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Research Article

Energy-Efficient Power and Subcarrier Allocation in Downlink OFDMA Systems with Channel Estimation Errors

Yong Liu[1] **Fei Liu**[2] **Fuqiang Ren**[3] **Feng Hou**[4] **Yongsheng Zhu**[1] **Xiaolei Wang**[1] **and Yaoke Yang**[2]

[1]*School of Electronic and Information, Zhongyuan University of Technology, No. 41 Zhongyuan Road, Zhengzhou, 450007 Henan, China*
[2]*School of Computer Science, Zhongyuan University of Technology, No. 41 Zhongyuan Road, Zhengzhou, 450007 Henan, China*
[3]*School of Electrical Engineering, Shandong University, Shandong, China*
[4]*Training Center of State Grid Ningxia Electric Power Co. Ltd., Yinchuan, China*

Correspondence should be addressed to Yong Liu; liuyongly201@sina.com

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In this paper, we investigate the joint optimization of power and subcarrier allocation for maximizing the energy efficiency (EE) in downlink OFDMA systems. The problem of EE maximization is formulated as a stochastic optimization to determine the optimal power and subcarrier allocation, in which many practical factors including channel estimation errors, delay requirements, and time-varying channel are considered. We first propose a dynamic power and subcarrier allocation (DPSA) algorithm to solve the formulated problem. Then, we derive the two bounds of EE and delay and reveal the tradeoff between them. The theoretical analysis and simulation results demonstrate the variations of EE and delay with channel estimation errors.

1. Introduction

With a rapid increase in energy consumption associated with modern communication systems, energy efficiency (EE) is of paramount importance in the design and operation of wireless networks [1]. Meanwhile, orthogonal frequency division multiplexing access (OFDMA) technology is adopted as the major access scheme for the next wireless communications due to its ability of supporting high-data-rate services. Therefore, maximizing the EE in OFDMA systems is an urgent task for network design, particularly with the considerations of many practical factors, such as channel estimation errors, delay requirements, and time-varying channel.

The EE maximization problem has been studied extensively with various resource optimization, such as power, subcarrier, and rate [2–8]. However, many of these works merely made a simple assumption of perfect channel state information (CSI). Actually, the perfect CSI is impossible to implement in the real networks, that is due to the channel estimation error and the channel feedback delay. Recently, with consideration of imperfect CSI, a number of works for resource allocation have appeared [9–15]. To ensure communication with the required quality of service (QoS), an optimal resource allocation algorithm for power cost minimization in OFDMA was derived in [9–11]. In order to improve the whole-system EE, a power allocation algorithm was proposed in [12] and a joint power and rate allocation scheme was discussed in [13]. In [15], the authors investigated the power and subcarrier optimization problem to maximize each user's EE for multiuser OFDMA wireless networks. Then, this work was further extended to investigate the tradeoff between EE and SE in downlink OFDMA systems.

As a common feature, the abovementioned literatures neglected the bursty arrival of the data source and the delay requirement of users, which are also the main characteristics in realistic communication systems. With these practical constraints, there exists a vast literature on resource optimization. Most of the literature rely on the landmark papers, which employed Lyapunov methods for resource allocation. Subsequently, these Lyapunov techniques have been used to solve various joint resource assignment problems of optimizing performance and satisfying delay constraints (or stabilizing queue). In [16], the authors proposed network selection algorithms to study the energy-delay tradeoff problem. To maximize the throughput utility, the dynamic power allocation scheme was designed in [17]. The authors in [18] studied the problem of EE maximization with delay-aware resource allocation. However, neither of them take the channel estimation errors into account. In contrast, the resource optimization for minimizing power consumption was addressed in [19] with respect to the channel estimation errors but its algorithms cannot directly take effect in our interested scenario and model. To the best of our knowledge, the existing resource allocation schemes for maximizing EE do not jointly consider the estimation error, the bursty data arrivals, and the delay constraints.

In this paper, we investigate the joint optimization of the power and subcarrier to maximize the EE in downlink OFDMA systems. Specifically, many practical factors including channel estimation errors, delay constraints, and the time-varying channel are dealt with in our problem formulation. A dynamic power and subcarrier allocation (DPSA) algorithm is proposed by using the methods of fractional programming, Lyapunov optimization, and dual decomposition. The bounds of EE and delay were also derived, which reveal the tradeoff between EE and delay.

2. System Model and Problem Formulation

2.1. System Model. Consider a single-cell downlink OFDMA cellular system with one base station (BS), M users, and N subcarriers. Each subcarrier is exclusively occupied by at most one user at each time slot. The wireless channel between BS and each user is assumed to obey the frequency-selective block fading with L resolvable paths whose values are independent random variables with mean zero and variance σ_g^2, i.e., $\mathscr{CN}(0, \sigma_g^2)$. The channel is invariant during one time slot and changes independently for different time slots. Generally, the CSI is available by performing the channel estimation. That is, each user estimates its own CSI based on the received pilot symbols from BS and then sends it to BS through the feedback channel. The CSI received by the BS is clearly not perfect due to the estimation errors. Let the minimum-mean squared-error (MMSE) estimator be used as the channel estimation method; thus, the CSI $G_{ij}(\tau)$ of user i on subcarrier j at time slot τ is given by

$$G_{ij}(\tau) = \widehat{G}_{ij}(\tau) + \tilde{G}_{ij}(\tau), \tag{1}$$

where $\widehat{G}_{ij}(\tau)$ is the estimation of $G_{ij}(\tau)$ and $\tilde{G}_{ij}(\tau)$ is the estimation error. Specifically, $\widehat{G}_{ij}(\tau)$ and $\tilde{G}_{ij}(\tau)$ are zero-mean uncorrelated random variables with variances $\sigma^2_{\widehat{G}_{ij}} = L\sigma_g^4\gamma_p/(\sigma_g^2\gamma_p + 1)$ and $\sigma^2_{\tilde{G}_{ij}} = L\sigma_g^2/(\sigma_g^2\gamma_p + 1)$, respectively, where γ_p is the signal-to-noise ratio (SNR) for transmitting the pilot symbol.

