Performance of Adaptive MC-CDMA Detectors in Rapidly Fading Rayleigh Channels

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***Abstract*—Multicarrier code-division multiple access (MC-CDMA) combines multicarrier transmission with direct sequence spread spectrum. Recently, different approaches have been adopted which do not assume a perfectly known channel. In this paper, we examine the forward-link performance of decision-directed adaptive detection schemes, with and without explicit channel estimation, for MC-CDMA systems operating in fast fading channels. We analyze theoretically the impact of channel estimation errors by first considering a simpler system employing a threshold orthogonality restoring combining (TORC) detector with a Kalman channel estimator. We show that the performance deteriorates significantly as the channel fading rate increases and that the fading rate affects the selection of system parameters. We examine the performance of more realistic schemes based on the minimum mean square error (MMSE) criterion using least mean square (LMS) and recursive least square (RLS) adaptation. We present a discussion which compares the decision-directed and pilot-aided approaches and explores the tradeoffs between channel estimation overhead and performance. We find that there is a fading rate range where each method provides a good tradeoff between performance and overhead. We conclude that the MMSE per carrier decision-directed detector with RLS estimation combines good performance in low to moderate fading rates, robustness in parameter variations, and relatively low complexity and overhead. For higher fading rates, however, only pilot-symbol-aided detectors are appropriate.**

***Index Terms*—Adaptive detection, channel estimation, multicarrier code-division multiple-access (MC-CDMA) detection, multicarrier-CDMA, orthogonal frequency division multiplexing (OFDM)-CDMA.**

I. Introduction

SEVERAL different approaches that combine multicarrier transmission with direct-sequence code-division multiple access (DS-CDMA) have been proposed in the literature. The schemes which have attracted most research interest are the scheme proposed by Milstein and Kondo in [1] which has been adopted as an option in the IS-2000 next-generation CDMA cellular standard, and the scheme proposed independently in [2]–[4], which combines orthogonal frequency division multiplexing (OFDM) with DS-CDMA. In this paper, we refer to the latter as multicarrier (MC)-CDMA. This scheme appears to be an attractive alternative to DS-CDMA for broadband wireless integrated services networks (B-WISN) because it can sometimes offer higher spectral efficiency than its single carrier counterpart [5] and increased flexibility to support integrated, high data-rate applications with different quality-of-service (QoS) requirements [6]. The basic idea of this scheme is to divide the available bandwidth into a large number of narrow subchannels and spread each data symbol in the frequency domain by transmitting all the chips of a spread symbol at the same time, but in different orthogonal subchannels. Since the chips of all the symbols that form a multicarrier block overlap in time, even high-data rate information can be transmitted using a large MC symbol duration, which drastically reduces ISI, allows for approximately flat fading in each subchannel, and combats the frequency-selective fading of the channel by introducing a large degree of frequency diversity.

Earlier work that investigated the performance of MC-CDMA detectors (e.g., [7]–[9]) made the assumption that the channel is perfectly known to the receiver. Recently, the impact of channel estimation errors on the performance of MC-CDMA detectors attracted significant research interest and different approaches were adopted. According to the first approach [10]–[12], known pilot training symbols are inserted in the transmitted data in both the frequency dimension (every N_f subchannels of the same OFDM symbol) and the time dimension (every N_t OFDM symbols at the same subchannels). The estimates of the channel coefficients are then obtained through some form of two–dimensional (2-D) linear filtering. The pilot-symbol grid in [10] and [11] is designed using oversampling by a factor of two based on the generalized 2-D sampling theorem considering the worst expected channel fading conditions (N_f based on minimum coherence bandwidth, N_t based on maximum Doppler spread). A special case of the pilot-symbol-aided approach uses "pilot-carriers" [13], i.e., pilot symbols are inserted in a subset of the available subchannels in each OFDM symbol ($N_t = 1$, $N_f > 1$). The estimates of the channel coefficients are then obtained by filtering in the frequency dimension, although [13] also examines some type of 2-D filtering. The second approach proposed in [14] and [15] considers explicit channel estimation based on channel-sounding. The OFDM transmitter is bypassed and a "train of pulses" spaced by the maximum delay spread of the channel is transmitted instead (in effect $N_f = 1$, $N_t > 1$). The receiver uses the fast Fourier transform (FFT) to obtain the

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estimates of the channel coefficients, which are then used (or their linearly interpolated values) in the detection of data until a new snapshot of the channel is captured. Finally, our approach, introduced in part in [16], is to consider decision-directed, adaptive MC-CDMA detectors. This approach includes a new type of MC-CDMA detectors using explicit decision-directed channel estimation. It also includes decision-directed MC-CDMA detectors without explicit channel estimation. An example of the latter type is a form of the decision-directed minimum mean square error (MMSE) detector based on least mean square (LMS) adaptation which was proposed in [3] and whose transient performance and convergence in a static channel were examined in [17].

The motivation of this paper is to present a comprehensive examination of different decision-directed adaptive MC-CDMA detectors with and without explicit channel estimation and to analyze their performance under different fading rate scenarios; furthermore, to compare the decision-directed and pilot-aided approaches and explore the tradeoffs between channel estimation overhead and performance. Note that, as opposed to the pilot-symbol-aided and channel-sounding approaches, the decision-directed detectors do not require overhead symbols to be regularly inserted in the transmitted data, although in a practical system an initial training sequence and occasional retraining when there is a disruption in the channel are necessary before switching to the decision-directed mode. We start our investigation by performing a theoretical analysis that demonstrates the mechanism through which the channel estimation process affects the performance of adaptive MC-CDMA detectors operating in multipath, fast fading, Rayleigh channels. For this purpose we consider a simple detector, termed threshold orthogonality restoring combining (TORC) detector, and we make the simplifying assumption that the channel is described by a Gauss–Markov state–space model, whose parameters are known. The receiver uses the Kalman filter, which is the MMSE estimator for the channel described by the above model, to track the complex channel coefficients. We expand our investigation by considering the more realistic case in which the parameters of the channel model are not known and we examine the performance of more practical, although more complex, detectors based on the MMSE criterion. More specifically, we examine the performance of two forms of the MMSE detector, which were proposed in [3] as MMSE per user and MMSE per carrier, and we consider adaptive schemes with explicit channel estimation using the LMS and recursive least square (RLS) algorithms, which are compared with the optimal Kalman filter. We also consider adaptive MMSE detectors using the LMS and RLS algorithms without explicit channel estimation, and we compare them to the forms employing channel estimation. Finally, we present a discussion which compares the decision-directed and pilot-aided approaches.

This paper is organized as follows. In Section II, a description of the channel model, of the MC-CDMA transmitter and receiver structure, and of the decision-directed channel estimation process is given. In Section III, the TORC detector is introduced and a closed-form expression of its performance is derived. In Section IV, adaptive detectors based on the MMSE criterion are introduced. In Section V, numerical and simulation results on the performance of the adaptive MC-CDMA detectors are presented and comparisons are performed, and in Section VI, we summarize our conclusions.

