Joint Resource Allocation and Interference Mitigation Techniques for Cooperative Wireless Networks

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Abstract— **This chapter presents joint interference suppression and power allocation algorithms for DS-CDMA and MIMO networks with multiple hops and amplify-and-forward and decode-and-forward (DF) protocols. A scheme for joint allocation of power levels across the relays and linear interference suppression is proposed. We also consider another strategy for joint interference suppression and relay selection that maximizes the diversity available in the system. Simulations show that the proposed cross-layer optimization algorithms obtain significant gains in capacity and performance over existing schemes.**

I. Introduction

Multiple-antenna wireless communication systems can exploit the spatial diversity in wireless channels, mitigating the effects of fading and enhancing their performance and capacity. Due to the size and cost of mobile terminals, it is considered impractical to equip them with multiple antennas. However, spatial diversity gains can be obtained when single-antenna terminals establish a distributed antenna array via cooperation [1]- [3]. The use of cooperative strategies can lead to several types of gains [4], [13], namely, pathloss, diversity and multiplexing gains. Pathloss gains allow a significant reduction in the transmitted power for an equivalent performance, can increase the coverage [15] and enhance the interference suppression capability [4], [13]. The diversity gains improve the performance of the wireless system with respect to the probability of error because the transmission of multiple copies of the signals reduce the probability that the message will not be received correctly. The multiplexing gains [14], which correspond to the additional number of bits that the system can transmit as compared to a single-antenna link, can be obtained when a designer can use relays to form independent channels and increase the rate of communication.

Despite the many advantages in terms of gains as previously outlined, cooperative communications also entail some disadvantages such as signalling overheads [13], more computationally complex scheduling algorithms [4] and increased latency [16]. For this reason, it is important to weigh the pros and cons of cooperative techniques prior to their adoption and consider the practical scenarios of interest [17]. Motivated by their performance and diversity gains, cooperative techniques are now being considered for the next generation of mobile networks [12], [18], [19]. In cooperative systems, 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 resort to a cooperation protocol such as amplify-and-forward (AF) [3], decode-and-forward (DF) [3], [20] and compress-and-forward (CF) [21].

In order to obtain the benefits of cooperative techniques, designers must address a number of problems that are encountered in cooperative wireless systems. These problems include physical-layer strategies such as synchronization, interference mitigation, and parameter estimation. However, designers also have to consider a number of associated problems that belong to higher protocol layers and include the allocation of resources such as power, relays and rate. These tasks present an opportunity to perform cross-layer design and to obtain very significant gains in performance and capacity for cooperative wireless networks. This chapter is concerned with cross-layer design techniques for cooperative wireless networks and investigates the benefits of approaches that jointly mitigate interference and perform resource allocation.

In this chapter, we will consider two types of schemes, namely, direct-sequence code-division multiple access (DS-CDMA) [7], [8] and multi-input multi-output (MIMO) [5], [6] systems. The former is of fundamental importance in wireless ad-hoc and sensor networks [4], whereas the latter is one of the main ingredients of future wireless cellular networks. When implementing cooperative techniques in wireless systems, designers often consider the transmission technologies available and their suitability to certain applications. Therefore, the concept of distributed antenna arrays can be easily extended to techniques such as MIMO [5], [6] and DS-CDMA systems [7], [8].

In the context of MIMO systems, one can obtain substantial multiplexing [5], [6], [11] and diversity gains [9], [10] with the deployment of multiple antennas at both ends of the wireless system. MIMO technology is poised to equip most of the future wireless systems and can be incorporated in conjunction with other transmission systems. There are two basic configurations which exploit the nature of the wireless channel: spatial multiplexing [11] and diversity [10]. Spatial multiplexing relies on the concept of forming individual data stream between pais of transmit and receive antennas. The capacity gains of spatial multiplexing grow linearly with the minimum number of transmit and receive antennas [5], [6] and allow a MIMO system to obtain a considerable increase in data rates. Diversity configurations adopt space-time codes

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[9], [10] to transmit data from the antennas at the transmitter and can obtain a lower probability of error.

DS-CDMA systems are a key multiple access technology for current and future wireless communication systems. Such systems rely on the idea of transmitting data with the aid of unique signatures, which are also known as spreading codes. These signatures are responsible for spreading the information in frequency, and allow the system to have multiple users on the same channel. The advantages of DS-CDMA include good performance in multi-path channels, flexibility in the allocation of channels, increased capacity in bursty and fading environments and the ability to share bandwidth with narrowband communication systems without deterioration of either's systems performance [7], [8]. Demodulating a desired user in a DS-CDMA network requires processing the received signal in order to mitigate different types of interference, namely, narrowband interference (NBI), multi-access interference (MAI), inter-symbol interference (ISI) and the noise at the receiver. The major source of interference in most CDMA systems is MAI, which arises due to the fact that users communicate through the same physical channel with non-orthogonal signals.

The similarities between MIMO and CDMA systems include their mathematically similar descriptions and their fundamental need for interference mitigation. Indeed, the data streams of MIMO systems operating in a spatial multiplexing configuration are equivalent to the users of a DS-CDMA system. In order to separate data streams or users, a designer must resort to detection techniques [22], which are very similar when applied to either MIMO or DS-CDMA. The optimal maximum likelihood (ML) detector is often too complex to be implemented for systems with a large number of antennas. For this reason, designers often resort to suboptimal solutions that an attractive trade-off between performance and complexity. These include the sphere decoder (SD) algorithms [23], linear detectors [22], the successive interference cancellation (SIC) approach [11], the parallel interference cancellation (PIC) [22] and the decision feedback (DF) detectors [39], [62] are techniques that can offer an attractive trade-off between performance and complexity. These detection algorithms can be combined with cross-layer design techniques for enhanced interference mitigation and improved overall performance. In this chapter, we are specifically interested in exploring the advantages of linear detection with power allocation, data stream and relay selection.

A. Prior and Related Work

Prior work on cross-layer design for cooperative and multi-hop communications has considered the problem of resource allocation [24], [25] in generic networks. These include power and rate allocation strategies. Related work on cooperative multiuser DS-CDMA networks has focused on the assessment of the impact of multiple access interference (MAI) and intersymbol interference (ISI), the problem of partner selection [20], [26], the bit error ratio (BER) and outage performance analysis [27], and training-based joint power allocation and interference mitigation strategies [28], [29]. Previous works have also considered the problem of antenna selection, relay selection (RS) and diversity maximization, which are central themes in the MIMO relaying literature [31]–[33]. However, current approaches are often limited to stationary, single relay systems and channels which assume the direct path from the source to the destination is negligible [32].

Most of these resource allocation and interference mitigation strategies require a higher computational cost to implement the power allocation and a significant amount of signalling, decreasing the spectral efficiency of cooperative networks. This problem is central to ad-hoc and sensor networks [30] that employ spread spectrum systems and require multiple hops to communicate with nodes that are far from the source node. This is also of paramount importance in cooperative cellular networks.

