

On the Total Energy Efficiency for Multipoint Cooperative Communication of Massive MIMO

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ABSTRACT: This paper investigates the massive multiple-input multiple-output (MIMO) downlink where base stations (BSs) equipped with a very large number of antennas serve many single-antenna users. Maximum ratio transmission (MRT) beamforming scheme is applied at each BS via the use of local channel state information (CSI). The CSI is acquired through time-division duplex operation of uplink training signals transmitted by users. A closed-form expression for the energy efficiency (EE) is derived to design an optimal power allocation algorithm. The optimal power allocation algorithm aims at maximizing the total EE, and subjects to a quality of service (QoS) for per-user constraint and a BS maximum transmit power constraint. 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

Due to the rapid growth of smart terminal usage and high data rate requirements services, cellular network traffic increases greatly nowadays [1]-[2]. 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 point and increase SE for a large number of transmit antenna. However, circuit power consumption which connected to the number of antennas also increases. If circuit power consumption is not considered, unlimited number of transmit antenna is optimal to achieve maximum EE [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 authors maximize the energy efficiency defined as the ratio of the achieved throughput over the energy cost by optimizing the time allocation for the downlink [6]. While in [7], the authors investigate a joint uplink pilot and data power allocation strategy for energy efficient communications under pilot contamination in multi-cell multi-user massive MIMO systems. 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], quality of service (QoS) constraints are satisfied in EE optimal systems to provide a fair network.

To obtain channel state information (CSI), time division duplexing (TDD) protocol is used at the base stations (BSs). 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. It is impossible for all users in all cells to have orthogonal pilots due to resource limitation, 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, a minimum data rate should be provided to guarantee the QoS for each user. 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 multi cell multi user massive MIMO system. The system consists of L cells with one BS in each cell. Each BS has large number of fixed transmit antennas M which serve K single antenna users. It is assumed that all users are randomly located and $M \gg K$. 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 $\tau_p, \tau_p < \tau_c$, 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 their corresponding BSs. The received signal at BS in cell $j, j = 1, 2, \dots, L$, from users can be written as follows:

$$\mathbf{Y}_{u,j} = \sum_{l=1}^L \sum_{k=1}^K \sqrt{p^u} \mathbf{g}_{jlk} \boldsymbol{\phi}_{lk}^H + \mathbf{N}_{u,j}, \quad (1)$$

where $\boldsymbol{\phi}_{lk} \in \mathbb{C}^{\tau_p \times 1}$ is the pilot transmitted by user k in cell l which is normalized as $\|\boldsymbol{\phi}_{lk}\|^2 = 1$, $\mathbf{g}_{jlk} \in \mathbb{C}^{M \times 1}$ is the channel vector between the user k in cell l and the BS in cell j , and $\mathbf{N}_{u,j}$ is an $M \times \tau_p$ Gaussian additive noise matrix whose elements follow a complex Gaussian distribution, $CN(0, \sigma_w^2 I_N)$, in which σ_w^2 is the noise variance after data transmission. The channel \mathbf{g}_{jlk} models the propagation as follows:

$$\mathbf{g}_{jlk} = \beta_{jlk}^{1/2} \mathbf{h}_{jlk}, \quad (2)$$

where β_{jlk} is the large scale fading parameter which captures the effects of path loss and shadowing that changes slowly, and \mathbf{h}_{jlk} is an $M \times 1$ vector of small scale fading coefficients between the M antennas of the BS in cell j and the user k in cell l . Small scale fading is assumed to be Rayleigh fading, i.e., the elements of \mathbf{h}_{jlk} 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 $\hat{\mathbf{g}}_{jlk}$ can be obtained as follows:

$$\hat{\mathbf{g}}_{jlk} = \frac{1}{\sqrt{p^u}} \mathbf{Y}_{u,j} \boldsymbol{\phi}_{lk}. \quad (3)$$

2) *Downlink Payload Data Transmission:* After acquitting 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]. For BS in cell $j, j = 1, 2, \dots, L$, the MRT beamforming vector for its user $k, k = 1, 2, \dots, K$, can be obtained as follows:

$$\mathbf{w}_{jk} = \frac{\bar{\hat{\mathbf{g}}}_{jlk}}{\|\hat{\mathbf{g}}_{jlk}\|}, \quad (4)$$

