A Simulation Framework for WCDMA Wireless Systems

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Abstract—In this paper we report on performance evaluation of the WCDMA radio interface of UMTS through a detailed link level simulation tool. The motivation is to reproduce a possibly realistic scenario, where detailed behavior of various transmission techniques is modelled and their interaction evidenced in an actually integrated framework. Specifically, SINR (Signal-to-(Noise+Interference) Ratio) based power control is implemented without simplifying multiple access interference (MAI), and adaptive channel estimation techniques are evaluated in the presence of Doppler spectrum modifications induced by power control. Moreover, spatial-temporal channel models and related processing are introduced. Another relevant aspect concerns combining techniques for hybrid macrodiversity-microdiversity schemes. In this context, a SINR-based MRC (Maximal Ratio Combining) alternative is proposed for e.g. softer handover within Node B and, in the presence of radio-over-fiber technology for the link between Nodes B and RNC, also for soft handover at the RNC. The simulation framework has been developed in the CoCentric System Studio environment provided by Synopsys Ltd.

Keywords: WCDMA, simulation, power control, spread spectrum, multiple access interference, spatial-temporal processing.

I. INTRODUCTION AND OVERVIEW

Simulation techniques are often used to predict link level performance in communication systems, when system model complexity prevents from using an analytical approach. Specifically, we are interested on evaluating performance of the WCDMA alternative of the UMTS radio interface, with the specific aim of considering the simultaneous presence of relevant radio technologies and implicitly accounting for interactions among them. In this perspective, we have developed a comprehensive simulation tool in the CoCentric System Studio environment provided by Synopsys. The radio chain for the reverse link between a Mobile Station (MS) and a Node B is modelled according to recent releases of standard documents (see, e.g. [1], [2]). By combining already developed blocks available from a basic library with specifically developed blocks, we were able to define a setup for variable bit rate and variable spreading and, ultimately, various quality of service degrees.

In this frame, a complete transmission chain is built for any user in the system, that takes into account coding, multiplexing, channel mapping of DCCH and DTCH transport channels onto physical channel, etc. Moreover, a frequency selective channel model is adopted and classical rake receiver is implemented for each user signal, while multiuser detection is neglected at the present stage. A relevant feature of our framework is that, although the simulation environment is basically not intended for system level analysis, we have considered that multiple access interference (MAI) is a fundamental limitation of the radio capacity and its characteristics should not be simplified in performance evaluation. Therefore, we have actually modelled various transmission chains, each one corresponding to the link between an MS and the Node B. For each link a SINR-based power control algorithm, that requires both an inner loop and an outer loop mechanism, is implemented in the presence of a detailed behavior for the wireless channel and MAI.

On the DPCCH, SINR estimates are taken for closed-loop power control. Therefore, the channel is power controlled and Doppler spectrum may be substantially different from what usually assumed in the absence of power control. The view of the highest level DFG is provided in Fig. 1, where transmission...
of the closed-loop power control command on the dedicated physical control channel is also evidenced. Moving from the depicted framework, we have also addressed other specific topics, namely channel estimation (for rake reception), spatial processing and beamforming, soft and softer handover. We address these issues in the sequel and evidence interactions with other techniques in the transmission chain.

II. CODING, MULTIPLEXING AND PHYSICAL TRANSMISSION

In third generation wireless systems, user and control data are mapped onto dedicated transport channels (DTCH and DCCH) and then on physical channel(s) DPDCH. Further physical control informations are transmitted in the DPCCH. User information data arrives to the coding/multiplexing unit in form of transport blocks. In such unit, transport blocks are processed according to the following steps:

- CRC (Cyclic Redundancy Check) attachment;
- channel coding;
- radio frame equalization;
- rate matching;
- insertion of discontinuous transmission (DTX) indication bits;
- first interleaving;
- radio frame segmentation;
- multiplexing of transport channels (DCCH and DTCH);
- physical channel segmentation;
- mapping of transport channels into physical channels (DPDCH and DPCCH).

In Fig. 2 the coding/multiplexing functions are depicted for the implemented case of DTCH at 64 kbps and DCCH at 2.4 kbps.