B. Contributions

In this chapter, we present joint interference suppression and power allocation algorithms for DS-CDMA and MIMO networks with multiple hops and AF and DF protocols. A scheme that jointly considers the power allocation across the relays subject to group-based power constraints and the design of linear receivers for interference suppression is proposed. The idea of a group-based power allocation constraint is shown to yield close to optimal performance, while keeping the signalling and complexity requirements low. A constrained minimum mean-squared error (MMSE) design for the receive filters and the power allocation vectors is developed along with an MMSE channel estimator for the cooperative system under consideration. The linear MMSE receiver design is adopted due to its mathematical tractability and good performance. However, the incorporation of more sophisticated detection strategies including interference cancellation with iterative decoding [39] and advanced parameter estimation methods [45] is also possible. In order to solve the proposed optimization problem efficiently, a method to form an effective group of users and an alternating optimization strategy are presented with recursive alternating least squares (RALS) algorithms for estimating the parameters of the receiver, the power allocation and the channels. A joint relay selection and transmit diversity selection strategy for MIMO networks with linear receivers is also proposed which optimizes relay transmissions with minimal feedback requirements. Effectively a novel approach to 1-bit power allocation, two joint discrete optimization functions are formed which are solved using discrete stochastic algorithms.

C. Organisation of the Chapter

The chapter is organized as follows. Section II describes cooperative DS-CDMA and MIMO system models with multiple hops. Section III formulates the problem, details the constrained MMSE design of the receive filters and the power allocation vectors subject to a group-based power allocation constraint, and describes an MMSE channel estimator. An extension to cooperative MIMO systems is also presented and discrete optimization problems are formulated to jointly select the optimal relays and their transmit antennas. Section IV presents an algorithm to form the group and the alternating optimization strategy along with RLS-type algorithms for estimating the parameters of the receiver, the power allocation and the channels. For the solution of the combinatorial problems posed by the relay selection strategy, a pair of discrete stochastic algorithms are introduced and their joint operation detailed. Section V presents and discusses the simulation results and Section VI draws the conclusions of this work.

II. System and Data Models of Cooperative Wireless Systems

In this section, we consider system and data models of cooperative wireless systems. The basic idea is to use a linear algebra approach to describe models of the cooperative systems of interest. In particular, we focus on DS-CDMA and MIMO systems and we present a unified approach to the description of these systems.

A. Cooperative DS-CDMA System and Data Model

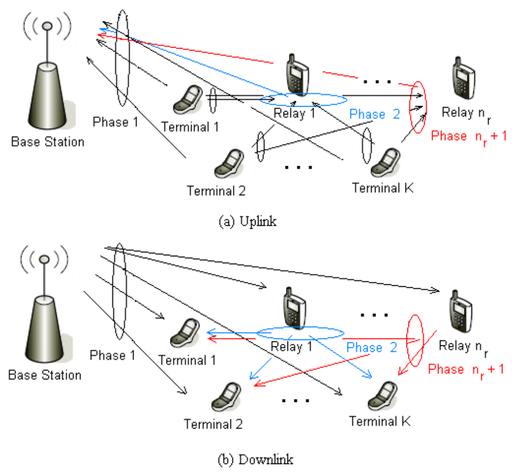

Fig. 1. (a) Uplink and (b) downlink of the cooperative DS-CDMA system.

Let us first consider a synchronous DS-CDMA network with multipath channels. The DS-CDMA system operates with QPSK modulation, K users, N chips per symbol and L as the maximum number of propagation paths for each link. An outline of the system is depicted in (1). The system is equipped with AF and DF protocols that allow communication in multiple hops using n_r fixed relays in a repetitive fashion. We assume that the source node or terminal transmits data organized in packets with P symbols, there is enough control data to coordinate transmissions and cooperation, and the linear receivers at the relay and destination terminals are synchronized with their desired signals. The received signals are filtered by a matched filter, sampled at chip rate and organized into $M \times 1$ vectors $\boldsymbol{r}_{sd}$, $\boldsymbol{r}_{sr_j}$ and $\boldsymbol{r}_{r_jd}$, which describe the signal received from the source to the destination, the source to the relays, and the relays to the destination, respectively,

$$\begin{aligned} \boldsymbol{r}_{sd} &= \sum_{k=1}^{K} a_{sd}^{k} \boldsymbol{C}_k \boldsymbol{h}_{sd,k} b_k + \boldsymbol{\eta}_{sd} \\ &\quad + \boldsymbol{n}_{sd}, \\ \boldsymbol{r}_{sr_j} &= \sum_{k=1}^{K} a_{sr_j}^{k} \boldsymbol{C}_k \boldsymbol{h}_{sr_j,k} b_k + \boldsymbol{\eta}_{sr_j} \\ &\quad + \boldsymbol{n}_{sr_1j}, \\ \boldsymbol{r}_{r_jd} &= \sum_{k=1}^{K} a_{r_jd}^{k} \boldsymbol{C}_k \boldsymbol{h}_{r_jd,k} \tilde{b}_k + \boldsymbol{\eta}_{r_jd} \\ &\quad + \boldsymbol{n}_{r_jd}, \\ & j = 1, \ldots, n_r, \ i = 1, \ldots, P \end{aligned} \quad (1)$$

where $M = N + L - 1$, P is the number of packet symbols, $n_p = n_r + 1$ is the number of transmission phases or hops, and n_r is the number of relays. The vectors $\boldsymbol{n}_{sd}$, $\boldsymbol{n}_{sr_j}$ and $\boldsymbol{n}_{r_jd}$ are zero mean complex Gaussian vectors with variance σ^2 generated at the receivers of the destination and the relays from different links, and the vectors $\boldsymbol{\eta}_{sd}$, $\boldsymbol{\eta}_{sr_j}$ and $\boldsymbol{\eta}_{r_jd}$ represent the intersymbol interference (ISI). The amplitudes of the source to destination, source to relay and relay to destination links for user k are denoted by a_{sd}^k, $a_{sr_j}^k$ and $a_{r_jd}^k$, respectively. The quantities b_k and $\tilde{b}_k$ represent the original and reconstructed symbols by the AF or DF protocol at the relays, respectively. The $M \times L$ matrix $\boldsymbol{C}_k$ contains versions of the signature sequences of each user shifted down by one position at each column as described by

$$\boldsymbol{C}_k = \begin{bmatrix} c_k(1) & & \mathbf{0} \\ \vdots & \ddots & c_k(1) \\ c_k(N) & & \vdots \\ \mathbf{0} & \ddots & c_k(N) \end{bmatrix}, \quad (2)$$

where $\boldsymbol{c}_k = [c_k(1),\ c_k(2),\ \ldots,\ c_k(N)]$ stands for the signature sequence of user k, the $L \times 1$ channel vectors from source to destination, source to relay, and relay to destination are $\boldsymbol{h}_{sd,k}$, $\boldsymbol{h}_{sr_j,k}$, $\boldsymbol{h}_{r_jd,k}$, respectively. By collecting the data vectors in (5) (including the links from relays to the destination) into a $J \times 1$ received vector at the destination, where $J = (n_r + 1)M$, we obtain

$$\begin{bmatrix} \boldsymbol{r}_{sd} \\ \boldsymbol{r}_{r_1d} \\ \vdots \\ \boldsymbol{r}_{r_{n_r}d} \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{K} a_{sd}^{k} \boldsymbol{C}_k \boldsymbol{h}_{sd,k} b_k \\ \sum_{k=1}^{K} a_{r_1d}^{k} \boldsymbol{C}_k \boldsymbol{h}_{r_1d,k} \tilde{b}_k^{r_1d} \\ \vdots \\ \sum_{k=1}^{K} a_{r_{n_r}d}^{k} \boldsymbol{C}_k \boldsymbol{h}_{r_{n_r}d,k} \tilde{b}_k^{r_{n_r}d} \end{bmatrix} + \boldsymbol{\eta} + \boldsymbol{n} \quad (3)$$

