Energy- and Spectral-Efficiency Tradeoff for Distributed Antenna Systems with Proportional Fairness

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***Abstract*—*Energy efficiency* (EE) has caught more and more attention in future wireless communications due to steadily rising energy costs and environmental concerns. In this paper, we propose an EE scheme with proportional fairness for the downlink multiuser *distributed antenna systems* (DAS). Our aim is to maximize EE, subject to constraints on overall transmit power of each *remote access unit* (RAU), *bit-error rate* (BER), and proportional data rates. We exploit multi-criteria optimization method to systematically investigate the relationship between EE and *spectral efficiency* (SE). Using the weighted sum method, we first convert the multi-criteria optimization problem, which is extremely complex, into a simpler single objective optimization problem. Then an optimal algorithm is developed to allocate the available power to balance the tradeoff between EE and SE. We also demonstrate the effectiveness of the proposed scheme and illustrate the fundamental tradeoff between energy- and spectral-efficient transmission through computer simulation.**

***Index Terms*—Energy efficiency, spectral efficiency, distributed antenna systems, multi-criteria optimization, power allocation, proportional fairness**

I. INTRODUCTION

SPECTRAL EFFICIENCY (SE) and *energy efficiency* (EE) are two key performance metrics for technological advances in current and emerging wireless communication networks. The demand for higher SE has become inevitable due to multimedia applications in wireless networks. In the past decade, there has been tremendous work to improve system capacity and SE. In recent years, EE has caught more and more attention due to steadily rising energy costs and environmental concerns [1]–[6]. It has been reported in [7] that *information and communication technology* (ICT) already contributes around 2% of the global carbon dioxide emission, of which wireless networks account about 0.2%, and this is expected to increase rapidly in the future. *Green radio* (GR) [8], which focuses on EE over SE, has thereby been proposed as an effective solution and is becoming the mainstream for future wireless communications. Unfortunately, some EE sometimes conflicts with SE. Hence, how to balance them is well-worth studying.

There has been much literature discussing the energy-efficient design from different layers of wireless communication networks. Four fundamental tradeoffs of energy-efficient networks have been addressed in [8]. A general EE-SE tradeoff framework in the downlink *orthogonal-frequency-division-multiple* (OFDM) networks has been studied in [4]. EE based on cognitive radio and cooperative relaying has been discussed in [2], [9], [10]. It has been shown in [11] that reducing cell size can increase EE. Different transmission techniques have been reconsidered from the point of view of EE instead of traditional SE. Energy-efficient OFDM has been first addressed in [12]. From [12], there is at least a 20% reduction in power consumption when performing EE optimization. It has been shown in [13] that *multiple-input single-output* (MISO) systems outperform *single-input single-output* (SISO) systems through changing modulation order to balance circuit power consumption and transmit power consumption. It has found in [14] that power can be saved by adaptively switching between *multiple-input multiple-output* (MIMO) with two transmit antennas and *single-input multiple-output* (SIMO). An energy-efficient link-adaptive transmission scheme for MIMO-OFDM systems has been proposed in [15] where the circuit power consumption is considered. The EE of the *distributed MIMO* (D-MIMO) and *co-located MIMO* (C-MIMO) in the uplink cellular systems have been compared in [16]. It has been demonstrated that D-MIMO systems are more energy-efficient than C-MIMO systems.

Distributed antenna system (DAS) has been introduced as a promising candidate for the next generation wireless communication systems [17]–[20] due to the advantages of increasing capacity, improving the link reliability, and extending the coverage. Different from a traditional *collocated antenna system* (CAS) where all antennas of a *base station* (BS) are collocated at the center of a cell, *remote access units* (RAUs) in the DAS are placed at different locations in a cell and connected to a *baseband processing unit* (BPU) through optical fibers. Thus, the DAS can reduce access distance, transmit power, and co-channel interference, which

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can improve system performance, especially for those users near the edge of the cell. So DAS techniques have been paid intensive attention in the standardization of the *third generation partnership project* (3GPP) *long-term evolution* (LTE) and LTE-Advanced [21], [22].

In this paper, we exploit a multi-criteria optimization method to systematically investigate the relationship between EE and SE for the downlink multiuser DAS with proportional fairness in wireless networks. As in [15], EE of a system is defined as the ratio of the overall throughput and overall power consumption, including both circuit power and transmit power. The optimization objective is to maximize EE, subject to constraints on overall transmit power of each RAU, *bit-error rate* (BER), and proportional fairness among *mobile stations* (MSs). Compared with the sum rates maximization under overall power constraints [23], our objective function is particularly suitable for green communications. However, the non-convex and multi-dimensional nature of the EE optimization problem in the downlink multiuser DAS with proportional fairness makes it more challenging and complicated than the sum rates maximization. To address the issue, we first convert the multi-criteria optimization problem, which is extremely complex, into a simpler single objective optimization problem. Then we develop an optimal algorithm to allocate the available power to balance the tradeoff between EE and SE effectively for the downlink multiuser DAS with proportional fairness.

