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Energy Efficient Power Allocation for Heterogeneous Cloud Radio Access Network with Partial CSI

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Abstract. In this paper, we consider power allocation for heterogeneous cloud radio access network (HC-RAN). All the channels in HC-RAN are assumed to be block fading and only the statistical information of these channels can be acquired by the based band unit (BBU) instead of perfect channel state information (CSI). The power of the users is optimized via maximization of the averaged energy efficiency (EE) of HC-RAN, under outage probability constraints and average transmit power constraint. First, the original nonconvex optimization problem is transformed into an equivalent optimization problem in subtractive form. Then, an efficient two loop iterative power allocation scheme is proposed. Simulation results demonstrate the improvements in terms of EE by using the proposed power allocation scheme compared with the traditional ergodic rate maximization algorithm.

Keywords: power allocation, energy efficient, heterogeneous cloud radio access network, fractional programming.

1. Introduction

In recent years, heterogeneous cloud wireless access network (HC-RAN) has attracted great research attention. HC-RAN can bring numerous benefits including low cost, flexible deployment of network and high utilization of resources[1]. Therefore, HC-RAN is considered one of the most promising solutions to address the key challenges in future wireless network [2].

Resource allocation is one of the key technologies for HC-RAN. In [3], a new economical spectral efficiency was defined to measure the cost of HC-RAN, and proposed a two loops algorithm to optimize the resource of HC-RAN. [4] studied joint user admission, association and power allocation problems for HC-RAN, the above problem was modeled as a mixed integers nonlinear problems, then an outer approximation approach based on linearization method was proposed. [5] studied power allocation problem for nonorthogonal multiple access (NOMA) HC-RAN, and proposed an energy efficient power allocation scheme to allocate the power for different types base station (BS). The multiplexing gain of virtual base station pooling based on multi-dimensional Markov mode was researched in [6], and recursive formula and closed form approximation for the blocking probability were also derived. In [7], energy efficient resource block assignment and power allocation were studied for OFDMA-based HC-RAN. To maximize the energy efficiency performance, an iterative algorithm was proposed to achieve the global optimal solution. To maximize the average throughput and maintain the network stability, [8] studied the joint congestion control and resource optimization problem and an energy efficiency algorithm was proposed to balance throughput and delay. [9] studied joint power allocation, relay selection and networking selection for relay HC-RAN, and proposed an efficient algorithm based on relaxation method and nonlinear fractional programming.

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However, all the above researches assume that HC-RAN can acquire perfect channel sate information (CSI). However, obtaining accurate estimation of CSI is challenging or even impossible. In this paper, we formulate the power allocation problem for energy efficient HC-RAN with Partial CSI as a nonconvex optimization problem. An efficient iterative power allocation scheme is proposed to solve the above problem.

2. System Model and Proposed Formulation

We consider an uplink resource sharing for HC-RAN with one macro cellular user (MU), one RRH user (RU). The MU and RU are served by MBS and RRH respectively. The MBS and RRH are connected to the Based Band Unit (BBU) via fronthual link. The RU reuses the same channel allocated to the MU. Denote the channel power gains (CPG) from MU to MBS by g_{MU}, the CPG from RU to RRH by g_{RU}, the CPG from RU to the MBS by h_{RM}, the CPG from the MU to the RRH by h_{MR}, respectively. Assume these channel power gains are ergodic over transmission blocks, and are independent, identically distributed. All these channels' statistical information is known at the BBU pool.

Let $\boldsymbol{\nu}=[g_{\mathrm{MU}}\ h_{\mathrm{RM}}\ g_{\mathrm{RU}}\ h_{\mathrm{MR}}]$ denotes the power gain vector, p_{MU} and $p_{\boldsymbol{\nu}}$ denote the transmit powers of MU and RU. Then, the rate of MU and RU in one fading channel state with channel realization $\boldsymbol{\nu}$ are, respectively:

$$R_{\mathrm{MU}}=\log_2\left(1+\frac{p_{\mathrm{MU}}g_{\mathrm{MU}}}{N_0+p_{\boldsymbol{\nu}}h_{\mathrm{RM}}}\right) \tag{1}$$

$$R_{\mathrm{RU}}=\log_2\left(1+\frac{p_{\boldsymbol{\nu}}g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right) \tag{2}$$

where N_0 is the noise power.