The received signal by user i on subcarrier j at time slot τ is given by

$$y_{ij}(\tau) = \widehat{G}_{ij}(\tau)\sqrt{\rho_{ij}(\tau)}x_{ij}(\tau) + \tilde{G}_{ij}(\tau)\sqrt{\rho_{ij}(\tau)}x_{ij}(\tau) + n_{ij}(\tau), \tag{2}$$

where $\rho_{ij}(\tau)$, $x_{ij}(\tau)$, and $n_{ij}(\tau)$ are the transmit power, the transmitted signal, and the additive noise, respectively, with $E[|x_{ij}(\tau)|^2] = 1$ and $n_{ij} \sim \mathscr{CN}(0, N_0)$. Similar to [20], the corresponding data transmission rate in terms of channel estimation error is expressed by

$$c_{ij}(\tau) = s_{ij}(\tau)B_0 \log_2\left(1 + \frac{\rho_{ij}(\tau)\left|\widehat{G}_{ij}(\tau)\right|^2}{\rho_{ij}(\tau)\sigma^2_{\tilde{G}_{ij}} + N_0}\right). \tag{3}$$

Here, B_0 is the bandwidth of each subcarrier and $s_{ij}(\tau)$ is an indicator function, which is equal to 1 when subcarrier j is allocated to user i during time slot τ and 0 otherwise. It is noted that the channel estimation error is treated as the "self-noise" in (3). Obviously, a larger estimation error increases the self-interference for user and results in a lower data rate.

The total power consumption of BS is calculated as

$$\rho_{\text{tot}}(\tau) = \sum_{i=1}^{M}\sum_{j=1}^{N} s_{ij}(\tau)\rho_{ij}(\tau) + \rho_c, \tag{4}$$

where ρ_c represents the circuit power consumption. We define the system EE as

$$\xi_{\text{EE}} = \frac{\lim_{T\longrightarrow\infty} \sum_{\tau=0}^{T-1} \mathbb{E}\{C_{\text{tot}}(\tau)\}}{\lim_{T\longrightarrow\infty} \sum_{\tau=0}^{T-1} \mathbb{E}\{\rho_{\text{tot}}(\tau)\}} = \frac{\bar{C}_{\text{tot}}}{\bar{\rho}_{\text{tot}}}, \tag{5}$$

where $C_{\text{tot}}(\tau) = \sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}(\tau)$ is the total data transmission rate of all users during time slot τ.

The data, which is queued separately for each user, is assumed to arrive at the BS randomly in every time slot. Without loss of generality, the queue for each user is labeled by its corresponding user index. Let $A_i(\tau)$ and $\Theta_i(\tau)$ be the new data arrivals and the amount of data (queue length) in queue i at time slot τ. Let $\mathbf{\Theta}(\tau) = (\Theta_i(\tau))$ and $\mathbf{A}(\tau) = (A_i(\tau))$. We assume that $\mathbf{A}(\tau)$ is independent and identical distribution over time slots with mean arrival rate $\lambda = (\lambda_i)$. For the arrival rate $A_i(\tau)$ and the departure rate $C_i(\tau) = \sum_{j=1}^{N} c_{ij}(\tau)$ in queue i, the queue length $\Theta_i(\tau)$ updates with

$$\Theta_i(\tau + 1) = \max\{\Theta_i(\tau) - C_i(\tau), 0\} + A_i(\tau). \tag{6}$$

In the spirit of [21], the mean-rate-stable condition of the queue is

$$\lim_{\tau\longrightarrow\infty} \frac{\mathbb{E}[\Theta_i(\tau)]}{\tau} = 0, \tag{7}$$

which implies that the queue length is finite. For simplicity, we will use the term "stable" to refer to the mean-rate-stable. Additionally, from Little's Law, the queue length is in direct proportion to the transmission delay. Hence, the terms of delay and queue length could be used interchangeably in this work.

2.2. Problem Formulation. The objective of our work is to maximize the system EE by jointly allocating the transmit power and the subcarrier, in which channel estimation errors, delay requirements, and time-varying channel are considered. Mathematically, the problem of EE maximization is formulated as

$$\mathscr{P}1: \max_{\rho_{ij}(\tau), s_{ij}(\tau)} \eta_{\mathrm{EE}} = \frac{\bar{C}_{\mathrm{tot}}}{\bar{\rho}_{\mathrm{tot}}}, \quad (8)$$

$$\text{s.t.} \quad \text{Queues } (\Theta_i(\tau)) \text{ are stable}, \quad \forall i, \quad (9)$$

$$\rho_{\mathrm{tot}}(\tau) \le \rho_{\max}, \quad \forall \tau, \quad (10)$$

$$\rho_{ij}(\tau) \ge 0, \quad \forall i, j, \tau, \quad (11)$$

$$s_{ij}(\tau) \in \{0, 1\}, \quad \forall i, j, \tau, \quad (12)$$

$$\sum_{i=1}^{M} s_{ij}(\tau) \le 1, \quad \forall \tau. \quad (13)$$

Constraint (9) is the queue stability constraint to ensure that all arrived data leave the queue in a finite time; the constraint (10) limits the maximum total power at BS; constraints (12) and (13) together ensure that each subcarrier is allocated to at most one user.

