Performance of Adaptive Multiuser Receivers for the WCDMA Uplink

M. Surendra Raju†, GVLN Babu† and A. Chockalingam‡

† Wireless and Broadband Communications
Synopsys (India) Pvt. Ltd, Bangalore 560095

‡ Department of Electrical Communication Engineering
Indian Institute of Science, Bangalore 560012

Abstract— **In this paper, we investigate the performance of adaptive interference cancellation receivers for the wideband code division multiple access (WCDMA) uplink physical data channel. For the WCDMA uplink waveform, we derive a blind adaptive receiver (BAR) based on the constant modulus algorithm (CMA), and an multistage adaptive parallel interference cancellation (APIC) receiver. In order to improve the performance of the APIC receiver, we propose a hybrid APIC (H-APIC) receiver structure which uses the CMA based BAR as the first stage of the APIC. We evaluate and compare the performance of the above receivers in a near-far scenario and show that the proposed H-APIC receiver performs better than the APIC receiver.**

I. Introduction

Third generation (3G) systems are envisaged to provide a host of communication services, including voice, data, high quality images, and video to mobile users. Wideband code division multiple access (WCDMA), one of the air-interface standards for the 3G systems, enables high speed radio access up to 2 Mbps, and supports multiple services with different quality of service requirements [1]. One of the issues with CDMA transmissions on the uplink (mobile-to-base station link) is the near-far effect. Receivers using multiuser detection [2] can alleviate the near-far effect and improve system capacity significantly, at the expense of increased receiver complexity. Several studies have investigated the performance and complexity of various multiuser detectors in a variety of scenarios [2]-[5]. Most of these studies consider generic system models, which are not specific to any standards-defined air-interface. It is noted that multiuser detection can be optionally employed at the base station on the WCDMA uplink to improve system performance. Our contribution in this paper is the derivation and performance evaluation of multiuser receiver structures for the WCDMA uplink waveform. Specifically, we consider multistage adaptive parallel interference cancellation receivers for the WCDMA uplink and evaluate their performances in a near-far scenario.

On the WCDMA uplink, each active user transmits one or more (up to six) dedicated physical data channels (DPDCH) and a dedicated physical control channel (DPCCH). While DPDCHs carry the user data traffic, DPCCH carries control information. The DPDCHs and DPCCH are orthogonal code multiplexed using orthogonal variable spreading factor (OVSF) codes. The data rate for each user can be varied by varying the spreading factor on a DPDCH and/or by using multiple DPDCHs. The orthogonal code multiplexed DPDCHs and DPCCH are further multiplied by the user-specific complex scrambling codes [6],[7]. A conventional receiver for the above multiuser system will be a bank of matched filters, each matched to a user-specific complex scrambling code and the corresponding dedicated channel specific OVSF code. Here, we are interested in multiuser receivers for the WCDMA uplink transmission. Particularly, we develop adaptive multiuser receivers for detecting data on the DPDCH. Since DPDCHs do not carry known symbols for training, we derive a blind adaptive multiuser receiver (BAR) based on the constant modulus algorithm (CMA) [8]. We show that this blind adaptive receiver performs better than the conventional matched filter receiver (CMFR) in near-far scenarios. We also derive a multistage adaptive parallel interference cancellation (APIC) receiver, which is similar to the one proposed in [5], but modified for the WCDMA uplink waveform. In this APIC receiver, the interference is estimated at every stage and cancelled from the received signal so as to provide an almost interference-free signal for data estimation. Since the performance of the APIC receiver at a given stage is dependent on the reliability of the data estimates from the previous stage, we propose a hybrid APIC (H-APIC) receiver structure which uses the CMA based BAR as the first stage. Our performance results show that the H-APIC performs better than the APIC receiver with a moderate increase in receiver complexity.

The rest of this paper is organized as follows. In Section II, we present the WCDMA uplink system model considered. The receiver structures for the WCDMA uplink, including CMFR, BAR, APIC and H-APIC receivers are derived in Section III. Performance results are presented in Section IV, and conclusions are given in Section V.

