Energy-Efficient Resource Allocation in Distributed Antenna Systems

Xiaoge Huang, Weipeng Dai, Zhifang Zhang, Qiong Huang, and Qianbin Chen(✉)

School of Communication and Information Engineering, Chongqing University of Posts and Telecommunications, Chongqing, China
{Huangxg,Huangqiong,Chenqb}@cqupt.edu.cn, daiweipeng@hotmail.com

Abstract. In this paper, we introduce an energy-efficient resource allocation scheme in distributed antenna systems (DASs). Throughout the paper, the resource allocation includes distributed antenna units (DAU) selection, subcarriers assignment and power allocation. Our aim is to optimize energy efficiency (EE) of the whole system, which is defined as the ratio of total data rate to total consumed power, under the constraints of the overall transmit power of each DAU and minimum required data rate of each user. Due to the mixed combinatorial features of the formulation, we focus on low-complexity suboptimal algorithm design. Firstly, a joint DAU selection and subcarriers assignment algorithm is developed with equal power allocation. Secondly, EE maximization problem is a non-convex fractional programming problem, we transform the problem into a subtractive form, then solve it by using the Lagrangian dual decomposition. The simulation results show the convergence performance, and demonstrate the advantage of the proposed resource allocation scheme compared with the random resource allocation scheme.

Keywords: Distributed antenna systems · Energy efficiency · Resource allocation

1 Introduction

With the rapid development of economy and society, the proliferation of mobile devices and diverse mobile applications demand high data rate and ubiquitous access. To meet such mobile data challenges, DAS has been considered as a promising candidate for future wireless communication networks. Due to its advantages of reducing access distance, transmit power, and co-channel interference, DAS can increase the network capacity and expand coverage, thus it is considered as a key technology for next generation communications in the future

This work is supported by the National Natural Science Foundation of China (NSFC) (61401053, 61201205), the 863 project No. 2014AA01A701, and Changjiang Scholars and Innovative Research Team in University (IRT1299), Special Fund of Chongqing Key Laboratory (CSTC).

Q. Chen et al. (Eds.): ChinaCom 2016, Part I, LNICST 209, pp. 97–106, 2018.
DOI: 10.1007/978-3-319-66625-9_10

[1,2]. In DAS, a certain number of distributed antenna units (DAU) are located in different positions in cell and connected to a central processing unit via optical fibers or high speed cable. The central processing unit is used to process information and resource allocation.

Recently, due to the rapid growth of global energy consumption and the environmental problems, EE has attracted more attention in both academia and industry [3,4]. EE is proposed as a metric which is defined as the sum-rate divided by the total power consumption measured in bits/Hz/Joule. In [5], a scheme of maximizing EE is proposed, the authors demonstrate that there is a tradeoff between EE and spectrum efficient transmission. [6,7] study EE maximization in DAS through optimal power allocation. In [6] the authors consider multi-cell DAS and use successive Taylor expansion to formulate subproblems which are solved by iterative power allocation algorithm; [7] studys a practical case where the channel state information (CSI) is slowly-varying, the authors propose an iterative algorithm to achieve the global optimal solution. On the other hand, orthogonal frequency division multiplexing (OFDM) is regarded as a potential transmission technology for the future wireless network due to its flexibility in resource allocation and effectiveness in anti-multipath fading. There are many relevant research works on EE optimization and resource allocation. In [8], the authors develop an energy-efficient resource allocation scheme including subcarriers allocation and power allocation under different constraints with fixed DAU assignment. [9] investigates EE optimization problem and the authors consider power consumption of the transmitter and receiver to capture the impact of subcarriers and users on EE, and propose a joint optimization method for optimal solution.

