Circumventing Base Station Cooperation through Kalman Prediction of Intercell Interference

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***Abstract*— We consider the downlink of a cellular *multiple input single output* (MISO) system with multiple users per cell. Fast scheduling and spatial signal processing at the base stations result in unpredictable *non-stationary* intercell interference when the base stations do not cooperate. We show how the per cell sum-rate can be increased when Kalman filters are employed to forecast the interference power for the next transmission. We compare these results for dirty-paper coding and beamforming to systems where the intercell interference powers are perfectly known through feedback channels or cooperating base stations and to systems where outdated information is used.**

I. Introduction

Future wireless communication standards will merge two techniques: *cellular* network architectures, like IS-95 or GSM, which enable *anytime anywhere* connectivity as well as *spatial multiplexing* and *fast scheduling*, like IEEE 802.11n and IEEE 802.16, which facilitate high data rates. The employment of temporal scheduling and spatial multiplexing using multiple transmit antennas in the downlink induces *non-stationary* variations in the intercell interference that is different for each user and unpredictable for the base stations of a multi-cell network. The costliness of bandwidth as a resource also demands for a universal frequency reuse, which aggravates the effects of intercell interference further.

The downlink of a cellular *multiple input multiple output* (MIMO) channel was considered in [1], [2] for both linear and non-linear processing at both the transmitting and receiving end. In [3], [4], intercell interference was reduced by minimizing the transmit power given a target signal-to-interference-plus-noise ratio. Opportunistic beamforming approaches were analyzed in [5], [6] and dirty-paper coding was considered in [1], [7]–[9]. All these papers assume cooperation between the base stations, which was first introduced in [10]. Limitations in the backhaul network connecting the base stations were recently analyzed in [11], [12].

Addressing the problem of intercell interference in a cellular network by assuming cooperation between the base stations increases costs, delays, and complexity. On the other hand, unknown non-stationary interference may increase outage and reduce data throughput. In this paper, we propose the employment of Kalman filters at the transmitting end to predict the interference power a user will experience when it decodes a codeword. Accordingly, system performance can be improved without the need for base station cooperation. We shall investigate three different precoding schemes, namely, dirty-paper coding, opportunistic and coherent beamforming, and compare their maximum per cell sum-rates and outage performances for different degrees of “interference blindness” at the base stations.

The system model is introduced in Section II and an extensive problem formulation is given in Section III. Section IV establishes a state-space model for the non-stationary intercell interference to which a Kalman filter can be applied. In Section V, we define the precoding schemes that we simulate and compare in Section VI. The paper concludes its results in Section VII.

Notation: Vectors and matrices are denoted by bold lower and upper case letters, respectively. $\mathbb{E}[\bullet]$, j, $\mathbf{1}_M$, $\|\bullet\|_2$, $(\bullet)^*$, $(\bullet)^{\mathrm{T}}$, and $(\bullet)^{\mathrm{H}}$ denote expectation, imaginary unit, $M \times M$ identity matrix, Euclidean norm, complex conjugation, transposition, and conjugate transposition, respectively. $\boldsymbol{e}_i$ is the i-th column of $\mathbf{1}_M$, M given by the context.

II. System Model

We are investigating network topologies like the one depicted in Fig. 1, where three base stations (“•”) are co-located and the users (“×”) are uniformly distributed within the cell area. Each of the B base stations serves K users in a dedicated hexagonal cell, i.e., users cannot benefit from macro-diversity offered through adjacent base stations. Each base station is equipped with a uniform linear array of N_{a} antennas with half-wavelength spacing.

The respective transmission chains for the K users in cell b are depicted in Fig. 2. The data stream $s_{b,k}[n] \in \mathbb{C}$ intended for the k-th user in cell b is weighted with $\sqrt{P_{b,k}^{[m]}}$ and then multiplexed on the N_{a} transmit antennas through the unit-norm vector $\boldsymbol{t}_{b,k}^{[m]} \in \mathbb{C}^{N_{\mathrm{a}}}$. The superposition of all transmit signals per cell results in the transmitted signal $\boldsymbol{x}_b \in \mathbb{C}^{N_{\mathrm{a}}}$ of the b-th base station. The scheduling decisions are assumed to be synchronized among the base stations and are labeled with the time index $[m]$. The MISO vector channel from the b'-th base station to user k in cell b is denoted by $\boldsymbol{h}_{b,k,b'} \in \mathbb{C}^{N_{\mathrm{a}}}$ with

$$\boldsymbol{e}_\zeta^{\mathrm{T}} \boldsymbol{h}_{b,k,b'} = \sum_{\xi=1}^{M} \sqrt{\frac{\rho(d_{b,k,b'}, \theta_{b,k,b'} + \varphi_\xi)}{M}} \times \exp\left\{\mathrm{j}\left[\pi(\zeta-1)\sin(\theta_{b,k,b'}+\varphi_\xi) + \psi_{b,k,b',\xi}\right]\right\},$$