II. System Model

We consider the WCDMA uplink transmission from K active users. Each user is assumed to be transmitting one DPDCH (on I-branch) and DPCCH (on Q-branch). In WCDMA, the user-specific complex scrambling codes can be either short codes (of length 256) or long codes (of length 38400). Here, we assume that all users use short scrambling codes. The baseband transmitted signal from the k^{th} user, $x_k(t)$, is given by

$$x_k(t) = \sqrt{2P_k}\left(\sum_{i=-\infty}^{\infty} \beta_d\, d_k^I(i)\, C_k^I(t - iT_1) + j \sum_{r=-\infty}^{\infty} \beta_c\, d_k^Q(r)\, C_k^Q(t - rT_2)\right) \cdot \left(S_k^I(t) + jS_k^Q(t)\right), \quad (1)$$

where P_k is the power of the transmitted signal of the k^{th} user, $d_k^I(i)$, $d_k^Q(r) \in \{-1, +1\}$ represent the modulating DPDCH and DPCCH data streams, respectively, for the k^{th} user, and β_d and β_c are the gain factors for the DPDCH and the DPCCH, respectively. The DPDCH and DPCCH data streams are spread

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using the waveforms $C_k^I(t)$ and $C_k^Q(t)$, respectively, which can be written as

$$C_k^I(t) = \sum_{n=0}^{N_1-1} c_k^I(n)\psi(t-nT_c), \quad 0 \le t \le T_1 \tag{2}$$

and

$$C_k^Q(t) = \sum_{n=0}^{N_2-1} c_k^Q(n)\psi(t-nT_c), \quad 0 \le t \le T_2, \tag{3}$$

where $c_k^I(n)$, $c_k^Q(n) \in \{-1,+1\}$ represent the n^{th} chip of the k^{th} user's OVSF spreading codes for the DPDCH and the DPCCH, respectively, and $\psi(t)$ represents the chip waveform of duration T_c and unit energy. N_1 and N_2 are the spread factor values for the DPDCH and the DPCCH, respectively, and T_1 and T_2 are the symbol durations of the DPDCH and the DPCCH data streams, respectively. Hence, $T_1 = N_1T_c$ and $T_2 = N_2T_c$. Also, $S_k^I(t) + jS_k^Q(t)$ represents the complex scrambling waveform for the k^{th} user, where

$$S_k^I(t) = \sum_{i=-\infty}^{\infty}\sum_{n=0}^{N-1} s_k^I(n)\psi(t-iNT_c-nT_c) \tag{4}$$

and

$$S_k^Q(t) = \sum_{i=-\infty}^{\infty}\sum_{n=0}^{N-1} s_k^Q(n)\psi(t-iNT_c-nT_c), \tag{5}$$

such that $s_k^I(n)+js_k^Q(n) \in \{\pm 1 \pm j\}$ represents the n^{th} complex chip of the k^{th} user's scrambling code. N is the periodicity of the scrambling code. For the short scrambling codes considered here, $N = 256$.

Although the uplink is asynchronous, in order to focus mainly on the relative performance of different multiuser receiver structures, we assume that all the users' transmissions arrive at the base station synchronously. The received signal at the base station due to all the active users is then given by

$$r(t) = \Re e\left(\sum_{k=1}^{K} s_k(t)\exp(j\omega_c t+\theta_k)\right) + n(t), \tag{6}$$

where ω_c is the carrier frequency, θ_k is the random carrier phase of the k^{th} user, which is assumed to be uniformly distributed in $[0,2\pi)$, and $n(t)$ is the additive white Gaussian noise with zero mean and two sided power spectral density, $N_o/2$ W/Hz.

The received signal is down converted and the resulting sequence after chip matched filtering is given by $r^I(l) + jr^Q(l)$, where

$$\begin{aligned} r^I(l) &= \sum_{k=1}^{K}\sqrt{2P_k}\left(\beta_d d_k^I(i)c_k^I(l)s_k^I(l) - \beta_c d_k^Q(r)c_k^Q(l)s_k^Q(l)\right) \\ &+ n^I(l) \\ r^Q(l) &= \sum_{k=1}^{K}\sqrt{2P_k}\left(\beta_d d_k^I(i)c_k^I(l)s_k^Q(l) + \beta_c d_k^Q(r)c_k^Q(l)s_k^I(l)\right) \\ &+ n^Q(l) \end{aligned} \tag{7}$$

In the above equation, i is the integer part of l/N_1 and r is the integer part of l/N_2, and $n^I(l)+j\,n^Q(l)$ is a complex Gaussian noise sample of zero mean and variance of $N_o/2$ W/Hz.

III. Receiver Structures

In this section, we derive various receiver structures, including CMFR, BAR, APIC and H-APIC receivers, for the WCDMA uplink signal model described in the previous section.

