE or optimal combination. We use some existent algorithms to compute the maximum EE by simulation, and then find out the relationship by curve-fitting. Therefore, for a given combination of N_{BS} , K_t , and K_r , the optimization problem can be written as

$$\max_{w_{k,j}, \forall k,j} EE = \frac{E[R_k]}{P_d + P_s} \quad (9)$$

where $k=1, 2, \dots, K_r$ is the index of users, $j=1, 2, \dots, M$ is the index of antennas.

In order to obtain the relationship of N_{BS} , K_t , and K_r when EE reaches the maximum, we solve Eq. (9) in different combinations by simulation. Then we match the optimal combination using curve-fitting toolbox. It can be expressed as

$$f(N_{BS}, K_t, K_r) = \arg \max_{N_{BS}, K_t, K_r} \left(\max_{w_{k,j}, \forall k,j} EE \right) \quad (10)$$

It can be seen from Eq. (9) that the maximum EE is correlative with $E[R_k]$ as the numerator and $P_d + P_s$ as the denominator. $E[R_k] \geq \gamma_k$ when the minimum rate γ_k of each user is satisfied. Meanwhile, EE achieves maximum where $P_d + P_s$ gets the minimum. We choose $E[R_k] \geq \gamma_k$ as a fairness criterion to ensure the QoS of each user when we solve the optimization problem. To prevent P_d and $E[R_k]$ from increasing unrealistically, the power of each antenna is restrained. Thus in order to achieve the maximize value of energy efficiency, there are two primary ideas. One fundamental idea is to minimize the total power with the constrains of QoS for each user. The other is to maximize the average information rate on condition that the power of each antenna is stable.

A. Transmit Power Minimization

In this subsection, we are going to recommend a suboptimal algorithm proposed in [11] in a concise

pattern. We maximize the energy efficiency by minimizing the total power consumption.

For the k -th user, the QoS is represented by the target rate γ_k (bits/s/Hz). Due to the existence of SINR, Eq. (9) is not a convex optimization problem. However, for a given combination of N_{BS}, N_{SCA}, K_t , the static power P_s is a constant obtained in Eq. (7). $P_d + P_s$ minimization is equivalent to P_d minimization, Eq. (9) can be written as

$$\begin{cases} \min_{w_{k,j}, \forall k,j} & P_d \\ \text{s.t.} & S_k \geq (2^{\gamma_k} - 1)(I_k + \sigma^2), \forall k \\ & \text{tr}(\mathbf{w}_j^H \mathbf{w}_j) \leq p_j, \forall j \end{cases} \quad (11)$$

where p_j is the maximum power of the j -th antenna, γ_k is the minimum rate of the k -th user. The optimization problem Eq. (11) is a convex optimization problem. It can be solved by the convex optimization toolbox CVX in Matlab though in a time-consuming ways [19].

We refer to the low-complexity algorithm for fast simulation with very little performance loss in reference [11]. The regularized zero-forcing (RZF) beamforming vector $\mathbf{U} \in \mathbf{C}^{K \times K_t}$ is computed by

$$U_{k,n} = \frac{\tilde{U}_{k,n}}{\|\tilde{U}_{k,n}\|}, \forall k \in \{1, 2, \dots, K\}, n \in \{1, 2, \dots, K_t\} \quad (12)$$

where $\tilde{U}_{k,n}$ is given by

$$\tilde{U}_{k,n} = \left(\frac{1}{\sigma^2} \sum_{i=1}^K H_{k,j} H_{k,j}^H + \frac{K}{(2^{\gamma_k} - 1)P_j} \right)^{-1} H_{k,j} \quad (13)$$

Let $g_{k,n}$ be a scalar which denotes the equivalent channel status of each access point, given by

$$g_{k,n} = \|\mathbf{H}_{k,j}^H \mathbf{U}_{k,n}\|^2 \quad (14)$$

With the above equivalence, we transform the Eq. (11) from the centralized algorithm to a distributed algorithm. The concentrative computer system can solve the Low-complexity convex optimization problem

$$\begin{cases} \min_{V_{k,j} \in \mathbf{C}^{K_t \times K}} & \sum_{j=1}^{K_t} \sum_{k=1}^K V_{k,j} \\ \text{s.t.} & \sum_{k=1}^K V_{k,j} \leq P_j, \forall j = 1, \dots, K_t \\ & \sum_{j=0}^{K_t} V_{k,j} g_{k,j} \left(1 + \frac{1}{2^{\gamma_k} - 1} \right) \geq \sum_{j=0, i=1, i \neq k}^{K_t} V_{i,j} g_{k,j} + \sigma_k^2 \end{cases} \quad (15)$$

where $V_{k,j}$ is the equivalent beamforming matrix of each access point and user. P_j is the power constraint of each access point. k ($1 \leq k \leq K_t$) is the index of each user. The algorithm can be summarized as Algorithm 1.

