Adaptive Energy Efficient Power Allocation Scheme for DAS with Multiple Receive Antennas

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Abstract: Energy efficiency (EE) of downlink distributed antenna system (DAS) with multiple receive antennas is investigated over composite Rayleigh fading channel that takes the path loss and lognormal shadow fading into account. Our aim is to maximize EE which is defined as the ratio of the transmission rate to the total consumed power under the constraints of the maximum transmit power of each remote antenna. According to the definition of EE, the optimized objective function is formulated with the help of Lagrangian method. By using the Karush-Kuhn-Tucker (KKT) conditions and numerical calculation, considering both the static and dynamic circuit power consumptions, an adaptive energy efficient power allocation (PA) scheme is derived. This scheme is different from the conventional iterative PA schemes based on EE maximization since it can provide closed-form expression of PA coefficients. Moreover, it can obtain the EE performance close to the conventional iterative scheme and exhaustive search method while reducing the computation complexity greatly. Simulation results verify the effectiveness of the proposed scheme.

Key words: distributed antenna system(DAS); energy efficiency(EE); power allocation(PA); composite fading; multiple receive antennas

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0 Introduction

Distributed antenna system (DAS) has emerged as a promising technology for future wireless communications, thanks to its ability of enhancing the system capacity, improving the signal quality and reducing the power[1-4]. In DAS, the remote antennas (RAs) are separated geographically and connected to a central control module via dedicated wires, fiber optics, or an exclusive radio frequency link[3]. Traditionally, the spectral efficiency (SE) has been used to measure the efficiency of a communication system[5]. However, it fails to evaluate how the energy is efficiently consumed. Green communication, which pursues high energy efficiency (EE), has drawn increasing attentions these days. Due to the growing energy demand and increasing energy price, pursuing high EE is becoming a mainstream for future mobile systems[6-8].

EE is defined as the sum-rate divided by the total power consumption measured in bit/J/Hz. Based on this, different energy efficient methods have been proposed for DAS[9-13]. In Ref. [9], an approximate power allocation (PA) method through an iterative numerical search was provided for generalized DAS, but the large-scale fading was not considered. An optimal PA algorithm with antenna selection relying on numerical search was proposed for DAS in Ref. [10]. A novel PA algorithm to achieve maximum EE while satisfying SE requirement in downlink multiuser DAS was proposed in Ref. [11]. In Ref. [12],

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fractional programming theory was adopted to transform the fractional form of non-convex EE optimization into its equivalent subtractive form, leading to an energy efficient PA algorithm in orthogonal frequency division multiple access (OFDMA) system. However, the above algorithms still need iterative calculation. For this, a low-complexity energy efficient PA scheme for DAS was proposed in Ref. [13], but some errors exists in the derivation of Eqs. (7) and (11). Moreover, for analysis convenience, the above studies basically consider single receive antenna and assume the circuit power consumption to be a constant, and thus the derived PA schemes lack generality. Based on this, the EE performance is not studied well, and the corresponding performance improvement and practicability will be limited.

Therefore, a composite fading channel including path loss, log-normal shadowing and Rayleigh fading is presented for DAS considering the practical case. According to this, an energy efficient PA optimization problem for DAS with multiple receive antennas is formulated by means of Lagrange multiplier method. Besides, a more practical circuit power consumption model is considered which includes both static part and dynamic part. By using the Karush-Kuhn-Tucker (KKT) conditions and the Lambert *W* function, an adaptive energy efficient scheme is derived and closed-form PA coefficients are obtained. It is shown that this scheme can effectively lower the computation complexity when compared with the conventional scheme with dual loops iteration, and may obtain almost the same EE as the latter.

1 System and Channel Models

A distributed antenna system with N_t RAs and N_r receive antennas in a single-cell environment is considered as shown in Fig. 1. The RAs are distributed in the cell and linked to the base station (BS, also named as RA_1) via dedicated wired connection, and the ith RA is denoted as RA_i. The mobile station (MS) is equipped with N_r antennas. For remote transmit antenna i, the corresponding received signals at MS can be ex-

