Engineering and Scientific International Journal (ESIJ)
Volume 2, Issue 2, April - June 2015
ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

Resource Allocation of Efficient Energy in OFDM Systems using Distributed Antennas

Samatha Maditham[1], Dr. A.Rajendra Babu[2]

[1] M.Tech (DECS),Department *of ECE, BCETFW, Kadapa*
Samatha.maditham@gmail.com
[2] Associate professor, Department of ECE*, BCETFW, Kadapa*
arajendrababuavula@gmail.com

Abstract— We develop an energy-efficient resource-allocation scheme with proportional fairness for downlink multiuser orthogonal frequency-division multiplexing (OFDM) systems with distributed antennas. Our aim is to maximize energy efficiency (EE) under the constraints of the overall transmit power of each remote access unit (RAU), proportional fairness data rates, and bit error rates (BERs). Because of the non convex nature of the optimization problem, obtaining the optimal solution is extremely computationally complex. Therefore, we develop a low-complexity suboptimal algorithm, which separates subcarrier allocation and power allocation. For the low-complexity algorithm, we first allocate subcarriers by assuming equal power distribution. Then, by exploiting the properties of fractional programming, we transform the non convex optimization problem in fractional form into an equivalent optimization problem in subtractive form, which includes a tractable solution. Next, an optimal energy-efficient power-allocation algorithm is developed to maximize EE while maintaining proportional fairness. Through computer simulation, we demonstrate the effectiveness of the proposed low-complexity algorithm and illustrate the fundamental tradeoff between energy and spectral-efficient transmission designs.

Keywords— *Distributed Antenna System (DAS), Energy Efficiency (EE), Fractional Programming, Proportional Fairness, Resource Allocation, Spectral Efficiency (SE).*

1. Introduction

1.1 Distributed Antenna System

The distributed antenna system (DAS) has been proposed as a capable candidate for future wireless communication systems due to its advantages of increased capacity, extended coverage, and improved link reliability In the DAS, remote access units (RAUs) are geographically separated and are connected to a baseband processing unit via optical fibers. Thus, the DAS can decrease access distance, transmit power, and co-channel interference, which can progress system performance, mainly for those mobile stations (MSs) near the edge of a cell. Therefore, DAS techniques have been paid intensive attention in the standardization of the Third-Generation Partnership Project (3GPP) Long-Term Evolution (LTE), LTE-Advanced, and IEEE 802.16 Worldwide Interoperability for Microwave Access (Wi MAX), where they are also referred to as cooperative multiple point techniques On the other hand, orthogonal frequency division multiplexing (OFDM) can effectively combat multipath fading and has been used in or proposed for many wireless communication systems, such as 3GPP LTE-Advanced and Wi MAX. In an OFDM system, the maximum sum capacity can be achieved by first allocating each subcarrier to the user with high channel gain and then by adjusting the corresponding transmit power through water-filling.

1.2 Energy Efficiency

In recent years, energy efficiency (EE) has received much more attention due to steadily rising energy consumption and environmental concerns It has been reported in that information and communication technology already contributes to around 2% of the global carbon dioxide emissions. Recently, the dramatic growth in high-rate multimedia data traffic driven by usage of smart Android and iPhone devices, tablets, eBook readers, and other wireless devices has been straining the capacity of today’s networks and has caused a large amount of energy consumption.

It has been anticipated that mobile traffic will grow further by over 100 times in the next ten years. As a result, energy-efficient system design has recently drawn much attention in both academic and industrial worlds, and is becoming the mainstream for the next-generation of wireless communications. Four EE-related trade-offs for wireless networks have been revealed .A general EE–spectral efficiency (SE) trade off framework in the downlink OFDM networks has been addressed .EE design based on cooperative relaying and cognitive radio has been discussed An optimal energy-efficient covariance matrix algorithm for a multiple-input–multiple-output (MIMO) broadcast channel has been proposed .Energy-efficient power-allocation and mode-selection methods in virtual MIMO systems have been proposed .We have compared the EE between distributed MIMO (D-MIMO) systems and collocated MIMO (C-MIMO) systems and showed that D-MIMO systems are more energy efficient than C-MIMO

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

systems. We have demonstrated that a trade-off exists between EE and SE in a downlink DAS when proportional fairness among MSs is considered. However, to the best of our knowledge, there is no study about energy-efficient resource allocation with proportional fairness among MSs in OFDM with a DAS.

Here, we exploit the fractional programming method to investigate energy-efficient resource allocation with proportional fairness over composite fading channels consisting of small- and large-scale fading for a downlink multiuser OFDM DAS. The optimization objective is to maximize EE under the constraints of overall transmit power of each RAU, proportional fairness data rates, and bit error rates (BER). Because of the non convex nature of the optimization problem, obtaining the optimal solution is extremely computationally complex. By exploiting the properties of fractional programming, we transform the non convex optimization problem in fractional form into an equivalent optimization problem in subtractive form, which include a tractable solution. Then, a low-complexity suboptimal algorithm is developed to maximize EE while maintaining proportional fairness for the downlink multiuser OFDM DAS.

