Advanced Transceiver Architectures for

Downlink MIMO CDMA Evolution

Raphaël Visoz, Member, IEEE, Antoine O. Berthet, Member, IEEE, and Nicolas Gresset, Member, IEEE

Abstract

This paper investigates the combination of spatial multiplexing and overloading as an evolution of the UMTS-HSDPA (High Speed Downlink Packet Access) toward very high spectral efficiencies in the case of no (or very limited) channel state information at transmitter. Overloaded spreading is carried out in the time domain only (independent per antenna), transmit space diversity is partially recovered employing Space-Time BICM for each user. A low complexity soft interference cancellation based iterative receiver for channel estimation, space-time chip-equalization and multiuser detection is proposed. Two scenarios are considered for the intracell interference: either the spreading codes and the modulation of the interfering users are known or no-knowledge of the interfering signals is available at the receiver whatsoever.

Index Terms

MIMO systems, Space-Time Coding, Space-Time BICM with Linear Precoding, Code Division Multiple Access, Overloading, Least mean square methods, Iterative methods, Iterative space-time equalization, Iterative space-time channel estimation, Iterative interference substraction.

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Raphaël Visoz and Nicolas Gresset are with France Telecom Div. R&D, Issy Les Moulineaux, France.

Antoine O. Berthet is with Ecole Supérieure d’Electricité (SUPELEC), Department of Telecommunications, Gif-sur-Yvette, France.
I. INTRODUCTION

Any communication system managing the multiple access of users on the same channel through the attribution of specific spreading codes (Code Division Multiple Access or CDMA) is limited in capacity by the interference between users (Multiple User Interference or MUI). The precursory work carried out by S. Verdú in the 80s [1] clearly revealed the interest to exploit the structural properties of those distinct sources of interference in order to improve the performance given a fixed number of users per chip (also called “load”) or to improve the load for a given fixed performance. It paved the way to Multiple User Detection (MUD). Many types of linear multiple user detectors were studied. In theory, the maximum supportable load conditioned by the receiver type can be evaluated analytically in the asymptotic regime [2] [3]. Past investigations highlight that the performance of detectors, based on Zero-Forcing (ZF) or Minimum Mean Square Error (MMSE) criterion remains much lower than the one a Maximum A Posteriori (MAP) detector would provide [4]. On the contrary, the class of non-linear detectors built on the idea of an iterative interference cancellation (in MMSE sense) embedded within the decision process offers an excellent compromise between performance and complexity (see, e.g., for single carrier transmission with linear precoding [5]-[9] and without precoding [10]-[20]). Such non-linear MMSE-based detectors deliver decisions on the transmitted modulated data whose reliability increases in a monotonous way at each new iteration. Another remarkable point is that they can be easily and naturally combined with the hard or soft decisions delivered by the channel decoder, thus carrying out detection and decoding of the data in a disjoint iterative way (see, for example, [21] for a unifying framework on that topic and the references therein). When a recursive strategy is chosen at the receiver, the only option for lowering the computational complexity consists of simplifying to the maximum the treatments by iteration.

As long as some kind of orthogonality exists between the various users at the transmitter, an attractive low-complexity (sub-optimal for an underloaded scenario) approach is to restore it at the chip level before any attempt of MUD (contrary to the strategy adopted in [5]-[9] where these two tasks are performed jointly). In that light, MUD (following chip equalization) comes down to a bench of simple adapted filters to each user. This approach, first developed in [22]-[28] and later extended within an iterative structure in [29] [30] for a non-overloaded CDMA communication
model transmitted on a single-input single-output frequency selective channel, proves to be very efficient in the presence of unknown codes and when an aperiodic spreading is used. This paper, among other things, enlarges the framework of these references by considering a downlink communication model of overloaded CDMA, with long scrambling sequences, transmitted on a Multiple-Input Multiple-Output (MIMO) frequency selective channel. This ambitious scenario lays the groundwork for proposing Space-Time Modulation and Coding Schemes (ST-MCSs) for the WCDMA High Speed Downlink Packet Access (HSDPA) evolution that are both spectrally and power efficient while ensuring the requirement of backward compatibility in the existing allocated UMTS bands [31]. On the other hand, the level of interference is such that the resort to sophisticated iterative space-time chip equalization and MUD proves to be essential in reception.

We chose to design our ST-MCSs from a potentially (outage) capacity achieving transmission scheme known as Space-Time Bit-Interleaved Coded Modulation (STBICM) with Linear Precoding (LP), which may induce Multiple User Interference (MUI), Co-Antenna Interference (CAI), and Inter-Chip-Interference (ICI) at the receiver side. We intentionally restrict the Linear Precoding to be carried out in the time domain only (independent per antenna), since this precoding strategy facilitates significantly the MUD part of the receiver. Indeed, the MUD can be performed independently per antenna and under perfect space-time chip equalization assumption the per-antenna orthogonality between spreading codes is maintained at the receiver side (which can be also considered as a HSDPA legacy requirement). Moreover, transmit space diversity can be partially recovered by the Space-Time BICM employed by each user through interleaving and outer coding. Nonetheless, we are well aware of the optimisation attempts of non-overloaded periodic Space-Time precoding illustrated in [9] [32] [33]. Our transmission strategy allows slow link adaptation (following the shadowing only) relying on a single Channel Quality Indicator (CQI) feedback to identify the ST-MCS to be transmitted. Since simultaneous downlink transmission to several users is investigated in this paper, the overloading flexibility appears both in terms of ST-MCS design and radio resource allocation.

This paper investigates two scenarios for the intracell interference. Scenario 1 corresponds to no-knowledge of the interfering signals whatsoever [22]-[30]. On the contrary, scenario 2 assumes that the spreading sequences and the modulation used by the intracell interfering users are known
(or estimated) to the receiver [34]-[36]. In this paper, we refer to the intracell interference cancellation of scenario 1 and 2 as blind and semi-blind, respectively. Moreover, it is well known that the channel estimation is a delicate issue for MIMO systems. This is particularly the case in the HSDPA context where pilot symbols are superimposed to the data via a code multiplexing approach. Indeed, the classical channel estimation techniques (i.e., matched filtering and accumulation) heavily suffer of interferences from the other antennas caused by ICI and overloading. In order to remedy this impairment, we suggest to embed the channel estimation into the iterative structure with respect to scenario 1 and 2, respectively (see e.g., [37] in case of single-input single-output channel and scenario 1).

The paper is organized as follows. In Section II, the communication model is reviewed and the notation introduced. Section III is the core of the manuscript and describes the proposed iterative receiver architectures, comprising equalization, detection and decoding of the user of interest, intracell interference cancellation (both scenarios) and channel estimation (both scenarios). Section IV is devoted to numerical results and comments. Section V concludes the paper.

II. COMMUNICATION MODEL AND ASSUMPTIONS

We consider a downlink transmission scenario (point-to-multipoint) where the Base Transceiving Station (BTS) carries $N_T$ transmit antennas and each Mobile Terminal (MT) $N_R$ receive antennas. The resulting $N_R \times N_T$ MIMO channel is assumed frequency selective and quasi-static, i.e., constant for the duration of a coded block but changing independently from one coded block to another. No Channel State Information (CSI) is assumed at transmitter and imperfect CSI is assumed at receiver. Common PIlot CHannel (CPICH) is required for estimating the quasi-static MIMO channel coefficients.

