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Energy Efficient Resource Allocation for Massive MIMO Cellular Systems

Yingchu Guo, Gang Wu, Zhenzhen Hu, and Shaoqian Li
National Key Laboratory of Science and Technology on Communications,
University of Electronic Science and Technology of China,
Chengdu, P. R. China

ABSTRACT: *In this paper, a massive multiple-input multiple-output (MIMO) downlink where a base station (BS) equipped with a very large number of antennas serve many single-antenna users is investigated. The considered problem is modeled as a non-convex optimization problem which takes into account the circuit power consumption, channel state information (CSI), and quality of service (QoS) requirements including a minimum required data throughput rate. The power allocation scheme is optimized for maximization of the energy efficiency (EE) of data transmission. To solve the fractional programming, the non-convex optimization problem is transformed into an equivalent optimization problem in subtractive form, which leads to an efficient iterative resource allocation algorithm. Compared with the existing algorithms, the proposed power allocation scheme can reach a global optimization range whether users in high signal to interference plus noise ratio (SINR) area or low SINR area. Simulation results show that the total EE increases significantly with the proposed power allocation algorithm.*

KEYWORDS - *massive MIMO; energy efficiency; power allocation; green communication.*

I. INTRODUCTION

Because of the rapid growth of smart terminal usage and high data rate requirements services, cellular network traffic increases greatly nowadays [1]-[2]. To keep up with these requirements, massive multiple-input multiple-output (MIMO), which means using large number of transmit antenna, is proposed for the wireless networks to increase the spectral efficiency (SE) and energy efficiency (EE) up to around ten times and enhance communication reliability [3]-[4].

Massive MIMO can focus energy at desired points and increase SE due to a large number of transmit antenna. Meanwhile, circuit power consumption which connected to the number of antennas also increases. Unlimited number of transmit antenna is optimal to achieve maximum EE if circuit power consumption is not considered [5]. But in reality, to evaluate network energy efficiency, which is throughput to power consumption ratio, circuit power consumption should be taken into consideration.

Energy efficient resource allocation is one of open problems in wireless system design, which is considered in [6]-[16]. The EE defined as the ratio of the achieved throughput over the energy cost is maximized by the authors maximize with optimizing the time allocation for the downlink [6]. While in [7], a joint uplink pilot and data power allocation strategy for energy efficient communications under pilot contamination in multi-cell multi-user massive MIMO systems is investigated by the authors. In [8]-[10], the authors study the optimal EE with maximum ratio transmission (MRT) precoding. The optimal number of antennas and active users for covering a given area with maximal EE is investigated in [11]. A practical EE optimal model of massive MIMO systems considering PA efficiency as a variable is proposed in [12]. The authors in [13] consider the EE and SE tradeoff with antenna selection for massive MIMO. And in [14]-[16], to provide a fair network, quality of service (QoS) constraints are satisfied in EE optimal systems.

Time division duplexing (TDD) protocol is used at the base stations (BSs) to obtain channel state information (CSI). Users send a pilot sequence to the BSs. The BSs estimate the user's channel using the received pilot and send the data back to users. Because of resource limitation, it is impossible for all users in all cells to have orthogonal pilots, so each pilot is reused by users of neighbor cells, which creates pilot contamination. Pilot contamination leads to imprecisely channel estimation and reduces system performance [17].

In this paper, energy efficient power allocation in cellular networks with massive MIMO is investigated. EE is considered as users' utility where overall transmit power in a cell is limited. In addition, to guarantee the QoS for each user, a minimum data rate should be provided. Since the EE objective function is a fractional function, fractional programming technique and a series of convex approximations are used to find a closed form for optimal transmit power of users. The numerical results show the power of cellular users can be brought into a global optimization range.

The remainder of this paper is organized as follows. In Section II, the multi cells system model is presented and the downlink total throughput is derived. In Section III, the power consumption model is presented and the EE optimization problem is formulated. The power allocation scheme is discussed in Section IV. Numerical results are provided in Section V and Section VI concludes the paper.

II. SYSTEM MODEL AND TOTAL THROUGHPUT

A. System Model

Consider a single cell massive MIMO system. The system consists of one BS equipped with large number of fixed transmit antennas M and K single antenna users. It is assumed that all users are randomly located and $M >> K$. With TDD CSI acquisition, the channel estimation overhead scales as K , and is independent of M . So M can be made as large as desired, while K is limited by mobility.