In Section II, we first describe the multiuser OFDM DAS circuit and fiber optic power consumption models, and we then formulate the problem of energy-efficient resource-allocation optimization for the downlink multiuser OFDM DAS with proportional fairness. In Section III, a suboptimal energy-efficient resource-allocation scheme is developed. Numerical results are presented to demonstrate the effectiveness of the proposed energy-efficient resource-allocation scheme in Section IV. Section V concludes.

2. Energy Efficiency of an Orthogonal Frequency-Division Multiplexing Distributed Antenna System

After briefly discussing OFDM DAS and circuit and fiber-optic power consumption models, we introduce the EE of an OFDM DAS.

2.1 OFDM DAS Model

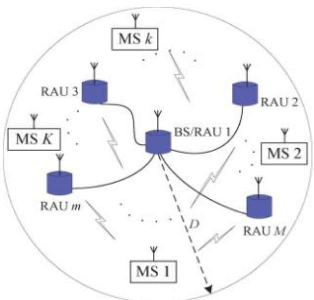

Fig.1: Circular layout of the OFDM DAS configuration.

We consider the downlink of a multiuser OFDM DAS in a single cell with N subcarriers, K MSs, and M RAUs; both MSs and RAUs are equipped with a single antenna, as shown in Fig. 1. The base station (BS) can be regarded as a special RAU and is denoted by RAU 1. The regular RAUs are equipped with only up/down converters and low-noise amplifiers (LNAs). Each RAU is physically connected with BS/RAU 1 via an optical fiber. We assume that channel state information (CSI) is available at both transmitter and receiver.

The base station (BS) can be regarded as a special AU and is denoted by RAU 1. The regular RAUs are equipped with only up/down converters and low-noise amplifiers (LNAs). Each RAU is physically connected with BS/RAU 1 via an optical fiber. We assume that channel state information (CSI) is available at both transmitter and receiver. The SNR of MS k on subcarrier n from RAU m can be expressed as

$$\gamma_{k,n,m} = \frac{p_{k,n,m}|h_{k,n,m}|^2}{\sigma_z^2} \qquad (1)$$

modeled as

$$h_{k,n,m} = g_{k,n,m} w_{k,m} \qquad (2)$$

Where $g_{k,n,m}$ denotes the small-scale fading of a wireless channel and is an independent and identically distributed complex Gaussian random variable for different *k*'s, *n*'s or *m*'s with zero mean and unit variance, and $w_{k,,m}$ denotes the large-scale fading and is independent of $g_{k,n,m}$. The large-scale fading can be expressed

$$w_{k,m} = \sqrt{\frac{cs_{k,m}}{d_{k,m}^{\alpha}}} \qquad (3)$$

Where α is the path-loss exponent and is typically between 3 and 5, $d_{k,m}$ denotes the distance from MS *k* to RAU *m*, *c* is the median of the mean path gain at reference distance $d_{k,m}$ = 1 km, and $s_{k,m}$ is a lognormal shadow fading variable, i.e., 10 $\log_{10} s_{n,m}$ is a zero-mean Gaussian random variable with standard deviation σ_{sh}.If continuous-rate adaptation is used, the overall date rate or the SE of MS *k* can be written as

$$R_k = \frac{1}{N}\sum_{n=1}^{N}\sum_{m=1}^{M}\log_2(1+\beta\gamma_{k,n,m}) \qquad (4)$$

Where $\beta = -1.5/(\ln(5P_{\text{BER}}))$ is a constant for a specific probability of a BER (P_{BER}) requirement

2.2 Circuit Power Consumption

To design energy-efficient communication systems, the total power consumption should be included in the optimization model. It contains three parts: 1) the power

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

consumption of amplifiers; 2) the circuit power consumption by RAUs; and 3) the power consumption by the fiber-optic transmission, which can be expressed as

$$P_{\text{Total}} = \frac{P_t}{\tau} + P_c + MP_o \tag{5}$$

$$P_t = \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} p_{k,n,m}.$$

The circuit power consumption in the given equation includes the power dissipation in the digital-to-analog converter, the mixer, the active filters at the transmitter side, the frequency synthesizer, the LNAs, the intermediate frequency amplifier, the active filters at the receiver side, and the analog-to-digital converter. Moreover, the circuit power consumption is independent of the actual transmit power.

2.3 Circuit Power Consumption

As in most literature, the EE of an OFDM DAS is defined as the ratio of the overall data rate or SE over the total power consumption (in bits/J/Hz) i.e.,

$$\eta_{\text{EE}}(R) = \frac{R}{\frac{P_t}{\tau} + P_c + MP_o} \tag{6}$$

Where *R* is the overall data rate or the SE, and it can be written as

$$R = \sum_{k=1}^{K} R_k.$$

As in most literature, the EE of an OFDM DAS is defined as the ratio of the overall data rate or SE over the total power consumption (in bits/J/Hz)

