Optimized Power Allocation for Multiple Access Systems with Practical Coding and Iterative Multi-User Detection

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Abstract

In this paper, we present an optimized power allocation technique based on an interior-point method (IPM) for practically coded code-division multiple-access (CDMA) or interleave-division multiple-access (IDMA) systems over multiple access channels. A variety of numerical results are presented to demonstrate the efficiency of the proposed technique. It is shown that significant performance improvements (compared with orthogonal systems such as TDMA and FDMA) are achievable by applying iterative multi-user detection (MUD) to CDMA or IDMA in fading channels.

1. Introduction

It is known that in fading environments the performance of multi-user systems over multiple access channels (MACs) can be significantly enhanced by adopting random-waveform schemes such as code-division multiple-access (CDMA) together with multi-user detection (MUD) [1]-[4]. The related advantage of CDMA over orthogonal schemes (such as time-division multiple-access (TDMA) and frequency-division multiple-access (FDMA)) is referred to as multi-user (MU) gain in [5, p. 253]. Un-equal power allocation and successive interference cancellation (SIC) are key strategies in achieving MU gain based on ideal coding. Using SIC, analytic formulae have been developed for the optimal power allocation levels in MACs [5]-[9].

A power allocation strategy based on SIC is, however, effective only when ideal or nearly ideal channel codes are available. When a practical code (e.g., a convolutional code or a turbo code with relatively short code length) is used, the SIC-based method can become inefficient since practical codes may, compared with the capacity limit, require a few more dB of signal-to-noise-ratio (SNR) to achieve satisfactory performance and using SIC the accumulated extra SNR may incur an excessive power cost.

Iterative MUD is a more efficient solution than SIC for practically coded systems [3][10][11]. Recently, there has been significant progress in the development of low-cost, high-performance iterative MUD techniques and excellent performance has been demonstrated at low-to-medium throughputs. When the system sum-rate is high, it has been shown that un-equal power allocation can also be a useful technique for practically coded systems with iterative MUD. In this case, finding the optimal power profiles is however quite a difficult issue. Linear programming has been employed in received power optimization for multiple access systems [10][11], but this involves approximation and is only effective for systems with a large number of users. For a multiple access system with a small number of users, e.g., in the case that each user requires a high throughput, linear programming may not be efficient (see Section III).

In this paper, we first formulate the power optimization problems for practically coded systems over MACs. Such problems are generally nonlinear and non-convex. We develop a general approach based on an interior-point method (IPM) [12] and illustrate by various numerical results that the IPM approach is versatile and can provide good solutions. We show that, in fading environments, significant performance gains can be achieved using the proposed technique. The findings in this paper demonstrate that the performance of practical wireless systems can potentially be greatly enhanced by exploiting the recent progress in multi-user information theory.

Our discussion will work within the general framework of CDMA. However, different from conventional CDMA, we assume user-specific chip-level interleavers in the systems discussed below, which greatly simplifies the receiver design and analysis issues: this is a special case of CDMA referred to as interleave-division multiple-access (IDMA) [13]. Furthermore, we assume the channel for each user is single-input-single-output (SISO) in this work. The discussion of multiple-input-multiple-output (MIMO) MACs [6] is beyond the scope of this paper.

2. Multiple Access Systems

2.1. System Model

Consider the K-user multiple access system shown in Fig. 1. At the transmitter side, the information bit stream $d_k$ for user-$k$ is first encoded by a generalized encoder $(ENC_k)$ and then transmitted over a Gaussian MAC with proper power control factor $p_k$ as indicated in Fig. 1.

Denote by $x_k = \{x_k(j)\}$ the length-$J$ signal sequence after encoding. Using the equivalent discrete channel model, we can write the received signal as

$$ r(j) = \sum_{k=1}^{K} \sqrt{p_k} h_k x_k(j) + n(j) \quad , \quad j = 1, 2, \ldots, J \quad (1) $$
where $h_k$ is the channel coefficient for user-$k$, and $\{n(j)\}$ are samples of an additive white Gaussian noise (AWGN) process with zero-mean and variance $\sigma^2 = N_0/2$.

Fig. 1 can be used to represent a variety of systems. For examples, if each of the encoders in Fig. 1 includes a spreader, we obtain a conventional CDMA system. If such a CDMA system contains chip-level interleavers, we obtain the system discussed in [11][14].