Outage probability constraints of MU link and RU link are repressed as:

$$\mathcal{P}\left(\log_2\left(1+\frac{p_{\mathrm{MU}}g_{\mathrm{MU}}}{N_0+p_{\boldsymbol{\nu}}h_{\mathrm{RM}}}\right)<R_{\min}^{\mathrm{MU}}\right)\le\sigma_{\mathrm{MU}} \tag{3}$$

$$\mathcal{P}\left(\log_2\left(1+\frac{p_{\boldsymbol{\nu}}g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)<R_{\min}^{\mathrm{RU}}\right)\le\sigma_{\mathrm{RU}} \tag{4}$$

where σ_{RU} and σ_{MU} are the maximum outage probability of RU and MU, respectively

The average transmit power constraint of RU link over all fading channel states is expressed as:

$$\mathcal{E}\left[p_{\boldsymbol{\nu}}\right]\le P_{\max} \tag{5}$$

where $\mathcal{E}$ denotes the expectation, $P_{\max}$ is the average transmit power threshold of RU.

Let ξ_{EE} denote the energy efficiency of the RU link averaged over all the fading states, and it can be defined as follows:

$$\xi_{\mathrm{EE}}=\frac{\mathcal{E}\left[\log_2\left(1+\frac{p_{\boldsymbol{\nu}}g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)\right]}{\mathcal{E}\left[p_{\boldsymbol{\nu}}\right]+P_{\mathrm{c}}} \tag{6}$$

where P_{c} denote the circuit power consumption of the RU.

Mathematically, the EE optimization problem can be written as:

$$\begin{aligned}
&\mathrm{OP1}\ \max_{p_{\boldsymbol{\nu}}}\frac{\mathcal{E}\left[\log_2\left(1+\frac{p_{\boldsymbol{\nu}}g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)\right]}{\mathcal{E}\left[p_{\boldsymbol{\nu}}\right]+P_{\mathrm{c}}}\\
&s.t\quad \mathrm{C1}:\mathcal{E}\left[p_{\boldsymbol{\nu}}\right]\le P_{\max}\\
&\qquad \mathrm{C2}:\mathcal{P}\left(\log_2\left(1+\frac{p_{\boldsymbol{\nu}}g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)<R_{\min}^{\mathrm{RU}}\right)\le\sigma_{\mathrm{RU}}\\
&\qquad \mathrm{C3}:\mathcal{P}\left(\log_2\left(1+\frac{p_{\mathrm{MU}}g_{\mathrm{MU}}}{N_0+p_{\boldsymbol{\nu}}h_{\mathrm{RM}}}\right)<R_{\min}^{\mathrm{MU}}\right)\le\sigma_{\mathrm{MU}}
\end{aligned} \tag{7}$$

where C1 is the average power constraint of RU. C2 and C3 are the outage constraints of RU and MU, respectively.

3. Energy Efficient Power Allocation Algorithm

Due to the fractional form of objective function, problem (7) is a non-convex optimization problem and hard to be solved.

Before solving problem (7), we introducing a new problem:

$$\max_{p_\nu \in \mathbb{Q}} \phi(p_\nu, \lambda) \tag{8}$$

where $\mathbb{Q}$ denote the feasible domain defined by constraints C1-C3 in (7) and $\phi(p_\nu, \lambda)$ is defined as:

$$\phi(p_\nu, \lambda) = \left\{ \mathcal{E}\left[\log_2\left(1 + \frac{p_\nu g_{\mathrm{RU}}}{N_0 + p_{\mathrm{MU}} h_{\mathrm{MR}}}\right)\right] - \lambda\left(\mathcal{E}[p_\nu] + P_{\mathrm{c}}\right)\right\} \tag{9}$$

Let $\mathcal{S}(\lambda) = \max_{p_\nu \in \mathbb{Q}} \phi(p_\nu, \lambda)$ and $p_\nu(\lambda) = \arg\max_{p_\nu \in \mathbb{Q}} \phi(p_\nu, \lambda)$ be the optimal value and optimal solution of problem (8), respectively.

Theorem 1: The optimal solution $p_\nu^* = \arg\max_{p_\nu \in \mathbb{Q}} \xi_{\mathrm{EE}}$ achieves the optimal value $\lambda^* = \max_{p_\kappa \in \mathbb{Q}} \xi_{\mathrm{EE}}$ of problem (7), if and only if:

$$\mathcal{S}(\lambda^*) = 0 \text{ and } p_\nu(\lambda^*) = p_\nu^* .$$

Proof: Similar proof of Theorem 1 can be found in [10].

Therefore, solving problem (7) is equivalent to find the optimal solution of problem (8) for a given parameter λ and then update λ until Theorem 1 is fulfilled. By exploiting Dinkelbach method [10], the outer loop algorithm can be summarized in algorithm 1.