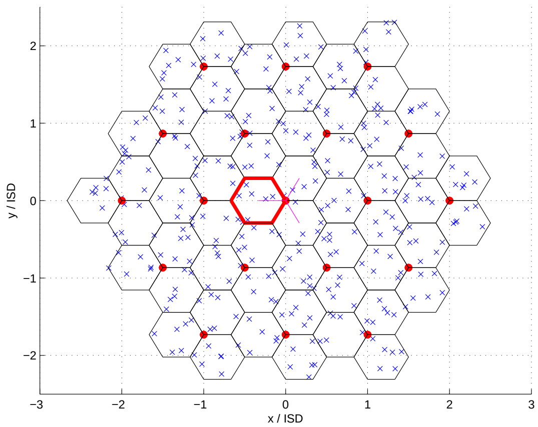

Fig. 1. Cellular network with base station sectorization.

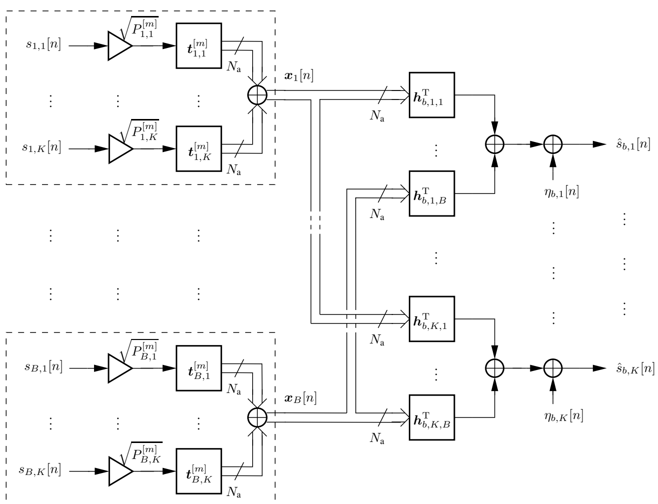

Fig. 2. Block diagram of a cellular multiple input single output system.

where φ_ξ models the angular spread of M unresolvable sub-paths.[1] The function $\rho(d,\theta)$ incorporates the maximum antenna gain in boresight direction $\hat{A}$ (in dB), the path-loss, the log-normal shadowing, and the antenna beam pattern $A(\theta)$ and is given by

$$\rho(d,\theta) = 10^{0.1\hat{A}} \cdot \left(\frac{\lambda}{4\pi}\right)^2 \cdot d^{-\gamma} \cdot 10^{0.1\chi} \cdot 10^{0.1A(\theta)},$$

where λ and γ are the carrier wavelength and the path-loss exponent, respectively, and

$$A(\theta) = -\min\left\{12\left(\frac{\theta}{70^\circ}\right)^2, 20\right\} \quad \text{in dB}.$$

χ is Gaussian distributed with zero mean and variance equals 36, and $\psi_{b,k,b',\xi}$ is uniformly distributed within $[-\pi,\pi)$. $d_{b,k,b'}$ and $\theta_{b,k,b'}$ are the distance and the angle to base station b' (w.r.t. its boresight direction) for the k-th user in cell b, respectively. In order to not violate the far-field assumption, we also have $\min d_{b,k,b'} \geq 200\lambda$. See [8], [13] for details.