II. System Description

We consider a multiple access system where N_u users are transmitting simultaneously in a synchronous manner using Walsh–Hadamard orthogonal codes of length N_s. Therefore, up to N_s users can transmit at the same time. The system corresponds to the forward-link (downlink) from the base station to the users. The nth MC block symbol (of duration T_b) for user i is formed by taking μ symbols $b_i^1(n), \ldots, b_i^{\mu}(n)$ in parallel, spreading them with the user's spreading sequence $\mathbf{c}_i = [c_{1,i} \ldots c_{N_s,i}]^T$, $c_{j,i} = \pm 1$, performing frequency interleaving, and placing the resulting $u_i^1(n), \ldots u_i^{\mu N_s}(n)$ chips into the $N > \mu N_s$ available subchannels, each having width $\Delta f = 1/T_b$, by using an inverse fast Fourier transform (IFFT) of size N. In practice, N is larger than the number of subchannels μN_s required for the tranmission of the data in order to avoid frequency aliasing after sampling at the receiver. For that reason, the data vector at the input of the IFFT is padded with zeros at its edges so that the $(N - \mu N_s)$ unmodulated carriers are split in both sides of the useful spectrum. The function of the identical frequency interleavers is to ensure that the N_s chips corresponding to each of the μ symbols are transmitted over approximately independently faded subchannels. This is possible only if μ/T_b is larger than the coherence bandwidth $(\Delta f)_c \approx 1/T_m$ of the channel. After performing a parallel to serial conversion, a guard interval is added in the form of a cyclic prefix, and the signals of all the users are added and transmitted through the channel. The block diagram of the transmitter is depicted in Fig. 1. In the rest of this paper, for simplicity of notation, we concentrate only on one of the μ symbols each user transmits and the corresponding N_s subchannels and we drop or modify the indices where μ appears, while keeping in mind that the frequency-interleaving function still exists. Also, we will consider binary symbols $b_k(n) = \pm 1$, $k = 1, \ldots, N_u$ forming the data vector $\mathbf{b}(n) = [b_1(n), \ldots, b_{N_u}(n)]^T$, where n is the time index denoting the nth symbol interval. The transmitted signal during the nth MC block symbol period can be approximately written as follows:

$$s(t) = \sum_{k=1}^{N_u} \sum_{l=1}^{N_s} \sqrt{E_c} c_{l,k} b_k(n) e^{j(2\pi l(t-nT_G)/T_b)} \qquad (1)$$

where $t \in [nT, (n+1)T]$, $T = T_b + T_G$, T_G is the guard interval chosen to be at least equal to the delay spread T_m of the channel and E_c is the energy per chip.

We assume a fast-fading, multipath, Rayleigh channel whose impulse response has N_p path arrivals at delays $\tau_p(t)$, which are described by independent zero-mean, complex Gaussian distributed path gain processes $a_p(t)$, $p = 1, \ldots, N_p$. We assume that the channel is not changing during one MC symbol interval; however, we allow for variations during successive symbol intervals. Because of the large symbol duration, the fading of the subchannels is approximately flat and is described by multiplicative complex channel coefficients $h_l(n)$, $l = 1, \ldots, N_s$,

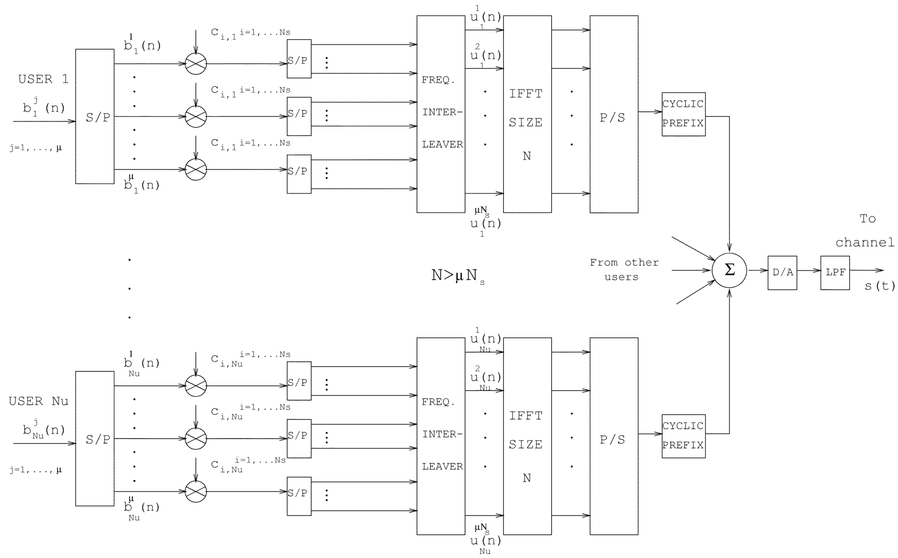

Fig. 1. MC-CDMA transmitter block diagram.

which are samples of the channel frequency response at the center frequency f_l of the lth subchannel at $t = nT$. Therefore, $h_l(n) = \sum_{p=1}^{N_p} a_p(n)e^{-2\pi f_l \tau_p(n)}$. Because of the independence of $a_p(n)$ $p = 1, \ldots, N_p$, the variance $\mathcal{E}\{|h_l(n)|^2\} = \sum_{p=1}^{N_p} \mathcal{E}\{|a_p(n)|^2\}$ is the same for all subchannels and we assume it is time invariant. Because of the frequency-interleaving function, the channel complex coefficient processes will be considered independent. We assume that each of these random processes is described by a first-order Gauss–Markov model. In performance results presented in Section V, we also use the more realistic Jakes' model [18]. The channel model has the following form:

$$h_l(n+1) = fh_l(n) + \chi_l(n), \qquad l = 1, \ldots, N_s \tag{2}$$

where $\chi_l(n)$ is a zero-mean, white Gaussian noise process, with autocorrelation

$$E\{\chi_l(n)\chi_l^*(k)\} = 2\sigma_h^2 \delta_{n,k} \tag{3}$$

and $\delta_{n,k}$ is the Kronecker delta. The parameter f corresponds to an exponentially decaying channel time-correlation function, and is related to the 3-dB frequency f_d of the corresponding Doppler power spectrum as

$$f = e^{-\omega_d T} \tag{4}$$

where $\omega_d = 2\pi f_d$.

Because of the existence of a guard interval with duration at least equal to the channel's delay spread, there is no intersymbol interference, and the signal received by user i can be approximately described by

$$r(t) = \sum_{k=1}^{N_u} \sum_{l=1}^{N_s} \sqrt{E_c} h_l^{(i)}(n) c_{l,k} b_k(n) e^{j(2\pi l(t-nT_G)/T_b)} + n(t) \tag{5}$$

where $t \in [nT, (n+1)T]$, $h_l^{(i)}(n)$ are the complex channel coefficients which describe the channel between the transmitter and the user i, and $n(t)$ is the additive white Gaussian noise (AWGN). For simplicity of notation in the rest of the paper, the superscript (i) will be dropped. At the receiver, the signal is sampled at a rate N/T_b, the samples which correspond to the cyclic prefix are discarded, an FFT of size N is performed, and frequency deinterleaving takes place. The vector $\mathbf{r}(n) = [r_1(n), \ldots, r_{N_s}(n)]^T$ at the output of the deinterleaver is given in matrix notation by

$$\mathbf{r}(n) = \sqrt{E_c}\mathbf{H}(n)\mathbf{C}\mathbf{b}(n) + \boldsymbol{\eta}(n) \tag{6}$$

where $\mathbf{H}(n) = \text{diag}\{h_1(n), \ldots, h_{N_s}(n)\}$, matrix $\mathbf{C} = [\mathbf{c}_1 \mid \cdots \mid \mathbf{c}_{N_u}]$ is the $N_s \times N_u$ matrix whose columns are the spreading sequences of the users, $\mathbf{b}(n)$ is the data vector of the users, and $\boldsymbol{\eta}(n) = [\eta_1(n), \ldots, \eta_{N_s}(n)]^T$ is a vector containing zero mean, uncorrelated complex Gaussian noise samples, with variance $2\sigma^2$.

In this paper, we consider two forms of decision-directed adaptive detectors, depending on the channel estimation process. When the MC-CDMA detectors are implemented adaptively without explicit channel estimation, the observation vector $\mathbf{r}(n)$ is used by each detector to obtain an estimate of the current data vector $\hat{\mathbf{b}}(n)$, and both $\mathbf{r}(n)$ and $\hat{\mathbf{b}}(n)$ are used to update the detector coefficients for the next symbol interval. On the other hand, when the detectors use explicit channel estimates, the observation vector $\mathbf{r}(n)$ is fed to both the detector and the channel estimator, which in addition uses estimates of previous data vectors from the output of the detector. The block diagram of the general form of the decision-directed MC-CDMA receivers that we propose is depicted in Fig. 2.