Algorithm 1 - Low-complexity algorithm based on Multiflow-RZF

- 1: For a given \mathbf{H} at each small cell
- 2: Calculate the RZF beamforming vector $\mathbf{U}_{k,n}$ for

each access point with Eq.(12)

- 3: Each access point sends $\mathbf{g}_{k,n}$ to the concentrative computer system
 - 4: Solve the suboptimal optimization problem Eq. (15) at the concentrative computer system
 - 5: The concentrative computer system feedback the power allocation vector $\mathbf{V}_{k,j}^*$ to the j -th access point.
 - 6: Each AP obtain the final beamforming vector through $w_{k,j} = \sqrt{V_{k,j}^*} \mathbf{U}_{k,j}$
-

B. Sum Rate Maximization

In this subsection, we try to associate the precoding algorithm with the EE-maximized beamformer. There are many precoding algorithms used to maximize the information rate. For numerical analysis, we choose the MMSE algorithm because of its highest performance in contrast with other linear precoding algorithms. The MMSE algorithm can be described as

$$\mathbf{W} = (\mathbf{H}\mathbf{P}\mathbf{H}^H + \sigma^2\mathbf{I})^{-1} \mathbf{H} \quad (16)$$

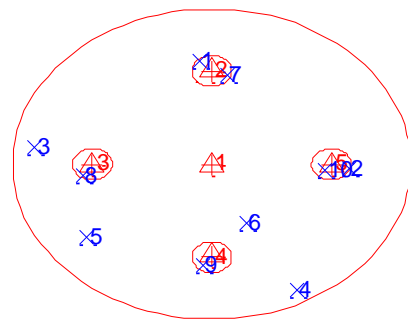
where \mathbf{W} denotes the beamforming matrix, \mathbf{P} is a diagonal matrix which contains the transmit power of each antenna, σ^2 is the noise covariance. It implements a simple approach to maximize the useful signal power and eliminate the interference with consideration of noise at the cost of a great deal of data interchange between BS and SCs. The algorithm can be described as Algorithm 2.

Algorithm 2 - MMSE

- 1: For given \mathbf{H} (exchanged with each small cell real time dynamically) at BS
 - 2: Calculate Eq. (16) at the concentrative computer system
 - 3: Each AP obtain the final beamforming vector from \mathbf{W} columns
-

IV. NUMERICAL RESULTS AND ANALYSIS

In this section, the simulation results and analysis are given for the heterogenous networks with massive MIMO and several SCs. The channel parameters are given in Table I. The number of antennas in small cells N_{SCA} is 4.



(a) Scenario distribution

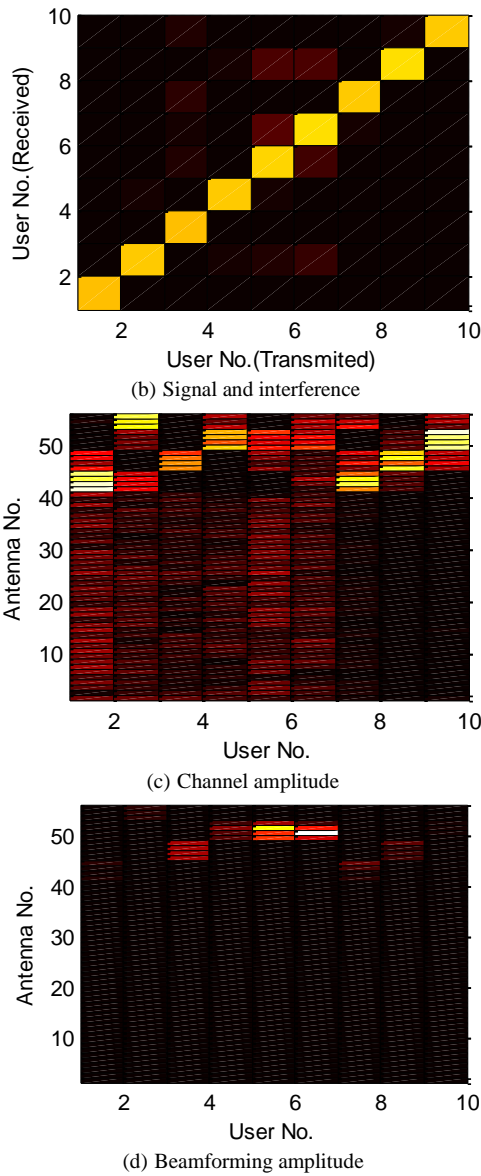


Fig. 2. A typical scenario and its channel gain, beamforming matrix, and its signal power for each user.

