A Dual-Decomposition-Based Resource Allocation for OFDMA Networks With Imperfect CSI

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***Abstract*—This paper presents a novel scheme for the allocation of subcarriers, rates, and power in orthogonal frequency-division multiple-access (OFDMA) networks. The scheme addresses practical implementation issues of resource allocation in OFDMA networks: the inaccuracy of channel-state information (CSI) available to the resource allocation unit (RAU) and the diversity of subscribers' quality-of-service (QoS) requirements. In addition to embedding the effect of CSI imperfection in the evaluation of the subscribers' expected rate, the resource-allocation problem is posed as a network utility maximization (NUM) one that is solved via decomposing it into a hierarchy of subproblems. These subproblems coordinate their allocations to achieve a final allocation that satisfies aggregate rate constraints imposed by the call-admission control (CAC) unit and OFDMA-related constraints. A complexity analysis shows that the proposed scheme is computationally efficient. In addition, performance evaluation findings support our theoretical claims: A substantial data rate gain can be achieved by considering the CSI imperfection, and multiservice classes can be supported with QoS guarantees.**

***Index Terms*—Broadband wireless access networks, call-admission control, dual decomposition, imperfect channel state information, orthogonal frequency-division multiple-access (OFDMA), resource management.**

I. Introduction

THE INCREASING demand to support multimedia services (e.g., Internet Protocol television, online gaming, and tele-medicine) has led to an increase in transmission bandwidth. As the bandwidth increases, performance degradation is observed due to frequency-selective fading that results in intersymbol interference (ISI) [1], [2]. Orthogonal frequency-division multiple-access (OFDMA) physical (PHY) and medium-access control (MAC) technologies avoid frequency selectivity by transmitting the wideband signal as multiple narrow-band signals over subbands that are supported by subcarriers and with a bandwidth that is less than the channel coherence bandwidth [2], [3]. In addition, OFDMA assigns a subset of the available subcarriers to each subscriber station that is not required to transmit over the full bandwidth; thus, transmission power can be conserved. Furthermore, as the subcarriers' gains change over time, OFDMA updates its subcarriers' assignment, which results in exploiting multiuser diversity. OFDMA is being considered in current broadband standards because of its indispensable features: exploitation of multiuser diversity, flexibility in resource allocation, conservativity in link budget, and robustness to ISI in frequency-selective fading channels. Examples of networks that adopt OFDMA are the Broadband Wireless Access Networks IEEE 802.16[1] and the Third-Generation Partnership Project Long-Term Evolution (3GPP-LTE) networks [4].

All the aforementioned salient features of OFDMA hinge on the availability of perfect channel state information (CSI) at the resource allocation unit (RAU), which is not the situation in practical networks. Thus, the development of practical resource allocation schemes requires accounting for the inaccuracy of CSI. In addition, the support of multiple services implies diverse throughput requirements in which the call-admission control (CAC) unit becomes important to provide quality-of-service (QoS) guarantees by distributing the network throughput among the supported services. These considerations motivate us to propose a resource allocation scheme for OFDMA networks that allocates subcarriers, power, and rates in conjunction with a CAC unit under the assumption of imperfect CSI.

Although most recent works have posed the resource-allocation problem of OFDMA networks as a network utility maximization (NUM) problem [5]–[9], they depend too heavily on the accuracy of CSI and overlook the availability of the allocated throughput. The works in [6], [8], and [9] have generally focused on maximizing the sum of utilities, without considering the limit imposed by the CAC unit on each service aggregate rate. In other words, the higher the channel gain and the available power, the higher the throughput granted to subscribers. However, in multiservice networks, the aggregate rate allocated to subscribers of each service cannot exceed the prescribed partition of the network throughput, particularly when subscribers have diverse QoS requirements. For example, a particular group of subscribers may be more demanding than the rest of the subscribers, which results in an allocation of the network resources to the former and leaves the latter unsupported. Limiting the aggregate rate that the group of demanding subscribers receives imposes fairness among supported classes and guarantees QoS for each service. Although

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[1]Worldwide Interoperability for Microwave Access (WiMAX) is a commercialization of IEEE 802.16.

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the works in [5], [6], and [10] propose joint resource allocation and CAC schemes that avoid overusing the network throughput by partitioning it over the supported services, the CSI in these schemes is assumed to be perfectly known. However, such perfection is rare, and the performance of multicarrier systems is severely degraded by considering an inaccurate and delayed CSI as perfect and allocating resources based on it [11]–[13].

The main focus of this paper is the resource allocation for OFDMA-based networks with imperfect CSI and multiple classes of services that demand diverse QoS requirements. Allocating resources for OFDMA networks is cross layer in nature; the PHY layer feeds the CSI of all subscribers to the RAU at the MAC layer, which, in turn, allocates resources. The inaccuracy of the reported CSI is modeled as an additive random variable with a known distribution, based on which the expected rate is evaluated. Power allocation is performed by inverting the expected rate function. The OFDMA resource allocation problem is combinatorial in nature with a nonconvex structure; thus, it cannot be solved by convex optimization methods. However, as the number of subcarriers becomes infinitely large, the duality gap tends to zero[2]; hence, the nonconvex problem can be solved in the dual domain [14]. With this dual approach, decomposition methods for NUM [15] can be applied to solve the problem under consideration [8], [25]. Solutions obtained via decomposition have the inherent property of being implementable in both a distributed and a centralized manner; we adopt the centralized implementation and highlight subroutines of the proposed scheme that are distributable. The proposed scheme is presented for OFDMA systems in the downlink mode, and modifications can be incorporated for uplink resource allocation.

The remainder of this paper is organized as follows. Section II introduces the system model of the OFDMA-based point-to-multipoint (PMP) network under consideration. The expected data rate for imperfect CSI is presented in Section III. The mathematical formulation of the resource-allocation problem, along with the proposed scheme, is presented in Section IV. Computational complexity is analyzed in Section V. The performance of the proposed scheme is evaluated in Section VI, followed by conclusions in Section VII.

II. System Model

We consider a single-cell scenario of a PMP network. The network consists of one base station (BS) at the center of the cell and multiple subscriber stations. There are S subscriber stations forming the set $\mathcal{S} = \{1, \ldots, s, \ldots, S\}$. The subscriber stations share a set of $N_{\rm sc}$ subcarriers available to the cell. In OFDMA networks, a subset $\mathcal{N}_s$[3] of the network subcarriers is exclusively assigned to one subscriber station. Although, for simplicity, the general presentation focuses on the downlink mode, the proposed resource-allocation scheme is generally applicable to both uplink and downlink modes, as will be shown later.