The signal $\hat{s}_{b,k}[n] \in \mathbb{C}$ that the k-th user in the b-th cell receives is thus given by

$$\hat{s}_{b,k}[n] = \boldsymbol{h}_{b,k,b}^{\mathrm{T}} \boldsymbol{t}_{b,k}^{[m]} \sqrt{P_{b,k}^{[m]}} s_{b,k}[n] + \sum_{\substack{i=1\\ i\neq k}}^{K} \boldsymbol{h}_{b,k,b}^{\mathrm{T}} \boldsymbol{t}_{b,i}^{[m]} \sqrt{P_{b,i}^{[m]}} s_{b,i}[n]$$
$$+ \sum_{\substack{b'=1\\ b'\neq b}}^{B} \sum_{i=1}^{K} \boldsymbol{h}_{b,k,b'}^{\mathrm{T}} \boldsymbol{t}_{b',i}^{[m]} \sqrt{P_{b',i}^{[m]}} s_{b',i}[n] + \eta_{b,k}[n].$$

$\eta_{b,k}[n]$ is a *stationary* zero-mean additive white Gaussian noise process with variance σ_η^2.

III. Problem Formulation

Let $i_{b,k}[n]$ be the additive noise plus out-of-cell interference for user k in cell b, viz.,

$$i_{b,k}[n] = \eta_{b,k}[n] + \sum_{\substack{b'=1\\ b'\neq b}}^{B} \sum_{i=1}^{K} \boldsymbol{h}_{b,k,b'}^{\mathrm{T}} \boldsymbol{t}_{b',i}^{[m]} \sqrt{P_{b',i}^{[m]}} s_{b',i}[n].$$

Then, $i_{b,k}[n]$ is Gaussian distributed with zero mean and variance

$$\sigma_{i_{b,k}}^2[m] = \sigma_\eta^2 + \sum_{\substack{b'=1\\ b'\neq b}}^{B} \sum_{i=1}^{K} \boldsymbol{h}_{b,k,b'}^{\mathrm{T}} P_{b',i}^{[m]} \boldsymbol{t}_{b',i}^{[m]} \boldsymbol{t}_{b',i}^{[m],\mathrm{H}} \boldsymbol{h}_{b,k,b'}^{*}$$

assuming *independent and identically distributed* (i.i.d.) *stationary* Gaussian symbols $s_{b,k}[n]$ with zero mean and unit variance. Because of the fast scheduling at the base stations, the precoders $\boldsymbol{p}_{b,i}^{[m]} = \sqrt{P_{b,i}^{[m]}} \boldsymbol{t}_{b,i}^{[m]}$ vary much faster in time than the vector channels, which we will therefore consider to be constant ("block fading" assumption). On the other hand, the intercell-interference-plus-noise power $\sigma_{i_{b,k}}^2[m]$, which is usually not assumed to vary over time (stationarity assumption), will heavily vary over time. To account for that, let us define a random variable $z_{b,k}[m]$ as the conditional expectation conditioned on the scheduling decisions at the interfering base stations,

$$z_{b,k}[m] := \sigma_{i_{b,k}}^2[m] = \mathbb{E}\left[|i_{b,k}[n]|^2 \,\middle|\, \left\{ P_{b',i}^{[m]}, \boldsymbol{t}_{b',i}^{[m]} \right\}_{b'=1, b'\neq b, i=1}^{B,K} \right].$$

The index m emphasizes the time series character of $z_{b,k}[m]$ and one can clearly see that intercell interference is a *non-stationary* phenomenon even with constant channels when scheduling and spatial filtering are performed at the senders! Thus, we are facing the problem that the optimum transmit covariance structure $\boldsymbol{Q}_b^{[m]}$ at base station b,

$$\boldsymbol{Q}_b^{[m]} := \mathbb{E}\left[\boldsymbol{x}_b[n] \boldsymbol{x}_b^{\mathrm{H}}[n]\right] = \sum_{i=1}^{K} P_{b,i}^{[m]} \boldsymbol{t}_{b,i}^{[m]} \boldsymbol{t}_{b,i}^{[m],\mathrm{H}},$$

depends on the transmit processing at the $B-1$ other base stations in the network, $\left\{\boldsymbol{Q}_{b'}^{[m]}\right\}_{b'=1, b'\neq b}^{B}$, through the intercell

[1]We assume $M = 20$ and take φ_ξ as specified in the 3GPP Spatial Channel Model for MIMO simulations for an urban macro-cell [13].

interference

$$z_{b,k}[m] = \sigma_\eta^2 + \sum_{\substack{b'=1 \\ b'\neq b}}^{B} \boldsymbol{h}_{b,k,b'}^{\mathrm{T}} \boldsymbol{Q}_{b'}^{[m]} \boldsymbol{h}_{b,k,b'}^{*}.$$

In other words, the maximal achievable sum-rate R_b in cell b is a function of all transmit covariance matrices $\left\{\boldsymbol{Q}_b^{[m]}\right\}_{b=1}^{B}$ in the entire network. If the base stations do not cooperate, they have no means to predict $z_{b,k}[m]$ for the next transmission frame and system performance will suffer in terms of sum-rate and outage.