A. Channel model

Denote $P$ the maximal number of significant paths and $c_{r,t}(\tau)$ the continuous time propagation channel impulse response of the path linking transmit antenna $t$ to receive antenna $r$

$$c_{r,t}(\tau) = \sum_{i=0}^{P-1} \alpha_{r,t,i} \delta(\tau - \tau_{r,t,i})$$ (1)
with complex coefficients \( \alpha_{r,t,i} \) being circularly symmetric random variables with finite second order moment. Let \( \chi(\tau) \) be the impulse response of a square root raised cosine with a given roll-off factor and chip period \( T_c \), truncated to \( L_\chi \) chip periods. The equivalent continuous time channel impulse response of the path linking transmit antenna \( t \) to receive antenna \( r \) is, for a given coded block (codeword):

\[
h_{r,t}(\tau) = \sum_{i=0}^{P-1} \alpha_{r,t,i} \chi(\tau - \tau_{r,t,i}) .
\] (2)

Fractional sampling is used at the receiver. It allows to avoid the expensive implementation of the matched filter and the noise whitening filter required in the symbol (chip) spaced receiver [38]. Moreover, the oversampling and polyphase filtering makes the receiver robust to time synchronization error. Hence, perfect time synchronization is assumed. The received \( N_e \)-oversampled signal is then demultiplexed into \( N_e \) parallel polyphase streams. Let \( M + 1 = L_\chi + \lceil \tau_{\text{max}}/T_c \rceil + 1 \) define the length of each polyphase filter with \( \tau_{\text{max}} = \max \{\tau_{r,t,i}\} \), the \( n_e \)-th polyphase oversampled FIR (Finite Impulse Response) associated to \( h_{r,t}(\tau) \) has coefficients

\[
h_{r,N_e+n_e,t,m} = h_{r,t} \left( \left( -\frac{L_\chi}{2} + \frac{n_e}{N_e} + m \right) T_c \right),
\] (3)

\( L_\chi \) being even. The coefficients \( h_{r,N_e+n_e,t,m} \) \((0 \leq n_e \leq N_R N_e - 1, 0 \leq t \leq N_T - 1 \) and \( 0 \leq m \leq M \)) satisfy the normalization mean power constraint

\[
\forall 0 \leq r \leq N_R - 1, \quad \mathbb{E} \left\{ \sum_{n_e=0}^{N_e-1} \sum_{t=0}^{N_T-1} \sum_{m=0}^{M} |h_{r,N_e+n_e,t,m}|^2 \right\} = N_T
\] (4)

B. Space-time coding scheme

Since downlink multiple-access is discussed in the context of no cooperation between users at transmitter (no or very limited CSI at transmitter), one may consider without loss of generality the encoding of the data of a particular user. In the following, the superscript \( D \) will be associated to the considered user data variables, \( J \) to the intracell interference produced by the other users’ data and \( P \) to the CPICH pilot symbols. Moreover, the superscript \( T \) will be associated to the total transmission of CPICH and data. Let \( C \) be a binary code of dimension \( k_c \), length \( n_c \) and rate \( \rho_c \) over \( \mathbb{F}_2 \), made of the concatenation of \( N_0 \) independent block codes (terminated turbo codes are emphasized in this paper), which transforms a given message \( m \in \mathbb{F}_2^{k_c} \) into the code word \( c \in \mathbb{F}_2^{n_c} \) (where \( \mathbb{F}_2 \) stands for the Galois binary field). Produced code words enter a bitwise
interleaver \(\Pi\), chosen at random or using semi-deterministic optimizations. The output of \(\Pi\) is a binary matrix \(D^P\) of dimension \(qK^DN_T \times L\), where \(q\) is the number of bits per constellation symbol (index \(\ell\)), \(K^D\) is the total number of data streams per antenna, \(K^T\) the number of transmit antennas (index \(t\)). Columns of matrices \(D^P\) are vectors \(d^P_n \in \mathbb{R}_2^{K^DN_T}\) containing one subvector \(d^P_{k,t,n}\) per symbol input with \(q\) stacked binary components. Within each column \(d^P_n\), all subvectors \(\{d^P_{k,t,n}\}\) are mapped, through a labeling rule \(\varphi_{k,t} : \mathbb{R}_2^q \rightarrow \mathcal{X} \subset \mathbb{C}\), into a complex symbol \(s^P_{k,t,n}\) belonging to the complex signal set \(\mathcal{X}\) of cardinality \(|\mathcal{X}| = 2^q\). Denote \(d^P_{k,t,n,\ell} = \varphi^{-1}_{k,t}(s^P_{k,t,n})\) the \(\ell\)-th bit of the binary labeling of \(s^P_{k,t,n}\). The common pilot channel (CPICH) can be introduced as a supplementary data stream, one for each transmit antenna, whose modulated Quadrature Phase-shift Keying (QPSK) symbols are known at the receiver. Equivalently, the other users in the cell are represented by \(K^T\) supplementary data streams per antenna. The aperiodic spreading is carried out independently per antenna and the spreading matrix (linear precoder) \(W_\ell\) of dimension \(K^T N_T\) is the same for each transmit antenna since no CSI is assumed at transmitter. Let \(K^T\) denote the total number of superimposed spreading sequences per antenna, i.e., \(K^T = K^D + K^T + 1\). Since we aim at maximizing the spectral efficiency \(\rho\), overloaded cases where \(K^T \geq N_Z\) are emphasized. After signal mapping followed by the addition of CPICH pilot symbols and other users’ symbols, the matrix symbol digit \(D^P\) is thus transformed into a complex matrix \(S^T\) of dimension \(K^T N_T \times L\), columns of which are denoted \(s^T_n\) and constructed as follows

\[
\begin{align*}
    s^T_{t,n} &= \begin{bmatrix} s^P_{1,t,n}, \ldots, s^P_{K^P,t,n} \end{bmatrix}^\top \in \mathbb{C}^{K^P} \\
    s^T_{t,n} &= \begin{bmatrix} s^T_{1,t,n}, \ldots, s^T_{K^T,t,n} \end{bmatrix}^\top \in \mathbb{C}^{K^T} \\
    s^T_{t,n} &= \begin{bmatrix} s^T_{t,n}, s^T_{t,n}^\top, s^T_{t,n}^\top \end{bmatrix}^\top \in \mathbb{C}^{K^T} \\
    s^T_{t,n} &= \begin{bmatrix} 0, s^T_{t,n}^\top, s^T_{t,n}^\top \end{bmatrix}^\top \in \mathbb{C}^{K^T} \\
    s^T_{t,n} &= \begin{bmatrix} s^T_{0,n}^\top, \ldots, s^T_{N_T-1,n}^\top \end{bmatrix}^\top \in \mathbb{C}^{K^T N_T}
\end{align*}
\]

where \(^\top\) denotes the transpose operator, and where \(s^T_{k,t,n}\) and \(s^P_{t,n}\) denote the other users’ symbols and the pilot symbols, respectively. For simplicity reasons, we assume that all users use the same constellation \(\mathcal{X}\), the extension to different constellations per spreading sequence is straightforward. Due to the presence of \(\Pi\) and given that the data streams are uncorrelated between different users, the columns \(s^T_{n} \in \mathbb{C}^{K^T N_T}\) of the \(K^T N_T \times L\) matrix \(S^T\) are white, and
by construction we choose $\mathbb{E}\{s_{l,n}^{D} s_{l,n}^{D} \dagger\} = I_{K^D}$ where $I_{K^D}$ is a $K^D \times K^D$ identity matrix. The $N_Z \times K^T$ linear precoding matrix (or spreading matrix) $W_n$ is then applied to each vector $s_{l,n}^{T}$ for $t = 0, \ldots, N_T - 1$.