Rewriting the above signals in a compact form yields

$$\begin{aligned}\boldsymbol{r}[i] &= \sum_{k=1}^{K} \widetilde{\boldsymbol{B}}_k[i]\widetilde{\boldsymbol{A}}_k[i]\underbrace{\widetilde{\boldsymbol{\mathcal{C}}}_k\boldsymbol{h}_k[i]}_{\boldsymbol{p}_k[i]}+\boldsymbol{\eta}[i]+\boldsymbol{n}[i]\\ &= \sum_{k=1}^{K} \widetilde{\boldsymbol{B}}_k[i]\widetilde{\boldsymbol{A}}_k[i]\widetilde{\boldsymbol{\mathcal{C}}}_k\boldsymbol{h}_k[i]+\boldsymbol{\eta}[i]+\boldsymbol{n}[i] \\ &= \sum_{k=1}^{K} \boldsymbol{P}_k[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i]+\boldsymbol{\eta}[i]+\boldsymbol{n}[i],\end{aligned} \tag{4}$$

where the $J \times (n_r+1)L$ matrix $\widetilde{\boldsymbol{\mathcal{C}}}_k = \text{diag}\{\boldsymbol{C}_k \dots \boldsymbol{C}_k\}$ contains copies of $\boldsymbol{C}_k$ shifted down by M positions for each group of L columns and zeros elsewhere. The $Q \times 1$ vector $\boldsymbol{h}_k[i]$, where $Q = (n_r+1)L$ contains the channel gains of the links between the source, the relays and the destination, and $\boldsymbol{p}_k[i]$ is the effective signature for user k. The $(n_r+1) \times (n_r+1)$ diagonal matrix $\boldsymbol{B}_k[i] = \text{diag}(b_k[i]\ \tilde{b}_k^{r_1 d}[i] \dots \tilde{b}_k^{r_n d}[i])$ contains the symbols transmitted from the source to the destination ($b_k[i]$) and the n_r symbols transmitted from the relays to the destination ($\tilde{b}_k^{r_1 d}[i] \dots \tilde{b}_k^{r_n d}[i]$) on the main diagonal, and the $J \times J$ diagonal matrix $\widetilde{\boldsymbol{B}}_k[i] = \text{diag}(b_k[i] \bigotimes \boldsymbol{I}_M\ \ \tilde{b}_k^{r_1 d}[i] \bigotimes \boldsymbol{I}_M \dots \tilde{b}_k^{r_n d}[i] \bigotimes \boldsymbol{I}_M)$, where $\bigotimes$ denotes the Kronecker product and $\boldsymbol{I}_M$ is an identity matrix with dimension M. The $(n_r+1) \times 1$ power allocation vector $\boldsymbol{a}_k[i] = [a_{sd}^k\ a_{r_1 d}^k \cdots a_{r_{n_r} d}^k]^T$ has the amplitudes of the links, the $(n_r+1) \times (n_r+1)$ diagonal matrix $\boldsymbol{A}_k[i]$ is given by $\boldsymbol{A}_k[i] = \text{diag}\{\boldsymbol{a}_k[i]\}$, and the $J \times J$ diagonal matrix $\widetilde{\boldsymbol{A}}_k[i] = [a_{sd}^k \bigotimes \boldsymbol{I}_M\ a_{r_1 d}^k \bigotimes \boldsymbol{I}_M \dots a_{r_{n_r} d}^k \bigotimes \boldsymbol{I}_M]^T$. The $J \times (n_r+1)$ matrix $\boldsymbol{P}_k$ has copies of the effective signature $\boldsymbol{p}_k[i]$ shifted down by M positions for each column and zeros elsewhere. The $J \times 1$ vector $\boldsymbol{\eta}[i]$ represents the ISI terms and the $J \times 1$ vector $\boldsymbol{n}[i]$ has the noise components.

B. Cooperative MIMO System and Data Model

Let us now consider a synchronous MIMO system model, which has similarities with the DS-CDMA system model of the previous subsection. We consider a narrowband MIMO system with flat fading channels, QPSK modulation, K transmit antennas, and M receive antennas as illustrated in Fig. 2. The cooperative MIMO network is equipped with DF protocol that allows communication in $n_p = 2$ hops using n_r fixed relays in a repetitive fashion where a non-negligible, direct source to destination link exists during the first phase. We assume that the source node or terminal transmits data organized in packets with P symbols, there is enough control data to coordinate transmissions and cooperation, and the linear receivers at the relay and destination terminals are synchronized with their desired signals. It should be noted that the MIMO and CDMA system and data models are mathematically equivalent and the main difference is that we employ for the MIMO version a spreading code matrix $\boldsymbol{C}_k = 1$.

The received signals are filtered by a matched filter, sampled at chip rate and organized into $M \times 1$ vectors $\boldsymbol{r}_{sd}$, $\boldsymbol{r}_{sr_j}$ and $\boldsymbol{r}_{rd}$, which describe the signal received from the source to the destination, the source to the relays, and the relays to the destination, respectively,

$$\begin{aligned}\boldsymbol{r}_{sd} &= \sum_{k=1}^{K} a_{sd}^k \boldsymbol{h}_{sd,k} b_k[i] + \boldsymbol{\eta}_{sd}\\ &\quad + \boldsymbol{n}_{sd},\\ \boldsymbol{r}_{sr_j} &= \sum_{k=1}^{K} a_{sr_j}^k \boldsymbol{h}_{sr_j,k} b_k[i] + \boldsymbol{\eta}_{sr_j}\\ &\quad + \boldsymbol{n}_{sr_j},\\ \boldsymbol{r}_{r_j d} &= \sum_{k=1}^{K} a_{r_j d}^k \boldsymbol{h}_{r_j d,k} \tilde{b}_k[i] + \boldsymbol{\eta}_{r_j d}\\ &\quad + \boldsymbol{n}_{r_j d},\\ &j = 1,\dots,n_r,\ i = 1,\dots,P,\ p = 1,2\end{aligned} \tag{5}$$

where P is the number of packet symbols, $n_p = 2$ is the number of transmission phases or hops, and n_r is the number of relays. The vectors $\boldsymbol{n}_{sd}$, $\boldsymbol{n}_{sr_j}$ and $\boldsymbol{n}_{r_j d}$ are zero mean complex Gaussian vectors with variance σ^2 generated at the receivers of the destination and the relays from different links, and the vectors $\boldsymbol{\eta}_{sd}$, $\boldsymbol{\eta}_{sr_j}$ and $\boldsymbol{\eta}_{r_j d}$ represent the intersymbol interference (ISI).

