OFDMA Downlink Resource Allocation via ARQ Feedback

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***Abstract*—In OFDMA downlink resource allocation, the base station exploits knowledge of the users' channel realizations in order to opportunistically assign users to appropriate subchannels, as well as to optimize the rates and powers across those subchannels. Because reverse-link bandwidth is scarce, the base station's channel knowledge must be obtained via some form of limited feedback. While the typical assumption for this feedback is that it comes in the form of heavily quantized SNR estimates computed at the user terminals, we propose to use ACK/NAK feedback that is already provided by higher-layer ARQ. Towards this aim, we propose a greedy resource allocation scheme, based on distributional (rather than point) estimates of SNR. We also show how these SNR distributions can be updated recursively for Markov time-varying channels.**[1]

I. Introduction

In the downlink of a wireless orthogonal frequency division multiple access (OFDMA) system, the base station (BS) must deliver data to a pool of users whose channels vary in both time and frequency. Since bandwidth and power resources are limited, the BS would like to use them most efficiently, e.g., by pairing users with strong subchannels and by distributing power across users in the most effective manner. At the same time, the BS must maintain per-user quality-of-service (QoS) constraints, such as a minimum reliable rate for each user. Overall, the BS faces a resource allocation problem that aims to maximize an efficiency-related quantity (like sum throughput) subject to certain constraints. This problem has addressed extensively in a number of publications, e.g., [1]–[7]. In [1], a subcarrier, bit and power allocation algorithm is developed to minimize power consumption while maintaining a data rate requirement. [2] proposed a low complexity power adaptation algorithm to maximize the total data rate achieved by all users. They found that the data rate of a multiuser OFDM system is maximized when each subcarrier is assigned to only one user with the best channel gain for that subcarrier and the transmit power is distributed over the subcarriers by a water-filling policy. In [5], a weighted sum ergodic capacity maximization problem was formulated to exploit time, frequency, and multi-user diversity while enforcing different notions of fairness. Non-convex optimization problems of weighted sum-rate maximization and weighted sum-power minimization were solved using the Lagrange dual decomposition method in [7].

All these previous works assume the availability of perfect channel state information at the transmitter. In order to exploit the favorable channel conditions due to channel variations in OFDMA resource allocation, the BS must have adequate knowledge of the current channel states. It is very difficult, however, to supply the BS with full channel state information (CSI), i.e., the exact channel gains of all users at all subchannels, since the bandwidth of reverse channels is scarce. Hence, practical resource allocation schemes must use some form of limited feedback. In conventional resource allocation schemes, the limited feedback comes in the form of heavily quantized SNR estimates computed at the user terminals, and this feedback might come intermittently from only a subset of the previously scheduled users [8]–[10]. In [8], channel prediction was used to overcome the effect of outdated channel information on the performance of adaptive OFDM systems. The effect of channel estimation error, as well as that of outdated channel state information, on the performance of adaptive OFDM for the variable bit rate case was studied in [9]. In [10], a power allocation algorithm for OFDM rate maximization was developed based on average and outage capacity criteria. It was shown that the outage probability may be significantly reduced due to CSI errors. These works focused on single-user OFDM scenarios. For multiple users employing OFDMA and limited feedback, much less work has been done. In [11], the impact of channel estimation error on the performance of OFDMA was studied. In [12], an adaptive resource allocation framework to cope with feedback delay and outdated channel state information was studied.

We propose to use a different form of feedback, namely ARQ (automatic repeat request) feedback, that is already present in existing wireless systems for multiuser OFDMA systems. Although the theory developed can be easily extended to other forms of limited feedback, we will show that, even with ARQ feedback, significant gains in terms of throughput can be obtained. ARQ is the standard mechanism for providing the transmitter with an acknowledgement (ACK) that a given packet has been correctly received, or a negative acknowledgement (NAK) in the case that it has not. Though ACK/NAKs do not provide explicit channel information, they can be used to infer channel quality when considered in conjunction with the corresponding transmission rates [13], [14]. For example, if a NAK was received for a particular packet, then it is likely that the channel signal-to-noise ratio (SNR) was below than that required to support the used transmission rate for that particular packet.