Algorithm 1: Outer Loop of Deriving λ in (8)

1:Set tolerance ϑ, initialize $\tau = 0$ and $\lambda_\tau = 0$

2:Solve problem (8) with λ_τ to obtain the optimal solution p_ν, i.e., $p_{\nu,\tau}$

3:while $|\mathcal{S}(\lambda)| > \vartheta$ do

4: $\tau = \tau + 1$, update $\lambda_\tau \leftarrow \xi_{\mathrm{EE}}$ with $p_{\nu,\tau-1}$

5: solve (8) with λ_τ to obtain $p_{\kappa,\tau}$

6:end while

The convergence of Algorithm 1 has been proved in [10].

In step2, we need to solve problem (8) for a given λ_τ. In the following, we will discuss how to solve this problem.

Introducing two new functions to express the RU link and CU link outage event:

$$\delta_{\mathrm{MU}}^{\nu}(p_\nu) = \begin{cases} 0, \log_2\left(1 + \frac{p_{\mathrm{MU}} g_{\mathrm{MU}}}{N_0 + p_\nu h_{\mathrm{RM}}}\right) \geq R_{\min}^{\mathrm{MU}} \\ 1, \log_2\left(1 + \frac{p_{\mathrm{MU}} g_{\mathrm{MU}}}{N_0 + p_\nu h_{\mathrm{RM}}}\right) < R_{\min}^{\mathrm{MU}} \end{cases} \tag{10}$$

$$\delta_{\mathrm{RU}}^{\nu}(p_\nu) = \begin{cases} 0, \log_2\left(1 + \frac{p_\nu g_{\mathrm{RU}}}{N_0 + p_{\mathrm{MU}} h_{\mathrm{MR}}}\right) \geq R_{\min}^{\mathrm{RU}} \\ 1, \log_2\left(1 + \frac{p_\nu g_{\mathrm{RU}}}{N_0 + p_{\mathrm{MU}} h_{\mathrm{MR}}}\right) < R_{\min}^{\mathrm{RU}} \end{cases} \tag{11}$$

Thus, the RU link and MU link outages constraints can be repressed as:

$$\mathcal{E}\left[\delta_{\mathrm{MU}}^{\nu}(p_\nu)\right] \leq \sigma_{\mathrm{MU}} \tag{12}$$

$$\mathcal{E}\left[\delta_{\mathrm{RU}}^{\nu}(p_\nu)\right] \leq \sigma_{\mathrm{RU}} \tag{13}$$

The Lagrangian function of problem (8) is:

$$\begin{aligned} \mathfrak{L}(p_\nu, \alpha, \beta, \gamma) = \mathcal{E}\left[\log_2\left(1 + \frac{p_\nu g_{\mathrm{RU}}}{N_0 + p_{\mathrm{MU}} h_{\mathrm{MR}}}\right)\right] - \lambda_\tau\left\{\mathcal{E}[p_\nu] + P_{\mathrm{c}}\right\} - \alpha\left\{\mathcal{E}[p_\nu] - P_{\max}\right\} \\ -\beta\left\{\mathcal{E}\left[\delta_{\mathrm{MU}}^{\nu}(p_\nu)\right] - \sigma_{\mathrm{MU}}\right\} - \gamma\left\{\mathcal{E}\left[\delta_{\mathrm{RU}}^{\nu}(p_\nu)\right] - \sigma_{\mathrm{RU}}\right\} \end{aligned} \tag{14}$$

where α, β, γ are the nonnegative dual variables.

Then, the Lagrange dual function of the primal problem (8) can be written as:

$$\mathfrak{D}(\alpha,\beta,\gamma)=\max_{p_\nu\ge 0}\mathfrak{L}(p_\nu,\alpha,\beta,\gamma) \tag{15}$$

The dual problem is:

$$\min_{\alpha,\beta,\gamma\ge 0}\mathfrak{D}(\alpha,\beta,\gamma) \tag{16}$$

Observing that (15) can be rewritten as:

$$\mathfrak{D}(\alpha,\beta,\gamma)=\mathcal{E}\left[\overline{\mathfrak{D}}\right]-\lambda P_{cir}+\alpha P_{\max}+\beta\sigma_{\mathrm{MU}}+\gamma\sigma_{\mathrm{RU}} \tag{17}$$

where $\overline{\mathfrak{D}}$ is defined as:

$$\overline{\mathfrak{D}}=\max_{p_\nu\ge 0}\left\{\mathcal{F}(p_\nu)-\beta\delta_{\mathrm{MU}}^{\nu}(p_\nu)-\gamma\delta_{\mathrm{RU}}^{\nu}(p_\nu)\right\} \tag{18}$$

with $\mathcal{F}(p_\nu)=\log_2\left(1+\frac{p_\nu g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)-(\lambda_\tau+\alpha)p_\nu$.