A. Conventional MF Receiver (CMFR)

The conventional matched filter receiver is essentially a bank of matched filters with each filter matched to the user-specific complex scrambling code and the corresponding dedicated channel specific OVSF code. This is a low complexity receiver which needs information of only the scrambling and OVSF codes and the timing of all the active users.

Using the CMFR, soft estimates of the DPDCH and DPCCH data symbols, $\hat{d}_k^I(i)$ and $\hat{d}_k^Q(r)$ for the k^{th} user are given by

$$\begin{aligned} \hat{d}_k^I(i) &= \sum_{n=iN_1}^{i(N_1+1)-1}\Big\{r^I(iN_1+n)\,c_k^I(n)\,s_k^I(iN_1+n) \\ &+ r^Q(iN_1+n)\,c_k^I(n)\,s_k^Q(iN_1+n)\Big\} \\ \hat{d}_k^Q(r) &= \sum_{n=rN_2}^{r(N_2+1)-1}\Big\{r^Q(rN_2+n)\,c_k^Q(n)\,s_k^I(rN_2+n) \\ &- r^I(rN_2+n)\,c_k^Q(n)\,s_k^Q(rN_2+n)\Big\}. \end{aligned} \tag{8}$$

The DPDCH and DPCCH bit estimates are obtained to be the sign of the above soft estimates.

B. Blind Adaptive Receiver (BAR)

Since the DPDCH on the uplink do not carry known symbols for training, we derive a blind adaptive receiver (BAR). The BAR consists of a bank of adaptive receivers, one for each active user, which estimate the DPDCH and DPCCH symbols from the received signal. Like the CMFR, the BAR requires the knowledge of scrambling and OVSF codes and the timing of all the active users. The adaptive receivers considered here are linear transversal filters whose coefficients are updated according to the constant modulus algorithm [8],[9], so as to minimize the cost function, J_{cm}, given by

$$J_{cm} = \frac{1}{4}\left\{\left(y^2-1\right)^2\right\}. \tag{9}$$

In the context of the system model considered, y represents the estimates of DPDCH or DPCCH symbols. The adaptive receiver for the k^{th} user can be implemented using four linear transversal filters, the impulse responses of which are given as $\{h_k^I(n)\}$, $\{h_k^Q(n)\}$, $\{g_k^I(n)\}$, $\{g_k^Q(n)\}$, $n = 0,\cdots,N-1$. We define the following vectors:

$$\begin{aligned} \mathbf{h_k^I} &\triangleq [h_k^I(0),h_k^I(1)),\cdots,h_k^I(N-1)]^T \\ \mathbf{h_k^Q} &\triangleq \left[h_k^Q(0),h_k^Q(1)),\cdots,h_k^Q(N-1)\right]^T \\ \mathbf{g_k^I} &\triangleq [g_k^I(0),g_k^I(1)),\cdots,g_k^I(N-1)]^T \\ \mathbf{g_k^Q} &\triangleq \left[g_k^Q(0),g_k^Q(1)),\cdots,g_k^Q(N-1)\right]^T. \end{aligned} \tag{10}$$

The elements of the vectors defined above are the coefficients of the transversal filters. The estimates of the DPDCH and DPCCH symbols, $\hat{d}_k^I(i)$ and $\hat{d}_k^Q(r)$ are given, respectively, as

$$\begin{aligned}\hat{d}_k^I(i) &= [\mathbf{h}_k^I]_i{}^T \cdot [\mathbf{r}^I]_i + [\mathbf{h}_k^Q]_i{}^T \cdot [\mathbf{r}^Q]_i \\ \hat{d}_k^Q(r) &= [\mathbf{g}_k^Q]_r{}^T \cdot [\mathbf{r}^Q]_r - [\mathbf{g}_k^I]_r{}^T \cdot [\mathbf{r}^I]_r, \end{aligned} \quad (11)$$

where the vectors $[\mathbf{h}_k^I]_i$, $[\mathbf{h}_k^Q]_i$, $[\mathbf{g}_k^I]_r$, $[\mathbf{g}_k^Q]_r$, $[\mathbf{r}^I]_i$, $[\mathbf{r}^Q]_i$, $[\mathbf{r}^Q]_r$ and $[\mathbf{r}^Q]_r$ are defined as