2.4 EE Optimization

From (6), the objective of EE optimization for the downlink multiuser OFDM DAS with proportional fairness can be expressed as

$$\max_{\boldsymbol{\delta},\mathbf{p}} \quad \eta_{\text{EE}} = \frac{1}{N} T \tag{7}$$

$$\text{s.t.} \quad \delta_{k,n,m} \in \{0,1\} \qquad \forall k,n,m \tag{7a}$$

$$\sum_{k=1}^{K} \sum_{m=1}^{M} \delta_{k,n,m} = 1 \qquad \forall n \tag{7b}$$

$$p_{k,n,m} \in [0, p_m^{\max}] \qquad \forall k,n,m \tag{7c}$$

$$\sum_{k=1}^{K} \sum_{n=1}^{N} \delta_{k,n,m} p_{k,n,m} \le p_m^{\max} \qquad \forall m \, \forall i \tag{7d}$$

$$R_i : R_j = \phi_i : \phi_j \qquad \forall i,j \in \{1,2,\ldots,K\}, i \ne j \tag{7e}$$

where

$$T = \frac{\sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{k,n,m} \log_2(1 + p_{k,n,m} H_{k,n,m})}{\frac{1}{\tau} \sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{k,n,m} p_{k,n,m} + P_c + MP_o}.$$

$$H_{k,n,m} = \beta |h_{k,n,m}|^2 / \sigma_z^2, \ \delta_{k,n,m} = 1,$$

Indicates that subcarrier *n* is assigned to MS *k* from RAU *m*; otherwise, *δk, n,m* = 0. *P*max *m* denotes the maximum transmit.

In our previous work, we exploited a multi criteria optimization method to get a Pareto optimal solution of EE. In this paper, we will obtain the optimal solution of the EE problem according to the fractional programming theory different from the EE problem, we take the frequency selectivity of wireless channels into consideration in (7), which is more practical but is more complex.

3. Energy-Efficient Resource Allocation

Here, we will investigate the energy-efficient resource-allocation scheme for an OFDM DAS.

3.1 Subcarrier Allocation

The optimization problem in (7) is non convex and combinatorial and has nonlinear constraints. It is impossible to get a closed-form solution. It is also very complicated to obtain a numerical solution. Therefore, we focus on the low-complexity and suboptimal solution of (7). In this paper, we assume that the proportion of subcarriers assigned to each MS is approximately the same as their data rates after power allocation, which has been confirmed in According to the nature of the optimization problem, we will first perform subcarrier allocation and then power allocation, as shown in the following steps.

- Number of subcarriers per RAU. According to the large scale fading $W_{k,m}$ in (2), calculate the access probability between MS k and RAU m.
- We first allocate the MSs and subcarriers to each RAU, and the remaining N∗ unallocated subcarriers is then assigned in a way to maximize the overall SE while maintaining rough proportionality by assuming equal power allocation among the subcarriers. Table I shows how subcarriers are allocated, where K, N, and Mare the sets of MSs, subcarriers, and RAUs, respectively.

Table I shows how subcarriers are allocated, where K, N, and M are the sets of MSs, subcarriers, and RAUs, respectively.

Step (b) assigns the unallocated subcarriers and RAUs to each MS with high channel gain.

Step (c) first finds the MS that has the least SE divided by its proportionality constant and then assigns the unallocated subcarrier and RAU to each MS with high channel gain.

Step (d) assigns the remaining N ∗unallocated subcarriers to the best MSs, Where in each MS can get at most one unassigned subcarriers.

3.2 Power Allocation for Each RAU

After the MSs and the subcarriers have been determined for each RAU, we have the following energy - efficient

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

optimization:

$$\max_{\mathbf{p}} \eta_{EE} = \frac{1}{N} \frac{\sum_{k=1}^{K} \sum_{n\epsilon\Omega_m} \log_2(1 + p_{k,n,m} H_{k,n,m})}{\frac{1}{\tau} \sum_{k=1}^{K} \sum_{n\epsilon\Omega_m} p_{k,n,m} + P_c + M P_o} \tag{8}$$

$$\text{s.t.} \quad p_{k,n,m} \geq 0 \qquad \forall\, k, n \tag{8a}$$

$$\sum_{k=1}^{K} \sum_{n\epsilon\Omega_m} p_{k,n,m} \leq p_m^{\max} \qquad \forall\, k, n \tag{8b}$$

$$R_i^{(m)} : R_j^{(m)} = \sum_{n=1}^{N} \delta_{i,n,m} : \sum_{n=1}^{N} \delta_{j,n,m},$$

