Joint Power Allocation and Interference Mitigation Techniques for Cooperative Spread Spectrum Systems with Multiple Relays

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Abstract

This paper presents joint power allocation and interference mitigation techniques for the downlink of spread spectrum systems which employ multiple relays and the amplify and forward cooperation strategy. We propose a joint constrained optimization framework that considers the allocation of power levels across the relays subject to an individual power constraint and the design of linear receivers for interference suppression. We derive constrained minimum mean-squared error (MMSE) expressions for the parameter vectors that determine the optimal power levels across the relays and the linear receivers. In order to solve the proposed optimization problem efficiently, we develop joint adaptive power allocation and interference suppression algorithms that can be implemented in a distributed fashion. The proposed stochastic gradient (SG) and recursive least squares (RLS) algorithms mitigate the interference by adjusting the power levels across the relays and estimating the parameters of the linear receiver. SG and RLS channel estimation algorithms are also derived to determine the coefficients of the channels across the base station, the relays and the destination terminal. The results of simulations show that the proposed techniques obtain significant gains in performance and capacity over non-cooperative systems and cooperative schemes with equal power allocation.

1 Introduction

The use of multiple collocated antennas enables the exploitation of the spatial diversity in wireless channels, mitigating the effects of fading and enhancing the performance of wireless communications systems. Unfortunately, due to size and cost it is often impractical to equip mobile terminals with multiple antennas. However, spatial diversity gains can be obtained when terminals with single antennas establish a distributed antenna array through cooperation [1]-[3]. In a cooperative transmission system, terminals or users relay signals to each other in order to propagate redundant copies of the same signals to the destination user or terminal. To this end, the designer must employ a cooperation strategy such as amplify-and-forward (AF) [3], decode-and-forward (DF) [3, 4] and compress-and-forward (CF) [5].

Recent contributions in the field have considered the problem of interference mitigation and resource allocation in the context of cooperative communications with relays [6]-[16]. This problem is of paramount importance in wireless cooperative cellular, ad-hoc and sensor networks [10, 13] that utilize spread spectrum systems. Prior work on cooperative multiuser spread spectrum DS-CDMA systems in interference channels has not received much attention and has focused on the assessment of the impact of multiple access interference (MAI) and intersymbol interference (ISI), the problem of partner selection [4, 8] and the bit error rate (BER) and outage performance analyzes [9]. Other related contributions on resource allocation investigated the capacity of ad hoc networks [11], cooperative spatial multiplexing [12], power and rate control [14, 15], and scheduling [16]. There has been no attempt to jointly consider the problem of resource allocation and interference mitigation in cooperative multiuser spread spectrum systems so far.

In this work, we study the downlink of spread spectrum systems which employ multiple relays and the AF cooperation strategy. Specifically, we consider the problem of resource allocation and interference mitigation in multiuser DS-CDMA with a general number of relays, which have been originally reported in [17]. In order to facilitate the receiver design, we adopt linear multiuser receivers [18, 19] which only require a training sequence and the timing. More sophisticated receiver techniques are also possible [18, 20]. We propose a joint constrained optimization framework that considers the allocation of power levels among the relays subject to an individual power constraint

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and the design of linear receivers. We derive constrained minimum mean-squared error (MMSE) expressions for the parameter vectors that determine the optimal power levels across the relays and the linear receivers. In order to solve the proposed optimization problem efficiently, we also develop joint adaptive power allocation and interference suppression algorithms. Specifically, we derive computationally efficient stochastic gradient (SG) and recursive least squares (RLS) algorithms that can be employed in a distributed fashion. The proposed SG and RLS algorithms are employed to mitigate the effects of the MAI and the ISI, and to adjust the power levels, increasing the capacity of CDMA networks with cooperative diversity. These algorithms can be implemented in a distributed fashion, which means the mobile units compute the coefficients and employ a low-rate feedback channel to update the coefficients for the power allocation. In addition, other SG and RLS algorithms are developed to estimate the parameters of the channels across the base station, the relays and the destination terminal of the cooperative DS-CDMA system under consideration. The proposed algorithms are compared with non-cooperative and cooperative techniques without power allocation via computer simulations.

This paper is organized as follows. Section 2 briefly describes a cooperative DS-CDMA system and data model with multiple relays. Section 3 is devoted to the problem statement and the constrained linear MMSE design of the interference mitigation receiver and the power allocation. Section 4 is dedicated to the derivation of constrained adaptive SG and RLS algorithms for the estimation of the parameters of the receiver and the power allocation across the base station, the relays and the destination terminal. Section 5 is devoted to the development of adaptive channel estimation algorithms for the cooperative system under consideration. Section 6 presents and discusses the simulation results and Section 7 draws the conclusions of this paper.

2 System and Data Model

Consider the downlink of a synchronous DS-CDMA system communicating over multipath channels with QPSK modulation, K users, N chips per symbol and L as the maximum number of propagation paths for each link. The synchronous DS-CDMA systems is considered for simplicity as it captures most of the effects of asynchronous systems with low delay spread [19, 20]. The system is equipped with an AF protocol that allows communications in multiple hops using n_r relays in a repetitive fashion. It should be remarked that other cooperation protocols such as DF can be employed without significant modifications, however, the AF has been adopted for simplicity and due to its lower complexity for implementation [3]. We assume that the base station transmits data organized in packets with P symbols, there is enough training and control data to coordinate transmissions and cooperation, and the linear receivers at the terminals are perfectly synchronized. Since the focus of this work is on the resource allocation and interference mitigation, we assume perfect synchronization, however, this assumption can be relaxed in order to account for more realistic synchronization effects in the network The cooperative DS-CDMA system under consideration is illustrated in Fig. 1.

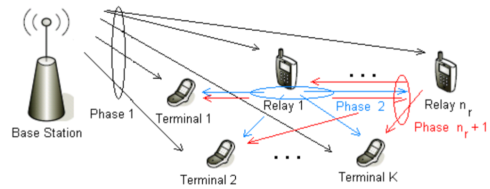

Figure 1: Downlink of proposed cooperative multihop DS-CDMA system.

