Optimizing the Downlink Power of Macrodiversity Antennas in an Indoor DS-CDMA System

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Abstract— **This paper investigates the downlink performance of an indoor DS-CDMA system that performs an optimization on the transmit power of macrodiversity antennas. Our results show that the power optimization significantly increases system capacity. We present a global optimization strategy that allocates power at the various macrodiversity antennas so that the average of all users' BERs is minimized. In practice, the complexity of this global optimization problem is reduced as many of the links are extremely weak and can be removed from the optimization. Our simulation results demonstrate that when compared to traditional soft handoff power allocation, our optimization algorithm increases the capacity for a given quality of service. The simulation results indicate downlink capacity gains on the order of 10-20%.**

I. INTRODUCTION

Macrodiversity in a DS-CDMA system is related to soft handoff, as a mobile unit is transferred from one base station to another. In this paper, however, we generalize macrodiversity from a simple soft handoff to active participation by multiple base stations throughout a call. We examine indoor systems in particular.

The three dimensional environment of an indoor wireless system presents new opportunities in the area of macrodiversity combining. A mobile unit could be potentially connected to multiple base stations on the same floor along with base stations on floors located above and below the mobile unit. The possibility of connecting to base stations on various floors of a building is supported by recent studies in indoor wireless propagation [1], [2]. The authors of [1] and [2] have identified correlated shadowing between the floors of a building as an important characteristic that has a direct effect on system performance. Indeed, correlated shadowing combined with independent fast fading implies that macrodiversity can be extended beyond its traditional use in soft handoff.

Macrodiversity always improves the quality of the reverse link. The base stations connected to the mobile unit (i.e. the base stations in the Active Set) forward their demodulated (or possibly undemodulated) signals to the system controller for diversity combining. Therefore, reverse link diversity combining causes increased traffic in the wireline network, but no extra interference is generated in the wireless portion of the network.

In contrast, macrodiversity on the downlink is equivalent to generating artificial multipath. The advantage of this artificial multipath is the increased diversity present at the mobile unit's RAKE receiver. However, the disadvantage of artificial multipath is the increase in the overall level of interference. Previous studies into the effects of soft handoff on downlink capacity suggest that the increased interference generally neutralizes the added diversity for unsectorized cells [3], [4] and [5]. In these papers, all of the base stations in the Active Set transmit the same power to the mobile unit in soft handoff. The authors of [6] investigate the allocation of different transmit powers at the base stations in the Active Set, based on the premise that a base station with a better link to the mobile unit should transmit with a higher power. However, this type of power allocation does not balance the decrease in one user's BER due to a transmit power increase against the interference experienced by the other users. In [7], a centralized downlink power control algorithm is introduced for multi-antenna transmission. The authors simplify their solution and create a decentralized algorithm called the "Greedy Algorithm." Their results indicate that the "Greedy Algorithm" meets the same BER requirement as equal power multi-antenna transmission, but with less overall transmit power. In this paper, we focus on optimizing the macrodiversity antenna transmit powers by minimizing the average of all users' BERs. We quantify the improvement of our optimization algorithm in terms of downlink capacity gains realized in an indoor DS-CDMA system.

Power allocation among the macrodiversity antennas is not straightforward. For example, as seen in Fig. 1, it may seem reasonable for two antennas (A1 and A2) to allocate equal powers to a mobile unit (U1) if the signals are received with equal strength. However, if A2 has a stronger link to another mobile unit (U2), it will be advantageous for A1 to allocate most of the power to U1 in order to reduce interference at U2. Our global optimization addresses this kind of situation by minimizing the sum of the individual mobile unit's estimated BERs. The BER at each mobile unit is estimated as a piecewise linear

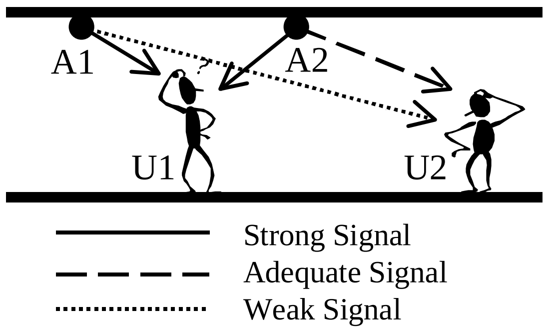

Fig. 1. A typical indoor wireless propagation scenario

function that is based on the asymptotic behavior of coded diversity reception with unequal SNRs. The optimization is implemented as a steepest descent algorithm operating at the relatively slow shadowing rate.