We consider three decision-directed ways of obtaining the channel estimates $\hat{h}_1(n), \ldots, \hat{h}_{N_s}(n)$. If the channel process model (2) is assumed known to the receiver, the Kalman filter gives the best estimates in the MMSE sense. In the general case, when the process model is not known, the estimate of the channel coefficients can be obtained by using the LMS or the RLS algorithm. In all three cases, the estimator's input is the vector $\mathbf{r}(n)$, which represents the measured quantity, and the estimate of the data vector $\hat{\mathbf{b}}(n)$. The equation that describes the channel measurement vector is derived from (6) by rearranging its terms

$$r_l(n) = d_l(n)h_l(n) + \eta_l(n), \quad l = 1, \ldots, N_s \tag{7}$$

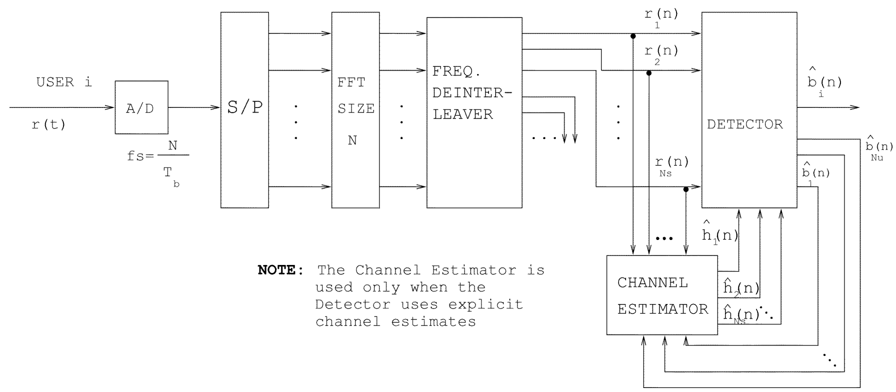

Fig. 2. Decision-directed MC-CDMA receiver block diagram.

where

$$d_l(n) = \sqrt{E_c}\sum_{k=1}^{N_u} c_{l,k} b_k(n) \tag{8}$$

and $\eta_l(n)$ is the measurement noise process, which is white Gaussian, with zero mean and variance $2\sigma^2$. The algorithms of the three estimators are described as follows [19], [20].

A. Kalman Filter

The Kalman filter is the optimal in a class of linear filters, minimizing the estimation error variance $E_l(n) = \mathcal{E}\{|h_l(n) - \hat{h}_l(n)|^2\}$. The new channel estimate at time $n+1$ using information available up to time n is

$$\hat{h}_l(n+1) = [f - K_l(n)\hat{d}_l(n)]\hat{h}_l(n) + K_l(n)r_l(n) \tag{9}$$

where the term $K_l(n), l = 1, \ldots, N_s$ is the Kalman gain, which is related to the error variance $E_l(n)$

$$K_l(n) = \frac{fE_l(n)\hat{d}_l(n)}{\hat{d}_l^2(n)E_l(n) + 2\sigma^2}. \tag{10}$$

The estimation error variance is calculated in an iterative way

$$E_l(n) = f^2\frac{2\sigma^2 E_l(n-1)}{\hat{d}_l^2(n-1)E_l(n-1) + 2\sigma^2} + 2\sigma_h^2. \tag{11}$$

B. LMS Estimator

The LMS estimator calculates the estimates of the channel by minimizing the MSE $\mathcal{E}\{|r_l(n) - \hat{h}_l(n)\hat{d}_l(n)|^2\}$. The new channel estimate at time $n+1$ using information available up to time n is

$$\hat{h}_l(n+1) = \hat{h}_l(n) + \tilde{\mu}[r_l(n) - \hat{h}_l(n)\hat{d}_l(n)]\hat{d}_l^*(n) \tag{12}$$

where $l = 1, \ldots, N_s$, and $\tilde{\mu} > 0$ is the step size of the LMS algorithm.

C. RLS Estimator

The RLS estimator calculates the estimates of the channel by minimizing the cost function $\sum_{i=0}^{n}\lambda^{n-i}|r_l(i) - \hat{h}_l(i)\hat{d}_l(i)|^2$, where $0 < \lambda < 1$. The new channel estimate at time $n+1$ using information available up to time n is

$$\hat{h}_l(n+1) = \hat{h}_l(n) + [r_l(n) - \hat{h}_l(n)\hat{d}_l(n)]K_l^*(n) \tag{13}$$

where the term $K_l(n)$ is the Kalman gain given by

$$K_l(n) = \frac{P_l(n)\hat{d}_l(n)}{\lambda + P_l(n)\hat{d}_l^2(n)}. \tag{14}$$

$P_l(n)$ is given by the following recursion:

$$P_l(n+1) = \lambda^{-1}(1 - K_l(n)\hat{d}_l^*(n))P_l(n) \tag{15}$$

and $0 < \lambda < 1$ is called the forgetting factor of the RLS algorithm.

In the above equations, $\hat{d}_l(n)$ denotes the estimate of the quantity given in (8), as it is obtained by using the estimate of the data vector $\hat{\mathbf{b}}(n)$. In the rest of this paper, we will assume that the estimates of the previous data are correct and, therefore, that $\hat{d}_l(n) = d_l(n)$.

III. Performance Analysis: The TORC Detector

In this section, we present a theoretical analysis of the impact of channel estimation on the performance of MC-CDMA detectors. We select the TORC detector because it combines low complexity, relatively good performance, and it admits a closed-form performance expression. We make the simplifying assumption that the channel is described by the state–space model (2) whose parameters are known and that Kalman filtering is used for channel estimation. The TORC detector uses the channel estimates to invert the effect of the channel by attempting to invert matrix $\mathbf{H}(n)$ in (6). In order to avoid excessive noise enhancement by inverting channel coefficients with very small amplitude, the detector discards the chips which correspond to subchannels with magnitude below a chosen threshold. It then correlates the resulting signal with the user's spreading sequence and performs a threshold decision. The decision rule it uses to obtain the estimate of symbol n of user i is the following:

$$\hat{b}_i(n) = \mathrm{sgn}[\Re e\{\mathbf{c}_i^T\widehat{\mathbf{U}}(n)\widehat{\mathbf{H}}^{-1}(n)\mathbf{r}(n)\}] \tag{16}$$

where $\widehat{\mathbf{H}}(n) = \mathrm{diag}\{\hat{h}_1(n), \ldots, \hat{h}_{N_s}(n)\}$ is the estimate of matrix $\mathbf{H}(n)$ obtained by using information available up to the time interval $n-1$, $\widehat{\mathbf{U}}(n) = \mathrm{diag}\{u(|\ \hat{h}_l(n)\ | - h_{\mathrm{THR}})\}$, $l = 1, \ldots, N_s$, h_{THR} is the selected threshold, and $u(x)$ is the unit step function.

The decision variable for symbol $b_i(n)$ of user i, $i = 1, \ldots, N_u$ has the following form:

$$v_i(n) = \Re e\left\{\mathbf{c}_i^T \widehat{\mathbf{U}}(n)\widehat{\mathbf{H}}^{-1}(n)\mathbf{r}(n)\right\}. \quad (17)$$

We denote by $\hat{\rho}_l(n)$ and $\hat{\phi}_l(n)$ the magnitude and the phase, respectively, of the estimate $\hat{h}_l(n)$, and by $e_l(n) = h_l(n) - \hat{h}_l(n)$, the error in the estimation of $h_l(n)$, $l = 1, \ldots, N_s$. If we also define $\eta_{lr}(n) = \Re e\{\eta_l(n)e^{-j\hat{\phi}_l(n)}\}$ and $e_{lr}(n) = \Re e\{e_l(n)e^{-j\hat{\phi}_l(n)}\}$, the decision variable given in (17) can be rewritten in the following form:

$$\begin{aligned} v_i(n) =& \sqrt{E_c}\sum_{l=1}^{N_s} u(\hat{\rho}_l(n) - h_{\mathrm{THR}})b_i(n) \\ &+ \sqrt{E_c}\sum_{\substack{j=1\\ j\neq i}}^{N_u}\sum_{l=1}^{N_s} u(\hat{\rho}_l(n) - h_{\mathrm{THR}})c_{l,i}c_{l,j}b_j(n) \\ &+ \sum_{l=1}^{N_s} c_{l,i}u(\hat{\rho}_l(n) - h_{\mathrm{THR}})\frac{\eta_{lr}(n)}{\hat{\rho}_l(n)} \\ &+ \sqrt{E_c}\sum_{j=1}^{N_u}\sum_{l=1}^{N_s} u(\hat{\rho}_l(n) - h_{\mathrm{THR}})c_{l,i}c_{l,j}\frac{e_{lr}(n)}{\hat{\rho}_l(n)}b_j(n) \\ =& S_i(n) + I_i(n) + \xi_i(n) + \Delta_i(n). \end{aligned} \quad (18)$$

In (18), the first term $S_i(n)$ corresponds to the desired signal, the second term $I_i(n)$ to the multiuser interference, the third term $\xi_i(n)$ to the noise, while the fourth term $\Delta_i(n)$ arises from the channel estimation errors.