The DPCCH is used to carry control information for channel estimation and coherent detection (Pilot bits), transmit power control commands (TPC), feedback informations (FBI) and optional transport-format combination indicator (TFCI). Pilot bits are used also for the SINR estimation in the closed loop power control procedure. In Fig. 3 the structure of reverse link DPDCH and DPCCH is depicted. Each frame is composed of 15 slot and has the duration of 10 ms with fixed chip rate of 3.84 Mchip/s. Different DPDCHs of the same user are distinguished by different spreading codes, while different users are associated to different scrambling codes. The spreading factor used for DPDCH can be varied between 4 to 256, according to the data transmitted class. The spreading factor used for the DPCCH is always 256. An OQPSK (Offset Quadrature Shift Keying) modulation is adopted.

III. CHANNEL ESTIMATION

Channel estimation is a fundamental component of receiver architecture in DS-CDMA systems. In particular, it is an essential feature for Rake reception in multipath fading channels, where each finger is assigned to one of the strongest multipath components and related outputs are optimally combined before detection. As stated above, in third generation wireless systems (see, e.g. [3]), dedicated pilot sequences are included in the DPCCH. In order to mitigate the effects of noise and MAI, filtering of detected pilot bits is required. The bandwidth of this low-pass filter should be wide enough to accomodate the Doppler Spectrum bandwidth. In fact, if the filter bandwidth is too narrow, the channel estimation cannot take into account the fast variation of the channel. However, if the filter bandwidth is too large, the noise effect is not reduced and channel estimation may be inaccurate.
Adaptive techniques have been recently proposed to improve performance of channel estimation in time-varying contexts, as it is observed in mobile radio. Recent contributions on this topic can be found in [4], [5]. With regard to channel estimation, two alternatives have been investigated in this work: i) Weighted Multi-Slot Average (WMSA), that implicitly assumes a slowly varying channel and provides one estimate per slot, with eventual low-pass filtering of a sequence of estimates related to subsequent slots; ii) adaptive low-pass filtering of the pilot sequence. According to standard directives, in our simulation framework channel estimation is performed on the DPCCH.

A. WMSA

Let us consider the problem for a generic finger of the rake receiver, and denote with $b_k$ the k-th pilot bit and with $\alpha_k$ the channel gain (tap gain) on the k-th bit on such finger. The despread sequence of the quadrature component, denoted as $y_k^b$, can be expressed as

$$y_k^b = \alpha_k b_k + n_k$$

where $n_k$ denotes the additive noise. If $N_b$ is the number of pilot bits in a DPCCH slot, then the WMSA method performs the sliding window average to yield channel tap estimation $\tilde{\alpha}_k$:

$$\tilde{\alpha}_k = \frac{1}{N_p} \sum_{i=1}^{N_p} y_i^b b_i .$$

The estimated coefficients may be further filtered by a low-pass filter to smooth the transition between consecutive coefficients.

B. Adaptive low-pass filtering

In many situations of practical interest, the channel is rapidly time-variant. In such cases, channel coefficients may no longer be considered constant over a slot, but only over a few bits. Thus, IIR smoothing of channel estimates at the bit time can be adopted, the filter having the following transfer function:

$$p(z) = \frac{a}{1 - (1 - a)z^{-1}}$$

where $a$ is the forgetting factor, with $0 < a < 1$. The parameter $a$ is clearly related to the filter bandwidth and should be chosen according to the Doppler spectrum. Wiener’s theory provides the theoretical framework for optimal design of the low-pass filter, given the Doppler spectrum or, at least, the Doppler spread. A scenario with variable user velocity and, consequently, with variable Doppler frequency, requires that $a$ has to be adaptively changed according to the Doppler spectrum in order to increase system performance. As the mobile speed may change, adaptation is based on on-line estimation of Doppler spread to drive the values of pilot filter parameters. In this regard, we resort to the approach devised in [6] for speed estimation, and take particular care to pass-band filter design and setting of energy thresholds.