$$\begin{aligned}
\left[\mathbf{h}_k^I\right]_i &\triangleq \left[h_k^I((iN_1)\,mod\,N), \cdots, h_k^I((iN_1+N_1-1)\,mod\,N\right]^T \\
\left[\mathbf{h}_k^Q\right]_i &\triangleq \left[h_k^Q((iN_1)\,mod\,N), \cdots, h_k^Q((iN_1+N_1-1)\,mod\,N\right]^T \\
\left[\mathbf{g}_k^I\right]_r &\triangleq \left[gI_k((rN_2)\,mod\,N), \cdots, g_k^I((rN_2+N_2-1)\,mod\,N\right]^T \\
\left[\mathbf{g}_k^Q\right]_r &\triangleq \left[g_k^Q((rN_2)\,mod\,N), \cdots, g_k^Q((rN_2+N_2-1)\,mod\,N\right]^T \\
\left[\mathbf{r}^I\right]_i &\triangleq \left[r^I((iN_1)), \cdots, r^I((iN_1+N_1-1)\right]^T \\
\left[\mathbf{r}^Q\right]_i &\triangleq \left[r^Q((iN_1)), \cdots, r^Q((iN_1+N_1-1)\right]^T \\
\left[\mathbf{r}^I\right]_r &\triangleq \left[r^I((iN_2)), \cdots, r^I((rN_2+N_2-1)\right]^T \\
\left[\mathbf{r}^Q\right]_r &\triangleq \left[r^Q((iN_2)), \cdots, r^Q((rN_2+N_2-1)\right]^T
\end{aligned} \quad (12)$$

We define cost functions, J_{cm}^I and J_{cm}^Q, corresponding to DPDCH and DPCCH symbols, respectively, as

$$\begin{aligned}
J_{cm}^I &= \frac{1}{4}\left\{\left(\left(\hat{d}_k^I(i)\right)^2 - 1\right)^2\right\} \\
J_{cm}^Q &= \frac{1}{4}\left\{\left(\left(\hat{d}_k^Q(i)\right)^2 - 1\right)^2\right\}.
\end{aligned} \quad (13)$$

The objective is to minimize the above cost functions by adapting the filter coefficients. The filter coefficients are updated according to the following relations:

$$\begin{aligned}
\left[\mathbf{h}_k^I\right]_i(m+1) &= \left[\mathbf{h}_k^I\right]_i(m) - \mu \nabla_{\mathbf{h}_k^I} J_{cm}^I \\
\left[\mathbf{h}_k^Q\right]_i(m+1) &= \left[\mathbf{h}_k^Q\right]_i(m) - \mu \nabla_{\mathbf{h}_k^Q} J_{cm}^I \\
\left[\mathbf{g}_k^I\right]_r(m+1) &= \left[\mathbf{g}_k^I\right]_r(m) - \mu \nabla_{\mathbf{g}_k^I} J_{cm}^Q \\
\left[\mathbf{g}_k^Q\right]_r(m+1) &= \left[\mathbf{g}_k^Q\right]_r(m) - \mu \nabla_{\mathbf{g}_k^Q} J_{cm}^Q,
\end{aligned} \quad (14)$$

where $\nabla_{\mathbf{f}} J$ is the gradient of J w.r.t $\mathbf{f}$. The constant μ refers to the step size and m refers to the iteration index. Substituting the expressions for $\nabla_{\mathbf{h}_k^I} J_{cm}^I$, $\nabla_{\mathbf{h}_k^Q} J_{cm}^I$ $\nabla_{\mathbf{g}_k^I} J_{cm}^Q$ and $\nabla_{\mathbf{g}_k^Q} J_{cm}^Q$, in (14), we obtain the following update equations:

$$\begin{aligned}
\left[\mathbf{h}_k^I\right]_i(m+1) &= \left[\mathbf{h}_k^I\right]_i(m) - \mu\left(\hat{d}_k^I(i)^2 - 1\right)\left[\mathbf{r}^I\right]_i \hat{d}_k^I(i) \\
\left[\mathbf{h}_k^Q\right]_i(m+1) &= \left[\mathbf{h}_k^Q\right]_i(m) - \mu\left(\hat{d}_k^I(i)^2 - 1\right)\left[\mathbf{r}^Q\right]_i \hat{d}_k^I(i) \\
\left[\mathbf{g}_k^I\right]_i(m+1) &= \left[\mathbf{g}_k^I\right]_i(m) + \mu\left(\hat{d}_k^Q(i)^2 - 1\right)\left[\mathbf{r}^I\right]_i \hat{d}_k^Q(i) \\
\left[\mathbf{g}_k^Q\right]_i(m+1) &= \left[\mathbf{g}_k^Q\right]_i(m) - \mu\left(\hat{d}_k^Q(i)^2 - 1\right)\left[\mathbf{r}^Q\right]_i \hat{d}_k^Q(i)
\end{aligned} \quad (15)$$

