Downlink Beamforming Algorithms with Inter-Cell Interference in Cellular Networks

Tianmin Ren and Richard J. La *Member, IEEE*

***Abstract*— We study the issue of handling unknown inter-cell interference in multi-cell environments with antenna arrays at the base stations. First, we demonstrate that the presence of unknown inter-cell interference that cannot be predicted accurately, can significantly degrade the system performance when unaccounted for. Second, we propose two algorithms that are aimed at providing a quality-of-service guarantee in the form of packet error rate (PER) in the presence of unknown inter-cell interference. The first algorithm is based on a derived expression for average PER as a function of the distribution of experienced signal to interference and noise ratio and dynamically adjusts the input parameters based on the channel condition and interference. The second algorithm makes use of the observation that the distribution of inter-cell interference experienced by a mobile can be well approximated by a log-normal distribution. We demonstrate that these algorithms achieve the target PER.**

***Index Terms*— Array signal processing, interference, power control.**

I. Introduction

INCREASING demand for data applications over wireless networks has stimulated much research on improving network capacity and providing quality of service (QoS) guarantees over unreliable, time-varying wireless channels with limited bandwidth. Many approaches that reuse the communication resources in time, frequency and/or space domain, have been proposed to this end. Among these approaches smart antennas that exploit the spatial diversity of the mobiles, are emerging as one of the most promising solutions.

Most of previous research on downlink beamforming using antenna arrays at the base stations in a cellular network can be categorized into two classes. The first class of research focuses on designing algorithms for computing the beamforming weights (*i.e.,* relative amplitudes and phase shifts of antenna elements) and transmission power for each user given a set of scheduled users [17], [19], [20]. This is often modeled as an optimization problem, where the objective is to minimize the total transmission power subject to the constraint that each user's signal to interference and noise ratio (SINR) requirement is satisfied. The second class of research focuses on the medium access control (MAC) layer with physical layer user separability constraints. The goal of this class of research is to maximize the number of scheduled users while satisfying their SINR constraint. This problem is extended to be combined with other multi-user access schemes such as TDMA, OFDM and CDMA in [6]. The performance of various beamforming techniques has also been studied in the context of UMTS [11], [13], [14].

Most of previous work on adaptive downlink beamforming focuses on either (i) a single cell network where inter-cell interference is neglected or (ii) a multiple cell network where the calculation of the beamforming weights and transmission powers for all BSs is conducted by a *central* resource manager. In the latter it is assumed that the inter-cell interference can be computed by the central resource manager and is known to the beamforming algorithm. In both cases the beamforming algorithm attempts to achieve a fixed target SINR for every scheduled user assuming that the total interference, including inter-cell interference, at each user can be accurately estimated. However, centralized resource allocation is becoming impractical due to increasing complexity of sophisticated wireless resource allocation algorithms, the large size of the network, and growing interest to move the intelligence in a wireless network to the edge of the network (*i.e.,* BSs) to reduce the feedback delays in channel estimation between the BSs and a central resource manager.

Under distributed resource allocation at the BSs without coordination, while the intra-cell interference can be estimated by the BSs, the inter-cell interference can no longer be accurately estimated by them. As a result, the earlier assumption that the total interference at a scheduled user can be accurately predicted needs to be reconsidered. Moreover, the traditional approach of aiming to achieve a fixed target SINR is not suitable, if not impossible, as it requires that the *total* interference at the scheduled users be known.

To the best of our knowledge there is a lack of a careful investigation of the effect of unknown inter-cell interference on the performance of beamforming and power control algorithms and how to deal with it. In this paper we address these issues. The main contributions of the paper can be summarized as follows: First, we study the performance of a class of scheduling and beamforming algorithms in a multi-cell environment where each BS has channel information only of the users in its own cell. We demonstrate that the algorithms that do not account for inter-cell interference result in unacceptably high packet error rates (PERs). Here we select the achieved PER as the suitable parameter that reflects the performance of the physical and data link layers, since (i) the performance of the upper layers, especially transport layer protocol, depends critically on the round-trip delays and delay jitter packets experience and (ii) as mentioned earlier, the traditional approach of aiming at a fixed target SINR is not possible. Second, we propose two robust beamforming and power control algorithms that can achieve target average PERs even when inter-cell interference cannot be predicted

Tianmin Ren is with the Department of ECE, University of California, San Diego, CA, 92093. Email:tren@ucsd.edu

Richard J. La is with the Department of ECE and ISR, University of Maryland, College Park, MD, 20742. Email:hyongla@eng.umd.edu

accurately.

The first algorithm is based on a closed form approximation of PER as a function of the realized SINR (given by link curves). Although link curves have been used in the past to simulate more realistic physical and link layer behavior, to the best of our knowledge, our work is the first to exploit a property of link curves to design algorithms for providing QoS in the form of a guaranteed average PER in the presence of *unpredictable* interference. The second algorithm exploits the observation that the distribution of inter-cell interference experienced by a user can be well approximated by a log-normal distribution. We show that both algorithms achieve the target average PERs.

The paper is organized as follows. We describe the multi-cell network model under investigation in Section II. Section III introduces optimal beamforming algorithms for a single cell, and the performance degradation of these algorithms in the presence of inter-cell interference is shown in Section IV. We derive the average PER as a function of the target SINR in Section V. The first proposed algorithm is outlined in Section VI, followed by the second proposed algorithm in Section VII. We conclude in Section VIII.

II. Multiple Cell Network and Channel Models

In this section we describe the multiple cell network model used for our analysis and the adopted wireless channel models employed in simulation.

A. Network model

We consider a network that consists of 7 co-channel cells shown as the shaded cells in Fig. 1. The closest co-channel cells of a cell can be found by (1) moving x cells along any chain of hexagons, (2) turning 60 degrees counter-clockwise, and (3) moving y cells (p. 28 [16]). In Fig. 1, $x = 1$ and $y = 1$. A total of $x^2 + x \cdot y + y^2$ cells share the available spectrum. We call this pair (x, y) the reuse pattern. The radius of each cell is denoted by R.

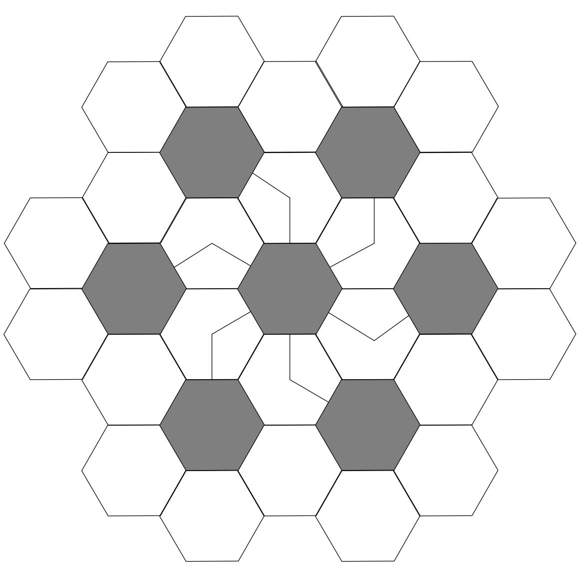


Fig. 1. Co-channel cells

We adopt a TDMA system model with FDD for the simplicity of illustration, and time is assumed to be divided into contiguous equal-sized timeslots. A BS is located at the center of a cell and transmits packets to N users uniformly distributed in the cell. We assume that a user always has a packet ready for transmission when scheduled, *i.e.*, infinite traffic model. In each timeslot, each BS schedules a set of users for transmission, and calculates the beamforming weights and transmission powers for the scheduled users. We assume the transmissions of the BSs are synchronized in our simulations.

Although we model a network consisting of 7 co-channel cells, since we are interested in the performance of the system with inter-cell interference, we focus on the cell at the center. In this paper we approximate the inter-cell interference experienced by a user with the interference from the closest co-channel cells. However, as one will see, the performance of our proposed algorithms will not be affected by this assumption.