Different from existing works, in this paper, we study the energy-efficient resource allocation optimization, joint antenna units selection, subcarriers assignment and power allocation for a downlink multiuser OFDM DAS. The optimization objective is to maximize EE under the constraints of total transmit power of each BS and minimum rate requirement of each user. Nevertheless, due to the non-convex nature of the problem, it is especially challenging to manage DAUs and subcarriers assignment, thus the optimal solution is extremely computationally complicated. Therefore, we divide the optimization problem into two suboptimal problems. Namely, DAU-subcarrier assignment optimization and power allocation optimization. In the DAU-subcarrier optimization process, we ensure that each user can be served by at least one DAU, and optimize the DAU-subcarrier assignment with equal allocation power to maximize EE of network. In the power allocation optimization process, we transform the fractional programming problem into an equivalent optimization problem in subtractive form, which can easily be solved by using the Lagrangian dual decomposition.

The rest of the paper is organized as follows. We describe the system model and formulate the problem of EE optimization in Sect. 2. Section 3 gives the EE resource allocation algorithm consisting of two sub-optimization algorithms that are DAU-subcarrier assignment and power allocation optimization. Simulation results and performance evaluation are given in Sect. 4. Followed by the conclusion drawn in Sect. 5.

2 System Model and Problem Formulation

A. System Model Description
We consider a downlink single-cell OFDM DAS, where both M DAUs and K users (M ≥ K) with single antenna are uniform randomly distributed in the cell area. N orthogonal subcarriers are used for serving users simultaneously. The bandwidth of each subcarrier is $B = \frac{W}{N}$, W is the total bandwidth. All DAUs are physically connected with a central processing unit via optical fibers. The received signal for the user k on the nth subcarrier from the mth DAU is written as

$$y_{k,n,m} = \sqrt{p_{k,n,m}} h_{k,n,m} x_{k,n,m} + z_{k,n,m} \tag{1}$$

where $p_{k,n,m}$ is the transmit power allocated to the mth DAU on the nth subcarrier. $h_{k,n,m}$ denotes composite flat-fading channel impulse response between the mth DAU on nth subcarrier and user k. It consists of small-scale and large-scale fading, which is modeled as $h_{k,n,m} = g_{k,m} \cdot l_{k,n,m}$, $g_{k,m} = \sqrt{s_{k,m} \cdot d_{k,m}^{-\alpha}}$ represents the large-scale fading, $s_{k,m}$ is a lognormal shadow fading variable, $10 \log_{10} s_{k,m}$ is a zero-mean gaussian random variable with standard deviation σ_{sh}, $d_{k,m}$ is the distance between DAU m and user k, α is the path-loss exponent. $l_{k,n,m}$ denotes the small-scale fading of channel which is an independent and identically distributed complex gaussian random variable with zero mean and unit variance. $z_{k,n,m}$ is additive white gaussian noise with zero mean and variance equal to 1.

B. EE Optimization Problem Formulation
According to Shannon's Theorem, the overall data rate of user k can be expressed as

$$r_k = B \sum_{m=1}^{M} \sum_{n=1}^{N} a_{k,m} b_{n,m} \log_2 \left(1 + \frac{p_{k,n,m} |h_{k,n,m}|^2}{\Gamma \sigma_z^2}\right) \tag{2}$$

where $a_{k,m}$ and $b_{n,m}$ are binary variables. $a_{k,m} = 1$ indicates that DAU m is assigned to user k, otherwise, $a_{k,m} = 0$. $b_{n,m} = 1$ denotes that subcarrier n is assigned to DAU m, otherwise, $b_{n,m} = 0$. $\Gamma = -\frac{1.5}{\ln(5 P_{BER})}$ is a constant for a specific probability of a BER (P_{BER}) requirement. The overall data rate of the system is

$$R_{tot} = \sum_{k=1}^{K} r_k \tag{3}$$

Furthermore, the total power consumption of the system is modeled as

$$P_{tot} = \tau p_t + M p_c + p_o \tag{4}$$

where $p_t = \sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{n=1}^{N} a_{k,m} b_{n,m} p_{k,n,m}$, τ is the drain efficiency of the radio-frequency power amplifier. p_c is the circuit power consumption. p_o is the dissipated power by the fiber-optic transmission. We define EE of an OFDM DAS as the ratio of the total data rate R_{tot} to the total power consumption P_{tot}, i.e.