Let us now describe the construction of $W_n$. Let $G_1$ and $G_2$ be respectively the quotient and remainder of the Euclidean division of $K^T$ by $N_Z$, i.e., $K^T = G_1 N_Z + G_2$. For each antenna, $G = G_1 + \left[ \frac{G_2}{N_Z} \right]$ groups are defined where the number of saturated groups $G_1$ (i.e., comprised of $N_Z$ symbol components) is maximized following the strategy described in [39]. Let $R_{N_Z \times N_Z}$ denote a rotation matrix of dimension $N_Z \times N_Z$ and $\Sigma_n \in \mathbb{C}^{N_Z \times N_Z}$ denote a diagonal matrix associated with the time instant $n$, whose diagonal elements are i.i.d. QPSK chips normalized to unity. Let the matrices $\Xi_1, \ldots, \Xi_G$ be well chosen outcomes of $\Sigma_n$ (made of low-correlated QPSK chip sequences). We construct the precoding matrix $W_n$ as

$$W_n = \Sigma_n \mathcal{W} \in \mathbb{C}^{N_Z \times K^T}$$

where

$$\mathcal{W} = [\Xi_1, \ldots, \Xi_G] \begin{bmatrix} R_{N_Z \times N_Z} & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & R_{N_Z \times N_Z} & 0 \\ 0 & \cdots & 0 & R_{N_Z \times G_2} \end{bmatrix} \in \mathbb{C}^{N_Z \times K^T} \tag{11}$$

with $R_{N_Z \times G_2}$ being any truncation of $R_{N_Z \times N_Z}$ to $G_2$ columns. For $K^T \leq N_Z$, $\mathcal{W}$ is orthonormal, i.e., $\mathcal{W}^\dagger \mathcal{W} = I_{K^T}$ where $\dagger$ is the transpose conjugate operator. Otherwise $\mathcal{W}$ is at least orthonormal by subgroups. Note that the multiplicative matrices $\Xi_1, \ldots, \Xi_G$ ensure mutual independence between subgroups $\Xi_1 R_{N_Z \times N_Z}, \ldots, \Xi_G R_{N_Z \times G_2}$. As an example, in the WCDMA downlink system, $R_{N_Z \times N_Z}$ is a Walsh Hadamard matrix and the diagonal elements of $\Sigma_n$ are obtained from a long complex scrambling sequence, with pseudo-noise properties, obtained from a unique Gold sequence (delayed between the I and Q branches).

Matrices $w_n^P, w_n^D, w_n^T$ of dimension $N_Z \times 1$, $N_Z \times K^D$ and $N_Z \times K^T$, respectively, are extracted from $W_n$ following the position of the pilot, data and other users in $s_{l,n}^{T}$. For the $n$-th symbol period and the $t$-th antenna, after multiplication of the vectors $s_{l,n}^{T}$ by $W_n$, the produced
vectors $z_{t,n}^T$ of dimension $N_Z$ satisfy

$$z_{t,n}^T = W_n s_{t,n}^T = z_{t,n}^P + z_{t,n}^D + z_{t,n}^T = w_n^P s_{t,n}^P + W_n s_{t,n} = w_n^P s_{t,n}^P + W_n^D s_{t,n}^D + W_n s_{t,n}^T. \quad (12)$$

The vectors $z_{t,n}^P, z_{t,n}^D, z_{t,n}^T$ are the columns of matrices $Z_t^P \in \mathbb{C}^{N_Z \times L}, Z_t^D \in \mathbb{C}^{N_Z \times L}$ and $Z_t^T \in \mathbb{C}^{N_Z \times L}$ which are finally multiplexed into complex (chip) vectors $x_t^P$ (known to the receiver), $x_t^D$ and $x_t^T$ of dimension $L_c$ where $L_c = N_Z L$. Note that the multiplexing is done independently per antenna. In practice, the CPICH pilot sequences are $N_Z^P$ chips long, $N_Z$ divides $N_Z^P$, and thus one CPICH is the concatenations of $N_Z^P/N_Z$ spread sequences. These spread sequences differ only by a phase factor that is taken into account in the carried symbols $\{s_{t,n}^P\}$. This assumption allows for considering at the same time data and pilots as in (12), although the spreading factor of data and pilots are different. CPICH sequences of $N_Z^P$ chips associated to different antennas are assumed mutually orthogonal by construction. Falling into the general class of space-time codes, this transmit architecture, drawn in Fig. 1, offers a spectral efficiency $\rho = \frac{\log_2 N_Z^P N_Z q}{N_Z}$ bits per channel use (bpcu) per user under ideal Nyquist band-limited filtering assumption. The discrete-time base-band equivalent vector channel output $y_{r_e,l}^T$ received on $r_e$-th antenna (including virtual antennas originating from the oversampling) at time $l = -\infty, \ldots, +\infty$, where $l = 0$ defines the beginning of the considered coded block, can be written as

$$\forall 0 \leq r_e \leq N_R N_c - 1, \quad y_{r_e,l}^T = \sum_{t=0}^{N_R-1} \sum_{m=0}^{M} h_{r_e,t,m} x_{r_e,t,m}^T + \nu_{r_e,l} \quad (13)$$

where $x_{t,l}^T = x_{t,l}^P + x_{t,l}^D + x_{t,l}^T$ and $x_{t,l} = x_{t,l}^P + x_{t,l}^D$ are the ”overall” chip transmitted by the $t$-th antenna of the BTS during the $l$-th chip period with and without CPICH, respectively. The variable $\nu_{r_e,l}$ is the additive complex white Gaussian noise of variance $N_0$ which includes thermal noise and inter-cell interference powers. Let us now define $E_c = \sigma_D^2 = N_T K^D / N_Z$ the per chip received power of the data, $\frac{E_r}{N_0} = \frac{N_T K^D}{N_Z p N_0}$ and $I_{\text{intra}} = \sigma_D^2 + \sigma_Z^2$ the downlink intracell interference where $\sigma_D^2$ and $\sigma_Z^2$ are the per chip received power of the CPICH and the other users’ data, respectively. Moreover, we define $\alpha_p = \sigma_D^2 / (\sigma_Z^2 + \sigma_D^2 + \sigma_D^2)$ as the proportion of the BTS power allocated for CPICH symbols transmission.

### III. ITERATIVE RECEIVER ARCHITECTURES

In this Section, we assume perfect channel knowledge allowing the subtraction of the CPICH interference on the received signal without any error. Channel estimation will be discussed in
Section III-C. The previous convolution model (13) can be well approximated by a length-$L_w$ sliding window version

$$\mathbf{y}_j = \mathbf{y}_j^T - \mathbf{H}\mathbf{x}_j = \mathbf{H}\mathbf{x}_j + \mathbf{v}_j$$  \hspace{1cm} (14)

where $\mathbf{x}_j^P \in \mathbb{C}^{N_T(L_w+M)}$, $\mathbf{x}_j \in \mathbb{C}^{N_T(L_w+M)}$, $\mathbf{y}_j^T \in \mathbb{C}^{N_R N_e L_w}$, $\mathbf{v}_j \in \mathbb{C}^{N_R N_e L_w}$ are stacked vectors

$$\mathbf{x}_j^P = \begin{bmatrix} x_{0,l+1}^P, \ldots, x_{N_T-1,l+1}^P, \ldots, x_{0,l-L_2-M}^P, \ldots, x_{N_T-1,l-L_2-M}^P \end{bmatrix}^T$$  \hspace{1cm} (15)

$$\mathbf{x}_j = \begin{bmatrix} x_{0,l+1}, \ldots, x_{N_T-1,l+1}, \ldots, x_{0,l-L_2-M}, \ldots, x_{N_T-1,l-L_2-M} \end{bmatrix}^T$$  \hspace{1cm} (16)

$$\mathbf{v}_j^T = \begin{bmatrix} y_{0,l+1}, \ldots, y_{N_R N_e-1,l+1}, \ldots, y_{0,l-L_2}, \ldots, y_{N_R N_e-1,l-L_2} \end{bmatrix}^T$$  \hspace{1cm} (17)

$$\mathbf{v}_j = \begin{bmatrix} v_{0,l+1}, \ldots, v_{N_R N_e-1,l+1}, \ldots, v_{0,l-L_2}, \ldots, v_{N_R N_e-1,l-L_2} \end{bmatrix}^T$$  \hspace{1cm} (18)

with $L_w = L_1 + L_2 + 1$ and where $\mathbf{H}$ is the Sylvester channel matrix

$$\mathbf{H} = \begin{bmatrix} \mathbf{H}_0 & \cdots & \mathbf{H}_M \\ \vdots & \ddots & \vdots \\ \mathbf{H}_0 & \cdots & \mathbf{H}_M \end{bmatrix} \in \mathbb{C}^{N_R N_e L_w \times N_T(L_w+M)}$$  \hspace{1cm} (19)

and

$$\mathbf{H}_m = \begin{bmatrix} h_{0,0,m} & \cdots & h_{0,N_T-1,m} \\ \vdots & \ddots & \vdots \\ h_{N_e-1,0,m} & \cdots & h_{N_e-1,N_T-1,m} \\ \vdots & \ddots & \vdots \\ h_{N_R N_e-1,0,m} & \cdots & h_{N_R N_e-1,N_T-1,m} \end{bmatrix} \in \mathbb{C}^{N_R N_e \times N_T}$$  \hspace{1cm} (20)