It is noted that the cost functions J_{cm}^I and J_{cm}^Q are multi-modal, as a result of which there can be more than one achievable minima [8]. Hence, the initialization of the linear filters is important. A natural choice of initialization would be to use

$$\begin{aligned}
h_k^{I(0)}(n) &= c_k^I(n\,mod\,N_1) \cdot s_k^I(n), \\
h_k^{Q(0)}(n) &= c_k^I(n\,mod\,N_1) \cdot s_k^Q(n), \\
g_k^{I(0)}(n) &= c_k^Q(n\,mod\,N_2) \cdot s_k^Q(n), \\
g_k^{Q(0)}(n) &= c_k^Q(n\,mod\,N_2) \cdot s_k^I(n),
\end{aligned} \quad (16)$$

where the superscript '0' indicates the initial state of the filters.

C. Adaptive Parallel Interference Canceller (APIC)

The adaptive parallel interference canceller derived by Xue *et al* in [5] is an adaptive multistage receiver. The objective is to minimize the Euclidean distance between the received signal and the weighted sum of the estimates of each user's signal during a bit interval w.r.t the weighting factors. These weighting factors are updated through an adaptive algorithm for each user.

Let $\hat{r}^{I^{(j)}}(l)$ and $\hat{r}^{Q^{(j)}}(l)$ be the estimates of $r^I(l)$ and $r^Q(l)$, respectively, for the j^{th} stage. These estimates are defined as

$$\begin{aligned}
\hat{r}^{I^{(j)}}(l) &= \sum_{k=1}^{K}\left\{\lambda_{11,k}^{(j)}\,\hat{d}_k^{I^{(j-1)}}(i)\,c_k^I(l)\,s_k^I(l)\right. \\
&\quad - \left.\lambda_{12,k}^{(j)}\,\hat{d}_k^{Q^{(j-1)}}(r)\,c_k^Q(l)\,s_k^Q(l)\right\} \\
\hat{r}^{Q^{(j)}}(l) &= \sum_{k=1}^{K}\left\{\lambda_{21,k}^{(j)}\,\hat{d}_k^{I^{(j-1)}}(i)\,c_k^I(l)\,s_k^Q(l)\right. \\
&\quad + \left.\lambda_{22,k}^{(j)}\,\hat{d}_k^{Q^{(j-1)}}(r)\,c_k^Q(l)\,s_k^I(l)\right\},
\end{aligned} \quad (17)$$

where $\hat{d}_k^{I^{(j-1)}}(i)$ and $\hat{d}_k^{Q^{(j-1)}}(r)$ are the estimates of $d_k^I(i)$ and $d_k^Q(r)$, respectively, at the $(j-1)^{th}$ stage for the k^{th} user. The initial estimates, $\hat{d}_k^{I^{(0)}}(i)$, $\hat{d}_k^{Q^{(0)}}(r)$ are provided by the CMFR, i.e.,

$$\begin{aligned}
\hat{d}_k^{I^{(0)}}(i) &= sgn\left\{\hat{d}_k^I(i)\right\} \\
\hat{d}_k^{Q^{(0)}}(r) &= sgn\left\{\hat{d}_k^Q(r)\right\},
\end{aligned} \quad (18)$$

where $\hat{d}_k^I(i)$ and $\hat{d}_k^Q(i)$ are given by (8). The factors $\lambda_{11,k}^{(j)}$, $\lambda_{12,k}^{(j)}$, $\lambda_{21,k}^{(j)}$ and $\lambda_{22,k}^{(j)}$, are the weighting coefficients corresponding to the j^{th} stage for the k^{th} user. Let $e^{I^{(j)}}$ and $e^{Q^{(j)}}$ represent the error between the desired received signal and its estimate at the j^{th} stage for the l^{th} chip. Then,

$$\begin{aligned}
e^{I^{(j)}} &= r^I(l) - \hat{r}^{I^{(j)}}(l) \\
e^{Q^{(j)}} &= r^Q(l) - \hat{r}^{Q^{(j)}}(l).
\end{aligned} \quad (19)$$