IV. Modeling of Non-Stationary Intercell Interference and State-Space Representation

To predict future realizations of the random variable[2] $z[m]$, a good model for the underlying random process is crucial. To this end, we will first review *autoregressive integrated moving average* (ARIMA) models. We will then define a state-space model to which a Kalman predictor can be applied to predict the intercell interference power a user will experience in the next time frame based on previous measurements.[3]

It is well known [15] that *autoregressive moving average* (ARMA) processes can be used to model a stationary time series $w[m]$:

$$\phi(B)w[m] = \theta(B)a[m], \tag{1}$$

where $a[m]$ is a stationary zero-mean Gaussian distributed random variable with variance σ_a^2. $\phi(B)$ and $\theta(B)$ are polynomials in B of order p and q and given by

$$\phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p,$$
$$\theta(B) = 1 - \theta_1 B - \ldots - \theta_q B^q.$$

B is called the backward shift or lag operator with $B^\iota w[m] = w[m-\iota]$. We also define the backward difference operator Δ by $\Delta^\delta w[m] = (1-B)^\delta w[m]$, e.g., $\Delta w[m] = w[m] - w[m-1]$. The roots of $\phi(B)$ must lie outside the unit circle such that it is invertible.

Now, assume the δ-th difference of the *non-stationary* process $z[m]$ can be modeled by a stationary process $w[m]$, viz. $w[m] = \Delta^\delta z[m]$. Then, from (1),

$$\phi(B)\Delta^\delta z[m] = \varphi(B)z[m] = \theta(B)a[m] \tag{2}$$

with $\varphi(B) = \phi(B)\Delta^\delta$. Furthermore, for a stationary process $w[m]$ [16],

$$w[m] = \sum_{j=0}^{\infty} \psi_j a[m-j] = \psi(B)a[m], \tag{3}$$

where $\psi(B) = 1 + \psi_1 B + \psi_2 B^2 + \ldots$ is a stable filter. Combining (2) and (3), we obtain

$$\varphi(B)z[m] = \varphi(B)\psi(B)a[m] \overset{!}{=} \theta(B)a[m] \tag{4}$$

and the ψ_j can recursively be obtained from equating the coefficients of the last equality in (4) with $\psi_0 = 1$ and $\psi_j = 0$ for $j < 0$. The solution to the difference equation (2) can be split in a homogeneous part $\varphi(B)C_k[m-k] = 0$ and a particular part $\varphi(B)I_k[m-k] = \theta(B)a[m]$ such that[4]

$$z[m] = I_k[m-k] + C_k[m-k] \overset{!}{=} \psi(B)a[m] = \sum_{j=0}^{\infty} \psi_j a[m-j],$$

where

$$I_k[m-k] = \sum_{j=0}^{m-k-1} \psi_j a[m-j],$$
$$C_k[m-k] = \sum_{j=m-k}^{\infty} \psi_j a[m-j].$$

We define the *minimum mean square error* (MMSE) predictor

$$\hat{z}_m[\ell] := \mathbb{E}_m\left[z[m+\ell]\right] := \mathbb{E}\left[z[m+\ell] | z[m], \ldots, z[1]\right]$$

by[5] $\hat{z}_{m+1}[\ell] = \hat{z}_m[\ell+1] + \psi_\ell a[m+1]$ and the time-invariant state-space model by

$$\boldsymbol{Y}[m] = \boldsymbol{\Phi}\boldsymbol{Y}[m-1] + \boldsymbol{\Psi}a[m] \qquad \text{state equation,}$$
$$z[m] = \boldsymbol{H}\boldsymbol{Y}[m] \qquad \text{observation equation.}$$