We assume that each $x_k = \{x_k(j)\}$ in Fig. 1 is randomly and independently interleaved. This assumption greatly simplifies the system analysis task, since it avoids the need to model the correlation among spreading sequences [11][13]. Correlation modeling can be a complicated issue for conventional CDMA, especially when considering a small number of users in which case the performance is dependent on the selection of spreading sequences. For a system with a large number of users, the large system model discussed in [15] can be applied to simplify the analysis. The small system model is one of focuses in this paper.

If the users in Fig. 1 are solely distinguished by interleavers, we obtain the IDMA scheme in [13]. IDMA is actually a special case of CDMA with the advantages of high performance and low receiver cost [13]. A very efficient correlation among spreading sequences [11][13]. Correlation focusing in this paper.

The receiver in Fig. 1 performs an iterative interference cancellation process. It consists of an elementary signal estimator (ESE) and a bank of $L$ single-user $a$ posteriori probability (APP) decoders (DECs). We follow the iterative detection principle developed in [13], as outlined below. For simplicity, we only consider binary $x_k(j) \in \{+1, -1\}$ and real $\{h_k\}$ here.

- **The output of the ESE for user-$k$ is**
  \[
e_{ESE}(x_k(j)) = \frac{2\sqrt{p_i h_k (r(j) - E(\xi_k(j)))}}{\text{Var}(\xi_k(j))} \tag{2}
\]
  where $\{\xi_k(j)\}$ is the noise-plus-interference component in $r(j)$ in (1) with respect to $x_k(j)$, i.e.,
  \[
  \xi_k(j) = r(j) - p_i h_k x_j + n(j).
  \tag{3}
\]

In (2), $E(\xi_k(j))$ and $\text{Var}(\xi_k(j))$ (the mean and variance of $\xi_k(j)$) can be estimated using (3) provided that all $\{E(x_k(j))\}$ and $\{\text{Var}(x_k(j))\}$ are known. The latter are initialized as $E(x_k(j)) = 0$ and $\text{Var}(x_k(j)) = 1$, $\forall k$. The above results can be easily extended to more general cases (such as complex $h_k$).


- **Using $\{e_{ESE}(x_k(j))\}$ as the $a$ priori information, DEC$_i$ generates extrinsic log-likelihood ratios (LLRs) $\{e_{DEC}(x_k(j))\}$, based on which $\{E(x_k(j))\}$, $\{\text{Var}(x_k(j))\}$, $\{E(\xi_k(j))\}$ and $\{\text{Var}(\xi_k(j))\}$ can be updated.
- **The updated values of $\{E(\xi_k(j))\}$ and $\{\text{Var}(\xi_k(j))\}$ are used to repeat the ESE operation in (2). This iterative process continues for a preset number of times before a hard decision is made to produce the final output.
- **The above detection procedure can be realized by either a parallel or a serial schedule [16]. With the parallel schedule, ESE operations are conducted simultaneously for all users and then DEC operations for all users. With the serial schedule, the operations are conducted in a consecutive manner such as: ESE operations for user-1, DEC operations for user-1, ESE operations for user-2, DEC operations for user-2, …, and so on. We observed that for small $L$, the serial schedule outperforms the parallel one. And when $L$ is large, both schedules lead to roughly the same performance.**

### 2.2. Performance Evaluation

The performance of the above iterative process can be quickly predicted using the following signal to noise-plus-interference ratio (SNIR) evolution technique [13]. The prediction results using this technique are in good agreement with simulation results as demonstrated in [13].

Denote by $\{\gamma_k^{(n)}\}$ the average SNIR for the outputs of the ESE after the $n$-th iteration. Let $f(\gamma^{(n)})$ be the average variance of the outputs of DEC$_i$ driven by an input sequence with SNIR $\gamma_i$. We can approximately track $\gamma_k^{(n)}$ using the following parallel and serial schedules as follows:

**Parallel Schedule:** For the first iteration,
\[
\gamma_k^{(1)} = \sum_{j \in \mathcal{I}_k} p_i |h_k|^2 + \sigma^2, \forall k, \tag{4a}
\]
and thereafter,
\[
\gamma_k^{(n)} = \sum_{j \in \mathcal{I}_k} p_i |h_k|^2 + \sigma^2, \forall k. \tag{4b}
\]

Some comments on (4) are as follows.