The rest of this paper is organized as follows. We describe the multiuser DAS and circuit power consumption models in second II. In Section III, we first formulate problem of energy-efficient optimization for the downlink multiuser DAS with proportional fairness and then develop an algorithm to allocate the available power to balance EE and SE effectively. Numerical results are presented in Section IV to demonstrate the effectiveness of the developed algorithm. Section V concludes the paper.

II. EE of a DAS

After briefly discussing DAS model and circuit power consumption model, we introduce energy efficiency of a DAS.

A. Distributed Antenna Systems

We consider the downlink of a multiuser DAS in a single cell with M MSs and N RAUs, both of which are equipped with single antenna, as shown in Figure 1 [24]. The RAUs are usually connected with the center BS/RAU 1 through cable or optical fibers, and are low-complexity processing nodes and are equipped with only up/down converters and *low noise amplifiers* (LNA). Signals received by RAUs just go through simple joint processing, and then are forwarded to BPU by the cable or optical fibers. The channels assigned to different MSs are orthogonal or non-overlap, as a result, there is no interference among MSs. Assuming the *channel state information* (CSI) is available at both transmitter and receiver. The *signal-to-noise ratio* (SNR) of MS m by using the *maximal ratio combining* (MRC) at the receiver can be expressed as [25]

$$\gamma_m(\boldsymbol{p_m}) = \frac{\sum_{n=1}^{N} p_{n,m}|h_{n,m}|^2}{\sigma_z^2}, \tag{1}$$

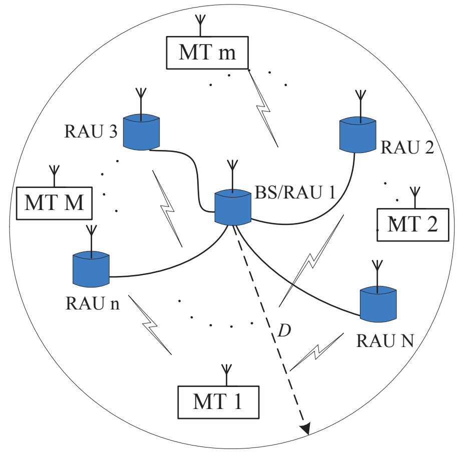

Fig. 1. Circular layout DAS configuration

where $h_{n,m}$ and $p_{n,m}$ denote the composite fading channel impulse response and the transmit power from RAU n to MS m, respectively, $\boldsymbol{p_m} = [p_{1,m}, p_{2,m}, ..., p_{N,m}]$, and σ_z^2 denotes the complex *additive white Gaussian noise* (AWGN) power.

In this paper, channel is assumed to have a small and a large scale fading and can be expressed as [24]

$$h_{n,m} = g_{n,m} w_{n,m}, \tag{2}$$

where $g_{n,m}$ represents the small-scale fading and is an independent and identically distributed complex Gaussian random variables for different n's and m's with zero mean and unit variance, and $w_{n,m}$ is the large scale fading and is independent of $g_{n,m}$. The large scale fading can be expressed as [26]

$$w_{n,m} = \sqrt{\frac{c s_{n,m}}{d_{n,m}^{\alpha}}}, \tag{3}$$

where c is the median of the mean path gain at the distance $d_{n,m}$ = 1 km, α is the path loss exponent and is typically between 3 and 5, $d_{n,m}$ is the distance between MS m and RAU n, and $s_{n,m}$ is log-normal shadow fading variable, i.e., $10\log_{10} s_{n,m}$ is a zero-mean Gaussian random variable with standard deviation σ_{sh}.

The SE or data transmission rate of MS m when using the continuous rate adaptation can be expressed as [24]

$$R_m(\boldsymbol{p_m}) = \log_2(1 + \beta\gamma_m(\boldsymbol{p_m})), \tag{4}$$

where $\beta = -\frac{1.5}{\ln(5P_{BER})}$ is a constant for a specific probability of bit-error rate (P_{BER}) requirement [27].

B. Circuit Power

In this paper, the total power consumption contains two main parts: the power consumption of all the power amplifiers and that of all the other circuit power consumption blocks.

The power consumption of the power amplifiers can be approximated as [13]

$$P_{PA} = (1+\tau)P_t, \tag{5}$$

where P_t is the transmit power consumption, $\tau = \frac{\xi}{\eta} - 1$, ξ is the *peak-to-average ratio* (PAR), and η is the drain efficiency of the *radio frequency* (RF) power amplifier, which depends on the associated constellation size and the modulation scheme [28].

From [4], [29], the circuit power consumption can be modeled as a linear function of throughput

$$P_c = P_s + \zeta R, \tag{6}$$

where P_s is a static power consumption term, ζ is a constant denoting dynamic power consumption per unit throughput, R is the SE or data transmission rate and can be written as

$$R = \sum_{m=1}^{M} \log_2(1 + \beta\gamma_m(\boldsymbol{p_m})).$$

C. EE of a DAS

As in most of literature, we define EE as the ratio of SE or data transmission rate over the total power consumption (unit: bits/Joule/Hz):

$$\eta_{EE}(R) = \frac{R}{P_{PA} + P_c}. \tag{7}$$

III. Energy- and Spectral-Efficiency Tradeoff

After formulating the problem of EE optimization, we investigate tradeoff of EE and SE in a DAS.