$\boldsymbol{Y}[m]$, $z[m]$, $\boldsymbol{\Phi}$, $\boldsymbol{H}$, and $\boldsymbol{a}[m]$ are the unobservable state vector, the noise-free measurement, the time-invariant transition matrix, the time-invariant observation matrix, and the process noise, respectively. $\boldsymbol{a}[m] = \boldsymbol{\Psi}a[m]$ is zero-mean Gaussian with covariance matrix $\boldsymbol{\Sigma}_a = \sigma_a^2 \boldsymbol{\Psi}\boldsymbol{\Psi}^{\mathrm{H}}$. We choose $p = 0$, $\delta = 1$, $q = 1$ for our problem setting and obtain (see [14])

$$\begin{bmatrix} z[m] \\ \hat{z}_m[1] \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & \varphi_1 \end{bmatrix} \begin{bmatrix} z[m-1] \\ \hat{z}_{m-1}[1] \end{bmatrix} + \begin{bmatrix} 1 \\ \psi_1 \end{bmatrix} a[m], \tag{5}$$

$$z[m] = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} z[m] \\ \hat{z}_m[1] \end{bmatrix} \tag{6}$$

as our state-space model.[6] The first equality in (5) is obtained from the one-step forecast error

$$z[m] - \hat{z}_{m-1}[1] = \sum_{j=0}^{\infty} \psi_j a[m-j] - \sum_{j=1}^{\infty} \psi_j a[m-j] = a[m],$$

the second equality in (5) is obtained via

$$\hat{z}_m[1] = \mathbb{E}_m\left[\varphi_1 z[m] + a[m+1] - \theta_1 a[m]\right] = \varphi_1 \hat{z}_{m-1}[1] + \psi_1 a[m].$$

[2] For notational convenience, we drop the indices b and k in this section.

[3] This section closely follows the treatment in [14] to which we refer for particulars.

[4] Note that this representation is informal as $z[m]$ is non-stationary and hence cannot be represented as an infinite weighted sum (cf. Eq. (4)).

[5] This definition follows from

$$\mathbb{E}_m\left[z[m+\ell]\right] = \mathbb{E}_m\left[\left[I_k[m+\ell-k] + C_k[m+\ell-k]\right]_{k=m}\right]$$
$$= \underbrace{\mathbb{E}_m\left[\sum_{j=0}^{\ell-1} \psi_j a[m+\ell-j]\right]}_{=0} + \mathbb{E}_m\left[\sum_{j=\ell}^{\infty} \psi_j a[m+\ell-j]\right] = \sum_{j=\ell}^{\infty} \psi_j a[m+\ell-j].$$

[6] We set $\varphi_1 = 1$. θ_1 and σ_a^2 can be calculated offline from measurements and standard estimation techniques.

The MMSE predictor is the conditional mean estimator $\hat{\boldsymbol{Y}}_m[m+\ell] = \mathbb{E}\left[\boldsymbol{Y}[m+\ell] \mid z[m],\ldots,z[1]\right]$ with error covariance matrix

$$\boldsymbol{V}_m[m+\ell] = \mathbb{E}\left[\left(\boldsymbol{Y}[m+\ell]-\hat{\boldsymbol{Y}}_m[m+\ell]\right)\left(\boldsymbol{Y}[m+\ell]-\hat{\boldsymbol{Y}}_m[m+\ell]\right)^{\mathrm{H}}\right].$$

We define the Kalman gain matrix as

$$\boldsymbol{K}[m] = \boldsymbol{V}_{m-1}[m]\boldsymbol{H}^{\mathrm{T}}\left[\boldsymbol{H}\boldsymbol{V}_{m-1}[m]\boldsymbol{H}^{\mathrm{T}}\right]^{-1}$$

resulting in

$$\hat{\boldsymbol{Y}}_m[m] = \hat{\boldsymbol{Y}}_{m-1}[m] + \boldsymbol{K}[m]\left(z[m]-\boldsymbol{H}\hat{\boldsymbol{Y}}_{m-1}[m]\right)$$
$$\boldsymbol{V}_m[m] = \left(\mathbf{1}-\boldsymbol{K}[m]\boldsymbol{H}\right)\boldsymbol{V}_{m-1}[m]$$

as the respective update equations and in

$$\hat{\boldsymbol{Y}}_m[m+1] = \boldsymbol{\Phi}\hat{\boldsymbol{Y}}_m[m]$$
$$\boldsymbol{V}_m[m+1] = \boldsymbol{\Phi}\boldsymbol{V}_m[m]\boldsymbol{\Phi}^{\mathrm{H}} + \boldsymbol{\Sigma}_a$$

as the respective prediction equations for the Kalman filter with initial values $\boldsymbol{Y}[0] = \hat{\boldsymbol{Y}}_0[0]$ and $\boldsymbol{V}[0] = \boldsymbol{V}_0[0]$.