We need to find the optimal weighting coefficients so that the square of the error terms, given in the above equation, is minimized. The optimum weights are derived via a LMS algorithm as follows:

$$\begin{aligned}
\lambda_{11,k}^{(j)}(n+1) &= \lambda_{11,k}^{(j)}(n) + 2\mu_\lambda e^{I^{(j)}}(n)\,\hat{d}_k^{I^{(j-1)}}(i)\,c_k^I(n)\,s_k^I(n) \\
\lambda_{12,k}^{(j)}(n+1) &= \lambda_{12,k}^{(j)}(n) - 2\mu_\lambda e^{I^{(j)}}(n)\,\hat{d}_k^{Q^{(j-1)}}(r)\,c_k^Q(n)\,s_k^Q(n) \\
\lambda_{21,k}^{(j)}(n+1) &= \lambda_{21,k}^{(j)}(n) + 2\mu_\lambda e^{Q^{(j)}}(n)\,\hat{d}_k^{I^{(j-1)}}(i)\,c_k^I(n)\,s_k^Q(n) \\
\lambda_{22,k}^{(j)}(n+1) &= \lambda_{22,k}^{(j)}(n) + 2\mu_\lambda e^{Q^{(j)}}(n)\,\hat{d}_k^{Q^{(j-1)}}(i)\,c_k^Q(n)\,s_k^I(n),
\end{aligned} \quad (20)$$

where μ_λ is the step size used in the adaptation. The choice of the initial values of the coefficients is important to achieve faster convergence of the weighting coefficients to their optimal values. Generally, if knowledge of all user's amplitudes are available, the initial values of the weighting coefficients for each user are set to its corresponding amplitudes.

The above updation is done for N iterations and the resulting weights at the end of the N^{th} iteration are used in the interference cancellation. The interference-free estimates for the k^{th}

user is obtained as

$$
\begin{aligned}
\xi_k^{I(j)}(l) &= r^I(l) - \sum_{q=1,\, q\neq k}^{K} \Big\{ \lambda_{11,k}^{(j)}(N-1)\, \hat{d}_k^{I(j-1)}(i)\, c_k^I(l)\, s_k^I(l) \\
&\quad - \lambda_{12,k}^{(j)}(N-1)\, \hat{d}_k^{Q(j-1)}(r)\, c_k^Q(l)\, s_k^Q(l) \Big\} \\
\xi_k^{Q(j)}(l) &= r^Q(l) - \sum_{q=1,\, q\neq k}^{K} \Big\{ \lambda_{21,k}^{(j)}(N-1)\, \hat{d}_k^{I(j-1)}(i)\, c_k^I(l)\, s_k^Q(l) \\
&\quad + \lambda_{22,k}^{(j)}(N-1)\, \hat{d}_k^{Q(j-1)}(r)\, c_k^Q(l)\, s_k^I(l) \Big\}, \qquad (21)
\end{aligned}
$$

where the notation $\lambda(N-1)$ indicates the value of the weighting coefficient at the N^{th} iteration. The above interference-free estimates are used in forming the estimates of DPDCH and DPCCH symbols to be used by the next stage. Thus, we have

$$
\begin{aligned}
\hat{d}_k^{I(j)}(i) &= sgn\Bigg\{ \sum_{n=iN_1}^{i(N_1+1)-1} \Big\{ \xi^{I(j)}(iN_1+n)\, c_k^I(n)\, s_k^I(iN_1+n) \\
&\quad + \xi^{Q(j)}(iN_1+n)\, c_k^I(n)\, s_k^Q(iN_1+n) \Big\} \Bigg\} \\
\hat{d}_k^Q(r) &= sgn\Bigg\{ \sum_{n=rN_2}^{r(N_2+1)-1} \Big\{ \xi^{Q(j)}(rN_2+n)\, c_k^Q(n)\, s_k^I(rN_2+n) \\
&\quad - \xi^{I(j)}(rN_2+n)\, c_k^Q(n)\, s_k^Q(rN_2+n) \Big\} \Bigg\}. \qquad (22)
\end{aligned}
$$

D. Hybrid-Adaptive Parallel Interference Canceller (H-APIC)

In a near-far scenario, the performance of APIC for a weak user can be good at high near-far ratios[1] (NFR) because the stronger intereferers' data can be reliably detected in the first stage by the CMFR, and hence the interference signal can be reconstructed and removed effectively for the next stage. For example, in a 2-user scenario with a high NFR value, the performance of the weak user using APIC can approach single-user performance since the CMFR in the first stage can reliably detect the strong interferer's data so that the input to the second stage can be almost interference-free. However, at low NFR scenarios, the reliability of the interferers' data may not be as good, and hence the APIC may perform poor because of which more stages may be required to achieve a desired performance. To alleviate the performance of APIC in such low NFR scenarios, we propose the following hybrid APIC (H-APIC) which uses the BAR in the first stage, instead of CMFR.