Before we investigate the distribution of the four terms in (18), we note that each of the channel coefficients $h_l(n)$, which is described by the process (2), is Gaussian with zero mean and with variance [19]

$$\mathrm{Var}\{h_l(n)\} = \mathcal{E}\{|h_l(n)|^2\} = 2\sigma_h^2\left[f^{2n} + \frac{1 - f^{2n}}{1 - f^2}\right]. \quad (19)$$

Clearly, for large n, $\mathrm{Var}\{h_l(n)\} = 2\sigma_h^2/(1 - f^2)$ since $0 < f < 1$. On the other hand, each of the channel estimates $\hat{h}_l(n)$ is conditionally Gaussian given the data symbols and since the Kalman estimator is the minimum variance, linear, unbiased estimator, it has zero mean and is orthogonal to the estimation error $e_l(n)$

$$\mathcal{E}\{e_l(n)\hat{h}_l^*(n)\} = 0. \quad (20)$$

The error $e_l(n) = h_l(n) - \hat{h}_l(n)$ is also zero-mean Gaussian, and its variance $E_l(n)$ can be calculated in an iterative way from (11), where it can be seen that the error variance depends on the data vector $\mathbf{b}(n-1)$ through the term $d_l^2(n-1)$. In order to eliminate this dependency and to obtain a quasi-steady form of (11), we approximate the term $d_l^2(n-1)$ by its average value N_uE_c. Then, in the steady state, the error variance is approximately given by

$$\begin{aligned} \tilde{E}_l \approx& \frac{2\sigma_h^2 N_u E_c - 2\sigma^2(1 - f^2)}{2N_uE_c} + \\ &+ \frac{\sqrt{(2\sigma^2(1 - f^2) + 2\sigma_h^2 N_u E_c)^2 + 16\sigma^2\sigma_h^2 N_u E_c f^2}}{2N_uE_c}. \end{aligned} \quad (21)$$

Simulation tests [16] showed that the approximate error variance in (21) is smaller than the actual variance by less than 1 dB, for fading rates ($\omega_d T$) between 10^{-4} and 10^{-1}. Finally, we notice that, as a result of the orthogonality property (20) and the definition of the error, $\mathrm{Var}\{\hat{h}_l(n)\} = \mathrm{Var}\{h_l(n)\} - E_l(n)$ and in the steady-state

$$\mathrm{Var}\{\hat{h}_l(n)\} = \frac{2\sigma_h^2}{(1 - f^2)} - \tilde{E}_l. \quad (22)$$

In deriving the analytical expression of the probability of error, we follow a similar approach as in [9] and we denote with $\hat{N}_0$ the random variable of the estimated number of subchannels with the property $\hat{\rho}_l(n) > h_{\mathrm{THR}}$. We will say that these subchannels are ON (as opposed to OFF). Since we have assumed that the channel coefficients $h_l(n)$ are independent, the random variable $\hat{N}_0$ is binomially distributed and its probability mass function is

$$P(\hat{N}_0 = n_0) = \binom{N_s}{n_0} e^{-\frac{n_0 h_{\mathrm{THR}}^2}{2\hat{\sigma}_h^2}} \left(1 - e^{-\frac{h_{\mathrm{THR}}^2}{2\hat{\sigma}_h^2}}\right)^{(N_s - n_0)} \quad (23)$$

where $2\hat{\sigma}_h^2 = 2\tilde{\sigma}_h^2 - \tilde{E}_l$, and $\tilde{\sigma}_h^2 = \sigma_h^2/(1 - f^2)$. Conditioned on the number n_0 of channels that are *ON*, the signal term $S_i(n)$ takes the value

$$S_i(n)|n_0 = \sqrt{E_c}n_0 b_i(n). \quad (24)$$

The interference term $I_i(n)$ can be considered approximately Gaussian and its distribution has the form [9]

$$I_i(n)|n_0 \sim \mathcal{N}\left(0, n_0(N_u - 1)\left(\frac{N_s - n_0}{N_s - 1}\right)E_c\right). \quad (25)$$

The estimate $\hat{h}_l(n)$ depends on the previous noise samples, but is independent of $\eta_l(n)$. Therefore, it can be shown [9] that

$$\begin{aligned} \mathcal{E}\left\{\frac{\eta_{lr}(n)}{\hat{\rho}_l(n)}|l \text{ is ON}\right\} =& 0 \\ \mathrm{Var}\left\{\frac{\eta_{lr}(n)}{\hat{\rho}_l(n)}|l \text{ is ON}\right\} =& 2\frac{\sigma^2}{\hat{\sigma}_h^2}e^{\frac{h_{\mathrm{THR}}^2}{2\hat{\sigma}_h^2}} \\ &\times Gi\left(\frac{h_{\mathrm{THR}}}{\hat{\sigma}_h}\right) \end{aligned} \quad (26)$$

where

$$Gi(x) = \int_0^\infty \frac{Q(x\sqrt{t^2 + 1})}{\sqrt{t^2 + 1}}dt \quad x > 0 \quad (27)$$

and $Q(x) = (1/2)\mathrm{erfc}(x/\sqrt{2})$. The noise term $\xi_i(n)$ can be considered approximately Gaussian so that

$$\xi_i(n)|n_0 \sim \mathcal{N}\left(0, 2n_0\frac{\sigma^2}{\hat{\sigma}_h^2}e^{\frac{h_{\mathrm{THR}}^2}{2\hat{\sigma}_h^2}}Gi\left(\frac{h_{\mathrm{THR}}}{\hat{\sigma}_h}\right)\right). \quad (28)$$

The estimate $\hat{h}_l(n)$ and the error $e_l(n)$ are Gaussian, and because of (20) they are independent. Therefore, the last term in (18) can also be approximated as Gaussian with

$$\Delta_i(n)|n_0 \sim \mathcal{N}\left(0, 2n_0 N_u E_c \frac{\tilde{E}_l}{2\hat{\sigma}_h^2}e^{\frac{h_{\mathrm{THR}}^2}{2\hat{\sigma}_h^2}}Gi\left(\frac{h_{\mathrm{THR}}}{\hat{\sigma}_h}\right)\right). \quad (29)$$

Given the conditional distributions of the signal (24), interference (25), noise (28), and error (29) terms, we average over the distribution (23) of the estimated number $\hat{N}_0$ of subchannels which are ON, and we obtain the following expression for the average probability of bit error, as shown in (30), at the bottom of the page, where $\tilde{\sigma}_h^2 = \sigma_h^2/(1-f^2)$ and we define the average SNR per bit γ_b at the input of the detector as follows:

$$\gamma_b = \frac{N_s E_c \mathcal{E}\{|h_l(n)|^2\}}{2\sigma^2} = \frac{N_s E_c \sigma_h^2}{(1-f^2)\sigma^2}. \tag{31}$$

Note that in practice there is a signal-to-noise ratio (SNR) degradation (e.g., 0.4 dB for a guard interval overhead of 10%) because of the energy wasted in the cyclic prefix which is not reflected in definition (31). We notice that the expression for the probability of error obtained in [9] is a special form of (30), in the case of perfect channel estimation.

IV. A Family of Adaptive MMSE Detectors

While useful in demonstrating the mechanism through which fast-fading channels affect the performance of MC-CDMA detectors, the TORC detector, as shown in the case of perfectly known channels [21], is outperformed by detectors based on the MMSE criterion. Two different forms (termed MMSE per user and MMSE per carrier) of the MMSE detector have been proposed and examined under the assumption of perfectly known channels in [3]. The MMSE per carrier detector has been analyzed for perfectly known channels also in [8], while its performance using pilot-symbol-aided channel estimation has been evaluated in [10]. The two detectors defer in the optimization criterion as follows.