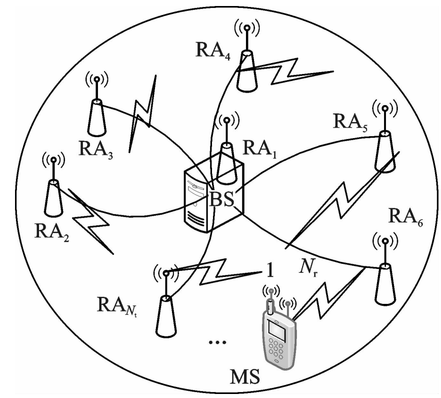

Fig. 1 A circle-cell DAS structure

pressed as

$$\boldsymbol{y}_i = \sqrt{p_i}\,[h_i^1, \cdots, h_i^{N_r}]^{\mathrm{T}} \kappa_i + \boldsymbol{z} \tag{1}$$

where the superscript $(\cdot)^{\mathrm{T}}$ denotes the transpose, p_i the transmit power consumed by the ith RA, h_i^j the composite fading channel coefficient between RA_i and the jth antenna of the MS, κ_i the transmitted symbol from the ith RA with unit energy, and $\boldsymbol{z}$ the complex Gaussian noise vector with zero-mean and variance N_0. h_i^j can be modeled as[14]

$$h_i^j = g_i^j \Omega_i \tag{2}$$

where g_i^j represents the small-scale fading between RA_i and the jth receive antenna of the MS. For Rayleigh fading channel, $\{g_i^j\}$ are modeled as independent complex Gaussian random variables with zero-mean and unit variance. $\Omega_i = \sqrt{S_i d_i^{-\alpha_i}}$ denotes the large-scale fading between RA_i and the MS, where α_i is the path loss exponent and d_i the distance from RA_i to MS. S_i is a log-normal shadow fading variable, i.e., $10\log_{10} S_i$ is a Gaussian random variable with zero-mean and standard deviation σ_i.

For the DAS, the achievable data transmission rate for the MS can be expressed as

$$R = \log_2\left(1 + \sum_{i=1}^{N_t} \gamma_i p_i\right) \tag{3}$$

where $\gamma_i = \sum_{j=1}^{N_r} |g_i^j|^2 \Omega_i^2 / N_0$ is defined as the channel to noise ratio (CNR) of RA_i after employing maximal ratio combining (MRC) at the receiver. It is assumed that per RA power constraint is $0 \leqslant p_i \leqslant P_{\max,i}$, where $P_{\max,i}$ is the maximum transmit power available at RA_i.

Energy efficiency is usually defined as the ratio of data transmission rate to the total power consumption, i. e.

$$\eta_{\mathrm{EE}} = R \Bigg/ \left(\sum_{i=1}^{N_t} p_i + p_c \right) \tag{4}$$

where p_c denotes the circuit consumption which can be modeled as a linear function of throughput [15]

$$p_c = p_s + \xi R \tag{5}$$

where p_s is the static circuit consumption term and ξ a constant denoting dynamic power consumption per unit data rate. Obviously, the constant circuit consumption model used in Refs. [9-13] is a special case that ξ in Eq. (5) equals 0.

2 Energy Efficient Power Allocation and Algorithm Procedure

In this section, the optimized objective function on PA for maximizing EE is firstly formulated. Then, by using the KKT conditions and the Lambert W function, a suboptimal closed-form energy efficient PA scheme is developed for DAS, and the corresponding algorithm procedure is presented.

The optimized objective function of the optimal PA can be expressed as

$$\max_{p} \eta_{\mathrm{EE}} = \frac{\log_2\left(1 + \sum_{i=1}^{N_t} \gamma_i p_i\right)}{\sum_{i=1}^{N_t} p_i + p_s + \xi \log_2\left(1 + \sum_{i=1}^{N_t} \gamma_i p_i\right)}$$

$$\text{s. t. } 0 \leqslant p_i \leqslant P_{\max,i} \quad \forall i \in \{1,\cdots,N_t\} \tag{6}$$

where $\boldsymbol{p} = [p_1,\cdots,p_{N_t}]^{\mathrm{T}}$. Since the optimization problem in Eq. (6) is non-convex, it is hard to find the optimal solution directly. For this, the following lemmas and corollaries are introduced.