The network supports L QoS classes. Network parameters related to the lth class are denoted by a superscript $^{(l)}$. For example, the set of subscriber stations that subscribe for the lth class is denoted by $\mathcal{S}^{(l)}$. A utility function $U^s(\overline{r}^s)$ models the sth subscriber station's satisfaction of the expected data rate $\overline{r}^s$ assigned to it. The characteristics of utility functions depend on the class of service that each subscriber station opts for. We consider a frequency-selective fading channel between any pair of communicating stations. In OFDMA, the subband bandwidth is smaller than the channel coherence bandwidth; therefore, each subcarrier experiences flat fading. During the jth slot, the sth subscriber receives the following OFDM signals:

$$\mathbf{y}^s[j] = \sqrt{\mathbf{P}^s[j]}\mathbf{H}^s[j]\mathbf{x}[j] + \mathbf{z}^s[j] \qquad (1)$$

where $\sqrt{\mathbf{P}^s}[j]$ is a diagonal $N_s \times N_s$ matrix of $p_n^s[j] \forall n \in \mathcal{N}_s$, which is the power allocated by the MAC resource allocation scheme to the sth subscriber on the nth subcarrier during the jth slot. $\mathbf{H}^s[j]$ is a diagonal matrix of the channel gains, and $\mathbf{x}[j]$ denotes the data source symbols. The vector $\mathbf{z}^s$ represents the additive noise, which is modeled as circularly symmetric complex Gaussian random variable $\mathbf{z}^s \sim \mathcal{CN}(\mathbf{0}, (\sigma_z^s)^2\mathbf{I})$.

The CSI is updated every OFDMA frame. At the beginning of the frame, a sequence of OFDM symbols is transmitted by the BS to the subscribers for channel estimation [16]. Each subscriber estimates the channel and forwards its estimate $\hat{\mathbf{H}}^s$ of the perfect CSI $\mathbf{H}^s$ to the BS. $\mathbf{H}^s$ is assumed to be ergodic, and its elements are independent. The slot index $[j]$ is dropped for notational convenience. Note that the matrix of channel gains is a diagonal of the subcarriers' channel gain vector $\hbar^s$. Let $\hat{\hbar}^s$ be its estimate available at the RAU; before the next frame estimates arrive, the current frame estimates are treated as deterministic [17], and their delay and estimation error are modeled by $\tilde{\hbar}^s$. Hence, given the channel estimate $\hat{\hbar}^s$, the imperfect CSI can be modeled as

$$\breve{\hbar}^s = \hat{\hbar}^s + \tilde{\hbar}^s \qquad (2)$$

and assumed to be $\sim\mathcal{CN}(\hat{\hbar}^s, \mathbf{\Sigma}_{\tilde{\hbar}^s})$. The matrix $\mathbf{\Sigma}_{\tilde{\hbar}^s}$ is the error covariance matrix that captures the quality of the channel estimation [18]–[20]. We assume that the estimation errors on different subcarriers are independent; thus, $\mathbf{\Sigma}_{\tilde{\hbar}^s} = (\tilde{\sigma}_\epsilon^s)^2\mathbf{I}$, where $(\tilde{\sigma}_\epsilon^s)^2$ is the estimation error variance. The nth subcarrier[4] imperfect CSI ($[\breve{\hbar}^s]_n = \breve{H}_n^s$) is modeled as $\sim \mathcal{CN}(\hat{H}_n^s, (\tilde{\sigma}_\epsilon^s)^2)$. Therefore, its square follows a noncentral chi-square probability density function (pdf) given by [21]

$$f_X(x) = \frac{1}{(\tilde{\sigma}_\epsilon^s)^2} e^{-\frac{\left(|\hat{H}_n^s|^2 + x\right)}{(\tilde{\sigma}_\epsilon^s)^2}} \mathfrak{I}_0\left(2\sqrt{\frac{\left|\hat{H}_n^s\right|^2 x}{(\tilde{\sigma}_\epsilon^s)^4}}\right) \qquad (3)$$

where $\mathfrak{I}_0(\cdot)$ is the zeroth-order modified Bessel function of the first kind. The random variable $|\breve{H}_n^s|^2$ is denoted by X for notational convenience. Fig. 1 shows the aforementioned modeling parameters on an illustrative PMP network.

[2]A zero duality gap implies that both the primal and the dual problems have the same optimal value [14].

[3]The cardinality of the subset $\mathcal{N}_s$ is denoted by N_s.

[4]$[\boldsymbol{x}]_n$ denotes the nth element of vector $\boldsymbol{x}$.

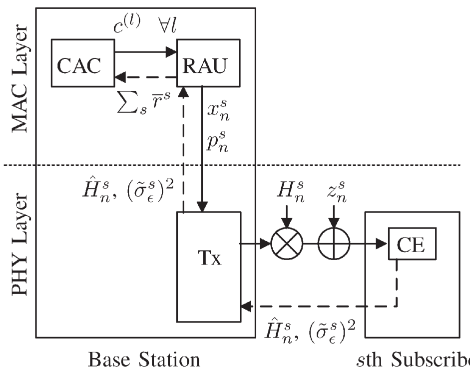

Fig. 1. Illustrative PMP network of one subscriber station and a BS showing various components involved in resource allocation. Tx and CE, respectively, stand for transmitter and channel estimator.

III. Expected Rate With Imperfect Channel-State Information

The BS receives a deterministic channel gain estimate of each subcarrier $\hat{H}_n^s$ and the estimation error statistical information for each subscriber. Based on the model in (2), the achievable rate r_n^s is a function of the imperfect CSI random variable X (i.e., $|\hat{H}_n^s|^2$), which can be written as

$$r_n^s = \log_e\left(1 + \frac{p_n^s X}{\Delta\left(\sigma_z^s\right)^2}\right). \tag{4}$$

Because Shannon's capacity is an upper bound and cannot be achieved in practice, Δ is added to model the gap between the expected rate achieved by a specific modulation scheme and the upper bound [3]. The pdf of the random variable $Q = p_n^s X/\Delta(\sigma_z^s)^2$ is given by

$$f_Q(q) = \frac{1}{\Omega_Q^2} e^{-\frac{\theta_Q^2 + q}{\Omega_Q^2}} \Im_0\left(2\sqrt{\frac{\theta_Q^2 q}{\Omega_Q^4}}\right) \tag{5}$$

where $1/\Omega_Q^2 = \Delta(\sigma_z^s)^2/2p_n^s(\tilde{\sigma}_\epsilon^s)^2$, and $\theta_Q^2 = p_n^s|\hat{H}^s|^2/\Delta(\sigma_z^s)^2$. By substituting the series representation of $\Im_0(\cdot)$ [22, eq. 8.447(1)] in (5), we obtain

$$f_Q(q) = \frac{1}{\Omega_Q^2} e^{-\frac{\theta_Q^2 + q}{\Omega_Q^2}} \sum_{t=0}^{\infty} \frac{\theta_Q^{2t} q^t}{\Omega_Q^{4t}(t!)^2}. \tag{6}$$