A. EE Optimization

The objective of *rate-adaptive* (RA) optimization for the downlink multiuser DAS with proportional fairness can be formulated as

$$\max_{\mathbf{p}} \quad \sum_{m=1}^{M} \log_2(1 + \beta\frac{\sum_{n=1}^{N} p_{n,m}|h_{n,m}|^2}{\sigma_z^2}), \tag{8}$$

$$\text{s. t.} \quad p_{n,m} \in [0, p_n^{max}], \quad \forall m \in \{1,2,...,M\},\ \forall n \in \{1,2,...,N\}, \tag{8a}$$

$$\sum_{m=1}^{M} p_{n,m} \le p_n^{max},\ \forall n \in \{1,2,...,N\}, \tag{8b}$$

$$R_i : R_j = \phi_i : \phi_j,\ \forall i,j \in \{1,2,...,M\},\ i \ne j, \tag{8c}$$

where p_n^{max} denotes the maximum transmit power of RAU n. R_i and R_j are the SE of MS i and MS j, respectively. $\{\phi_i\}_{i=1}^{M}$ is a set of predetermined values which are used to ensure proportional fairness among MSs [23]. The reason to introduce proportional fairness into the DAS is to explicitly control the throughput ratios among MSs so that each MS is able to satisfy its target data rate.

We will focus on EE optimization here. The objective for the downlink multiuser DAS with proportional fairness can be expressed as

$$\max_{\mathbf{p}} \quad \eta_{EE} = \frac{\sum_{m=1}^{M} \log_2(1 + \beta\frac{\sum_{n=1}^{N} p_{n,m}|h_{n,m}|^2}{\sigma_z^2})}{(1+\tau)\sum_{m=1}^{M}\sum_{n=1}^{N} p_{n,m} + P_s + \zeta R} \tag{9}$$

$$\text{s. t.} \quad p_{n,m} \in [0, p_n^{max}], \quad \forall m \in \{1,2,...,M\},\ \forall n \in \{1,2,...,N\}, \tag{9a}$$

$$\sum_{m=1}^{M} p_{n,m} \le p_n^{max},\ \forall n \in \{1,2,...,N\}, \tag{9b}$$

$$R_i : R_j = \phi_i : \phi_j,\ \forall i,j \in \{1,2,...,M\},\ i \ne j, \tag{9c}$$

Since the objective problem (9) is an non-convex function with non-linear constraints, we can not obtain the optimal solution directly by using the standard convex optimization methods. Therefore, we first convert it into the following multi-criteria optimization problem

$$\begin{aligned}
\max_{\mathbf{p}} \quad & P = -(1+\tau)\sum_{m=1}^{M}\sum_{n=1}^{N} p_{n,m} - \zeta R - P_s \\
\max_{\mathbf{p}} \quad & R = \sum_{m=1}^{M} \log_2(1 + \beta\frac{\sum_{n=1}^{N} p_{n,m}|h_{n,m}|^2}{\sigma_z^2}), \\
\text{s. t.} \quad & p_{n,m} \in [0, p_n^{max}], \\
& \sum_{m=1}^{M} p_{n,m} \le p_n^{max} \\
& R_i : R_j = \phi_i : \phi_j,\ \forall i,j \in \{1,2,...,M\},\ i \ne j.
\end{aligned} \tag{10}$$

Two objective functions in (10) conflict each other. For example, when P reaches its maximum -P_s, the transmission powers, $p_{n,m}$, are all zero and the SE, R, in this case is zero and is obviously not optimized. Therefore, there exists no solution that maximize both objectives simultaneously. Then, a natural question is what kind of solutions we should pursue when investigating the multi-criteria optimization problem (10).

Before discussing it, we first introduce the concept of Pareto optimal solution [30]. (P_1, R_1) is called to dominate (P_2, R_2) if both are feasible solutions and $P_1 \le P_2$ and $R_1 \ge R_2$. A feasible solution $(\widehat{P}, \widehat{R})$ is called efficient or Pareto optimal if there is no other feasible solution dominating it. Note that there may be multiple Pareto optimal solutions for the multi-criteria optimization problem.

Using the weighted sum method in multi-criteria optimization [30], we can then convert the multi-criteria optimization problem with high complexity into a simpler single objective optimization problem. That is

$$\begin{aligned}
\max_{\mathbf{p}} \quad & \omega_1 \sum_{m=1}^{M} \log_2(1 + \beta\frac{\sum_{n=1}^{N} p_{n,m}|h_{n,m}|^2}{\sigma_z^2}) \\
& - \omega_2 \left[(1+\tau)\sum_{m=1}^{M}\sum_{n=1}^{N} p_{n,m} + \zeta R + P_s\right] \\
\text{s. t.} \quad & p_{n,m} \in [0, p_n^{max}], \\
& \sum_{m=1}^{M} p_{n,m} \le p_n^{max}, \\
& R_i : R_j = \phi_i : \phi_j,\ \forall i,j \in \{1,2,...,M\},\ i \ne j, \\
& \omega_1 > 0,\ \omega_2 \ge 0,
\end{aligned} \tag{11}$$

where ω_1 and ω_2 are the introduced scalar weights.