The downlink performance of a DS-CDMA system will become increasingly important as third generation cellular systems incorporate different kinds of traffic. Services such as voice, image, and possibly video will only be made possible if the network can transmit with a high data rate while achieving an acceptable quality of service. In order to address the issue of utilizing DS-CDMA with a different data rate and a different BER requirement than is normally used for voice communications, we compare the performance of our optimization algorithm to that for traditional soft handoff in a number of different situations. In all cases, the optimization algorithm outperforms traditional soft handoff power allocation and significantly increases the downlink capacity.

II. SYSTEM MODEL

The model described below for the downlink of a DS-CDMA system is similar in formulation to that used for multiuser detection on the uplink [8]. The signal received at mobile i is given as:

$$r_i(t) = \mathbf{c}_i^{\mathrm{T}} \left(\mathbf{S}_i \mathbf{b} + \mathbf{s}_{p_i}\right) + n_i(t) \tag{1}$$

where: $\mathbf{c}_i^{\mathrm{T}} = [c_{1i}, ..., c_{li}, ..., c_{Li}]$ is a vector of complex Gaussian channel gains from L macrodiversity antennas to the i^{th}mobile. $\mathbf{b} = [b_1, ..., b_k, ..., b_K]^{\mathrm{T}}$ is a vector of BPSK information bits destined for the K users. $n_i(t)$ is the additive white Gaussian noise (AWGN); it is a complex Gaussian process with zero mean and a power spectral density of N_o. $\mathbf{s}_{p_i} = A_p \left[s_p(t-\tau_{1i}), ..., s_p(t-\tau_{Li})\right]^{\mathrm{T}}$ where A_p is the amplitude of the pilot signal transmitted from each antenna, and $\mathbf{S}_i$ is a matrix defined as follows:

$$\mathbf{S}_i = \begin{bmatrix} A_{11}s_1(t-\tau_{1i}) & ... & A_{1K}s_K(t-\tau_{1i}) \\ ... & ... & ... \\ A_{L1}s_1(t-\tau_{Li}) & ... & A_{LK}s_K(t-\tau_{Li}) \end{bmatrix} \tag{2}$$

A_{li} is the amplitude of the signal transmitted from the l^{th} antenna to the i^{th} mobile, and τ_{li} is the delay incurred between the l^{th} antenna and the i^{th} mobile. $s_i(t)$ and $s_p(t)$ are the normalized unit-energy waveforms with support $[0, T]$ for user i and the pilot signal respectively. The vector of the normalized matched filter output for the i^{th} user from the l^{th} antenna, sampled at the symbol rate, $1/T$, is

$$\begin{aligned} y_{li} &= \int_{\tau_i}^{T+\tau_i} r_i(t) s_i^*(t-\tau_{li}) dt \\ &= \mathbf{c}_i^{\mathrm{T}} \left(\mathbf{R}_{li}\mathbf{b} + \mathbf{r}_{p_{li}}\right) + e_{li} \end{aligned} \tag{3}$$

where $e_{li} = \int_{\tau_i}^{T+\tau_i} s_i^*(t-\tau_{li}) \cdot n_i(t) dt$ is the noise at the matched filter output. $\mathbf{r}_{p_{li}} = \int_{\tau_i}^{T+\tau_i} s_i^*(t-\tau_{li}) \cdot \mathbf{s}_{p_i} dt$ contains the cross-correlations between an intended user's waveform and pilot signal waveforms. $\mathbf{R}_{li} = \int_{\tau_i}^{T+\tau_i} s_i^*(t-\tau_{li}) \cdot \mathbf{S}_i dt$ is the cross-correlation matrix with elements

$$R_{(n,l)(k,i)} = \int_{\tau_i}^{T+\tau_i} s_i^*(t-\tau_{li}) s_k(t-\tau_{ni}) \tag{4}$$