Define $p_{\mathcal{F}}^{*}=\arg\max_{p_\nu\ge 0}\mathcal{F}(p_\nu)$, since $\mathcal{F}(p_\nu)$ is a concave in p_ν, we have:

$$p_{\mathcal{F}}^{*}=\left(\frac{1}{(\lambda_\tau+\alpha)\ln 2}-\frac{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}{g_{\mathrm{RU}}}\right)^{+} \tag{19}$$

where $(x)^{+}=\max\{x,0\}$. Let p_ν^{MU} and p_ν^{RU} denote the key value that make the value of $\varepsilon_{\mathrm{MU}}^{\nu}$ and $\varepsilon_{\mathrm{RU}}^{\nu}(p_\nu)$ changes from 0 to 1, respectively. Thus, we have:

$$p_\nu^{\mathrm{MU}}=\frac{p_{\mathrm{MU}}g_{\mathrm{MU}}-N_0\gamma_{\min}^{\mathrm{MU}}}{h_{\mathrm{RM}}\gamma_{\min}^{\mathrm{MU}}}\ge 0 \tag{20}$$

$$p_\nu^{\mathrm{RU}}=\frac{\gamma_{\min}^{\mathrm{RU}}(N_0+p_{\mathrm{MU}}h_{\mathrm{MR}})}{g_{\mathrm{RU}}}\ge 0 \tag{21}$$

where $\gamma_{\min}^{\mathrm{MU}}=2^{R_{\min}^{\mathrm{MU}}}-1$ and $\gamma_{\min}^{\mathrm{RU}}=2^{R_{\min}^{\mathrm{RU}}}-1$

Therefore, (10) and (11) can be rewritten as

$$\delta_{\mathrm{MU}}^{\nu}(p_\nu)=\begin{cases}0, & p_\nu\le p_\nu^{\mathrm{MU}}\\ 1, & p_\nu> p_\nu^{\mathrm{MU}}\end{cases} \tag{22}$$

$$\delta_{\mathrm{RU}}^{\nu}(p_\nu)=\begin{cases}0, & p_\nu\ge p_\nu^{\mathrm{RU}}\\ 1, & p_\nu< p_\nu^{\mathrm{RU}}\end{cases} \tag{23}$$

Let p_κ^{*} be the optimal solution of problem (18), we have the following Theorem.

Theorem 2: With $p_{\mathcal{F}}^{*}$, p_ν^{MU} and p_ν^{RU}, the optimal solution of (18) is given by the following cases:

case 1: if $p_\nu^{\mathrm{MU}}<p_{\mathcal{F}}^{*}<p_\nu^{\mathrm{RU}}$, then we have:

$$p_\nu^{*}=\begin{cases}p_\nu^{\mathrm{MU}}, \mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)-\gamma>\max\left\{\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta-\gamma,\mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)-\beta\right\}\\ p_{\mathcal{F}}^{*}, \mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta-\gamma>\max\left\{\mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)-\gamma,\mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)-\beta\right\}\\ p_\nu^{\mathrm{RU}}, \mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)-\beta>\max\left\{\mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)-\gamma,\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta-\gamma\right\}\end{cases}$$

case 2: if $p_\nu^{\mathrm{RU}}\le p_{\mathcal{F}}^{*}\le p_\nu^{\mathrm{MU}}$, then we have: $p_\nu^{*}=p_{\mathcal{F}}^{*}$.

case 3: if $p_{\mathcal{F}}^{*}\le p_\nu^{\mathrm{MU}}<p_\nu^{\mathrm{RU}}$, then we have: $p_\nu^{*}=\begin{cases}p_{\mathcal{F}}^{*}, \mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\gamma>\mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)-\beta\\ p_\nu^{\mathrm{RU}}, \mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)-\beta>\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\gamma\end{cases}$.

case 4: if $p_{\mathcal{F}}^{*}<p_\nu^{\mathrm{RU}}<p_\nu^{\mathrm{MU}}$, then we have: $p_\nu^{*}=\begin{cases}p_{\mathcal{F}}^{*}, \mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\gamma>\mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)\\ p_\nu^{\mathrm{RU}}, \mathcal{F}\left(p_\nu^{\mathrm{RU}}\right)>\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\gamma\end{cases}$.