Lemma 1 For the optimization problem

$$\max_{x \geqslant 0} y(x) = \max_{x \geqslant 0} \frac{\ln(mx+n)}{x+s+\xi \ln(mx+n)} \tag{7}$$

where $m>0, n \geqslant 1, s>0$, the optimal solution x^* is obtained as

$$x^* = [\hat{x}]^+ \tag{8}$$

where

$$\hat{x} = m^{-1}\left[\exp\{W((ms-n)\mathrm{e}^{-1})+1\} - n\right] \tag{9}$$

where $[x]^+$ represents $\max(x,0)$ and $W(x)$ the Lambert W function which is defined as the reverse function of $g(x)=x\mathrm{e}^x$ [16].

Proof By taking the derivative of the objective function $y(x)$ with respect to x yields

$$y'(x) = \frac{-(mx+n)\ln(mx+n) + m(x+s)}{(mx+n)[x+s+\xi \ln(mx+n)]^2} \tag{10}$$

Equating Eq. (10) to zero gives

$$m(x+s) = (mx+n)\ln(mx+n) \tag{11}$$

Using the Lambert W function[16] and considering the non-negativity of x, the optimal closed-form solution of x can be obtained as Eq. (8).

Corollary 1 $y(x)$ achieves the maximum value at $x=x^*$.

Proof Defining the numerator of Eq. (10) as

$$g(x) = -(mx+n)\ln(mx+n) + m(x+s) \tag{12}$$

The derivative of $g(x)$ with respect to x is written as

$$g'(x) = -m\ln(mx+n) < 0 \tag{13}$$

Thus, $g(x)$ is a strictly decreasing function.

If $x^* > 0$, we will easily obtain $y'(x) > 0 (0 \leqslant x < x^*)$ and $y'(x) < 0 (x > x^*)$. Therefore, $y(x)$ will reach the maximum value at $x = x^*$. If $x^*=0$, $y'(x)$ always has a negative value for $x>0$ and thus $y(x)$ is a strictly decreasing function and obtains the maximum value at $x = x^* = 0$.

Corollary 2 As a special case when $n=1$, x^* in Eq. (8) is always positive.

Proof For $x>-1/\mathrm{e}$, the Lambert W function $W(x)$ is an increasing function and $W(-1/\mathrm{e}) = -1$. When $n=1 (m>0, s>0)$, $(ms-n)/\mathrm{e} > -1/\mathrm{e}$, and thus $W((ms-n)\mathrm{e}^{-1}) > -1$. Therefore, it can be easily seen that x^* must be positive from Eq. (8).

Considering that the distances between RA_i and the MS are different, γ_i may be different, and thus they can be sorted in descending order as

$$\gamma_1 > \gamma_2 > \cdots > \gamma_{N_t} \tag{14}$$

The Lagrangian duality function of Eq. (6) is constructed as follows

$$J(\{p_i,\lambda_i,\nu_i\}) = \frac{\ln\left(1+\sum_{i=1}^{N_t}\gamma_i p_i\right)}{\sum_{i=1}^{N_t}p_i + p_s + \xi\ln\left(1+\sum_{i=1}^{N_t}\gamma_i p_i\right)} + \sum_{j=1}^{N_t}\lambda_j p_j + \sum_{j=1}^{N_t}\nu_j(P_{\max,j}-p_j) \quad (15)$$

where λ_i and ν_i are the introduced Lagrange multipliers.

As the constraints of the optimization problem in Eq. (6) are linear, they satisfy linearity constraint qualification[17]. Therefore, the duality gap is zero, which implies that KKT conditions are necessary for optimality[18].

Using KKT conditions, the optimal values $\{p_i^*, \lambda_i^*, \nu_i^*\}(i=1,\cdots,N_t)$ should satisfy the following equations

$$\frac{\partial J}{\partial p_i} = f_i(p_1^*,\cdots,p_{N_t}^*) + \lambda_i^* - \nu_i^* = 0 \quad (16)$$

$$\lambda_i^* p_i^* = \nu_i^*(P_{\max,i} - p_i^*) = 0 \quad (17)$$

$$0 \leqslant p_i^* \leqslant P_{\max,i},\ \lambda_i^*, \nu_i^* \geqslant 0 \quad (18)$$

where

$$f_i(p_1^*,\cdots,p_{N_t}^*) = \frac{\gamma_i\left(\sum_{j=1}^{N_t}p_j^* + p_s\right)}{(1+\Psi)\left[\sum_{j=1}^{N_t}p_j^* + p_s + \zeta\ln(1+\Psi)\right]^2} - \frac{\ln(1+\Psi)}{\left[\sum_{j=1}^{N_t}p_j^* + p_s + \xi\ln(1+\Psi)\right]^2} \quad (19)$$

where $\Psi = \sum_{j=1}^{N_t}\gamma_j p_j^*$. For notation simplicity, we rewrite $f_i(p_1^*,\cdots,p_{N_t}^*)$ as f_i. Substituting Eq. (14) into Eq. (19) leads to

$$f_1 > f_2 > \cdots > f_{N_t} \quad (20)$$

Lemma 2 The following conclusions hold for any j $(j=1,\cdots,N_t)$.