Note that the resource allocation decision $\rho_{ij}(\tau)$ and $s_{ij}(\tau)$ of problem $\mathscr{P}1$ are affected by the value and the accuracy of CSI estimation. Given the integer assignment variables $s_{ij}(\tau)$, problem $\mathscr{P}1$ belongs to the mixed-integer stochastic programming. Furthermore, the fractional objective makes the problem even more complicated. However, we propose a resource allocation algorithm in the following, which can efficiently solve the abovementioned difficulties with respect to problem $\mathscr{P}1$.

Inspired by Dinkelbach's method [22], problem $\mathscr{P}1$ can be transformed into the following optimization problem:

$$\begin{aligned} \mathscr{P}2: & \max_{\rho_{ij}(\tau), s_{ij}(\tau)} \bar{C}_{\mathrm{tot}} - \xi_{\mathrm{EE}}(\tau)\bar{\rho}_{\mathrm{tot}} \\ \text{s.t.} \quad & (9), (10), (11), (12), (13), \end{aligned} \quad (14)$$

where

$$\xi_{\mathrm{EE}}(\tau) = \frac{\sum_{\kappa=0}^{\tau-1} C_{\mathrm{tot}}(\kappa)}{\sum_{\kappa=0}^{\tau-1} \rho_{\mathrm{tot}}(\kappa)}. \quad (15)$$

From [23], the above transformation can be effective to solve the stochastic optimization problem with ratio objective. In the next section, a dynamic power and subcarrier allocation algorithm is proposed to solve the transformed version.

3. Dynamic Power and Subcarrier Allocation

Lyapunov optimization technology is adopted in this section to solve the transformed problem $\mathscr{P}2$, since it can optimize the time-averaged objective meanwhile ensuring stable queue. Define the Lyapunov function as

$$L(\boldsymbol{\Theta}(\tau)) = \frac{1}{2}\sum_{i=1}^{M} \Theta_i(\tau)^2. \quad (16)$$

Then, the Lyapunov conditional drift-plus-penalty is written as

$$\begin{aligned} &\Delta(\boldsymbol{\Theta}(\tau)) - V\mathbb{E}\{C_{\mathrm{tot}}(\tau) - \xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}(\tau) \mid \boldsymbol{\Theta}(\tau)\} \\ &\quad = \mathbb{E}\{L(\boldsymbol{\Theta}(\tau+1)) - L(\boldsymbol{\Theta}(\tau)) | \boldsymbol{\Theta}(\tau)\} \\ &\qquad - V\mathbb{E}\{C_{\mathrm{tot}}(\tau) - \xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}(\tau) | \boldsymbol{\Theta}(\tau)\} \\ &\quad \le D + V\xi_{\mathrm{EE}}(\tau)\mathbb{E}\{\rho_{\mathrm{tot}}(\tau) \mid \boldsymbol{\Theta}(\tau)\} \\ &\qquad + \mathbb{E}\left\{\sum_{i=1}^{M} \Theta_i(\tau)A_i(\tau) | \boldsymbol{\Theta}(\tau)\right\} \\ &\qquad - \mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N} (\Theta_i(\tau) + V)C_{ij}(\tau) \mid \boldsymbol{\Theta}(\tau)\right\}, \end{aligned} \quad (17)$$

where

$$D \ge \frac{1}{2}\mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N} C_{ij}^2(\tau) + A_i^2(\tau) | \boldsymbol{\Theta}(\tau)\right\}. \quad (18)$$

Proof. Please refer to Appendix A for proof. □

Here, V is a nonnegative parameter, which controls the tradeoff between maximizing the system EE and minimizing the queue length (delay). According to the Lyapunov optimization method, to solve problem $\mathscr{P}2$, it is sufficient to find the joint power and subcarrier allocation that minimizes the right-hand-side of inequality sign in (17), while satisfying constraints (10)–(13).

The detailed DPSA algorithm descriptions, which can solve $\mathscr{P}1$, are listed in Algorithm 1. Problem $\mathscr{P}3$ in DPSA is a mixed-integer nonlinear programming due to the fact that it involves both continuous variables $\rho_{ij}(\tau)$ and binary variables $s_{ij}(\tau)$. Additionally, the nonlinear crossmultiplication terms $\rho_{ij}(\tau)s_{ij}(\tau)$ in (10) impose a great challenge on algorithm design, since they result in nonconvexity. Generally, the nonconvex mixed-integer programming often has a prohibitive computational complexity. Here, we employ the dual decomposition technique to solve problem $\mathscr{P}3$, similarly to [24]. However, due to the queue stability constraint in terms of $\Theta(\tau)$ and the imperfect channel estimation in terms of $\widehat{G}_{ij}(\tau)$ and $\sigma^2_{\widetilde{G}_{ij}}$, the algorithm in [24] cannot be directly used to solve $\mathscr{P}3$. Fortunately, with the specific structure of $\mathscr{P}3$, we can derive its optimal solution.