Given the pdf $f_Q(q)$, the expected achievable rate can be written as

$$E\left[r_n^s\right] = E\left[\log_e(1+Q)\right] \tag{7}$$

$$= \int_0^\infty \log_e(1+q) f_Q(q)\, dq \tag{8}$$

$$= \frac{e^{-\frac{\theta_Q^2}{\Omega_Q^2}}}{2\Omega_Q^2} \sum_{t=0}^{\infty} \frac{\theta_Q^{2t}}{\Omega_Q^{4t}(t!)^2} \int_0^\infty \log_e(1+q) e^{-\frac{q}{\Omega_Q^2}} q^t\, dq. \tag{9}$$

By [22, eq. 4.222(8)], we obtain

$$E\left[r_n^s\right] = \frac{e^{-\frac{\theta_Q^2}{\Omega_Q^2}}}{2\Omega_Q^2} \sum_{t=0}^{\infty} \frac{\theta_Q^{2t}\Omega_Q^{2(t+1)}}{\Omega_Q^{4t}(t!)^2} \sum_{m=0}^{t} \frac{t!}{(t-m)!}$$
$$\times \left[\frac{(-1)^{t-m-1}}{\Omega_Q^{2(t-m)}} e^{\frac{1}{\Omega_Q^2}} Ei\left(\frac{-1}{\Omega_Q^2}\right) + \sum_{j=1}^{t-m} \frac{(j-1)!}{-\Omega_Q^{2(t-m-j)}}\right] \tag{10}$$

where $Ei(\cdot) = -\int_{-(\cdot)}^{\infty}(e^t/t)dt$ is the exponential integral function.

Given the expected data rate to be supported, the power allocation phase of the proposed scheme requires solving (10) for p_n^s, which is computationally extensive. Alternatively, after evaluating (10) offline, the expected achievable rate can be represented by a simpler function that can efficiently be inverted for power. Note that $E[\log_e(1+x)] \approx E[\log_e(x)] + \vartheta(x)$, where $\vartheta(x)$ is an approximation error correction term that approaches zero for large values of x. Similarly, (7) can be written as

$$E\left[r_n^s\right] = E\left[\log_e(1+Q)\right] \tag{11}$$

$$\backsimeq E\left[\log_e(Q)\right] + \vartheta\left(p_n^s\right) \tag{12}$$

$$\backsimeq \log_e\left(\frac{\left|\hat{H}_n^s\right|^2}{\left(\tilde{\sigma}_\epsilon^s\right)^2}\right) - Ei\left(\frac{-\left|\hat{H}_n^s\right|^2}{\left(\tilde{\sigma}_\epsilon^s\right)^2}\right)$$
$$+ \log_e\left(\frac{\left(\tilde{\sigma}_\epsilon^s\right)^2}{\triangle\left(\sigma_z^s\right)^2}\right) + \log_e\left(p_n^s\right) + \vartheta\left(p_n^s\right) \tag{13}$$

where $E[\log_e(Q)]$ is given in [23], and $\vartheta(p_n^s) = \alpha(\hat{H}_n^s, (\tilde{\sigma}_\epsilon^s)^2) \times (p_n^s)^{-\beta(\hat{H}_n^s, (\tilde{\sigma}_\epsilon^s)^2)} + \gamma(\hat{H}_n^s, (\tilde{\sigma}_\epsilon^s)^2)$ is an approximation error-correction term. The parameters α, β, and γ are found by curve fitting the difference $E[r_n^s] - E[\log_e(Q)]$ to a power decaying function; $E[r_n^s]$ is evaluated by (10). These parameters are stored in lookup tables for a range of practical values of $|\hat{H}_n^s|^2$ and $(\tilde{\sigma}_\epsilon^s)^2$. Rearranging (13) results in the following:

$$\log_e\left(p_n^s\right) + \vartheta\left(p_n^s\right) \backsimeq -\log_e\left(\frac{\left|\hat{H}_n^s\right|^2}{\left(\tilde{\sigma}_\epsilon^s\right)^2}\right) + Ei\left(\frac{-\left|\hat{H}_n^s\right|^2}{\left(\tilde{\sigma}_\epsilon^s\right)^2}\right)$$
$$- \log_e\left(\frac{\left(\tilde{\sigma}_\epsilon^s\right)^2}{\triangle\left(\sigma_z^s\right)^2}\right) + E\left[r_n^s\right]. \tag{14}$$

Note that the right-hand side of (14) is a function of $|\hat{H}_n^s|^2$ and $(\tilde{\sigma}_\epsilon^s)^2$, which are known deterministic values to the RAU. For notational convenience, we denote the constant term $-\log_e(|\hat{H}_n^s|^2/(\tilde{\sigma}_\epsilon^s)^2) + Ei(-|\hat{H}_n^s|^2/(\tilde{\sigma}_\epsilon^s)^2) - \log_e((\tilde{\sigma}_\epsilon^s)^2/\Delta(\sigma_z^s)^2)$ by Ψ. The required power to support the expected rate $E[r_n^s]$ for given $|\hat{H}_n^s|^2$ and $(\tilde{\sigma}_\epsilon^s)^2$ is found by Maple[5] to be

$$p_n^s = \exp\left\{\frac{W_0\left(-\beta\alpha e^{\beta(E[r_n^s]-\gamma-\Psi)}\right)+\beta\left(E\left[r_n^s\right]-\gamma-\Psi\right)}{\beta}\right\} \tag{15}$$

where $W_0(\cdot)$ is the Lambert's W function given by $W_0(\cdot) = \sum_{i=1}^{\infty}((-i)^{i-1}/i!)(\cdot)^i$.

IV. Problem Formulation and Proposed Solution

We formulate the resource allocation problem as a constrained NUM problem, where the objective function is a maximization of the sum of the subscribers' utility functions. The constraints are related to the specifications of the network under consideration, namely, the per-service allocated aggregate rate limit, power limitation, and exclusive subcarrier assignment. Let $x_n^s \in \{0,1\}$, where $x_n^s = 1$ means that the nth subcarrier is allocated to the sth subscriber, and $x_n^s = 0$ otherwise. Furthermore, let $\overline{r}^s$ be the expected rate allocated to the sth subscriber of the subcarriers assigned to it (i.e., $\mathcal{N}_s$); mathematically, $\overline{r}^s = \sum_{n\in\mathcal{N}_s} E[r_n^s]$. The CAC unit receives the allocation results from the RAU and updates the RAU with the throughput partitioning results $c^{(l)}$ $\forall l$ (see Fig. 1). The CAC schemes available in the literature (e.g., [5], [7], [10], and [24]) can be applied here. In the downlink mode, the power available to the network is limited by the BS power, which is denoted by P_{BS}. Mathematically, the optimization problem is

$$\max_{x_n^s, p_n^s} \quad \sum_s U^s(\overline{r}^s) \tag{16}$$

$$\text{s.t.} \quad \sum_{s\in\mathcal{S}^{(l)}} \overline{r}^s \le c^{(l)}, \qquad \forall l \tag{17}$$

$$\sum_s x_n^s \le 1, \qquad \forall n \tag{18}$$

$$\sum_s \sum_{n=1}^{N_{\mathrm{sc}}} p_n^s \le P_{\mathrm{BS}} \tag{19}$$

$$x_n^s \in \{0,1\}. \tag{20}$$

The set of constraints in (17) limits the lth-class subscribers' allocated aggregate expected rate to $c^{(l)}$. Constraints in (18) satisfy the exclusive subcarrier allocation of OFDMA [3]. Constraint (19) limits the total power allocated to P_{BS}.