If $f_j < 0$, $p_l^* = 0$ $(l > j)$; if $f_j > 0$, $p_k^* = P_{\max,k}$ $(k < j)$; If $f_j = 0$, $p_l^* = P_{\max,l}(l < j)$ and $p_k^* = 0(k > j)$.

Proof

If $f_j < 0$, based on Eqs. (16) and (20), $f_l = -\lambda_l^* + \nu_l^* < 0$ holds for $l > j$. Thus $\lambda_l^* \neq 0$, and then from the complementary slackness condition in Eq. (17), it can be derived $p_l^* = 0$.

If $f_j > 0$, based on Eqs. (16) and (20), $f_l = -\lambda_l^* + \nu_l^* > 0$ holds for $l < j$. Thus $\nu_l^* \neq 0$, and then from the complementary slackness condition in Eq. (17), it can be derived that $p_l^* = P_{\max,l}$.

If $f_j = 0$, we have $f_l > 0$ and $f_k < 0$ for $l < j$ and $k > j$ from Eq. (20), respectively. Based on the two conclusions above, it can be easily derived that $p_l^* = P_{\max,l}(l < j)$ and $p_k^* = 0$ $(k > j)$.

According to the complementary slackness condition in Eq. (17), a possible set of PA solutions can be divided into three mutually exclusive cases as

$$(p_i^*, \lambda_i^*, \nu_i^*) = \{(0,\lambda_i^*,0), (x_i^*,0,0)\,|_{0<x_i^*<P_{\max,i}}, (P_{\max,i},0,\nu_i^*)\} \quad (21)$$

After further derivation of Eq. (21) based on Lemma 2, an adaptive PA scheme is presented, and the corresponding algorithm procedure is summarized as follows:

Suboptimal power allocation algorithm
(1) Set γ_i as $\gamma_1 > \gamma_2 > \cdots > \gamma_{N_t}$. (2) Initialize $i=1$, for the power of RA_1 (i. e. p_1^*), by substituting $m=\gamma_1$, $n=1$, $s=p_s$ into Eqs. (8) and (9), x_1^* can be computed as $x_1^* = \gamma_1^{-1}\{\exp[W((\gamma_1 p_s - 1)e^{-1}) + 1] - 1\}$ (22) From Corollary 2, it is known that $x_1^* > 0$. If $0 < x_1^* < P_{\max,1}$, $f_1 = -\lambda_1^* + \nu_1^* = 0$. Using Lemma 2, p_i^* $(i=2,\cdots,N_t)$ becomes zero. In this case, the solution of PA is $(p_1^*,\cdots,p_{N_t}^*) = (x_1^*,0,\cdots,0)$, and the algorithm stops. If $x_1^* \geqslant P_{\max,1}$, p_1^* should be set to $P_{\max,1}$ since the objective is a strictly increasing function for $0 < p_1 < x_1^*$ by Corollary 1. In this case, the solution of PA is $(p_1^*,\cdots,p_{N_t}^*) = (P_{\max,1},x_2,\cdots,x_{N_t})$. Then, go to Step (3). (3) **While** ($p_i^* = P_{\max,i}$ and $i < N_t$) $i = i+1$; Substitute $m=\gamma_i$, $n = 1+\sum_{k=1}^{i-1}\gamma_k P_{\max,k}$, $s = p_s + \sum_{k=1}^{i-1}P_{\max,k}$ into Eq. (8) to compute $x_i^* = [\hat{x}_i]^+$, yields $\hat{x}_i = \gamma_i^{-1}\left\{\exp\left[W\left(\left(\gamma_i\left(p_s + \sum_{k=1}^{i-1}P_{\max,k}\right) -\right.\right.\right.\right.$

$$\left[1+\sum_{k=1}^{i-1}\gamma_k P_{\max,k}\right]\right]\mathrm{e}^{-1}\right]+1\right]-$$

$$\left[1+\sum_{k=1}^{i-1}\gamma_k P_{\max,k}\right]\right\} \quad (23)$$

Therefore, the PA solution can be given by

$$p_i^* = \min(x_i^*, P_{\max,i}) \quad (24)$$

end

(4) Set $p_j^* = 0$ for $j > i$.