- In (4a), $\gamma_k^{(1)}$ is clearly the SNIR for the received signal $r(j)$ in (1) with respect to $x_k(j)$.
- In (4b), $f(\gamma^{(n-1)})$ is the average variance at the output of DEC$_i$ for given input SNIR $\gamma^{(n-1)}$. It represents the remaining average uncertainty about $\{x(i)\}$ in the output of DEC$_i$ after the $(l-1)$-th iteration, which determines the residual interference to other users.
- The $f(\cdot)$ function is only determined by the code used. For a rate-$R$ ideal code, the $f(\cdot)$ function (the subscript $i$ is omitted) is obtained based on the Shannon capacity formula. We assume that if the input SNIR $\gamma < 2^{2R-1}$, the output is random binary error (in BPSK format) and so the variance is 1. Otherwise if $\gamma \geq 2^{2R-1}$, the output is error free i.e., and so the variance is 0. Mathematically, we have
  \[
f(\gamma) = \begin{cases} 1, & \text{if } \gamma < 2^{2R} - 1 \\ 0, & \text{if } \gamma \geq 2^{2R} - 1. \end{cases} \tag{5}
\]

And for a practical code, it can be obtained by the Monte-Carlo method [11]. Fig. 2 shows some examples of $f(\cdot)$ functions.

**Serial Schedule:** For the first iteration,
\[
\gamma_k^{(1)} = \sum_{j \in \mathcal{I}_k} p_i |h_k|^2 + f(\gamma^{(n-1)}) + \sum_{j \in \mathcal{I}_k} p_i |h_k|^2 + \sigma^2, \forall k, \tag{6a}
\]
and thereafter,
The parallel schedule has more concise expressions and so it is often used for illustration. However, all of the numerical results in this paper are based on the serial schedule due to its superior performance.

Fig. 2. Some examples of \( f(\cdot) \) functions. The corresponding codes are a rate-1/2 convolutional code (generators: (23, 35)) with length-1, 2 and 4 spreading, a rate-1/2 ideal code with length-1, 2 and 4 spreading and rate-1/4 and 1/8 ideal codes. The numbers marked beside the curves are the coding rates.

### 2.3. Relationship to the Large System Model

When \( K \) is large, (4b) can be approximated by

\[
\gamma_k^{(i)} \approx \gamma_k^{(i)} \approx \sum_{i=0}^{K} p_i |h_i|^2 f(\gamma_i^{(i-1)}) + \frac{1}{\sigma^2} - 2\sum_{i=0}^{K} p_i |h_i|^2 f(\gamma_i^{(i-1)}) + \frac{1}{\sigma^2} \tag{7}
\]

Define the multi-user efficiency \( \eta_k^{(i)} \) as

\[
\eta_k^{(i)} = \frac{1}{\gamma_k^{(i)} \approx \eta_k^{(i)} \approx 1 + \sum_{i=0}^{K} \frac{p_i |h_i|^2}{\sigma^2}} \tag{8}
\]

With the above approximation, \( \{ \eta_k^{(i)} \} \) are the same for all \( k \) [10], so we omit the subscript in the following. In this case, (7) can be rewritten as

\[
\eta_k^{(i)} \approx 1 + \sum_{i=0}^{K} \frac{p_i |h_i|^2}{\sigma^2} f(\eta_i^{(i-1)}) p_i |h_i|^2 / \sigma^2 \tag{9}
\]

It can be verified that (9) is equivalent to the multi-user efficiency evolution formula for the large CDMA model with the single-user matched filter (SUMF) in [10]. The results based on (9) are accurate only when \( K \) is large.

### 2.4. The Power Optimization Problem

The optimization method discussed below applies to both parallel and serial schedules, so we will not distinguish them unless necessary. For simplicity, we introduce the following function

\[
\gamma = \Omega(p) \tag{10}
\]

where \( p = \{p_k\} \) is a power profile and \( \Omega \{ \gamma_k^{(L)} \} \) contains the corresponding final SNIR values obtained by either (4) or (6).

We now consider minimizing either the sum received power \( \sum_k p_k |h_k|^2 \) or the sum transmitted power \( \sum_k p_k \) of a multi-user system over a MAC while achieving required performance \( \gamma_k^{(L)} \geq \Gamma_k, \forall k \). We assume that \( \{h_k\} \) are fixed and known. The optimization problems are formulated as follows.

**Received power optimization (RPO):** Find the distribution \( \{p_k\} \) that minimizes

\[
\Phi = \sum_k p_k |h_k|^2 \tag{11}
\]

subject to \( \gamma_k^{(L)} \geq \Gamma_k, \forall k \), where \( \{ \gamma_k^{(L)} \} = \Omega(p) \).