TDD is considered in the existing literature that there are three phases within each coherence interval: uplink training, uplink payload data transmission, and download payload data transmission [18]. Denote τ_c be the length of each coherence interval, and τ_p , $\tau_p < \tau_c$, be the length of a part of the coherence interval which is used for uplink training. Then the remaining duration, $\tau_c - \tau_p$, is used for the downlink payload data transmission.

1) *Uplink Training:* All users simultaneously transmit their pilot sequences with power p^u to the BS. The received signal at BS from users can be written as follows:

$$\mathbf{Y}_u = \sum_{k=1}^{K} \sqrt{p^u}\mathbf{g}_k \boldsymbol{\varphi}_k^H + \mathbf{N}_u , \tag{1}$$

where $\boldsymbol{\varphi}_k \in \mathbb{C}^{\tau_p \times 1}$ is the pilot transmitted by user k , which is normalized as $\|\boldsymbol{\varphi}_k\|^2 = 1$, $\mathbf{g}_k \in \mathbb{C}^{M\times 1}$ is the channel vector between the user k and the BS, and $\mathbf{N}_u$ is an $M \times \tau_p$ Gaussian additive noise matrix whose elements follow a complex Gaussian distribution, $CN\left(0,\sigma_W^2 I_N\right)$, in which σ_W^2 is the noise variance after data transmission. The channel $\mathbf{g}_k$ models the propagation as follows:

$$\mathbf{g}_k = \beta_k^{1/2}\mathbf{h}_k , \tag{2}$$

where β_k is the large scale fading parameter which captures the effects of path loss and shadowing that changes slowly, and $\mathbf{h}_k$ is an $M \times 1$ vector of small scale fading coefficients between the M antennas of the BS and the user k . Small scale fading is assumed to be Rayleigh fading, i.e., the elements of $\mathbf{h}_k$ follow a complex Gaussian distribution $CN(0,1)$.

The channel estimate is obtained using the low complexity least square (LS) channel estimation method. The LS mean error has been proved to remain constant as the number of antennas increase, which make it ideal for massive MIMO networks [19]. The LS channel estimation of $\hat{\mathbf{g}}_k$ can be obtained as follows:

$$\hat{\mathbf{g}}_k = \frac{1}{\sqrt{p^u}}\mathbf{Y}_u \boldsymbol{\varphi}_k . \tag{3}$$

2) *Downlink Payload Data Transmission:* After acquiring the channels from the uplink pilots, the BSs use MRT beamforming to transmit signals to the users, which offers excellent performance with low processing complexity in massive MIMO systems [20]. The MRT beamforming vector for the user k , $k = 1,2,\cdots,K$, can be obtained as follows:

$$\mathbf{w}_k = \frac{\overline{\hat{\mathbf{g}}}_k}{\|\hat{\mathbf{g}}_k\|} , \tag{4}$$

where $\bar{\hat{\mathbf{g}}}_k$ is the conjugate of $\hat{\mathbf{g}}_k$, and $\|\cdot\|$ denotes the Euclidean norm of a matrix.

Denote the symbol intended for the user k by s_k, where $\mathbb{E}\left\{|s_k|^2\right\}=1$. The vector of transmitted signal from the BS to all its users, $\mathbf{x}$, can be expressed as

$$\mathbf{x}=\sum_{k=1}^{K}\sqrt{p_k}\mathbf{w}_k s_k=\sum_{k=1}^{K}\sqrt{p_k}\frac{\bar{\hat{\mathbf{g}}}_k}{\|\hat{\mathbf{g}}_k\|}s_k, \qquad (5)$$

where p_k is transmit power for user k which is an element of transmit power matrix $\mathbf{p}\in\mathbb{R}_+^{K\times 1}$. With the transmitted signal vector $\mathbf{x}$ given in (5), the received signal by user i, $i=1,2,\cdots,K$, can be written as

$$\begin{aligned} y_i &= \mathbf{g}_i^T\mathbf{x}+n_i \\ &= \sum_{k=1}^{K}\sqrt{p_k}\mathbf{g}_i^T\frac{\bar{\hat{\mathbf{g}}}_k}{\|\hat{\mathbf{g}}_k\|}s_k+n_i \\ &= \sqrt{p_i}\mathbf{g}_i^T\frac{\bar{\hat{\mathbf{g}}}_i}{\|\hat{\mathbf{g}}_i\|}s_i+\sum_{k=1,\neq i}^{K}\sqrt{p_k}\mathbf{g}_i^T\frac{\bar{\hat{\mathbf{g}}}_k}{\|\hat{\mathbf{g}}_k\|}s_k+n_i, \end{aligned} \qquad (6)$$

where $n_i\sim CN(0,\sigma^2)$ is the Gaussian additive noise.