Since transmission rates and powers are usually considered

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to be physical-layer quantities, while ARQ is usually considered to be a higher-layer mechanism, the use of ARQ for resource allocation can be regarded as a cross-layer technique. We note that, if ARQ is used to supplement conventional forms of limited feedback for physical-layer resource allocation, the associated performance increase comes essentially "for free", since ARQ is already present. However, one could also imagine using ARQ to *replace* conventional forms of limited feedback, thereby reducing both reverse-channel bandwidth and overall system complexity.

II. Problem Setup

We consider a packetized downlink OFDMA system with N subchannels and K active users. Each user's channel is assumed to be be time-invariant over the packet duration but is allowed to vary across packets in a Markovian manner. Henceforth, "time" will refer to the packet index. At each time, the base station must decide — for each subchannel — which user to schedule, which modulation-and-coding scheme (MCS) to use, and how much power to allocate. We assume M choices of MCS, where MCS index $m \in \{1, \ldots, M\}$ corresponds to transmission rate r_m and packet error rate $\epsilon_m(\gamma, p) = a_m e^{-b_m p \gamma}$ under transmit power p and SNR γ. Specifically, we use $p^t_{n,k,m}$ and $\gamma^t_{n,k}$ to denote the power allocated to and the SNR experienced by, respectively, user k at MCS m on subchannel n at time t.

We denote, by $U(g)$, the concave utility function which represents the utility attained by a user that achieves goodput g. At any given point in time, t, our resource allocation problem is designed to obtain the joint power, rate, and subchannel allocation that maximizes the total conditional expected future utility given the feedback received until that time, subject to an instantaneous sum-power constraint. We now define an allocation indicator variable $I^t_{n,k,m} \in \{0, 1\}$ that takes the value 1 if subchannel n is allocated to user k with MCS m at time t, and 0 otherwise. In the sequel, we use $[I^t_{n,k,m}]$ to denote the $N \times K \times M$-dimensional matrix of indicators (at time t), and $[p^t_{n,k,m}]$ to denote the corresponding matrix of powers. Then, the finite horizon problem can be stated as:

$$\max_{\substack{[I^\tau_{n,k,m}]\in\mathcal{I} \\ [p^\tau_{n,k,m}]\in\mathcal{P}}} \sum_{\tau=t+1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{m=1}^{M} \Big[I^\tau_{n,k,m} \times \\ \mathrm{E}\Big\{ U\big((1 - a_m e^{-b_m p^\tau_{n,k,m} \gamma^\tau_{n,k}}))r_m\big) \big| \boldsymbol{F}^t_1 \Big\} \Big] \tag{1}$$

$$\text{s.t.} \quad \sum_{n,k,m} I^\tau_{n,k,m} p^\tau_{n,k,m} \le P_{max}, \quad \forall \tau, \tag{2}$$

where $\mathcal{I} \subset \{0, 1\}^{N\times K\times M}$ is the set of feasible indicator matrices that guarantee that no more than one user is allocated to a subchannel at a time, $\mathcal{P} := \{\mathbb{R}^+ \cup 0\}^{N\times K\times M}$ is the set of non-negative power matrices, and $\boldsymbol{F}^t_1$ denotes the set of feedback matrices (for all users and subchannels) obtained by the base station from time 1 to t. The constraint (2) does not allow the total power usage on all subchannels exceed P_{max} at any instant. One can observe that the resource allocation made on the basis of ACK/NAK at time t affects not only the immediate utility, but also the probabilities of subsequent ACK/NAK feedbacks, and thereby the expected future utilities. For example, if the assigned transmission parameters are likely to yield a low packet error rate (i.e., "exploitation"), little will be learned about the changing channel state. On the other hand, if the allocation is more suited to estimating channel conditions rather than maximizing instantaneous goodput (i.e., "exploration"), then the instantaneous expected utility may be low. This illustrates the classic tradeoff between exploration and exploitation that is faced in the optimization problem (1)-(2). More on this tradeoff can be found in [15].