As proved in Appendix A, if $p_{n,m}^{opt}$ is a solution to the optimization problem of (11), then it is a Pareto optimal solution to the multi-criteria optimization problem of (10).

We can get the optimal solution of (11) as following, which is proved in Appendix B.

For $m = 1$, the optimal solution of (11) can be expressed as

$$p_{n,1}^{opt} = \min\{T_1, p_n^{max}\}, \tag{12}$$

where

$$T_1 = \left[\frac{1 - \sum_{m=2}^{M} \mu_m}{\left(\lambda_n + \frac{\omega(1+\tau)}{1-\zeta\omega}\right) \ln 2} - \frac{\sigma_z^2}{\beta |h_{n,1}|^2} - \frac{\sum_{k=1,k\neq n}^{N} p_{k,1} |h_{k,1}|^2}{|h_{n,1}|^2} \right]^+, \quad (13)$$

$[x]^+$ equals to 0 when x is less than zero, and otherwise equals to x.

For $m \geq 2$, the optimal solution of (11) can be expressed as

$$p_{n,m}^{opt} = \min\{T_2, p_n^{max}\}, \quad (14)$$

where

$$T_2 = \left[\frac{1 + \frac{\phi_1}{\phi_m} \mu_m}{\left(\lambda_n + \frac{\omega(1+\tau)}{1-\zeta\omega}\right) \ln 2} - \frac{\sigma_z^2}{\beta |h_{n,m}|^2} - \frac{\sum_{k=1,k\neq n}^{N} p_{k,m} |h_{k,m}|^2}{|h_{n,m}|^2} \right]^+. \quad (15)$$

In (12) and (14), μ_m and λ_n should satisfy the following equation

$$\sum_{m=1}^{M} p_{n,m}^{opt} = p_n^{max}. \quad (16)$$

From (16), it is a combination complex optimization problem and there is no closed-form solution for it. But, we can exploit the sub-gradient iteration approach to obtain the optimal solution.

The multipliers λ_n and μ_m can be updated using the sub-gradient method [31] in each step such that

$$\lambda_n^{i+1} = \left[\lambda_n^i - \vartheta^i \left(\sum_{m=1}^{M} p_{n,m} - p_n^{max} \right) \right]^+, \quad (17)$$

$$\mu_m^{i+1} = \left[\mu_m^i - \delta^i Q \right]^+, \quad (18)$$

where

$$Q = \log_2(1 + \beta \frac{\sum_{n=1}^{N} p_{n,1} |h_{n,1}|^2}{\sigma_z^2}) - \frac{\phi_1}{\phi_m} \log_2(1 + \beta \frac{\sum_{n=1}^{N} p_{n,m} |h_{n,m}|^2}{\sigma_z^2}),$$

ϑ^i and δ^i are small positive step sizes for the ith iteration. The sub-gradient update of (17) and (18) is guaranteed to converge to the optimal λ_n and μ_m as long as ϑ^i and δ^i are chosen to be sufficiently small. For example, $\vartheta^i = \frac{0.1}{\sqrt{i}}$ [31].

B. Energy-Efficient Power Allocation Algorithm

According to the analysis in Section III-A, we obtain the following algorithm to allocate the available power to balance EE and SE for the downlink multiuser DAS with proportional fairness.

Step 1: Initialize $i = 0$, $p_{n,m} = 0$, $\lambda_i(0) = 0.01$, $\mu_i(0) = 0.001$, for $n = 1, 2, ..., N, m = 1, 2, ..., M$.

Step 2: Initialize $n = 1$.

Step 3: Initialize $m = 1$. go to step 7 if $n > N$; otherwise go to step 4.

Step 4: If $m = 1$, calculate $p_{n,1}^{opt}$ according to equation (12); Otherwise calculate $p_{n,m}^{opt}$ according to equation (14).

Step 5: $m = m + 1$, go to step 6 if $m > M$; Otherwise go to step 4.

Step 6: $n = n + 1$, go to step 3.

Step 7: $i = i + 1$, updates λ_i and μ_i according to (17) and (18). Stop the algorithm if the multipliers λ_i and μ_i are convergent; Otherwise go to step 2.

If ϑ^i and δ^i are a sufficiently small positive step size for the ith iteration, then this algorithm will converge to the global optimal solution, which is proved in Appendix C.

C. Property of Energy Efficiency

Here, we present an interesting property for the optimal EE versus transmission power curve.