The resource allocation problem is combinatorial in nature due to the subcarrier exclusive assignment constraint, which results in a nonconvex feasible space. Generally, solving nonconvex problems in the dual domain provides only an upper bound that is at a distance from the optimum known as the "duality gap." However, resource allocation for multicarrier transmissions is a special case in which the duality gap becomes zero as the number of subcarriers approaches infinity [14]. In networks with a number of subcarriers as small as 64, a duality gap of less than 10^{-5} can be achieved, which is acceptable in practice [25].

[5]Maplesoft, version 11.02.

These results suggest solving the problem in the dual domain. One of the effective methods for solving NUM problems is dual decomposition, where the dual problem is decomposed into multiple subproblems that are easier to solve than the primal. The master dual problem sets the prices for resources and reports them to the decomposed subproblems, which, in turn, decide the amount of resources to be consumed [15].

A Lagrangian is formed by relaxing the constraints in (17) as follows:

$$D(\overline{r}^s, \boldsymbol{\lambda}) = \sum_l \left[\sum_{s\in\mathcal{S}^{(l)}} \left[U^s(\overline{r}^s) - \lambda^{(l)}\overline{r}^s\right] + \lambda^{(l)}c^{(l)}\right] \tag{21}$$

where $\lambda^{(l)} \ge 0$ $\forall l$ are the classes' set of Lagrange multipliers (i.e., prices). If the lth-class throughput is overutilized, $\lambda^{(l)}$ increases, and the converse is true. The problem can be solved by solving its dual as follows:

$$\min_{\boldsymbol{\lambda}} \quad d(\boldsymbol{\lambda})$$
$$\text{s.t.} \quad \boldsymbol{\lambda} \ge \mathbf{0} \tag{22}$$

where $d(\boldsymbol{\lambda}) = \min_{\overline{r}^s} D(\overline{r}^s, \boldsymbol{\lambda})$, and $\boldsymbol{\lambda}$ is a vector of $\lambda^{(l)}$ $\forall l$. The Lagrange multipliers are updated with the following subgradient method for each multiplier [14], [15], [26]:

$$\lambda^l(t+1) = \left[\lambda^l(t) - \kappa\left(c^{(l)} - \sum_{s\in\mathcal{S}^{(l)}} \overline{r}^{s^\star}\left(\lambda^l(t)\right)\right)\right]^+ \tag{23}$$

where $\kappa = 0.1/\sqrt{t}$ is a diminishing step size, $[\cdot]^+$ denotes $\max(\cdot, 0)$, and t is the iteration index. Here, $\overline{r}^{s^\star}(\lambda^l(t))$ is the optimum value obtained by solving the following problem for a given $\lambda^{(l)}$ $\forall l$:

$$\max_{x_n^s, p_n^s} \quad \sum_l \sum_{s\in\mathcal{S}^{(l)}} \left[U^s(\overline{r}^s) - \lambda^{(l)}\overline{r}^s\right] \tag{24}$$

$$\text{s.t.} \quad \sum_s x_n^s \le 1, \qquad \forall n \tag{25}$$

$$\sum_s \sum_{n=1}^{N_{\mathrm{sc}}} p_n^s \le P_{\mathrm{BS}} \tag{26}$$

$$x_n^s \in \{0,1\}. \tag{27}$$

The problem in (24) can be rewritten by introducing the set of auxiliary variables b^s $\forall s$ as follows:

$$\max_{x_n^s, p_n^s} \quad \sum_l \sum_{s\in\mathcal{S}^{(l)}} \left[U^s(b^s) - \lambda^{(l)}b^s\right] \tag{28}$$

$$\text{s.t.} \quad \sum_s x_n^s \le 1, \qquad \forall n \tag{29}$$

$$\sum_s \sum_{n=1}^{N_{\mathrm{sc}}} p_n^s \le P_{\mathrm{BS}} \tag{30}$$

$$x_n^s \in \{0,1\} \tag{31}$$

$$\overline{r}^s \ge b^s, \qquad \forall s. \tag{32}$$

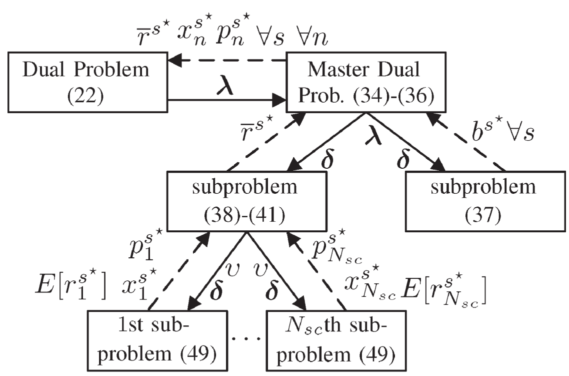

Fig. 2. Hierarchy of the decomposed dual problem.

Constraint (32) is relaxed by forming the Lagrangian

$$W(b^s,\lambda^{(l)},\delta^s)=\sum_l\sum_{s\in\mathcal{S}^{(l)}}\left[U^s(b^s)-\lambda^{(l)}b^s+\delta^s\left(\overline{r}^s-b^s\right)\right] \tag{33}$$

where δ^s is the Lagrange multiplier associated with the sth subscriber. δ^s demands a rate allocation for the sth subscriber. The dual problem[6] is given by

$$\min_{\boldsymbol{\lambda},\boldsymbol{\delta}} \quad w(\boldsymbol{\lambda},\boldsymbol{\delta}) \tag{34}$$

$$\text{s.t.} \quad \text{constraints } (29)-(31)$$

$$\boldsymbol{\lambda}\geq \mathbf{0} \tag{35}$$

$$\boldsymbol{\delta}\geq \mathbf{0} \tag{36}$$

where $w(\boldsymbol{\lambda},\boldsymbol{\delta})=\max_{b^s} W(b^s,\lambda^{(l)},\delta^s)$. The dual problem can be separated into two problems [8]. The first is a utility maximization problem, i.e.,

$$w'(\boldsymbol{\lambda},\boldsymbol{\delta})=\max_{b^s}\sum_l\sum_{s\in\mathcal{S}^{(l)}}\left[U^s(b^s)-\lambda^{(l)}b^s-\delta^s b^s\right] \tag{37}$$

and the second is a subcarrier, rate, and power allocation problem, i.e.,

$$w''(\boldsymbol{\delta})=\max_{p_n^s,x_n^s}\sum_l\sum_{s\in\mathcal{S}^{(l)}}\delta^s\overline{r}^s \tag{38}$$

$$\text{s.t.} \quad \sum_s x_n^s\leq 1, \qquad \forall n \tag{39}$$

$$\sum_s\sum_{n=1}^{N_{\rm sc}}p_n^s\leq P_{\rm BS} \tag{40}$$

$$x_n^s\in\{0,1\}. \tag{41}$$

Note that each of the dual problems (37) and (38) can individually be solved to obtain their optimums (i.e., $b^{s^\star}$ and $\overline{r}^{s^\star}$) while being coordinated by the master dual problem (34) (see Fig. 2). Multipliers $\delta^s\ \forall s$ are iteratively updated at each iteration $\dot{t}$ by the subgradient method, i.e.,

$$\delta^s(\dot{t}+1)=\left[\delta^s(\dot{t})+\dot{\kappa}\left(b^{s^\star}\left(\delta^s(\dot{t})\right)-\overline{r}^{s^\star}\left(\delta^s(\dot{t})\right)\right)\right]^+ \tag{42}$$