$$\forall\, i, j \in \{1, 2, \ldots, K\}, i \neq j \tag{8c}$$

Table 1: Subcarrier Allocation

(a) Initialization
Set $\delta_{k,n,m} = 0$, for $k = 1, 2, \ldots, K$, $n = 1, 2, \ldots, N$,
and $m = 1, 2, \ldots, M$; $R_k = 0$, for $k = 1, 2, \ldots, K$;
$\mathcal{K} = 1, 2, \ldots, K$;
$\mathcal{N} = 1, 2, \ldots, N$;
$\mathcal{M} = 1, 2, \ldots, M$;
$p_m = p_m^{max}/N_m$, for $m = 1, 2, \ldots, M$.
(b) for $k = 1$ to K
find $(n, m) = \arg \max_{n \epsilon \mathcal{N}, m} |H_{k,n,m}|$;
Let $\delta_{k,n,m} = 1$, $\mathcal{N} = \mathcal{N} - \{n\}$,
and $N_m = N_m - 1$;
$R_k = \frac{1}{N} \log_2(1 + p_m H_{k,n,m})$.
(c) while $\|\mathcal{N}\| > N^*$
find $k = \arg \min_k \frac{R_k}{\phi_k}$;
find $(n, m) = \arg \max_{n \epsilon \mathcal{N}, m \epsilon \mathcal{M}} |H_{k,n,m}|$;
if $N_m > 0$
$\delta_{k,n,m} = 1$;
$N_m = N_m - 1$, $\mathcal{N} = \mathcal{N} - \{n\}$;
$R_k = R_k + \frac{1}{N} \log_2(1 + p_m H_{k,n,m})$.
else
$\mathcal{M} = \mathcal{M} - \{m\}$.
(d) for $n = 1$ to N^*
find $(k, m) = \arg \max_{k \epsilon \mathcal{K}, m} |H_{k,\mathcal{N}(n),m}|$;
$\delta_{k,\mathcal{N}(n),m} = 1$, $\mathcal{K} = \mathcal{K} - \{k\}$.

$$R_i^{(m)} = \sum_{n\epsilon\Omega_m} \log_2(1 + p_{i,n,m} H_{i,n,m}) \cdot \sum_{n=1}^{N} \delta_{i,n,m}$$

is the proportional fairness constants among MSs on RAU *m*. Define a new optimal problem as

$$\max_{\mathbf{P}} h(\mathbf{p}, \omega) \tag{9}$$

$$\text{s.t.} \quad p_{k,n,m} \geq 0 \qquad \forall\, k, n \tag{9a}$$

$$\sum_{k=1}^{K} \sum_{n\epsilon\Omega_m} p_{k,n,m} \leq p_m^{\max} \qquad \forall\, k, n \tag{9b}$$

$$R_i^{(m)} : R_j^{(m)} = \sum_{n=1}^{N} \delta_{i,n,m} : \sum_{n=1}^{N} \delta_{j,n,m}$$

$$\forall\, i, j \in \{1, 2, \ldots, K\},\ i \neq j \tag{9c}$$

p = { $p_{k,n,m}$ for *k* = 1, 2, . . . , *K*, *n* = 1, 2, . . . , *N*, *m* = 1, 2, . . . , *M* }.

Let F (ω) = max p h(p, ω) and f (ω) = arg max p h(p, ω). It has been proven that problems are equivalent to each other if and only if F (ω∗) = 0 and f (ω∗) = p∗.

That is, for any optimization problem with an objective function in fractional form, there always exists an equivalent objective function in subtractive form. As a result, we only need to focus on the equivalent objective function .For *k* = 1, the optimal solution can be obtained by

$$p_{1,n,m}^{\text{opt}} = \min\left\{\left[\frac{1 - \sum_{k=2}^{K} \lambda_k}{\left(\frac{\omega}{\tau} + \lambda_1\right) N \ln 2} - \frac{1}{H_{1,n,m}}\right]^+, p_m^{\max}\right\}. \tag{10}$$

[*x*]+ is equal to 0 when *x* is less than zero; otherwise, it is equal to *x*. For *k* >= 2, the optimal solution can be

$$p_{k,n,m}^{\text{opt}} = \min\left\{\left[\frac{1 + \lambda_k \frac{\sum_{n=1}^{N} \delta_{i,n,m}}{\sum_{n=1}^{N} \delta_{j,n,m}}}{\left(\frac{\omega}{\tau} + \lambda_1\right) N \ln 2} - \frac{1}{H_{k,n,m}}\right]^+, p_m^{\max}\right\}. \tag{11}$$

The multipliers λ_k, for $k \geq 1$, can be updated using the subgradient method [31] in each step such that

$$\lambda_1^{(i+1)} = \left[\lambda_1^{(i)} - \vartheta^{(i)}\left(\sum_{k=1}^{K} \sum_{n\epsilon\Omega_m} p_{k,n,m} - p_m^{\max}\right)\right]^+ \tag{12}$$

$$\lambda_k^{(i+1)} = \left[\lambda_k^{(i)} - \eta^{(i)} Q\right]^+ \tag{13}$$

where

$$Q = \sum_{n\epsilon\Omega_m} \frac{1}{N} \log_2(1 + p_{1,n,m} H_{1,n,m}) - \sum_{n\epsilon\Omega_m} \frac{\sum_{n=1}^{N} \delta_{i,n,m}}{N \sum_{n=1}^{N} \delta_{j,n,m}} \log_2(1 + p_{k,n,m} H_{k,n,m})$$

And $\vartheta(i)$ and $\eta(i)$ are small positive step sizes for the *i*th iteration. The sub gradient updates of (12) and (13) are guaranteed to converge to the optimal λk for $k \geq 1$ as long as $\vartheta(i)$ and $\eta(i)$ are chosen to be sufficiently small. For example, $\vartheta(i) = 0.1/\sqrt{i}$.