In (4), if $l \neq n$ and $i = k$, the same, but time shifted, signature waveform is sent to mobile i from two different antennas. If $l = n$ and $i \neq k$, two different signature waveforms intended for two different users are sent from the same antenna. In (3) the interfering signals result from correlations with the pilot sequences and from correlations with other user sequences when $l \neq n$ and/or $i \neq k$.

When using DS-CDMA, the information sequence is spread using a pseudo-random (PN) code, and it can be shown that:

$$\begin{aligned} \frac{1}{2}E\left[y_{li}^* y_{li}\right] &= \sigma_{c_{li}}^2 p_{li} + \sigma_s^2 \left[\sum_{n=1}^{L} \sigma_{c_{ni}}^2 \cdot \right. \\ &\left. \left(\sum_{k=1}^{K} p_{nk} + p_p\right) - \sigma_{c_{li}}^2 p_{li}\right] + N_o \end{aligned} \tag{5}$$

where $p_{li} = A_{li}^2$ and $p_p = A_p^2$. $\sigma_{c_{li}}^2 p_{li}$ is the energy of the signal and the rest is the energy of the interference and noise. Therefore, the SINR can be given as

$$\Gamma_{li} = \left[\sigma_s^2 \left(\frac{X_i}{x_{lii}} - 1\right)\right]^{-1} \tag{6}$$

where:

$$x_{nki} = \sigma_s^2 \sigma_{c_{ni}}^2 p_{nk} \tag{7}$$

$$X_i = \sum_{n=1}^{L}\sum_{k=1}^{K} x_{nki} + \sigma_s^2 p_p \sum_{n=1}^{L} \sigma_{c_{ni}}^2 + N_o \tag{8}$$

The interfering signals are binomial random variables with zero mean and variance $\sigma_s^2 = 1/L_{PN}$ where L_{PN} is the length of the PN sequence. However, for purposes of analysis, we will approximate the probability distribution of the interfering signals with a Gaussian distribution.

In [9] it is shown that the error probability of diversity reception with unequal SNRs can be estimated in the asymptotic region as the branch SNRs become increasingly large. In this paper, we modify the expression in [9] to include the effects of the convolutional code used on the downlink of the DS-CDMA system. The theoretical performance of the convolutional code was calculated with a union bound using a similar approach to that proposed in [10] and [11]. The effects of the convolutional code can be included in the error probability estimates for mobile, i, as follows:

$$P_{ei} = \alpha_i \prod_{l \in \psi_i} M\left(\Gamma_{li}\right) \cdot \Gamma_{li}^{-D(\Gamma_{li})} \tag{9}$$

where ψ_i represents user i's Active Set which is composed of L_i macrodiversity antennas. $\alpha_i = \binom{2L_iD_\infty - 1}{L_iD_\infty}\left(2\left(1-\rho\right)\right)^{-L_iD_\infty}$ is a multiplicative factor similar to that found in [9] where $\rho = -1$ for BPSK signals. In order to account for the fact that the system operates in the non-asymptotic region at low SINRs, $M\left(\Gamma_{li}\right)$ and $D\left(\Gamma_{li}\right)$ are both functions of the SINR. $M\left(\Gamma_{li}\right)$ is a multiplicative factor that is determined by mapping the estimate of P_{ei} onto the theoretical P_{ei}, and $D\left(\Gamma_{li}\right)$ is the derivative of $\log(P_{ei})$ with respect to Γ_{li} in dB. In other words, $D(\Gamma_{li})$ is an equivalent order of diversity. $D_\infty = D\left(\Gamma_{li}\right)\big|_{\Gamma_{li}\to\infty}$ is the equivalent order of diversity in the asymptotic region of the BER curve. In this study we have assumed perfect interleaving by bit; therefore, D_∞ is equal to the minimum free distance of the convolutional code. The error probability estimate given in (9) can be used in both the traditional soft handoff and optimization algorithms discussed in the following sections.