1: At each time slot τ, obtain the current queue state $\boldsymbol{\Theta}(\tau)$, $\xi_{EE}(\tau)$ and the estimated CSI $\widehat{G}_{ij}(\tau)$;
2: Allocate power $\rho_{ij}(\tau)$ and subcarrier $s_{ij}(\tau)$ by solving the following optimization:

$$\mathscr{P}3: \max_{\rho_{ij}(\tau), s_{ij}(\tau)} \sum_{i=1}^{M} (\Theta_i(\tau) + V) C_i(\tau) - V\xi_{EE}(\tau)\rho_{tot}(\tau)$$
$$s.t. (10), (11), (12), (13),$$

3: Update $\Theta_i(\tau)$ and $\xi_{EE}(\tau)$ according to (6) and (15), respectively.

Algorithm 1: Dynamic Power and Subcarrier Allocation (DPSA).

Problem $\mathscr{P}3$ is firstly reformulated by relaxing $s_{ij}(\tau)$ to a continuous interval $[0, 1]$ and replacing $\rho_{ij}(\tau)$ with $a_{ij}(\tau) = \rho_{ij}(\tau)s_{ij}(\tau)$. Then, by using the standard optimization techniques and the Karush-Kuhn-Tucker (KKT) conditions [25], we derive the optimal power and subcarrier allocation for $\mathscr{P}3$ as follows:

$$\rho_{ij}^*(\tau) = s_{ij}^*(\tau)\Phi_{ij}(\tau),$$
$$s_{ij}^*(\tau) = \begin{cases} 1, & i = \arg\max_{l} \Lambda_{lj}(\tau) \text{ and } \Lambda_{lj}(\tau) > 0, \\ 0, & \text{otherwise}, \end{cases} \tag{19}$$

where

$$\Lambda_{lj}(\tau) = -(V\xi_{\mathrm{EE}}(\tau) + \mu^*)\rho_{lj}^*(\tau) + (\Theta_l(\tau) + V)B_0 \log_2\left(1 + \frac{\rho_{lj}^*(\tau)\left|\widehat{G}_{lj}(\tau)\right|^2}{\rho_{lj}^*(\tau)\sigma_{\tilde{G}_{lj}}^2 + N_0}\right),$$

$$\Phi_{ij}(\tau) = \begin{cases} \dfrac{w_{ij}(\tau)}{N_0\left|\widehat{G}_{ij}(\tau)\right|^2}, & \sigma_{\tilde{G}_{ij}}^2 = 0; \\ \dfrac{N_0\left(2\sigma_{\tilde{G}_{ij}}^2 + \left|\widehat{G}_{ij}(\tau)\right|^2\right)}{2\left(\sigma_{\tilde{G}_{ij}}^4 + \sigma_{\tilde{G}_{ij}}^2\left|\widehat{G}_{ij}(\tau)\right|^2\right)}\left(-1 + \sqrt{1 + \dfrac{4\sigma_{\tilde{G}_{ij}}^2\left(\sigma_{\tilde{G}_{ij}}^2 + \left|\widehat{G}_{ij}(\tau)\right|^2\right)}{N_0^2\left(2\sigma_{\tilde{G}_{ij}}^2 + \left|\widehat{G}_{ij}(\tau)\right|^2\right)^2}\left[w_{ij}(\tau)\right]^+}\right), & \text{otherwise}; \end{cases} \tag{20}$$

$$w_{ij}(\tau) = \frac{(\Theta_i(\tau) + V)B_0\left|\widehat{G}_{ij}(\tau)\right|^2 N_0 \log_2 e}{V\xi_{\mathrm{EE}}(\tau) + \mu^*} - N_0^2.$$
$$[x]^+ = \max\{0, x\}.$$

Parameter μ is the Lagrange multiplier for the constraint (10). We employ the subgradient method to obtain the optimal value μ^* [25].

From (19), when the channel state is good (i.e., a large value $\widehat{G}_{ij}(\tau)$ and/or a small value of channel estimation error $\sigma_{\tilde{G}_{ij}}^2$), a high level of transmit power is allocated for maximizing system EE. Additionally, the optimal power is closely related with the current queue state, which perfectly agrees with our intuitional understanding. For example, the user, whose queue length is large, should be allocated with high transmit power to guarantee the queue stability (i.e., reduce the delay).

4. Performance Analysis

To analyze the performance of our DPSA, the total transmit power and the transmission rate are assumed to satisfy the following boundedness conditions:

$$\rho_{\mathrm{tot}}^{\min} \le \mathbb{E}\{\rho_{\mathrm{tot}}(\tau)\} \le \rho_{\mathrm{tot}}^{\max},$$
$$C_{\mathrm{tot}}^{\min} \le \mathbb{E}\{C_{\mathrm{tot}}(\tau)\} \le C_{\mathrm{tot}}^{\max}, \tag{21}$$

where $\rho_{\mathrm{tot}}^{\min}$, $\rho_{\mathrm{tot}}^{\max}$, $C_{\mathrm{tot}}^{\min}$, and $C_{\mathrm{tot}}^{\max}$ are some positive constants. With these assumptions, we can derive the bounds of EE and delay as shown in the following theorem.