The received signals are filtered by a matched filter, sampled at the chip rate and organized into $M \times 1$ vectors $\boldsymbol{r}_{bd}[i]$ and $\boldsymbol{r}_{br_i}[i]$, which describe the signals received from the base station to the destination and from the base station to the relays, respectively, as follows

$$\begin{aligned} \boldsymbol{r}_{bd}[n] &= \sum_{k=1}^{K} a_{bd}^{k}[n]\boldsymbol{D}_k \boldsymbol{h}_{bd}[n] b_k[i] \\ &\quad + \boldsymbol{\eta}_{bd}[n] + \boldsymbol{n}_{bd}[n], \\ \boldsymbol{r}_{br_j}[m] &= \sum_{k=1}^{K} a_{br_j}^{k}[m]\boldsymbol{D}_k \boldsymbol{h}_{br_j}[m] b_k[i] \\ &\quad + \boldsymbol{\eta}_{br_j}[m] + \boldsymbol{n}_{br_j}[m], \\ & r_j = 1,2,\ldots,n_r, \quad i = 0,1,\ldots,P-1 \\ & n = n_r i + 1, \quad m = n_r i + r_j + 1 \end{aligned} \tag{1}$$

where $M = N + L - 1$, $\boldsymbol{n}_{bd}[i]$ and $\boldsymbol{n}_{br_j}[i]$ are zero mean complex Gaussian vectors with variance σ^2 generated at the receiver of the destination and the relays, and the vectors $\boldsymbol{\eta}_{bd}[i]$ and $\boldsymbol{\eta}_{br_j}[i]$ represent the intersymbol interference (ISI).

The $M \times L$ matrix $\boldsymbol{D}_k$ contains versions of the signature sequences of each user shifted down by one position at each column as illustrated by

$$\boldsymbol{D}_k = \begin{bmatrix} d_k(1) & & \mathbf{0} \\ \vdots & \ddots & d_k(1) \\ d_k(N) & & \vdots \\ \mathbf{0} & \ddots & d_k(N) \end{bmatrix}, \tag{2}$$

where $\boldsymbol{d}_k = [d_k(1),\ d_k(2),\ \ldots,\ d_k(N)]$ stands for the signature sequence of user k, the $L \times 1$ channel vectors from base station to destination, base station to relay, and relay to destination are $\boldsymbol{h}_{bd}[n]$, $\boldsymbol{h}_{br_j}[n]$, $\boldsymbol{h}_{r_jd}[n]$, respectively. By collecting the data vectors in (1) (including the links from relays to destination) into a $(n_r+1)M \times 1$ received vector at the destination we obtain

$$\begin{bmatrix} \boldsymbol{r}_{bd}[n] \\ \boldsymbol{r}_{r_1d}[m] \\ \vdots \\ \boldsymbol{r}_{r_{n_r}d}[m] \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{K} a_{bd}^k[n]\boldsymbol{D}_k\boldsymbol{h}_{bd}[n]b_k[i] \\ \sum_{k=1}^{K} a_{r_1d}^k[m]\boldsymbol{D}_k\boldsymbol{h}_{r_1d}[m]\tilde{b}_k^{r_1d}[i] \\ \vdots \\ \sum_{k=1}^{K} a_{r_{n_r}d}^k[m]\boldsymbol{D}_k\boldsymbol{h}_{r_{n_r}d}[m]\tilde{b}_k^{r_{n_r}d}[i] \end{bmatrix} + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]$$

Rewriting the above signals in a compact form yields

$$\boldsymbol{r}[i] = \sum_{k=1}^{K} \boldsymbol{\mathcal{C}}_k\boldsymbol{\mathcal{H}}[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i], \quad (3)$$

where the $(n_r+1)M \times (n_r+1)L$ block diagonal matrix $\boldsymbol{\mathcal{C}}_k$ contains versions of the spreading sequences of each user, the $(n_r+1)L \times (n_r+1)$ matrix $\boldsymbol{\mathcal{H}}[i]$ contains the channel gains of the links between the base station and the destination, and the relays and the destination. The $(n_r+1)\times(n_r+1)$ diagonal matrix $\boldsymbol{B}_k[i] = \mathrm{diag}(b_k[i]\ \tilde{b}_k^{r_1d}[i]\ldots\tilde{b}_k^{r_nd}[i])$ contains the symbols transmitted from the base station to the destination ($b_k[i]$) and the n_r symbols transmitted from the relays to the destination ($\tilde{b}_k^{r_1d}[i]\ldots\tilde{b}_k^{r_nd}[i]$) on the main diagonal, the $(n_r+1)\times 1$ vector $\boldsymbol{a}_k[i] = [a_{bd}^k[n]\ a_{r_1d}^k[m]\ldots a_{r_{n_r}d}^k[m]]^T$ of the amplitudes of the links, the $(n_r+1)M \times 1$ vector $\boldsymbol{\eta}[i]$ with the ISI terms and $(n_r+1)M\times 1$ vector $\boldsymbol{n}[i]$ with the noise components at the destination.

3 Problem Statement and Proposed MMSE Design

We are interested in jointly designing a linear receiver and determining the optimal power levels across the relays subject to an individual power constraint. Let us consider an MMSE approach for the design of the receiver for user k represented by a $(n_r+1)M \times 1$ parameter vector $\boldsymbol{w}_k[i]$ and for the computation of the $(n_r+1)\times 1$ optimal power allocation vector $\boldsymbol{a}_k[i]$. This problem can be cast as

$$[\boldsymbol{w}_{k,\mathrm{opt}}[i], \boldsymbol{a}_{k,\mathrm{opt}}[i]] = \arg \min_{\boldsymbol{w}_k[i],\boldsymbol{a}_k[i]} E[|b_k[i] - \boldsymbol{w}_k^H[i]\boldsymbol{r}[i]|^2]$$
$$\text{subject to } \boldsymbol{a}_k^H[i]\boldsymbol{a}_k[i] = P_{A,k}, \quad k = 1,\ 2,\ \ldots,\ K. \quad (4)$$

The expressions for the parameter vectors $\boldsymbol{w}_k[i]$ and $\boldsymbol{a}_k[i]$ can be obtained by transforming the above constrained optimization problem into an unconstrained one with the help of the method of Lagrange multipliers [21] which leads to

$$\mathcal{L}_{\mathrm{I}_k} = E\big[\big|b_k[i] - \boldsymbol{w}_k^H[i]\big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\boldsymbol{\mathcal{H}}[i]\boldsymbol{B}_l[i]\boldsymbol{a}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\big)\big|^2\big]$$
$$+ \lambda(\boldsymbol{a}_k^H[i]\boldsymbol{a}_k[i] - P_{A,k}), \quad k = 1,\ 2,\ \ldots,\ K. \quad (5)$$