**Transmitted power optimization (TPO):** Find the distribution \( \{p_k\} \) that minimizes

\[
\Phi = \sum_k p_k \tag{12}
\]

subject to \( \gamma_k^{(L)} \geq \Gamma_k, \forall k \), where \( \{ \gamma_k^{(L)} \} = \Omega(p) \).

The problems of (11) and (12) are generally nonlinear and non-convex. This is illustrated by the following example. Consider five users using the same rate-1/2 convolutional code with the \( f(\cdot) \) function given in Fig. 2. We call a power profile feasible if it satisfies the system requirements, and define the feasible region as the set of all feasible power profiles. Clearly, if a power profile \( \{p_k\} \) is within the feasible region, \( \gamma_k^{(L)} \geq \Gamma_k, \forall k \).

Since it is difficult to show a multi-dimensional space, we fix \( p_1 = 3, p_2 = 30, \) and \( p_3 = 300 \) for three users. Fig. 3 shows a part of feasible region when \( p_1 \) and \( p_2 \) vary. The non-convex property of the problem is evident. When the number of users \( K \) is small, the optimal solution can be found by an exhaustive search. However, for large \( K \) such an exhaustive search method becomes impractical.

**Fig. 3.** Illustration of the feasible region (the shaded area) of a five-user IDMA system with \( \sigma^2 = 1 \) and \( |h_i|^2 = 1, \forall k \) and \( \{\Gamma_k\} \) are selected to ensure BER \( \leq 10^{-4}, \forall k \).
3. Received Power Optimization

The power allocation problems under consideration require a search for minimizing sum-power solutions within feasible regions. The interior-point method (IPM) [12] is a very promising technique for this type of constrained optimization problem.

3.1. Interior-Point Method (IPM)

We use the RPO problem in (11) to illustrate the IPM principle, which can be easily extended to the TPO problem in (12). The key principle is to modify the RPO in Section II.D to the following form.

RPO with IPM (RPO-IPM): Find the distribution \( p_i^* = \{p_k\} \) that minimizes
\[
\Phi = \sum_k p_k |h_k|^2 + \alpha \cdot \Phi(p).
\]
(14)

In RPO-IPM, the constraints of (11) (i.e., \( \gamma_k^{(f)} \geq \Gamma_k, \forall k \), where \( \{\gamma_k^{(f)} = \Omega(p)\} \) are incorporated in \( \Phi(p) \) that is a barrier function to be discussed in more detail below. The parameter \( \alpha \) (\( \alpha \geq 0 \)) is a constant used to control the impact of the barrier function. When \( \alpha = 0 \), the target functions in RPO-IPM and RPO are the same. By gradually reducing \( \alpha \) close to zero, we can guide the solution of the RPO-IPM problem towards the desired RPO solution.

For simplicity, we use the standard steepest descend method [12] in RPO-IPM and the required derivative values \( \{d\Phi dp_k\} \) can be obtained using numerical methods. In the following, we discuss the selections for the barrier function and the initial power profile.

3.2. The Barrier Function

To confine searching within the feasible region, we can use a barrier function \( \Phi(p) \) that establishes a “lofty wall” on the border of the feasible region. Such a function can be constructed as follows.
\[
\Phi(p) = \sum_k \varphi_k(\gamma_k^{(f)})
\]
(15a)
where \( \{\gamma_k^{(f)} = \Omega(p)\} \) and
\[
\varphi_k(\gamma_k^{(f)}) = \begin{cases} 
\log \left( \frac{\gamma_k^{(f)}}{\gamma_k^{(i)} - \Gamma_k} \right), & \gamma_k^{(f)} > \Gamma_k \\
\infty, & \gamma_k^{(f)} \leq \Gamma_k
\end{cases}
\]
(15b)

In the interior of a feasible region, \( \gamma_k^{(f)} > \Gamma_k, \forall k \). If \( p \) is in the area far away from the border of the feasible region, \( \gamma_k^{(f)} >> \Gamma_k, \forall k \), so \( \varphi(p) \approx 0 \). However, if \( p \) is close to the border, i.e., \( \gamma_k^{(f)} \rightarrow \Gamma_k \) for some \( k \), then \( \varphi(p) \rightarrow \infty \). Thus introducing \( \Phi(p) \) in (13) can effectively ensure that searching is confined to the feasible region provided that a proper starting point is selected.