$$EE = R_{tot}/P_{tot} \tag{5}$$

Our goal is to maximize EE while meet the minimum rate requirement of each user, as well as the total transmit power constraint of each DAU. The EE optimization problem for a downlink multiuser OFDM DAS is given as

$$\begin{aligned}
\textbf{P1:} \max_{\mathbf{a},\mathbf{b},\boldsymbol{P}} \quad & EE = \frac{R_{tot}(\mathbf{a},\mathbf{b},\boldsymbol{P})}{P_{tot}(\mathbf{a},\mathbf{b},\boldsymbol{P})} \qquad (6)\\
\text{s.t.} \quad & C1: r_k \geq R_k^{req}, \forall k \\
& C2: \sum_{n=1}^{N} a_{k,m} b_{n,m} p_{k,n,m} \leq p_m^{max}, \forall k, m \\
& C3: 1 \leq \sum_{m=1}^{M} a_{k,m} \leq M - K + 1, \forall k \\
& C4: \sum_{k=1}^{K} a_{k,m} \leq 1, \forall m; \sum_{m=1}^{M} b_{n,m} \leq 1, \forall n \\
& C5: \sum_{n=1}^{N} b_{n,m} \leq N_m, \forall m \\
& C6: a_{k,m} \in \{0,1\}, b_{n,m} \in \{0,1\}, \forall k, n, m \\
& C7: p_{k,n,m} \geq 0, \forall k, n, m
\end{aligned}$$

The constraints $C1$ and $C2$ ensure that each user's data rate requirement and each DAU's maximum transmit power budget are satisfied. The constraint $C3$ guarantees that each user can be served by at least one DAU. The constraints $C4$ and $C6$ indicate that each DAU and each subcarrier can only be allocated to one user and one DAU respectively. $C5$ denotes the number of subcarriers assigned to each DAU is N_m. Notice that if the parameter setting on R_k^{req} and p_m^{max} is not appropriate, the optimization problem **P1** is infeasible, here we assume that the optimization problem **P1** is always feasible.

3 Energy Efficient Resource Allocation with Distributed Antennas

Notice that problem **P1** with nonlinear constraints is a mixed integer nonlinear programming problem, due to problem's high computation complexity, we focus on low-complexity algorithm. Therefore, we divide the optimization problem into two sub-optimization problems, which are joint DAU-subcarrier assignment and power allocation optimization.

3.1 Joint DAU and Subcarrier Assignment

A. Number of subcarriers per DAU
In general, the closer the distance between user and DAU is, the better the channel condition is. The contribution to throughput is greater and the probability of serving this user is also larger [10]. For unity transmit power, SNR of user k from DAU m on subcarrier n is given by $snr_{k,n,m} = |h_{k,n,m}|^2/\sigma_z^2$. Similarly, we can get $M \times K \times N$ $SNRs$ of the whole network, then construct a $M \times K \times N$ three dimensional matrix denoted by $SNR_{k,n,m}(K, N, M)$, for a specific subcarrier n, the matrix can be expressed as

$$SNR_{k,m}(n) = \begin{bmatrix} snr_{1,n,1} & snr_{2,n,1} & \cdots & snr_{K,n,1} \\ snr_{1,n,2} & snr_{2,n,2} & \cdots & snr_{K,n,2} \\ \vdots & \vdots & \ddots & \vdots \\ snr_{1,n,M} & snr_{2,n,M} & \cdots & snr_{K,n,M} \end{bmatrix} \tag{7}$$

Summing up all elements by row of matrix $SNR_{k,m}(n)$, we can get a new matrix

$$SNR_m(n) = \left[\sum_{k=1}^{K} snr_{k,n,1}, \sum_{k=1}^{K} snr_{k,n,2}, \cdots, \sum_{k=1}^{K} snr_{k,n,M} \right]^T \tag{8}$$