Table II shows the details of the optimal power-allocation algorithm.

Table 2: Subgradient Power-Allocation Algorithm

Algorithm 1 Sub-gradient Power Allocation Algorithm

1: Initialization $i = 0$, $p_{k,n,m} = 0$, $\lambda_1^{(i)} = 1$, $\lambda_k^{(i)} = 0.001$, for $k = 2, \ldots, K, n = 1, 2, \ldots, N$;
2: Initialization $k = 1$ and $n = 1$;
3: Calculate $p_{1,n,m}$ and $p_{k,n,m}$ according to equations (10) and (11), respectively.
4: $i = i + 1$, update $\lambda_1^{(i+1)}$ and $\lambda_k^{(i+1)}$ according to (12) and (13), respectively.
5: if the multipliers λ_1 and λ_k are convergent, return $\mathbf{p}^*$, and stop the Algorithm 1; Otherwise go to step 2.

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

where

$$h(\mathbf{p},\omega) = \frac{1}{N}\sum_{k=1}^{K}\sum_{n\epsilon\Omega_m}\log_2(1+p_{k,n,m}H_{k,n,m}) - \frac{\omega}{\tau}\sum_{k=1}^{K}\sum_{n\epsilon\Omega_m}p_{k,n,m} - \omega(P_c + MP_o).$$

$\mathbf{p} = \{p_{k,n,m} \quad \text{for} \quad k = 1,2,\ldots,K, \quad n = 1,2,\ldots,N, m = 1,2,\ldots,M\}$.

Table 3: Optimal Energy-Efficient Power-Allocation Algorithm

Rate Constraint Index k	0	1	2	3	4
$\phi_1 = 2^k$	2^0	2^1	2^2	2^3	2^4
$\phi_2 = \phi_3 = \cdots = \phi_K$	1	1	1	1	1

After the optimal solution for (9) is derived, we can obtain the optimal energy-efficient power allocation of (8), which is described in Table -III.

Algorithm 1 will converge to the global optimal solution for sufficiently small positive step sizes for the ith iteration ϑ(i) and η(i), which can be proven in a similar method in our previous work .The convergence of Algorithm 2 has been proven.

The low-complexity suboptimal solution developed here can be summarized as follows.

1) Determine the number of subcarriers initially assigned to each RAU by the algorithm

2) Assign the MSs and the subcarriers to each RAU proportionally using the algorithm in Table I.

3) For each RAU, assign the overall power $p_{max,m}$ for the selected subcarriers and MSs to maximize the EE while enforcing proportional fairness using the algorithm.

4. Numerical Results

Here, the proposed energy-efficient resource-allocation scheme is evaluated via Monte Carlo simulations. In our simulation, the number of RAUs M = 5 and subcarriers N = 64. Noise power σz2 is − 104 dBm, and the maximum power $p_{max,n}$ is 36 dBm. Cell radius R is 1 km, and the system BER requirement is 0.001. Circuit power consumption Pc is 40 dBm, and fiber-optic power consumption Po is −0.6 dBm. Power amplifier efficiency τ = 38%. Path-loss exponent α = 3.7, and the standard deviation of the shadow fading is σ_{sh} = 8 dB [23]. The rate constraints are listed in Table IV.

Table 4: Rate Constraints

Algorithm 2 Optimal Energy-Efficient Power Allocation Algorithm

Initialization $\omega = 0.01$, $F(\omega) = 100$ and $\xi > 0$;
for $m = 1 : M$
  while $F(\omega) > \xi$
    do use Algorithm 1 to find the optimal $\mathbf{p}^*$, then calculate $F(\omega)$ and update

$$\omega = \frac{1}{N}\frac{\sum_{k=1}^{K}\sum_{n\epsilon\Omega_m}\log_2(1+p^*_{k,n,m}H_{k,n,m})}{\frac{1}{\tau}\sum_{k=1}^{K}\sum_{n\epsilon\Omega_m}p^*_{k,n,m} + P_c + MP_o};$$

return $\mathbf{p}^*$ and ω.

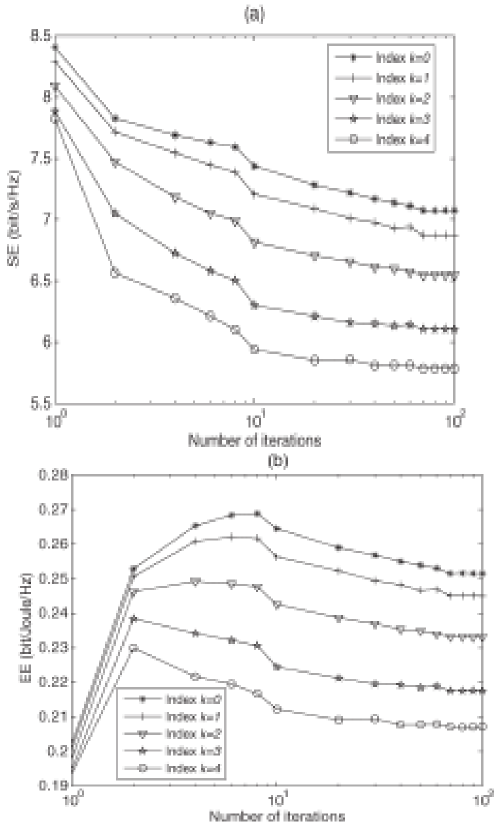

Fig.2: SE and EE versus number of iterations with different rate constraints for p= 30 dBm and K = 10.