From Appendix D, if all the constraints are satisfied in equation (9) and P is the optimal power allocation scheme, then EE has the following property

$$\frac{d\eta_{EE}(P)}{dP} \begin{cases} > 0 & \text{if} \quad \eta_{EE}(P) < \frac{\frac{dR(P)}{dP}}{(1+\tau)+\zeta\frac{dR(P)}{dP}}, \\ = 0 & \text{if} \quad \eta_{EE}(P) = \frac{\frac{dR(P)}{dP}}{(1+\tau)+\zeta\frac{dR(P)}{dP}}, \\ < 0 & \text{if} \quad \eta_{EE}(P) > \frac{\frac{dR(P)}{dP}}{(1+\tau)+\zeta\frac{dR(P)}{dP}}. \end{cases} \quad (19)$$

From equation (19), the circuit power consumption, P_c, has played an important role in the EE versus transmission power curve. For example, if P_c is small, the value of $\eta_{EE}(P)$ is always larger than $\frac{\frac{dR(P)}{dP}}{(1+\tau)+\zeta\frac{dR(P)}{dP}}$. So the EE always strictly decreases with transmission power P. From the above, EE is either strictly decreases or first strictly increases and then strictly decreases with the transmission power when the circuit power consumption is considered, which agrees with [4].

IV. Numerical Results

In this section, we present simulation results to demonstrate the effectiveness of the developed energy-efficient power allocation scheme. The parameters and rate constraints in our simulation are listed in Tables I and II, respectively. For analytical convenience, assuming the cell shape is approximated by a circle of radius D. The RAUs are uniformly distributed over a circle with radius d. As a result, the polar coordinate of the center BS/RAU 1 is $(0, 0)$, and the other RAU's polar coordinates are $(d, \frac{2\pi(n-1)}{N-1}), n = 1, 2, ..., N - 1$. Also assuming the MSs in the cell are uniformly distributed. In our simulation, $d = (3 - \sqrt{3})D/2$.

The objective of the optimization problem in (8) is to maximize the sum data transmission rates in the downlink multiuser DAS with proportional fairness. By setting $\omega_1 = 1$ and $\omega_2 = 0$, the objective of the optimization problem in (11) is identical to the problem (8). Hence, the problem of rate-adaptive optimization in (8) is a special case of the proposed energy-efficient method. Fig. 2 compares the SE versus the total power of each RAU between the proposed energy-efficient power allocation scheme and rate-adaptive power

TABLE I
SIMULATION PARAMETERS

Parameters	Value
Number of MSs M	10
Noise power σ_z^2	-104 dBm
Number of RAUs N	9
Target BER	0.001
Cell radius D	1000 m
Path loss exponent α	3.7
Power amplifier efficiency	38%
Static power consumption P_s	5 W
Maximum power $p_n^{\max}$	30 dBm
Drain efficiency η	0.35
Dynamic power consumption per unit throughput ζ	0.1 W/bps
Shadow fading σ_{sh}	8 dB

TABLE II
RATE CONSTRAINTS (Γ-SETS)

Fairness Index k	0	1	2	3	4	5
$\phi_1 = \phi_2 = \phi_3 = \phi_4 = 2^k$	2^0	2^1	2^2	2^3	2^4	2^5
$\phi_5 = \phi_6 = \cdots = \phi_{10}$	1	1	1	1	1	1

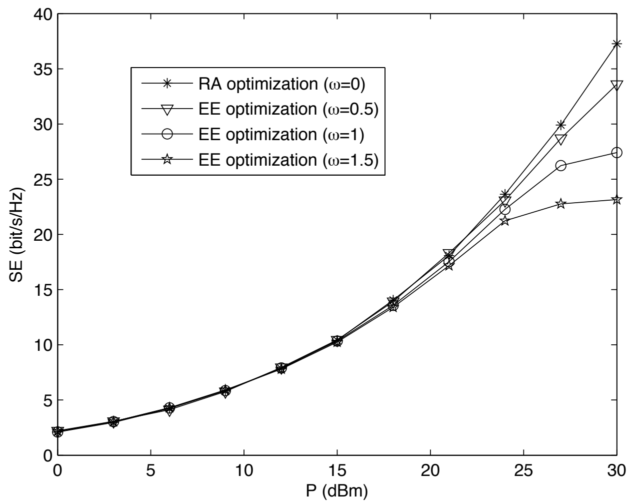

Fig. 2. SE versus total power of each RAU

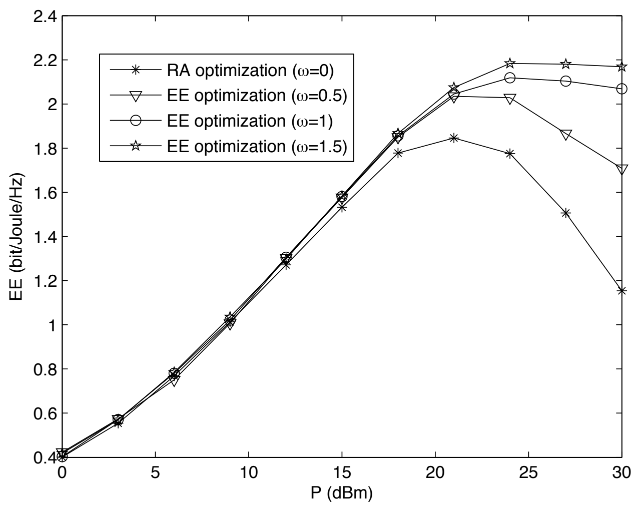

Fig. 3. EE versus total power of each RAU

allocation scheme for fairness index $k = 2$ in Table II. In this case, the proposed energy-efficient power allocation scheme is obviously worse than the rate-adaptive power allocation scheme in terms of SE. As we can see from Fig. 2, when $\omega = 1.5$, the SE of the rate-adaptive power allocation scheme is approximately 11.3% higher than the proposed energy-efficient power allocation scheme when the total power of RAU is 24 dBm. From the figure, the SE gradually decreases as ω increases, and the SE increases with the total power of RAUs.