A. MMSE per User Detector

The optimization criterion is to find a matrix $\mathbf{W_0}(n)$ such that

$$\mathbf{W_0}(n) = \underset{\mathbf{W}(n)}{\operatorname{argmin}} \mathcal{E}\{\|\mathbf{b}(n) - \mathbf{W}(n)\mathbf{r}(n)\|^2\}. \tag{32}$$

Then, the data vector estimate is obtained as follows:

$$\hat{\mathbf{b}}(n) = \operatorname{sgn}[\Re e\{\mathbf{W_0}(n)\mathbf{r}(n)\}]. \tag{33}$$

The solution of (32) is obtained by applying the orthogonality principle and has the form

$$\mathbf{W_0}(n) = \mathbf{R_{br}}(n)\mathbf{R_{rr}}^{-1}(n) \tag{34}$$

where

$$\mathbf{R_{br}}(n) = \mathcal{E}\{\mathbf{b}(n)\mathbf{r}^H(n)\} = \sqrt{E_c}\mathbf{C}^T\mathbf{H}^*(n)$$
$$\mathbf{R_{rr}}(n) = \mathcal{E}\{\mathbf{r}(n)\mathbf{r}^H(n)\} = E_c\mathbf{H}(n)\mathbf{C}\mathbf{C}^T\mathbf{H}^*(n) + 2\sigma^2\mathbf{I}.$$

B. MMSE per Carrier Detector

The MMSE per carrier detector attempts to invert each subchannel coefficient, applying the MMSE criterion in order to avoid excessive noise enhancement. The optimization criterion is to find for each subchannel l, $l = 1, \ldots, N_s$ a filter coefficient $W_{0,l}(n)$ that multiplies the observation $r_l(n)$ given in (7) such that

$$W_{0,l}(n) = \underset{W_l(n)}{\operatorname{argmin}} \mathcal{E}\{|\, d_l(n) - W_l(n)r_l(n)\,|^2\}. \tag{35}$$

The solution to (35) is obtained by applying the orthogonality principle and has the form

$$W_{0,l}(n) = \frac{\mathcal{E}\{d_l(n)r_l^*(n)\}}{\mathcal{E}\{r_l(n)r_l^*(n)\}} = \frac{h_l^*(n)}{|h_l(n)|^2 + \frac{2\sigma^2}{N_u E_c}} \tag{36}$$

where the expression of $r_l(n)$ in (7) was used. Note that in the limit when there is no AWGN, (36) gives $W_{0,l}(n) = h_l^{-1}(n)$, and the MMSE per carrier becomes the decorrelating detector. Finally, the data vector estimate is given by

$$\hat{\mathbf{b}}(n) = \operatorname{sgn}[\Re e\{\mathbf{C}^T\mathbf{W_0}(n)\mathbf{r}(n)\}] \tag{37}$$

where $\mathbf{W_0}(n) = \operatorname{diag}\{W_{0,1}(n), \ldots, W_{0,N_s}(n)\}$.

We consider two forms of adaptive implementation of the MMSE detectors. According to the first form, the channel coefficients $h_l(n)$ are explicitly estimated using one of the decision-directed methods described in Section II, and then the matrix $\mathbf{W_0}(n)$ is calculated by using the channel estimates $\hat{h}_l(n)$ instead of $h_l(n)$ in (34) and (36). According to the second form, (32) and (35) are solved in an adaptive manner using the LMS and RLS algorithms. In this case, the adaptive MMSE per User algorithm takes the following form.

1) LMS Algorithm:

$$\mathbf{W}(n+1) = \mathbf{W}(n) + \tilde{\mu}[\mathbf{b}(n) - \mathbf{W}(n)\mathbf{r}(n)]\mathbf{r}^H(n). \tag{38}$$

2) RLS Algorithm:

$$\mathbf{W}(n+1) = \mathbf{W}(n) + [\mathbf{b}(n) - \mathbf{W}(n)\mathbf{r}(n)]\mathbf{k}^H(n) \tag{39}$$
$$\mathbf{k}(n) = \frac{\mathbf{P}(n)\mathbf{r}(n)}{\lambda + \mathbf{r}^H(n)\mathbf{P}(n)\mathbf{r}(n)} \tag{40}$$
$$\mathbf{P}(n+1) = \lambda^{-1}(\mathbf{I} - \mathbf{k}(n)\mathbf{r}^H(n))\mathbf{P}(n). \tag{41}$$

Similar expressions can be derived for the MMSE per Carrier detector. The adaptive MMSE per user detector (38) using

$$\mathcal{P}[\text{error}] = \sum_{n_0=0}^{N_s} \binom{N_s}{n_0} e^{-\frac{n_0 h_{\text{THR}}^2}{2\tilde{\sigma}_h^2 - \tilde{E}_l}} \left(1 - e^{-\frac{h_{\text{THR}}^2}{2\tilde{\sigma}_h^2 - \tilde{E}_l}}\right)^{(N_s - n_0)} Q\left(\sqrt{\frac{n_0\gamma_b}{\frac{2N_s\tilde{\sigma}_h^2 + N_u\tilde{E}_l\gamma_b}{\tilde{\sigma}^2 - (\tilde{E}_{l/2})} e^{\frac{h_{\text{THR}}^2}{2\tilde{\sigma}_h^2 - \tilde{E}_l}} Gi\left(\sqrt{\frac{2h_{\text{THR}}^2}{2\tilde{\sigma}_h^2 - \tilde{E}_l}}\right) + (N_u - 1)\left(\frac{N_s - n_0}{N_s - 1}\right)\gamma_b}}\right) \tag{30}$$

the LMS algorithm has been suggested in [3] and [17], although no performance results were given. In Section V, we will focus on the performance of the MMSE per carrier detector with explicit channel estimation and on the adaptive MMSE per user detector described in (38) and (39). The reason is that the adaptive MMSE per user is too complex to be implemented using explicit channel estimation, since it involves an $N_s \times N_s$ matrix inversion and multiplication in each symbol period. Therefore, it is necessary to calculate the $N_u \times N_s$ matrix $\mathbf{W_0}(n)$ using the LMS (38) or RLS (39) algorithm. On the other hand, the MMSE per carrier detector can be easily implemented adaptively by using explicit channel estimates in the exact expression (36), since it involves only inversion and multiplication of N_s scalars.

V. Numerical and Simulation Results

In this section, we give several numerical and simulation results that illustrate the performance of the proposed adaptive MC-CDMA detectors. We examine the performance of the TORC detector by evaluating (30) for the probability of error and by presenting simulation results that demonstrate close agreement with the theoretically predicted performance. We present performance results of the different adaptive MMSE detectors, make comparisons with the TORC detector, and examine the performance sensitivity to the choice of adaptation parameters. In all cases, we normalize the channel coefficients so that

$$\mathcal{E}\{|h_l(n)|^2\} = 1. \quad (42)$$

Except where the Jakes' model is specified, the channel model described in (2) is used in simulations and then (42) becomes $2\sigma_h^2/(1-f^2) = 1$. The SNR refers to the definition in (31). It is obvious that, in order to keep a constant reference in the definition of SNR, the variance σ_h^2 should be varied accordingly as f changes for different fading rates $\omega_d T$.