C. Numerical Results

In Fig. 4 BER performance is plotted, as obtained with adaptive and WMSA channel estimation for a 64 kbps DTCH and 2.4 kbps DCCH in a cellular scenario with two interfering users and the reference user moving at 30 km/h. The power control mechanism has been included for each user, with a SINR target of 15 dB (after despreading). Moreover, a four taps channel is assumed. As it can be observed, adaptive channel estimation yields better performance with respect to the WMSA method for both the DCCH and the DTCH channel. In Fig. 5 BER performance is reported for the same scenario of the previous case, but with a larger speed of the reference user. The better performance of adaptive channel estimation is again evident. As one could expect, BER increases at larger speeds. In this context, performance worsening of WMSA is even more remarkable.

IV. MACRODIVERSITY

Prediction (optimal) combining techniques could be devised for simultaneous consideration of macro-diversity and micro-diversity. Therefore, instead of resorting to typical post-detection selective combining for macro-diversity, we can adopt some maximal ratio combining in a unique point. This can be achieved by a rake receiver with a larger number of fingers,
that resolve and combine multipath components coming with different delays, or by further weighting the output from e.g. two rakes and using SINR estimate from each rake to find the weights of the subsequent linear combination. SINR-based combining has been applied to microdiversity schemes (see e.g. [7] and [8]), but we are not aware of the fact that it has been already applied to macrodiversity contexts.

In the simulation environment, a MRC macrodiversity technique is considered, and combining is performed on the outputs of rake receivers from two Node B. SINR estimates on each rake output are performed and used as related weights in the MRC scheme. Such an MRC scheme is compared with a classical SC scheme. In the simulation, the same scenario of Fig. 5 in considered, where the reference user moves at 70 Km/h and an WMSA channel estimation is performed. As already stated, outputs from two rakes (each one with 4 fingers) are combined and the BER for the DTCH channel has been computed. As it can be observed from MRC provides better performance with respect to SC.

![Fig. 6. BER of DTCH for the case of SC and MRC with velocity of the reference user set to 70Km/h](image)

**V. SPATIAL PROCESSING AND RELATED CHANNEL MODELS**

Beamforming is a technique for interference management in wireless systems. In fact, smart antennas with beamforming algorithms can significantly enhance capacity of any system and are of particular interest for WCDMA. Consistent simulation of beamforming requires accurate reproduction of spatio-temporal characteristics of the wireless medium. In fact, the use of radio systems employing smart antennas requires both temporal and spatial information in the channel impulse response. In order to develop, simulate and test such radio systems, good models are of vital importance. In our framework we have implemented a flexible cluster-based model according to COST 259 specifications [10], as well as a simpler one based on Geometrical Single Bounce Elliptical Model [9]. A relevant feature of our modelling effort is to actually embed beamforming into the radio resource management framework and thus consider its interaction with other components, such as power control and allocation.

In a mobile radio channel, the signal from the transmitter arrives at the receiver with multiple copies due to multipath propagation. Each multipath component is due to a scattering object. The dispersion of the channel in the temporal and angular domain can be described by the time-variant Directional Channel Impulse Response (DCIR) $h(t, \tau, \Omega)$, where $t$ is the time, $\tau$ is the time delay and $\Omega = (\phi, \theta)$ is the direction of arrival in azimuth and elevation angle. If there are $L$ multipath components, that can be separated both in time delay and angle, the DCIR at the receiver can be written as:

$$h(t, \tau, \Omega) = \sum_{l=1}^{L} h_l(t, \tau, \Omega)$$

with

$$h_l(t, \tau, \Omega) = a_l(t) \delta(\tau - \tau_l) \delta(\Omega - \Omega_l)$$

where $a_l(t)$ is the complex amplitude of the multipath component having time delay $\tau_l$ and direction $\Omega_l$.

If an $M$ elements antenna is used at the receiving side, the channel impulse response (CIR) can be written as:

$$h(t, \tau) = \sum_{l=1}^{L} a(\Omega_l) a_l(t) \delta(\tau - \tau_l)$$

The vector $a(\Omega_l)$ is the steering vector in direction $\Omega_l$, and it is defined as:

$$a(\Omega) = [a_1(\Omega), \cdots, a_{M-1}(\Omega)]^T$$

with:

$$a_m(\Omega) = e^{-j\beta(x_m \cos \theta + y_m \sin \theta + z_m \cos \theta)}$$

where $(x_m, y_m, z_m)$ is the generic position of $m$ antenna element, and $\beta = 2\pi/\lambda$, with $\lambda$ denoting the wavelength [9], [11].