[6] $\boldsymbol{\delta}$ denotes a vector of $\delta^s\ \forall s$.

where $\dot{\kappa}$ is a diminishing step size. At each iteration, $b^{s^\star}(\delta^s(\dot{t}))$ is obtained for each subscriber by maximizing (37) for b^s, where the utility functions are assumed to be concave. The coupling constraints (39) and (40) pose complication in solving (38). However, relaxing constraint (40) decouples the problem into multiple per-subcarrier subproblems, which also satisfies (39). Therefore, a Lagrangian can be formed, i.e.,

$$Z\left(\overline{r}^s,p_n^s,\boldsymbol{\delta},\upsilon\right)=\sum_l\sum_{s\in\mathcal{S}^{(l)}}\delta^s\sum_n^{N_s}E\left[r_n^s\right] + \upsilon\left(P_{\rm BS}-\sum_s\sum_{n=1}^{N_{\rm sc}}p_n^s\right). \tag{43}$$

The Lagrange multiplier υ is interpreted as the price of using $P_{\rm BS}$. Let $\min_{\boldsymbol{\delta},\upsilon} z(\boldsymbol{\delta},\upsilon)=\max_{p_n^s,x_n^s} Z(\overline{r}^s,p_n^s,\boldsymbol{\delta},\upsilon)$. Because the duality gap is zero, the dual problem

$$\min_{\boldsymbol{\delta},\upsilon} \quad z(\boldsymbol{\delta},\upsilon) \tag{44}$$

$$\text{s.t.} \quad \sum_s x_n^s\leq 1, \qquad \forall n \tag{45}$$

$$x_n^s\in\{0,1\} \tag{46}$$

$$\boldsymbol{\lambda}\geq\mathbf{0} \tag{47}$$

$$\upsilon\geq 0 \tag{48}$$

is now decoupled into $N_{\rm sc}$ maximization subproblems, i.e.,

$$\arg\max_s \delta^s E\left[r_n^s\right]-\upsilon p_n^s, \qquad \forall n. \tag{49}$$

For each expected rate $E[r_n^s]$ to be supported, the required power p_n^s is obtained by (15). These maximization subproblems are solved per subcarrier. In other words, the subcarrier is exclusively assigned to the sth subscriber that maximizes (49) on that particular subcarrier; thus, constraint (39) is also satisfied. $\boldsymbol{\delta}$ is passed down from (34), and υ is updated by the following subgradient method:

$$\upsilon(\ddot{t}+1)=\left[\upsilon(\ddot{t})-\ddot{\kappa}\left(P_{\rm BS}-\sum_s\sum_n^{N_{\rm sc}}p_n^{s^\star}\left(\upsilon(\ddot{t})\right)\right)\right]^+ \tag{50}$$

where $\ddot{\kappa}$ is the step size, and $\ddot{t}$ is the iteration index. $p_n^{s^\star}(\upsilon(\ddot{t}))$ is obtained by solving the per-subcarrier problems (49) for a specific $\upsilon(\ddot{t})$. Fig. 2 shows the decomposition of the master dual problem into a hierarchy of subproblems and the interaction among them.

Algorithm 1 Pseudocode of the proposed scheme

```
Pre-optimization phase
for s = 1 to S do
    for n = 1 to N_sc do
        Search lookup tables for α, β and γ
        for k = 1 to K do
            Solve (15) for p_n^s
        end for
    end for
```

9: **end for**
10: *Optimization phase*
11: Initialize $\lambda^l\ \forall l$
12: Initialize $\delta^s\ \forall s$
13: **for** $s = 1$ to S **do**
14: Solve the derivative of (37) for $b^{s^\star}$
15: $b^{s^\star} \leftarrow b^s$
16: **end for**
17: Initialize υ
18: **for** $n = 1$ to $N_{\rm sc}$ **do**
19: $\arg\max_s \delta^s E[r_n^s] - \upsilon p_n^s$
20: $s^\star \leftarrow s$
Allocate nth subcarrier
21: $\mathcal{N}_{s^\star} \leftarrow \mathcal{N}_{s^\star} \cup \{n\}$
Allocate power
22: $p_n^{s^\star} \leftarrow p_n^s$
23: **end for**
24: update $\upsilon(\ddot{t}+1) = [\upsilon(\ddot{t}) - \ddot{\kappa}(P_{\rm BS} - \sum_s \sum_n^{N_{\rm sc}} p_n^{s^\star}(\upsilon(\ddot{t})))]^+$
25: Repeat lines 17 to 23 until convergence
26: $\overline{r}^{s^\star} \leftarrow \sum_n^{N_s} E[r_n^s]\ \forall s$
27: update $\delta^s(\dot{t}+1) = [\delta^s(\dot{t}) + \dot{\kappa}(b^{s^\star}(\delta^s(\dot{t})) - \overline{r}^{s^\star}(\delta^s(\dot{t})))]^+$
28: Repeat lines 12 to 26 until convergence
29: update $\lambda^l(t+1) = [\lambda^l(t) - \kappa(c^{(l)} - \sum_{s\in\mathcal{S}^{(l)}} \overline{r}^{s^\star}(\lambda^l(t)))]^+$
30: Repeat lines 11 to 28 until convergence

Based on the mathematical formulations and derivations presented earlier, the pseudocode of the proposed scheme is outlined in Algorithm 1. The scheme is divided into two phases: a preoptimization phase and an optimization phase. The preoptimization phase prepares the possible expected rate levels K and their corresponding power allocations, which are given by (15), based on the received imperfect CSI (lines 2 to 9). This phase can be implemented in both a centralized manner, as in lines 2 to 9 at the BS, and a distributed manner, by which each subscriber searches the lookup tables for α, β, and γ, evaluates the required power allocations, and reports them to the BS. Either of the implementations provides the same result, but questions arise about how much computation the subscriber station can perform and how much reporting overhead the feedback channel can support. Hence, it is a tradeoff between the computational complexity at the BS and the feedback reporting overhead.