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

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

$$\mathbf{x}_j = \sum_{k=1}^K \sqrt{p_{jk}} \mathbf{w}_{jk} s_{jk} = \sum_{k=1}^K \sqrt{p_{jk}} \frac{\bar{\mathbf{g}}_{jjk}}{\|\bar{\mathbf{g}}_{jjk}\|} s_{jk}, \quad (5)$$

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

$$\begin{aligned} y_{ji} &= \sum_{l=1}^L \mathbf{g}_{lji}^T \mathbf{x}_l + n_{ji} \\ &= \sum_{l=1}^L \sum_{k=1}^K \sqrt{p_{lk}} \mathbf{g}_{lji}^T \frac{\bar{\mathbf{g}}_{llk}}{\|\bar{\mathbf{g}}_{llk}\|} s_{lk} + n_{ji} \\ &= \sqrt{p_{ji}} \mathbf{g}_{jji}^T \frac{\bar{\mathbf{g}}_{jji}}{\|\bar{\mathbf{g}}_{jji}\|} s_{ji} + \sum_{l=1, l \neq j}^L \sum_{k=1, k \neq i}^K \sqrt{p_{lk}} \mathbf{g}_{lji}^T \frac{\bar{\mathbf{g}}_{llk}}{\|\bar{\mathbf{g}}_{llk}\|} s_{lk} + n_{ji}, \end{aligned} \quad (6)$$

where $n_{ji} \sim CN(0, \sigma^2)$ is the Gaussian additive noise.

B. Total Throughput

The user i in cell j will detect its desired signal s_{ji} from the received signal y_{ji} 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 in cell j can be expressed as follows:

$$\gamma_{ji}(\mathbf{p}) = \frac{p_{ji} \|\mathbf{g}_{jji}^T \mathbf{w}_{ji}\|^2}{\sum_{l=1}^L \sum_{k=1, k \neq i}^K p_{lk} \|\mathbf{g}_{lji}^T \mathbf{w}_{lk}\|^2 + \sigma^2}. \quad (7)$$

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

$$r_{ji}(\mathbf{p}) = \frac{\tau_c - \tau_p}{\tau_c} B \log_2(1 + \kappa_{ji} \gamma_{ji}), \quad (8)$$

where B is bandwidth and κ_{ji} is SINR gap between Shannon channel capacity and a practical modulation and coding scheme. The SINR gap is equal to $-1.5/\ln(5e_{ji})$, where e_{ji} is target bit error rate for user i in cell j [21].

The total throughput of the system can be obtained as:

$$r_{tot}(\mathbf{p}) = \sum_{l=1}^L \sum_{k=1}^K r_{lk}. \quad (9)$$

III. POWER CONSUMPTION MODEL AND ENERGY EFFICIENCY MAXIMIZATION

A. Power consumption Model

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

$$P_l = \frac{1}{\rho} \sum_{k=1}^K p_{lk} + MP_a + P_{fix}, \quad (10)$$

where ρ is the power amplifier efficiency, p_{lk} is transmit power for user k in cell l , 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.

The total power consumption of the system can be expressed as

$$\begin{aligned} P_{total}(\mathbf{p}) &= \sum_{l=1}^L P_l \\ &= \frac{1}{\rho} \sum_{l=1}^L \sum_{k=1}^K p_{lk} + LMP_a + LP_{fix}. \end{aligned} \quad (11)$$

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:

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

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:

$$\begin{aligned} \max_{\mathbf{p}} \quad & \eta(\mathbf{p}) \\ \text{s.t.} \quad & C1: r_{lk}(\mathbf{p}) \geq R_{\min}, \forall k, \forall l, \\ & C2: \sum_{k=1}^K p_{lk} \leq P_{\max}, \forall l, \\ & C3: p_{lk} \geq 0, \forall k, \forall l. \end{aligned} \tag{13}$$

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 each 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 $\max_{\mathbf{p}} r_{tot}(\mathbf{p}) - \eta^* P_{total}(\mathbf{p}) = 0$, where η^* is the maximum