B. Total Throughput

The user i will detect its desired signal s_i from the received signal y_i given by (6). It is easy to find that there are three parts in (6): desired signal, interference and noise. According to (6), received signal to interference plus noise ratio (SINR) of user i can be expressed as follows:

$$\gamma_i(\mathbf{p})=\frac{p_i\left\|\mathbf{g}_i^T\mathbf{w}_i\right\|^2}{\sum_{k=1,\neq i}^{K}p_k\left\|\mathbf{g}_i^T\mathbf{w}_k\right\|^2+\sigma^2}. \qquad (7)$$

The corresponding throughput rate (expressed in bit/s) for user i in cell j can be written as follows:

$$r_i(\mathbf{p})=\frac{\tau_c-\tau_p}{\tau_c}B\log_2\left(1+\kappa_i\gamma_i\right), \qquad (8)$$

where B is bandwidth and κ_i is SINR gap between Shannon channel capacity and a practical modulation and coding scheme. The SINR gap is equal to $-1.5/\ln\left(5e_i\right)$, where e_i is target bit error rate for user i [21].

The total throughput of the system can be obtained as:

$$r_{tot}(\mathbf{p})=\sum_{k=1}^{K}r_k. \qquad (9)$$

III. POWER CONSUMPTION MODEL AND ENERGY EFFICIENCY MAXIMIZATION

A. Power consumption Model

The power consumption for BS is modeled as [22], [23]

$$P(\mathbf{p})=\frac{1}{\rho}\sum_{k=1}^{K}p_k+MP_a+P_{fix}, \qquad (10)$$

where ρ is the power amplifier efficiency, p_k is transmit power for user k, P_a is the circuit power for hardware components that are needed at each antenna branch and computational complexity of MRT scheme that is proportional to the number of antennas M, and P_{fix} is the constant part to keep operations of the BS involved site cooling and static circuit power that is independent of M such as baseband processing.

B. Total Energy Efficiency

According to [24] and [25], the total EE (bit/Joule) is defined as the sum throughput (bit/s) divided by the total power consumption (Watt) in the system:

$$\eta(\mathbf{p}) = \frac{r_{tot}(\mathbf{p})}{P(\mathbf{p})}. \quad (12)$$

C. Total Energy Efficiency Maximization

Aiming at allocating the power $\mathbf{p}$ to maximize the total EE, under constraints on per-user minimum data rate and maximum transmit power at each BS, the optimization problem is formulated as follows:

$$\begin{aligned} \max_{\mathbf{p}} \quad & \eta(\mathbf{p}) \\ s.t. \quad & C1: \mathrm{r}_k(\mathbf{p}) \geq R_{\min}, \forall k, \\ & C2: \sum_{k=1}^{K} p_k \leq P_{\max}, \\ & C3: p_k \geq 0, \forall k. \end{aligned} \quad (13)$$

The system should allocate transmit power to each user such that maximize the total EE. In (13), constraint $C1$ is the minimum data rate $R_{\min}$ that must be provided for each user, which is a QoS requirement, and constraint $C2$ is the power constraint where $P_{\max}$ is total maximum transmit power at the BS.

IV. OPTIMAL POWER ALLOCATION

The objective function in (13) is generally non-convex and this optimization problem is known as a nonlinear fractional programming problem. In order to derive an efficient power allocation algorithm for this optimization problem, Dinkelbach's parametric approach is adopted [26]. It is easy to prove that solving the problem in (13) is equivalent to obtaining η^* that makes $\max_{\mathbf{p}} r_{tot}(\mathbf{p}) - \eta^* P(\mathbf{p}) = 0$, where η^* is the maximum EE. Based on Dinkelbach's approach, the problem (13) is transformed to following problem:

$$\begin{aligned} \max_{\mathbf{p}} \quad & r_{tot}(\mathbf{p}) - \eta P(\mathbf{p}) \\ s.t. \quad & C1: \mathrm{r}_k(\mathbf{p}) \geq R_{\min}, \forall k, \\ & C2: \sum_{k=1}^{K} p_k \leq P_{\max}, \\ & C3: p_k \geq 0, \forall k. \end{aligned} \quad (14)$$

In order to solve problem (13), the problem (14) should be solved first with specific value of EE η and obtain the transmit power $\mathbf{p}$ for users iteratively, and compute the objective function $\delta = r_{tot}(\mathbf{p}) - \eta P(\mathbf{p})$, until δ goes to zero.