Fig. 3 compares the EE versus the total power of each RAU between the proposed energy-efficient power allocation scheme and rate-adaptive power allocation scheme for fairness index $k = 2$. Compared with rate-adaptive power allocation, the proposed energy-efficient power allocation scheme outperforms the rate-adaptive power allocation scheme in terms of EE. When $\omega = 1.5$, the EE of the proposed energy-efficient power allocation scheme is approximately 23.1% higher than the rate-adaptive power allocation scheme when the total power of RAU is 24 dBm. From Fig. 3, the EE first increases and then decreases with total power, as discussed in Section III. From the above discussion, no optimal solution exists for a DAS to optimize both SE and EE simultaneously. Therefore, we can select the appropriate ω to balance SE and EE. For example, if we want to design high EE network, we should set ω as large as possible, and vice versa.

Fig. 4 shows the EE versus SE for the proposed energy-efficient power allocation scheme and rate-adaptive power allocation scheme for fairness index $k = 2$. From Fig. 4, when $\omega = 1.5$, the EE of the proposed energy-efficient power allocation scheme is approximately 20.2% higher than the rate-adaptive power allocation scheme when SE is 21.4 bit/s/Hz. It also shows the optimal envelop of the entire EE-SE region under different power allocation optimization methods. The optimal EE-SE curve in Fig. 4 shows the existence of a saturation point, beyond which the EE no longer increases, regardless of how much additional power is used. Based on this results, we can design optimal power consumption communication networks. On the other hand, we can reduce as much power consumption as possible while satisfying given SE requirement.

Fig. 5 compares the EE versus SE under different static and dynamic circuit power consumption levels. From the figure, the EE decreases as the circuit power consumption, P_s, increases, or the dynamic circuit power consumption per

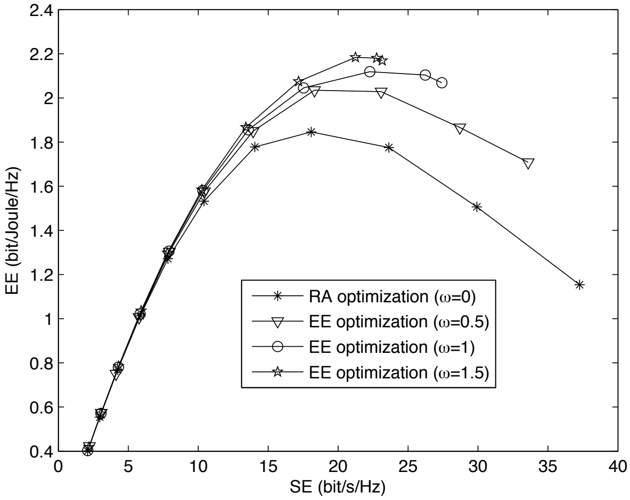

Fig. 4. EE versus SE

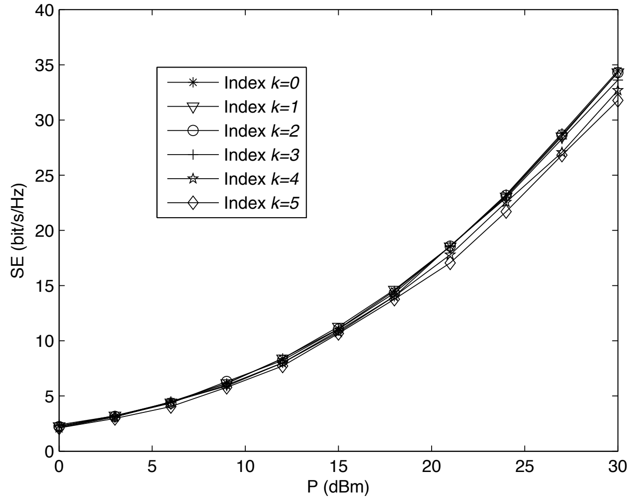

Fig. 6. SE versus different fairness indexes ($\omega = 0.5$)