The optimal solution to the problem defined in (1)-(2) can be obtained through partially observable Markov decision processes (POMDP) [15]. Due to its extremely high complexity (i.e., PSPACE complete), POMDPs are impractical to implement for our problem [16]. We, therefore, propose a greedy suboptimal approach that allocates resources to maximize the sum utility for the current instant without considering the effects on the future (i.e., "exploitation"). A similar greedy approach was introduced in [14] for the single-user single-channel scenario. There, it was found that greedy rate allocation achieves a performance that is reasonably close to optimal under practical scenarios. We now extend this idea to the multi-user multi-channel problem under consideration. The greedy resource allocation problem at time t is formally stated as follows:

$$\max_{\substack{[I^{t+1}_{n,k,m}]\in\mathcal{I} \\ [p^{t+1}_{n,k,m}]\in\mathcal{P}}} \sum_{n=1}^{N} \sum_{k=1}^{K} \sum_{m=1}^{M} \Big[I^{t+1}_{n,k,m} \times \\ \mathrm{E}\Big\{ U\big((1 - a_m e^{-b_m p^{t+1}_{n,k,m} \gamma^{t+1}_{n,k}})r_m\big) \big| \boldsymbol{F}^t_1 \Big\} \Big] \\ \text{s.t.} \quad \sum_{n,k,m} I^{t+1}_{n,k,m} p^{t+1}_{n,k,m} \le P_{max}. \tag{3}$$

In the next section, we will propose an algorithm to solve (3).

III. Greedy Resource Allocation Algorithm

In the sequel, for the sake of simplicity, we take the utility function in (3) to be the identity function $U(x) = x$. However, we note that our analysis can be easily extended to the case of more general concave utility functions. To proceed, we write the Lagrangian associated with (3) as follows:

$$L^{t+1}(\mu) = \mu\Big(\sum_{n,k,m} I^{t+1}_{n,k,m} p^{t+1}_{n,k,m} - P_{max} \Big) \tag{4} \\ - \sum_{n,k,m} \mathrm{E}\Big\{ I^{t+1}_{n,k,m} (1 - a_m e^{-b_m p^{t+1}_{n,k,m} \gamma^{t+1}_{n,k}}) r_m \big| \boldsymbol{F}^t_1 \Big\},$$

where the expectation is over $p(\gamma^{t+1}_{n,k} | \boldsymbol{F}^t_1)$. To simplify the notation, we suppress the t superscripts for the remainder of this section. The associated unconstrained problem can then be stated as:

$$\max_{\mu>0} \min_{[I_{n,k,m}]\in\mathcal{I}, [p_{n,k,m}]\in\mathcal{P}} L(\mu). \tag{5}$$

In the sequel, we find it useful to denote the μ-optimal $N \times K \times M$-dimensional matrices of indicators and powers as

$$\big(\mathcal{I}^*(\mu), \mathcal{P}^*(\mu)\big) \;:=\; \arg\min_{[I_{n,k,m}]\in\mathcal{I},[p_{n,k,m}]\in\mathcal{P}} L(\mu). \quad (6)$$

Furthermore, we write $\mathcal{I}^*(\mu) = [I^*_{n,k,m}(\mu)]$ and $\mathcal{P}^*(\mu) = [p^*_{n,k,m}(\mu)]$, and define the optimal total power for any fixed value of μ as

$$P^*_{tot}(\mu) \;:=\; \sum_{n,k,m} I^*_{n,k,m}(\mu) p^*_{n,k,m}(\mu). \quad (7)$$

Lemma 1: The value $P^*_{tot}(\mu)$ is monotonically non-increasing in μ.

Proof: See [17] ■

Based on this lemma, we can find the value of μ optimizing (5) as follows. We start with a very small positive value of μ, for which the power constraint will not be met. Then we gradually increase the value of μ until the power constraint is met with equality. Lemma 1 guarantees that the unique optimal μ will be attained when the power constraint is met with equality.