The decoding of a coded block is based on the observations $y_{r,v,l}$, with $-L_2 \leq l \leq L_c + L_1$ . For complexity reasons (in part due to the time-dependency of the spreading matrix), the detection of transmitted symbols $s_{k,l,r}$ (CAI+ICI treatment) and second a despreading operation (MUI treatment). All treatments are iterative. For the sake of notation complexity and keeping in mind that the treatments are the same for each

$^1$The channel impulse response may be longer than $L_w$, in this case, we only take into account the significant coefficients of the estimated channel and synchronize the sliding window with a maximum energy criterion. In practice, we look for the integer $j_{opt}$ that maximizes

$$j_{opt} = \arg \max_j \left[ \sum_{k=0}^{L_w-1} \sum_{r=0}^{N_R-1} \sum_{t=0}^{N_e-1} |h_{r,v,t,k+j}|^2 \right]$$  \hspace{1cm} (21)
iteration, we omit the iteration index in the following. The spatial and time equalization followed by the MUD yields an estimate $\tilde{s}_{k,t,n}^{D(i)}$ that can be expressed as

$$\tilde{s}_{k,t,n}^{D(i)} = s_{k,t,n}^{D} + \eta_{k,t,n}^{D(i)} \quad i = 1, 2$$

(22)

in which $\eta_{k,t,n}^{D(i)}$ is a zero-mean random variable with variance $\sigma_{\eta_{k,t,n}^{D(i)}}^2$ and where the superscript $(i)$ refer to scenario $i$. As an instance of the turbo-principle [40], the EXTtrinsic (EXT) probability mass functions (pmfs) on symbol digit involved in $d_{k,t,n,\ell}^{D} = \varphi_{k,t,n}^{-1}(s_{k,t,n}^{D})$ are computed using a Gaussian Approximation (GA) on $\eta_{k,t,n}^{D(i)}$ and with the knowledge of the prior pmfs on symbol digit $d_{k,t,n,\ell}^{D}$ provided by probabilistic decoding. Given the A Posterior Probabilities (APPs) (and not the EXT pmfs [35] [41] [20]) on symbol digits, the non-linear conditional soft estimate $\tilde{s}_{k,t,n}^{D(i)}$ of $s_{k,t,n}^{D}$ is classically computed. From $\tilde{s}_{k,t,n}^{D(i)}$ it is straightforward to obtain (by spreading, scrambling and reshaping) the non-linear conditional soft estimate $\tilde{s}_{k,t,n}^{T}$ on chip vector $s_{k,t,n}^{T}$ (see, e.g., [29] [30]). In the case of scenario 2, it is possible to apply the MUD on the whole vector $s_{t,n}$ since $\mathcal{W}^F$ is known (or estimated [34] [36]). As a result, an estimate $\tilde{s}_{t,n}^{T}$ on the other users’ interference vector $s_{t,n}$ can be obtained

$$\tilde{s}_{k,t,n}^{T} = s_{k,t,n}^{T} + \eta_{k,t,n}^{T}$$

(23)

From (23), a non-linear conditional soft estimate $\tilde{s}_{k,t,n}^{T}$ of $s_{k,t,n}^{T}$ can be built by again resorting to the GA provided that the modulations employed by the other users are known or estimated. This yields

$$\tilde{s}_{k,t,n}^{T} = \frac{\sum_{s \in \mathcal{X}} s \exp \left( -\frac{1}{\sigma_{\eta_{k,t,n}^{T}}^2} \left\| \tilde{s}_{k,t,n}^{T} - s \right\|^2 \right)}{\sum_{s \in \mathcal{X}} \exp \left( -\frac{1}{\sigma_{\eta_{k,t,n}^{T}}^2} \left\| \tilde{s}_{k,t,n}^{T} - s \right\|^2 \right)}$$

(24)

From $\tilde{s}_{k,t,n}^{T}$ it is straightforward to obtain (by spreading and reshaping) the non-linear conditional soft estimate $\tilde{s}_{k,t,n}^{T}$ on chip vector $s_{k,t,n}^{T}$.

A. Iterative space-time chip equalization

Let $\tilde{s}_{k,t,n}^{(1)} = \tilde{s}_{k,t,n}^{D(1)}$ and $\tilde{s}_{k,t,n}^{(2)} = \tilde{s}_{k,t,n}^{D(2)} + \tilde{s}_{k,t,n}^{T}$ be the soft estimates on chip vector $s_{k,t,n}$ associated to scenario 1 and 2, respectively. Introducing $e_\ell \in \mathbb{C}^{N_T(L_w + M)}$ the vector with a 1 at position $N_T L_1 + \ell$ and 0’s elsewhere, we create the tentative soft decision vector $\tilde{x}_{k,t,n}^{(i)} - e_\ell \tilde{x}_{k,t,n}^{(i)\ell}$ used to softly regenerate the (ICI+CAI) corrupting chip component $x_{t,n}$. The Minimum Variance Distortionless
Response (MVDR) filters \( f_t^{(i)} \in \mathbb{C}^{1 \times N_R N_e L_w} \), which minimize the constrained unconditional MSE [42] [13, Section III-B]

\[
\begin{align*}
\left\{ \mathbb{E} \left\{ \left| x_{t,l} - \hat{x}_{t,l}^{(i)} \right|^2 \right\} \right. \\
\left. \quad \text{subject to } f_t^{(i)} \mathcal{H} e_t = 1 \right. \\
\end{align*}
\]

are expressed using the projection theorem and the inversion lemma [19] as

\[
\begin{align*}
\begin{cases}
    f_t^{(i)} &= \frac{1}{(\mathcal{H} e_t)^\dagger (\mathcal{H} e_t)^\dagger (\mathcal{H} e_t)^\dagger} \left( \mathcal{H} e_t \right)^\dagger \Xi^{(i)} \Xi^{(i)^{-1}} \\
    \Xi^{(i)} &= \mathcal{H} \Theta^{(i)} \mathcal{H}^\dagger + N_0 I_{L_w N_R N_e} \\
    \Theta^{(i)} &= \mathcal{I}_{L_w + M} \otimes \Theta_{x}^{(i)} \\
    \Theta_{x}^{(i)} &= \text{diag} \left\{ \sigma_{x_0}^2 - \sigma_{z_0}^2, \ldots, \sigma_{x_{N_T-1}}^2 - \sigma_{z_{N_T-1}}^2 \right\}
\end{cases}
\end{align*}
\]