For convenience, assume that the cell shape is approximated by a circle of radius D. The polar coordinates of RAUs relative to the center of the cell are denoted as (d, θ_m), m = 1, 2, . . ,M. We assume that the MSs are uniformly distributed in the cell. For the cell with five RAUs, the polar coordinates of the RAUs are (0, 0), (d, 0), (d, π/2), (d, π), (d, 3π/2) Where d = (3 − √3)D/2.

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

4.1 Convergence of Algorithms 1 and 2

Fig. 2 and 3 shows the evolution of Algorithms 1 and 2 for different rate constraints defined in Table IV, respectively. The results in Figs. 2 and 3 are averaged over 100 000 channel realizations. In Figs. 2 and 3,Algorithms 1 and 2 converge to the optimal value within 70 and 3 iterations for the maximum transmit power of each RAU $p_{max,m}$ = 30 dBm and the number of the MS K = 10, respectively. The overall algorithm takes around 210 iterations in total to converge.

4.2 SE and EE Versus Different Transmit Power

Fig. 4 compares the SE versus the total power of RAUs for different rate constraints and resource-allocation methods. In this case, the SE of the proposed energy-efficient resource-allocation scheme is better than the equal resource-allocation scheme. In Fig. 4, the gap between the proposed energy-efficient resource-allocation scheme and the equal resource-allocation scheme is becoming smaller when the transmit power is increasing. The reason is that the CSI is not very good when the transmit power is small, but when the transmit power is increasing, the CSI is becoming better. Therefore, the performance of the equal resource-allocation scheme is close to the proposed energy-efficient resource-allocation scheme. As in Fig. 4, when rate constraint index k = 0, the SE of the proposed energy-efficient resource-allocation scheme is approximately 91.8% higher than the equal resource-allocation scheme when the total power of RAU is 36 dBm.

Above figure compares the EE versus SE for different rate constraints and resource-allocation methods. Compared with equal resource allocation, the proposed energy-efficient resource-allocation scheme outperforms the equal resource-allocation scheme in terms of EE. When rate constraint index k = 0, the EE of the proposed energy-efficient resource-allocation scheme is approximately 169.3% higher than the equal resource-allocation scheme when SE is 5 bit/s/Hz.

In Fig., the EE–SE curve shows the existence of a saturation point, beyond which the EE no longer increases with SE, regardless of how much additional transmit power is used. Based on this result, we can design optimal energy-efficient networks. On the other hand, we can reduce as much power consumption as possible while satisfying the given SE requirement.

In figures 4 & 5, the low-transmit-power regime, the proposed energy efficient resource-allocation scheme that achieves the maximum EE also achieves the maximum SE. However, in the high-transmit-power regime, no solution exists for a OFDM DAS to optimize both SE and EE simultaneously.

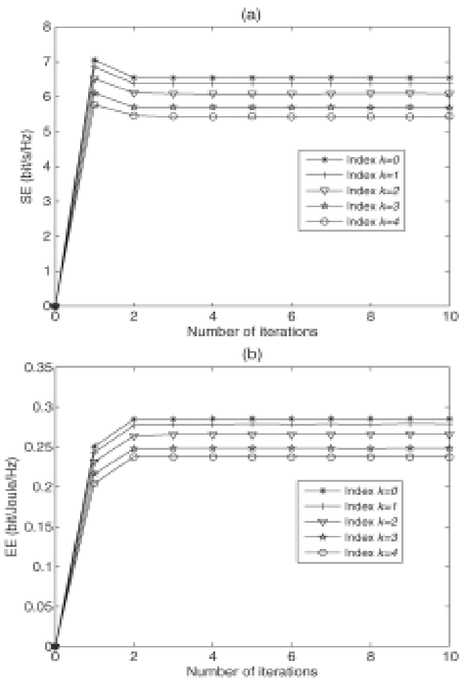

Fig.3: SE versus total power of RAU with different rate constraints for $p_{max,m}$ = 30 dBm and K = 10

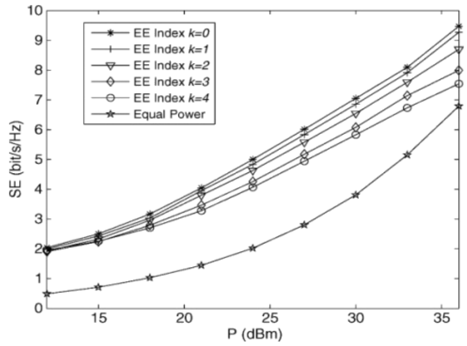

Fig.4: SE versus total power of RAU with different rate constraints for $p_{max,m}$=30 dBm and K =10

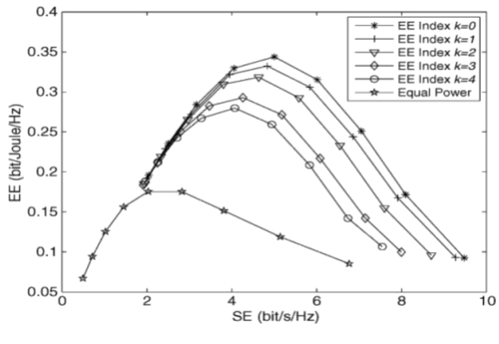

Fig.5: EE versus SE with different rate constraints and transmit power for $p_{max,m}$ = 30 dBm and K = 10.