In order to demonstrate the validity of the basic assumptions of the paper, we present a system design example without, however, restricting the scope of our results to the specific design. An MC-CDMA system design could consider central carrier frequency $f_C = 2$ GHz, total bandwidth $BW = 10.24$ MHz, total number of subchannels $N = 1024$, and the number of simultaneous user symbols $\mu \geq 16$, which allows for $N_s \leq 64$. In practice, μ would be slightly smaller to allow for 64 or 128 unmodulated carriers to be used against frequency aliasing at the receiver. The subchannel spacing is then $\Delta f = 10$ kHz and the symbol duration $T_b = 100$ μs. We also assume the delay spread is $T_m = 10$ μs (coherence bandwidth $(\Delta f)_c = 100$ kHz) and user speeds are up to $v = 100$ km/h. We notice that this design allows for the frequency-interleaved chips corresponding to each user symbol to be transmitted through approximately independently faded subchannels ($\mu/T_b > 1/T_m$) and for a reasonable guard interval overhead of 10% ($T = 110$ μs). The Doppler spread of the $l = 1, \ldots, N$ subcarrier of the system is given by $f_D^l = (f_C + (l - N/2)\Delta f)v/c$. Since the difference in the fading rate experienced by any two subchannels is at most 0.5% ($\frac{f_D^N - f_D^1}{f_D^1} \approx 10/1995$) it is reasonable to assume that all subchannels experience approximately the same fading rate. For $v \leq 100$ km/h we have $(\Delta t)_c/T \geq 49$ and, therefore, it

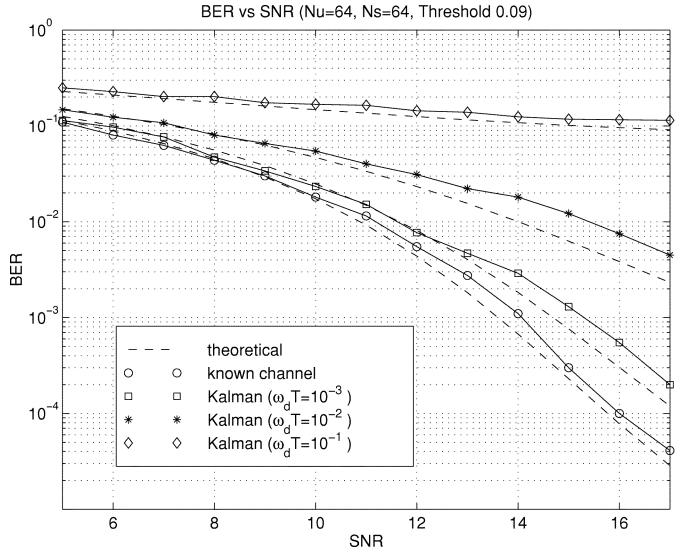

Fig. 3. Performance of TORC detector with Kalman estimation as a function of SNR.

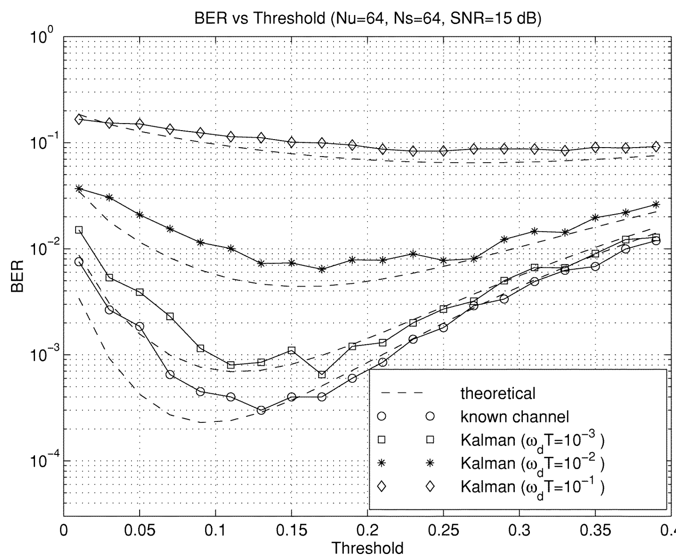

Fig. 4. Performance of TORC detector with Kalman estimation as a function of the threshold h_{THR}.

is reasonable to assume that the channel remains approximately constant during one MC symbol period.

The performance analysis of the TORC detector in Section III provides insight into the mechanism affecting the performance of MC-CDMA detectors in fast-fading channels. As the channel fading becomes faster ($\omega_d T$ increases), the estimation error and its variance $\tilde{E}_l$ in (21) grow larger, thus increasing the variance of the term $\Delta_i(n)$ as shown in (29). This, in turn, degrades the performance of the TORC detector, as depicted in Fig. 3. We see that for a probability of error 10^{-3}, the performance deteriorates by 1 dB for a fading rate of $\omega_d T = 10^{-3}$, by 3 dB for a fading rate of $\omega_d T = 10^{-2}$, while for very fast fading, $\omega_d T = 10^{-1}$, the detector performance is unacceptable. Similar performance degradation is observed in Fig. 4, which depicts the dependence of the probability of error on the threshold h_{THR}. There is an optimal selection of the threshold that balances excessive multiuser interference when too many subchannels are rejected (threshold too large), and excessive

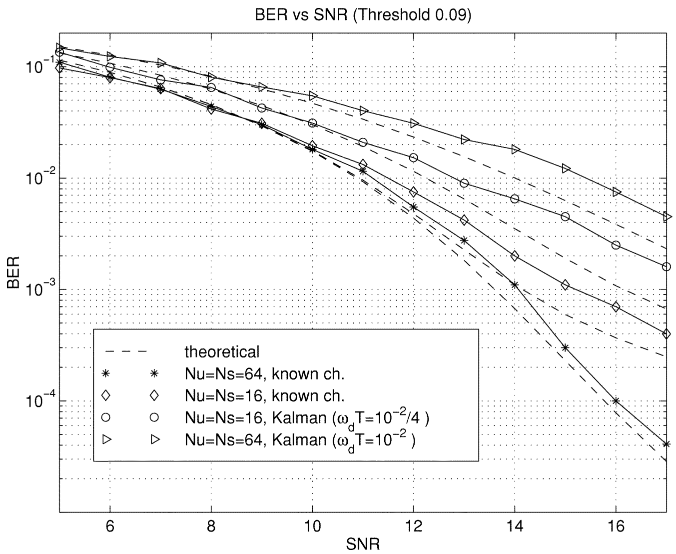

Fig. 5. Impact of fading rate on the selection of N_s (TORC detector).

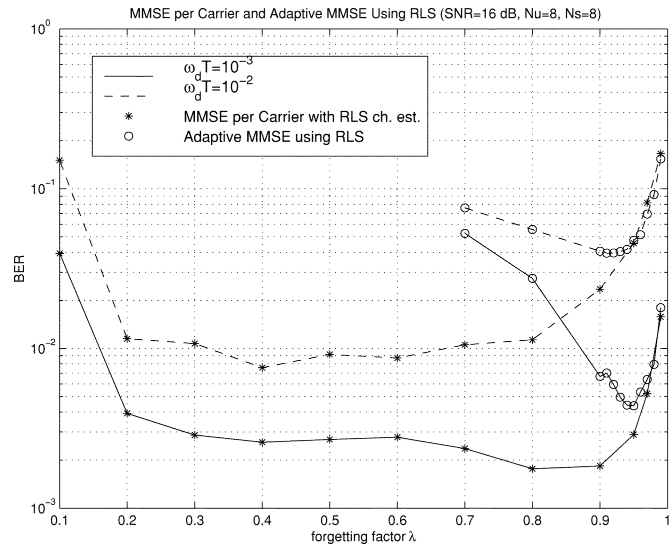

Fig. 6. Performance of RLS-based MMSE detectors as a function of forgetting factor λ.

thermal and channel estimation noise enhancement when subchannels with lower amplitudes are inverted (threshold too low). We notice in Fig. 4 that as the channel fading becomes faster, the optimal threshold h_{THR} increases because of the larger impact of the channel estimation noise enhancement.

Another implication of the channel estimation process is on the selection of system parameters, such as the length of the spreading sequences N_s. We expect that increasing N_s will improve the performance of the system, by introducing a larger degree of frequency diversity. This is, indeed, true in the case when the channel is perfectly estimated at the receiver [8], [9]. However, for a fixed bandwidth per symbol $W = N_s \Delta f$, increasing N_s by a factor λ_F, implies that $\Delta f_{\mathrm{new}} = \Delta f / \lambda_F$, and that the new symbol duration should be $T_{b,\mathrm{new}} = 1/\Delta f_{\mathrm{new}} = \lambda_F T_b$. Therefore, the fading rate $\omega_d T$ experienced by the system is also increased λ_F times, thus affecting adversely the performance of the system. This performance loss can even overshadow the frequency-diversity gain. Fig. 5 shows that, although in the case of perfect channel knowledge the system with $N_s = 64$ outperforms the one with $N_s = 16$, in the case of imperfect channel estimation it performs worse, because it is subject to fading whose rate is four times higher. This example illustrates the importance of the fading rate in the design of a MC-CDMA system. Note that the processing gain N_s cannot be increased arbitrarily in the described way without violating our basic assumptions.