B. Channel model

In this paper we adopt the same multi-path wireless channel models in [4]. Each BS is equipped with an antenna array, where M omni-directional antenna elements are uniformly located on a circle of radius r. Beamforming vector $\mathbf{w} = [w^1, w^2, \cdots, w^M]^T$ satisfies $\mathbf{w}^H\mathbf{w} = 1$. We assume that there are L paths. The $M \times 1$ antenna steering vector $\mathbf{v}(\theta_\ell)$ at direction θ_ℓ of the ℓ-th path is defined to be $[e^{j\omega\tau_\ell^m}; m = 1, \ldots, M]$, where ω is the carrier frequency, and τ_ℓ^m is the delay to the m-th antenna with respect to the first antenna. If we assume that all paths are independent and $\mathbf{E}\left[|s(t)|^2\right] = 1$, where $s(t)$ is the signal, the expected received signal power is given by $p\mathbf{w}^H\mathcal{H}\mathbf{w}$, where p is the transmission power, $\mathcal{H} = \sum_{\ell=1}^{L} A_\ell \mathbf{v}(\theta_\ell)\mathbf{v}^H(\theta_\ell)$, and A_ℓ is the variance of the complex gain of the ℓ-th path. The matrix $\mathcal{H}$ is called a spatial covariance matrix.

We denote the spatial covariance matrix of user j with respect to BS b as $\mathcal{H}_j^b$ and the BS assigned to user j as b_j. The SINR of user j, denoted by $SINR_j$, is given by $S_j/(I_j^{intra} + I_j^{inter} + n_j^2)$, where S_j, I_j^{intra}, and I_j^{inter} are the signal power, intra-cell interference, and inter-cell interference received by user j, respectively, and n_j^2 is the noise power at user j.

For time varying channels, the variance of the channel gain $\{A_\ell(t); t = 1, 2, \ldots\}$ is a stochastic process. The random variable (rv) $A_\ell(t) = (s_\ell(t)f_\ell(t))^2/d_\ell^\kappa$, where $s_\ell(t)$ and $f_\ell(t)$ are sequences of log-normal and Rayleigh rvs, respectively, accounting for slow shadow fading and fast fading. The variable d_ℓ denotes the distance from the BS to the user along the ℓ-th path and κ is the path loss exponent. We consider the following four types of wireless channels in this paper.

1) *Independent and identically distributed (i.i.d.) shadow fading channel:* $A_\ell(t) = s_\ell^2(t)/d_\ell^\kappa = e^{2r_\ell(t)}/d_\ell^\kappa$, where $\{r_\ell(t), t = 1, 2, \cdots\}$ is a sequence of i.i.d. Gaussian rvs with zero mean.

2) *Temporally correlated shadow fading channel:* $A_\ell(t) = s_\ell^2(t)/d_\ell^\kappa = e^{2r_\ell(t)}/d_\ell^\kappa$ where $\{r_\ell(t)\}$ is a sequence of Gaussian rvs generated by $r_\ell(t+1) = (1-\rho)r_\ell(t) + \rho \cdot u_\ell(t)$ and $\{u_\ell(t)\}$ is a sequence of i.i.d. Gaussian rvs with zero mean.

3) *Rayleigh fading channel:* $A_\ell(t) = f_\ell(t)^2/d_\ell^\kappa$ where $\{f_\ell(t)\}$ is a sequence of i.i.d. Rayleigh rvs, and thus $\{f_\ell^2(t)\}$ is a sequence of i.i.d. exponential rvs.

4) *Temporally correlated shadow fading plus Rayleigh fading channel:* $A_\ell(t) = (s_\ell(t)f_\ell(t))^2/d_\ell^\kappa$ where the sequence $\{s_\ell(t)\}$ is generated in the same manner as in the temporally correlated shadow fading channel model, and $\{f_\ell(t)\}$ is a sequence of i.i.d. Rayleigh rvs.

III. Optimal beamforming for single cell

In this section we briefly summarize a *downlink* beamforming algorithm proposed in [19]. This algorithm equalizes the ratios of the achieved SINRs to some target SINRs (called relative SINRs) in a single cell under the assumption that the noise power at each user available to the BS is constant. It consists of two phases; in the first phase, the minimum relative SINR among the scheduled users is maximized (Algorithm I). This is equivalent to finding the largest common relative SINR η_c^* under a power budget constraint $||\mathbf{p}||_1 = P_{max}$, where $\mathbf{p}$ is the transmission power vector. Here $||\cdot||_1$ denotes an L_1 norm. Let $\mathbf{W} = \{\mathbf{w}_j, j \in \mathcal{U}\}$ be the ensemble of beamforming vectors, where $\mathcal{U}$ is the set of scheduled users and $|\mathcal{U}| = U$, and γ_j denotes the target SINR of user j. A set of users can be scheduled with their respective SINR requirement satisfied if $\eta_c^* \geq 1$, and a set of users that satisfies this condition is called a *feasible set*.

Algorithm I: feasibility(P_{max}; $\mathcal{H}_j, n_j^2, \gamma_j, \forall j \in \mathcal{U}$)

STEP 1: Set $n = 0$, $\mathbf{q}^{(0)} = [0, \cdots, 0]^T$, and $\lambda_{max}^{(0)} = \infty$.
STEP 2: While 1, do

- Set $n \leftarrow n + 1$. Solve a set of U generalized eigenproblems:

$$\mathbf{w}_j^{(n)} = \arg \max_{||\mathbf{w}_j||=1} \frac{\mathbf{w}_j^H \tilde{\mathcal{H}}_j \mathbf{w}_j}{\mathbf{w}_j^H \mathcal{R}_j(\mathbf{q}^{(n-1)})\mathbf{w}_j}, \quad \forall j \in \mathcal{U} \tag{1}$$

  where $\tilde{\mathcal{H}}_j = \mathcal{H}_j/n_j^2$, and $\mathcal{R}_j(\mathbf{q}^{(n-1)}) = \sum_{k\in\mathcal{U},k\neq j} q_k^{(n-1)}\tilde{\mathcal{H}}_k + I$ with I being the $M \times M$ identity matrix. The solutions to the above generalized eigenproblems are given by the dominant generalized eigenvectors of the matrix pairs $[\tilde{\mathcal{H}}_j, \mathcal{R}_j(\mathbf{q}^{(n-1)})]$ for all $j \in \mathcal{U}$.
- Find the largest eigenvalue $\lambda_{max}^{(n)}$ of $\Lambda(\mathbf{W}^{(n)}, P_{max})$ and the corresponding eigenvector $\mathbf{q}_{ext}^{(n)}$ of the form $\mathbf{q}_{ext}^{(n)} = [\mathbf{q}^{(n)};\ 1]$, where

$$\Lambda(\mathbf{W}, P_{max}) = \begin{bmatrix} \mathbf{D}(\mathbf{W})\Psi^T(\mathbf{W}) & \mathbf{D}(\mathbf{W})\sigma \\ \frac{1}{P_{max}}\underline{1}^T\mathbf{D}(\mathbf{W})\Psi^T(\mathbf{W}) & \frac{1}{P_{max}}\underline{1}^T\mathbf{D}(\mathbf{W})\sigma \end{bmatrix},$$

  $\underline{1} = [1 \ \cdots \ 1]^T$, $\mathbf{D}(\mathbf{W}) = \text{diag}\{\gamma_1/(\mathbf{w}_1^H\mathcal{H}_1\mathbf{w}_1), \cdots, \gamma_U/(\mathbf{w}_U^H\mathcal{H}_U\mathbf{w}_U)\}$, $\sigma = [n_1^2, \cdots, n_U^2]^T$, $\mathbf{\Psi}(\mathbf{W}) = [\psi_{ij}, i, j \in \mathcal{U}]$, and the interference caused by user j to user i per unit power $\psi_{ij} = \mathbf{w}_j^H\mathcal{H}_i\mathbf{w}_j$ if $i \neq j$ and $\psi_{ij} = 0$ if $i = j$.
- If $\lambda_{max}^{(n-1)} - \lambda_{max}^{(n)} \leq \varepsilon$, break.

STEP 3: If $\lambda_{max}^{(n)} \leq 1$, *i.e.*, the set of users can be scheduled in the same timeslot, output 1. Otherwise, output 0.