3.3. Power Profile Initialization

In the optimization process, an initial power profile \( p \) within the feasible region is required. We can obtain it using the following technique. Recall the serial SNIR evolution process in (6). Setting \( L = 1 \) and \( \gamma_k^{(i)} = \Gamma_k, \forall k \), we have
\[
G_k = \sum_i p_i |h_i|^2 f_i(G_i) = \sum_i p_i |h_i|^2 + \sigma^2, \forall k.
\]
(16)
We rewrite (16) in matrix form as
\[
A p = \sigma^2, \Gamma^T
\]
(17)
where \( A = \{A_k\}_{K \times K} \) satisfies
\[
A_{k,k} = \begin{cases} 
-\Gamma_k |h_k|^2, & k < i \\
|h_k|^2, & k = i \\
-\Gamma_k |h_k|^2 f_i(G_i), & k > i
\end{cases}
\]
(18)
and \( \Gamma = [\Gamma_1, \Gamma_2, ..., \Gamma_K] \).

The \( K \) equations in (17) are linear with respect to the \( K \) variables \( \{p_k\} \). If \( f_i(G_i) = 0, \forall k \), then the matrix \( A \) is upper-triangular and so the solution of \( p \) is unique. In practice, \( \{G_i\} \) are usually selected to ensure very small \( \{f_i(G_i)\} \) (corresponding to very low BERs), which implies good solvability of (17). (We have observed that (17) is solvable in all our simulations.) Note that further iterations can only improve performance, so for any \( L > 1 \) the \( p \) obtained using (17) must be inside the feasible region and is a valid initial power profile.

3.4. Simulation Examples

So far, we are not able to provide a comprehensive analysis of the convergence properties of the IPM proposed above. We therefore demonstrate its efficiency using numerical results.

![Simulation Example](image)

**Fig. 4.** Performance comparison between the IPM and LPM. \( L = 30 \) and the system sum-rate is fixed at 4 bits/symbol. The spreading lengths are 1, 2 and 4 for \( K = 4, 8 \) and 16, respectively.

**Table 1.** Relative power profiles obtained by IPM in Fig. 4.

<table>
<thead>
<tr>
<th>( K )</th>
<th>Relative power levels (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>0.0021, 5.4647, 7.5530</td>
</tr>
<tr>
<td>8</td>
<td>0.0004, 0.0021, 0.009, 4.0177, 7.5718, 6.8848, 7.7535</td>
</tr>
<tr>
<td>16</td>
<td>0.0002, 0.0005, 0.0111, 0.024, 0.050, 0.103, 0.209, 3.0501, 4.9935, 5.1017, 5.3528, 5.5739, 7.0597, 7.5528, 7.8468</td>
</tr>
</tbody>
</table>

Consider a \( K \)-user IDMA system with QPSK.
modulation, where a rate-1/2 convolutional code with different spreading lengths (the corresponding $f(\cdot)$ functions are shown in Fig. 2.) is used by all users. The system sum-rate is fixed to be 4 bits/symbol and the system requirements $\{G_k\}$ are selected to ensure $\text{BER}_k \leq 10^{-4}$, $\forall k$. Fig. 4 compares the SNIR evolution performance for the IPM and the linear programming method (LPM). From Fig. 4 we can see that when the number of users $K$ is small, the power profile obtained by the IPM is much better than that obtained by the LPM. For a larger $K$, the gap between the methods becomes smaller. When $K = 16$, the two methods lead to almost the same performance.

To verify the optimality of the proposed method, we carried out exhaustive search for small $K$ and obtained almost the same result as that obtained by IPM, which implies the proposed method is rather reliable at least for small $K$. We have also carried out simulations for the power profiles obtained by the IPM to verify the evolution results. The corresponding relative power values are listed in Table I, and the data length is 4096. The performance shown is for the user with the lowest power level, and that of other users is always better, because they have higher power levels. We can see from Fig. 4 that the evolution and simulation results are in good agreement. The minor gap between them is due to the fact that an infinitely long code length is assumed in the evolution results, while a finite code length is used in simulation. It can be expected that this gap will diminish as the code length increases.

4. Transmitted Power Optimization

In practice, minimizing the total transmitted power, $\sum \rho_k$, may be of more interest since it is directly related to power consumption as well as interference reduction to other systems (or cells).