The amplitudes of the source to destination, source to relay and relay to destination links for user k are denoted by a_{sd}^k, $a_{sr_j}^k$ and $a_{r_j d}^k$, respectively. The quantities $b_k[i]$ and $\tilde{b}_k[i]$ represent the original and reconstructed symbols by the AF or DF protocol at the relays, respectively. The $M \times 1$ spatial channel vectors from source to destination, source to relay, and relay to destination are $\boldsymbol{h}_{sd,k}$, $\boldsymbol{h}_{sr_j,k}$, $\boldsymbol{h}_{r_j d,k}$, respectively. By collecting the data vectors in (5) (including the links from relays to the destination) into a $J \times 1$ received vector at the destination, where $J = n_p M$ for MIMO systems, we obtain

$$\begin{aligned}\boldsymbol{r}[i] = &\begin{bmatrix} \sum_{k=1}^{K} a_{sd}^k \boldsymbol{h}_{sd,k} b_k[i] \\ \sum_{j}^{n_r} \sum_{k=1}^{K} a_{r_{n_r} d}^k \boldsymbol{h}_{r_{n_r} d,k} \tilde{b}_k^{r_{n_r} d}[i] \end{bmatrix}\\ &+ \boldsymbol{n}[i]\end{aligned} \tag{6}$$

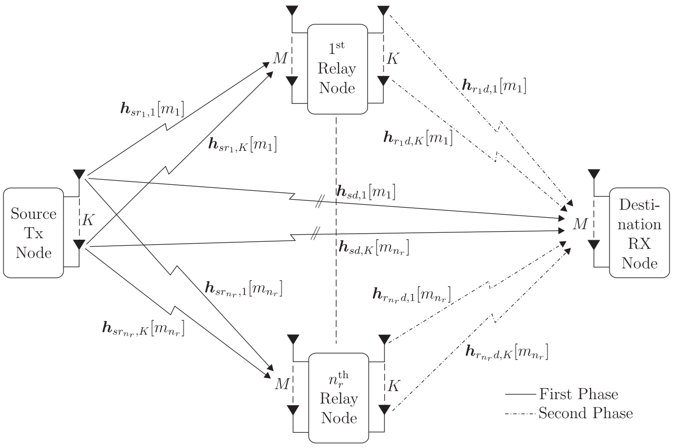

Fig. 2. Block diagram of 2-phase cooperative MIMO system.

Rewriting the above signals in a compact form yields

$$\begin{aligned} \boldsymbol{r}[i] &= \sum_{k=1}^{Kn_r} \widetilde{\boldsymbol{B}}_k[i]\widetilde{\boldsymbol{A}}_k[i]\boldsymbol{h}_k[i] + \boldsymbol{n}[i] \\ &= \sum_{k=1}^{K} \boldsymbol{P}_k[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i] + \boldsymbol{n}[i], \end{aligned} \tag{7}$$

The $J \times 1$ vector $\boldsymbol{h}_k[i]$ contains the spatial channel gains of the links between the source, the relays and the destination. The $n_p \times n_p$ diagonal matrix $\boldsymbol{B}_k[i] = \mathrm{diag}(b_k[i] \ \tilde{b}_k^{r_k d}[i])$, for $1 \leq k \leq K$, and $\boldsymbol{B}_k[i] = \mathrm{diag}(0 \ \tilde{b}_k^{r_k d}[i])$, for $K < k \leq Kn_r$, contains the symbols transmitted from the source to the destination ($b_k[i]$) and the n_r symbols transmitted from the relays to the destination ($\tilde{b}_k^{r_k d}[i]$) on the main diagonal, and the $J \times J$ diagonal matrix $\widetilde{\boldsymbol{B}}_k[i] = \mathrm{diag}(b_k[i] \bigotimes \boldsymbol{I}_M \ \tilde{b}_k^{r_k d}[i] \bigotimes \boldsymbol{I}_M)$, for $1 \leq k \leq K$, and $\widetilde{\boldsymbol{B}}_k[i] = \mathrm{diag}(0 \bigotimes \boldsymbol{I}_M \ \tilde{b}_k^{r_k d}[i] \bigotimes \boldsymbol{I}_M)$, for $K < k \leq Kn_r$,. The $n_p \times 1$ power allocation vector $\boldsymbol{a}_k[i] = [a_{sd}^k \ \dots \ a_{r_k d}^k]^T$ has the amplitudes of the links, the $n_p \times n_p$ diagonal matrix $\boldsymbol{A}_k[i]$ is given by $\boldsymbol{A}_k[i] = \mathrm{diag}\{\boldsymbol{a}_k[i]\}$, and the $J \times J$ diagonal matrix $\widetilde{\boldsymbol{A}}_k[i] = [a_{sd}^k \bigotimes \boldsymbol{I}_M \ \dots \ a_{r_{n_k} d}^k \bigotimes \boldsymbol{I}_M]^T$. The $J \times n_p$ matrix $\boldsymbol{P}_k$ has copies of the spatial signatures $\boldsymbol{h}_k[i]$ shifted down by M positions for each column and zeros elsewhere. The $J \times 1$ vector $\boldsymbol{n}[i]$ has the noise components.

III. Joint MMSE Receiver Design, Power Allocation, Relay Selection and Channel Estimation

In this section, our aim is to describe techniques to mitigate interference and allocate the power and select the best relays according to the mean square error (MSE) criterion. We present a joint receiver design and power allocation strategy using constrained linear MMSE estimation and group-based power constraints along with a linear MMSE channel estimator. The interesting aspect of the group-based power constraints is that a designer can choose a subset of users or data streams for power adjustment. Another technique that is detailed here is a method called transmit diversity selection (TDS) which operates with the linear MMSE receivers. With the TDS technique the relay selection is used to jointly optimize the selection of antennas in a strategy equivalent to a 1-bit transmit antenna power allocation.

In order to describe the techniques necessary for interference mitigation and resource allocation, we introduce an alternative way of expressing the $J \times 1$ received vector in (7). Our goal is to separate the subset of users or data streams that will be used for resource allocation with the group-based power constraints. The modified $J \times 1$ received vector can be expressed as

$$\boldsymbol{r}[i] = \boldsymbol{P}_{\mathcal{S}}[i]\boldsymbol{B}_{\mathcal{S}}[i]\boldsymbol{a}_{\mathcal{S},k}[i] + \sum_{k \neq \mathcal{S}} \boldsymbol{P}_k[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i], \tag{8}$$