It is shown [19] that the sequence of eigenvalues $\{\lambda_{max}^{(n)}\}$ is monotonically decreasing and converges to the global minimum λ_{max}^*, which is related to the maximum common SINR ratio η_c^* by the relation $\eta_c^* = (\min_{\mathbf{W}} \lambda_{max}(\Lambda(\mathbf{W}, P_{max})))^{-1} = (\lambda_{max}^*)^{-1}$.

The second phase of the algorithm attempts to minimize the total transmission power subject to SINR requirement given a feasible set (Algorithm II).

Algorithm II: minimize_power(P_{max}; $\mathcal{H}_j, n_j^2, \gamma_j, \forall j \in \mathcal{U}$)

STEP 1: Set $n = 0$, and $\mathbf{q}^{(0)} = [0, \cdots, 0]^T$.
STEP 2: While 1, do

- Set $n \leftarrow n + 1$. Solve a set of U generalized eigenproblems defined in (1).
- Compute $\mathbf{q}^{(n)} = (I - \mathbf{D}(\mathbf{W}^{(n)})\mathbf{\Psi}^T(\mathbf{W}^{(n)}))^{-1}\mathbf{D}(\mathbf{W}^{(n)})\underline{1}$.
- If $||\mathbf{q}^{(n-1)}||_1 - ||\mathbf{q}^{(n)}||_1 \leq \varepsilon$, break.

STEP 3: Compute the optimal downlink transmission power vector given by $\mathbf{p}^{(n)} = (I - \mathbf{D}(\mathbf{W}^{(n)})\mathbf{\Psi}(\mathbf{W}^{(n)}))^{-1}\mathbf{D}(\mathbf{W}^{(n)})\underline{1}$.

STEP 4: Output $\mathbf{p}^{(n)}, \mathbf{W}^{(n)}$.

Our first proposed algorithm in Section VI uses Algorithms I and II as the basic underlying algorithms and adjusts the target PER (and hence target SINR) fed to these algorithms for each user based on the observed inter-cell interference in order to achieve the real target PER.

IV. Performance Degradation due to Inter-cell Interference

In this section we illustrate the effect of the inter-cell interference on the realized average PERs of the users under Algorithms I and II. For the numerical examples we adopt the following scheduling algorithm at each BS [1]. Denote the sets of co-cell users and scheduled users by $\mathcal{N}$ and $\mathcal{U}$, respectively. Each user $j \in \mathcal{N}$ is assigned a credit c_j at the beginning of simulation. The throughput of user j up to the beginning of timeslot $t = 1, 2, \ldots$, is given by $T_j(t)$.

Algorithm III: scheduling_1(P_{max}; $c_j, T_j(t), \mathcal{H}_j, n_j^2, \gamma_j, \forall j \in \mathcal{N}$)

STEP 1: Initialize $\mathcal{U} = \emptyset$ and $\mathcal{N}_1 = \mathcal{N}$.
STEP 2: While $\mathcal{N}_1 \neq \emptyset$, do

- $j^* = \arg\min_{j\in\mathcal{N}_1} T_j(t)/c_j$
- $\mathcal{U} = \mathcal{U} \cup \{j^*\}$, $\mathcal{N}_1 = \mathcal{N}_1 \setminus \{j^*\}$
- If feasibility(P_{max}; $\mathcal{H}_j, n_j^2, \gamma_j, \forall j \in \mathcal{U}$) = 0, then $\mathcal{U} = \mathcal{U} \setminus \{j^*\}$.

STEP 3: minimize_power(P_{max}; $\mathcal{H}_j, n_j^2, \gamma_j, \forall j \in \mathcal{U}$) .

This scheduling algorithm attempts to equalize the normalized throughput $T_j(t)/c_j$ of the users. Hence, these credits c_j are used to provide differentiated classes of service in terms of the provided rates [1].

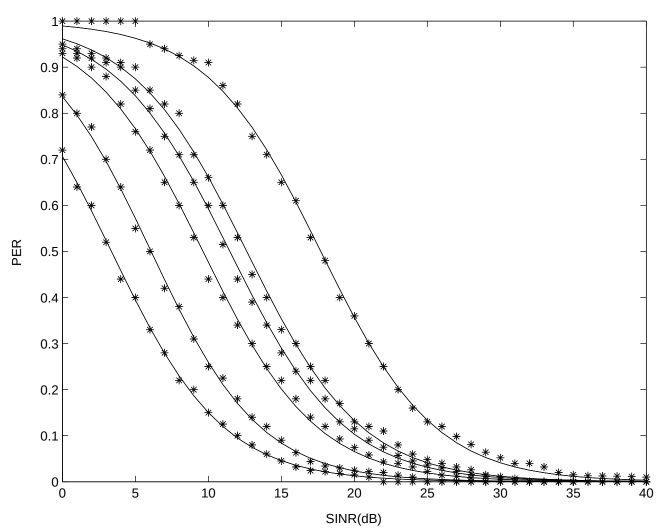


Fig. 2. Link curves of a TDMA system. (Transmission rate from the left-most curve to the right-most curve: 14.5 kbps, 22.8 kbps, 33 kbps, 41 kbps, 48 kbps, and 65.2 kbps.

TABLE I
SIMULATION PARAMETERS.

reuse pattern	$(1,1)$	P_{max}	10^{15}	PER$_{target}$	2 %
N	15	M	6	r	λ
R	1,000 m	L	6	ρ	0.1
$\mathbf{E}\left[s_\ell(t)\right]$	1.78	$\sqrt{Var[s_\ell(t)]}$	2.61	κ	3.5
$\mathbf{E}\left[f_\ell^2(t)\right]$	1	$\sqrt{Var[f_\ell^2(t)]}$	1		

In each timeslot the scheduling algorithm selects a set of users $\mathcal{U}$ for transmission at each BS. For each scheduled user j a target SINR value γ_j is determined from the target PER and a link curve that gives the PER as a function of SINR for a selected modulation and/or coding scheme. The link curve we adopt in this section is the one for the lowest transmission rate in a TDMA system, which is the left most curve in Fig. 2 [8]. The corresponding modulation scheme is binary offset quadrature amplitude modulation (B-O-QAM) [2]. The data points are shown as '*' and the solid curves are the fitting curves explained in Section V. Given target SINRs for the scheduled users in the cell, the BS computes their beamforming weights and transmission powers using Algorithms I and II. The realized SINR at each scheduled user, including both intra-cell and inter-cell interference, is computed from the beamforming weights and transmission powers of the scheduled users at all 7 BSs. After calculating the realized SINR values at the users, we use link curves to decide whether a packet transmission is successful or not.

We conduct the experiment under various settings with several randomly generated scenarios. Although different reuse patterns have been studied, here we only present the results for the reuse pattern of $(x, y) = (1, 1)$. The noise powers are set to $n_j^2 = 1$. The values of the parameters are listed in Table I, where λ is the wavelength of the carrier electro-magnetic wave.

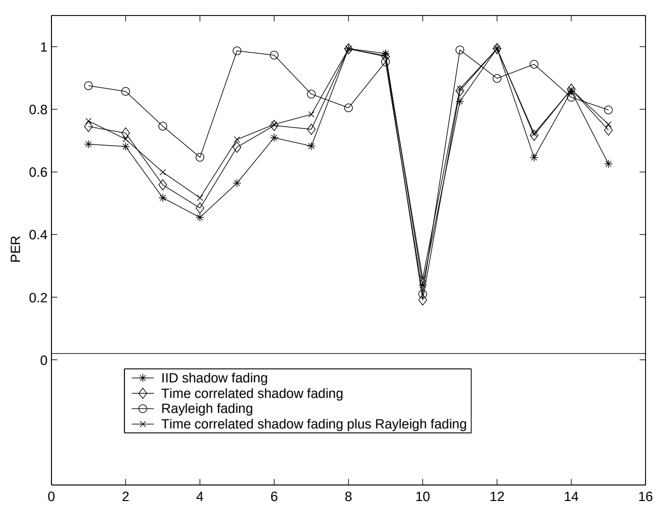


Fig. 3. PER for SCHEDULING_1 algorithm with single class of service.