Let p_m^n denotes the accessing probability of DAU m on subcarrier n, given by

$$p_m^n = \sum_{k=1}^{K} snr_{k,n,m} / \sum_{m=1}^{M} \sum_{k=1}^{K} snr_{k,n,m} \tag{9}$$

The accessing probability of each DAU on subcarrier n is a vector, i.e. $\mathbf{p}^n = \left[p_1^n, p_2^n, \cdots, p_M^n\right]^T$. For N subcarriers, the total accessing probability of DAU m is $\mathbf{p}_m = \sum_{n=1}^{N} p_m^n = p_m^1 + p_m^2 + \cdots + p_m^N$, thus we can get $\varnothing_m = \frac{\sum_{n=1}^{N} p_m^n}{\sum_{m=1}^{M} \sum_{n=1}^{N} p_m^n}$, where $\varnothing_m$ denotes the ratio of the total accessing probability of DAU m to the total accessing probability of all the DAUs. Hence, the number of subcarriers of assigning to DAU m is expressed as $N_m = \lfloor \varnothing_m \cdot N \rfloor$.

B. Optimal DAU selection and subcarriers allocation
We assign DAUs to users based on the CSI. Assignment procedure is consisted of following steps:

- Step 1: Sorting DAUs based on the CSI and assign the best DAU with the best subcarrier to the corresponding user, then the pairs of DAU-subcarrier will be erased from the selection list. Repeating until all the users are served by one DAU.
- Step 2: Assigning the rest of DAUs in the selection list based on the CSI until all remaining DAUs are assigned to users.
- Step 3: Assigning the rest of subcarriers to DAUs until the number of subcarriers of DAU is N_m.

The proposed optimal algorithm is summarized in Algorithm 1.

Algorithm 1. Joint DAU selection and Subcarriers Assignment Algorithm

1: **Initialization** : $S_k = \emptyset$, $\Omega_m = \emptyset$, let $\overline{M} = \{1, \cdots, M\}$, $\overline{K} = \{1, \cdots, K\}$, $\overline{N} = \{1, \cdots, N\}$;
2: Step 1: Construct a three-dimensional matrix $\mathrm{H(K, N, M)}$.
   2.1 Find maximum $h_{k^*,n^*,m^*} \in \mathrm{H}$; let $m^* \in S_{k^*}$, $n^* \in \Omega_{m^*}$; $\Omega_{m^*} = \Omega_{m^*}+1$, $S_{k^*}=S_{k^*}+1$; $i=k$, then $\overline{M}= \overline{M} - m^*$, $\overline{K} = \overline{K} - k^*$, $\overline{N} = \overline{N} - n^*$;
   2.2 Remove $\mathrm{H}(:, :, \mathrm{m}^*)$, $\mathrm{H}(\mathrm{k}^*, :, :)$ and $\mathrm{H}(:, \mathrm{n}^*, :)$. Set $i=i-1$, Repeat 2.1.
   2.3 Until $|\overline{M}|_r=M-K$, $|\overline{N}|_r=N-K$, $i=0$.
3: Step 2: Based on step 1, construct matrix $\mathrm{H'(K, N-K, M-K)}$.
   3.1 Find maximum $h_{k^*,n^*,m^*} \in \mathrm{H'(K, N-K, M-K)}$; let $m^* \in S_{k^*}$, $n^* \in \Omega_{m^*}$; $\Omega_{m^*}= \Omega_{m^*}+1$; $\overline{M} = M-K-m^*$, $\overline{N} = N-K-n^*$;
   3.2 Remove $\mathrm{H}'(:, :, \mathrm{m}^*)$ and $\mathrm{H}'(:, \mathrm{n}^*, :)$. Set $M=M-K-1$, Repeat 3.1.
   3.3 Until $|\overline{M}|_r=0$; $|\overline{N}|_r=N-M$; $\Omega_m = 1, \forall m$.
4: Step 3: Get $S_k \neq \emptyset$, and $\sum_{k=1}^{K} |S_k| = M$, $\sum_{m=1}^{M} \Omega_m = M$;
   4.1 Construct matrix $\mathrm{H_k(k, N-M, |S_k|)}$;
   4.2 Traverse H_k, find maximum channel gain $h_{k^*,n^*,m^*}, m^* \in S_{m^*}$; Let $n^* \in \Omega_{m^*}$, remove $\mathrm{H_k(k, n^*, :)}$. $\overline{N}=\overline{N}-M-n^*$, when $|\Omega_m|=N_m$, stop.