where $\mathcal{S} = \{\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_G\}$ denotes the group of G users to consider in the design. The $J \times G(n_r + 1)$ matrix $\boldsymbol{P}_{\mathcal{S}} = [\boldsymbol{P}_{\mathcal{S}_1} \ \boldsymbol{P}_{\mathcal{S}_2} \ \dots \ \boldsymbol{P}_{\mathcal{S}_G}]$ contains the G effective signatures of the group of users. The $G(n_r + 1) \times G(n_r + 1)$ diagonal matrix $\boldsymbol{B}_{\mathcal{S}}[i] = \mathrm{diag}(b_{\mathcal{S}_1}[i] \ \ \tilde{b}_{\mathcal{S}_1}^{r_1 d}[i] \dots \tilde{b}_{\mathcal{S}_1}^{r_n d}[i] \ \ \dots \ \ b_{\mathcal{S}_G}[i] \ \ \tilde{b}_{\mathcal{S}_G}^{r_1 d}[i] \dots \tilde{b}_{\mathcal{S}_G}^{r_n d}[i])$ contains the symbols transmitted from the sources to the destination and from the relays to the destination of the G users in the group on the main diagonal, the $G(n_r + 1) \times 1$ power allocation vector $\boldsymbol{a}_{\mathcal{S},k}[i] = [a_{sd}^{\mathcal{S}_1}[i] \ a_{r_1 d}^{\mathcal{S}_1}[i] \dots a_{r_{n_r} d}^{\mathcal{S}_1}[i], \ \dots, \ a_{sd}^{\mathcal{S}_G}[i] \ a_{r_1 d}^{\mathcal{S}_G}[i] \dots a_{r_{n_r} d}^{\mathcal{S}_G}[i]]^T$ of the amplitudes of the links used by the G users or data streams in the group.

A. Linear MMSE Receiver Design and Power Allocation Scheme with Group-Based Constraints

The linear MMSE interference mitigation for user or data stream k is performed by the receive filter $\boldsymbol{w}_k[i] = [w_{k,1}[i], \ \dots, \ w_{k,J}[i]]$ with J coefficients on the received data vector $\boldsymbol{r}[i]$ and yields

$$z_k[i] = \boldsymbol{w}_k^H[i]\boldsymbol{r}[i], \tag{9}$$

where $z_k[i]$ is an estimate of the symbols, which are processed by a slicer $Q(\cdot)$ that performs detection and obtains the desired symbol as $\hat{b}_k[i] = Q(z_k[i])$.

Let us now detail the linear MMSE-based design of the receivers for user or data stream k represented by $\boldsymbol{w}_k[i]$ and for the computation of the $G(n_r+1) \times 1$ power allocation vector $\boldsymbol{a}_{\mathcal{S},k}[i]$. This problem can be cast as the following constrained optimization

$$\begin{gathered} [\boldsymbol{w}_k^{\mathrm{opt}}, \ \boldsymbol{a}_{\mathcal{S},k}^{\mathrm{opt}}] = \arg \min_{\boldsymbol{w}_k[i], \boldsymbol{a}_{\mathcal{S},k}[i]} \ E[(|b_k[i] - \boldsymbol{w}_k^H[i]\boldsymbol{r}[i]|^2] \\ \text{subject to } \boldsymbol{a}_{\mathcal{S},k}^H[i]\boldsymbol{a}_{\mathcal{S},k}[i] = P_G, \end{gathered} \tag{10}$$

In order to obtain expressions for the receive filter $\boldsymbol{w}_k[i]$ and the power allocation vector $\boldsymbol{a}_{\mathcal{S},k}[i]$ subject to the group-based power constraints, we need the help of the method of Lagrange multipliers (10) [46] that transforms a constrained optimization into an unconstrained one. The MMSE expressions for $\boldsymbol{w}_k[i]$ and $\boldsymbol{a}_{\mathcal{S},k}[i]$ are given by

$$\begin{aligned} \mathcal{L}_k = E\big[|b_k[i] - \boldsymbol{w}_k^H[i]\big(&\boldsymbol{P}_{\mathcal{S}}[i]\boldsymbol{B}_{\mathcal{S}}[i]\boldsymbol{a}_{\mathcal{S},k}[i] \\ &+ \sum_{k \neq \mathcal{S}} \boldsymbol{P}_k[i]\boldsymbol{B}_k[i]\boldsymbol{a}_k[i] + \boldsymbol{\eta}[i] + \boldsymbol{n}[i]\big)|^2\big] \\ &+ \lambda_k(\boldsymbol{a}_{\mathcal{S},k}[i] - P_G), \end{aligned} \tag{11}$$

where λ_k is a Lagrange multiplier.

Since the Lagrangian in (11) is a function of both $\boldsymbol{w}_k[i]$ and $\boldsymbol{a}_{\mathcal{S},k}[i]$, we need to employ a strategy for optimization the function with respect to both parameter vectors. The main idea is to fix one of the parameter vectors and compute the gradient terms with respect to the other parameter vector that minimizes the Lagrangian and obtain the expression of interest. In particular, an expression for $\boldsymbol{a}_{\mathcal{S},k}[i]$ is obtained by fixing $\boldsymbol{w}_k[i]$, taking the gradient terms of the Lagrangian and equating them to zero, which yields

$$\boldsymbol{a}_{\mathcal{S},k}[i] = (\boldsymbol{R}_{\mathcal{S},k}[i] + \lambda_k \boldsymbol{I})^{-1}\boldsymbol{p}_{\mathcal{S},k}[i] \tag{12}$$

where the $G(n_r + 1) \times G(n_r + 1)$ covariance matrix $\boldsymbol{R}_{\mathcal{S},k}[i] = E[\boldsymbol{B}_{\mathcal{S}}^H[i]\boldsymbol{P}_{\mathcal{S}}^H[i]\boldsymbol{w}_k[i]\boldsymbol{w}_k^H[i]\boldsymbol{P}_{\mathcal{S}}[i]\boldsymbol{B}_{\mathcal{S}}[i]]$ and the vector $\boldsymbol{p}_{\mathcal{S},k}[i] = E[b_k[i]\boldsymbol{B}_{\mathcal{S}}^H[i]\boldsymbol{P}_{\mathcal{S}}^H[i]\boldsymbol{w}_k[i]]$ is a $G(n_r+1) \times 1$ cross-correlation vector. The Lagrange multiplier λ_k plays the role of a regularization term and has to be determined numerically due to the difficulty of evaluating its expression.

In order to compute the expression for $\boldsymbol{w}_k[i]$, we fix $\boldsymbol{a}_{\mathcal{S},k}[i]$, calculate the gradient terms of the Lagrangian and equate them to zero which leads to

$$\boldsymbol{w}_k[i] = \boldsymbol{R}^{-1}[i]\boldsymbol{p}_k[i], \tag{13}$$

where the covariance matrix of the received vector is given by $\boldsymbol{R}[i] = E[\boldsymbol{r}[i]\boldsymbol{r}^H[i]]$ and $\boldsymbol{p}_k[i] = E[b_k^*[i]\boldsymbol{r}[i]]$ is a $J \times 1$ cross-correlation vector. The quantities $\boldsymbol{R}[i]$ and $\boldsymbol{p}_k[i]$ depend on the power allocation vector $\boldsymbol{a}_{\mathcal{S},k}[i]$. The expressions in (12) and (13) do not have a closed-form solution as they have a dependence on each other. Moreover, the expressions also require the estimation of the channel vector $\boldsymbol{h}_k[i]$. Thus, it is necessary to iterate (12) and (13) with initial values to obtain a solution and to estimate the channel. The network has to convey the information from the group of users which is necessary to compute the group-based power allocation including the filter $\boldsymbol{w}_k[i]$. The expressions in (12) and (13) require matrix inversions with cubic complexity ($O((J)^3)$ and $O((G(n_r+1))^3)$.