First of all, one typical scenario and its simulation status was presented in Fig. 2. It is a single cell contains one macro massive MIMO base station equipped with 40 antennas, 4 SCs each equipped with 4 antennas and 10 single-antenna users.

Fig. 2(a) is the distribution of each SC and user. It shows that one small cell must serve at least one user. The rest of users distribute in the cell randomly. Fig. 2(c) stands for the current channel gains among all users and antennas of the scenario in Fig. 2(a). It can be seen that Rayleigh small-scale fading distribution, path loss, shadowing fading and penetration loss are expressed accurately. In Fig. 2(d), we highlight the amplitude of the beamforming vector computed by multiflow-RZF algorithm between each antenna and user. Fig. 2(b) shows the useful signal power and interference power for each user, where the coordinate (x, y) indicates the power strength of user y caused by the transmit signal for user x .

In other word, the diagonal highlight represents the useful signal while the other of the row is the interference induced by other user. As shown in Fig. 2(b), all user signal is much higher than its sum interference. This implies that the transmit power tend to be as small as possible on condition that the QoS is satisfied.

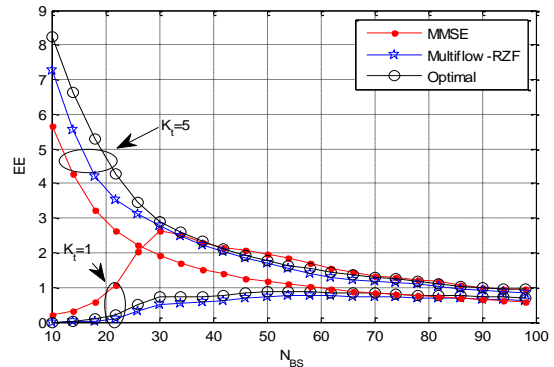


Fig. 3. EE (bit/J/Hz) v.s. N_{BS} with different algorithms

The performance of the algorithms described in Sec. III is compared in Fig. 3, where the legend "Optimal" stands for the optimal algorithm of Eq. (11). There are one massive MIMO macro base station, 4 SCs and 10 users distributed in the cell as depicted in Fig. 2.

From Fig. 3, we can clarify that the optimal algorithm for minimizing the total power can't always maximize the energy efficiency in massive MIMO network. MMSE shows better performance in massive MIMO network when $K_r=1$. In heterogeneous networks with $K_r=5$, MMSE is worse than optimal and multiflow-RZF algorithm with tiny performance loss. The multiflow-RZF algorithm is almost the same performance with the optimal algorithm no matter how many SCs. However, the time consumption of optimal is thousands of times than that of MMSE, and dozens of times than that of multiflow-RZF. Thus the multiflow-RZF algorithm is the substitute for optimal algorithm practically, since MMSE requires tremendous backhaul consumption although it is time economical. As a tradeoff between time consumption and performance, we choose MMSE algorithm for the following simulation.

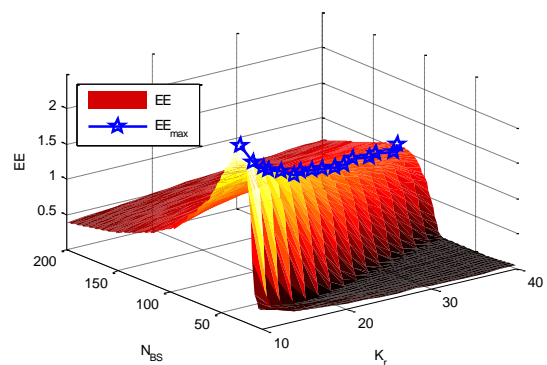


Fig. 4 EE v.s. N_{BS} and K_r in massive MIMO system.

Fig. 4 illustrates the tendency of EE when N_{BS} and K_r increase. The EE_{max} highlights the maximal EE of each K_r .

As proved in [12], energy efficiency can't increase with the number of antennas infinitely. An optimal antenna number can maximize the EE in massive MIMO network. Meanwhile, it can be seen from Fig. 4 that the optimal energy efficiency decreases with the number of users.