IRP Group of Journals

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

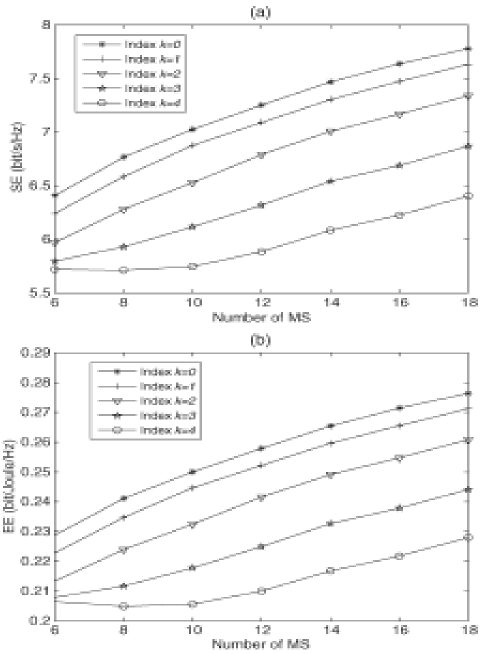

Fig. 6: SE and EE versus number of Mss with different rate constraints for P_m^{max} = 30 dBm.

The SE and EE achieved by the proposed energy-efficient resource-allocation scheme vary with the data rate constraints. This result demonstrates that the proportional fairness constraints can explicitly control the SE and EE ratios among MSs. Therefore, we can always ensure the target data rates and EE for each MS if there is sufficient transmit power for RAUs.

4.3 SE and EE Versus Number of MSs

Fig.6 shows the EE and SE versus the number of MSs for different rate constraints and $p_{max,m}$ = 30 dBm, respectively. Both the EE and SE grow with the number of MSs under different rate constraints since the proposed energyefficient resource-allocation scheme is able to exploit multiuser diversity.

5. Conclusion

In this paper, we have investigated the optimal energy-efficient resource-allocation methods for the downlink multiuser OFDM DAS with proportional fairness, and proposed a suboptimal energy-efficient resource-allocation scheme to maximize EE. Numerical results have shown that the proposed algorithm converges to the optimal solution within a small number of iterations and demonstrated the tradeoff between EE and SE, which is very important for future wireless communication systems.

References

[1] X.-H.You, D.-M. Wang, B. Sheng,X.-Q. Gao, X.-S. Zhao, and M. Chen “Cooperative distributed antenna systems for mobile communications,” IEEE Wireless Communication., vol. 17, no. 3, pp. 35–43, Jun. 2010.

[2] H .- L. Zhu, “Performance comparison between distributed antenna and microcellular systems,” IEEE J. Sel. Areas Communication., vol. 29, no. 6, pp. 1151–1163, Jun. 2011.

[3] H. - L. Zhu, S. Karachontzitis, and D. Toumpakaris, “Low-complexity resource allocation and its application to distributed antenna systems,” IEEE Wireless Communication., vol. 17, no. 3, pp. 44–50, Jun. 2010.

[4] H. Kim, S.-R. Lee, K.-J. Lee, and I. Lee, “Transmission schemes based on sum rate analysis in distributed antenna systems,” IEEE Trans. Wireless Communication., vol. 11, no. 3, pp. 1201–1209, Mar. 2012.

[5] X.-H. You D.-M. Wang,P.-C. Zhu, and B. Sheng,“Cell edge performance of cellular mobile systems,” IEEE J. Sel. Areas Communication., vol. 29, no. 6, pp. 1139–1150, Jun. 2011.

[6] Z.-K. Shen, J. Andrews, and B. Evans, “Adaptive resource allocation in multiuser OFDM systems with proportional rate constraints,” IEEE Trans. Wireless Commun., vol. 4, no. 6, pp. 2726–2737, Nov. 2005.

[7] G.-W. Miao, N. Himayat, G. Y. Li, and A. Swami, “Cross- layer optimiza-tion for energy-efficient wireless communications: A survey,” J. Wireless Commun. Mobile Computer., vol. 9, no. 4, pp. 529–542, Apr. 2009.

[8] Z. Hasan, H. Boostanimehr, and V. K. Bhargava, “ Green cellular net-works: A survey, some research issues and challenges,” IEEE Commun. Surveys Tuts., vol. 13, no. 4, pp. 524–540, 4th Quart., 2011.

[9] W. Miao, N. Himayat, G. Y. Li, and S. Talwar, “Distributed interference-aware energy-efficient power optimization,” IEEE Trans. Wireless Commun., vol. 10, no. 4, pp. 1323–1333, Apr. 2011.