Recall that solving the unconstrained problem involves finding $\big(\mathcal{I}^*(\mu), \mathcal{P}^*(\mu)\big)$ for each value of μ. For this, we rewrite the problem as follows. Let us define

$$V_{n,k,m}(p) \;:=\; \mu p - \mathrm{E}\left\{(1 - a_m e^{-b_m p \gamma_{n,k}}) r_m \mid \boldsymbol{F}_1^t\right\}, \quad (8)$$

so that

$$L(\mu) \;=\; -\mu P_{max} + \sum_{n,k,m} I_{n,k,m} V_{n,k,m}(p_{n,k,m}). \quad (9)$$

Note that $V_{n,k,m}(p)$ is convex and its minimization over p can be solved using KKT conditions, i.e., $\frac{\partial}{\partial p} V_{n,k,m}(p) = 0 \;\forall n,k,m$. This implies that

$$\mu \;=\; a_m b_m r_m \,\mathrm{E}\{\gamma_{n,k} e^{-b_m p_{n,k,m} \gamma_{n,k}} | \boldsymbol{F}_1^t\} \quad (10)$$

Finally, subchannel n is allocated to the user/MCS combination (k,m) whose value of $V_{n,k,m}$ is smallest.

Based on the analysis provided above, we propose the following algorithm:

1) Initialize μ at a very small positive value.
2) For each subcarrier $n = 1, \ldots, N$:
   a) For each (k,m), calculate $p_{n,k,m}$ from (10). Notice that $p_{n,k,m}$ describes the power consumed by assigning subcarrier n to user k with MCS m. If $p_{n,k,m} < 0$, then force $p_{n,k,m} = 0$.
   b) For each (k,m), calculate $V_{n,k,m}(p_{n,k,m})$ via (8).
   c) Find $(k^*, m^*) = \mathrm{argmin}_{(k,m)} V_{n,k,m}$ and set $I_{n,k,m} = 1$ for $(k,m) = (k^*, m^*)$ and $I_{n,k,m} = 0$ for all $(k,m) \neq (k^*, m^*)$. Consequently set $p_n = p_{n,k^*,m^*}$ (i.e., the subchannel is allocated to the user whose $V_{n,k,m}$ is minimum).
3) If $\sum_n p_n > P_{max}$, then increase μ by a very small amount and repeat step 2), else end.

Upon termination, we get $\sum_n p_n \approx P_{max}$. (The situation $\sum_n p_n < P_{max}$ would arise if the initial μ was too large or if the last increase in μ was too large).

IV. SNR Update Using ACK/NAKs

The previous section gives details of the proposed greedy algorithm for resource allocation. For its implementation, one needs to compute the distribution $p(\gamma^{t+1}_{n,k} | \boldsymbol{F}_1^t)$ at each time t for all user/subchannel combinations (k,n). Let the channel impulse response coefficients for user k at time t be collected in the vector $\boldsymbol{h}_k^t = [h^t_{1,k}, \ldots, h^t_{L,k}]^\intercal \in \mathbb{C}^L$, where L is the impulse response length and $\intercal$ denotes transpose. The frequency-domain channel response $\boldsymbol{H}_k^t = [H^t_{1,k}, \ldots, H^t_{N,k}]^\intercal \in \mathbb{C}^N$ is then

$$\boldsymbol{H}_k^t \;=\; \boldsymbol{G}\boldsymbol{h}_k^t, \quad (11)$$

where $\boldsymbol{G} \in \mathbb{C}^{N\times L}$ is determined by the OFDMA scheme. For example, $\boldsymbol{G}$ could be the first L columns of a DFT matrix. In any case, we can write

$$p(\gamma^{t+1}_{n,k} | \boldsymbol{F}_1^t) = \int_{\boldsymbol{h}_k^{t+1}} p(\gamma^{t+1}_{n,k} | \boldsymbol{h}_k^{t+1}) p(\boldsymbol{h}_k^{t+1} | \boldsymbol{F}_1^t), \quad (12)$$

noticing that $p(\gamma^{t+1}_{n,k} | \boldsymbol{h}_k^{t+1})$ is a Dirac-delta function because the SNR $\gamma^t_{n,k} = C|H^t_{n,k}|^2$ is a deterministic function of the impulse response $\boldsymbol{h}_k^{t+1}$. By assumption, $\boldsymbol{h}_k^t$ is Markovian. Consequently, the posterior distribution $p(\boldsymbol{h}_k^{t+1} | \boldsymbol{F}_1^t)$ can be rewritten using the Markov property and Bayes rule, respectively, as follows:

$$p(\boldsymbol{h}_k^{t+1} | \boldsymbol{F}_1^t) \;=\; \int_{\boldsymbol{h}_k^t} p(\boldsymbol{h}_k^{t+1} | \boldsymbol{h}_k^t) p(\boldsymbol{h}_k^t | \boldsymbol{F}_1^t), \quad (13)$$

$$p(\boldsymbol{h}_k^t | \boldsymbol{F}_1^t) \;=\; \frac{p(\boldsymbol{f}_k^t | \boldsymbol{h}_k^t) p(\boldsymbol{h}_k^t | \boldsymbol{F}_1^{t-1})}{\int_{\boldsymbol{h'}_k^t} p(\boldsymbol{f}_k^t | \boldsymbol{h'}_k^t) p(\boldsymbol{h'}_k^t | \boldsymbol{F}_1^{t-1})}, \quad (14)$$

where $\boldsymbol{f}_k^t = [f^t_{1,k}, \ldots, f^t_{N,k}]^\intercal$ is the vector of feedbacks corresponding to user k at time t (for all subchannels), and where $f^t_{i,k} \in \{0, 1, \emptyset\}$. Here, 0 denotes NAK, 1 denotes ACK, and $\emptyset$ denotes void (i.e., no feedback received). We assume that the receiver generates ARQ feedbacks independently across subchannels, so that

$$p(\boldsymbol{f}_k^t | \boldsymbol{h}_k^t) = \prod_{n=1}^{N} p(f^t_{n,k} | \gamma^t_{n,k}(\boldsymbol{h}_k^t)) \quad (15)$$

where

$$p(f^t_{n,k} = f | \gamma^t_{n,k}) \quad (16)$$
$$= \begin{cases} \sum_m I^t_{n,k,m} a_m e^{-b_m p^t_{n,k,m} \gamma^t_{n,k}}, & f = 0 \\ \sum_m I^t_{n,k,m} a_m \left(1 - e^{-b_m p^t_{n,k,m} \gamma^t_{n,k}}\right), & f = 1 \\ 1 - \sum_m I^t_{n,k,m}, & f = \emptyset. \end{cases}$$

Equations (12)-(16) give a straightforward method of *recursively* updating the SNR distributions from the new feedbacks obtained at each time instant. In summary, we perform the following steps at each time t. For each user k, and using $p(\boldsymbol{h}_k^t | \boldsymbol{F}_1^{t-1})$ calculated at the previous time step,

1) Obtain feedbacks $\boldsymbol{f}_k^t \in \{0, 1, \emptyset\}^N$,
2) Compute $p(f^t_{n,k} \mid \gamma^t_{n,k}(\boldsymbol{h}_k^t))$ for all n on a lattice of points for $\boldsymbol{h}_k^t$ using the error-rate rule (16),

3) Compute $p(\boldsymbol{h}_k^t \mid \boldsymbol{F}_1^t)$ on a lattice of points for $\boldsymbol{h}_k^t$ using the Bayes-rule steps (14)-(15).
4) Compute $p(\boldsymbol{h}_k^{t+1} \mid \boldsymbol{F}_1^t)$ on a lattice of points for $\boldsymbol{h}_k^t$ using the Markov-prediction step (13),
5) For each n, compute $p(\gamma_{n,k}^{t+1} \mid \boldsymbol{F}_1^t)$ on a grid of points for $\gamma_{n,k}^{t+1}$ via the lattice-to-grid conversion step (12).