Fig. 3 plots the achieved average PERs of the 15 users in the center cell under various channel models with a single class of service, *i.e.*, all users have the same credit. The experimental results with multiple classes of service are similar. Note that the realized average PERs of the center cell users are significantly higher than the target PER, which is set to 2 percent in our experiments (shown as the solid horizontal line in the figure). This is because the inter-cell interference is ignored in scheduling the users and calculating the beamforming weights and transmission powers. In the case of temporally correlated shadow fading plus Rayleigh fading channel, on the average, 4.273 users are scheduled in each timeslot. However, only 0.449 packets are successfully transmitted per timeslot. Hence, the PERs achieved by the beamforming algorithms that do not account for the inter-cell interference (Fig. 3) are not acceptable for data traffic. This calls for a design of a practical beamforming algorithm that can take into account the presence of unknown inter-cell interference and achieve (close to) target PERs in multi-cell environments, which is the focus of the remainder of this paper.

V. APPROXIMATION OF AVERAGE PACKET ERROR RATE

In this section we derive an expression for the average PER as a function of the distribution of realized SINR. Most of the link curves, including the ones we used in the previous experiments (*e.g.*, [8], [15]), can be fitted using a function of the form

$$PER(SINR) = \frac{1}{1 + e^{k(SINR_{dB} - z)}} \tag{2}$$

where $SINR_{dB}$ is the SINR in dB, *i.e.*, $SINR_{dB} = 10\log_{10}(SINR)$, and k and z are two fitting parameters that determine the slope and the position of the link curve, respectively.

The fitting curves are shown in Fig. 2 as solid curves for different modulation and/or coding schemes. One can clearly see that these fitting curves match the collected link data very closely. Link curves for systems other than the TDMA system we studied are similar in shape but with different parameters. Several example link curves are given in [15] for a CDMA system. The slope of a link curve reflects the sensitivity of PER to SINR and is determined by the modulation and/or coding scheme, packet length, characteristics of interference and noise, etc.

For a reasonable target PER (less than 5-10 percent), we can approximate (2) as follows:

$$\begin{aligned} PER(SINR) &= \frac{1}{1 + e^{k(SINR_{dB} - z)}} \\ &\approx e^{-k(SINR_{dB} - z)} \\ &= e^{kz} SINR^{-\alpha} \end{aligned} \tag{3}$$

where $\alpha = 10k/\ln 10$. Since the realized SINR is a rv due to random inter-cell interference, the (time) average PER $\overline{PER}$ is given by[1]

$$\overline{PER} = e^{kz}\overline{SINR^{-\alpha}} \tag{4}$$

where an overline is used to denote the (time) average. In the following section we will use this approximation of the average PER (4) to design a robust beamforming algorithm.

[1] We replace the approximation in (3) with an equality.

VI. First Proposed Algorithm

In this section we describe our first proposed beamforming algorithm for handling unpredictable inter-cell interference at the scheduled users. The basic idea behind the proposed algorithm is to understand the relation between the average PER and the intended target PER of the beamforming algorithm when the average inter-cell interference is used as an estimate of the *unknown* inter-cell interference at a scheduled user and, based on this relation, to feed the beamforming algorithm with a suitable *virtual* target PER (typically smaller than the target PER) so that the realized average PER equals the target PER.

Assume that the inter-cell interference process at a user is ergodic, and the time average of inter-cell interference at a user converges to its expected value. Suppose that we estimate the *unknown* inter-cell interference at a scheduled user using the average inter-cell interference value in Algorithms I and II. In other words, for each scheduled user j we replace the noise power n_j^2 with the sum of the noise power n_j^2 and the average inter-cell interference at the user. Then, assuming that inter-cell interference is independent of the intra-cell interference, one can show that the expected value of the inverse of achieved SINR equals the inverse of target SINR $SINR_{target}$ as follows.

$$\begin{aligned}\mathbf{E}\left[SINR^{-1}\right] &= \mathbf{E}\left[\mathbf{E}\left[\frac{I^{intra}+I^{inter}+n^2}{S}\Big|S, I^{intra}\right]\right] \\ &= \mathbf{E}\left[\frac{I^{intra}+\mathbf{E}\left[I^{inter}\right]+n^2}{S}\right] \\ &= SINR_{target}^{-1} \end{aligned} \quad (5)$$

where the last equality follows the fact that the beamforming weights and transmission powers are selected so as to achieve $SINR_{target}$ and the assumption that $\overline{I^{inter}} = \mathbf{E}\left[I^{inter}\right]$.

When the beamforming algorithm can achieve the target SINR perfectly for each scheduled user, by substituting (5) in (3) it is plain to see that the intended target PER $PER^{\star}$ of the beamforming algorithm corresponding to the selected target SINR is given by

$$\begin{aligned} PER^{\star} &= e^{kz} SINR_{target}^{-\alpha} \\ &= e^{kz}\mathbf{E}\left[SINR^{-1}\right]^{\alpha} = e^{kz}\overline{SINR^{-1}}^{\;\alpha} . \end{aligned} \quad (6)$$

It is clear that if the link curve parameter $\alpha \approx 1$, then

$$\overline{PER} = e^{kz}\overline{SINR^{-\alpha}} \approx e^{kz}\overline{SINR^{-1}}^{\alpha} = PER^{\star} .$$

Thus, if $\alpha \approx 1$, the realized $\overline{PER}$ will be close to $PER^{\star}$. However, if α deviates considerably from one, since $\overline{SINR^{-1}}^{\;\alpha} \neq \overline{SINR^{-\alpha}}$ in general, the realized $\overline{PER}$ may significantly differ from $PER^{\star}$. Moreover, from (6) and (4), if $\alpha > 1$, from Jensen's inequality [12] we have $e^{kz}\overline{SINR^{-\alpha}} \geq e^{kz}\overline{SINR^{-1}}^{\;\alpha}$, *i.e.*, $\overline{PER} \geq PER^{\star}$. In other words, the realized average PERs tend to be larger than the intended target PER of the beamforming algorithm, which is not desirable.

The value of α for the link curves in Fig. 2 is approximately 1.1. Thus, when estimated average inter-cell interference is used as an estimate of the unknown inter-cell interference in the calculation of beamforming weights and transmission powers, the realized average PERs are close to $PER^{\star}$. However, the value of α of the link curves in [15] is considerably larger than one, and the average PERs are larger than $PER^{\star}$.

A. Proposed algorithm

From (4) and (6) we observe that the discrepancy between $PER^{\star}$ and $\overline{PER}$ arises from the fact that $\overline{SINR^{-1}}^{\;\alpha}$ and $\overline{SINR^{-\alpha}}$ differ. As mentioned earlier, if $\alpha > 1$ we have $\overline{SINR^{-\alpha}} \geq \overline{SINR^{-1}}^{\;\alpha}$ (from Jensen's inequality). As a result, in order to achieve an average PER $\overline{PER}$ equal to a target PER PER_{target} the beamforming algorithm should aim at a virtual target PER $PER^{\star}$ smaller than PER_{target}.

From the relation

$$\begin{aligned}\overline{PER} = e^{kz}\overline{SINR^{-\alpha}} &= e^{kz}\overline{SINR^{-1}}^{\;\alpha}\cdot\frac{\overline{SINR^{-\alpha}}}{\overline{SINR^{-1}}^{\;\alpha}} \\ &= PER^{\star}\cdot\frac{\overline{SINR^{-\alpha}}}{\overline{SINR^{-1}}^{\;\alpha}} ,\end{aligned}$$

it is clear that in order to achieve $\overline{PER} = PER_{target}$ the virtual target PER $PER^{\star}$ aimed at by the beamforming algorithm must be set to

$$\begin{aligned} PER^{\star} = \overline{PER}\cdot\frac{\overline{SINR^{-1}}^{\;\alpha}}{\overline{SINR^{-\alpha}}} &= PER_{target}\cdot\frac{\overline{SINR^{-1}}^{\;\alpha}}{\overline{SINR^{-\alpha}}} \\ &= \epsilon\cdot PER_{target} , \end{aligned} \quad (7)$$

where $\epsilon = \overline{SINR^{-1}}^{\;\alpha}/\overline{SINR^{-\alpha}}$. We observe that ϵ depends on both the SINR distribution and the value of link curve parameter α. Qualitatively, a larger fluctuation in SINR leads to a smaller value of ϵ because SINR is more likely to degrade enough to cause large PERs at times and this needs to be compensated for by setting a smaller virtual target PER. For a similar reason, a larger slope of the link curve, captured by α, leads to a smaller value of ϵ because the link curve is more sensitive to a fluctuation in SINR.