To address non-concavity of the objective function of (13), a global optimization solution is proposed for global SINR approximation by means of the inequality as follows [27]:

$$\log_2(1+x) \geq a \log_2(x) + b, \quad (15)$$

where a and b are approximation constants at $x = x_0$, respectively

$$\begin{aligned} a &= \frac{x_0}{1+x_0}, \\ b &= \log_2(1+x_0) - a\log_2(x_0). \end{aligned} \quad (16)$$

With the inequality (15), it is easy to find that

$$\log_2(1+\kappa_k \gamma_k(\mathbf{p})) \geq a_k \log_2(\kappa_k \gamma_k(\mathbf{p})) + b_k. \quad (17)$$

Instead of (8), the data rate for user i is changed to:

$$\hat{r}_i(\mathbf{p}) = \frac{\tau_c - \tau_p}{\tau_c} B\left(\mathrm{a}_i \log_2\left(\kappa_i \gamma_i\right) + b_i\right). \tag{18}$$

Change all the elements p_{lk} of power matrix $\mathbf{p}$ to $\hat{p}_k = \ln p_k$, and let $\hat{p}_k$ be the elements of matrix $\hat{\mathbf{p}} \in \mathbb{R}^{K\times 1}$. Therefore the optimization problem (14) can be rewritten as:

$$\begin{aligned} \max_{\hat{\mathbf{p}}} \quad & \hat{r}_{tot}(\hat{\mathbf{p}}) - \eta P(\hat{\mathbf{p}}) \\ s.t. \quad & C1: \hat{\mathrm{r}}_k(\hat{\mathbf{p}}) \ge R_{\min}, \forall k, \\ & C2: \sum_{k=1}^{K} e^{\hat{p}_k} \le P_{\max}. \end{aligned} \tag{19}$$

Since log-sum-exp is concave [28], the problem (19) is a convex optimization problem. In order to solve (14), the problem (19) should be solved iteratively until transmit power converged. Also a_k and b_k are updated in each iteration by obtained transmit power form current iteration with following equations:

$$\begin{aligned} a_k &= \frac{\kappa_k \gamma_k(\hat{\mathbf{p}})}{1 + \kappa_k \gamma_k(\hat{\mathbf{p}})}, \\ b_k &= \log_2\left(1 + \kappa_k \gamma_k(\hat{\mathbf{p}})\right) - a_k \log_2\left(\kappa_k \gamma_k(\hat{\mathbf{p}})\right). \end{aligned} \tag{20}$$

Dual Lagrangian function is used to solve problem (19) since it is a convex optimization problem. Let λ_k and μ be the Lagrangian multipliers corresponding to minimum data rate and maximum transmit power constraints, and the dual Lagrangian function of (19) can be obtained as [28]:

$$\begin{aligned} L(\hat{\mathbf{p}}, \boldsymbol{\lambda}, \mu) = & \hat{r}_{tot}(\hat{\mathbf{p}}) - \eta P(\hat{\mathbf{p}}) \\ & + \sum_{k=1}^{K} \lambda_k \left(\hat{\mathrm{r}}_k(\hat{\mathbf{p}}) - R_{\min}\right) \\ & + \mu\left(P_{\max} - \sum_{k=1}^{K} e^{\hat{p}_k}\right). \end{aligned} \tag{21}$$

Optimal transmit power for user i can be obtained by the Karush Kuhn Tucker (KKT) conditions as follows:

$$\frac{L(\hat{\mathbf{p}}, \boldsymbol{\lambda}, \mu)}{\hat{p}_i} = 0. \tag{22}$$

According to (22), optimal transmit power for user i can be obtained as follows:

$$e^{\hat{p}_i} = p_i = \frac{(1+\lambda_i)\left(\tau_c - \tau_p\right) B a_i}{\ln 2 \cdot \tau_c \left(\frac{\eta}{\rho} + \mu\right)}. \tag{23}$$

By the subgradient method, the Lagrange multipliers can be updated as follows:

$$\lambda_i^{(t+1)} = \left[\lambda_i^{(t)} - \varepsilon_\lambda \left(\frac{\tau_c - \tau_p}{\tau_c} B\left(a_i \log_2\left(\kappa_i \gamma_i\right) + b_i\right) - R_{\min}\right)\right]^+, \tag{24}$$

$$\mu^{(t+1)} = \left[\mu^{(t)} - \varepsilon_\mu \left(P_{\max} - \sum_{k=1}^{K} p_k\right)\right]^+. \tag{25}$$

where $[\,\cdot\,]^+ = \max(0, \cdot)$, ε_λ and ε_μ are step size for $\boldsymbol{\lambda}$ and μ respectively. Algorithm for cooperative energy efficient power allocation is presented in Table I.