V. Simulation Setup and Results

In this section, we evaluate the performance of our greedy algorithm and compare it with the optimal solution. We assume that there are $K = 2$ users, $N = 2$ available OFDMA subchannels, and channel impulse response lengths of $L = 2$. Each impulse response coefficient varies according to the following Markov model, independently of the other coefficients:

$$h_{l,k}^{t+1} = (1-\alpha)h_{l,k}^t + \alpha w_{l,k}^t, \quad w_{l,k}^t \sim \mathcal{CN}(0,1), \qquad (17)$$

where α is a known constant that determines the fading rate. For the modulation matrix $\boldsymbol{G}$ in (11), we used[2]

$$\boldsymbol{G} = \begin{bmatrix} \sqrt{1/3} & \sqrt{2/3} \\ -\sqrt{1/3} & \sqrt{2/3} \end{bmatrix}. \qquad (18)$$

When computing packet error rate $\varepsilon_m(\gamma, p)$, we used $a_m = 1\ \forall m$ and chose b_m to match the error rate of m-QAM at 25 dB (based on equation number (3) in [14] considering 25 symbols per packet). The performance of the proposed greedy algorithm is compared to two reference schemes. The "round robin" scheme does not use any feedback and allocates the users in a round robin fashion on each subchannel. The "global genie" scheme solves the optimization problem (1)-(2) assuming perfect knowledge of all SNRs at all times. In this case, the problem (1)-(2) simplifies significantly. In particular, the conditional expectation vanishes, so that goodput maximization at future time instants is no longer a function of the current resource allocation. In other words, the perfect-CSI solution is greedy in nature. Moreover, the perfect-CSI solution serves as an upper bound to the optimal POMDP solution of the limited-feedback optimization problem. These claims can be rigorously proved by straightforward extensions of the single-user single-channel proofs given in [14].

Figure 1 shows the change of rate and estimated SNR as a function of time t for a typical realization, when $\alpha = 10^{-2}$. The top two plots show, for the first subchannel (i.e., $n = 1$), the allocated rate r_m and the error bars on the estimated mean of $\gamma_{n,k_*,t}$ versus time t. The bottom two plots show the same for the second subchannel (i.e., $n = 2$). Focusing on the first subchannel, it can be seen that, after reception of an ACK (denoted by the point marker "$\cdot$"), the SNR estimate always increases. This is expected because an ACK conveys that the channel was good enough to support the previously allocated rate. It can also be seen that an increase in estimated-SNR results in a subsequent increase in rate. After reception of a NAK, however, the SNR estimate and the subsequent rate both decrease. Although it is not shown in the figure, we have observed that, for an adequately dense set of rates, the optimal powers remain relatively constant. From the SNR estimation subplots in Fig. 1, it is clear that the algorithm tracks the SNRs reasonably well.

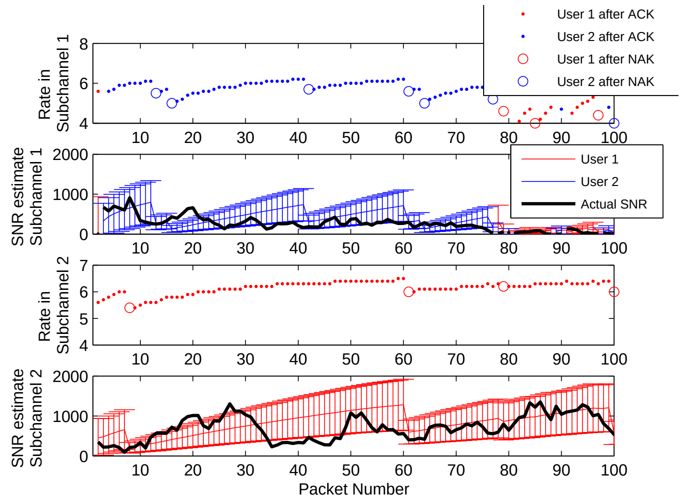

Fig. 1. Typical rates and SNR estimates versus time t.

Figure 2 shows the instantaneous goodput summed over both subchannels versus time t for a typical realization, when $\alpha = 10^{-2}$. While the greedy and round-robin algorithms start from the same (feedback ignorant) starting point, it can be seen that the greedy algorithm quickly optimizes the resource allocation parameters, approaching near to the performance of the global genie within about 20 packets. For this simulation, the fading rate $\alpha = 10^{-2}$ was chosen fast enough to make the SNRs somewhat difficult to track, which led the greedy algorithm to select non-optimal allocations at some times.