Theorem 1. *Let λ be strictly interior to the capacity region $\boldsymbol{\Gamma}$ and $\lambda + \vartheta$ be in $\boldsymbol{\Gamma}$ for a positive ϑ. The proposed DPSA has the following properties:*

(a) The EE is bounded by

$$\xi_{EE} \ge \xi_{EE}^{opt} - \frac{D}{V\rho_{tot}^{\min}} \tag{22}$$

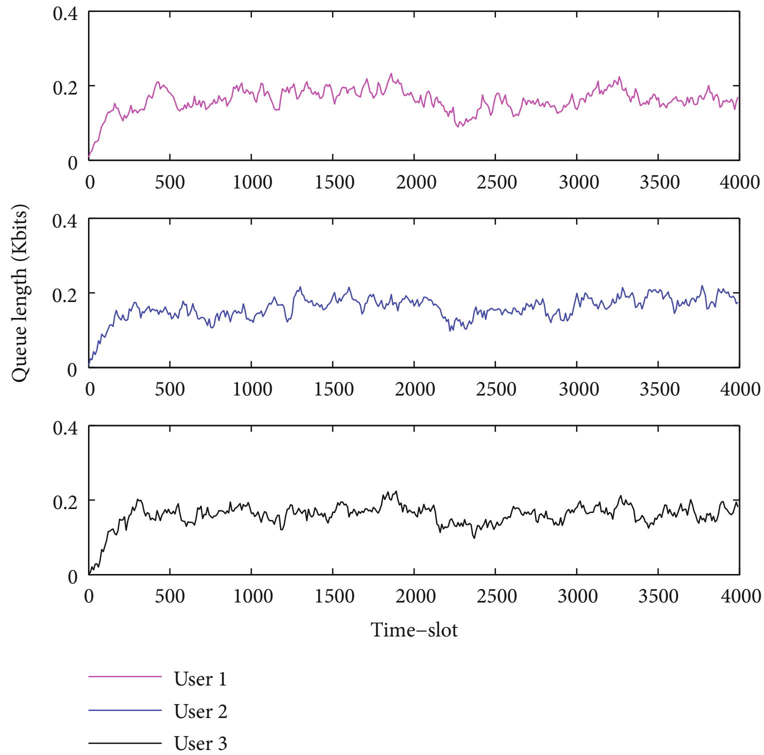


FIGURE 1: Illustration of queue stability with $V = 100$, $\lambda = 3$, and $\sigma^2_{\tilde{G}_{ij}} = 0.1$.

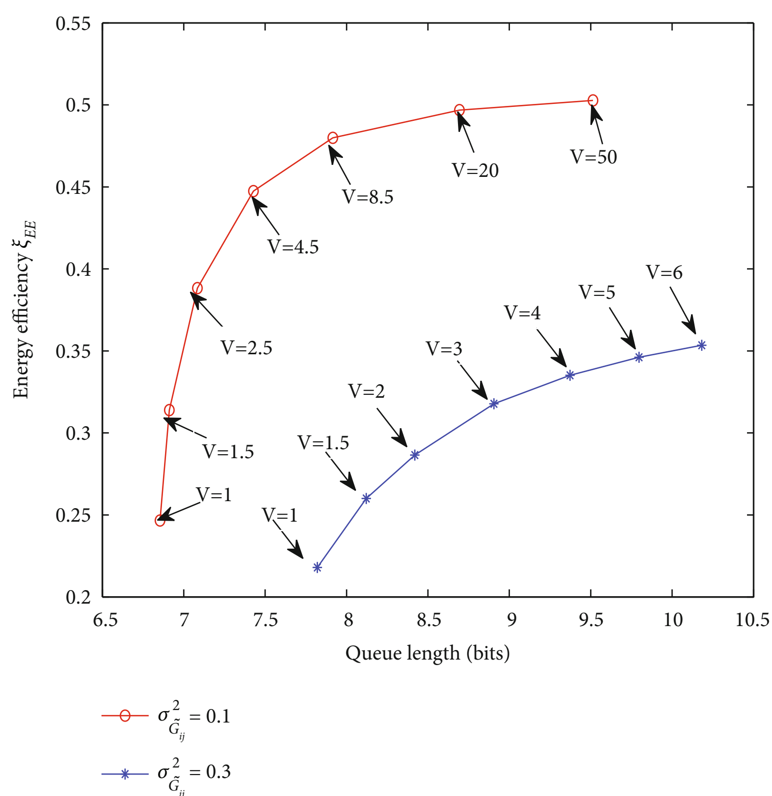
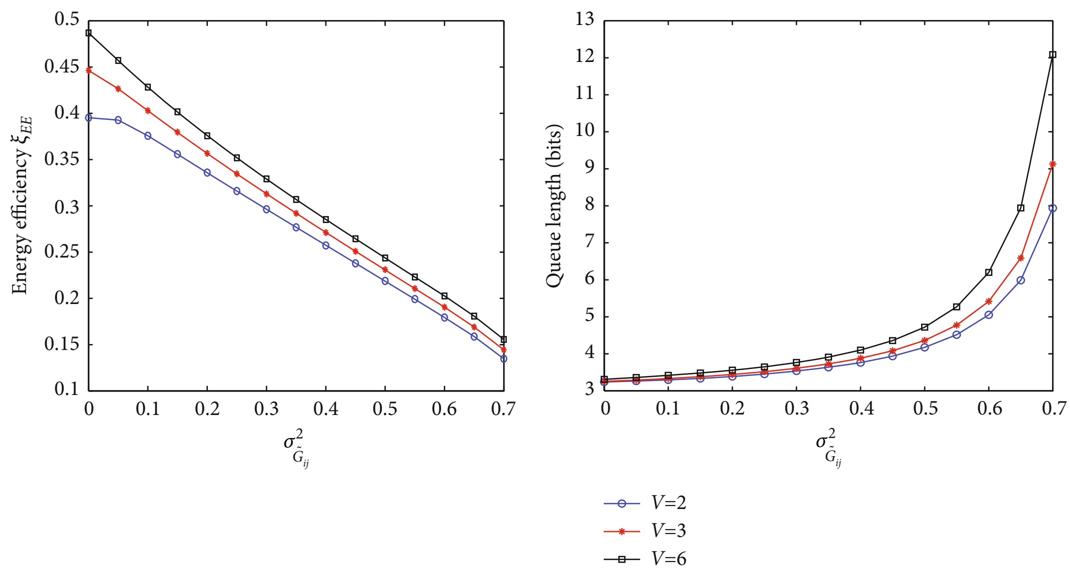