Fixing $\boldsymbol{a}_k[i]$, computing the gradient terms of the Lagrangian with respect to $\boldsymbol{w}_k[i]$ and equating them to zero yields

$$\boldsymbol{w}_{k,\mathrm{opt}}[i] = \boldsymbol{R}^{-1}[i]\boldsymbol{p}_{\boldsymbol{\mathcal{C}}\boldsymbol{\mathcal{H}}}[i], \quad k = 1,\ 2,\ \ldots,\ K, \quad (6)$$

where $\boldsymbol{R}[i] = \sum_{k=1}^{K}\boldsymbol{\mathcal{C}}_k\boldsymbol{\mathcal{H}}[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i]\boldsymbol{a}_k^H[i]\boldsymbol{B}_k^H[i]\boldsymbol{\mathcal{H}}^H[i]\boldsymbol{\mathcal{C}}_k^H + \sigma^2\boldsymbol{I}$ is the covariance matrix and $\boldsymbol{p}_{\boldsymbol{\mathcal{C}}\boldsymbol{\mathcal{H}}}[i] = E[b_k^*[i]\boldsymbol{r}[i]] = \boldsymbol{\mathcal{C}}_k\boldsymbol{\mathcal{H}}[i]\boldsymbol{a}_k[i]$ is the cross-correlation vector. The quantities $\boldsymbol{R}[i]$ and $\boldsymbol{p}_{\boldsymbol{\mathcal{C}}\boldsymbol{\mathcal{H}}}[i]$ depend on $\boldsymbol{a}_k[i]$. By fixing $\boldsymbol{w}_k[i]$, computing the gradient terms of the Lagrangian with respect to $\boldsymbol{a}_{k,\mathrm{opt}}[i]$ and equating them to zero, we obtain the following expression for the power allocation vector

$$\boldsymbol{a}_{k,\mathrm{opt}}[i] = (\boldsymbol{R}_{\boldsymbol{a}_k}[i] + \lambda\boldsymbol{I})^{-1}\boldsymbol{p}_{\boldsymbol{a}_k}[i], \quad k = 1,\ 2,\ \ldots,\ K, \quad (7)$$

where $\boldsymbol{R}_{\boldsymbol{a}_k}[i] = \sum_{k=1}^{K}\boldsymbol{B}_k^H[i]\boldsymbol{\mathcal{H}}^H[i]\boldsymbol{\mathcal{C}}_k^H\boldsymbol{w}_k[i]\boldsymbol{w}_k^H[i]\boldsymbol{\mathcal{C}}_k\boldsymbol{\mathcal{H}}[i]\boldsymbol{B}_k[i]$ is the $(n_r+1)\times(n_r+1)$ covariance matrix and the $(n_r+1)\times 1$ cross-correlation vector is $\boldsymbol{p}_{\boldsymbol{a}_k}[i] = E[b_k[i]\boldsymbol{B}_k^H[i]\boldsymbol{\mathcal{H}}[i]^H\boldsymbol{\mathcal{C}}_k^H\boldsymbol{w}_k[i]]$.

The expressions in (6) and (7) depend on each other and require the estimation of the channel matrix $\boldsymbol{\mathcal{H}}[i]$, which is identical for each user as we are dealing with a downlink channel. The expressions in (6) and (7) require matrix inversions with cubic complexity ($O(((n_r+1)M)^3)$ and $O((n_r+1)^3)$, should be iterated as they depend on each other and on user k. It should be remarked that the proposed optimization problem is non-convex and may present multiple solutions due to the joint optimization of parameters. However, the experience with the proposed algorithms suggest that the solutions may be identical because we did not notice problems with local minima or loss of performance under different initialization. A study of the optimization problem is beyond the scope of this work but seems to be an interesting topic for future investigation. In what follows, we will develop algorithms for computing $\boldsymbol{a}_{k,\mathrm{opt}}[i]$, $\boldsymbol{w}_{k,\mathrm{opt}}[i]$ and estimating the channel matrix $\boldsymbol{\mathcal{H}}[i]$.

4 Proposed Constrained Estimation Algorithms for Receiver Design and Power Allocation

In this section we present adaptive constrained SG and RLS estimation algorithms to estimate the parameters of the linear receiver and the power allocation. A key feature of the proposed algorithms is that they can be employed in a distributed fashion. The only information that needs to be sent via a feedback channel is the power allocation vector.

4.1 Adaptive Constrained Estimation and Power Allocation with SG Algorithms

In this subsection, we will develop SG algorithms for computing $\hat{\boldsymbol{w}}_k[i]$ and $\hat{\boldsymbol{a}}[i]$ recursively. Let us consider the proposed constrained optimization in (4), resort to the method of Lagrange multipliers [21] and express the following Lagrangian

$$\mathcal{L} = E\Big[|b_k[i] - \hat{\boldsymbol{w}}_k^H[i]\Big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_l[i]\hat{\boldsymbol{a}}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\Big)|^2\Big] + \lambda(\hat{\boldsymbol{a}}_k^H[i]\hat{\boldsymbol{a}}_k[i] - P_{A,k}), \quad (8)$$

where $\hat{\boldsymbol{w}}_k[i]$, $\hat{\boldsymbol{\mathcal{H}}}[i]$, and $\hat{\boldsymbol{a}}[i]$ are parameter estimates of the receiver, the channel and the power allocation to be determined. Due to the nature of the problem, we need to jointly estimate these parameters. To this end, we will develop joint SG algorithms that can perform this task with low complexity.

We consider the Lagrangian in (8) and calculate the instantaneous gradient terms of it with respect to $\hat{\boldsymbol{w}}_k[i]$, and $\hat{\boldsymbol{a}}[i]$, respectively, as follows:

$$\begin{aligned}\nabla\mathcal{L}_{\hat{\boldsymbol{w}}_k^*[i]} &= -\Big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_l[i]\hat{\boldsymbol{a}}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\Big)\cdot\Big(b_k[i] \\ &\quad - \hat{\boldsymbol{w}}_k^H[i]\Big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_l[i]\hat{\boldsymbol{a}}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\Big)\Big)^* \\ &= -\boldsymbol{r}[i]e^*[i],\end{aligned} \quad (9)$$

$$\begin{aligned}\nabla\mathcal{L}_{\hat{\boldsymbol{a}}_k^*[i]} &= -\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]\Big(b_k[i] \\ &\quad - \hat{\boldsymbol{w}}_k^H[i]\Big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_l[i]\hat{\boldsymbol{a}}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\Big)\Big) + \lambda\hat{\boldsymbol{a}}_k[i] \\ &= -\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]e[i] + \lambda\hat{\boldsymbol{a}}_k[i],\end{aligned} \quad (10)$$

where $e[i] = b_k[i] - \hat{\boldsymbol{w}}_k^H[i]\boldsymbol{r}[i] = b_k[i] - \hat{\boldsymbol{w}}_k^H[i]\big(\sum_{l=1}^{K}\boldsymbol{\mathcal{C}}_l\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_l[i]\hat{\boldsymbol{a}}_l[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\big)$ is the error signal, which is a function of $\hat{\boldsymbol{w}}_k[i]$, $\hat{\boldsymbol{\mathcal{H}}}[i]$, and $\hat{\boldsymbol{a}}[i]$.