In the case of perfectly known channels, the TORC detector is outperformed by detectors based on the MMSE criterion [21]. We conducted simulation experiments which showed that the MMSE per carrier outperforms the TORC detector for all fading rates also when the detectors are implemented adaptively. The intuition behind this is that the TORC detector tries to invert the channel coefficients without enhancing the noise excessively by making "hard" decisions (ON or OFF) on which subchannels will be inverted, while the MMSE per carrier detector does the same by making "soft" decisions, as expressed in (36), in the optimal MSE manner. In terms of complexity, although both detectors have to calculate N_s scalars, the MMSE per carrier is moderately more complex mainly because it requires an estimate of the SNR in (36).

We continue by investigating the performance of the different forms of the MMSE detector. We begin by examining the effect of the adaptation parameters on the performance of the different forms of the MMSE detector. When LMS and RLS based channel estimators are used by the MMSE detector, the selection of the step size $\tilde{\mu}$ and the forgetting factor λ depends on the channel fading rate. For each fading rate there is an optimal selection of the adaptation parameters, as depicted in Fig. 6 for the RLS case. Simulation results on the performance of the MMSE per carrier detector with LMS channel estimation showed that it is more sensitive to the selection of the step size $\tilde{\mu}$, than the performance of the corresponding RLS-based detector to the variations of the forgetting factor λ. For fading rates between $10^{-3} \leq \omega_d T \leq 10^{-2}$ the optimal selection is approximately $\tilde{\mu} \approx 0.002$. Fig. 6 also shows that the RLS-based MMSE per User detector without explicit channel estimation is also relatively more sensitive to the selection of the forgetting factor λ.

Since the Kalman filter gives the optimal estimates in the MMSE sense, it is expected that the performance of the MMSE detector using the Kalman filter presents a lower bound on the probability of error when other channel estimators such as the LMS and RLS are used. Therefore, in Figs. 7 and 8 we use the performance of the MMSE per carrier detector with Kalman channel estimation as a reference against which more realistic implementations of the MMSE detector, which do not require knowledge of the channel model, are compared. Fig. 7 illustrates the performance of the MMSE per carrier detector with LMS and RLS channel estimation. It can be seen that the performance of the detector, when RLS channel estimation is used, is closer to that of the Kalman filter than when LMS estimation is used, at the expense of increased complexity. We also notice that the performance of the MMSE detector deteriorates with increasing channel fading rate in a similar manner as it was previously observed for the TORC detector.

As it was described in Section IV, the MMSE detector can be implemented adaptively without explicit channel estimation. In [17], the transient performance and convergence of the MMSE per User detector using LMS proposed in [3] was examined

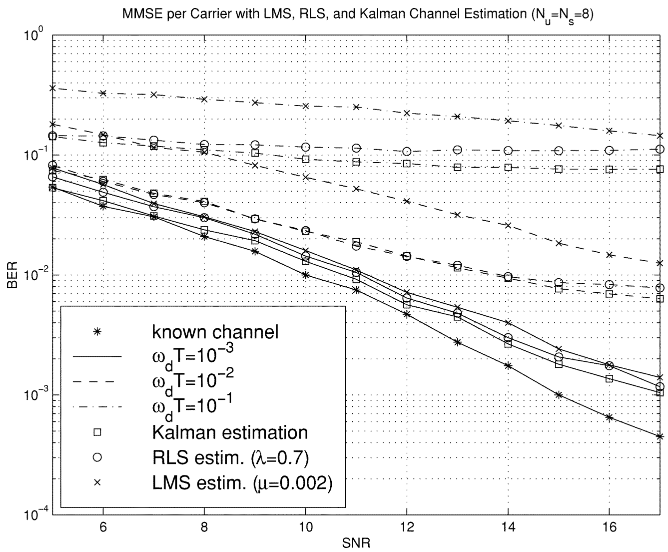

Fig. 7. Performance of the MMSE per carrier detector with explicit channel estimation based on LMS and RLS.

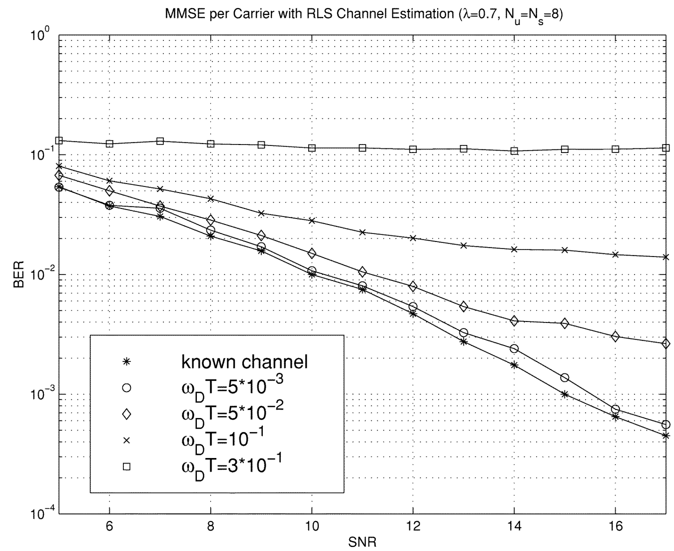

Fig. 9. Performance of MMSE per carrier detector with RLS channel estimation, when the Jakes' channel model is used.

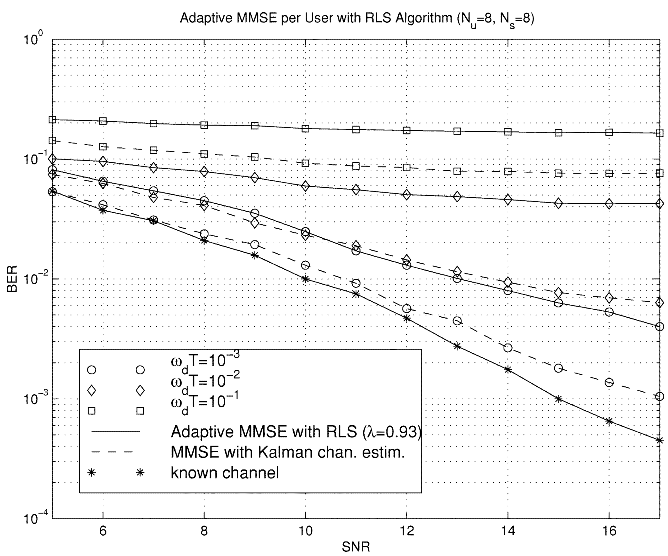

Fig. 8. Performance of the RLS-based MMSE per user adaptive detector without explicit channel estimation.

in a static channel and it was shown that even then its convergence is very slow because of the large eigenvalue spread of the observation autocorrelation matrix. Our computer experiments in different fading rates showed that the LMS adaptive detector indeed demonstrates very slow convergence and is unable to perform well (BER $< 10^{-1}$) even for slowly fading channels ($\omega_d T = 10^{-4}$), for any value of the step size $\tilde{\mu}$. Although in the case of perfectly known channel the MMSE per user detector performs slightly better than the MMSE per carrier detector [3], in an adaptive implementation the adaptation errors dominate the performance of the MMSE per User detector and make it perform worse. Fig. 8 shows that the RLS adaptive MMSE per User detector (39) manages to track the channel variations up to a certain point, although it still performs worse than the MMSE per Carrier detector employing explicit channel estimation.