[10] C. Xiong, G. Y. Li, S.-Q. Zhang,Y. Chen, and S.-G. Xu, “Energy-and spectral-efficiency tradeoff in downlink OFDMA networks,” IEEE Trans. Wireless Commun., vol. 10, no. 11, pp. 3874–3886, Nov. 2011.

[11] D.-Q. Feng,C.-Z. Jiang,G. Lim, L. Cimini, G. Feng, and G. Y. Li, “A survey of energy-efficient wireless communications,” IEEE Communication. Surveys Tuts., vol. 15, no. 1, pp. 167–178, 1st Quart., 2012.

[12] L. Deng, Y. Rui, P. Cheng, J. Zhang,Q.-T.Zhang, and M.-Q. Li, “A unified energy efficiency and spectral efficiency trade off metric in wireless networks,”IEEE Communication. Lett., vol. 17, no. 1, pp. 55–58, Jan. 2013.

[13] G. P. Fettweis and E. Zimmermann, “ICT energy consumption-trends and challenges,” in Proc. 11th Int. Symp. WPMC, Sep. 2008, pp. 1–4.

[14] Cisco Visual Networking Index, Global Mobile Data Traffic Data Forecast Update, Cisco Systems, Inc., San Jose, CA, USA, White Paper, pp. 2011– 2016, 2012.

[15] Y. Chen,S.-Q. Zhang,S.-G. Xu, and G. Y. Li, “Fundamental trade-offs on green wireless networks,” IEEE Communication. Mag., vol. 49, no. 6, pp. 30–37, Jun. 2011.

[16] C.-M. Jiang, Y.Shi, Y. Hou, and S. Kompella, “On optimal throughput-energy curve for multi-hop wireless networks,” in Proc. IEEE INFOCOM, Apr. 2011, pp. 1341–1349.

[17] G. Gur and F. Alagoz, “Green wireless communications via cogni-tive dimension: An overview,” IEEE Netw., vol. 25, no. 2, pp. 50–56, Mar./Apr. 2011.

[18] Y. Wang,W.-J. Xu, K.-W. Yang, and J.-R. Lin, “Optimal energy-efficient power allocation for OFDM-based cognitive radio networks, “IEEE Commun. Lett., vol. 16, no. 9, pp. 1420–1423, Sep. 2012.

ISSN 2394-187(Online)
ISSN 2394-7179 (Print)

[19] S. Althunibat and F. Granelli, "On the reduction of power loss caused by imperfect spectrum sensing in OFDMA-based cognitive radio access," in Proc. IEEE GLOBECOM, 2012, pp. 3383–3387.

[20] J. Xu and L. Qiu, "Energy efficiency optimization for MIMO broadcast channels," IEEE Trans. Wireless Communication., vol. 12, no. 2, pp. 690–701, Feb. 2013.

[21] Y. Rui, Q. T. Zhang, L. Deng, P. Cheng, and M.-Q. Li, "Mode selection and power optimization for energy efficiency in uplink virtual MIMO systems," IEEE J. Sel. Areas Communication., vol. 31, no. 5, pp. 926–936, May 2013.

[22] C.-L. He, B. Sheng, P.-C. Zhu, D.-M. Wang, and X.-H. You, "Energy efficiency comparison between distributed MIMO and co-located MIMO systems," Int. J. Communication. Syst., pp. 1–14, 2012. [Online]. Available: http://onlinelibrary.wiley.com/doi/10.1002/dac.2345/pdf.

[23] C.-L. He, B. Sheng, P.-C. Zhu, X.-H. You, and G. Y. Li, "Energy- and spectral-efficiency tradeoff for distributed antenna systems with propor-tional fairness," IEEE J. Sel. Areas Commun., vol. 31, no. 5, pp. 894–902, May 2013.

[24] C.-L. He, B. Sheng, P.-C. Zhu, and X.-H. You, "Energy efficiency and spectral efficiency tradeoff in downlink distributed antenna systems," IEEE Wireless Commun. Lett., vol. 1, no. 3, pp. 153–156, Jun. 2012.

[25] L.-S. Ling, T. Wang, Y. Wang, and C. Shi,"Schemes of power allocation and antenna port selection in OFDM distributed antenna systems," in Proc. IEEE VTC-Fall, Sep. 2010, pp. 1–5.

[26] D.-M. Wang, X.-H. You, J.-Z. Wang, Y. Wang, and X.-Y. Hou, "Spectral efficiency of distributed MIMO cellular systems in a composite fading channel," in Proc. IEEE ICC, May 2008, pp. 1259–1264.

[27] X .- X. Qiu and K. Chawla, "On the performance of adaptive modulation in cellular systems," IEEE Trans. Commun., vol. 47, no. 6, pp. 884–895, Jun. 1999.

[28] O. Arnold, F. Richter, G. Fettweis, and O. Blume, "Power consump-tion modeling of different base station types in heterogeneous cellular networks," in Proc.Future Netw. Mobile Summit, 2010, pp.1–8.