With the algorithm above, the energy efficient PA coefficients $\{p_i^*\}$ can be obtained. Substituting these coefficients into Eq. (4) obtains the corresponding energy efficiency.

Considering that the optimization problem in Eq. (6) is non-convex, the KKT conditions are not sufficient but necessary condition only. Thus, the solution for Eq. (6) by solving the above KKT condition possibly does not give the optimal one, and may be suboptimal one. Namely, the obtained $\{p_i^*\}$ may be suboptimal. As a result, the proposed adaptive PA scheme will become suboptimal as well.

The conventional iterative PA scheme in Ref. [12] will be used to solve our EE maximizing problem by some extensions since it does not consider the dynamic power consumption and only considers single receive antenna. Then, the complexity comparison of these two schemes is provided.

When the dynamic power consumption is considered, the EE maximizing problem can still be transformed into standard convex optimization by the method in Ref. [12] based on fractional programming theory, and thus the extended scheme from Ref. [12] is optimal. For this scheme, during the process of computing each p_i^*, the dual loops are performed, and both the inner and outer loop need $O(\log(1/\varepsilon))$ iterations to guarantee the error tolerance of ε. On the other hand, in our proposed scheme, each p_i^* can be directly computed by Eq. (24) at each stage successively, and the computation stops immediately when $p_i^* \neq P_{\max,i}$ is fulfilled. As a result, our scheme has lower complexity, which can also be seen from Table 1, where the average number of iterations of two schemes is compared.

Table 1 Complexity comparison

Comparison point	The proposed scheme	The conventional scheme
Convergence case for $\{p_i^*\}$	Closed-form computation by Eq. (24)	Dual loops iteration
Average number of iterations	1.6	41.2

3 Simulation Results and Analyses

In this section, the validity of the proposed scheme will be evaluated via computer simulation. For convenience, assume $P_{\max,i}=P_{\max}$ for $\forall i$ in the simulations. The RAs are uniformly distributed over a circle with radius r. As a result, the polar coordinate of the BS/RA_1 is (0, 0), and the polar coordinates of other RAs are $(r, \frac{2\pi(i-1)}{N_t-1})$, $i=2,\cdots,N_t$ with $r=\sqrt{3/7}D$, where D is the radius of the cell. Also assuming the MS in the cell is uniformly distributed. Unless otherwise specified, the main parameters used in simulations are listed in Table 2. The simulation results are obtained through Monte Carlo simulations, and are illustrated in Figs. 2—5, where the "conventional scheme" denotes the iterative power allocation scheme in Ref. [12] after some extensions, and the exhaustive search means examining all possible power allocation combinations with a resolution of 0.01 W.

Table 2 Simulation parameters

Parameter	Value
Number of remote antennas N_t	7
Path loss exponent α_i	4
Shadow fading standard deviation σ_i /dB	8
Noise power N_0 /dBm	−104
Static power consumption p_c /W	5
Dynamic power consumption factor $\xi/(\mathrm{W}\cdot\mathrm{bit}^{-1}\cdot\mathrm{s})$	0.1
Cell radius D /m	1 000
Number of channel realizations	10 000
Number of receive antennas N_r	2

Fig. 2 shows the EE of DAS with different PA schemes, where the proposed scheme, conventional scheme, and exhaustive search method are compared. As shown in Fig. 2, the proposed scheme has the EE performance very close to the exhaustive search method and the conventional scheme for different numbers of remote antennas, and the EE gradually improves and is finally saturated as P_{max} increases. This is due to the fact that $\hat{x}_i$ in Eq. (23) will become smaller than P_{max} when P_{max} increases, and thus p_i^* in Eq. (24) does not change any more as the latter increases. Moreover, because of greater space diversity, the EE of the system with more remote antennas is higher than that with fewer remote antennas as expected. In Table 1, the average numbers of iterations of the proposed scheme and the conventional scheme are compared. It is found that the proposed scheme requires less iteration than the latter, which accords with the complexity analysis in Section 2. Namely, our scheme has relatively lower complexity.