TABLE I. ITERATIVE RESOURCE ALLOCATION ALGORITHM

Algorithm 1 Iterative Resource Allocation Algorithm
1: Initialize the maximum tolerance δ and the maximum

number of iterations $T_{\max}$
Set maximum EE $\eta = 0$, $a_k = 1$, $b_k = 0$ and iteration index $t = 0$, and initialize $\boldsymbol{\lambda}$, μ, ε_λ, and ε_μ
Repeat
  Solve the problem in (14) and obtain power allocation policies according (23)
If $r_{tot}(\mathbf{p}) - \eta P(\mathbf{p}) < \delta$ **then**
    Convergence = **true**
Return $\mathbf{p}^*$ and η^*
else
    Set η according to (12)
    Update a_k and b_k according to (20)
    Update $\boldsymbol{\lambda}$ and μ according to (24) and (25)
 $t = t + 1$
    Convergence = **false**
End if
Until Convergence = **true** or $t = T_{\max}$

V. ANALYSIS AND SIMULATION RESULTS

In this section, the system performance is evaluated through simulations. The simulation parameters can be found in Table II. In practice, the values of P_a and P_{fix} depend on the application-specific integrated circuits (ASIC) and the implementation. The values of P_a and P_{fix} adopted in this paper are for illustration purpose and are based on [29] and [30], respectively. On the other hand, in the following results, the "number of iterations" is referring to the number of iterations of Algorithm 1 in Table Ⅰ. Besides, throughput and EE are directly computed by (8) and (12), respectively. In addition, the length of each coherence interval $\tau_c = 200$ and the length for unlink training $\tau_p = 20$ are chosen for simulations.

TABLE II. SYSTEM PARAMETERS

Cell radius	1 km
Reference distance d_0	35 m
Users distribution	Uniformly distributed
Total bandwidth	10 MHz
Noise power σ^2	-104 dBm
Channel path loss model	3GPP- Urban Micro
Lognormal shadowing	Standard deviation of 8 dB
Circuit power per antenna P_a	30 dBm
Static circuit power consumption P_{fix}	40 dBm
Minimum data rate requirement $R_{\min}$	10 Mbps
Power amplifier efficiency ρ	0.3
Target bit error rate	0.001
Number of antennas in each cell M	100

Figure 1 illustrate the evolution of the proposed iterative algorithm for different values of the maximum transmit power, $P_{\max}$, at the BSs and $K = 15$ users. It can be observed that the iterative algorithm converges to the upper bound performance within 10 iterations.