case 5: if $p_\nu^{\mathrm{MU}}<p_\nu^{\mathrm{RU}}\le p_{\mathcal{F}}^{*}$, then we have: $p_\nu^{*}=\begin{cases}p_\nu^{\mathrm{MU}}, \mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)-\gamma>\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta\\ p_{\mathcal{F}}^{*}, \mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta>\mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)-\gamma\end{cases}$.

case 6: if $p_\nu^{\mathrm{RU}}<p_\nu^{\mathrm{MU}}<p_{\mathfrak{g}}^{*}$, then we have: $p_\nu^{*}=\begin{cases}p_\nu^{\mathrm{MU}}, \mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)>\mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta\\ p_{\mathcal{F}}^{*}, \mathcal{F}\left(p_{\mathcal{F}}^{*}\right)-\beta>\mathcal{F}\left(p_\nu^{\mathrm{MU}}\right)\end{cases}$.

Proof:

Combing with formula (16) and concave function $\mathcal{F}(p_\nu)$, for $p_\nu^{\mathrm{MU}}<p_\nu^{\mathrm{RU}}$, we have:

$$\mathcal{F}(p_\nu)-\beta\varepsilon_\nu^{\mathrm{MU}}(p_\nu)-\gamma\varepsilon_\nu^{\mathrm{RU}}(p_\nu)=\begin{cases}\mathcal{F}(p_\nu)-\gamma, p_\nu\le p_\nu^{\mathrm{MU}}\\ \mathcal{F}(p_\nu)-\beta-\gamma, p_\nu^{\mathrm{MU}}<p_\nu<p_\nu^{\mathrm{RU}}\\ \mathcal{F}(p_\nu)-\beta, p_\nu\ge p_\nu^{\mathrm{RU}}\end{cases} \tag{24}$$

For $p_\nu^{\mathrm{RU}}<p_\nu^{\mathrm{MU}}$, we have:

$$\mathcal{F}(p_\nu)-\beta\varepsilon_\nu^{\mathrm{MU}}(p_\nu)-\gamma\varepsilon_\nu^{\mathrm{RU}}(p_\nu)=\begin{cases}\mathcal{F}(p_\nu)-\gamma, p_\nu< p_\nu^{\mathrm{RU}}\\ \mathcal{F}(p_\nu), p_\nu^{\mathrm{RU}}\le p_\nu\le p_\nu^{\mathrm{MU}}\\ \mathcal{F}(p_\nu)-\beta, p_\nu> p_\nu^{\mathrm{MU}}\end{cases} \tag{25}$$

Based on (24) and (25), take $p_{\mathcal{F}}^*$ into consideration, we have six different forms of the objective function $\mathcal{F}(p_\nu)-\beta\varepsilon_{\mathrm{MU}}^\nu(p_\nu)-\gamma\varepsilon_{\mathrm{RU}}^\nu(p_\nu)$ as shown in Fig.1-Fig.6. Note: In the figures, the dotted line denotes function $\mathcal{F}(p_\nu)$ and the solid line denotes function $\mathcal{F}(p_\nu)-\beta\delta_{\mathrm{MU}}^\nu(p_\nu)-\gamma\delta_{\mathrm{RU}}^\nu(p_\nu)$.

case 1: In Fig.1, $y_1=\mathcal{F}(p_\nu^{\mathrm{MU}})-\gamma$, $y_2=\mathcal{F}(p_{\mathcal{F}}^*)-\beta-\gamma$, $y_3=\mathcal{F}(p_\nu^{\mathrm{RU}})-\beta$. The optimal p_ν^* rely on y_1,y_2,y_3.

case 2: In Fig.2, $y_1=\mathcal{F}(p_\nu^{\mathrm{RU}})$, $y_2=\mathcal{F}(p_{\mathcal{F}}^*)$, $y_3=\mathcal{F}(p_\nu^{\mathrm{MU}})$. Since $\mathcal{F}(p_\kappa)$ is a concave function, thus $p_\nu^*=p_{\mathcal{F}}^*$

case 3: In Fig.3, $y_1=\mathcal{F}(p_{\mathcal{F}}^*)-\gamma$, $y_2=\mathcal{F}(p_\nu^{\mathrm{MU}})-\gamma$, $y_3=\mathcal{F}(p_\nu^{\mathrm{RU}})-\beta$. Since $y_1>y_2$, the optimal p_ν^* rely on y_1,y_3.

case 4: In Fig.4, $y_1=\mathcal{F}(p_{\mathcal{F}}^*)-\gamma$, $y_2=\mathcal{F}(p_\nu^{\mathrm{RU}})$, $y_3=\mathcal{F}(p_\nu^{\mathrm{MU}})$. Since $y_2>y_1$, the optimal p_ν^* rely on y_1,y_2.