V. PRECODERS

In this paper, we are not concerned with the optimization of the precoders. Rather, we want to demonstrate how the serious performance losses—when precoders are applied in multi-cell networks that have been originally designed for single-cell networks or for multi-cell networks with the assumption of stationary (Gaussian) out-of-cell interference—can be diminished through the application of a Kalman predictor.

We will look into three different kinds of precoding, namely opportunistic beamforming, coherent beamforming, and dirty-paper precoding. The total transmit power a base station can allocate is limited to E_{tr}. For the case of opportunistic beamforming, each base station generates a random beam and the users feed back the rates they can support [17]. In every cell, the user with the largest rate is served and we have[7]

$$R_b = \log_2\left(1+\frac{E_{\text{tr}}\left|\boldsymbol{h}_{b,\hat{k},b}^{\mathrm{T}}\boldsymbol{t}_b^{[m]}\right|^2}{z_{b,\hat{k}}[m]}\right). \tag{7}$$

The precoder is defined by

$$\boldsymbol{e}_\zeta^{\mathrm{T}}\boldsymbol{t}_b^{[m]} = \left|\boldsymbol{e}_\zeta^{\mathrm{T}}\boldsymbol{q}_b^{[m]}\right|\exp\left\{\mathrm{j}\,\pi(\zeta-1)\sin\left(\nu_b^{[m]}\right)\right\},$$

where $\boldsymbol{q}_b^{[m]}$ and $\nu_b^{[m]}$ are an isotropically distributed complex random unit-norm vector and a uniformly distributed real random variable, whose mean is the boresight direction of cell b and whose variance equals $\pi^2/27$. For the case of coherent beamforming [17], we assume that the b-th base station knows the vector channels $\left\{\boldsymbol{h}_{b,k,b}^{\mathrm{T}}\right\}$ for all k. The precoder is then chosen according to $\boldsymbol{t}_b^{[m]} = \boldsymbol{h}_{b,\hat{k},b}^{*}/\|\boldsymbol{h}_{b,\hat{k},b}\|_2$ with

$$\hat{k} = \underset{k=1,\ldots,K}{\operatorname{argmax}}\frac{\|\boldsymbol{h}_{b,k,b}\|_2^2}{z_{b,k}^{\text{est}}[m]}.$$

The estimated intercell interference power $z_{b,k}^{\text{est}}[m]$ is taken from the previous frame (*gambling algorithm*). For the *genie algorithm*, a feedback channel provides the true $z_{b,k}[m]$ based on that $\boldsymbol{t}_b^{[m]}$.[8] The dirty-paper precoding algorithms (both genie and gambling) are extensively treated in [8] to which we refer. When Kalman prediction is applied, we apply the gambling algorithm but exchange the outdated information with the forecast. When $z_{b,k}[m]$ is not perfectly known (gambling and Kalman prediction), the symbols $s_{b,k}[n]$ are encoded with a back-off β, viz. $R_{b,k}^{\text{set}} = (1-\beta)R_{b,k}^{\text{est}}$ (see [8] for details). An outage occurs ($R_{b,k}=0$) when $R_{b,k}^{\text{set}}$ was not an achievable rate, otherwise $R_{b,k} = R_{b,k}^{\text{set}}$.

TABLE I

OVERVIEW OF SIMULATION PARAMETERS

Number of cells:	57 (three tiers of base stations)
Distance between BSs (ISD):	2km
Number of users per cell:	6
Number of antennas per BS:	4
Transmit power:	10W
Thermal noise power:	-100.8dBm
Carrier wavelength:	15cm
Path-loss exponent:	3.8
Maximum antenna gain:	14dBi
Maximum antenna attenuation:	20dB

TABLE II

OVERVIEW OF SIMULATION RESULTS

	dirty-paper coding			coherent beamforming		
	genie	outdated	Kalman	genie	outdated	Kalman
sum-rate	8.52	4.30	4.67	6.27	3.84	3.90
outage	—	6.9%	4.1%	—	20.4%	17.4%
back-off	—	0.29	0.22	—	0.30	0.29
MSE	—	5.84	2.91	—	5.99	3.05