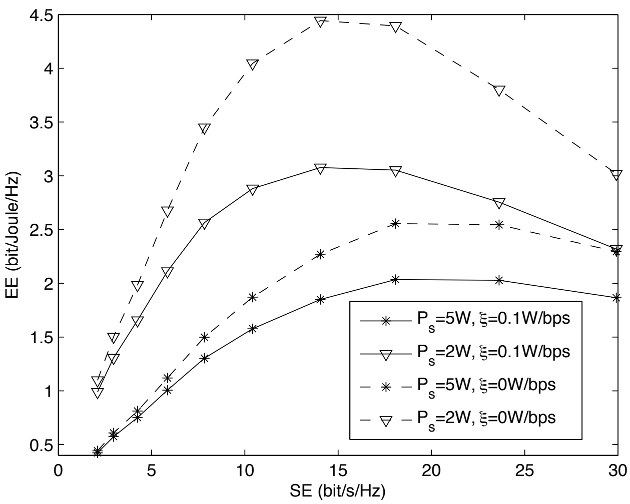

Fig. 5. EE versus SE under different circuit power parameters

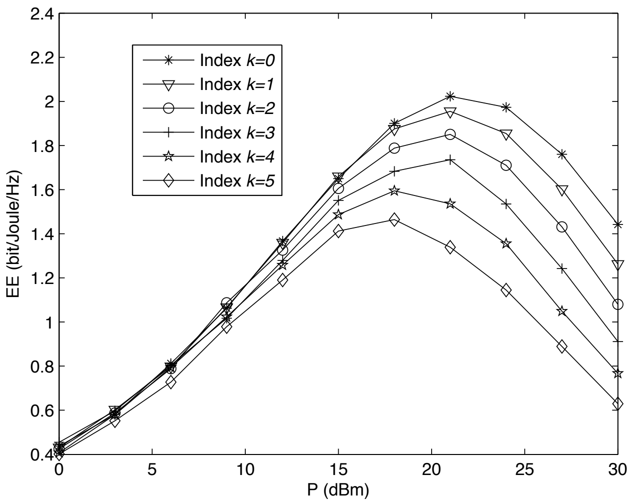

Fig. 7. EE versus different fairness indexes ($\omega = 0.5$)

unit throughput factors, ζ. More importantly, there is always a tradeoff between EE and SE no matter how the circuit power parameters change.

Figs. 6 and 7 compare the SE and EE of the proposed energy-efficient power allocation scheme in the downlink multiuser DAS versus different fairness constraints defined in Table II. From the figures, the SE and EE achieved by the proposed energy-efficient power allocation scheme vary with the data rate constraints. This results demonstrate 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 a sufficient transmit power for RAUs.

V. Conclusion

In this paper, we have investigated the relationship between EE and SE for the downlink multiuser DAS with proportional rate constraints, and developed an algorithm to allocate the available power to balance EE and SE of the system. Numerical results have illustrated the effectiveness of the energy-efficient power algorithm and the tradeoff between EE and SE, which is very important in designing energy-efficient communication systems.

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Appendix A

Proof: Assuming that $\{p_{n,m}^{opt}, n = 1, 2, ..., N, m = 1, 2, ..., M\}$ is an optimal solution to the optimization problem (11). For problem (11), let

$$f_1(p_{n,m}) = R = \sum_{m=1}^{M} \log_2(1 + \beta \frac{\sum_{n=1}^{N} p_{n,m} |h_{n,m}|^2}{\sigma_z^2}),$$

$$f_2(p_{n,m}) = P = -\sum_{m=1}^{M}\sum_{n=1}^{N} p_{n,m},$$

$\{g_i(p_{n,m}), i = 1, 2, ..., N\}$ and $\{h_j(p_{n,m}), j = 1, 2, ..., M-1\}$ denote the inequality constraints and equality constraints, respectively.

The optimal solution $p_{n,m}^{opt}$ in (11) satisfy the following Kuhn-Tucker conditions [30]

$$\lambda_i g_i(p_{n,m}^{opt}) = 0, \tag{20}$$

$$\nabla\left(\sum_{k=1}^{2}\omega_k f_k(p_{n,m}^{opt})\right) - \sum_{i=1}^{N}\lambda_i \nabla g_i(p_{n,m}^{opt}) - \sum_{j=1}^{M-1}\mu_j \nabla h_j(p_{n,m}^{opt}) = 0, \tag{21}$$

where λ_i and μ_j are the introduced Lagrange multipliers.
For

$$\nabla\left(\sum_{k=1}^{2}\omega_k f_k(p_{n,m}^{opt})\right) = \sum_{k=1}^{2}\omega_k \nabla f_k(p_{n,m}^{opt}).$$

So we can get the following equation

$$\sum_{k=1}^{2}\omega_k \nabla f_k(p_{n,m}^{opt}) - \sum_{i=1}^{N}\lambda_i \nabla g_i(p_{n,m}^{opt}) - \sum_{j=1}^{M-1}\mu_j \nabla h_j(p_{n,m}^{opt}) = 0. \tag{22}$$

Equations (20) and (22) are the Kuhn-Tucker conditions of the problem (10). Because of the concavity of function $f_1(p_{n,m})$ and $f_2(p_{n,m})$, the Kuhn-Tucker conditions are both necessary and sufficient for the Pareto optimal solution of the problem (10). So $p_{n,m}^{opt}$ is the Pareto optimal solution of the problem (10). This completes the proof.