Adaptive SG algorithms can be developed by using the expressions for the instantaneous gradients above and using them with SG descent rules [21], yielding

$$\begin{aligned}\hat{\boldsymbol{w}}_k[i+1] &= \hat{\boldsymbol{w}}_k[i] - \mu\nabla\mathcal{L}_{\hat{\boldsymbol{w}}_k^*[i]} \\ &= \hat{\boldsymbol{w}}_k[i] + \mu e^*[i]\boldsymbol{r}[i],\end{aligned} \quad (11)$$

$$\begin{aligned}\hat{\boldsymbol{a}}_k[i+1] &= \hat{\boldsymbol{a}}_k[i] - \alpha\nabla\mathcal{L}_{\hat{\boldsymbol{a}}_k^*[i]} \\ &= \hat{\boldsymbol{a}}_k[i] + \alpha\big(\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]e[i] + \lambda\hat{\boldsymbol{a}}_k[i]\big),\end{aligned} \quad (12)$$

where μ and α are the step sizes for the recursions for the receiver and the power allocation, respectively. Notice that in the recursion for computing $\hat{\boldsymbol{a}}_k[i]$, the designer needs to determine the value of the Lagrange multiplier λ. There are two alternative approaches to that. The first is to substitute (6) into the constraint $\hat{\boldsymbol{a}}_k^H[i+1]\hat{\boldsymbol{a}}_k[i+1] = P_{A,k}$ and then solve the following quadratic equation:

$$a\lambda^2 + b\lambda + c = 0, \quad (13)$$

where the coefficients of the equation are

$$\begin{aligned}a &= P_{A,k}, \\ b &= 2P_{A,k} - \alpha^2(\hat{\boldsymbol{w}}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\hat{\boldsymbol{a}}_k[i] \\ &\quad + \hat{\boldsymbol{a}}_k^H[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]), \\ c &= \alpha(\hat{\boldsymbol{a}}_k^H[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]e[i] + \hat{\boldsymbol{w}}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\hat{\boldsymbol{a}}_k[i]) \\ &\quad + \alpha^2(\hat{\boldsymbol{w}}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]|e[i]|^2).\end{aligned}$$

The solutions of this quadratic equation are

$$\begin{aligned}\lambda_1 &= (-b - b\sqrt{b^2 - 4ac})/2a, \\ \lambda_2 &= (-b + b\sqrt{b^2 - 4ac})/2a.\end{aligned}$$

These solutions have to be computed for every time instant i and checked before substituting them into (6).

The second approach to computing the power allocation and ensuring the constraint is as follows. The constraint is relaxed at first by making $\lambda = 0$ and performing the following recursion:

$$\hat{\boldsymbol{a}}_k[i+1] = \hat{\boldsymbol{a}}_k[i] + \alpha\big(\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]e[i]\big). \quad (14)$$

This is followed by a procedure to enforce the individual power constraint for each user k, i.e., $\hat{\boldsymbol{a}}_k^H[i+1]\hat{\boldsymbol{a}}_k[i+1] = P_{A,k}$, which is described by

$$\hat{\boldsymbol{a}}_k[i+1] \leftarrow P_{A,k}\ \hat{\boldsymbol{a}}_k[i+1]\Big(\sqrt{\hat{\boldsymbol{a}}_k^H[i+1]\hat{\boldsymbol{a}}_k[i+1]}\Big)^{-1} \quad (15)$$

The algorithms for recursive computation of $\hat{\boldsymbol{w}}_k[i]$ and $\hat{\boldsymbol{a}}_k[i]$ require estimates of the channel matrix $\boldsymbol{\mathcal{H}}[i]$, which will also be developed in what follows. A comparison between the two approaches for deriving SG algorithms will be illustrated via simulations. The complexity of the proposed algorithm is $O((n_r+1)M)$ for calculating $\hat{\boldsymbol{w}}_k[i]$ and $O((n_r+1)^2M)$ for obtaining $\hat{\boldsymbol{a}}_k[i]$.

4.2 Adaptive Constrained Estimation and Power Allocation with RLS Algorithms

Specifically, we consider the problem of the previous section using an exponentially weighted least squares criterion and develop an RLS algorithm for the proposed task. Let us now consider the following proposed least squares (LS) optimization problem

$$\begin{aligned}[\hat{\boldsymbol{w}}_k[i], \hat{\boldsymbol{a}}_k[i]] &= \arg\min_{\boldsymbol{w}_k[i],\boldsymbol{a}_k[i]}\ \sum_{l=1}^{i}\alpha^{i-l}|b_k[l] - \boldsymbol{w}_k^H[i]\boldsymbol{r}[l]|^2 \\ &\text{subject to } \boldsymbol{a}_k^H[i]\boldsymbol{a}_k[i] = P_{A,k}, \quad \text{for } k = 1,\ 2,\ \ldots,\ K,\end{aligned} \quad (16)$$

where α is a forgetting factor. The LS expressions for the parameter vectors $\hat{\boldsymbol{w}}_k[i]$ and $\hat{\boldsymbol{a}}_k[i]$ can be obtained in a similar way to the previous section and are given for each user by

$$\hat{\boldsymbol{w}}_k[i] = \hat{\boldsymbol{R}}^{-1}[i]\hat{\boldsymbol{p}}_{\boldsymbol{\mathcal{CH}}}[i] \quad (17)$$

$$\hat{\boldsymbol{a}}_k[i] = (\hat{\boldsymbol{R}}_{\boldsymbol{a}_k}[i] + \lambda \boldsymbol{I})^{-1}\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i] \quad (18)$$