In Fig. 3, the EE of DAS with different receive antennas are plotted as a function of P_{max}. It can be found that the EE performance of the proposed scheme is almost the same as that of the conventional scheme. Moreover, the EE of the system can increase as the number of receive antenna N_r increases. Namely, the EE with $N_r=2$ performs approximately 8.2% better than that with $N_r=1$, while an extra 4.2% EE gain can be observed for $N_r=3$ compared with $N_r=2$. Because the increase of the receive antennas will bring about more spatial diversity gain. Based on the analysis above, the application of multiple receive antennas does improve the EE performance obviously. These results further indicate that the proposed scheme is valid.

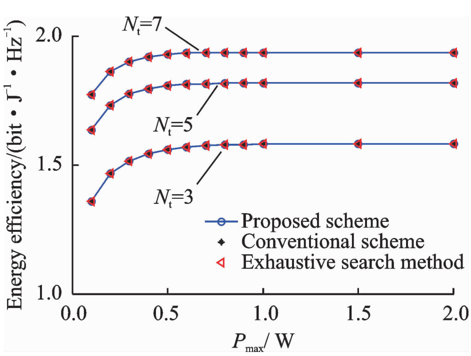

Fig. 2 EE of DAS with different remote antennas

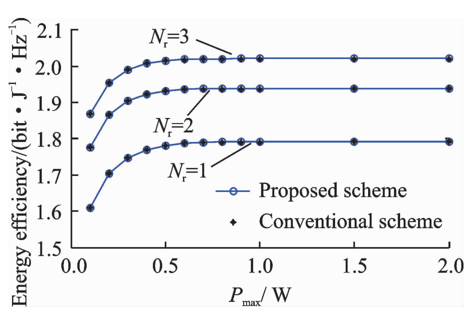

Fig. 3 EE of DAS with different receive antennas

In Fig. 4, the EE performances with different schemes and dynamic power consumption factors are compared, where $\xi=0$, 0.05, 0.1 are considered. From Fig. 4, it is found that the proposed scheme exhibits the EE performance very close to the conventional iterative scheme. Besides, for these two schemes, their EEs both decrease as the dynamic circuit power consumption factor ξ increases as expected. Because η_{EE} is a decreasing function with respect to ξ. Thus, it is derived that the system EE under $\xi=0.1$ is lower than that at $\xi=0.05$, and the system EE at $\xi=0.05$ is lower that without dynamic power consumption ($\xi=0$). The above results show that the proposed scheme is also reasonable.

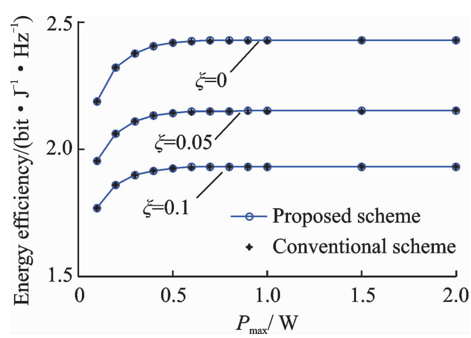

Fig. 4 EE of DAS with different dynamic power consumption factors

Fig. 5 shows the EE of DAS with different path loss exponents, where the proposed scheme and the conventional scheme are compared. It is observed that the EE of the system can increase as path loss exponent α_i decreases for both two schemes, which accords with the existing knowledge. The reason is that the decrease of α_i means the decrease of path loss, which reduces the impact on EE. Besides, the proposed scheme can

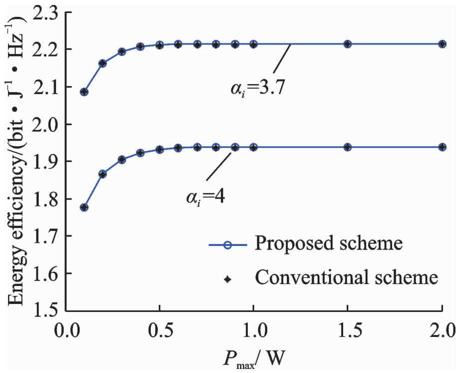

Fig. 5 EE of DAS with different path loss exponents

obtain almost the same EE as the conventional scheme.