3.2 Power Allocation Optimization

Based on the optimal DAU selection and subcarriers allocation algorithm, we determine the set of DAU S_k to serve user k and the set of subcarriers to DAU m is denoted as Ω_m. Therefore, the Eqs. (2) and (4) can be changed into (10) and (11), respectively.

$$r_k = B \sum_{m \in S_k} \sum_{n \in \Omega_m} \log_2\left(1 + \frac{p_{k,n,m}|h_{k,n,m}|^2}{\Gamma \sigma_z^2}\right) \tag{10}$$

$$P_{tot} = \sum_{k=1}^{K} \sum_{m \in S_k} \sum_{n \in \Omega_m} \tau p_{k,n,m} + M p_c + p_o \tag{11}$$

Thus, the optimization problem **P1** is converted to optimization problem **P2**

$$\begin{aligned} \max_{\boldsymbol{P}} \quad & EE = R_{tot}(\boldsymbol{P})/P_{tot}(\boldsymbol{P}) \\ \text{s.t.} \quad & C1 : r_k \geq R_k^{req}, \forall k \\ & C2 : \sum_{n \in \Omega_m} p_{k,n,m} \leq p_m^{max}, \forall k, m \\ & C7 : p_{k,n,m} \geq 0, \forall k, n, m \end{aligned} \tag{12}$$

Due to the non-convexity of problem **P2**, it is difficult to solve. However, the numerator and denominator of Eq. (12) are differentiable concave and affine functions with respect to $\boldsymbol{P}$ respectively. So problem **P2** can be transformed into a equivalent subtractive form, and solved by using Lagrangian dual decomposition method [11]. The subtractive form problem **P3** is given as

$$\begin{aligned} \max_{\boldsymbol{P}} \quad & U(q) = R_{tot}(\boldsymbol{P}) - q \cdot P_{tot}(\boldsymbol{P}) \\ \text{s.t.} \quad & C1, C2, C7. \end{aligned} \tag{13}$$

Theorem 1. There is $q^* = \max \frac{R_{tot}(\boldsymbol{P}^*)}{P_{tot}(\boldsymbol{P}^*)}$, if and only if, $U(q^*) = R_{tot}(\boldsymbol{P}^*) - q^* \cdot P_{tot}(\boldsymbol{P}^*) = 0$.

In Theorem 1, q^* is the optimal EE to be determined, $\boldsymbol{P}^*$ is the optimal power to be allocated. The Lagrangian function of optimization problem (13) can be expressed as

$$\begin{aligned} L(\boldsymbol{P}, \boldsymbol{\alpha}, \boldsymbol{\beta}) =& B \sum_{k=1}^{K} \sum_{m \in S_k} \sum_{n \in \Omega_m} \log_2(1 + \frac{p_{k,n,m}|h_{k,n,m}|^2}{\Gamma \sigma_z^2}) - \sum_{k=1}^{K} \alpha_k (R_k^{req} - r_k) \\ & - q(\sum_{k=1}^{K} \sum_{m \in S_k} \sum_{n \in \Omega_m} \tau p_{k,n,m} + M p_c + p_o) - \sum_{m=1}^{M} \beta_m (\sum_{n \in \Omega_m} p_{k,n,m} - p_m^{max}); \end{aligned} \tag{14}$$