where $\hat{\boldsymbol{R}}[i] = \sum_{l=1}^{i} \alpha^{l=i}\boldsymbol{r}[l]\boldsymbol{r}^H[l]$ is the estimate of the covariance matrix and $\hat{\boldsymbol{p}}_{\boldsymbol{\mathcal{CH}}}[i] = \sum_{l=1}^{i} \alpha^{l=i} b_k^*[l]\boldsymbol{r}[l]$ is the estimate of the cross-correlation vector, $\hat{\boldsymbol{R}}_{\boldsymbol{a}_k}[i] = \sum_{l=1}^{i} \alpha^{l=i}\boldsymbol{B}_k^H[l]\boldsymbol{\mathcal{H}}^H[l]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[l]\hat{\boldsymbol{w}}_k^H[l]\boldsymbol{\mathcal{C}}_k\boldsymbol{\mathcal{H}}[l]\boldsymbol{B}_k[l]$ and $\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i] = \sum_{l=1}^{i} \alpha^{l=i} b_k[l]\boldsymbol{B}_k^H[l]\boldsymbol{\mathcal{H}}[l]^H\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[l]$. The quantity λ is the Lagrange multiplier and also plays the role of regularization term. Due to the difficulty of obtaining a closed form for this parameter, we will rely on a numerical solution for obtaining an appropriate value for it. The expressions in (17) and (18) require matrix inversions with cubic complexity ($O(((n_r+1)M)^3)$ and $O((n_r+1)^3)$, should be iterated as they depend on each other and still require channel estimates.

Our goal now is to obtain a recursive solution to the expressions in (17) and (18) and reduce the required computations. To this end, we will resort to the theory of adaptive algorithms [21] and derive a constrained joint iterative recursive least squares (RLS) algorithm. This algorithm will compute $\hat{\boldsymbol{w}}_k[i]$ and $\hat{\boldsymbol{a}}_k[i]$ and will exchange information between the recursion for improved performance. In order to develop the algorithm, we fix $\hat{\boldsymbol{a}}_k[i]$ and compute the inverse of $\hat{\boldsymbol{R}}[i]$ using the matrix inversion lemma [21] to obtain $\hat{\boldsymbol{w}}_k[i]$. If we define $\boldsymbol{\Phi}[i] = \hat{\boldsymbol{R}}[i]$ then we can obtain the recursions

$$\boldsymbol{k}[i] = \frac{\alpha^{-1}\boldsymbol{\Phi}[i]\boldsymbol{r}[i]}{1 + \alpha^{-1}\boldsymbol{r}^H[i]\boldsymbol{\Phi}[i]\boldsymbol{r}[i]} \quad (19)$$

and

$$\boldsymbol{\Phi}[i] = \alpha^{-1}\boldsymbol{\Phi}[i-1] - \alpha^{-1}\boldsymbol{k}[i]\boldsymbol{r}^H[i]\boldsymbol{\Phi}[i-1] \quad (20)$$

Using the LS expression in (17) and the recursion $\hat{\boldsymbol{p}}_{\boldsymbol{\mathcal{CH}}}[i] = \alpha\boldsymbol{p}_{\boldsymbol{\mathcal{CH}}}[i-1] + b_k^*[i]\boldsymbol{r}[i]$ we get

$$\hat{\boldsymbol{w}}_k[i] = \hat{\boldsymbol{R}}^{-1}[i]\hat{\boldsymbol{p}}_{\boldsymbol{\mathcal{CH}}}[i] = \alpha\boldsymbol{\Phi}[i]\boldsymbol{p}_{\boldsymbol{\mathcal{CH}}}[i-1] + \boldsymbol{\Phi}[i]\boldsymbol{r}[i]b_k^*[i] \quad (21)$$

Using the expression in (20) for $\boldsymbol{\Phi}[i]$, substituting in (21) and manipulating the terms yields

$$\boldsymbol{w}_k[i] = \boldsymbol{w}_k[i-1] + \boldsymbol{k}[i]\xi^*[i] \quad (22)$$

where the *a priori* estimation error is given by

$$\xi[i] = b_k[i] - \boldsymbol{w}_k^H[i-1]\boldsymbol{r}[i]. \quad (23)$$

The derivation for the recursion that estimates the power allocation follows a similar approach to the computation of $\hat{\boldsymbol{w}}_k[i]$. However, there are some difficulties related to the enforcement of the constraint and how to incorporate it into an efficient RLS algorithm. At this point, a modification is required in order to complete the derivation of the proposed RLS algorithm. This is because the LS expression in (18) incorporates a Lagrange multiplier (λ) to ensure the individual power constraint, which is difficult to embed within the matrix inversion lemma. Our approach is to obtain the LS expression for the problem in (16) without the constraint and then ensure the constraint is incorporated via a subsequent normalization procedure. In order to develop the recursions for $\hat{\boldsymbol{a}}_k[i]$, we need to compute the inverse of $\hat{\boldsymbol{R}}_{\boldsymbol{a}_k}[i]$. To this end, let us first define $\boldsymbol{\Phi}_{\boldsymbol{a}_k} = \hat{\boldsymbol{R}}_{\boldsymbol{a}_k}[i]$ and employ the matrix inversion lemma [21] as follows:

$$\boldsymbol{k}_{\boldsymbol{a}_k}[i] = \frac{\alpha^{-1}\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]}{1 + \alpha^{-1}\hat{\boldsymbol{w}}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]} \quad (24)$$

and

$$\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i] = \alpha^{-1}\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i-1] - \alpha^{-1}\boldsymbol{k}_{\boldsymbol{a}_k}[i]\hat{\boldsymbol{w}}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i-1] \quad (25)$$

Now a recursive equation for computing $\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i]$ can be devised by relying on time averages as given by

$$\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i] = \alpha\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i-1] + b_k[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i] \quad (26)$$

The substitution of (26) into the unconstrained LS expression yields

$$\begin{aligned}\hat{\boldsymbol{a}}_k[i] &= \hat{\boldsymbol{R}}_{\boldsymbol{a}_k}^{-1}[i]\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i] \\ &= \alpha\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i]\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i-1] + b_k[i]\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i]\end{aligned} \quad (27)$$

Substituting (25) into the above expression and after some algebraic manipulations with the terms we obtain

$$\begin{aligned}\hat{\boldsymbol{a}}_k[i] &= \boldsymbol{\Phi}_{\boldsymbol{a}_k}[i-1]\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i-1] \\ &\quad - \boldsymbol{k}_{\boldsymbol{a}_k}[i]\boldsymbol{w}_k^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\boldsymbol{B}_k[i]\boldsymbol{\Phi}_{\boldsymbol{a}_k}[i]\hat{\boldsymbol{p}}_{\boldsymbol{a}_k}[i-1] + \boldsymbol{k}_{\boldsymbol{a}_k}b_k^*[i]\end{aligned} \quad (28)$$