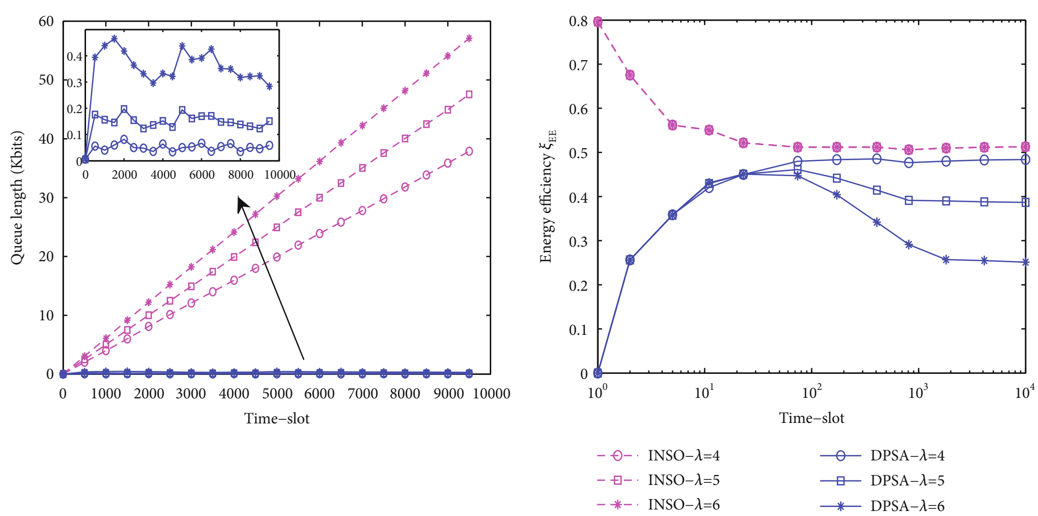
FIGURE 2: EE-delay tradeoff with $\lambda = 3$.



(a) EE vs. channel estimation errors

(b) Queue length vs. channel estimation errors

Figure 3: EE and delay vs. channel estimation errors ($\lambda = 1$).



(a) Queue length vs. time slot

(b) EE vs. time slot

Figure 4: Performance comparison under different λ with $V = 100$.

(b) The time-averaged queue length satisfies

$$\lim_{T\longrightarrow\infty}\frac{1}{T}\sum_{\tau=1}^{T-1}\sum_{i=1}^{M}\mathbb{E}\{\Theta_i(\tau)\} \le \frac{D+V\left(C_{tot}^{\max}+\xi_{EE}^{opt}\left(\rho_{tot}^{\max}-\rho_{tot}^{\min}\right)\right)}{\vartheta}. \tag{23}$$

Here, ξ_{EE}^{opt} represents the maximum system EE over all possible power and subcarrier allocation.

Proof. Please refer to Appendix B for proof.

Equations (22) and (23) together indicate that there exists a tradeoff between EE and queue length (i.e., delay), which is quantitatively depicted by $[O(1/V), O(V)]$. Moreover, these bounds are also affected by the channel estimation errors, which will be further explored in simulations.

5. Simulations

A specifical downlink OFDMA system is employed as an example to illustrate the proposed algorithm. That is, $M = 3$, $N = 6$, $L = 4$, $\sigma_g^2 = 1/4$, and $T = 4000$ time slots. The noise power is normalized to 1 and $P_{\max}$ is set to 100. The data arrival of each queue is subject to Poisson distribution with the mean rate λ. For simplicity of simulation, the subcarrier bandwidth is also normalized to 1, i.e., $B_0 = 1$.

The variation of queue length with the time slot is shown in Figure 1. We observe that the queue length of each user is no more than 0.4 kbits, that is, all data departures from queues in a finite time, which means that our proposed algorithm can ensure delay requirement of all users.

Figure 2 plots the tradeoff between EE and queue length (i.e., delay). Obviously, the improvement of EE is at the cost of the deterioration of delay. Fortunately, the network can operate in the predefined state by adjusting the value of V. For example, if the large EE is desired, the value of V should be increased. Otherwise, if the small delay is pursued, the value of V should be decreased.

The impacts of channel estimation errors on EE and delay are investigated as shown in Figure 3. As channel estimation error increases, the EE decreases and the queue length increases, which means that the performance is degraded with estimation error. Furthermore, given the estimation error, a large V value brings about in a large EE and a long queue length.

Figure 4 shows the comparison between DPSA and the instantaneous energy efficiency optimization policy (labeled as INSO, i.e., power and subcarrier allocation police to maximize EE in each time slot with consideration of channel estimation error). Since the variation tendency of queue length against time slot is similar for each user, user3 is taken as an example and the corresponding curse is displayed in Figure 4(a). Obviously, INSO can obtain higher EE but the queue is instable. The reason is that the INSO policy always maximizes EE in each time slot and does not adjust the transmission power and subcarrier to the fluctuation of arrival traffic, with consequence that its queue length grows with the time slot (i.e., the queue is instable). Compared with INSO, DPSA adapts to the variation of random incoming traffic. In other words, DPSA can adjust users' transmission power and subcarriers to the fluctuation of arrival traffic, with consequence that the network stable can be guaranteed, i.e., the queue length is finite.