**A. COST259 Model**

COST259 deals with cluster-based channel models. In fact, in many propagation environment, scatterers are not uniformly distributed in delay time and angle, but tend to occur in groups or clusters. This means that the multipath components can be grouped in disjoint clusters. The multipaths of a cluster exhibit close time delay and angles. Therefore, the DCIR can be expressed as:

$$h(t, \tau, \Omega) = \sum_{c=1}^{C} \sum_{j=1}^{J_c} \alpha_{c,j}(t) \delta(\tau - \tau_{c,j}) \delta(\Omega - \Omega_{c,j})$$

where $C$ is the number of clusters and $J_c$ is the number of multipath components related to cluster $c$.

In COST259 specifications, the radio propagation is characterized with different topographical and electrical features of the surrounding. There are three types of cells: macrocell, microcell and picocell. For each kind of cell, various radio environments are defined, such as General Typical Urban, General Office LOS, etc. Moreover, in picocellular environment clusters are distinguished between principal cluster and additional clusters. The principal cluster, if it is present, extends around the mobile station, while additional clusters are far from the mobile station and may appear and disappear as time elapses.
In the frame of COST259, different choices can be adopted to obtain a channel model suitable for simulations, as it can be argued by considering recent literature on the subject (see [13], [14] and [15]). In order to find a simplified channel model, a statistical approach can be adopted by the use of a multiple tapped delay line model [16]. In this case, by observing eq. (9), it is reasonable to suppose that some multipaths arrive approximately with the same time delay but from different directions. Therefore, Eq. (9) can be written as:

\[ h(t, \tau) = \sum_{c=1}^{C} \sum_{n=1}^{N_c} \sum_{k=1}^{K_{c,n}} a(\Omega_{c,n,k}) \alpha_{c,n,k}(t) \delta(\tau - \tau_{c,n}) \]
\[ = \sum_{c=1}^{C} \sum_{n=1}^{N_c} h_{c,n}(t, \tau) \]  

where \( K_{c,n} \) is the number of multipath components of cluster \( c \) arriving with the same time delay \( \tau_{c,n} \) and \( h_{c,n}(t, \tau) \) is the time variant vector channel. The aim of the statistical approach is to find an approximation for the process \( h_{c,n}(t, \tau) \).

This approximation moves from the spatial property of the channel at a particular time delay, by specifying the spatial correlation matrix \( R_{c,n}(t, t - \Delta t, \tau - \Delta \tau) = E[h_{c,n}(t, \tau) h_{c,n}^H(t - \Delta t, \tau - \Delta \tau)] = P_{c,n}(\Delta t) \delta(\Delta \tau) \), where

\[ P_{c,n}(0) = \sum_{k=1}^{K_c} a(\Omega_{c,n,k}) a^H(\Omega_{c,n,k}) E[\gamma_{c,n,k}^2(t)] \]  

with \( \gamma_{c,n,k} \) taking into account fading with a given power-delay-angle distribution. \( P_{c,n} \) can be expressed in terms of the matrix \( Q_{c,n} \) of eigenvectors and the diagonal matrix \( \Lambda_{c,n} \) of eigenvalues:

\[ P_{c,n} = Q_{c,n} \Lambda_{c,n} Q_{c,n}^H \]  

Finally, if there is a large number of terms with no dominant components, the vector \( h_{c,n}(t, \tau) \) is approximated in the form:

\[ h_{c,n}(t, \tau) \approx Q_{c,n} \Lambda_{c,n}^{1/2} g_{c,n}(t) \delta(\tau - \tau_{c,n}) \]  

where \( g_{c,n}(t) \) is a vector of \( M \) independent white complex Gaussian processes.