where \( \otimes \) is the Kronecker product and where \( \sigma_{x_t}^2 = \mathbb{E} \left\{ |x_{t,l}|^2 \right\} \) and \( \sigma_{z_t}^2 = \mathbb{E} \left\{ |\hat{x}_{t,l}|^2 \right\} \). In practice, \( \sigma_{z_t}^2 \) is approximated by \( \frac{1}{L_T} \sum_{l=0}^{L_T-1} |x_{t,l}^2| \). The estimation of \( \sigma_{z_t}^2 \) is more cumbersome, we will assume hereafter that the total transmitted power by the BTS is known at the receiver. As a result of the unconditional approximation, the matrix inversion, which leads the complexity of the equalizer, is made once per frame and iteration. The highly structured nature of matrix \( \Xi^{(i)} \) allows to employ efficient inversion algorithms [43] [44]. Moreover, many suboptimal matrix inversion methods can be employed. For example, \( \Xi^{(i)} \) can be accurately approximated by a circulant matrix when the sliding window length is sufficiently large allowing its low complexity inversion in the frequency domain [10] [20]. On the other hand, the Matched Filter (MF) approximation replaces \( f_t^{(i)} \) by \( f_t^{MF} = \frac{1}{(\mathcal{H} e_t)^\dagger (\mathcal{H} e_t)^\dagger} (\mathcal{H} e_t)^\dagger \) under the assumption \( \mathbf{X} = \bar{\Xi}^{(i)} \) [11] [14, Section IV-A-3]. At the output of the MVDR filter, we get

\[
\hat{x}_{t,l} = x_{t,l} + \xi_{t,l}^{(i)}
\]

where \( \xi_{t,l}^{(i)} \) is a complex random variable with zero-mean and variance

\[
\sigma_{\xi_t}^2 = \mathbb{E} \left\{ |\xi_{t,l}^{(i)}|^2 \right\} = \frac{1}{(\mathcal{H} e_t)^\dagger (\mathcal{H} e_t)^\dagger} (\sigma_{x_t}^2 - \sigma_{z_t}^2)
\]

After proper serial-to-parallel procedure, we recreate the \( N_T \)-independent equalized precoded models

\[
\hat{z}_{t,n} = W_{n}^P S_{t,n}^P + W_{n}^I S_{t,n}^I + \xi_{t,n}
\]
Since the vector \( \tilde{z}_{t,n}^{(i)} \) is built from \( \hat{x}_{t,l} \) (re-multiplexing independent per antenna), the diagonal elements of the covariance of \( \zeta_{t,n}^{(i)} \) are all equal to \( \sigma_{\xi_s}^2 \). First a descrambling is applied to (29) leading to

\[
\tilde{z}_{t,n}^{(i)} = \Sigma_n \tilde{z}_{t,n} = \mathbf{W}_I^D s_{t,n}^D + \mathbf{W}_I^T s_{t,n}^T + \zeta_{t,n}^{(i)}
\]

(30)

In model (30), since \( \Sigma_n \) are made of i.i.d QPSK chips normalized to unity, covariance matrix \( \Theta_{\zeta_s} \) for the compound residual (ICI+CAI)+(thermal noise) term \( \tilde{\zeta}_{t,n}^{(i)} \), is expressed as

\[
\Theta_{\zeta_s} = \mathbb{E}[\Sigma_n \left[ \mathbb{E} \left[ \tilde{z}_{t,n}^{(i)} \tilde{z}_{t,n}^{(i)\dagger} | \Sigma_n \right] \right] = \sigma_{\xi_s}^2 \mathbb{I}_{N_Z},
\]

(31)

under the assumption of no knowledge of \( \Sigma_n \) but of its statistics which makes the subsequent multiuser detection time-invariant.

**B. Iterative multiuser detection**

Clearly, the detection of \( s_{t,n}^D \) and \( s_{t,n}^T \) is obvious in the case of \( \mathbf{W}_I^I \mathbf{W}_I = \mathbb{I}_{K_T} \), i.e., \( \tilde{s}_{t,n}^{(i)} = \mathbf{W}_I^D \tilde{z}_{t,n}^{(i)} \) and \( \tilde{s}_{t,n}^{(2)} = \mathbf{W}_I^T \tilde{z}_{t,n}^{(2)} \). Otherwise, for the overloaded case, MVDR filters can be derived as before. We define \( \tilde{s}_{t,n}^{(2)} = \tilde{s}_{t,n}^{T} \) and \( \tilde{s}_{t,n}^{(1)} = 0_{K_D} \) where \( 0_{K_D} \) is the null vector of dimension \( K_D \).

Thus, \( \tilde{s}_{t,n}^{(1)} = \begin{bmatrix} 0 \\ \tilde{s}_{t,n}^{D(1)\dagger} \\ \mathbf{0}_{K_D} \end{bmatrix} \) and \( \tilde{s}_{t,n}^{(2)} = \begin{bmatrix} 0 \\ \tilde{s}_{t,n}^{D(2)\dagger} \\ \mathbf{0}_{K_D} \end{bmatrix} \) represents the soft estimates on symbol vector \( s_{t,n} \) associated to scenario 1 and 2, respectively. Let \( e_k \in \mathbb{C}^{K_T} \) denotes the vector with a 1 at position \( k \) and 0’s elsewhere. The MVDR filters \( g_{k,n}^{(i)} \in \mathbb{C}^{1 \times N_Z}, k = 1, \ldots, K_T \), which minimize the constrained unconditional MSE

\[
\begin{align*}
\mathbb{E} \left\{ \left| \mathbf{s}_{k,t,n} - \mathbf{s}_{k,t,n}^{(i)} \right|^2 \right\} &= \mathbb{E} \left\{ \left| \mathbf{s}_{k,t,n} - g_{k,n}^{(i)} \left( \mathbf{W} \left( \tilde{s}_{k,n}^{(i)} - e_k \mathbf{s}_{k,t,n}^{(i)} \right) \right) \right|^2 \right\} \\
\text{subject to } &g_{k,n}^{(i)} \mathbf{W} e_k = 1
\end{align*}
\]

(32)

are, similarly to Section III-A, given by

\[
g_{k,n}^{(i)} = \frac{1}{\beta_{k,n}^{(i)}} (\mathbf{W} e_k)^\dagger \left[ \mathbf{W} \Theta_{s_t}^{(i)} \mathbf{W}^\dagger + \sigma_{\xi_s}^2 \mathbb{I}_{N_Z} \right]^{-1}
\]

(33)

where

\[
\beta_{k,n}^{(i)} = (\mathbf{W} e_k)^\dagger \left[ \mathbf{W} \Theta_{s_t}^{(i)} \mathbf{W}^\dagger + \sigma_{\xi_s}^2 \mathbb{I}_{N_Z} \right]^{-1} (\mathbf{W} e_k)
\]

(34)

and

\[
\Theta_{s_t}^{(i)} = \text{diag} \left\{ 0, \Theta_{s_t}^{D(i)}, \Theta_{s_t}^{T(i)} \right\}
\]

(35)
with
\[
\Theta_{n_t}^{D(i)} = \text{diag} \left\{ 1 - \sigma_{s_{1,t}}^{2}, \ldots, 1 - \sigma_{s_{K^D,t}}^{2} \right\}
\]
\[
\Theta_{n_t}^{I(i)} = \text{diag} \left\{ \sigma_{s_{1,t}}^{2} - \sigma_{s_{2,t}}^{2}, \ldots, \sigma_{s_{K^Z,t}}^{2} - \sigma_{s_{K^Z,t}}^{2} \right\}
\]
(36)

and where \( \sigma_{s_{k,t}}^{2} = \mathbb{E}\{ |s_{k,t,n}^{I}|^2 \} \) are supposed to be known by the receiver, \( \sigma_{s_{k,t}}^{2} = 0 \) while \( \sigma_{s_{k,t}}^{2} = \mathbb{E}\{ |s_{k,t,n}^{D(i)}|^2 \} \) and \( \sigma_{s_{k,t}}^{2} = \mathbb{E}\{ |s_{k,t,n}^{D(i)}|^2 \} \) can be approximated by \( \frac{1}{L} \sum_{n=0}^{L-1} |s_{k,t,n}^{I}|^2 \) and \( \frac{1}{L} \sum_{n=0}^{L-1} |s_{k,t,n}^{D(i)}|^2 \), respectively. Finally, it yields
\[
\hat{s}_{k,t,n}^{(i)} = s_{k,t,n} + \eta_{k,t,n}^{(i)} \quad k = 1, \ldots, K^T
\]
(37)