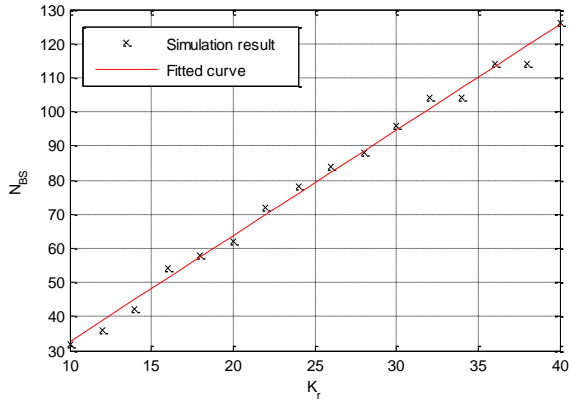


Fig. 5 Optimal N_{BS} v.s. K_r in massive MIMO system

Fig. 5 demonstrates the fluctuation of N_{BS} along with K_r when EE reaches the maximum in Fig. 4. Fig. 5 demonstrates the phenomena that the optimal antenna number is linear with user number in massive MIMO system. N_{BS} keeps approximately three times as many as the user number in this scenario according to fitted curve.

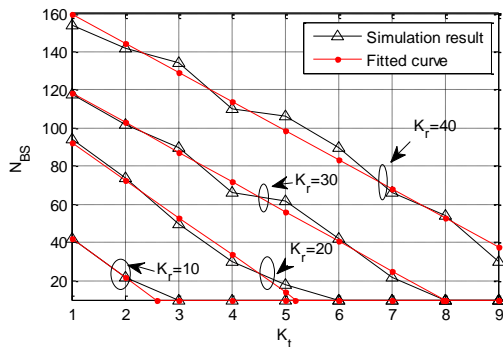


Fig. 6 Optimal N_{BS} v.s. K_t in heterogenous networks.

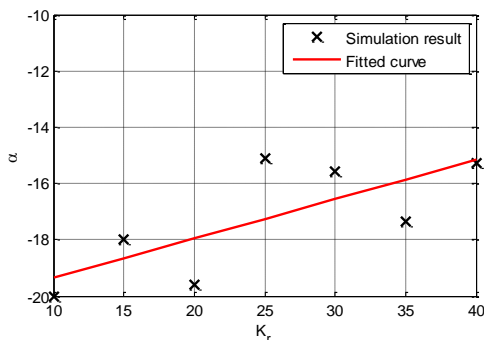


Fig. 7 Coefficient α v.s. K_r

Fig. 6 depicts that the optimal N_{BS} of maximum EE with different K_t and K_r . It can be seen that the optimal N_{BS} of maximum EE has linear correlation with K_t when K_r is fixed. The relationship can be expressed as $N_{BS} - \alpha \times K_t - \beta = 0$, which indicates that the solution of Eq. (10)

is a linear constrained function. Furthermore, the coefficient α and β is linear with K_r , as illustrated in Fig. 7 and Fig. 8.

From Fig. 7 and Fig. 8, the conclusion can be drawn from simulation and curve-fitting that the optimal combination of the three parameters is linear relevant. It can be expressed as Eq. (17).

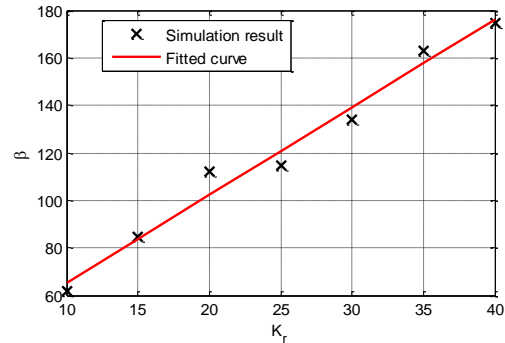


Fig. 8 Coefficient β v.s. K_r

$$N_{BS} = \alpha \times K_t + \beta = 0.14K_r K_t + 3.69K_r + 28.4 \quad (17)$$

However, we must acknowledge that more SCs brings higher EE.

V. CONCLUSIONS

Energy efficiency has become increasingly concerned along with the network densification. A prerequisite for practical deployment of massive MIMO and SCs is to determine how to promote energy efficiency. Compared with convex algorithm for total power minimization, the MMSE algorithm has better performance. We analyze the relationship among the number of antennas in macro base station, the number of small cells and the number of users. The following two conclusions are obtained when the EE reaches the maximum value: i) the optimal antenna number has linear relationship with the user number in massive MIMO system; ii) for a given user number, the relationship between the optimal antenna number and the number of small cells is linear.

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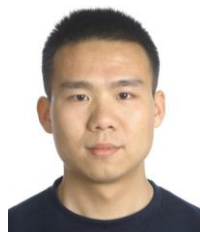
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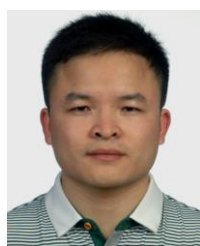
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