In order to calculate ϵ, both $\overline{SINR^{-1}}$ and $\overline{SINR^{-\alpha}}$ need to be estimated. These can be estimated by a user using an exponential averaging scheme. More precisely, when a user receives a packet, it carries out the following updates:

$$\begin{aligned}(1-\phi)\hat{\overline{SINR^{-1}}} + \phi\cdot SINR_{new}^{-1} &\rightarrow \hat{\overline{SINR^{-1}}} \\ (1-\phi)\hat{\overline{SINR^{-\alpha}}} + \phi\cdot SINR_{new}^{-\alpha} &\rightarrow \hat{\overline{SINR^{-\alpha}}}\end{aligned} \quad (8)$$

where $\hat{\overline{SINR^{-1}}}$ and $\hat{\overline{SINR^{-\alpha}}}$ are the estimates for $\overline{SINR^{-1}}$ and $\overline{SINR^{-\alpha}}$, respectively. The parameter ϕ is the exponential averaging weight and is set to 0.1 in our simulation studies. The variable $SINR_{new}$ is the SINR experienced by the user when it receives the packet.

Our new scheduling algorithm based on this observation, referred to as SCHEDULING_2, is described below. Here $\hat{I}_j^{inter}(t)$ denotes exponentially averaged inter-cell interference of user j.

ALGORITHM IV: SCHEDULING_2(P_{max}; c_j, $T_j(t)$, $\mathcal{H}_j$, n_j^2, $\hat{I}_j^{inter}(t)$, $\hat{\overline{SINR_j^{-1}}}$, $\hat{\overline{SINR_j^{-\alpha}}}$, $\forall j \in \mathcal{N}$)

STEP 1: Initialize $\mathcal{U} = \emptyset$ and $\mathcal{N}_1 = \mathcal{N}$.
STEP 2: While $\mathcal{N}_1 \neq \emptyset$, do

- $j^* = \arg\min_{j\in\mathcal{N}_1} T_j(t)/c_j$
- $\mathcal{U} = \mathcal{U}\cup\{j^*\}$, $\mathcal{N}_1 = \mathcal{N}_1 \setminus \{j^*\}$

- If FEASIBILITY(P_{max} ;$\mathcal{H}_j, n_j^2+\hat{I}_j^{inter}(t), \gamma_j, \forall j \in \mathcal{U}) = 0, \mathcal{U} = \mathcal{U}\backslash\{j^*\}$, where γ_j satisfies $e^{kz}\gamma_j^{-\alpha} = \epsilon_j \cdot PER_{target}$.

STEP 3: MINIMIZE_POWER(P_{max}; $\mathcal{H}_j, n_j^2 + \hat{I}_j^{inter}(t), \gamma_j, \forall j \in \mathcal{U}$)

Note that in this new algorithm, the target PER is replaced by the virtual target PER $\epsilon_j \cdot PER_{target}$ by selecting the target SINR γ_j satisfying $e^{kz}\gamma_j^{-\alpha} = \epsilon_j \cdot PER_{target}$ in both STEP 2 (Algorithm I) and STEP 3 (Algorithm II), and the noise power n_j^2 is replaced by the sum of the noise power and the average inter-cell interference of the scheduled user.

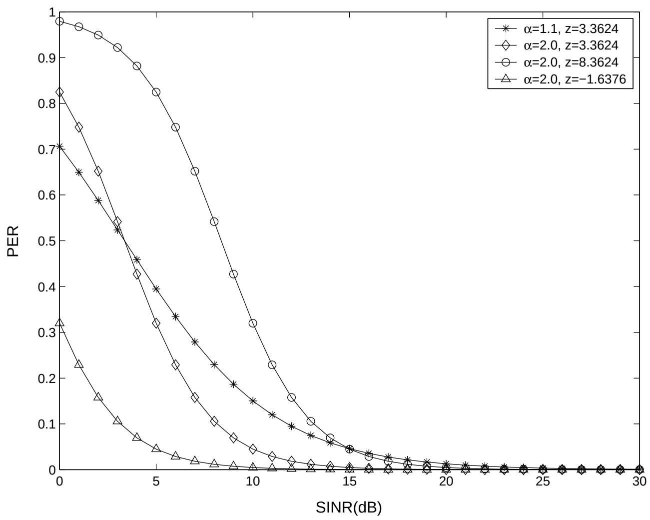


Fig. 4. Plot of link curves with $\alpha = 2$.

We evaluate the performance of SCHEDULING_2 algorithm using the same setup used for Fig. 3 with a link curve shown in Fig. 4. For the simulation we use the middle link curve with $\alpha = 2$ in the figure. The results are presented in Fig. 5 with both single service class and multiple service classes. For temporally correlated shadow fading plus Rayleigh fading channel model the average numbers of scheduled packets per timeslot are 2.072 and 2.045 for these two cases, respectively, and the numbers of successful transmissions are 2.032 and 2.006 correspondingly. For the multiple service classes case, there are 10 users with credit of 1, and 5 users with credit of 2. It is clear that all users achieve an average PER close to the target PER of 2 percent under SCHEDULING_2 algorithm under all considered channel models .

Using the sum of average inter-cell interference and noise in the beamforming algorithm with adjusted virtual target PER $PER^\star$ decreases the average number of scheduled users in a timeslot. The reason for this decrease in the number of scheduled users is as follows. In Algorithms I and II, the beamforming weights are computed to maximize the SINR of each user on the virtual uplink (see eq. (1)) [19]. The increase in noise reduces the elements in spatial covariance matrices $\tilde{\mathcal{H}}_j$ and the relative contribution from the identity matrix I in $\mathcal{R}_j(\mathbf{q}^{(n-1)})$ becomes larger. Unlike spatial covariance matrices the identity matrix has no directional sensitivity, *i.e.*, for any beamforming vector $\mathbf{w}$ with $\mathbf{w}^H\mathbf{w} = 1, \mathbf{w}^H I\mathbf{w} = 1$. This is similar to having additional interference coming in from *all* directions (pp. 225-226 [10]). As a result, the

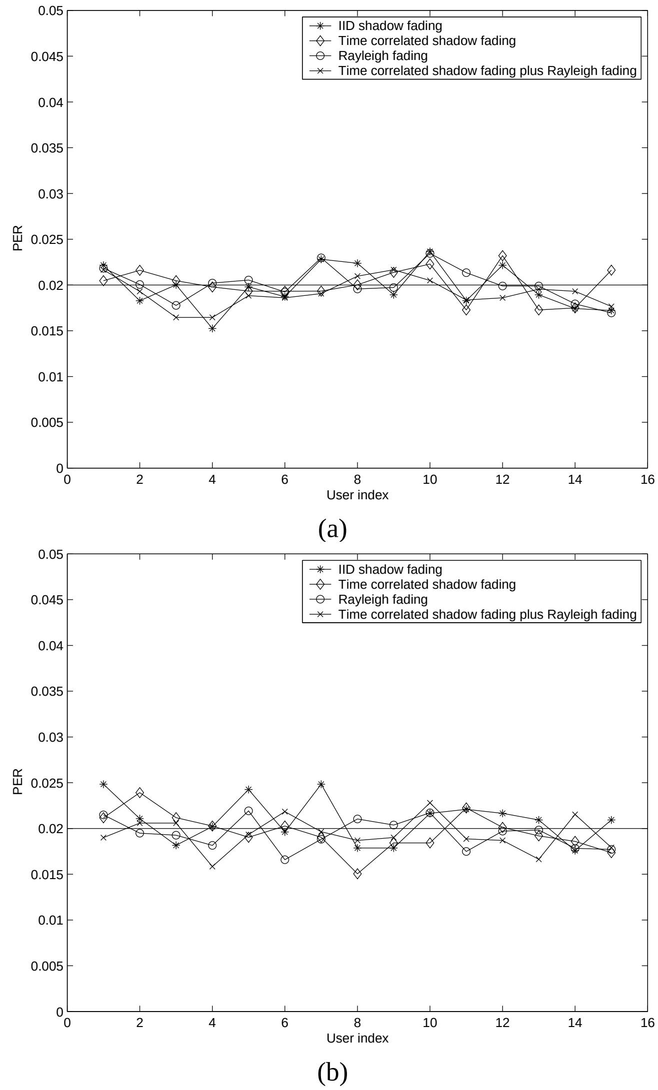


Fig. 5. PER for SCHEDULING_2 algorithm with a link curve of $\alpha = 2$. (a) single class, (b) multiple classes.

matrix $\mathcal{R}$ is more spatially uniform with the average inter-cell interference term. This results in the beam pattern calculated by (1) becoming less focused. This is in contrast to the case where the beamforming vectors are calculated to minimize the interference in certain directions when noise is negligible. Because these beams are not as focused with inter-cell interference, users become less spatially separable and consequently fewer number of users can be scheduled simultaneously in each timeslot. The trade-off between the system throughput and target PER is studied in the following subsection.