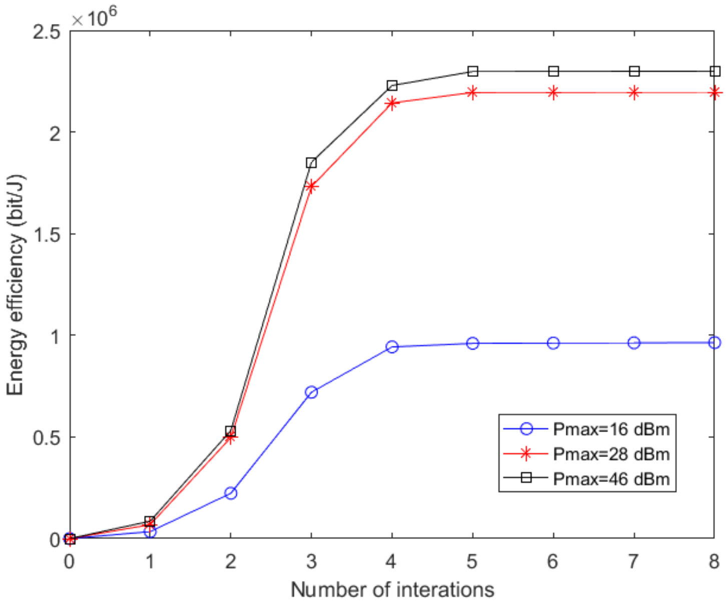

Fig.1. Energy efficiency versus the number of interatios

Figure 2 illustrates the EE versus the maximum transmit power for each BS. It can be observed that when the maximum transmit power at the power amplifier is large enough, e.g., $P_{\max} \geq 40\,\text{dBm}$, the EE of the propose algorithm approaches a constant value since the resource allocator is not willing to consume more power when the maximum EE is achieved. For comparison, Figure 2 also contains the EE of an average power allocation scheme in which the power is equally allocated to each user. It can be observed that in the high transmit power regime, the performance gain of the proposed algorithm over the average power allocation scheme is reduced. This is due tothe fact that in the high transmit power regime, the throughput rate increases slower than the power consumption.

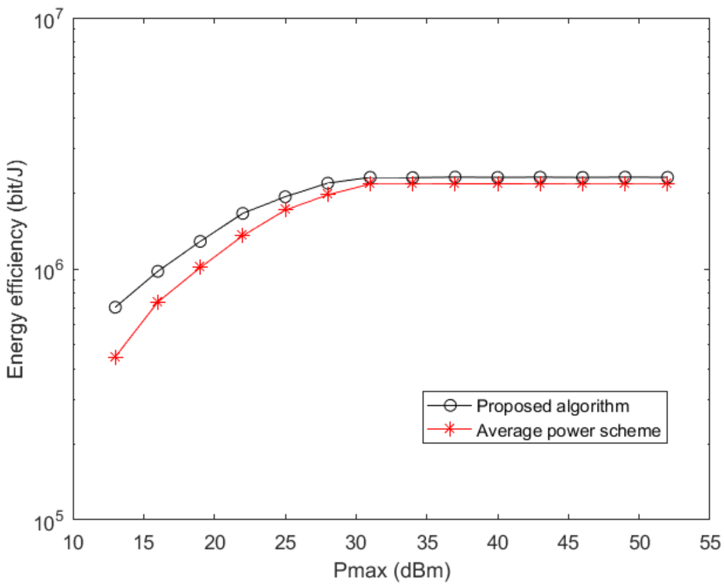

Fig.2. Energy efficiency versus maximum transmit power

Figure 3 depicts the EE versus the number of users. It can be observed that the EE grows first with the number of users since the proposed resource allocation is able to exploit multiuser diversity. In general, multiuser diversity introduces an extra power gain [31] to the system which provides further energy savings. Indeed, since a large number of transmit antennas reduces the multipath propagation fluctuations in each channel, the potentially achievable multiuser diversity gain due to the multipath channel vanishes.

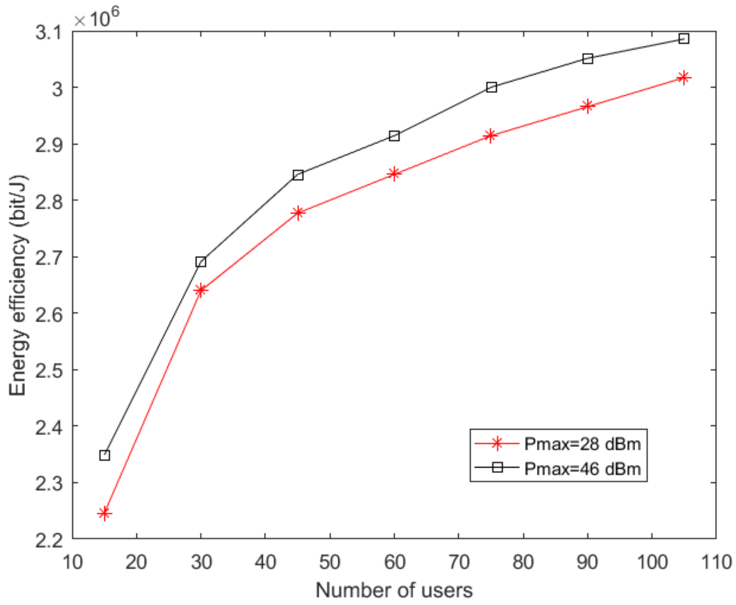

Fig.3. EE versus the number of users

VI. CONCLUSION

In this paper, a cooperative energy efficient power allocation algorithm for downlink massive MIMO system is proposed. Based on cooperation between users and BS, a closed form for optimal transmit power is found and an algorithm is proposed. Simulation results did not only show that the proposed algorithm converges to the solution within a small number of iterations, but also demonstrate the EE gain compared with existing resource allocation scheme.

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