VI. SIMULATION RESULTS

Table I summarizes the parameters used in our simulations. Average results are itemized in Table II and the corresponding cumulative distribution functions are plotted in Fig. 3 for the cell of interest $b = 30$ in the center of the network (see Fig. 1). As we would expect, genie dirty-paper coding performs best with an average sum-rate of 8.52 bits per channel use (bpcu). The fact that this average sum-rate is nearly *halved* when the intercell interference powers are unknown to the base stations shows that dirty-paper coding is impractical for cellular networks when base stations do not cooperate. Genie coherent beamforming performs mediocre with an average sum-rate of about two bits less (6.27 bpcu).

[7]Note that whenever a single user is served per cell, we drop the index k such that $\boldsymbol{t}_b^{[m]} := \boldsymbol{t}_{b,\hat{k}}^{[m]}$, where $\hat{k}$ is the user that is served. Because only one user is served at a time, it is allocated the entire power budget E_{tr} available in the cell. Hence, (7) gives the per-cell sum-rate for all beamforming approaches we consider.

[8]If the feedback unveils that a user $\check{k}$ can achieve a higher rate with $\boldsymbol{t}_b^{[m]}$ than user $\hat{k}$, the base station is allowed to schedule that user without changing $\boldsymbol{t}_b^{[m]}$.

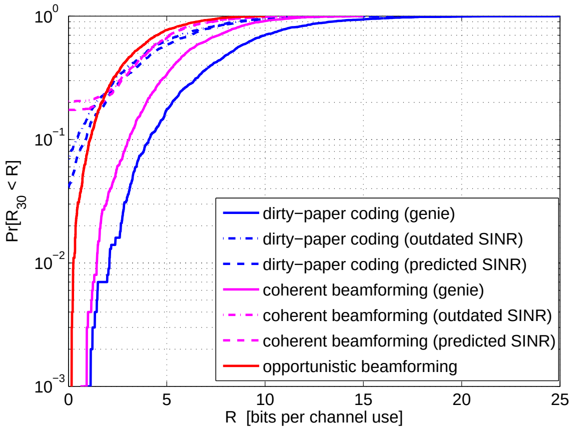

Fig. 3. Cumulative distribution functions of simulated scenarios.

Though the average sum-rate of coherent beamforming is also considerably compromised when intercell interference powers are unknown to the base stations, it appears to be a bit more robust than dirty paper coding, which performs only slightly better. This is especially interesting as coherent beamforming only requires local channel information ($K \times N_\mathrm{a}$ complex channel coefficients), whereas dirty-paper coding [8] requires $B \times B \times K \times N_\mathrm{a}$ complex channel coefficients to be estimated and exchanged between all base stations! Unfortunately, those algorithms which do not possess accurate information of the intercell interference suffer from poor outage performances. The situation is particularly serious for beamforming approaches as only one user is served at a time. The minimum achievable outage probability observed in our simulations is given in Table II. The back-off that maximized the *average* sum-rate, is also listed in Table II. Opportunistic beamforming achieves the worst average sum-rate (3.58 bpcu) but also requires neither channel state information, nor base station cooperation.

Last but not least, we give the *mean squared error* (MSE)

$$\frac{1}{K}\sum_{k=1}^{K}\mathbb{E}\left[\left|z_{30,k}^{\text{true}}[m]-z_{30,k}^{\text{est}}[m]\right|^2\right]$$

of our new algorithms compared to the application of outdated information. As Table II suggests, we can nearly halve the MSE through the application of Kalman prediction even though the intercell interference is non-stationary. However, this gain is diminished through the non-linear character of the $\log$-function in (7).