With the IPM, we can directly minimize the total transmitted power. Similar to (14), we can modify (12) by adding the same logarithmic barrier to the original target function. The initial transmitted power profile can then be obtained as in Section III.B. Hence we omit the details and only provide numerical results.

We consider a $K$-user IDMA system with QPSK modulation over quasi-static fading MACs. The channel coefficients are modeled as $h_k = A(\rho_k^{1-v} 10^{-2\kappa v})^{1/2} \chi_k$, where $A$ is a constant, $\rho_k (0 \leq \rho_k \leq 1)$ the normalized distance between user-$k$ and the receiver, $v$ the path-loss exponent, $\xi_k$ a zero-mean Gaussian random variable with variance $\sigma^2$, which characterizes shadow fading, and $\chi_k$ the complex Gaussian variable with unit power. For simplicity, we set $A = 1$, so the amplitude of $h_k$ is just a relative value. We set $v = 4$, $\sigma^2 = 8$ and the $\{\rho_k\}$ are generated assuming all users are uniformly located in a normalized circular cell area with unit radius.

Considering deep fading, we allow transmission outage for the users with channel gains below a given fading threshold $G_0$. That is to say, if $|h_k|^2 < G_0$, an outage is declared for user-$k$ and $\rho_k$ is set to zero (a similar strategy is adopted in [11],[17]). Then power allocation is applied to the remaining active users. We define the outage probability $P_{\text{out}}(G_0) = \Pr(|h_k|^2 < G_0)$, $\forall k$. And the $\{I_k\}$ for the active users are set to ensure $\text{BER}_k \leq 10^{-4}$.

Fig. 5 shows the required average transmitted power versus $P_{\text{out}}(G_0)$ with the IPM for an IDMA system where the system sum-rate is fixed at 4 and 8 bits/symbol. A rate-1/2 convolutional code with different spreading lengths is used by all users and the corresponding $f(\cdot)$ functions are shown in Fig. 2. User-specific chip-level interleavers are used which are all generated randomly and independently. In this case, a simple repetition code can be used as the spreading sequences for all users without affecting performance.

![Figure 5](image-url)
modulation. If rate higher than 1 bit/symbol is required for a user, we can assign two or more codes to each user. For example, in Fig. 5(a), two codes are assigned to each user for \(K = 2\) to achieve a sum-rate of 4 bits/symbol. This follows the super-position coding scheme [19].

The circles in Fig. 5 are obtained by numerical simulation (the data length is 4096) of convolutionally coded IDMA systems for \(K = 4\) and can be seen to be close to those obtained by evolution.

From Figs. 5(a) and (b), we can make several interesting observations:

- The MU gain discussed in [5, p. 253] based on capacity region analysis can be observed in Fig. 5 by comparing the performance for the ideally coded CDMA for different \(K\) values, relative to \(K = 1\). (Note: An IDMA system with \(K = 1\) is equivalent to an orthogonal system such as TDMA.)
- The MU gain can also be observed for convolutionally coded CDMA systems compared with TCM coded TDMA. At a sum-rate of 4 bits/symbol, the MU gain is about 4–5 dB for the convolutionally/spreading coded CDMA over the TCM based TDMA. At a sum-rate of 8 bits/symbol, the gap between the convolutionally/spreading coded CDMA (\(K = 8\)) and the TCM based TDMA increases to about 10–13 dB, which is quite significant. This indicates the potential performance advantage of multi-user systems for very high rate applications.

The above observations point to some interesting directions to improve the performance of wireless systems:

- For medium to high system sum-rates, a random-waveform system with MUD can lead to significant performance enhancement in fading environments.
- When the system sum-rate increases, the achievable MU gain also increases. Potentially, very significant gains can be achieved by IDMA with MUD at a high sum-rate.
- We may envisage that a mixed TDMA/IDMA or FDMA/IDMA scheme will achieve a good trade-off between complexity and MU gain. In such schemes, the users are divided into groups. The users in the same group share a common carrier in the CDMA manner to achieve the MU gain discussed above, and different groups of users can be supported in either TDMA or FDMA. This avoids the high complexity of conducting MUD for too many users.

5. Conclusions

In this paper, we have proposed a power optimization technique for practically coded multi-user systems over MACs based on an interior-point method. Considerable performance improvements (e.g., MU gain) can be achieved by the optimized IDMA scheme in fading environments over orthogonal schemes such as TDMA and FDMA.

6. Literature