In the optimization phase, the power, rate, and subcarrier allocations are optimized while satisfying the network constraints. In the following, the network constraints along with their related subroutines in Algorithm 1 are discussed.

1) *A subcarrier is exclusively allocated to one subscriber.* In lines 18 to 23, each subcarrier is allocated to the subscriber that maximizes the term $\delta^s E[r_n^s] - \upsilon p_n^s$ by searching over a matrix of supported expected rate levels for all subscribers. The required power to support the granted rate is allocated to the subscriber on the nth subcarrier (line 22). Note that the cardinality of the set $\mathcal{N}_s$ is denoted by N_s, which is the number of subcarriers allocated to the sth subscriber.
2) *The aggregate rate allocated to the* lth *service is limited to a partition of the throughput* $c^{(l)}$. The Lagrange multiplier $\lambda^{(l)}$ represents the price of utilizing $c^{(l)}$. As the scheme evolves, overutilizing $c^{(l)}$ increases $\lambda^{(l)}$, and the converse is true (line 29). The unavailability of throughput for a specific class of service l is signaled via $\lambda^{(l)}$ to line 14, where the minimum rate (i.e., auxiliary variable b^s) to be allocated to the subscribers is obtained. For example, let the utility function be the concave function $U^s(b^s) = \varsigma \log(b^s)$; therefore, solving the derivative of (37) for each term of the summation gives $b^s = \varsigma/\lambda^{(l)} + \delta^s$. Hence, an increase in $\lambda^{(l)}$ decreases b^s, and the scheme tends to allocate a lower rate to subscribers of the lth class of service by reducing the demand variable (i.e., Lagrange multiplier δ^s) (line 27).
3) *The total allocated power is limited to the BS power* $P_{\rm BS}$ *in the downlink mode, and the power allocated to each subscriber is limited to its specific power constraint* P_s *in the uplink mode*. The power supply is controlled by the Lagrange multiplier υ (line 24). If the BS power is overutilized, the price υ increases, resulting in a decrease in the term $\arg\max_s \delta^s E[r_n^s] - \upsilon p_n^s$. Thus, the scheme tends to allocate a lower rate, which requires less power. In the uplink mode, the allocated power to each subscriber is constrained by its maximum available power (i.e., device battery power), which is denoted by P_s. Therefore, the constraint in (19) is replaced with $\sum_{n\in\mathcal{N}_s} p_n^s \le P_s$, and the subgradient algorithm in line 24 is replaced with

$$\upsilon^s(\ddot{t}+1) = \left[\upsilon^s(\ddot{t}) - \ddot{\kappa}\left(P_s - \sum_{n\in\mathcal{N}_s} p_n^{s^\star}\left(\upsilon^s(\ddot{t})\right)\right)\right]^+ \quad \forall s. \tag{51}$$

Thus, each subscriber has a specific multiplier υ^s that prices the supply of its power.

V. Complexity Analysis

Computational complexity is a major factor in implementing resource allocation schemes for OFDMA networks. However, the resource allocation problem for OFDMA networks is known to be NP-hard, and obtaining an exhaustive search allocation is computationally very expensive. The exclusive subcarrier assignment constraint makes the problem a complex combinatorial one that becomes harder when the power and per-service aggregate rate constraints are considered. The proposed scheme is low in computational complexity due to the adopted decomposition approach. The following complexity analysis estimates the execution time of the proposed scheme in relation to the input size.

Let T_{24}, T_{27}, and T_{29} be, respectively, the number of iterations required for each of the subgradient methods in lines 24, 27, and 29 of the Algorithm 1 to converge. Furthermore, let J be the length of the lookup table (line 4). It can be seen that the preoptimization phase is $\mathcal{O}(SN_{\rm sc}(J + K))$. Starting with the most inner loop (lines 18 to 23), each

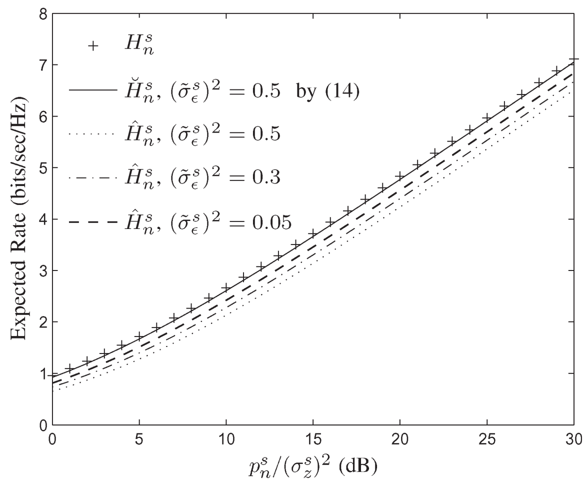

Fig. 3. Expected rate achieved given perfect CSI H_n^s (first scenario), estimated CSI with error ignored $\hat{H}_n^s$ (second scenario), and estimated CSI with error considered $\breve{H}_n^s$ (third scenario—proposed).

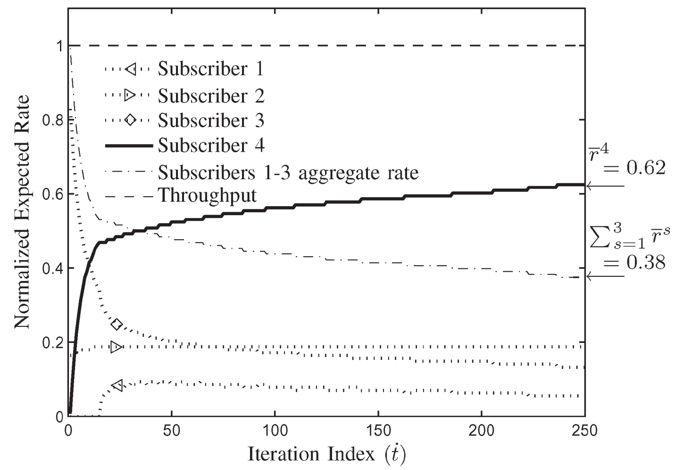

Fig. 4. Expected rate allocated as the scheme evolves *without* the classes' aggregate rate limit constraints.

cycle of the N_{sc} cycles requires KS comparisons, and it takes T_{24} for convergence, resulting in $\mathcal{O}(T_{24}N_{\mathrm{sc}}KS)$. The loop in lines 13 to 16 is $\mathcal{O}(S)$ because it cycles S times. Thus, the optimization phase is $\mathcal{O}(T_{27}T_{29}(S+T_{24}N_{\mathrm{sc}}KS))$. Therefore, the overall resource allocation scheme complexity is $\mathcal{O}(SN_{\mathrm{sc}}(J+K))+\mathcal{O}(T_{27}T_{29}(S+T_{24}N_{\mathrm{sc}}KS))$. Whereas an exhaustive search for allocating subcarriers and rates only is exponential (i.e., $\mathcal{O}((KS)^{N_{\mathrm{sc}}})$), the proposed scheme is linear (i.e., $\mathcal{O}(T_{24}KSN_{\mathrm{sc}})$) in terms of the number of subcarriers[7] available to the cell, which implies a major reduction in the computational complexity.