By further manipulating the above expressions we get the recursive equation for $\hat{\boldsymbol{a}}_k[i]$

$$\hat{\boldsymbol{a}}_k[i] = \hat{\boldsymbol{a}}_k[i] + \boldsymbol{k}_{\boldsymbol{a}_k}[i]\xi_{\boldsymbol{a}_k}^*[i] \quad (29)$$

where the *a priori* estimation error for this recursion is

$$\xi_{\boldsymbol{a}_k}[i] = b_k[i] - \hat{\boldsymbol{a}}_k^H[i]\boldsymbol{B}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\hat{\boldsymbol{w}}_k[i] \quad (30)$$

In order to ensure the individual power constraint $\boldsymbol{a}_k^H[i]\boldsymbol{a}_k[i] = P_{A,k}$, we apply the following rule

$$\hat{\boldsymbol{a}}_k[i] \leftarrow P_{A,k}\ \hat{\boldsymbol{a}}_k[i]\left(\sqrt{\hat{\boldsymbol{a}}_k^H[i]\hat{\boldsymbol{a}}_k[i]}\right)^{-1} \quad (31)$$

The algorithms for recursive computation of $\hat{\boldsymbol{w}}_k[i]$ and $\boldsymbol{a}_k[i]$ require estimates of the channel vector $\boldsymbol{\mathcal{H}}[i]$, which will also be developed in what follows. The complexity of the proposed algorithm is $O(((n_r+1)M)^2)$ for calculating $\hat{\boldsymbol{w}}_k[i]$ and $O((n_r+1)^2)$ for obtaining $\hat{\boldsymbol{a}}_k[i]$.

5 Adaptive Channel Estimation Algorithms

In this section, we describe adaptive SG and RLS channel estimation algorithms for the cooperative DS-CDMA system operating with the AF cooperation protocol considered in Section 2. The proposed algorithms are developed for use with the parameter estimation algorithms derived in the previous section for receiver design and power allocation.

5.1 Adaptive SG Channel Estimation

In this part we present an adaptive SG channel estimation algorithm for determining the parameters of the channels across the links comprising the base station, the relays and the destination terminal. In order to derive such channel estimator, we first cast it as the following optimization problem

$$\hat{\boldsymbol{\mathcal{H}}}[i] = \arg\min_{\boldsymbol{\mathcal{H}}[i]} \ E[||\boldsymbol{r}[i] - b_k[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i]||^2]. \tag{32}$$

In order to derive an SG channel estimation algorithm, we start with the description of a cost function associated with the optimization problem in (32) described by:

$$\begin{aligned}\mathcal{C} &= E[||\boldsymbol{r}[i] - b_k[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i]||^2] \\ &= E[(\boldsymbol{r}[i] - b_k[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i])^H(\boldsymbol{r}[i] - b_k[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i])] \\ &= E[\boldsymbol{r}^H[i]\boldsymbol{r}[i] - b_k^*[i]\hat{\boldsymbol{a}}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[i] \\ &\quad - b_k[i]\boldsymbol{r}^H[i]\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i] - \hat{\boldsymbol{a}}_k^H[i]\hat{\boldsymbol{\mathcal{H}}}^H[i]\boldsymbol{\mathcal{C}}_k^H\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i]]\end{aligned} \tag{33}$$

Computing the gradient terms of (33) with respect to the $(n_r+1)L \times (n_r+1)$ channel estimate matrix $\hat{\boldsymbol{\mathcal{H}}}[i]$, we get

$$\nabla\mathcal{C}_{\hat{\boldsymbol{\mathcal{H}}}^*[i]} = -\boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[i]\hat{\boldsymbol{a}}_k^H[i]b_k^*[i] + \boldsymbol{\mathcal{C}}_k^H\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i]\hat{\boldsymbol{a}}_k^H[i] \tag{34}$$

Using the above result on the gradient of the cost function and resorting to a SG optimization recursion, we obtain

$$\begin{aligned}\hat{\boldsymbol{\mathcal{H}}}[i+1] &= \hat{\boldsymbol{\mathcal{H}}}[i] - \nu\nabla\mathcal{C}_{\hat{\boldsymbol{\mathcal{H}}}[i]} \\ &= \hat{\boldsymbol{\mathcal{H}}}[i] + \nu(\boldsymbol{\mathcal{C}}_k^H\boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[i]\hat{\boldsymbol{a}}_k^H[i] \\ &\quad - \boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[i]\hat{\boldsymbol{a}}_k^H[i]b_k^*[i]),\end{aligned} \tag{35}$$

where ν is a step size. This SG algorithm for channel estimation works very well and can accurately determine the coefficients of the channels across the links comprising the base station, the relays and the destination terminal. The complexity of the proposed SG channel estimation algorithm is $O(((n_r+1)ML))$.

5.2 Adaptive RLS Channel Estimation

In this part we present an adaptive RLS channel estimation algorithm for determining the parameters of the channels across the links comprising the base station, the relays and the destination terminal. In order to derive such channel estimator, we first cast it as the following optimization problem

$$\hat{\boldsymbol{\mathcal{H}}}[i] = \arg\min_{\boldsymbol{\mathcal{H}}[i]} \ \sum_{l=1}^{i}\alpha^{i-l}||\boldsymbol{r}[l] - \boldsymbol{\mathcal{C}}_k\hat{\boldsymbol{\mathcal{H}}}[i]b_k[l]\hat{\boldsymbol{a}}_k[l]||^2 \tag{36}$$

Due to the structure of the $(n_r+1)L \times (n_r+1)$ channel matrix $\hat{\boldsymbol{\mathcal{H}}}[i]$ and its relationship with the power allocation vector $\hat{\boldsymbol{a}}_k[l]$, we found that it is convenient for the derivation and algorithm development to combine them into a $(n_r+1)L \times 1$ channel estimate vector

$$\hat{\hat{\boldsymbol{h}}}[i] = \hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[l] \tag{37}$$

and recast the optimization problem as

$$\hat{\hat{\boldsymbol{h}}}[i] = \arg\min_{\hat{\boldsymbol{h}}[i]} \ \sum_{l=1}^{i}\alpha^{i-l}||\boldsymbol{r}[l] - b_k[l]\boldsymbol{\mathcal{C}}_k\hat{\hat{\boldsymbol{h}}}[i]||^2 \tag{38}$$