VII. Conclusions

We compared different precoding algorithms for cellular networks that rely on different degrees of channel state information and base station cooperation. Dirty-paper coding with cooperating base stations outperforms all other approaches we looked at. Unfortunately, it requires knowledge of $B \times B \times K \times N_\mathrm{a}$ complex channel coefficients. Furthermore, the cooperation comes at the expense of additional infrastructure (backhaul network) and huge delays (both for propagation between and processing at base stations). Together with our fast scheduling assumption, these non-neglectable delays would result in outdated solutions. On the other hand, when dirty-paper coding is performed locally without base station cooperation, performance enormously suffers. We showed how the application of Kalman filters can considerably reduce the back-off and nearly halve the minimum outage probability when timely information about the intercell interference is not available. The latter also holds for coherent beamforming, which is a viable alternative to dirty-paper coding when base stations do not cooperate as it nearly performs as well as dirty-paper coding when the intercell interference powers are unknown to the base stations. This shows how heavily dirty-paper coding relies on good channel state information. Unfortunately, the outage performance is disappointing. All these approaches outperform opportunistic beamforming.

References

[1] H. Zhang and H. Dai, "Cochannel Interference Mitigation and Cooperative Processing in Downlink Multicell Multiuser MIMO Networks," *Wireless Communications and Networking, EURASIP Journal on*, vol. 2004, no. 2, pp. 222–235, 2004.

[2] H. Dai, A. F. Molisch, and H. V. Poor, "Downlink Capacity of Interference-Limited MIMO Systems with Joint Detection," *Wireless Communications, IEEE Transactions on*, vol. 3, no. 2, pp. 442–453, 2004.

[3] A. Ekbal and J. M. Cioffi, "Distributed Transmit Beamforming in Cellular Networks - a Convex Optimization Perspective," *Proc. IEEE Int. Conf. on Communications*, vol. 4, pp. 2690–2694, 2005.

[4] F. Rashid-Farrokhi, K. Liu, and L. Tassiulas, "Transmit Beamforming and Power Control for Cellular Wireless Systems," *Selected Areas in Communications, IEEE Journal on*, vol. 16, no. 8, pp. 1437–1450, 1998.

[5] D. Piazza and G. Tartara, "Opportunistic Frequency Reuse in Cooperative Wireless Cellular Systems," *Proc. IEEE Int. Symp. Personal, Indoor and Mobile Radio Communications*, pp. 1–5, 2006.

[6] ——, "Diversity and Multiplexing in Cooperative Wireless Cellular Networks," *Proc. IEEE Int. Conf. on Communications*, pp. 6067–6072, 2007.

[7] S. A. Jafar and A. J. Goldsmith, "Transmitter Optimization for Multiple Antenna Cellular Systems," *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, p. 50, 2002.

[8] M. Ivrlac and J. Nossek, "Intercell-Interference in the Gaussian MISO Broadcast Channel," *IEEE Global Telecommunications Conference*, pp. 3195–3199, 2007.

[9] M. Castaneda, A. Mezghani, and J. A. Nossek, "On Maximizing the Sum Network MISO Broadcast Capacity," *ITG Workshop in Smart Antennas (WSA 08)* , 2008.

[10] S. Shamai and B. M. Zaidel, "Enhancing the Cellular Downlink Capacity via Co-Processing at the Transmitting End," *Proc. IEEE Vehicular Technology Conference*, vol. 3, pp. 1745–1749 vol.3, Spring 2001.

[11] T. Tamaki, K. Seong, and J. M. Cioffi, "Downlink MIMO Systems Using Cooperation Among Base Stations in a Slow Fading Channel," *Proc. IEEE Int. Conf. on Communications*, pp. 4728–4733, 2007.

[12] A. Sanderovich, O. Somekh, S. Shamai, and G. Kramer, "Uplink Macro Diversity with Limited Backhaul Capacity," *Proc. IEEE Int. Symp. Inf. Theory (ISIT)*, 2007.

[13] 3GPP TSG-RAN-WG1, "Spacial Channel Model for Multiple Input Multiple Output (MIMO) Simulations," 3GPP, Tech. Rep. TR 25.996, 2003.

[14] G. Box, G. Jenkins, and G. Reinsel, *Time Series Analysis, Forecasting and Control*, 3rd ed. Prentice Hall, Englewood Cliffs, 1994.

[15] J. G. Proakis and D. K. Manolakis, *Digital Signal Processing: Principles, Algorithms and Applications*, 4th ed. Prentice Hall, 2006.

[16] G. U. Yule, "On a Method of Investigating Periodicities in Disturbed Series, with Special Reference to Wolfer's Sunspot Numbers," *Phil. Trans. Roy. Soc.*, vol. A226, pp. 267–298, 1927.

[17] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*, 1st ed. Cambridge University Press, 2005.