B. Transmit Diversity Selection and Relay Selection

In this subsection, we explore the idea of transmit diversity selection (TDS) and relay selection (RS) and how they can be used to improve the performance of cooperative systems. In cooperative wireless systems with multiple relays, there are links that have very poor propagation conditions that can degrade the performance of the overall system. These links can be identified and removed from the operation of the system via TDS and RS. To this end, we formulate a TDS and RS strategy for a 2 DF MIMO network as a discrete combinatorial MSE problem which optimizes the use of the channels of the second phase via 1-bit power allocation [50]. It turns out that the problems of TDS and RS are combinatorial problems which require either an exhaustive search or some relaxation approach. We specify that a subset of K_{sub} antennas of the n_rK relay antennas are active at each time instant in order to reduce the optimization complexity but also to ensure a minimum available level of diversity. The destination node's MSE TDS optimization function is given by

$$\begin{aligned}\boldsymbol{\mathcal{T}}_r^{opt} &= \arg\min_{\boldsymbol{\mathcal{T}}_r \in \Omega_T} \mathcal{C}\big[i, \boldsymbol{\mathcal{T}}_r, \boldsymbol{r}\big] \\ &= \arg\min_{\boldsymbol{\mathcal{T}}_r \in \Omega_T} \sum_{k=1}^{K} E\Big[\big\|b_k[i] - \boldsymbol{w}_k[i]\boldsymbol{r}[i]\big\|^2\Big],\end{aligned} \tag{14}$$

where $\boldsymbol{\mathcal{T}}_r = \mathrm{diag}(a_{r_1d}^1 \dots a_{r_1d}^K, \dots, a_{r_{n_r}d}^1 \dots a_{r_{n_r}d}^K)$ and $a_{r_jd}^k = \{0,1\}$, and $\boldsymbol{w}_k$ is the linear MMSE filter for the k^{th} symbol. Under the assumption of no inter-relay communication and that each data stream is allocated to its correspondingly numbered transmit antenna at each relay, the set Ω_T has a cardinality of $|\Omega_T| = \binom{n_rK}{K_{sub}}$ and contains all possible combinations of relay transmit antennas patterns. The performance and complexity of solutions to (14) depend on $|\Omega_T|$ and its elements. However, $|\Omega_T|$ is significant even for modest numbers of antennas and relays, e.g. $n_r \geq 4$ and $K \geq 2$. Further improvements can be achieved by a process we term RS which addresses the possibility of mismatching poor first phase channels with optimized second phase channels as well as reducing the cardinality of Ω_T.

By removing one or more relays based on their MSE performance from consideration by (14), Ω_T can be optimized and its cardinality improved without overly restricting the second-phase channels available to the TDS process. The selection of the single highest MSE relay can be expressed as a discrete maximization problem given by

$$\begin{aligned}j_{opt} &= \arg\max_{j \in \Omega_R} \mathcal{F}\big[i, \boldsymbol{r}_{sr_j},\big] \\ &= \arg\max_{j \in \Omega_{\mathrm{R}}} \sum_{k=1}^{K} E\Big[\big\|b_k[i] - \boldsymbol{w}_{j,k}[i]\boldsymbol{r}_{sr_j}[i]\big\|^2\Big],\end{aligned} \tag{15}$$

where Ω_{R} is the set of candidate relays and $\boldsymbol{w}_{j,k}[i]$ is the MMSE filter for the k^{th} symbol at the j^{th} relay. On the solution of (15), a refined subset, $\bar{\Omega}_T \in \Omega_T$, is generated by removing members of Ω_T which involve transmission from relay j_{opt}, i.e. members of Ω_T where $[a^1_{r_{j_{opt}}d} \dots a^K_{r_{j_{opt}}d}] \neq 0$. TDS then operates with this subset, where $|\bar{\Omega}_T| = \binom{K(n_r-1)}{K_{sub}}$. Extension to the selection of multiple relays involves summing the MSE from candidate relays and populating Ω_R with sets of these relays. However, the selection of the number of relays to remove is vital, as too high a value will result in a overly restricting the second phase channels available to the TDS process therefore increasing the probability of a channel mismatch.

C. Cooperative MMSE Channel Estimation

The next task that is necessary for the interference mitigation and resource allocation is to compute the channel gains of the links of the cooperative system. In order to estimate the channel in the cooperative system under study, let us first consider the transmitted signal for user k, $\boldsymbol{x}_k[i] = \widetilde{\boldsymbol{B}}_k[i]\widetilde{\boldsymbol{A}}_k[i]\widetilde{\boldsymbol{\mathcal{C}}}_k\boldsymbol{h}_k[i] = \boldsymbol{Q}_k[i]\boldsymbol{h}_k[i]$, and the covariance matrix given by

$$\begin{aligned}\boldsymbol{R} &= [\boldsymbol{r}[i]\boldsymbol{r}^H[i]] \\ &= \sum_{k=1}^{K} \boldsymbol{Q}_k[i]E[\boldsymbol{h}_k[i]\boldsymbol{h}_k^H[i]]\boldsymbol{Q}_k^H[i] + E[\boldsymbol{\eta}[i]\boldsymbol{\eta}^H[i]] + \sigma^2\boldsymbol{I} \\ &= \sum_{k=1}^{K} \boldsymbol{Q}_k[i]\boldsymbol{P}_{\boldsymbol{h}_k}\boldsymbol{Q}_k^H[i] + \boldsymbol{P}_\eta + \sigma^2\boldsymbol{I}\end{aligned} \tag{16}$$

A linear estimator of $\boldsymbol{h}_k[i]$ applied to $\boldsymbol{r}[i]$ can be represented as $\hat{\boldsymbol{h}}_k[i] = \boldsymbol{F}_k^H\boldsymbol{r}[i]$. The linear MMSE channel estimation problem for the cooperative system under consideration is formulated as

$$\begin{aligned}\boldsymbol{F}_{k,\mathrm{opt}} &= \arg\min_{\boldsymbol{F}_k} E\big[||\boldsymbol{h}_k[i] - \hat{\boldsymbol{h}}_k[i]||^2\big] \\ &= \arg\min_{\boldsymbol{T}_k} E\big[||\boldsymbol{h}_k[i] - \boldsymbol{T}_k^H\boldsymbol{r}[i]||^2\big].\end{aligned} \tag{17}$$

Computing the gradient terms of the argument and equating them to zero yields the MMSE solution

$$\boldsymbol{F}_{k,\mathrm{opt}} = \boldsymbol{R}^{-1}\boldsymbol{P}_k, \tag{18}$$

where $\boldsymbol{P}_k = E[\boldsymbol{r}[i]\boldsymbol{h}_k^H[i]] = \boldsymbol{Q}_k[i]E[\boldsymbol{h}_k[i]\boldsymbol{h}_k^H[i]] =$

$\boldsymbol{Q}_k[i]\boldsymbol{P}_{\boldsymbol{h}_k}$. Using the relation $\hat{\boldsymbol{h}}_k[i] = \boldsymbol{F}_k^H \boldsymbol{r}[i]$, we obtain

$$\begin{aligned}\hat{\boldsymbol{h}}_k[i] &= \boldsymbol{F}_{k,\text{opt}}^H \boldsymbol{r}[i] = \boldsymbol{P}_k^H \boldsymbol{R}^{-1}\boldsymbol{r}[i] \\ &= \boldsymbol{P}_{\boldsymbol{h}_k}^H \boldsymbol{Q}_k^H[i]\big(\sum_{k=1}^{K}\boldsymbol{Q}_k[i]\boldsymbol{P}_{\boldsymbol{h}_k}\boldsymbol{Q}_k^H[i] + \boldsymbol{P}_\eta + \sigma^2\boldsymbol{I}\big)^{-1}\boldsymbol{r}[i],\end{aligned} \tag{19}$$

The expressions in (19) require matrix inversions with cubic complexity ($O(J^3)$), however, this matrix inversion is common to (13) and needs to be computed only once for both expressions. In what follows, computationally efficient algorithms with quadratic complexity ($O(J^2)$) based on an alternating optimization strategy will be detailed.