The BAR would give reliable estimates of the data symbols of the other users in the initial stage itself, thus aiding better estimation of the interference for the weaker user. This also reduces the number of stages required to obtain reliable estimates. The initial estimates, $\hat{d}_k^{I(0)}(i)$ and $\hat{d}_k^{Q(0)}(r)$, are then given by

$$
\begin{aligned}
\hat{d}_k^{I(0)}(i) &= sgn\left\{\hat{d}_k^I(i)\right\} \\
\hat{d}_k^{Q(0)}(r) &= sgn\left\{\hat{d}_k^Q(r)\right\}, \qquad (23)
\end{aligned}
$$

[1]Near-Far ratio is defined as the ratio of the received power of interfering user to the received power of the desired user, i.e., NFR $= \frac{P_i}{P_1}, i \neq 1$, where user-1 is taken as the desired user. When $P_i = P_1$, NFR = 0 dB.

where $\hat{d}_k^I(i)$ and $\hat{d}_k^Q(i)$ are given by (11).

IV. Results and Discussion

We evaluated the performance of the various multiuser receivers described above in a near-far scenario through simulations. A system with four active users ($K = 4$) is considered and user-1 is taken to be the user-of-interest. The near-far ratio, P_k/P_1, $k \neq 1$ of all interfering users is assumed to be equal. The spread factor for the DPDCH and the DPCCH symbols for all the users is set to 256, i.e., $N_1 = N_2 = 256$. The bit error performance of the user-of-interest (user-1) as a function of E_b/N_0 and NFR is evaluated.

Fig. 1 shows the bit error performance as a function of E_b/N_0 for the various receivers including CMFR, BAR and APIC at a NFR value of 15 dB. The performance of APIC is plotted for different number of stages (1-stage APIC, 2-stage APIC and 4-stage APIC) without and with perfect knowledge of the amplitudes. The single user performance is also plotted for comparison. The following observations can be made from Fig. 1. As expected, the BAR and the APIC perform much better than the CMFR. Also, when perfect knowledge of the amplitudes is not available at the receiver, increasing the number stages in the APIC improves performance. In the unknown amplitudes case, more than four stages are required to perform close to the single user performance. However, with perfect knowledge of the amplitudes at the receiver, even a 1-stage APIC is shown to achieve close to single user performance.

Fig. 2 shows the bit error performance as a function of NFR for CMFR, BAR and APIC at a E_b/N_o value of 8 dB. The range of NFR values considered is 0 to 15 dB. The CMFR performance degrades with increasing NFR indicating its poor near-far resistance. The near-far resistance of BAR and APIC are shown to be much better. In the unknown amplitudes case, the near-far resistance of APIC improves as the number of stages is increased. Two key observations can be made in Fig. 2. Firstly, in the high NFR region (NFR > 10 dB), the APIC with known amplitudes performs better than BAR and achieves close to single user performance because of the high reliability of the interfering users' data estimates. Secondly, in the low NFR region (NFR < 8 dB), however, even in the known amplitudes case, the APIC performs poorer than BAR. This implies that at low NFRs, the number of stages in the APIC has to be increased to achieve a given performance, even though perfect knowledge of the users' amplitudes is available at the receiver. This is mainly because the reliability of the data estimates of the interfering users in the initial CMFR stage is poor at low NFRs.

Fig. 3 shows the bit error performance of the APIC and the proposed H-APIC as a function of E_b/N_o at a low NFR value of 5 dB. It is noted that, even with no knowledge of the users' amplitudes, a single stage H-APIC performs better than a single stage APIC with perfect knowledge of all the users' amplitudes. A single stage H-APIC with perfect knowledge of the users' amplitudes is shown to perform the best and its performance is close to the single user bound. Fig. 4 shows the bit error performance of the APIC and H-APIC as a function of NFR at a E_b/N_o value of 8 dB. It is observed that at low near-far ratios, in the range 0 to 7 dB, the near-far resistance of a single