where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \cdots, \alpha_K]^T$ and $\boldsymbol{\beta} = [\beta_1, \beta_2, \cdots, \beta_M]^T$ are non-negative Lagrange multipliers. The optimal power $p^*_{k,n,m}$ can be obtained through differentiating with respect to $p_{k,n,m}$, which is given as

$$p^*_{k,n,m} = \Big[\frac{(1 + \alpha_k)B}{(q\tau + \beta_m)\ln 2} - \frac{\Gamma \sigma_z^2}{|h_{k,n,m}|^2}\Big]^+. \tag{15}$$

where $[x]^+ = \max\ (0, x)$, the power allocation scheme can be regarded as the classical water-filling policy. Notably that there is a zero duality gap between the primal problem and its dual problem, if the problem is convex. For the optimization problem **P3**, the Lagrange dual function is derived by

$$\begin{aligned} & g(\boldsymbol{\alpha}, \boldsymbol{\beta}) = max\ L(\boldsymbol{P}, \boldsymbol{\alpha}, \boldsymbol{\beta}) \\ & s.t.\ C1, C2, C7. \end{aligned} \tag{16}$$

and we have the dual problem which is

$$\min_{\boldsymbol{\alpha}, \boldsymbol{\beta}} g(\boldsymbol{\alpha}, \boldsymbol{\beta}) \quad s.t. \boldsymbol{\alpha} \geq 0, \boldsymbol{\beta} \geq 0 \tag{17}$$

The sub-gradient method could be employed to solve the problem, The sub-gradient of dual function can be expressed as

$$\Delta \alpha_k^{(i)} = B \sum_{m \in S_k} \sum_{n \in \Omega_m} \log_2(1 + \frac{p^{*(i)}_{k,n,m}|h_{k,n,m}|^2}{\Gamma \sigma_z^2}) - R_k^{req}, \tag{18}$$

$$\Delta \beta_m^{(i)} = p_m^{max} - \sum_{n \in \Omega_m} p^{*(i)}_{k,n,m}. \tag{19}$$

where $p^{*(i)}_{k,n,m}$ is optimal allocation power in the i iteration. The multipliers α_k and β_m can be updated through following formulas

$$\alpha_k^{(i+1)} = \left[\alpha_k^{(i)} - \delta^{(i)} \Delta \alpha_k^{(i)}\right]^+,\ \beta_m^{(i+1)} = \left[\beta_m^{(i)} - \xi^{(i)} \Delta \beta_m^{(i)}\right]^+. \tag{20}$$

where i is iteration index, $\delta^{(i)}$ and $\xi^{(i)}$ are sufficiently small positive step size. In the paper, we assume $\delta^{(i)} = \xi^{(i)} = \frac{0.1}{i}$, According to all the above analysis and procedure, the process of optimal power allocation algorithm is outlined in Algorithm 2.

Algorithm 2. Energy Efficient Power Allocation Optimization Algorithm

Initialization : α, β, the maximal iterations I_{max}, T_{max}, error tolerance threshold ϵ,κ, set $t = 0$, $q^{(0)}$=0, $i = 0$.
repeat
  Given $q^{(0)}$, Solve (15) to obtain $p^*_{k,n,m}$
repeat
  Update α, β from (20), respectively.
  $i = i + 1$;
If $|\alpha_k^{(i+1)} - \alpha_k^{(i)}| \leq \kappa$, $|\beta_m^{(i+1)} - \beta_m^{(i)}| \leq \kappa$ **then**
    break.
end if
until $i \geq I_{max}$
If $|R_{tot}(\boldsymbol{P}^*) - q^{(t)} P_{tot}(\boldsymbol{P}^*)| \leq \epsilon$ or $t \geq T_{max}$ **then**
  $\boldsymbol{P}^{opt}$=$\boldsymbol{P}^*$. EE^{opt}=$q^{(t)}$=$\frac{R_{tot}(\boldsymbol{P}^*)}{P_{tot}(\boldsymbol{P}^*)}$.
break.
  else
  Set $q^{(t+1)} = \frac{R_{tot}(\boldsymbol{P}^*)}{P_{tot}(\boldsymbol{P}^*)}$, $t = t + 1$.
end if.
until $t \geq T_{max}$