IV. Adaptive Algorithms

In this section, we present algorithms to compute the parameters of interest and the expressions derived in the previous section with lower computational complexity. Specifically, we develop adaptive RALS algorithms using a method to build the group of G users based on the power levels, and then we employ an alternating optimization strategy for efficiently estimating the parameters of the receive filters, the power allocation vectors and the channels. Despite the joint optimization that is associated with a non-convex problem, the proposed RALS algorithms have been extensively tested and have not presented problems with local minima.

A. Group Allocation and Channel Estimation

The first step in the proposed strategy is to build the group of G users that will be used for the power allocation and receive filter design. A RAKE receiver [7], which is equivalent to a filter matched to the signature sequence of the desired user or the spatial signature of the desired data stream will be used for the group allocation. The RAKE receiver is employed to obtain $z_k^{\text{RAKE}}[i] = (\widetilde{\boldsymbol{C}}_k\hat{\boldsymbol{h}}_k[i])^H\boldsymbol{r}[i] = \hat{\boldsymbol{p}}_k^H[i]\boldsymbol{r}[i]$. The group is then formed according to

$$\text{compute the } G \text{ largest } |z_k^{\text{RAKE}}[i]|, \quad k = 1, 2, \ldots, K. \tag{20}$$

The design of the RAKE and the other tasks require channel estimation. The power allocation, receive filter design and channel estimation expressions given in (12), (13) and (19), respectively, are solved by replacing the expected values with time averages, and RLS-type algorithms with an alternating optimization strategy. In order to solve (19) efficiently, we develop a variant of the RLS algorithm that is described by

$$\hat{\boldsymbol{h}}_k[i] = \hat{\boldsymbol{P}}_{\boldsymbol{h}_k}^H[i]\boldsymbol{Q}_k^H[i]\hat{\boldsymbol{R}}^{-1}[i]\boldsymbol{r}[i], \tag{21}$$

where $\boldsymbol{Q}_k[i] = \widetilde{\boldsymbol{B}}_k[i]\widetilde{\boldsymbol{A}}_k[i]\widetilde{\boldsymbol{C}}_k$, the estimate of the inverse of the covariance matrix $\hat{\boldsymbol{R}}^{-1}[i]$ is computed with the matrix inversion lemma [46]

$$\boldsymbol{k}[i] = \frac{\alpha^{-1}\hat{\boldsymbol{R}}[i-1]\boldsymbol{r}[i]}{1 + \alpha^{-1}\boldsymbol{r}^H[i]\hat{\boldsymbol{R}}[i-1]\boldsymbol{r}[i]}, \tag{22}$$

$$\hat{\boldsymbol{R}}[i] = \alpha^{-1}\hat{\boldsymbol{R}}[i-1] - \alpha^{-1}\boldsymbol{k}[i]\boldsymbol{r}^H[i]\hat{\boldsymbol{R}}[i-1], \tag{23}$$

and

$$\hat{\boldsymbol{P}}_{\boldsymbol{h}_k}[i] = \alpha\hat{\boldsymbol{P}}_{\boldsymbol{h}_k}[i-1] + \hat{\boldsymbol{h}}_k[i-1]\hat{\boldsymbol{h}}_k^H[i-1], \tag{24}$$

where α is a forgetting factor that should be close to but less than 1.

B. Joint Interference Suppression and Power Allocation

The approach for allocating the power within a group is to drop the constraint, estimate the quantities of interest and then impose the constraint via a subsequent normalization. The group-based power allocation algorithm is computed by

$$\begin{aligned}\hat{\boldsymbol{a}}_{\mathcal{S},k}[i] &= \hat{\boldsymbol{R}}_{\mathcal{S},k}[i]\hat{\boldsymbol{p}}_{\mathcal{S},k}[i] \\ &= \hat{\boldsymbol{R}}_{\mathcal{S},k}[i](\alpha\hat{\boldsymbol{p}}_{\mathcal{S},k}[i-1] + b_k[i]\boldsymbol{v}_k[i]) \\ &= \hat{\boldsymbol{a}}_{\mathcal{S},k}[i-1] + \xi_a[i]\boldsymbol{k}_{\mathcal{S},k}[i],\end{aligned} \tag{25}$$

where $\xi_a[i] = b_k[i] - \hat{\boldsymbol{a}}_{\mathcal{S},k}^H[i-1]\boldsymbol{v}_k[i]$ is the a priori error, $\boldsymbol{v}_k[i] = \boldsymbol{B}_{\mathcal{S}}^H[i]\boldsymbol{P}_{\mathcal{S}}^H[i]\boldsymbol{w}_k[i]$ is the input signal to the recursion

$$\boldsymbol{k}_{\mathcal{S},k}[i] = \frac{\alpha^{-1}\hat{\boldsymbol{R}}_{\mathcal{S},k}[i-1]\boldsymbol{v}_k[i]}{1 + \alpha^{-1}\boldsymbol{v}_k^H[i]\hat{\boldsymbol{R}}_{\mathcal{S},k}[i-1]\boldsymbol{v}_k[i]}, \tag{26}$$

$$\hat{\boldsymbol{R}}_{\mathcal{S},k}[i] = \alpha^{-1}\hat{\boldsymbol{R}}_{\mathcal{S},k}[i-1] - \alpha^{-1}\boldsymbol{k}_{\mathcal{S},k}[i]\boldsymbol{v}_k^H[i]\hat{\boldsymbol{R}}_{\mathcal{S},k}[i-1]. \tag{27}$$

The normalization $\hat{\boldsymbol{a}}_{\mathcal{S},k}[i] \leftarrow P_G\ \hat{\boldsymbol{a}}_{\mathcal{S},k}[i]/||\hat{\boldsymbol{a}}_{\mathcal{S},k}[i]||$ is then performed to ensure the power constraint.