case 5: In Fig.5, $y_1=\mathcal{F}(p_\nu^{\mathrm{MU}})-\gamma$, $y_2=\mathcal{F}(p_\nu^{\mathrm{RU}})-\beta$, $y_3=\mathcal{F}(p_{\mathcal{F}}^*)-\beta$. Since $y_3>y_2$, the optimal p_ν^* rely on y_1,y_3.

case 6: In Fig.6, $y_1=\mathcal{F}(p_\nu^{\mathrm{RU}})$, $y_2=\mathcal{F}(p_\nu^{\mathrm{MU}})$, $y_3=\mathcal{F}(p_{\mathcal{F}}^*)-\beta$. Since $y_2>y_1$, the optimal p_ν^* rely on y_2,y_3.

□

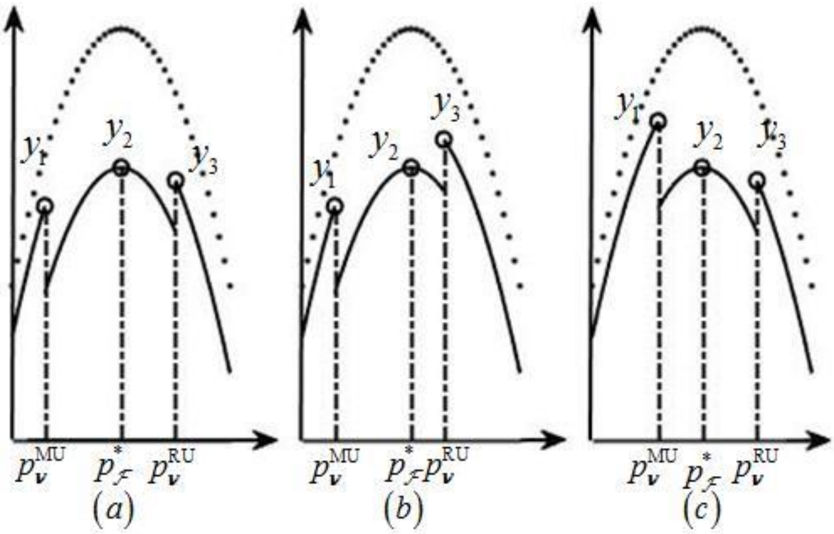

Fig. 1: Case 1.

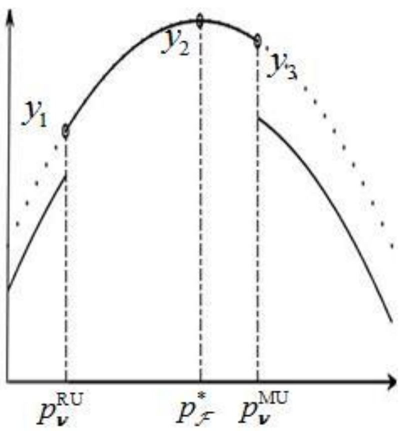

Fig. 2: Case 2.

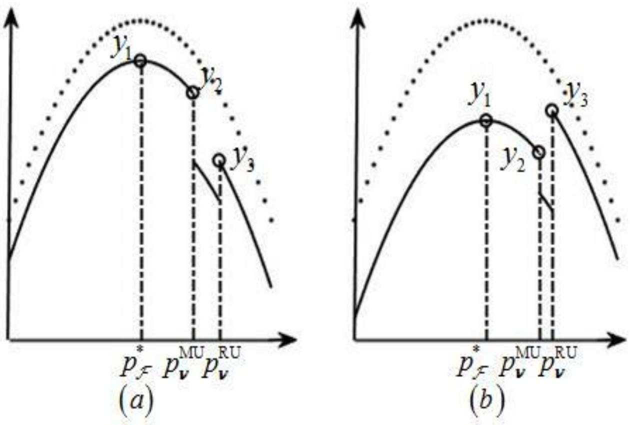

Fig. 3: Case 3.

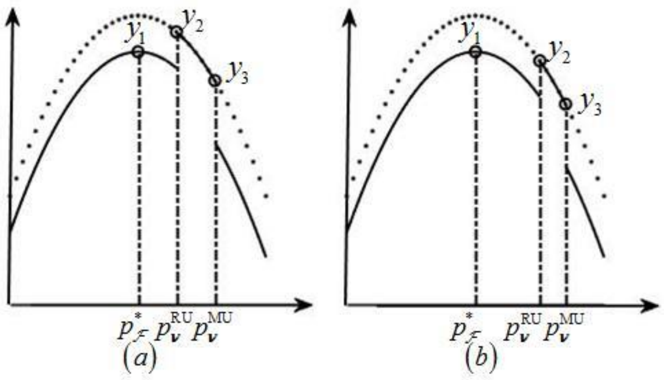

Fig. 4: Case 4.