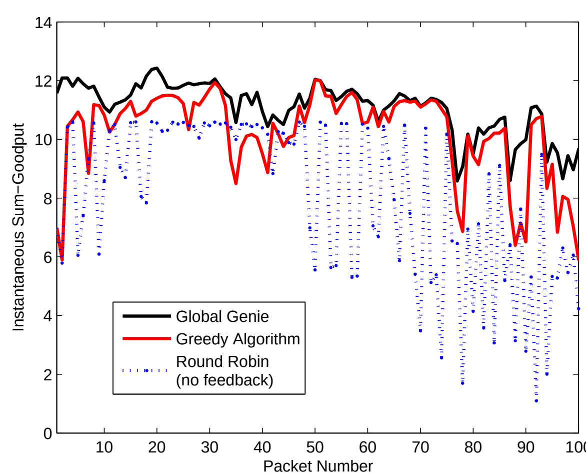

Fig. 2. Typical instantaneous sum-goodput versus time t.

To investigate the relationship between steady-state goodput and channel fading rate α, Fig. 3 plots steady state goodput

[2]We did not choose a DFT matrix for $\boldsymbol{G}$ because a 2×2 DFT matrix has orthogonal rows which would cause the subchannels gains to be statistically independent. This would prevent the algorithm from inferring the value of one subchannel SNR from the other.

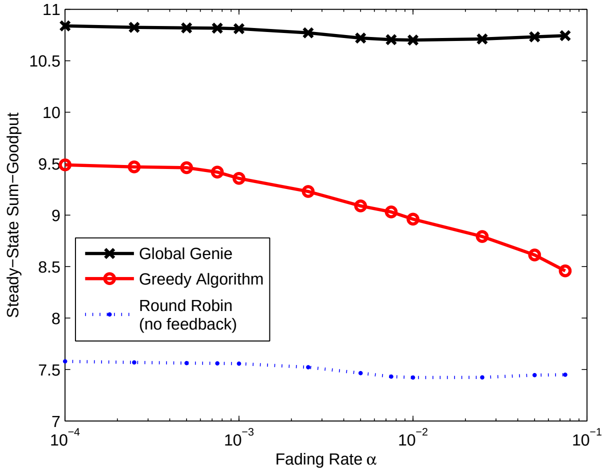

Fig. 3. Steady-state sum-goodput versus fading rate α.

(summed across subchannels) as a function of fading rate α. For each point in the plot, we averaged 500 realizations of 200-packet duration. For each α, the constant C in the relationship $\gamma_{n,k}^t = C|H_{n,k}^t|^2$ was chosen to keep the mean SNR at 25 dB. From the figure, it can be seen that the proposed greedy algorithm achieves significantly better steady-state goodput compared to the fixed rate scheme, for all fading rates. However, the improvement decreases with increase in channel fading rate α. This behavior is expected, because as α increases it becomes more difficult to infer the SNR reliably from previous ARQ feedback. From Fig. 3, we do, however, see a performance gap between the greedy algorithm and global genie, even for low values of α. We attribute this gap to the suboptimal nature of greedy adaptation under ARQ feedback. In particular, the greedy algorithm tends to continue scheduling a user whose channel remains "better than average," because the inferred SNRs of not-recently-scheduled users quickly revert to the apriori (i.e., "average") SNR. The problem is that there may exist a not-recently-scheduled user with a very good subchannel (that the greedy algorithm is not aware because of not doing "exploration").

VI. CONCLUSION

In this paper, we proposed a greedy algorithm for user, rate, and power allocation for the Markov OFDMA downlink, based only on ARQ feedback. Using ARQ feedback collected at each packet time, our algorithm recursively updates the SNR distribution for every combination of user and subchannel, and uses these distributions to optimize the user, rate, and power for each subchannel in order to maximize a goodput-based utility subject to an instantaneous sum-power constraint. Numerical experiments suggest that our system can achieve a significant goodput improvement compared to a non-adaptive round-robin system, despite the coarse nature of the CSI inferred from ARQ feedback. For example, our algorithm recovers about 60% of the difference in goodput between the no-CSI and full-CSI cases with slowly fading channels, and about 40% of the difference with quickly fading channels.