where
\[
\sigma_{\eta_{k,t,n}^{(i)}}^{2} = \begin{cases} \frac{1}{\beta_{t,k}^{(D)}} - (1 - \sigma_{s_{k,t}}^{2}) & 2 \leq k \leq K^D + 1 \\ \frac{1}{\beta_{t,k}^{(I)}} (\sigma_{s_{k-s_{k-k^D-1,t}}}^{2} - \sigma_{s_{k-t}}^{2}) & K^D + 2 \leq k \leq K^T \end{cases}
\]
(38)

with \( \sigma_{\eta_{k,t,n}^{(i)}}^{2} = \mathbb{E}\{ |\eta_{k,t,n}^{(i)}|^2 \} \). Note that the MF approximation here comes down to replacing \( g_{k,t}^{(i)} \) by \( g_{k,t}^{MF} = (\mathbf{W}e_{k})^{\dagger} \). In the case of scenario 1, \( \hat{s}_{k,t,n}^{D(1)} \) can be expressed as
\[
\hat{s}_{k,t,n}^{D(1)} = g_{k,t+1}^{(1)} \left( z_{t,n}^{(1)} - \mathbf{W}^{D} \left( \hat{s}_{k,t,n}^{(1)} - e_{k}^{D} \hat{s}_{k,t,n}^{D(1)} \right) \right) \quad \text{for} \quad k = 1, \ldots, K^D
\]
(39)

where
\[
g_{k,t+1}^{(1)} = \frac{1}{\beta_{t,k+1}^{(1)}} (\mathbf{W}^{D} e_{k}^{D})^{\dagger} \left[ \mathbf{W}^{D} \Theta_{n_t}^{D(i)} \mathbf{W}^{D\dagger} + \Gamma_{t} \right]^{-1}
\]
(40)

with
\[
\beta_{t,k+1}^{(1)} = (\mathbf{W}^{D} e_{k}^{D})^{\dagger} \left[ \mathbf{W}^{D} \Theta_{n_t}^{D(i)} \mathbf{W}^{D\dagger} + \Gamma_{t} \right]^{-1} (\mathbf{W}^{D} e_{k}^{D})
\]
(41)

and
\[
\Gamma_{t} = \sigma_{\xi_{t}^{(i)}}^{2} I + \mathbf{W}^{I} \Theta_{n_t}^{I(i)} \mathbf{W}^{I\dagger}
\]
(42)

where \( e_{k}^{D} \in \mathbb{C}^{K^D} \) is the vector with a 1 at position \( k \) and 0's elsewhere and \( \Gamma_{t} \) can be approximated by, for example,
\[
\hat{\Gamma}_{t} = \frac{1}{L} \sum_{n=0}^{L-1} z_{t,n}^{(1)} \hat{s}_{k,t,n}^{(1)} - \mathbf{W}^{D} \mathbf{W}^{D\dagger}
\]
(43)

Thus, no knowledge of \( \mathbf{W}^{I} \) is needed for scenario 1 if \( \hat{\Gamma}_{t} \) is used.
C. Iterative channel estimation

For simplicity, we will only consider a CPICH accumulation over a length equal to \( L_c \). An accumulation on a shorter length can be deduced in a straightforward way. The aim of this Section is to estimate the coefficients \( h_{r,N_e+n_e,t,m} \) taking into account our quasi-static channel model. Note that in the case of a time-varying channel for the duration of a coded block, the accumulation length should be lower than the channel coherence time and the channel estimation performed several times. We will omit the superscript associated to the scenarios 1 and 2 for the sake of notation simplicity. Let us define

\[
0 \leq r \leq N_R-1, \quad 0 \leq n_e \leq N_e-1, \quad 0 \leq t \leq N_T-1, \quad \mathbf{H}_{r,t,n_e} = \mathbf{A}_{L_e} (\mathbf{h}_{r,t,n_e}) \in \mathbb{C}^{(L_e+M) \times L_e}
\]

and \( \mathbf{h}_{r,t,n_e} = [h_{r,N_e+n_e,t,0}, \ldots, h_{r,N_e+n_e,t,M}]^\top \in \mathbb{C}^{M+1} \). The function \( \mathbf{A}_{L_e}(\mathbf{v}) \) builds a Toeplitz matrix with \( L \) repetitions of the vector \( \mathbf{v} \). Let \( \mathcal{E}_{t,m} \) be the projection vector of dimension \( L_e+M \) over the CPICH sequence \( \mathbf{x}_t^P \) for the \( m \)-th delay (\( 0 \leq m \leq M \)) and antenna \( t \)

\[
\mathcal{E}_{t,m}^l = [0, \ldots, 0, \mathbf{x}_t^P, 0, \ldots, 0]
\]

Without iterative processing (first iteration only), the channel coefficients can be evaluated classically from the observation of the vectors \( \mathbf{y}_r^T = [y_{r,N_e+n_e,0}^T, \ldots, y_{r,N_e+n_e,L_e+M-1}^T]^\top \) by

\[
\hat{h}^{[1]}_{r,N_e+n_e,t,m} = \frac{1}{\mathbf{x}_t^P \mathbf{x}_t^P} \mathcal{E}_{t,m}^l \mathbf{y}_r^T = h_{r,N_e+n_e,t,m} + \nu'_{r,n_e}
\]

where \( \nu'_{r,n_e} \) includes 4 sources of interference, the self-interference due to the non-null autocorrelation of the CPICH sequence, the interference coming from the CPICHs of the other antennas, the interference due to the considered user data symbols, the interference due to the other users’ data symbols, plus the projected noise. Let \( \hat{\mathbf{H}}^{[j]}_{r,t,n_e} \) be the estimation of \( \mathbf{H}_{r,t,n_e} \) at the \( j \)-th iteration and \( \hat{\mathbf{H}}^{[0]}_{r,t,n_e} \) initialized to a null matrix. At the beginning of iteration \([j]\), \( \hat{\mathbf{H}}^{[j-1]}_{r,t,n_e} \) is supposed to be known. Moreover, we assume that the detection/decoding steps provide soft estimates \( \tilde{\mathbf{x}}_{t}^{[j-1]} \) on the symbols \( \mathbf{x}_t^P \). The vector \( \tilde{\mathbf{x}}_t^{[0]} \) is initialized to zero. The estimated signal-plus-interference \( \hat{\mathbf{H}}^{[j-1]}_{r,t,n_e} \left( \tilde{\mathbf{x}}_{t}^{[j-1]} + \mathbf{x}_t^P \right) \) can be subtracted of the received vector \( \mathbf{y}_r^T \) for increasing the accuracy of the estimation:

\[
\hat{h}^{[j]}_{r,N_e+n_e,t,m} = \frac{1}{\mathbf{x}_t^P \mathbf{x}_t^P} \mathcal{E}_{t,m}^l \left( \mathbf{y}_r^T - \sum_{\nu'=0}^{N_T-1} \hat{\mathbf{H}}^{[j-1]}_{r,t',n_e} \left( \tilde{\mathbf{x}}_{t'}^{[j-1]} + \mathbf{x}_{t'}^P \right) \right) + \hat{h}^{[j]}_{r,N_e+n_e,t,m}
\]
Taking into account the assumptions of scenario 2, equation (47) becomes
\[
\hat{r}^{[j]}_{r, n_e, n_e, t, m} = \frac{1}{x_i^P x_l^P} \left( y_r^T - \sum_{t' = 0}^{N_T - 1} \hat{H}_{r, t', n_e}^{[j]} \left( x_i^P[t' - 1] + x_l^P[t' - 1] + \epsilon_{t'} \right) + \hat{r}_{r, n_e, n_e, t, m}^{[j]} \right)
\]

The interference due to the CPICH vectors \(x_i^T\) is then reconstructed based on the knowledge of all \(\hat{r}_{r, n_e, n_e, t, m}^{[j]}\) and finally subtracted to \(y_r^T\) in (14) to facilitate the estimation of symbols \(\hat{x}_{t, l}^{D[j]}\) and \(\hat{x}_{t, l}^{T[j]}\) of \(x_{t, l}^D\) and \(x_{t, l}^T\).