Appendix B

Proof: The Lagrangian function of optimization problem (11) can be written as

$$\begin{aligned}L(\mathbf{p},\boldsymbol{\lambda},\boldsymbol{\mu}) = &\sum_{m=1}^{M}\log_2(1+\beta\frac{\sum_{n=1}^{N}p_{n,m}|h_{n,m}|^2}{\sigma_z^2})\\ &-\frac{\omega(1+\tau)}{1-\zeta\omega}\sum_{m=1}^{M}\sum_{n=1}^{N}p_{n,m} - \frac{\omega P_s}{1-\zeta\omega}\\ &-\sum_{m=2}^{M}\mu_m\left[\log_2(1+\beta\frac{\sum_{n=1}^{N}p_{n,1}|h_{n,1}|^2}{\sigma_z^2})\right.\\ &\left.-\frac{\phi_1}{\phi_m}\log_2(1+\beta\frac{\sum_{n=1}^{N}p_{n,m}|h_{n,m}|^2}{\sigma_z^2})\right]\\ &-\sum_{n=1}^{N}\lambda_n(\sum_{m=1}^{M}p_{n,m}-p_n^{max}),\end{aligned} \tag{23}$$

where μ_m and λ_n are the introduced Lagrange multipliers, $\omega = \frac{\omega_2}{\omega_1}$. After differentiating with respect to $p_{n,m}$, we obtain

$$\begin{aligned}\frac{\partial L(\mathbf{p},\boldsymbol{\lambda},\boldsymbol{\mu})}{\partial p_{n,1}} = &\frac{\beta|h_{n,1}|^2}{(\sigma_z^2+\beta\sum_{n=1}^{N}p_{n,1}|h_{n,1}|^2)\ln 2}\\ &-\frac{\omega(1+\tau)}{1-\zeta\omega}-\lambda_n\\ &-\sum_{m=2}^{M}\mu_m\frac{\beta|h_{n,1}|^2}{(\sigma_z^2+\beta\sum_{n=1}^{N}p_{n,1}|h_{n,1}|^2)\ln 2},\end{aligned} \tag{24}$$

and

$$\begin{aligned}\frac{\partial L(\mathbf{p},\boldsymbol{\lambda},\boldsymbol{\mu})}{\partial p_{n,m}} = &\frac{\beta|h_{n,m}|^2}{(\sigma_z^2+\beta\sum_{n=1}^{N}p_{n,m}|h_{n,m}|^2)\ln 2}\\ &-\frac{\omega(1+\tau)}{1-\zeta\omega}-\lambda_n\\ &+\frac{\phi_1}{\phi_m}\mu_m\frac{\beta|h_{n,m}|^2}{(\sigma_z^2+\beta\sum_{n=1}^{N}p_{n,m}|h_{n,m}|^2)\ln 2}.\end{aligned} \tag{25}$$

for $m \geq 2$.

By applying the KKT conditions [32] as follows

$$\frac{\partial L(\mathbf{p},\boldsymbol{\lambda},\boldsymbol{\mu})}{\partial p_{n,m}}\begin{cases} > 0, & p_{n,m} = p_n^{max}, \quad (26a)\\ = 0, & 0 < p_{n,m} < p_n^{max}, \quad (26b)\\ < 0, & p_{n,m} = 0. \quad (26c)\end{cases}$$

Then we can derive (12) and (14) immediately. This completes the proof.

Appendix C

Proof: Algorithm consists of the inner and outer loops. The inner loop is to compute $p_{n,m}$, for $n = 1, 2, ..., N, m = 1, 2, ..., M$. In each iteration step, for fixed λ_n and μ_m, $p_{n,m}$ converges to the unique optimal solution because of the concavity of (23). The outer loop is to compute the Lagrangian multipliers λ_n and μ_m. The gradient/sub-gradient method is convergent to the optimal value when ϑ^i and δ^i is a sufficiently small positive step size [31]. So, there is a unique λ_n and μ_m that optimizes (12) and (14), and the algorithm converges to the global optimal solution. This completes the proof.

Appendix D

Proof: If all the constraints are satisfied in equation (9), and P is the optimal power allocation scheme. After first derivative of EE in (9) with respect to P, we obtain equation (27), show at the top of this page.

From equation (27), we can derive (19) immediately. This completes the proof.

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$$\begin{aligned}\frac{d\eta_{EE}(P)}{dP} &= \lim_{\Delta P\to 0}\frac{\frac{R(P+\Delta P)}{(1+\tau)(P+\Delta P)+P_s+\zeta R(P+\Delta P)}-\frac{R(P)}{(1+\tau)P+P_s+\zeta R(P)}}{\Delta P}\\ &= \lim_{\Delta P\to 0}\frac{\frac{dR(P)}{dP}-\left[(1+\tau)+\zeta\frac{dR(P)}{dP}\right]\eta_{EE}(P)}{(1+\tau)(P+\Delta P)+P_s+\zeta R(P+\Delta P)}\\ &= \frac{\frac{dR(P)}{dP}-\left[(1+\tau)+\zeta\frac{dR(P)}{dP}\right]\eta_{EE}(P)}{(1+\tau)P+P_c}. \end{aligned} \tag{27}$$

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