III. Traditional Soft Handoff

Once the Active Set for each user has been determined, each traffic channel is assigned a small and equal portion of the total traffic power. If the probability of error for mobile i, P_{ei}, is greater than a specified threshold, the powers allocated at each antenna for this user are increased by 1 dB. In contrast, if P_{ei} is less than the threshold, the powers transmitted to this mobile station are decremented by 1 dB. If the powers begin to oscillate around the threshold, a "do nothing" command can be sent to keep the powers at a constant level.

If the error probabilities for all mobiles are below the specified threshold, and the total transmitted power at each antenna is within the preset power limit, the soft handoff power allocation has successfully serviced all mobile units. However, if this requirement cannot be met, the downlink powers of the macrodiversity antennas are optimized with the algorithm discussed in the next section.

IV. Downlink Power Optimization

In order to achieve a global optimization, we minimize the sum of the error probabilities for the individual mobiles. The objective function to be minimized is

$$P_e = \sum_{i=1}^{K} P_{ei} \tag{10}$$

The optimization is implemented as a steepest descent algorithm. Therefore, we calculate

$$\frac{\partial P_e}{\partial p_{nk}} = \sum_{i=1}^{K} \frac{\partial P_{ei}}{\partial p_{nk}} \quad \forall n \& k \tag{11}$$

and it can be shown that

$$\left.\frac{\partial P_{ei}}{\partial p_{nk}}\right|_{k \neq i} = \sigma_s^2 \sigma_{c_{ni}}^2 P_{ei} \sum_{j \in \psi_i} \frac{D(\Gamma_{ji})}{X_i - x_{jii}} \tag{12}$$

$$\begin{aligned} \left.\frac{\partial P_{ei}}{\partial p_{nk}}\right|_{k=i} &= \sigma_s^2 \sigma_{c_{ni}}^2 P_{ei} \cdot \\ &\left\{ \sum_{j \in \psi_i, j \neq n} \frac{D(\Gamma_{ji})}{X_i - x_{jii}} - \frac{D(\Gamma_{ni})}{x_{nii}} \right\} \end{aligned} \tag{13}$$

In this paper, we present a global optimization strategy that allocates power at the various macrodiversity antennas so that the added diversity outweighs the increased interference and the average of all users' BERs is minimized. The complexity of this global optimization is reduced as can be seen in (12) and (13) since the summations are only performed over the antennas in each user's Active Set.

By moving in the direction opposite to the gradient, we approach the global minimum. When the algorithm is operating in the asymptotic region of the BER curve, i.e. when $D\left(\Gamma_{mi}\right) = D_\infty, \forall m \in \psi_i$, it can be proven that this objective function possesses only the one global minimum since the second derivative is always greater than zero. Even though this has not been proven for the non-asymptotic region, the second derivative has never been observed to go below zero in practice.

The power at each antenna is constrained as follows: $\sum_{k=1}^{K} P_{nk} = C$. This is actually a plane in hyperspace. Therefore, if the optimization attempts to exceed the power limit on any antenna, the result is simply projected onto the hyperplane ensuring that the antennas never exceed their power limit.