4 Simulation Results

In this section, we evaluate the performance of the proposed energy-efficient resource allocation scheme through Monte Carlo simulations. We consider a circular coverage area with radius equals to $\sqrt{112/3}$ km, in which DAUs and users are random uniformly distributed. We set DAU $P_m^{max} = 30$ dBm, noise power $\sigma_z^2 = -50$ dBm, $p_c = 0.03$ w, $p_o = 0.01$ w. Shadow fading $\sigma_{sh} = 8$ dB, path loss exponent $\alpha = 3.7$, user data rate $R^{req} = 20$ kbps, subcarrier bandwidth $B = 15$ kHz.

Figures 1 and 2 depict the EE versus the number of iterations in proposed scheme. It can be seen that the EE converge to the maximum value around seven iterations. In Fig. 1, we compare EE for different number of users and DAUs with $N = 8$. From the results, the EE with $M = 4$, $K = 3$ is higher compared with other conditions. Comparing with the case $M = 5$, $K = 3$, the fewer number of DAUs the less system power consumption which leads higher EE of the system. Similarly, with increasing number of users, the proposed scheme is able to achieve higher EE by the larger user diversity gain. Specifically, power consumption of DAUs have larger effect on EE of the system than diversity gain of users. In

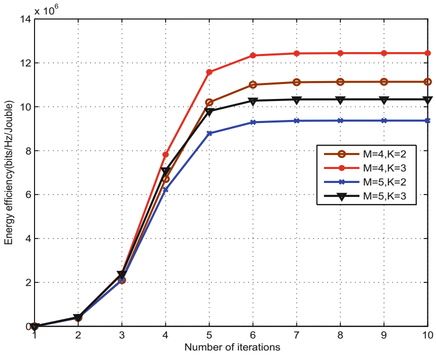

Fig. 1. EE versus number of iterations

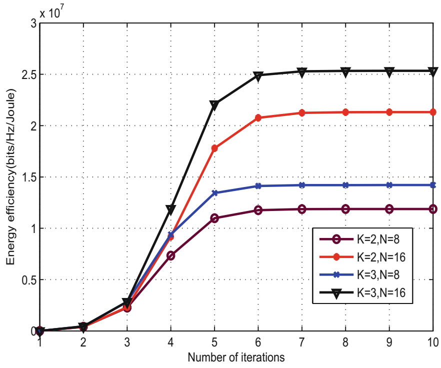

Fig. 2. EE versus number of iterations

Fig. 2, we obtain EE for different users and subcarriers with given DAU number. From the Fig, we can see that increase of the number of subcarriers can improve EE greatly, e.g., with fixed number of users. when subcarrier increases from 8 to 16, the performance of the system improved around 50%.

Figure 3 compares the EE of two algorithms which are the proposed algorithm and random selection algorithm, namely randomly allocating DAUs with subcarriers and users. EE of two algorithms increases with increasing number of subcarriers. Notably, the more number of subcarriers rises, the larger gap of EE between two algorithms. Therefore, Fig. 3 demonstrates the effectiveness of the proposed algorithm.