REFERENCES

[1] C. Y. Wong, R. S. Cheng, K. B. Letaief, and R. D. Murch, "Multiuser OFDM with adaptive subcarrier, bit and power allocation," *IEEE J. Select. Areas In Commun.*, vol. 17, pp. 1747–1758, Oct. 1999.

[2] J. Jang and K. B. Lee, "Transmit power adaptation for multiuser OFDM systems," *IEEE J. Select. Areas In Commun.*, vol. 21, pp. 171–178, Feb. 2003.

[3] T. J.Willink and P. H.Wittke, "Optimization and performance evaluation of multicarrier transmission," *IEEE Trans. Inform. Theory*, vol. 43, pp. 426–440, Mar. 1997.

[4] L. M. C. Hoo, B. Halder, J. Tellado, and J. M. Cioffi, "Multiuser transmit optimization for multicarrier broadcast channels: Asymptotic FDMA capacity region and algorithms," *IEEE Trans. Commun.*, vol. 52, pp. 922–930, Jun. 2004.

[5] I. C. Wong and B. L. Evans, "Optimal OFDMA resource allocation with linear complexity to maximize ergodic weighted sum capacity," *IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, vol. 3, pp. 601–604, 15-20 Apr. 2007.

[6] I. C. Wong and B. L. Evans, "Optimal OFDMA subcarrier, rate, and power allocation for ergodic rates maximization with imperfect channel knowledge," *Proc. IEEE Int. Conf. on Acoustics, Speech, and Signal Processing*, vol. 3, pp. 89–92, Apr. 2007.

[7] K. Seong, M. Mohseni, and J. M. Cioffi, "Optimal resource allocation for OFDMA downlink systems," *Proc. IEEE International Symposium on Information Theory*, pp. 1394–1398, Jul. 2006.

[8] M. R. Souryal and R. L. Pickholtz, "Adaptive modulation with imperfect channel information in OFDM," *Proc. Int. Conf. on Communications*, vol. 6, pp. 1861–1865, Jun. 2001.

[9] S. Ye, R. S. Blum, and L. J. Cimini, "Adaptive modulation for variable rate OFDM systems with imperfect channel information," *Proc. IEEE Vehicular Technology Conf.*, vol. 2, pp. 767–771, 2002.

[10] Y. Yao and G. B. Giannakis, "Rate-maximizing power allocation in OFDM based on partial channel knowledge," *IEEE Trans. Wireless Commun.*, vol. 4, pp. 1073–1083, May. 2005.

[11] I. C. Wong and B. L. Evans, "OFDMA downlink resource allocation for ergodic capacity maximization with imperfect chanel knowledge," *IEEE GLOBECOM*, pp. 3729–3733, Nov. 2007.

[12] A. Ayaz and M. Assaad, "Margin adaptive resource allocation in downlink OFDMA system with outdated channel state information," *Proc. of IEEE PIMRC*, Sept. 2009.

[13] A. K. Karmokar, D. V. Djonin, and V. K. Bhargava, "POMDP-based coding rate adaptation for type-I hybrid ARQ systems over fading channels with memory," *IEEE Trans. Wireless Commun.*, vol. 5, pp. 3512–3523, Dec. 2006.

[14] R. Aggarwal, P. Schniter, and C. E. Koksal, "Rate adaptation via link-layer feedback for goodput maximization over a time-varying channel," *IEEE Trans. Wireless Commun.*, vol. 8, pp. 4276–4285, Aug. 2009.

[15] G. E. Monahan, "A survey of partially observable Markov decision processes: Theory, models, and algorithms," *Management Science*, vol. 28, pp. 1–16, Jan. 1982.

[16] C. H. Papadimitriou and J. N. Tsitsiklis, "The complexity of Markov decision processes," *Mathematics of Operations Research*, vol. 12, no. 3, pp. 441–450, 1987.

[17] R. Aggarwal, M. Assaad, C. E. Koksal, and P. Schniter, "OFDMA downlink resource allocation via ARQ feedback," journal manuscript in preparation.