In Fig. 7 there is no temporal correlation, that must be reintroduced if either the receiver or the scatterers are in movement. Hence, the process \( g_{c,n}(t) \) has to be filtered in order to impress the desired Doppler spectrum [12]. Doppler spectrum has to be properly related to the multipath angle of departure, and, in general, it is not adherent to Clarke’s model [9].

We have implemented a picocellular cluster channel model based on Eq. (13), where all the parameters necessary to obtain the matrix of Eq. (12) are generated according to COST259 specifications [10]. The distance between the base station and the mobile station is set to 4 \( m \). In Fig. 7 the normalized Laplacian Power Azimuth Profile of a principal cluster is reported, as obtained from simulations. Azimuth angles are computed with reference to the line of sight. As it can be observed from this figure, the angle of arrival of multipaths generated by a principal cluster is distributed in the range \([-\pi, \pi]\), while additional clusters have a more tight angle distribution. In Fig. 8 the normalized one sided exponential Power Elevation Profile of a principal cluster is reported, as obtained from simulations, and elevation angles are computed with respect to the horizontal plane.

**B. Geometrically Based Single Bounce Elliptical Model (GBSBEM)**

The GBSBEM assumes that reflectors are uniformly placed within an ellipse, and the base station and the mobile station are at the foci of the ellipse [9]. Such model is used for microcellular and picocellular environment with low antenna heights, so that multipaths are uniformly distributed both around the base station and the mobile station. The maximum delay \( \tau_m \) determines the dimension of the ellipse. In fact, the major and minor axes of the ellipse are \( a_m = c \tau_m / 2 \) and \( b_m = \sqrt{c^2 \tau_m^2 - D^2} \), where \( c \) is the speed of the light and \( D \) is the distance between the base and mobile station. The probability density function of the angle of arrival and the delay of multipaths, is as follows:

\[ f_{\tau,\phi}(\tau, \phi) = \frac{(D^2 - \tau^2 c^2)(D^2 c + \tau^2 c^3 - 2 \tau c^2 D \cos(\phi))}{4 \pi a_m b_m (D \cos(\phi) - \tau c)^3} \]  

(14)

where \( D / c \leq \tau \leq \tau_m \). According to the PDF of Eq. (13) it is possible to compute the direction of arrival \( \phi_i \), the direction of departure \( \theta_j \) and the delay \( \tau_i \) of multipath component \( i \).
for $i = 1...L$. The power of each multipath component is determined according to:

$$P_i = P_{ref} - 10n \log(r_i) - L_r + G_r(\phi_i) - G_r(0) + G_t(\theta_i) - G_t(0)$$

(15)

where $P_0$ is the power of the direct path, $P_{ref}$ is a reference power, $L_r$ is the reflection loss, $r_i = \tau_i/T_m$, $G_r(\cdot)$ and $G_t(\cdot)$ are the receiver and transmitter antenna gain. The channel coefficients $c_i$ are given by:

$$c_i = 10^{P_i/P_0}/20e^{i\gamma_i}$$

(16)

where $\gamma_i$ is a uniformly distributed random phase.

We have implemented the GBSBEM in our simulation environment for a macrocellular and a microcellular scenario. In Fig. 9 we have reported the Power Delay-Angle profile as obtained through simulation for a microcellular environment with $L = 10$ maximum multipath components. The distance between the base station and the mobile station is set to 400 m. Angles are measured with reference to the line of sight. As it can be observed, delays exhibit an one side exponential power profile, while angle of arrival presents a power shape similar to a Laplacian, but with the difference of a depression around the origin, which is typical of the GBSBEM model.

In Fig. 10 we have reported the Power Delay-Angle profile as obtained for a microcellular environment with $L = 50$ multipath components. The larger number of multipath components leads to a more dense mapping.

VI. CONCLUSIONS AND FUTURE PERSPECTIVES

Performance analysis of the WCDMA radio interface has been carried out through a specifically developed simulation tool, that aims at capturing the combined behavior of major techniques in the transmission chain. Ongoing work is concerned with link level signal detection in the presence of softer (between sectors or even beams) or soft handover. Specifically, we are interested in integrating adaptive beamforming with softer handover between adjacent beams and power control and allocation.