IV. SIMULATION RESULTS AND ASSUMPTIONS

Each codeword is obtained from the concatenation of \(N_b\) rate-1/2 PCCC turbo-code codewords. The turbo code is based on two punctured rate-1/2 8-state Recursive Systematic Convolutional (RSC) codes, with generator polynomials \((1, 13/15)_8\). We consider QPSK modulation only (for lack of space, see [31] [45] for higher modulation performance curves for scenario 1 only). The precoding Matrix follows the WCDMA downlink example, i.e., \(R_{N_Z \times N_Z}\) is a Walsh Hadamard rotation and \(\Sigma_n\) are obtained from a long complex scrambling sequence built from a Gold sequence. The spreading factor is fixed to \(N_Z = 16\) and repetition factor of the CPICH sequence is \(N_P^Z = 16\). The channel profiles and transmit filters are the same for any pair of transmit/receive antennas. We assume that the \(N_R \times N_T\) MIMO channel is spatially decorrelated. The ITU Vehicular A channel profile [48] is chosen corresponding to a macro-cellular environment. The transmit filter is a square root raised cosine with roll-off factor 0.22 and chip period \(T_c = 1/3.84 \mu s\). Each of the \(N_b\) turbo-code codewords carries \(k_0\) \((k_0 < 5114)\) information bits, \(k_0\) is chosen such as \(L_c\) is the closest to (and lower than) 7680 chip periods. These 7680 chip periods define the length of a TTI in the HSDPA 3GPP standard. While the HSDPA standard considers a global Check Redundancy Code (CRC) on the whole TTI, we rather consider a CRC per coded block and define the BLER correspondingly. At the receiver, fractional sampling is performed. The oversampling factor \(N_e\) is chosen equal to 2. After low pass receive filtering, samples are taken at a rate of \(2/T_c\), ensuring that the noise samples are uncorrelated. The CPICH accumulation length is always chosen equal to \(L_c\) chips. The iterative MMSE chip equalizer relies on a sliding window of length \(L_w = 15\). One iteration of the proposed iterative equalization and MUD with iterative channel estimation comprises one path of channel estimation, space-time chip-equalization, despreading and a single turbo-decoding.
iteration. For scenario 2, semi-blind interference cancellation is added within each iteration. Its overall associated receiver architecture is depicted in Fig. 2. Particular attention is given to the region of BLock Error Rate (BLER) above $10^{-2}$ as an Automatic Repeat Request (ARQ) protocol is assumed on top of the physical layer. Hybrid ARQ (HARQ) exceeds the scope of this paper (see, e.g., [46] for an example of its embedding within an iterative receiver architecture). When performance are compared, we will systematically assume a target BLER of $10^{-2}$ if not otherwise stated. The performance given are obtained after 10 iterations which are sufficient to converge to the best achievable performance. However, 5 iterations are sufficient to perform close to this limit. For comparison purpose, the conventional receiver performs $\tau$ turbo-decoding iterations.

First, we consider a non-overloaded mono-user situation, i.e., $K_D = 15$ and $K_T = 0$. The resulting load per antenna, i.e., the ratio $\frac{K_T}{N_z}$, is always 100% (one code is allocated for the CPICH). In Fig. 3 and Fig. 4, we consider a $4 \times 4$ MIMO channel with QPSK input, i.e., $\rho = 3.75$ bpcu, $k_0 = 4800$ and $N_b = 6$. The CPICH power proportion $\alpha_p$ is fixed to 0.1 and 0.2 in Fig. 3 and Fig. 4, respectively. The outage probability [47], which defines the best achievable performance under perfect channel estimation, is drawn. The conventional receiver under the assumption of perfect channel estimation performs at 4.3 dB from the outage probability while the proposed iterative equalization and MUD is at 1.8 dB for BLER $10^{-2}$. In this case, the gain provided by the iterative equalization and MUD amounts to 2.5 dB with perfect channel estimation. We witness that the higher the modulation order, the more significant the gains in case of perfect channel estimation (7.75 dB adopting a 64-QAM modulation instead of QPSK [45]). We also plotted for both figures, again under the perfect channel estimation assumption, the coded Matched Filter Bound (MFB) which assumes both perfect ICI and CAI cancellations, i.e., $\tilde{\mathbf{x}}^D = \mathbf{x}^D$. The coded MFB is slightly better than the outage probability, this can be explained by the fact that under the Matched Filter (MF) assumptions only the MF outage probability is relevant, i.e, the outage probability with respect to the equivalent CAI and ICI free MF channel. As a remark, a gap of only 0.7 dB is observed between the MF outage probability and the MFB which illustrates the quality of the proposed transmission strategy. Let us focus on the channel estimation issue. When a conventional correlation based channel estimation is chosen,
catastrophic performance (the target BLER of $10^{-2}$ is never reached, whatever the SNR) are observed in Fig. 3, with either a conventional or iterative equalization and MUD. This comment appears to be valid for all simulations in this paragraph. This is explained by the high level of noise introduced by channel estimation errors that prevents a good convergence of the iterative equalization and MUD. When the level of interference of the data on the CPICH is reduced by iterative soft interference subtraction, the convergence properties are enhanced and the error floor disappears. The system performance are 2 dB and 4 dB away from the perfect CSI case at BLER $10^{-1}$ and $10^{-2}$, respectively. In order to enhance the performance with channel estimation, the CPICH power proportion may be increased to $\alpha_p = 0.2$ (this seems appropriate, considering the high number of channel coefficients to be estimated), i.e., 20% of the BTS transmit power. We observe in Fig. 4 that the conventional correlation-based channel estimation performs at 3.5 dB from the perfect channel estimation at BLER $10^{-2}$. An error floor is observed, corresponding to the interference produced by channel estimation errors. When an iterative channel estimation is used, we can achieve performance at less than 1.5 dB of the perfect CSI performance with no error floor.

Second, we consider a multiuser setting where $K^D = 10$ and $K^T = 10$ and a $4 \times 4$ MIMO channel with QPSK input. The CPICH power proportion is fixed to $\alpha_p = 0.1$. The load per antenna is 131.25% and the spectral efficiency of the considered user is 2.5 bpcu, $k_0 = 3200$ and $N_b = 6$. Fig. 5 shows the BLER as a function of the $E_c/I_{\text{intra}}$ ratio, with a fixed $E_c/N_0 = 6$ dB. The BLER at $E_c/I_{\text{intra}} = 8$ dB is near from the single user case limit $\sigma^2_2 = 0$. The three curves corresponding to iterative equalization and MUD with conventional, iterative or perfect channel estimation have a horizontal asymptote equal to their single user BLER at $E_c/I_{\text{intra}} = 8$ dB (for comparaison purpose, a fourth curve is given corresponding to conventional channel estimation and conventional receiver). Clearly, the better the channel estimation, the lower the asymptote. This asymptote is around $10^{-1}$ for the conventional channel estimation. The conventional estimation cannot reach the target BLER whereas the proposed iterative channel estimation is less than 6 dB away from the perfect channel estimation performance. Moreover, the noise level is particularly high in the presented scenario, as $N_0$ decreases, the performance with iterative channel estimation will approach the performance with perfect CSI. For $E_c/N_0 = 10$ dB,
we observe in Fig. 6 that the performance of the conventional channel estimation are enhanced but always far away from the perfect CSI case at the target BLER $10^{-2}$. When an iterative channel estimation is used, we can achieve 4 dB from the perfect channel estimation case.