4 Conclusions

The energy efficiency for DAS with multiple receive antennas in composite Rayleigh fading channel is investigated, and an adaptive energy-efficient PA scheme for downlink DAS is developed. This scheme considers both the static and dynamic parts of circuit power consumptions, and can provides closed-form expression for PA coefficients. Moreover, it has lower complexity than the existing iterative and search schemes due to closed-form calculation and less iteration. Simulation results show that the proposed scheme is valid, and may obtain the energy efficiency close to that of the existing iterative scheme and exhaustive search scheme.

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References:

[1] HEATH R, PETERS S, WANG Y, et al. A current perspective on distributed antenna systems for the downlink of cellular systems[J]. IEEE Communications Magazine, 2013, 51(4):161-167.

[2] PARK E, LEE S R, LEE I. Antenna placement optimization for distributed antenna systems[J]. IEEE Transactions on Wireless Communications, 2012, 11 (7):2468-2477.

[3] LEE H K , LEE S R, LEE K J, et al. Transmission schemes based on sum rate analysis in distributed antenna systems[J]. IEEE Transactions on Wireless Communications, 2012, 11(3):1201-1209.

[4] WU B B, YU X B, WANG Y, et al. Capacity analysis on distributed antenna system with imperfect CSI over Rayleigh fading channel[J]. Transactions of Nanjing University of Aeronautics and Astronautics, 2016, 33(6):733-738.

[5] WU Qihui, REN Jing. New paradigm of electromagnetic spectrum space: Spectrum situation[J]. Journal of Nanjing University of Aeronautics and Astronautics, 2016, 48(5):625-632. (in Chinese)

[6] FENG D Q, JIANG C Z, LIM G. A survey of energy-efficient wireless communications[J]. IEEE Communications Surveys and Tutorials, 2013, 15(1): 167-178.

[7] HÉLIOT F, IMRAN M A, TAFAZOLLI R. On the energy efficiency-spectral efficiency trade-off over the MIMO Rayleigh fading channel[J]. IEEE Transactions on Communications, 2012, 60(5):1345-1356.

[8] LI G Y, XU Z K, XIONG C, et al. Energy-efficient wireless communications: Tutorial, survey, and open issues[J]. IEEE Wireless Communications, 2011, 18(6):28-35.

[9] CHEN X, XU X D, TAO X F. Energy efficient power allocation in generalized distributed antenna system [J]. IEEE Communications Letters, 2012, 16(7): 1022-1025.

[10] LI Y Z, SHENG M, WANG X J, et al. Globally optimal antenna selection and power allocation for energy efficiency maximization in downlink distributed antenna systems[C]//IEEE Global Communications Conference. Austin: IEEE, 2014: 3856-3861.

[11] HE C L, SHENG B, ZHU P C, et al. Energy efficiency and spectral efficiency tradeoff in downlink distributed antenna systems[J]. IEEE Wireless Communications Letters, 2012, 1(3):153-156.

[12] HE C L, LI G Y, ZHENG F, et al. Energy-efficient resource allocation in OFDM systems with distributed antennas[J]. IEEE Transactions on Vehicular Technology, 2014, 63(3):1223-1231.

[13] WU J, LIU J W, LI W L, et al. Low-complexity power allocation for energy efficiency maximization in DAS[J]. IEEE Communications Letters, 2015, 19 (6):925-928.

[14] WANG D M, YOU X H, WANG J, et al. Spectral efficiency of distributed MIMO cellular systems in a composite fading channel[C]//IEEE International Conference on Communications. Beijing: IEEE, 2008:1259-1264.

[15] XIONG C, LI G Y, ZHANG S Q, et al. Energy-and spectral-efficiency tradeoff in downlink OFDMA networks[J]. IEEE Transactions on Wireless Communications, 2011, 10(11):3874-3886.

[16] CORLESS R M, GONNET G H, HARE D E, et al. On the Lambert W function[J]. Advances in Computational Mathematics, 1996, 5(1):329-359.

[17] BOYD S, VANDENBERGHE L. Convex optimization[M]. Cambridge, U. K.: Cambridge University Press, 2014.

[18] BOYD S, VANDENBERGHE L. Convex optimization[M]. Cambridge: Cambridge University Press, 2004: 215-264.

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