The solution to the above optimization problem is given by

$$\hat{\hat{\boldsymbol{h}}}[i] = \boldsymbol{\Phi}_{\boldsymbol{h}}\boldsymbol{p}_{\boldsymbol{h}}[i] \tag{39}$$

where $\boldsymbol{\Phi}_{\boldsymbol{h}} = (\boldsymbol{\mathcal{C}}_k^H\boldsymbol{\mathcal{C}}_k)^{-1}$ and $\boldsymbol{p}_{\boldsymbol{h}}[i] = \sum_{l=1}^{i}\alpha^{i-l}b_k^*[l]\boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[l]$. It should be remarked that the matrix inversion in $\boldsymbol{\Phi}_{\boldsymbol{h}}$ can pre-computed and stored at the receiver for systems with repetitive spreading codes. In order to develop a recursive algorithm for estimating the channel, we express $\boldsymbol{p}_{\boldsymbol{h}}[i]$ via the following recursion

$$\boldsymbol{p}_{\boldsymbol{h}}[i] = \alpha\boldsymbol{p}_{\boldsymbol{h}}[i-1] + b_k^*[i]\boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[i] \tag{40}$$

Substituting it into (39) we obtain

$$\hat{\hat{\boldsymbol{h}}}[i] = \alpha\hat{\hat{\boldsymbol{h}}}[i-1] + b_k^*[i]\boldsymbol{\Phi}_{\boldsymbol{h}}\boldsymbol{\mathcal{C}}_k^H\boldsymbol{r}[i] \tag{41}$$

Once $\hat{\hat{\boldsymbol{h}}}[i]$ is computed, we need to apply a transformation in order to obtain $\hat{\boldsymbol{\mathcal{H}}}[i]$. This is carried out by manipulating algebraically the relation in (37) with the post multiplication of $\hat{\boldsymbol{a}}_k^H[l]$, which yields

$$\hat{\hat{\boldsymbol{h}}}[i]\hat{\boldsymbol{a}}_k^H[l] = \hat{\boldsymbol{\mathcal{H}}}[i]\hat{\boldsymbol{a}}_k[l]\hat{\boldsymbol{a}}_k^H[l] \tag{42}$$

Now computing the Moore-Penrose pseudo-inverse of $\hat{\boldsymbol{a}}_k[l]\hat{\boldsymbol{a}}_k^H[l]$ we obtain the following relation

$$\hat{\boldsymbol{\mathcal{H}}}[i] = \hat{\hat{\boldsymbol{h}}}[i]\hat{\boldsymbol{a}}_k^H[l](\hat{\boldsymbol{a}}_k[l]\hat{\boldsymbol{a}}_k^H[l])^{\dagger} \tag{43}$$

where $(\cdot)^{\dagger}$ denotes Moore-Penrose pseudo-inverse [21]. This procedure for channel estimation also works well and can accurately determine the coefficients of the channels across the links comprising the base station, the relays and the destination terminal. The complexity of the proposed RLS channel estimation algorithm is $O(((n_r+1)ML))$.

6 Simulations

We evaluate the bit error rate (BER) performance of the proposed joint power allocation and interference suppression (JPAIS) algorithms and compare them with interference suppression schemes without cooperation (NCIS) [18] and with cooperation (CIS) using an equal power allocation across the relays [8]. We consider a stationary DS-CDMA network with randomly generated spreading codes with a processing gain $N = 16$. The block fading channels are generated considering a random power delay profile with gains taken from a complex Gaussian variable with unit variance and mean zero, $L = 3$ paths, and are normalized so that over the packets we have $E[\boldsymbol{\mathcal{H}}^H[i]\boldsymbol{\mathcal{H}}[i]] = 1$. We adopt the AF cooperative strategy with repetitions and all the relays and the destination terminal are equipped with linear MMSE receivers.It should be remarked that the noise amplification of the AF protocol is considered [3]. The receivers have either full knowledge of the channel and the noise variance or are adaptive and estimate all the required coefficients and the channels using the proposed SG and RLS algorithms with optimized parameters. We employ packets with 1500 QPSK symbols and average the curves over 1000 runs. For the adaptive receivers, we provide training sequences with 200 symbols placed at the preamble of the packets. After the training sequence, the adaptive receivers are switched to decision-directed mode.

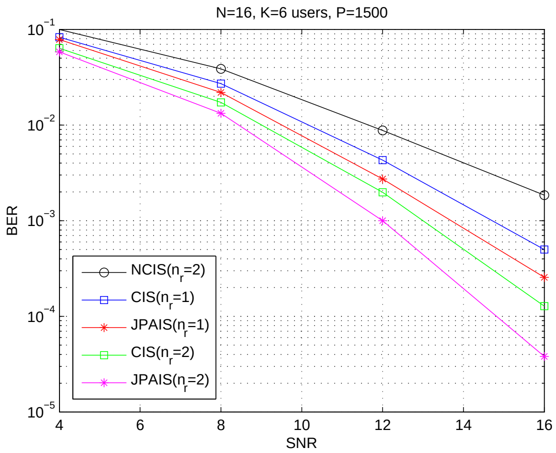

Figure 2: BER performance versus SNR for the optimal linear MMSE detectors. Parameters: $\lambda = 0.02$.

In the first experiment, we consider the proposed joint power allocation and interference suppression (JPAIS) method with the MMSE expressions of (6) and (7). We compare the proposed scheme with a non-cooperative approach (NCIS) and a cooperative scheme with equal power allocation (CIS) for $n_r = 1, 2$ relays. The results shown in Figs. 2 and 3 illustrate the performance improvement achieved by the proposed JPAIS scheme, which significantly outperforms the CIS and the NCIS techniques. As

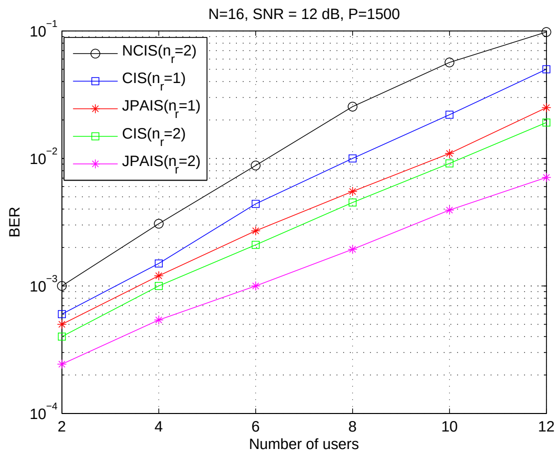

Figure 3: BER performance versus number of users for the optimal linear MMSE detectors. Parameters: $\lambda = 0.02$.

the number of relays is increased so is the performance, reflecting the exploitation of the spatial diversity. In the scenario studied, the proposed JPAIS approach can accommodate up to 3 more users as compared to the CIS scheme and double the capacity as compared with the NCIS for the same BER performance.