We now observe the performance improvement provided by semi-blind intracell interference cancellation with respect to scenario 2. Iterative equalization and MUD is always considered. We assume that the channel estimation is perfect and consider three signal to noise ratio 3, 6, 10 dB. In Fig. 7, we again assume that $K^D = 10$ and $K^F = 10$. The load per antenna is 131.25% and the spectral efficiency of the considered user is 2.5 bpcu ($4 \times 4$ MIMO channel with QPSK input). For $E_c/N_0 = 3$ dB, there is no gain provided by the semi-blind interference cancellation. Actually, semi-blind intracell interference cancellation performs slight worse for high $E_c/I_{\text{intra}}$. Indeed, the soft estimation of intracell interference may only be efficient if the uncoded performance at the output of the chip equalization and MUD are good enough, i.e., for a sufficiently high signal-to-noise ratio. For $E_c/N_0 = 6$ dB, we can observe that a substantial performance improvement is given by semi-blind interference cancellation for BLERs greater than $10^{-1}$. However, no gain is observed for the BLER region of interest. For $E_c/N_0 = 10$ dB, which corresponds to a moderate signal-to-noise ratio, we can observe the high gain provided by semi-blind interference cancellation. We can moreover observe the good performance obtained for an user that experiences a high level of intracell interference. For example, such a situation may occur when the BTS reduces the transmit power associated to the considered user who is near from the BTS. If the other users are far away from the BTS, the intracell interference level is high. For example, if $E_c/I_{\text{intra}} = -6$ dB, we observe that the performance of the considered user is equal to $4.10^{-1}$ without semi-blind interference cancellation and $10^{-2}$ with semi-blind interference cancellation. As $I_{\text{intra}}$ increases, the signal-to-noise ratio seen by the other users’ interference grows allowing its better detection and soft cancellation. In Fig. 8, we observe the behavior of semi-blind interference cancellation in the presence of channel estimation. We consider the same parameters as for Fig. 7, with a CPICH power proportion equal to $\alpha_P = 0.1$. With a conventional channel estimation, the performance are degraded by the use of semi-blind interference cancellation. In that particular case, even if iterative channel estimation is activated, the semi-blind interference cancellation gain is canceled out for that level of CPICH power. This
is explained by the high interference level created by the channel estimation errors. As a result, we increased the CPICH power proportion to $\alpha_p = 0.2$ to enhance the channel estimation. We can observe in Fig. 9 that the performance obtained with semi-blind interference cancellation and conventional channel estimation are degraded. However, better performance are always achieved by using semi-blind interference cancellation and iterative channel estimation, even if the gains are not substantial. Finally, we investigate non-symmetrical configuration such as $K^D = 14$ and $K^X = 1$ and inversely $K^D = 1$ and $K^X = 14$ with a $4 \times 4$ MIMO channel with QPSK input and CPICH power proportion fixed to $\alpha_p = 0.2$. In the first case, the spectral efficiency of the considered user is $3.5 \text{ bpcu}$, $k_0 = 4480$ and $N_b = 6$ with fixed $E_c/N_0 = 4 \text{ dB}$. We can observe in Fig. 10 that the semi-blind intracell interference cancellation together with iterative channel estimation is particularly efficient. Moreover, The BLER at $E_c/I_{\text{intra}} = 6 \text{ dB}$ is near from the single user case limit $\sigma^2 = 0$ and reaches $10^{-2}$. We checked that without any intracell interference and perfect channel estimation, the $E_c^{\text{free}}/N_0$ needed to reach the $10^{-2}$ BLER is approximately $4 \text{ dB}$. Surprisingly, the performance obtained with scenario 2 are close to the interference free case with perfect channel estimation for whatever the power of Intra. This can be explained by the robustness of the uncoded other users’ interference detection when it is made of a single code. In the second case, the spectral efficiency of the considered user is $0.25 \text{ bpcu}$ $k_0 = 1920$ and $N_b = 1$. The $E_c^{\text{free}}/N_0$ was simulated and gives approximately $-8.75 \text{ dB}$. However, for $E_c/N_0 = E_c^{\text{free}}/N_0$ the semi-blind intracell interference cancellation with iterative channel estimation never reaches the aimed BLER and gives poor improvement (it actually slightly degrades the performance). As a result, we rather considered in Fig. 11 $E_c/I_{\text{intra}} = -7.75 \text{ dB}$ where intracell interference cancellation begins to work at low $E_c/I_{\text{intra}}$ (but still slightly degrades the performance in the region of interest).

V. CONCLUSION

The classical approach which consists of treating separately channel estimation, MMSE chip equalization, symbol detection and turbo-decoding functionalities within the receiver is very sub-optimal in the case of MIMO HSDPA. Indeed, simulations prove that huge gains remain to be exploited if iterations include all the functionalities of the receiver chain rather than being limited to turbo-decoding. Moreover, the turbo-principle can also be beneficially applied to
intracell interference cancellation if some characteristics of the interfering signals are known. The work carried out in this paper can be completed in at least three ways. First, practical blind estimators on the modulation and spreading sequences used by the interfering signals remain an interesting research area [34] [36]. Second, the channel estimation based on superimposed pilot symbols highly suffers from all sources of interference at first iteration. It would be interesting to compare this strategy with the sequential (time multiplexed) channel estimation strategy for the same power and rate degradation. Third, the results presented here can be extended to deal with intercell interference [15] [17] [18] [49]. Those topics will be addressed separately in future contributions. As a last remark, this transceiver design can be easily adapted to a spreading in the frequency domain such as encountered for MultiCarrier CDMA (MC-CDMA) systems.

REFERENCES


Fig. 1. MIMO HSDPA transmitter scheme.
Fig. 2. Scenario 2, iterative equalization and MUD with iterative channel estimation and semi-blind interference cancellation.
Fig. 3. Single User, QPSK, 100% load, 4 × 4 MIMO Vehicular A channel, spectral efficiency $\rho = 3.75$ bpcu, $\alpha_P = 0.1$. 
Fig. 4. Single User, QPSK, 100% load, 4 × 4 MIMO Vehicular A channel, spectral efficiency $\rho = 3.75$ bpcu, $\alpha_P = 0.2$.
Fig. 5. Multiple Users, QPSK, 131.25% load (10 codes out of 16 for user 1), $\alpha_P = 0.1$, $4 \times 4$ MIMO Vehicular A channel, $E_c/N_0 = 6$ dB, iterative equalization and MUD.
Fig. 6. Multiple Users, QPSK, 131.25% load (10 codes out of 16 for user 1), $\alpha_P = 0.1$, 4 x 4 MIMO Vehicular A channel, $E_c/N_0 = 10$ dB, iterative equalization and MUD.
Fig. 7. Multiple Users, QPSK, 13.125% load (10 codes out of 16 for user 1), 4 x 4 MIMO Vehicular A channel, Perfect CSI at the receiver, with (scenario 2) and without (scenario 1) semi-blind interference cancellation (semi-blind).
Fig. 8. Multiple Users, QPSK, 13.125% load (10 codes out of 16 for user 1), 4 × 4 MIMO Vehicular A channel, with (scenario 2) and without (scenario 1) semi-blind interference cancellation (semi-blind), $\alpha_p = 0.1$, $E_b/N_0 = 10$ dB.
Fig. 9. Multiple Users, QPSK, 13.25% load (10 codes out of 16 for user 1), 4 × 4 MIMO Vehicular A channel, with (scenario 2) and without (scenario 1) semi-blind interference cancellation (semi-blind), $\alpha = 0.2$, $E_b/N_0 = 10$ dB.
Fig. 10. Multiple Users, QPSK, 100% load with $K^T = 14$ and $K^L = 1$, $4 \times 4$ MIMO Vehicular A channel, with (scenario 2) and without (scenario 1) semi-blind interference cancellation (semi-blind), $\alpha_p = 0.2$, $E_b/N_0 = 4$ dB.
Fig. 11. Multiple Users, QPSK, 100% load $R_T = 1$ and $K_T = 14$, 4 x 4 MIMO Vehicular A channel, with (scenario 2) and without (scenario 1) semi-blind interference cancellation (semi-blind), $\alpha_r = 0.2$, $E_b/N_0 = -7.75$ dB.