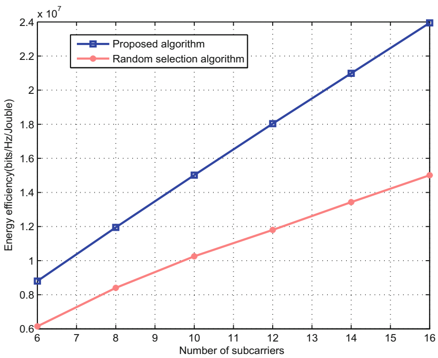

Fig. 3. EE versus number of sucarriers

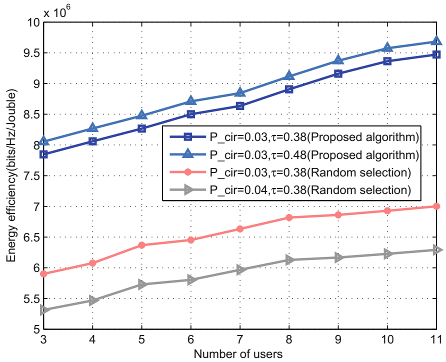

Fig. 4. EE versus number of users

Figure 4 shows the EE versus the number of users of two algorithms. We can see that the EE increases with the number of users with different parameters, the proposed algorithm can always achieve higher performance than random selection algorithm. Meanwhile, we evaluate the EE at different circuit power p_c

and power amplifier efficiency τ. It is seen that larger circuit power consumption leads to lower EE, and larger power amplifier efficiency can improve EE. This is because the larger power amplifier efficiency can increase data rate of the system.

5 Conclusion

In this paper, we formulated and studied a mixed combinatorial programming problem for EE optimization in a downlink multiuser OFDM DAS. We divided the optimization problem into two subproblems, which are DAU selection, and subcarriers assignment and power allocation optimization. Firstly, an energy efficient resource allocation scheme is presented. Then, we transform the optimization problem into a subtractive form, and solve it by Lagrangian dual decomposition. From simulation results, we can see that the proposed algorithm has better performance. In the future, the inter-cell interference and cell-edge users' performance will be taken into consideration to how to design EE optimization scheme.

References

1. Feng, W., Li, Y., Gan, J., Zhou, S., Wang, J., Xia, M.: On the deployment of antenna elements in generalized multi-user distributed antenna systems. ACM Mob. Netw. Appl. **16**(1), 35–45 (2011)
2. Zhu, H.: Performance comparison between distributed antenna and microcellular systems. IEEE J. Sel. Areas Commun. **29**(6), 1151–1163 (2011)
3. Correia, L.M., et al.: Challenges and enabling technologies for energy aware mobile radio networks. IEEE Commun. Mag. **48**(11), 66–72 (2010)
4. Chen, Y., Zhang, S., Xu, S., Li, G.Y.: Fundamental trade-offs on green wireless networks. IEEE Commun. Mag. **49**(6), 30–37 (2011)
5. He, C., Li, G.Y., Sheng, B., You, X.: Energy and spectral efficiency of distributed antenna systems. In: IEEE Wireless Communications and Networking Conference (WCNC), Shanghai, China, pp. 3225–3229 (2013)
6. Wang, J., Feng, W., Chen, Y., Zhou, S.: Energy efficient power allocation for multicell distributed antenna systems. IEEE Commun. Lett. **20**(1), 177–180 (2016)
7. Feng, W., Chen, Y., Ge, N., Lu, J.: Optimal energy-efficient power allocation for distributed antenna systems with imperfect CSI. IEEE Trans. Veh. Technol. **PP**(99), 1
8. He, C., Li, G.Y., Zheng, F.C., You, X.: Energy-efficient resource allocation in OFDM systems with distributed antennas. IEEE Trans. Veh. Technol. **63**(3), 1223–1231 (2014)
9. Wu, Q., Chen, W., Tao, M., Li, J., Tang, H., Wu, J.: Resource allocation for joint transmitter and receiver energy efficiency maximization in downlink OFDMA systems. IEEE Trans. Commun. **63**(2), 416–430 (2015)
10. Ge, X., Jin, H., Leung, V.C.M.: Opportunistic downlink scheduling with fair resource sharing for distributed antenna systems. In: 2014 IEEE International Conference on Communications (ICC), Sydney, NSW, pp. 5000–5005 (2014)
11. Dinkelbach, W.: On nonlinear fractional programming. Manag. Sci. **13**(7), 492–498 (1967)