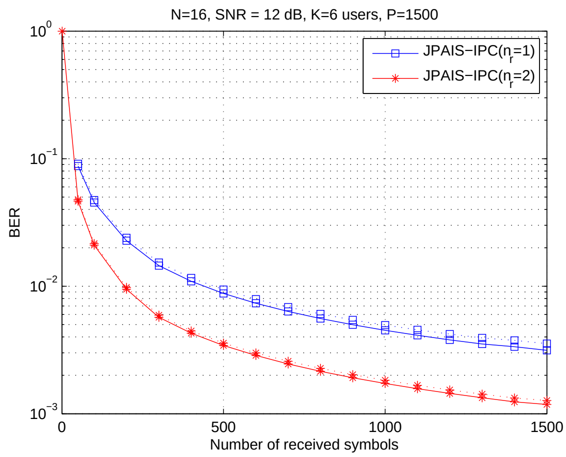

Figure 4: BER performance versus number of symbols. The curves for the adaptive SG algorithms using the solutions for the Lagrange multipliers are in solid lines, whereas those of the adaptive SG algorithms with a simple normalization are in dotted lines. Parameters: $\lambda = 0.02$ (for MMSE schemes), $\mu = 0.025$, $\alpha = 0.015$, $\nu = 0.01$ (for adaptive schemes).

The second experiment depicted in Fig. 4 shows the BER performance of the proposed adaptive SG algorithms (JPAIS) against the existing NCIS and CIS schemes with $n_r = 1$ and $n_r = 2$ relays. The aim of this experiment is to compare the proposed SG algorithms that utilize the solutions for the Lagrange multipliers in the recursions ( ) with the simpler method that introduces a normalization of the power allocation vector (, and). The techniques compared employ SG algorithms for estimation of the coefficients of the channel. From the results we notice that the SG recursions that obtain the values of the Lagrange multipliers via the solution of the quadratic equation have a slightly better performance than the normalization-based approach. This is basically due to a greater precision in the computation of the power allocation coefficients. For this reason, we will adopt this version for the remaining experiments.

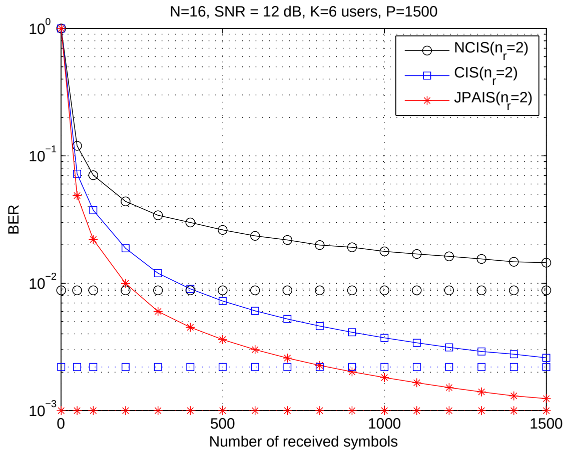

Figure 5: BER performance versus number of symbols. The curves for the adaptive SG algorithms are in solid lines, whereas those of the optimal MMSE schemes are in dotted lines. Parameters: $\lambda = 0.02$ (for MMSE schemes), $\mu = 0.025$, $\alpha = 0.015$, $\nu = 0.01$ (for adaptive schemes).

The third experiment depicted in Fig. 5 shows the BER performance of the proposed adaptive SG algorithms (JPAIS) against the existing NCIS and CIS schemes with $n_r = 2$ relays. All techniques employ SG algorithms for estimation of the coefficients of the channel, the receiver filters and the power allocation for each user (JPAIS only). The complexity of the proposed algorithms is linear with the filter length of the receivers times the number of relays n_r, whereas the optimal MMSE schemes require cubic complexity. From the results, we can verify that the proposed adaptive estimation algorithms converge to approximately the same level of the MMSE schemes, which have full channel and noise variance knowledge.

The fourth experiment depicted in Fig. 6 shows the BER performance of the proposed adaptive algorithms (JPAIS) against the existing NCIS and CIS schemes with $n_r = 2$ relays. The techniques NCIS and CIS employ RLS algorithms for estimation of the coefficients of the channel and the receiver. The proposed JPAIS scheme and RLS algorithms estimates the parameters of the channel, the receiver and the power allocation. The complexity of the proposed adaptive algorithms is quadratic with the filter length of the

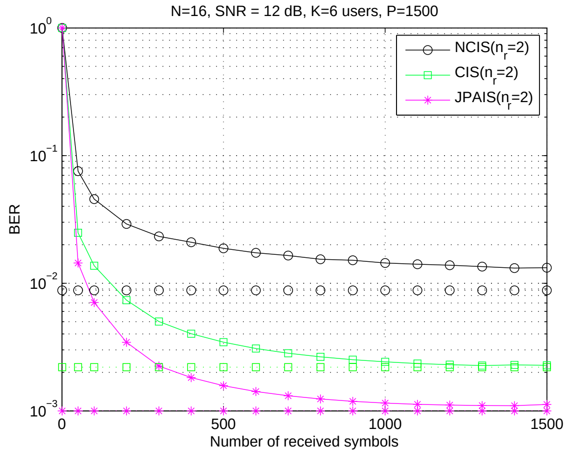

Figure 6: BER performance versus number of symbols. The curves for the adaptive schemes are in solid lines, whereas those of the optimal MMSE schemes are in dotted lines. Parameters: $\alpha = 0.998$.

receivers and the number of relays n_r, whereas the proposed optimal MMSE schemes require cubic complexity. From the results, we can verify that the proposed adaptive RLS estimation algorithms converge to approximately the same level of the MMSE schemes, which have full channel and noise variance knowledge. This indicates that the proposed RLS algorithms work very well and can determine the coefficients of the channels and the receivers.

7 Conclusions

This paper presented joint power allocation and interference mitigation techniques for the downlink of spread spectrum systems which employ multiple relays and the AF cooperation strategy. A joint constrained optimization framework that considers the allocation of power levels across the relays subject to an individual power constraint and the design of linear receivers for interference suppression was presented. We then derived MMSE expressions and SG and RLS algorithms for determining the power allocation and the parameters of the receiver. We also developed SG and RLS channel estimation algorithms were also developed to compute the coefficients of the channels across the base station, the relays and the destination terminal. The simulations showed that the proposed algorithms can obtain significant gains in performance and capacity over non-cooperative systems and cooperative schemes with equal power allocation. Future work will consider a study of the proposed algorithms and their extension to MIMO, OFDM systems, time-varying channels and limited feedback issues.

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