VI. Performance Evaluations

Simulations are presented in this section to evaluate the proposed scheme's performance in terms of the expected rate gain achieved by considering the CSI imperfection at the MAC layer, the performance in limiting the allocated classes' expected rate to a partition of throughput specified by the CAC scheme, and the satisfaction of OFDMA constraints.

A frequency-selective fading and Rayleigh distributed channel is simulated based on a six-tap time-varying model. A 512 discrete Fourier transform of the delay tap gains generates 512-subcarrier CSI. The subscribers' channels experience distance-dependent fading that follows the power inverse law [27]. In our simulation, the path loss exponent is set to 2. In the network under consideration, the RAU knows the estimated CSI of each subcarrier $\hat{H}_n^s$ for each particular subscriber s in addition to the estimation error variance $(\tilde{\sigma}_\epsilon^s)^2$. Various network parameters' distributions and assumptions are stated in the system model (see Section II).

Fig. 3 shows the expected rate achieved by one subscriber station over 500 samples of the channel for a range of power-to-noise ratios $p_n^s/(\sigma_z^s)^2$. To show the gain achieved by considering the channel estimation error, three scenarios are studied.

1) In the first scenario, the RAU has perfect knowledge of the CSI (i.e., H_n^s), which is shown to achieve the highest expected rate but is not possible in practice.
2) In the second scenario, the RAU assumes the estimate $\hat{H}_n^s$ to be perfect and ignores the estimation and delay error.

   The expected rate decreases as the estimation error variance increases as shown by lines labeled as $\hat{H}_n^s, (\tilde{\sigma}_\epsilon^s)^2 = 0.05,\ 0.0,$ and 0.5 in Fig. 3. Note that the plots are in bits per second per hertz; thus, the difference between the expected rate for the aforementioned two scenarios is scaled by the transmission bandwidth. Therefore, as the transmission bandwidth increases, the loss in expected rate increases in the second scenario.
3) The third scenario represents our proposed model where the RAU has knowledge of the estimate $\hat{H}_n^s$ and the estimation error statistics $(\tilde{\sigma}_\epsilon^s)^2 = 0.5$.

Based on this knowledge and (15), the expected rate (solid line in Fig. 3) is close to the one achieved when the RAU has perfect knowledge of the CSI, as in the first scenario (line marked with $+$).

Whereas the aforementioned simulation shows how a substantial rate gain can be achieved by considering the CSI imperfection, in the following, we show how the proposed resource allocation scheme maintains the aggregate rate limit for each service class in a multiservice network. In addition to the aforementioned PHY-layer simulation setup, consider a cell with four subscribers that are randomly distributed in the cell. The BS offers two classes of service; three of the subscribers subscribe to the first class $\{s \in \mathcal{S}^{(1)} : s = 1, 2, 3\}$, and the fourth subscriber subscribes to the second class $\{s \in \mathcal{S}^{(2)} : s = 4\}$. The first-class subscribers are considered to be less demanding for rate than the second-class subscribers. Thus, the first-class and second-class subscribers are considered, respectively, to have the following utility functions $U^s(\overline{r}^s) = \log(\overline{r}^s)$ for $s = 1$, 2, and 3 and $U^4(\overline{r}^4) = 15\log(\overline{r}^4)$. Intuitively, a large amount of resources is expected to be allocated to the fourth subscriber station if constraints are not imposed on

[7] In OFDMA networks, the number of subcarriers can be as large as 2048.

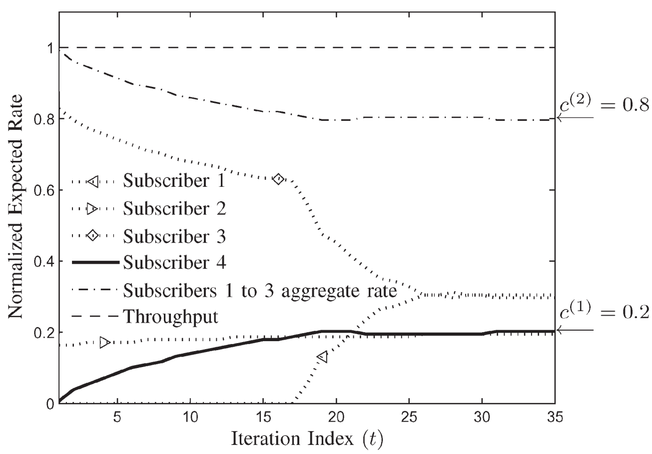

Fig. 5. Expected rate allocated as the scheme evolves *with* the classes' aggregate rate limit constraints (proposed scheme).

each class aggregate rate. This scenario is simulated by setting the Lagrange multipliers of problem (34) to zero, i.e., $\boldsymbol{\lambda} = \mathbf{0}$. Fig. 4 shows the expected rates allocated to subscribers. Subscribers 1–3 subscribe to class 1, while subscriber 4 subscribes to class 2. The rates are normalized to the network throughput over this allocation instance. It is clearly observed that the scheme allocates 62% of the network throughput to the demanding subscriber (i.e., second-class subscriber), while it allocates only 38% to the three subscribers of the first class, as shown by their aggregate rate $\sum_{s \in \mathcal{S}^{(1)}} \overline{r}^s = 0.38$, when the scheme converges. In this scenario, the scheme allocates an even higher rate if the demanding subscribers have a better channel condition than the rest, which may result in not supporting the less demanding subscribers. The difference among the rates allocated to the first-class subscribers is due to the difference in their subcarriers gains. Our proposed scheme constrains the aggregate rate allocated to each class subscriber to its limit reported by the CAC scheme while satisfying the power and subcarriers exclusive allocation constraints.

Consider that the CAC scheme limits the first-class aggregate rate to 80% and the second class to 20% (i.e., $c^{(1)} = 0.8$ and $c^{(2)} = 0.2$). We rerun the simulation with the same network parameters (i.e., utility functions, channels, and subscribers), while $\boldsymbol{\lambda}$ is evaluated by (34). Fig. 5 shows the expected rates allocated to subscribers when limits are imposed on the classes' aggregate rates. Subscribers 1–3 subscribe to class 1, while subscriber 4 subscribes to class 2. We observe that, at convergence, the rate allocated to the demanding subscriber is reduced from 62% to 20%. The 42% that became available is now shared among the first-class subscribers; thus, their aggregate rate increases from 38% to 80%. Both classes' allocated rates are limited to their capacities specified by the CAC scheme that satisfies the QoS requirements of each class of service. In both scenarios, the proposed scheme exclusively allocates each subcarrier to one subscriber and maintains a limit of P_{BS} on the power allocated to all subscribers.