B. Effects of target PER and the number of antenna elements on throughput

As mentioned earlier the number of users that can be scheduled together in a timeslot decreases when the beamforming algorithm needs to compensate for unknown inter-cell interference in multi-cell networks. This decrease in throughput depends on many factors, including the target PER. In this subsection, using numerical examples, we study how the target

PER affects the number of scheduled users per timeslot and the resulting throughput of the system.

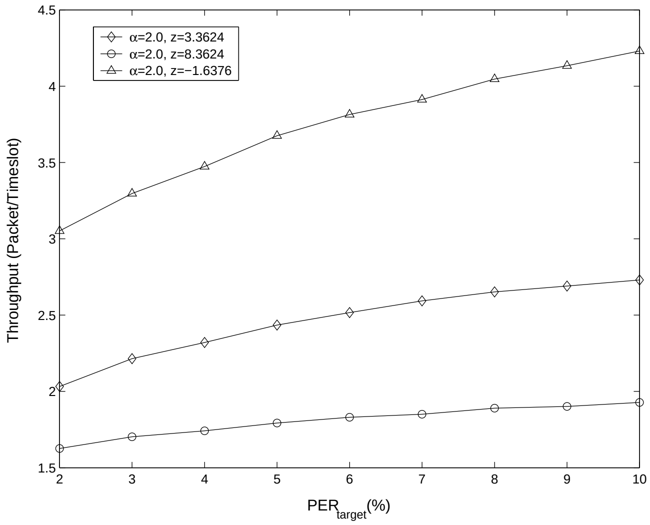


Fig. 6. Plot of target PER vs. throughput.

Fig. 6 shows the plot of the throughput in number of successfully transmitted packets per timeslot for different link curves with $\alpha = 2$ shown in Fig. 4. One can see that for reasonably small values of target PER, the system throughput is a concave, increasing function of the target PER. This increase in throughput with the target PER is in fact rather significant. For example, raising the target PER from 2 percent to 10 percent increases the system throughput by almost 20-40 percent. This suggests that in order to improve the system throughput by allowing larger target PERs, a new transport layer protocol that can handle a higher PER and larger round-trip delay jitter due to link layer retransmissions may be desired. Moreover, notice that the increase in the throughput with increasing target PER tends to be larger for link curves with smaller SINR requirements.

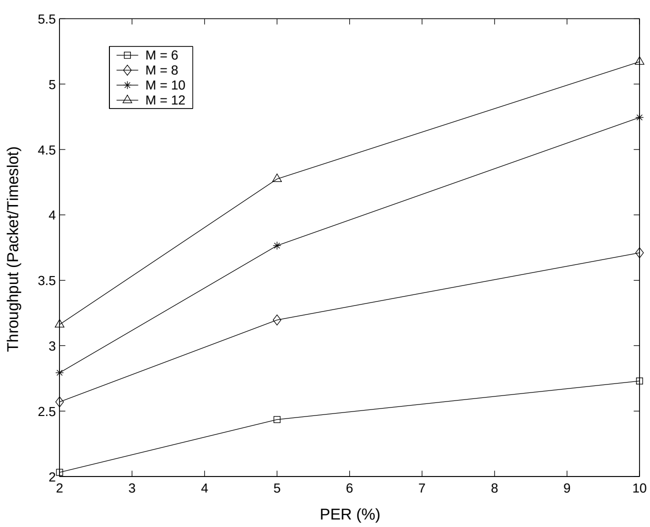


Fig. 7. Plot of target PER vs. throughput for antenna arrays with different numbers of elements.

We also plot the throughput of the system for different numbers of antenna elements M in Fig. 7, using the middle link curve with $\alpha = 2$ in Fig. 4. As expected, the throughput of the system increases with M, and the marginal increase in throughput with additional antenna elements decreases.

C. Discussion on inter-cell interference

In this subsection we comment on the characteristics of inter-cell interference experienced by the users in our simulations.

1) Log-normal distribution of inter-cell interference: Clearly the distribution of the inter-cell interference experienced by a user in practice will depend on the adopted scheduling and beamforming algorithms as the interference depends on the set of users scheduled in co-channel cells and their beam patterns. Since the performance and throughput of the network depends on the distribution of the inter-cell interference experienced by the users through the relation (7), it is of interest to understand its distribution. Our simulation results suggest that the distribution of the inter-cell interference can be well approximated by a log-normal distribution. The histograms of the natural logarithm of the inter-cell interference experienced by a selected user under different scheduling algorithms and for different channel models under SCHEDULING_2 are plotted in Figs. 8 and 9, respectively, of [18]. The D-statistics obtained from Kolmogorov-Smirnov test [12] using MLE fitting range from 0.0028 to 0.035, indicating the accuracy of normal fitting. We refer interested readers to [5] for a possible explanation for the emergence of a log-normal distribution.

2) Temporal correlation of inter-cell interference: Leung investigated power control schemes for a TDMA system with a single antenna element in a multiple cell environment [9]. He assumed that each packet from the higher layer gets broken into multiple blocks, and a BS schedules a user *continually* until the transmission of a packet is completed before scheduling a next user. These consecutive transmissions to the same user lead to strong temporal correlation in the inter-cell interference, and as a result the average inter-cell interference in the previous several timeslots gives a good prediction for the inter-cell interference in the next timeslot.

If the capacity of a wireless system is high enough, which is likely to be true in the future, a block or frame will be able to accommodate an entire packet, and it will take only one timeslot to complete the transmission of a packet, which is the model assumed in our study. The plot of empirical correlation coefficient of the inter-cell interference of a user under various scheduling algorithms with temporally correlated shadow fading channel model is shown in Fig. 10 of [18]. The plot shows that the inter-cell interference exhibits rather weak temporal correlation. This is because each BS typically schedules a different set of users for transmission in each timeslot, independently of other BSs. Therefore, the beamforming weights and transmission powers vary significantly from one timeslot to next. These characteristics of a packet switched cellular network lead to weak temporal correlation of inter-cell interference experienced by a user.

VII. An Alternate Algorithm for Log-Normal Inter-Cell Interference

When inter-cell interference exhibits weak temporal correlation as shown in the previous section, it is difficult to predict it accurately. However, if its distribution is known and the parameters of the distribution can be estimated, such information can be exploited to achieve the target PERs. In this section we propose an alternate algorithm for achieving target PER when the inter-cell interference is log-normally distributed. This is done by first estimating the parameters of the log-normal distribution and then using the estimated parameters in a beamforming algorithm to predict the PER as a function of transmission power.