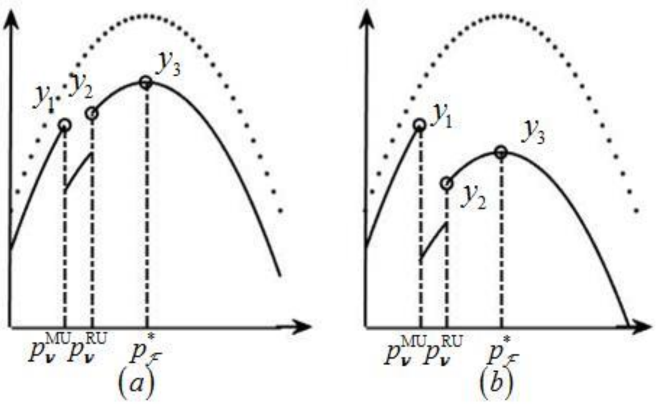

Fig. 5: Case 5.

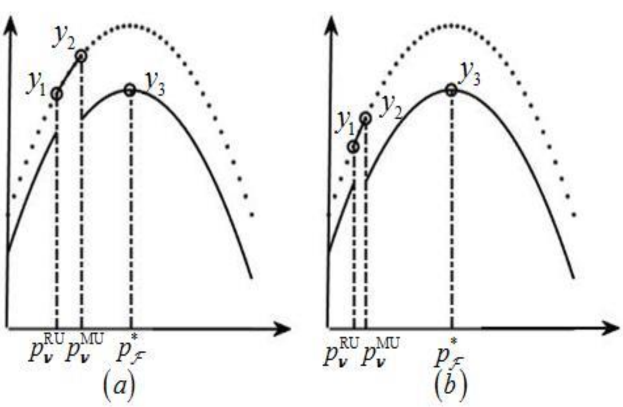

Fig. 6: Case 6.

Here, we use subgradient method [11] to obtain the optimal Lagrange multipliers:

$$\alpha_{t+1}=\left[\alpha_t-\eta_t^{\alpha}\left(\mathcal{E}\left[p_\nu\right]-P_{\max}\right)\right]^{+} \tag{26}$$

$$\beta_{t+1}=\left[\beta_t-\eta_t^{\beta}\left\{\mathcal{E}\left[\delta_{\mathrm{MU}}^{\nu}\left(p_\nu\right)\right]-\sigma_{\mathrm{MU}}\right\}\right]^{+} \tag{27}$$

$$\gamma_{t+1}=\left[\gamma_t-\eta_t^{\gamma}\left\{\mathcal{E}\left[\varepsilon_{\mathrm{RU}}^{\nu}\left(p_\nu\right)\right]-\sigma_{\mathrm{RU}}\right\}\right]^{+} \tag{28}$$

where η_t^{α}, η_t^{β}, η_t^{γ} are small positive step sizes for the t-th iteration. The subgradient updates of (26), (27), (28) are guaranteed to converge to the optimal α,β,γ as long as η_t^{α}, η_t^{β}, η_t^{γ} are chosen to be sufficiently small [11].

Algorithm2: Inner loop of solving (8) with given λ_τ based on sub-gradient method

1: Initialization t=0, $\alpha_t,\beta_t,\gamma_t$, calculate p_ν^{MU} and p_ν^{D} according to (20) and (21), respectively.

2: calculate p_g^* according to (19), then calculate p_ν^* according to Theorem 2.

3: t=t+1,update $\alpha_{t+1},\beta_{t+1},\gamma_{t+1}$ according to (26), (27), (28).

4: if the multipliers α,β,γ are convergent, return and stop the algorithm2; otherwise go to step2

4. Simulation

In this section, some numerical results are presented to evaluate the performance of the proposed schemes. All the channels are assumed to be Rayleigh-fading, the channel power gains are exponentially distributed with unit mean for g_{MU} and g_{RU}, and 0.5 mean for h_{RM} and h_{MR}.Without loss of generality, we set $\sigma_{\mathrm{MU}}=\sigma_{\mathrm{RU}}=\sigma$, N_0=10^{-5}mW, p_{MU}=200mW, $R_{\min}^{\mathrm{MU}}=R_{\min}^{\mathrm{RU}}$=2bit/s/Hz, P_c=10mW.