Next, we demonstrate the performance of the proposed scheme on the uplink mode. We consider a single cell with six subscriber stations. The first three subscribers are more demanding than the last three; thus, their utility functions are

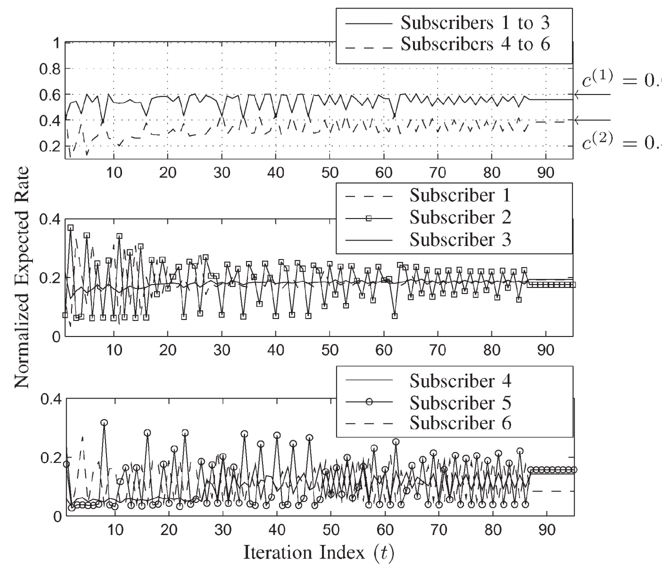

Fig. 6. Normalized expected rate allocated as the scheme evolves to (top) each class, (middle) subscribers of class 1, and (bottom) subscribers of class 2.

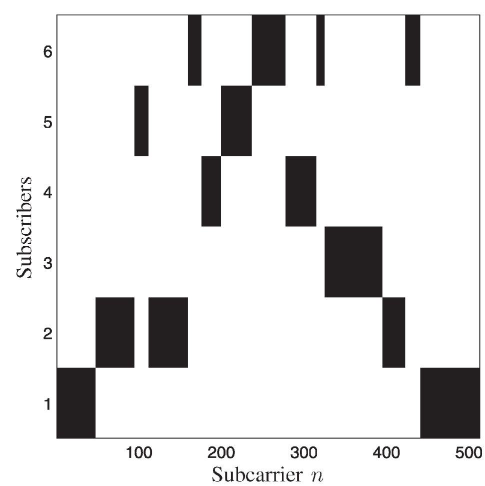

Fig. 7. Subcarrier allocation to each subscriber at convergence.

considered to be, respectively, $U^s(\overline{r}^s) = 5\log(\overline{r}^s)$ for $s = 1, 2,$ and 3, and $U^s(\overline{r}^s) = \log(\overline{r}^s)$ for $s = 4$, 5, and 6. In addition, they subscribe to two different classes, i.e., $\{s \in \mathcal{S}^{(1)} : s = 1, 2, 3\}$ and $\{s \in \mathcal{S}^{(2)} : s = 4, 5, 6\}$. In the uplink mode, each subscriber has a power constraint that corresponds to its available battery power (i.e., P_s); thus, the power allocated to each subscriber has to be limited to P_s. Subscribers are simulated to have equal power constraints for simplicity. The first and second classes of service aggregate rates, which are determined by the CAC scheme, are assumed to be $c^{(1)} = 60\%$ and $c^{(1)} = 40\%$, respectively. Fig. 6 shows the evolutions of expected rate allocation for each subscriber and the aggregate rate for each class. Similar to the downlink mode, the presented scheme limits the aggregate rate of each class to the partition of the throughput allocated to it. It is observed that the convergence speed for uplink is slower than that for downlink, as shown in Fig. 5. This decrease in convergence speed is due to the increase in the number of power constraints in uplink compared to that in downlink. To investigate the exclusive subcarrier assignment, the checkerboard plot in Fig. 7 shows that each subcarrier of

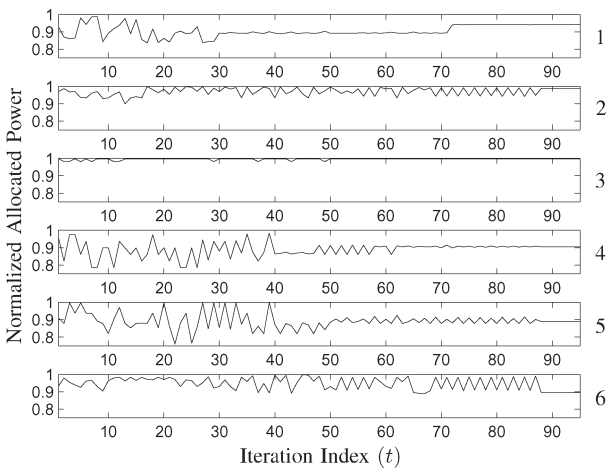

Fig. 8. Normalized allocated power to each subscriber station in the uplink mode (i.e., $\sum_{n \in \mathcal{N}_s} p_n^s / P_s$, for $s = 1, \ldots, 6$) as the scheme evolves. Numbers on the right indicate the subscriber index.

the 512 subcarriers is allocated to a subscriber station; black areas indicate the range of subcarriers allocated to a subscriber station. Similar performance in allocating subcarriers has also been observed for the downlink mode. In addition, the normalized power allocated to each subscriber (i.e., $\sum_{n \in \mathcal{N}_s} p_n^s / P_s$, for $s = 1, \ldots, 6$) is shown in Fig. 8. It can be seen that the power allocated to each subscriber never exceeds its power limit P_s, for $s = 1, \ldots, 6$. The power allocated to some subscribers is more than the power allocated to the rest because of their low channel gain on their allocated subcarriers.

VII. Conclusion

A novel resource-allocation scheme for OFDMA-based PMP networks has been proposed. The proposed scheme solves the resource allocation problem in the dual domain by decomposing it into several subproblems at the MAC layer while considering channel estimation and delay errors at the PHY layer. Simulation results show that the proposed scheme satisfies OFDMA network constraints (i.e., exclusive subcarrier and maximum power allocations) in addition to maintaining the classes' aggregate expected rate limits, which are imposed by a CAC unit to satisfy the QoS requirements of each class. The results supports our theoretical claim that the proposed scheme achieves an expected rate close to the one achieved when the RAU has perfect knowledge of the channel. These results demonstrate that a significant gain can be achieved by taking the CSI imperfection into consideration. Our future research work will focus on the development of a queuing model to analyze the performance of the proposed scheme in terms of the blocking probability and the average number of supported connections.

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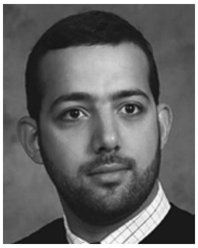

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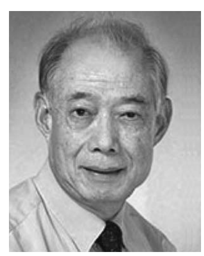

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