6. Conclusions

In this paper, the EE maximization problem was studied with consideration of channel estimation errors, delay requirements, and time-varying channel. We formulated this problem as a stochastic optimization to determine the optimal power and subcarrier. A dynamic power and subcarrier allocation algorithm was proposed by employing the methods of fractional programming, Lyapunov optimization, and dual decomposition. Furthermore, we derived the bounds of EE and delay and demonstrated the variations of EE and delay with channel estimation errors.

Appendix

A. Proof of Lemma 1

According to the inequality $(\max\{a-b,0\}+c)^2 \le a^2+b^2+c^2-2a(b-c)$, we square both sides of (6) and then get

$$\begin{aligned}\Theta_i(\tau+1)^2 &= (\max\{\Theta_i(\tau)-C_i(\tau),0\}+A_i(\tau))^2\\ &\le \Theta_i(\tau)^2 + C_i(\tau)^2 + A_i(\tau)^2\\ &\quad - 2\Theta_i(\tau)(C_i(\tau)-A_i(\tau)).\end{aligned} \tag{A.1}$$

From (A.1), (16) can be reformulated to

$$\begin{aligned}&L(\boldsymbol{\Theta}(\tau+1)) - L(\boldsymbol{\Theta}(\tau))\\ &\quad= \frac{1}{2}\sum_{i=1}^{M}\Theta_i(\tau+1)^2 - \frac{1}{2}\sum_{i=1}^{M}\Theta_i(\tau)^2\\ &\quad\le \frac{1}{2}\sum_{i=1}^{M}\left(C_i(\tau)^2 + A_i(\tau)^2\right) - \sum_{i=1}^{M}\Theta_i(\tau)(C_i(\tau)-A_i(\tau)).\end{aligned} \tag{A.2}$$

Further, taking conditional expectations to the above inequality, we obtain

$$\begin{aligned}&\mathbb{E}\{L(\boldsymbol{\Theta}(\tau+1)) - L(\boldsymbol{\Theta}(\tau)) \mid \boldsymbol{\Theta}(\tau)\}\\ &\quad\le \frac{1}{2}\sum_{i=1}^{M}\mathbb{E}\left\{C_i(\tau)^2 + A_i(\tau)^2 | \boldsymbol{\Theta}(\tau)\right\}\\ &\qquad - \sum_{i=1}^{M}\Theta_i(\tau)\mathbb{E}\{C_i(\tau)-A_i(\tau) | \boldsymbol{\Theta}(\tau)\}.\end{aligned} \tag{A.3}$$

Based on the definition of the Lyapunov conditional drift-plus-penalty (see equation (17)), we can have

$$\begin{aligned}&\Delta(\boldsymbol{\Theta}(\tau)) - V\mathbb{E}\{C_{\text{tot}}(\tau) - \xi_{\text{EE}}(\tau)\rho_{\text{tot}}(\tau) | \boldsymbol{\Theta}(\tau)\}\\ &\quad\le D + V\xi_{\text{EE}}(\tau)\mathbb{E}\{\rho_{\text{tot}}(\tau) | \boldsymbol{\Theta}(\tau)\}\\ &\qquad + \mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)A_i(\tau) | \boldsymbol{\Theta}(\tau)\right\}\\ &\qquad - \mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N}(\Theta_i(\tau)+V)C_{ij}(\tau)\Bigg] | \boldsymbol{\Theta}(\tau)\right\},\end{aligned} \tag{A.4}$$

where

$$D \ge \frac{1}{2}\mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(C_{ij}^2(\tau) + A_i^2(\tau)\right) | \boldsymbol{\Theta}(\tau)\right\}. \tag{A.5}$$

This completes the proof.

B. Proof of Theorem 1

Based on the proposed algorithm DPSA, we have the inequation

$$\begin{aligned}&\Delta(\boldsymbol{\Theta}(\tau)) - V\mathbb{E}\Big\{C_{\text{tot}}\left(\rho_{ij}^*(\tau), s_{ij}^*(\tau)\right)\\ &\qquad - \xi_{\text{EE}}(\tau)\rho_{\text{tot}}\left(\rho_{ij}^*(\tau), s_{ij}^*(\tau)\right) | \boldsymbol{\Theta}(\tau)\Big\}\\ &\quad\le D + V\xi_{\text{EE}}(\tau)\mathbb{E}\left\{\rho_{\text{tot}}\left(\rho_{ij}^*(\tau), s_{ij}^*(\tau)\right) | \boldsymbol{\Theta}(\tau)\right\}\\ &\qquad + \mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)A_i(\tau) | \boldsymbol{\Theta}(\tau)\right\}\\ &\qquad - \mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N}(\Theta_i(\tau)+V)C_{ij}\left(\rho_{ij}^*(\tau), s_{ij}^*(\tau)\right) | \boldsymbol{\Theta}(\tau)\right\}\end{aligned}$$

$$\leq D + V\xi_{\mathrm{EE}}(\tau)\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)|\mathbf{\Theta}(\tau)\right\} + \mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)A_i(\tau)|\mathbf{\Theta}(\tau)\right\} - \mathbb{E}\left\{\sum_{i=1}^{M}\sum_{j=1}^{N}(\Theta_i(\tau)+V)C_{ij}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)|\mathbf{\Theta}(\tau)\right\}, \quad \text{(B.1)}$$

where $\rho'_{ij}(\tau)$ and $s'_{ij}(\tau)$ represent resource allocation decisions which are obtained with any stationary randomized strategy. The second inequality sign of (B.1) holds because the proposed allocation scheme is optimal to minimize the RHS of the bounds in (17) compared with any other strategies.