Minimizing the objective function, $P_e = \sum_{i=1}^{K} P_{ei}$, brings the individual error probabilities closer together. However, it does not eliminate the separation entirely. Therefore, once the sum has been minimized, the optimization algorithm enters a second stage which focuses on equating the individual error probabilities in an attempt to reduce the maximum probability of error, $P_{e\max}$. In the second stage of optimization, if $P_{ei} > P_e/K$, the individual P_{ei}'s are minimized with $\partial P_{ei}/\partial p_{ni}$. If $P_{ei} \leq P_e/K$, $P_{e\max}$ is minimized with $\partial P_{e\max}/\partial p_{ni}$. In this way, the mobile units with high BERs receive more power, while those with low BERs give up a portion of their power.

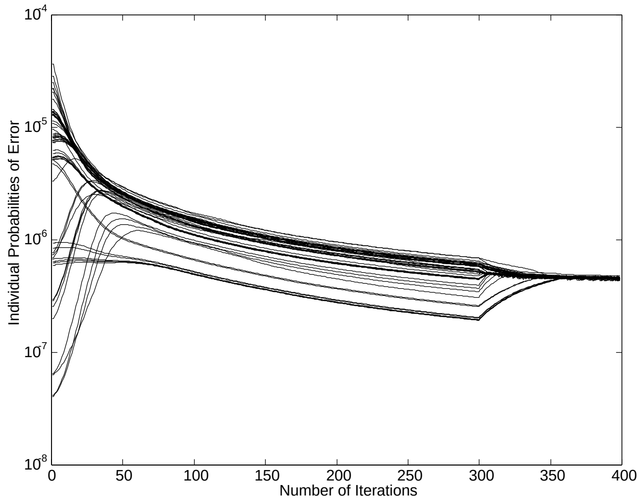

Fig. 2. The 2 Stages of Optimization

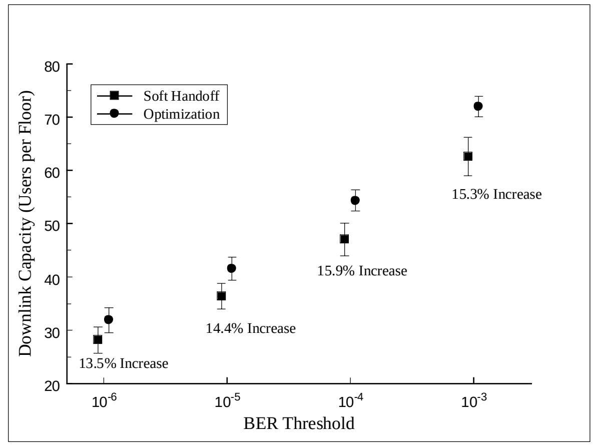

Fig. 3. Soft Handoff and Optimization Capacities for W/R = 128

The two stages of optimization can be seen in Fig. 2. These results are depicted for 57 users located on 2 floors of a building. The users are serviced by a total of 4 antennas with 2 antennas per floor.

As can be seen from this figure, the first stage of optimization (iterations 1-300) focuses on minimizing the average probability of error, and the second stage of optimization (iterations 300-400) focuses on equating the error probabilities in an attempt to reduce $P_{e\,\max}$. Both stages of the optimization are necessary for reducing the maximum BER. The result of eliminating the second stage of optimization is obvious from observing Fig. 2. However, eliminating the first stage of optimization causes the individual error probabilities to be simply equated, most often at a higher BER than desired. This optimization routine will now be compared with a typical soft handoff algorithm in the following section.

V. Simulations

The simulated system consists of 2 floors in a building with 2 antennas per floor. Each antenna allocates 80% of its power to traffic and 20% of its power to the pilot signal. In the simulations, we set $N_o = 0$ in order to investigate the interference limited case. The transmitted signals are assumed to undergo path loss, lognormal shadowing, and Rayleigh fading. The parameters for the indoor propagation model are similar to those in [2] which were based on a 1.8 GHz indoor propagation study. The attenuation between antenna l and user i is given as:

$$\sigma^2_{c_{li}} = (d_{li}^{\gamma})\left(10^{((FAF+y_{li})/10)}\right) \tag{14}$$

where d_{li} is the distance between the l^{th} antenna and the i^{th} mobile. $\gamma = 4.8$ is the path loss exponent. The FAF is the floor attenuation factor and is set to 0 or 16 dB for a 0 or 1 floor separation between the antenna and the user respectively [2]. The shadowing coefficient, y_{li}, is a normally distributed random variable whose variance is either 9.6 or 9.8 dB for a 0 or 1 floor separation between the antenna and the user respectively [2]. The authors of [2] have identified the existence of correlated shadowing between the floors of a building. This correlated shadowing is incorporated into the simulations in a similar manner to that proposed in [2].