EE. Based on Dinkelbach’s approach, the problem (13) is transformed to following problem:

$$\begin{aligned} \max_{\mathbf{p}} \quad & r_{tot}(\mathbf{p}) - \eta P_{total}(\mathbf{p}) \\ \text{s.t.} \quad & C1: r_{lk}(\mathbf{p}) \geq R_{\min}, \forall k, \forall l, \\ & C2: \sum_{k=1}^K p_{lk} \leq P_{\max}, \forall l, \\ & C3: p_{lk} \geq 0, \forall k, \forall l. \end{aligned} \tag{14}$$

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 $\delta = r_{tot}(\mathbf{p}) - \eta P_{total}(\mathbf{p})$, 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]:

$$\log_2(1+x) \geq a \log_2(x) + b, \tag{15}$$

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

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

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

$$\log_2(1 + \kappa_{lk} \gamma_{lk}(\mathbf{p})) \geq a_{lk} \log_2(\kappa_{lk} \gamma_{lk}(\mathbf{p})) + b_{lk}. \tag{17}$$

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

$$\hat{r}_{ji}(\mathbf{p}) = \frac{\tau_c - \tau_p}{\tau_c} B \left(a_{ji} \log_2(\kappa_{ji} \gamma_{ji}) + b_{ji} \right). \tag{18}$$

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

$$\begin{aligned} \max_{\hat{\mathbf{p}}} \quad & \hat{r}_{tot}(\hat{\mathbf{p}}) - \eta P_{total}(\hat{\mathbf{p}}) \\ \text{s.t.} \quad & C1: \hat{r}_{lk}(\hat{\mathbf{p}}) \geq R_{\min}, \forall k, \forall l, \\ & C2: \sum_{k=1}^K e^{\hat{p}_{lk}} \leq P_{\max}, \forall l. \end{aligned} \tag{19}$$

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_{lk} and b_{lk} are updated in each iteration by obtained transmit power form current iteration with following equations:

$$a_{lk} = \frac{\kappa_{lk} \gamma_{lk}(\hat{\mathbf{p}})}{1 + \kappa_{lk} \gamma_{lk}(\hat{\mathbf{p}})}, \tag{20}$$

$$b_{lk} = \log_2(1 + \kappa_{lk} \gamma_{lk}(\hat{\mathbf{p}})) - a_{lk} \log_2(\kappa_{lk} \gamma_{lk}(\hat{\mathbf{p}})).$$

Dual Lagrangian function is used to solve problem (19) since it is a convex optimization problem. Let λ_{lk} and μ_l 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]:

$$L(\hat{\mathbf{p}}, \boldsymbol{\lambda}, \boldsymbol{\mu}) = \hat{r}_{tot}(\hat{\mathbf{p}}) - \eta P_{total}(\hat{\mathbf{p}}) + \sum_{l=1}^L \sum_{k=1}^K \lambda_{lk} (\hat{r}_{lk}(\hat{\mathbf{p}}) - R_{min}) + \sum_{l=1}^L \mu_l \left(P_{max} - \sum_{k=1}^K e^{\hat{p}_{lk}} \right). \tag{21}$$

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

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

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

$$e^{\hat{p}_{ji}} = p_{ji} = \frac{(1 + \lambda_{ji})(\tau_c - \tau_p) B a_{ji}}{\ln 2 \cdot \tau_c \left(\frac{\eta}{\rho} + \mu_j \right)}. \tag{23}$$

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

$$\lambda_{ji}^{(t+1)} = \left[\lambda_{ji}^{(t)} - \varepsilon_\lambda \left(\frac{\tau_c - \tau_p}{\tau_c} B (a_{ji} \log_2(\kappa_{ji} \gamma_{ji}) + b_{ji}) - R_{min} \right) \right]^+, \tag{24}$$

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

where $[\cdot]^+ = \max(0, \cdot)$, ε_λ and ε_μ are step size for $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ 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}
2:	Set maximum EE $\eta = 0$, $a_{lk} = 1$, $b_{lk} = 0$ and iteration index $t = 0$, and initialize $\boldsymbol{\lambda}$, $\boldsymbol{\mu}$, ε_λ , and ε_μ
3:	Repeat
4:	Solve the problem in (14) and obtain power allocation policies according (23)
5:	If $r_{tot}(\mathbf{p}) - \eta P_{total}(\mathbf{p}) < \delta$ then
6:	Convergence = true
7:	Return \mathbf{p}^* and η^*
8:	else
9:	Set η according to (12)
10:	Update a_{lk} and b_{lk} according to (20)
11:	Update $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ according to (24) and (25)
12:	$t = t + 1$
13:	Convergence = false

- 14: **End if**
- 15: **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
Number of cells L	3

Fig.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.