Recall from (2) that, for a fixed signal strength S, the achieved PER, denoted by $PER(S)$, can be expressed as

$$PER(S) = e^{kz}\mathbf{E}\left[\left(\frac{I^{intra}+I^{inter}+n_j^2}{S}\right)^{\alpha}\right] = e^{kz}\int_0^{\infty}\left(\frac{I^{intra}+n_j^2+y}{S}\right)^{\alpha} f(y)dy \ .$$

We assume that the inter-cell interference I^{inter} is a log-normal rv with probability density function (pdf) $f(y)$. A log-normal rv I^{inter} can be written as $I^{inter}=e^X$ where X is a normal rv with parameters (μ,σ^2), and the pdf of I^{inter} is given by $f(y)=e^{-\frac{1}{2\sigma^2}(\ln(y)-\mu)^2}/(y\sigma\sqrt{2\pi})$. The j-th moment of I^{inter} can be computed from the pdf and is given by

$$\mathbf{E}\left[(I^{inter})^j\right] = e^{j\mu+\frac{1}{2}j^2\sigma^2} \ . \qquad (9)$$

In order to characterize the inter-cell interference of a user, we need to estimate the parameters μ and σ^2. Denote the estimated values of μ_j and σ_j^2 at the start of timeslot t by $\hat{\mu}_j(t)$ and $\hat{\sigma}_j^2(t)$, respectively. Each user updates its estimates $\hat{\mu}_j(t+1)$ and $\hat{\sigma}_j^2(t+1)$ using exponential averaging similar to (8) in each timeslot.

Given the inter-cell interference distributions of the users, the objective of the beamforming algorithm is to calculate the beamforming weights and transmission powers so that the total transmission power is minimized subject to the constraint that the PER of each user is no larger than a target PER. The PER constraint can be written as

$$PER(S) = e^{kz}\int_0^{\infty}\left(\frac{I^{intra}+n_j^2+y}{S}\right)^{\alpha} f(y)dy \le PER_{target}$$

The above integration needs to be computed numerically for an arbitrary value of α. However, for an integer-valued α, we can obtain a closed form solution using (9). Here we assume $\alpha=2$, in which case the PER is given by

$$PER(S) = e^{kz}\frac{(I^{intra}+n_j^2)^2+2(I^{intra}+n_j^2)e^{\mu+\frac{1}{2}\sigma^2}+e^{2\mu+2\sigma^2}}{S^2} \ .$$

It is clear that this constraint does not depend only on SINR, and it changes the structure of the previous beamforming problem in the sense that we no longer aim at a target SINR while computing beamforming weights and transmission powers. As a consequence, Algorithms I and II can no longer be used for computing beamforming weights and power control. Instead, we propose the following beamforming algorithm.

Algorithm V: beamforming(P_{max};$\mathcal{H}_j, n_j^2, \hat{\mu}_j, \hat{\sigma}_j^2, \forall j\in\mathcal{U}$)

STEP 1: Set $n=0$. Let $\mathbf{p}^{(0)}=[1,\cdots,1]^T$.
STEP 2: While 1, do

- Set $n\leftarrow n+1$, solve a set of U decoupled generalized eigenproblems.
$$\mathbf{w}_j^{(n)} = \arg\max_{\|\mathbf{w}_j\|=1}\frac{\mathbf{w}_j^H\mathcal{H}_j\mathbf{w}_j}{\mathbf{w}_j^H\mathcal{R}_j(\mathbf{p}^{(n-1)})\mathbf{w}_j}\ ,\quad \forall j\in\mathcal{U}.$$
where $\mathcal{R}_j(\mathbf{p}^{(n-1)})=\sum_{k\in\mathcal{U}\setminus\{j\}}p_k^{(n-1)}\mathcal{H}_k$.
- Calculate the gain $g_j^{(n)}={\mathbf{w}_j^{(n)}}^H\mathcal{H}_j{\mathbf{w}_j}^{(n)}$ and the intra-cell interference $I_j^{(n)}=\sum_{k\in\mathcal{U}\setminus\{j\}}p_k^{(n-1)}\left({\mathbf{w}_k^{(n)}}^H\mathcal{H}_j\mathbf{w}_k^{(n)}\right)$ for user $j\in\mathcal{U}$.
- Calculate the transmission power $p_j^{(n)}$ for user $j\in\mathcal{U}$
$$p_j^{(n)} = \left(\frac{(I_j^{(n)}+n_j^2)^2+2(I_j^{(n)}+n_j^2)e^{\hat{\mu}_j+\frac{1}{2}\hat{\sigma}_j^2}+e^{2\hat{\mu}_j+2\hat{\sigma}_j^2}}{(g_j^{(n)})^2\ PER_{target}\ e^{-kz}}\right)^{\frac{1}{2}}$$
- If (i) $\max_{j\in\mathcal{U}}|p_j^{(n)}-p_j^{(n-1)}|\le\epsilon$, (ii) $\sum_{j\in\mathcal{U}}p_j>\eta\cdot P_{max}$, or (iii) $n=thresh\_$, break.

STEP 3: If $\max_{j\in\mathcal{U}}|p_j^{(n)}-p_j^{(n-1)}|\le\epsilon$ and $\sum_{j\in\mathcal{U}}p_j\le P_{max}$, then set $flag=1$. Otherwise, set $flag=0$.

STEP 4: Output $flag$, $\mathbf{p}^{(n)}$, and $\mathbf{W}^{(n)}$.

Unfortunately, the convergence of this algorithm is not guaranteed and oscillation could occur. This is expected since we do not explicitly use the estimated probability distribution of inter-cell interference when computing the beamforming weights, and such information is applied only to the power control. Furthermore, the set of users being scheduled by the algorithm may not be feasible, which will prevent the algorithm from converging. For these reasons, the algorithm (STEP 2) is terminated when the number of iterations n reaches a preset threshold $thresh\_$ or the total transmission power exceeds η times of the maximum power constraint. However, we will show that the computed beamforming weights and transmission powers achieve PER_{target} when they do converge.

The scheduling algorithm using Algorithm V is outlined below.

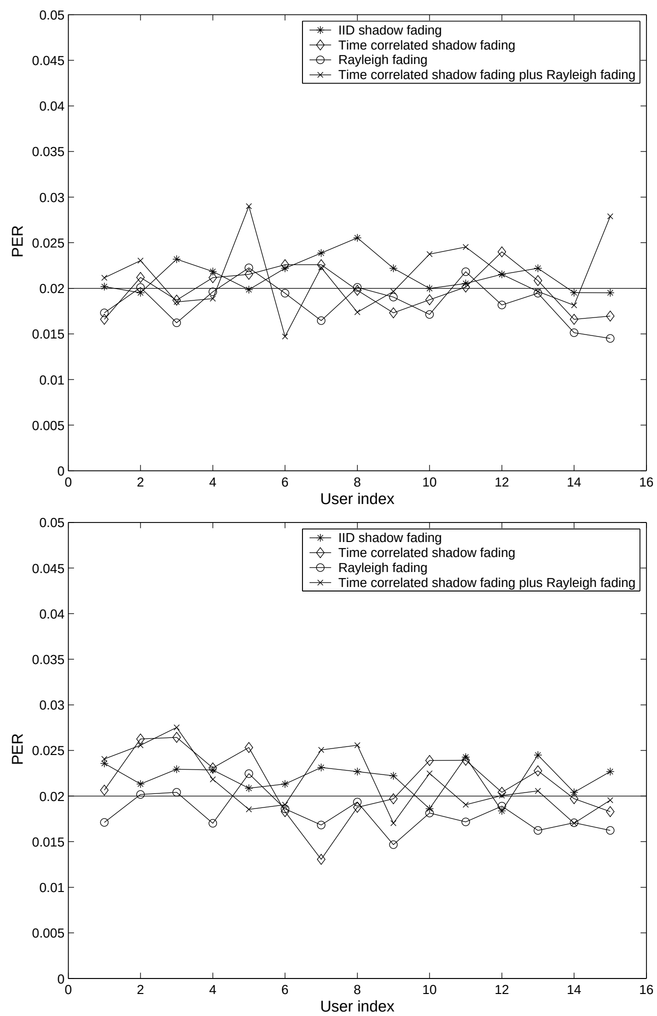
Algorithm VI: scheduling_3(P_{max};$c_j, T_j(t), \mathcal{H}_j, n_j^2, \hat{\mu}_j, \hat{\sigma}_j^2, \forall j\in\mathcal{N}$)

STEP 1: Initialize $\mathcal{U}=\emptyset$, $\mathcal{N}_1=\mathcal{N}$.
STEP 2: While $\mathcal{N}_1\neq\emptyset$, do

- $j^*=\arg\min_{j\in\mathcal{N}_1}T_j(t)/c_j$
- $\mathcal{U}=\mathcal{U}\cup\{j^*\}$, $\mathcal{N}_1=\mathcal{N}_1\setminus\{j^*\}$.
- beamforming(P_{max};$\mathcal{H}_j, n_j^2, \hat{\mu}_j, \hat{\sigma}_j^2, \forall j\in\mathcal{U}$).
- If $flag=0$, $\mathcal{U}=\mathcal{U}\setminus\{j^*\}$.