The above results suggest that the adaptive MMSE per carrier detector with RLS channel estimation is an attractive MC-CDMA detector which combines good performance with relatively low complexity, especially for relatively low fading rates. Because of these features, it is useful to examine the performance of the detector when a more practical channel model, the widely accepted Jakes' model, is used. The power spectrum of the first-order channel described in (2) has infinite support and decreases with frequency according to $2\omega_d(\omega_d^2 + \omega^2)^{-1}$, where $\omega_d = 2\pi f_d$ corresponds to the 3-dB frequency f_d. On the other hand, the power spectrum derived from the Jakes' channel model has finite support and depends on the frequency according to $2(\omega_D^2 - \omega^2)^{-1/2}$, where $\omega_D = 2\pi f_D$ corresponds to the maximum Doppler shift f_D. Therefore, the fading rates of the two channel models as measured by the products $\omega_d T$ and $\omega_D T$ are not directly comparable. The performance of the MMSE per carrier detector with RLS channel estimation when the Jakes' channel model is used is depicted in Fig. 9. It can be seen that the RLS estimator manages to track the channel variation described by Jakes' model well for low to moderate fading rates ($\omega_D T \leq 5 \cdot 10^{-2}$). However, its performance deteriorates significantly after that point.

In the remainder of this section, we present a discussion which compares the decision-directed and pilot-aided approaches and explores the tradeoffs between channel estimation overhead and performance. The channel-sounding method proposed in [14] uses entire OFDM symbols for periodic channel estimation. As the fading rate increases, so does the frequency of OFDM blocks required for channel sounding. Therefore, although in those OFDM symbols with data the processing gain N_s and the number of symbols μ are not reduced, this method becomes very inefficient even for moderately fading channels. This is pointed out in [14] and [15], where it is suggested that 10% of the OFDM symbols be used for channel estimation, even for very slowly fading channels. Performance results in static channels [15] show it is slightly better than the "pilot-carriers" method.

The pilot-symbol-aided method of [10], [11] requires the minimum pilot overhead among all pilot-aided schemes. Even with oversampling by a factor of 2, a typical overhead of only 5.5% ($N_f = 6$, $N_t = 3$) is reported in [10] and [11],

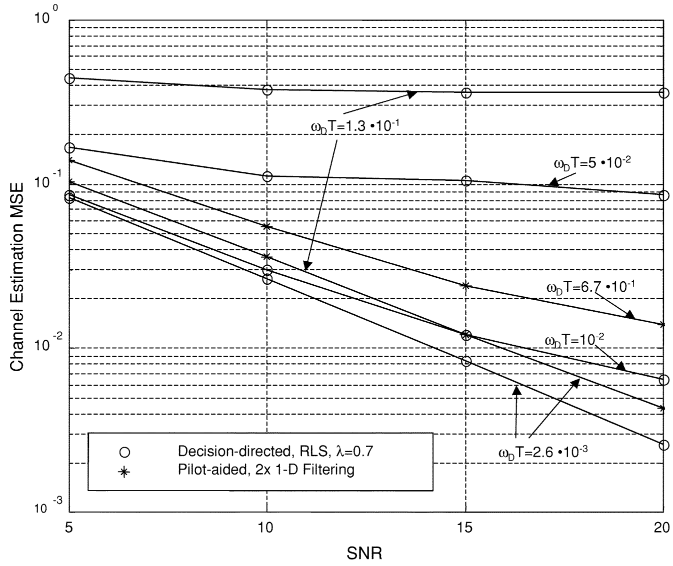

Fig. 10. Channel estimation MSE for RLS-based, decision-directed, and pilot-aided channel estimation ($N_u = N_s = 8$, Jakes' model).

which implies a 16.6% reduction in the processing gain or the data rate in every third OFDM symbol. The "pilot-carriers" method reduces the number of subchannels available for data in each OFDM symbol (lower N_s and/or μ). Its overhead is increased with decreasing coherence bandwidth and typical overhead of 10% to 25% is reported in [13] and [15]. The decision-directed approach is the only approach that does not require regular insertion of known symbols in the transmitted data and all available subchannels are used to transmit data. Therefore, even with occasional retraining that may occur in a practical system because of serious disruptions in the channel, the overhead is comparatively the lowest (on the order of 100 initial OFDM training symbols). This reduced overhead comes with a penalty since the detectors cannot trade increased overhead for better performance in very fast fading channels and the performance deteriorates significantly for high fading rates ($\omega_D T > 10^{-2}$) as can be seen in Figs. 9 and 10. Only the pilot-symbol-aided approach of [10], [11] is able to adjust its overhead to improve its performance in very fast fading channels. Since the design is based on the worst case scenario, in slower fading rates the "excess" oversampling in the time domain (inherently present also in "pilot-carriers") does not improve the system performance. This is demonstrated in [10] and [11] as depicted in Fig. 10, where the pilot grid is designed for a user speed of $v = 200$ km/h. The channel estimation MSE increases only when $v = 250$ km/h ($\omega_D T = 6.7 \cdot 10^{-1}$) and remains practically the same for all speeds between 3 and 150 km/h ($2.6 \cdot 10^{-3} \leq \omega_D T \leq 1.3 \cdot 10^{-1}$) for which the 2-D sampling theorem is satisfied [11]. This explains why the BER performance of the systems in [11] and [13] is more than 2-dB worse than with perfectly known channels, even for very slow fading rates ($\omega_D T \leq 10^{-3}$). As it can be seen in Figs. 9 and 10, the more complex decision-directed method using μN_s RLS estimators experiences smaller performance degradation compared with the case of known channel for low to moderate fading rates ($\omega_D T \leq 10^{-2}$). However, its performance deteriorates significantly in high fading rates and the decision-directed detectors become inapplicable.

VI. Concluding Remarks

In this paper, we examined the forward-link performance of different decision-directed adaptive detection schemes, with and without explicit channel estimation, for MC-CDMA systems operating in fast fading Rayleigh channels. The theoretical analysis of the performance of the TORC detector demonstrated the mechanism through which the channel estimation process degrades the system performance significantly as the channel fading rate increases. We examined the effect of other system parameters such as the selected threshold and the length of the spreading sequences. We expanded our investigation to examine the performance of more realistic adaptive schemes based on the MMSE criterion, which, as in the case of perfectly known channels, were observed to outperform the TORC detector. We found the MMSE per Carrier detector with RLS channel estimation to be robust with respect to adaptation parameter variations, approaching the performance of the detector using optimal Kalman filtering. The adaptive MMSE detector without channel estimation using the LMS algorithm was unable to follow the channel variations and demonstrated poor performance. The more complex MMSE detector using RLS adaptation performed better, but it too did not achieve very good performance.

Finally, we presented a discussion comparing the decision-directed detectors with other pilot-aided approaches in terms of overhead and performance in different fading rates. The "channel sounding" method had been shown to perform well at static or very slow fading rates, beyond which its overhead makes it inapplicable. The "pilot-carriers" method is a special case of the pilot-symbol-aided approach, which increases the pilot overhead regardless of the fading rate by oversampling the channel in the time dimension. The general approach of inserting pilot-symbols in both the frequency and time dimensions represents the best combination of pilot overhead and performance in moderate to fast fading channels; however, it becomes less efficient for lower fading rates. The decision-directed approach, which does not require regularly inserted pilot symbols, combines low overhead with good performance in low to moderate fading rates; however, its performance deteriorates rapidly for fast fading rates and the detectors become inapplicable.

Our analysis and performance results considered the forward-link and they are not, in general, representative of the performance of the same MC-CDMA configuration in the reverse-link. Since strict reverse-link synchronization is highly unlikely, the performance of the described MC-CDMA system is likely to degrade because of increased adjacent carrier interference and ISI. Some alternative MC-CDMA system design should be considered in the uplink. For example, N_u users could share the uplink channel in a TDMA manner, where only one user transmits at a time at a data-rate N_u times the base data-rate by using N_u orthogonal codes in a multicode CDMA configuration.

In conclusion, the MMSE detector per Carrier employing RLS-based decision-directed channel estimation combines relatively low complexity and overhead, robustness in parameter variations, and very good performance in low to moderate fading rates. These qualities make a MC-CDMA system employing this detector attractive for use in B-WISN. For higher fading rates, however, only pilot-symbol-aided MC-CDMA detectors are appropriate.

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