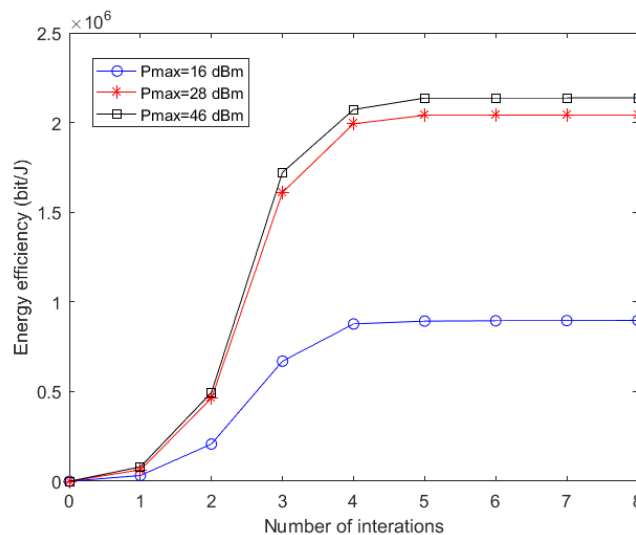


Fig.1. Energy efficiency versus the number of interatio

Fig.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., $P_{\max} \geq 40$ 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 to the fact that in the high transmit power regime, the throughput rate increases slower than the power consumption.

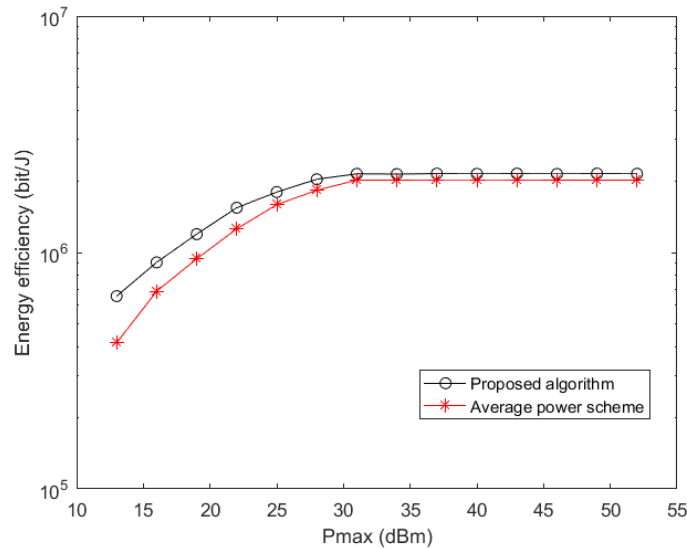


Fig.2. Energy efficiency versus maximum transmit power

Fig.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.

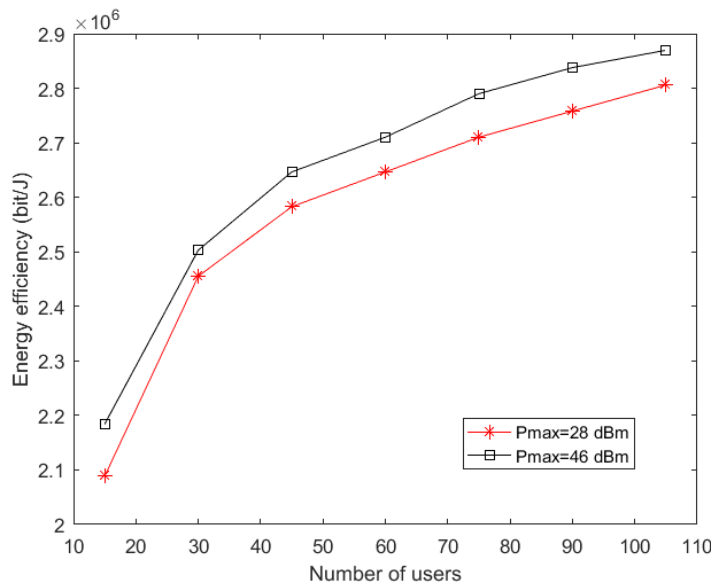


Fig.3. EE versus the number of users

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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