Fig.7 illustrates the evolution of the proposed algorithm with different P_{max} under $\sigma=0.2$. Note, the proposed algorithm consists of two loops, we only consider the effect of outer loop iterations τ. It is observed that the algorithm converge to the optimal λ fast.

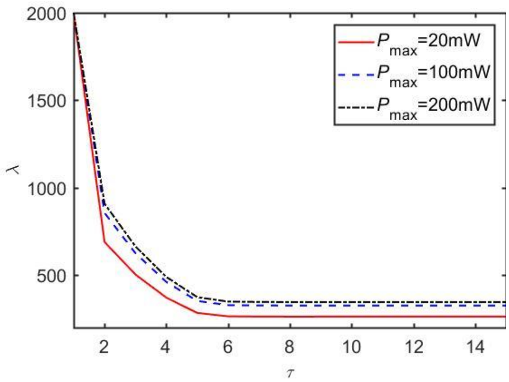

Fig. 7: Convergence evolution of the proposed algorithm.

To emphasize the advantages of the proposed scheme, we introduce a new power allocation problem:

$$\begin{aligned}
&\mathrm{OP2}\ \max_{p_\nu}\mathcal{E}\left[\log_2\left(1+\frac{p_\nu g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)\right]\\
&s.t\quad \mathrm{C1}:\mathcal{E}\left[p_\nu\right]\le P_{\max}\\
&\qquad \mathrm{C2}:\mathcal{P}\left(\log_2\left(1+\frac{p_\nu g_{\mathrm{RU}}}{N_0+p_{\mathrm{MU}}h_{\mathrm{MR}}}\right)<R_{\min}^{\mathrm{RU}}\right)\le\sigma_{\mathrm{RU}}\\
&\qquad \mathrm{C3}:\mathcal{P}\left(\log_2\left(1+\frac{p_{\mathrm{MU}} g_{\mathrm{MU}}}{N_0+p_\nu h_{\mathrm{RM}}}\right)<R_{\min}^{\mathrm{MU}}\right)\le\sigma_{\mathrm{MU}}
\end{aligned}$$

Then problem OP2 becomes the traditional ergodic rate maximization problem. Similar to problem (8), we can also use algorithm 2 to solve problem OP2 with appropriate medications. We name the scheme to solve the ergodic rate maximization problem as ERMP algorithm. Next, we will compare the proposed algorithm with the ERPA. As shown in Fig.8, the proposed algorithm has a higher energy efficiency than ERMP algorithm. This is because the proposed algorithm always obtains the optimal power allocation that achieves the highest energy efficiency.

As shown in Fig.9, the energy efficiency of the both algorithms increase with the increasing of σ . This is because small σ indicates strict outage constraint, large σ indicates loose outage constraint. In addition, the proposed algorithm has better performance than ERMP algorithm in improving energy efficiency.

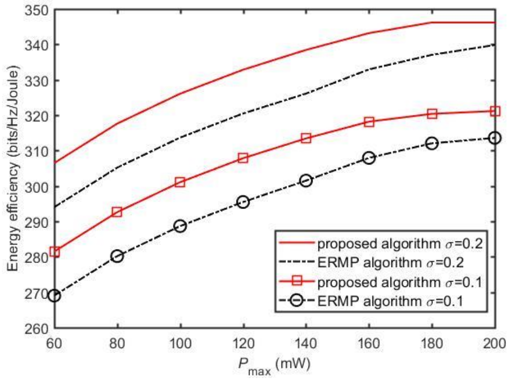

Fig. 8: Energy efficiency versus average transmit power threshold.

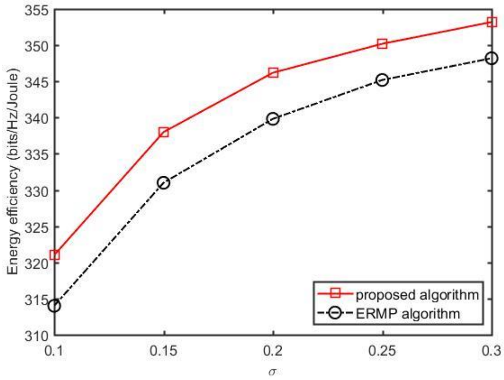

Fig. 9: Energy efficiency versus maximum outage probability.

5. Conclusions

Most of the previous works consider resource allocation of HC-RAN with perfect CSI. In fact, it is difficult and costly to acquire accurate CSI. In this paper, we investigate the energy efficient power allocation of HC-RAN with partial CSI. An efficient iterative power allocation scheme has been derived to maximize the averaged energy efficiency of HC-RAN.

6. Acknowledgements

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