The mobiles are initially added to either floor of the building in a random fashion. Each time a mobile is added, its active set is determined by comparing $(E_c/I_o)_{li}$ to a threshold of -14 dB. The E_c in $(E_c/I_o)_{li}$ represents the pilot signal energy received from antenna l, and the I_o represents the total interference and noise measured at mobile i. The simulations begin by performing a traditional soft handoff power allocation for all users each time an additional user is added to a floor. When a single user on either floor cannot be serviced, additional users are added only to the other floor. Once both floors contain a mobile that cannot be serviced by traditional soft handoff power allocation, the optimization algorithm takes over. If the optimization algorithm can service all of the above users, mobiles are added in a similar fashion to that described above.

The simulation results can be seen in Figs. 3 and 4. These figures depict downlink capacities achieved at different BER requirements for both soft handoff power allocation and optimization of downlink transmit powers. Figs. 3 and 4 contain downlink capacity estimates for a CDMA system with processing gains of W/R = 128 and W/R = 32 respectively, and each data point represents an average over 100 independent trials.

As can be seen from these figures, the optimization algorithm consistently outperforms traditional soft handoff power allocation, and the capacity gains typically range between 10-20%. In most cases, use of the optimization algorithm does not affect the capac-

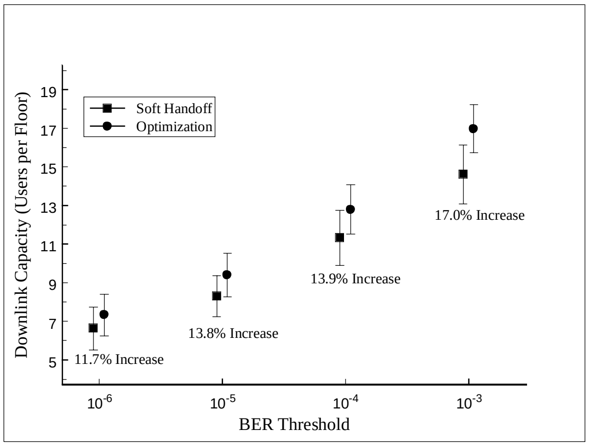

Fig. 4. Soft Handoff and Optimization Capacities for W/R = 32

ity estimate's variance. However, in a couple of cases, the optimization algorithm not only outperforms soft handoff, but it also reduces the variance of the capacity estimate, thus making the estimate more reliable.

Experiments were also performed which investigated the effect of increased accuracy in the soft handoff power allocation; this accurate allocation involves adjusting the powers transmitted to a mobile by 0.5 dB instead of 1 dB. The simulation results show that the optimization algorithm still outperforms the accurate soft handoff allocation with downlink capacity gains on the order of 10-13%. Therefore, simply decreasing the step size of the soft handoff algorithm can not provide the gains achievable with optimization since soft handoff does not address the issue of allocating different transmit powers among the macrodiversity antennas in a mobile's Active Set.

VI. Conclusions

To conclude, our simulation results show that significant capacity gains can be realized through the optimization of downlink transmit powers of macrodiversity antennas in an indoor DS-CDMA system. The downlink capacity gains typically range between 10-20% when compared to traditional soft handoff. Therefore, this study has shown that optimization of the downlink transmit powers of an indoor DS-CDMA system is successful in improving system performance. Further research will determine if these results can be extended to the outdoor environment, and future investigations will also determine how this algorithm can be best implemented in practice.

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