STEP 3: beamforming(P_{max};$\mathcal{H}_j, n_j^2, \hat{\mu}_j, \hat{\sigma}_j^2, \forall j\in\mathcal{U}$).

The performance of SCHEDULING_3 algorithm is illustrated in Fig. 8 with both single service class and multiple service classes. The figure shows that the achieved PERs are close to PER_{target} for all channel models. However, the achieved throughput of SCHEDULING_3 is considerably smaller than that of SCHEDULING_2. For the temporally correlated shadow fading plus Rayleigh fading channel model with a single service class, 1.3988 packets are scheduled and 1.3687 packets are successfully received in each timeslot on the average. An advantage of SCHEDULING_3 is, however, that the power control for different users can be carried out in parallel potentially on multiple processors. Therefore, it may lead to a more scalable algorithm when BSs are equipped with multiple processors for resource allocation.



(a) (b)

Fig. 8. PER for algorithm SCHEDULING_3 with (a) single service class and (b) multiple service classes.

A. Discussion

In this subsection we briefly compare the proposed algorithms SCHEDULING_2 and SCHEDULING_3. Algorithm SCHEDULING_2 utilizes the same optimal beamforming algorithms proposed in [19] by dynamically adjusting the virtual target PER $PER^{\star}$ (hence target SINR) provided to the algorithms. This is done based on the derived expression for PER in (4) for link curves of the form (2). The target PER $PER^{\star}$ fed to the algorithms is computed from the desired target PER and channel conditions summarized by the estimates of $\overline{SINR^{-1}}$ and $\overline{SINR^{-\alpha}}$. This allows us to keep the optimality of the previously proposed algorithms while satisfying the target PERs of the users.

In SCHEDULING_3 on the other hand, we only modify the part of the algorithm that computes the transmission powers while the beamforming weights are computed in a similar manner. The power control of the scheduled users is carried out *individually* while assuming that the transmission powers of other scheduled users remain the same. One can view this as a non-cooperative game among the scheduled users where each user iteratively attempts to minimize its own power based on the transmission powers of the other users subject to its own PER constraint. An equilibrium (or a solution concept) of such a non-cooperative game is called a Nash equilibrium, and it is well known that a Nash equilibrium is in general inefficient [3]. This provides a partial explanation for the decrease in system throughput compared to that of SCHEDULING_2.

VIII. CONCLUSION

We investigated the issue of unknown inter-cell interference in multiple cell networks and showed that unpredictable inter-cell interference that is not accounted for can significantly degrade the network performance. Then, we proposed two beamforming algorithms for handling unknown inter-cell interference. The first algorithm utilizes two input parameters based on the channel conditions and the adopted link curve. The second algorithm exploits the observations that the inter-cell interference exhibits a log-normal distribution with weak temporal correlation, and enables parallel computation of the transmission powers of scheduled users. Both algorithms are shown to achieve target packet error rates with a large family of link curves and scheduling algorithms under various wireless channel models.

In this paper we have assumed a TDMA system with FDD. However, we believe that the basic principles/approaches adopted in this paper can be easily extended to handle unpredictable interference not only in other cellular network technologies, but also in multi-hop wireless networks with distributed resource allocation.

REFERENCES

[1] R. Agrawal, A. Bedekar, R. J. La, and V. G. Subramanian, “C3WPF scheduler,” *Proc. of 17th ITC*, December 2001.

[2] J. Chuang, “Improvement of data throughput in wireless packet systems with link adaptation and efficient frequency reuse,” *IEEE Vehicular Technology Conference,* Houston, Texas, May 1999.

[3] P. Dubey, “Inefficiency of Nash equilibria,” *Math. Oper. Res.*, vol. 11, pp. 1-8, 1986.

[4] C. Farsakh and J. Nossek, “Spatial covariance based downlink beamforming in an SDMA mobile radio system,” *IEEE Transactions on Communications,* vol.46, no.11, pp.1497-1506, November 1998.

[5] W. Janos, “Tail of the distribution of sums of log-normal variates,” *IEEE Transactions of Information Theory,* vol.16, no.3, pp. 299-302, May 1970

[6] I. Koutsopoulos, T. Ren and L. Tassiulas, “The impact of space division multiplexing on resource allocation: a unified approach,” *IEEE INFOCOM*, San Francisco, CA, April 2003.

[7] T. V. Lakshman and U. Madhow, “The performance of TCP/IP for networks with high bandwidth-delay products and random loss,” *IEEE/ACM Transactions on Networking*, vol.5, no.3, pp. 336-350, June 1997.

[8] K. Leung, P. Driessen, K. Chawla and X. Qiu, “Link adaptation and power control for streaming services in EGPRS wireless networks,” *IEEE Journal on Selected Areas in Communications,* vol.19, no.10, pp. 2029-2039, October 2001.

[9] K. Leung, “Power control by interference predictions for wireless packet networks,” *IEEE Transactions on Wireless Communications,* vol.1, no.2, pp. 256 - 265, April 2002.

[10] J. Liberti, Jr., and T. Rappaport, *Smart antennas for wireless communications: IS-95 and third generation CDMA applications,* Prentice Hall, 1999.

[11] A. Osseiran, M. Ericson, J. Barta, B. Göransson, and B. Hagerman, “Downlink capacity comparison between different smart antenna concepts in a mixed service WCDMA system,” *Proc. of IEEE VTC*, Atlantic City, NJ, October 2001.

[12] A. Papoulis, and S. U. Pillai, *Probability, random variables, and stochastic processes*, McGraw Hill, New York, NY, 2002.

[13] K. I. Pedersen and P. E. Mogensen, “Performance of WCDMA HSPA in a beamforming environment under code constraints,” *Proc. of IEEE VTC*, Orlando, FL, October 2003.

[14] K. I. Pedersen and P. E. Mogensen, “Application and performance of downlink beamforming techniques in UMTS,” *IEEE Communication Magazine*, pp. 134-143, October 2003.

[15] M. Rajih and S. Sarkar, “Reference link level curves for Qualcomm cdma2000 Revision D R-ESCH,” *ftp://ftp.3gpp2.org,* May 2003.

[16] T. Rappaport, *Wireless communications: principles and practice,* Prentice Hall, 2002.

[17] F. Rashid-Farrokhi, K. R. Liu and L. Tassiulas, “Transmit beamforming and power control for cellular wireless systems,” *IEEE Journal on Selected Areas in Communications*, vol.16, no.10, pp.1437-1450, October 1998.

[18] T. Ren and R. J. La, “Downlink beamforming algorithms with inter-cell interference in cellular networks,” full draft, *available at http://www.enee.umd.edu/~ hyongla/publication.htm,* May 2004.

[19] M. Schubert and H. Boche, “Solution of the multiuser downlink beamforming problem with individual SINR constraints,” *IEEE Transactions on Vehicular Technology,* vol.53, no.1, pp.18-28, January 2004.

[20] R. Stridh, M. Bengtsson, and B. Ottersten, “System evaluation of optimal downlink beamforming in wireless communication,”*Proc. of IEEE VTC*, Atlantic City, NJ, October 2001.

PLACE PHOTO HERE

Tianmin Ren is a post doctoral researcher at the University of California, San Diego. He received his BS from Peking University, China, and M.S. and Ph.D from the University of Maryland, College Park, all in electrical engineering. His research interests include resource allocation algorithms and cross-layer design in wireless communications and networking.

PLACE PHOTO HERE

Richard J. La received the B.S.E.E. in 1994 from the University of Maryland at College Park, and the M.S. and Ph.D degrees in Electrical Engineering in 1997 and 2000, respectively, from the University of California at Berkeley. From 2000 to 2001 he was a senior engineer in the Mathematics of Communication Networks group at Motorola. Since August 2001 he has been on the faculty of the ECE department at the University of Maryland at College Park. His research interests include resource allocation in communication networks and application of game theory. He is a recipient of an NSF CAREER award.