Since λ is strictly interior to the capacity region $\mathbf{\Gamma}$ and $\lambda + \vartheta$ is in $\mathbf{\Gamma}$ for a positive ϑ, we can get

$$\mathbb{E}\left\{\sum_{j=1}^{N}C_{ij}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)|\mathbf{\Theta}(\tau)\right\} \geq \lambda_i + \theta. \quad \text{(B.2)}$$

According to the stochastic network optimization theory [21, 23], if constraints (9)–(13) are feasible, then, for any $\omega > 0$, there exists a stationary randomized policy satisfying

$$\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} \geq \mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}\left(\xi_{\mathrm{EE}}^{\mathrm{opt}} - \omega\right). \quad \text{(B.3)}$$

Substituting (B.2) and (B.3) into (B.1), we get the following inequation as $\omega \longrightarrow 0$.

$$\Delta(\mathbf{\Theta}(\tau)) - V\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right) - \xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)|\mathbf{\Theta}(\tau)\right\} \leq D + V\xi_{\mathrm{EE}}(\tau)\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} - \theta\mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)\right\} - V\xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}. \quad \text{(B.4)}$$

According to the definition of $\Delta(\mathbf{\Theta}(\tau))$ (see (17)), using telescoping sums over $\tau \in \{0, 1, 2, \cdots, T\}$ in the above inequality and exploiting the fact that $\Theta_i(\tau) > 0$, we get

$$\mathbb{E}\{L(\mathbf{\Theta}(T))\} - \mathbb{E}\{L(\mathbf{\Theta}(0))\} - \sum_{\tau=0}^{T-1}V\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right) - \xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)\right\} \leq TD + V\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}\sum_{\tau=0}^{T-1}\xi_{\mathrm{EE}}(\tau) - TV\xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}. \quad \text{(B.5)}$$

Dividing (B.5) by VT, rearranging terms, and using the fact that $\mathbb{E}\{L(\mathbf{\Theta}(T))\} \geq 0$ yield

$$\frac{1}{T}\sum_{\tau=0}^{T-1}\mathbb{E}\left\{\xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)\right\} - \frac{1}{T}\sum_{\tau=0}^{T-1}\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)\right\} \leq \frac{D}{V} + \frac{1}{T}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}\sum_{\tau=0}^{T-1}\xi_{\mathrm{EE}}(\tau) - \xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} + \frac{\mathbb{E}\{L(\mathbf{\Theta}(0))\}}{VT}. \quad \text{(B.6)}$$

Taking a limit as $T \longrightarrow \infty$, we have

$$0 \leq \frac{D}{V} + \xi_{\mathrm{EE}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} - \xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}. \quad \text{(B.7)}$$

Rearranging (B.7), we obtain

$$\xi_{\mathrm{EE}} \geq \xi_{\mathrm{EE}}^{\mathrm{opt}} - \frac{D}{V\rho_{\mathrm{tot}}^{\min}}. \quad \text{(B.8)}$$

Similarly, taking iterated expectation and using telescoping sums over $\tau \in \{0, 1, 2, \cdots, T\}$ to (B.4) yield

$$\mathbb{E}\{L(\mathbf{\Theta}(T))\} - \mathbb{E}\{L(\mathbf{\Theta}(0))\} - \sum_{\tau=0}^{T-1}V\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right) - \xi_{\mathrm{EE}}(\tau)\rho_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)\right\} \leq TD + V\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}\sum_{\tau=0}^{T-1}\xi_{\mathrm{EE}}(\tau) - TV\xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} - \theta\sum_{\tau=0}^{T-1}\mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)\right\}. \quad \text{(B.9)}$$

Dividing the above inequality by θT and taking a limit as $T \longrightarrow \infty$, we have

$$\lim_{T\longrightarrow\infty}\frac{1}{T}\sum_{\tau=0}^{T-1}\mathbb{E}\left\{\sum_{i=1}^{M}\Theta_i(\tau)\right\} \leq \frac{D - V\xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\}}{\theta} + \frac{1}{\theta}V\xi_{\mathrm{EE}}^{\mathrm{opt}}\mathbb{E}\left\{\rho_{\mathrm{tot}}\left(\rho'_{ij}(\tau), s'_{ij}(\tau)\right)\right\} + \lim_{T\longrightarrow\infty}\frac{1}{\theta T}\sum_{\tau=0}^{T-1}V\mathbb{E}\left\{C_{\mathrm{tot}}\left(\rho^*_{ij}(\tau), s^*_{ij}(\tau)\right)\right\} \leq \frac{D + V\left[C_{\mathrm{tot}}^{\max} + \xi_{\mathrm{EE}}^{\mathrm{opt}}\left(\rho_{\mathrm{tot}}^{\max} - \rho_{\mathrm{tot}}^{\min}\right)\right]}{\theta}. \quad \text{(B.10)}$$

Data Availability

Data is available upon request from the corresponding authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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