The linear receive filter is computed by

$$\hat{\boldsymbol{w}}_k[i] = \hat{\boldsymbol{w}}_k[i-1] + \boldsymbol{k}[i]\xi^*[i], \tag{28}$$

where the a priori error is given by $\xi[i] = b_k[i] - \hat{\boldsymbol{w}}_k^H[i-1]\boldsymbol{r}[i]$ and $\boldsymbol{k}[i]$ is given by (22). The proposed scheme employs the algorithm in (20) to allocate the users in the group and the channel estimation approach of (21)-(24). The alternating optimization strategy uses the recursions (25) and (28) with 1 or 2 iterations per symbol i.

C. Transmit Diversity Selection and Relay Selection Based on Discrete Stochastic Gradient Algorithms

In this part, we describe a low-complexity solution to the joint TDS and RS problem based on a discrete stochastic gradient algorithm (DSA) that can compute the optimal combinatorial solution outline in (14) and (15) with a substantially reduced cost as compared with the exhaustive search. We present a pair of low-complexity DSA that was first reported in [33], [47], which jointly optimizes RS and TDS in accordance with (14) and (15), and converges to the optimal exhaustive solution.

The RS portion of the DSA is given by the algorithm of Table I. At each iteration the MSE of a randomly chosen candidate relay (j^C) (step 2) and that of the worst performing relay currently known (j^W) are calculated (step 3). Via a comparison, the higher MSE relay is designated j^W for the next iteration (step 3). The current solution and the relay chosen for removal (j) is denoted as the current optimum and is the relay which has occupied j^W most frequently over the course of the packet up to the i^{th} time instant; effectively an average of the occupiers of j^W. This averaging/selection process is performed by allocating each member of Ω_R a $|\Omega_R| \times 1$ unit vector, $\mathbf{v}_l$, which has a one in its corresponding position in Ω_R, i.e., $\mathbf{v}_{j^W}[i]$ is the label of the worst performing relay at the i^{th} iteration. The current optimum is then chosen and tracked by means of a $|\Omega_R| \times 1$ state occupation probability

TABLE I

PROPOSED DISCRETE STOCHASTIC JOINT TDS AND RS ALGORITHM

Step
1. Initialization
choose $j[1] \in \Omega_{\rm R}, j^W[1] \in \Omega_R$, $\boldsymbol{\pi}_R\big[1, j[1]\big] = 1$, $\boldsymbol{\pi}_R[1, \bar{j}] = 0$ for $\bar{j} \neq j[1]$
2. For the time index $i = 1, 2, ..., N$
choose $j^C[i] \in \Omega_R$
3. Comparison and update of the worst performing relay
if $\mathcal{F}\big[i, \boldsymbol{r}_{sr_{j^C[i]}}\big] > \mathcal{F}\big[i, \boldsymbol{r}_{sr_{j^W[i]}}\big]$ then $j^W[i+1] = j^C[i]$
otherwise $j^W[i+1] = j^W[i]$
4. State occupation probability (SOP) vector update
$\boldsymbol{\pi}_R[i+1] = \boldsymbol{\pi}_R[i] + \mu[i+1](\mathbf{v}_{j^W[i+1]} - \boldsymbol{\pi}_R[i])$ where $\mu[i] = 1/i$
5. Determine largest SOP vector element and select the optimum relay
if $\boldsymbol{\pi}_R\big[i+1, j^W[i+1]\big] > \boldsymbol{\pi}_R[i+1, j[i]]$ then $j[i+1] = j^W[i+1]$
otherwise $j[i+1] = j[i]$
6. TDS Set Reduction
remove members of Ω_T which utilize relay $j[i+1]$ ($\Omega_T \rightarrow \bar{\Omega}_T$)

(SOP) vector, $\boldsymbol{\pi}_R$. This vector is updated at each iteration by adding $\mathbf{v}_{j^W}[i+1]$ and subtracting the previous value of $\boldsymbol{\pi}_R$ (step 4). The current optimum is then determined by selecting the largest element in $\boldsymbol{\pi}_R$ and its corresponding entry in Ω_R (step 5). Through this process, the current optimum converges towards and tracks the exhaustive solution [47]. An alternative interpretation of the proposed algorithm is to view the transitions, $j^W[i] \rightarrow j^W[i+1]$, as a Markov chain and the members of Ω_R as the possible transition states. The current optimum can then be defined as the most visited state.

Once RS is complete at each time instant, set reduction ($\Omega_T \rightarrow \bar{\Omega}_T$, step 6) and TDS can take place. To perform TDS, modified versions of steps $1-5$ are used. The considered set is replaced, $\Omega_R \rightarrow \bar{\Omega}_T$; the structure of interest is replaced, $j \rightarrow \boldsymbol{\mathcal{T}}_r$; the best performing matrix is sought $j^W \rightarrow \boldsymbol{\mathcal{T}}_r^B$; the SOP vector is replaced $\boldsymbol{\pi}_R \rightarrow \boldsymbol{\pi}_{\boldsymbol{\mathcal{T}}}$ and $\mathcal{C} \rightarrow \mathcal{F}$ from (14). Finally, the inequality of step 3 is reversed to enable convergence to the lowest MSE TDS matrix which is then feedback to the relays in the form of 1-bit per relay antenna.

Significant complexity savings result from the proposed algorithm; savings which increase with K, n_r and the number relays removed in the RS process. For example, when $n_r = 10$, $K = 2$ and 4 relays are removed, the number of complex multiplications for MMSE reception and exhaustive TDS, exhaustive TDS with RS, iterative TDS and iterative TDS with RS are 5.8×10^8, 1.7×10^8, 1.8×10^5 and 5.9×10^4, respectively, for each time instant.

V. Analysis and Requirements of the Algorithms

In this section, we assess the requirements of the proposed and existing algorithms for cross-layer design in terms of computational complexity and number of feedback bits. The basic idea is to show the computational cost of the algorithms presented and compare them with those of existing techniques for interference mitigation and/or resource allocation.

A. Computational Complexity Requirements

We discuss here the computational complexity of the proposed and existing algorithms. Specifically, we will detail the required number of complex additions and multiplications of the proposed JPAIS-GBC algorithms and compare them with interference suppression schemes without cooperation (NCIS) and with cooperation (CIS) using an equal power allocation across the relays. Both uplink and downlink scenarios are considered in the analysis. In Table I we show the computational complexity required by each recursion associated with a parameter vector/matrix for the JPAIS-GBC with $G = K$, which is more suitable for the uplink.

TABLE II

COMPUTATIONAL COMPLEXITY OF ALGORITHMS WITH A GLOBAL POWER CONSTRAINT $G = K$.

Parameter	Number of operations per symbol	
	Additions	Multiplications
$\hat{\boldsymbol{W}}[i]$	$2(J)^2$ $+2K(J)$ $-J+1$	$3(J)^2$ $+2K(J)$ $+3J+1$
$\hat{\boldsymbol{a}}_T[i]$	$3K(K(n_r+1))$ $+K(n_r+1)(L-1)$ $+K(M(n_r+1))$ $+K(K(n_r+1))$ $+6(K(n_r+1))^2$ $+3K(n_r+1)+n_r+2$	$K(K(n_r+1))^2$ $+4(K(n_r+1))^2$ $+(K+L)(K(n_r+1))^2$ $-(K(n_r+1))^2$ $+K(MQ)$ $+n_r$
$\hat{\boldsymbol{h}}_k[i]$	$5(KQ)^2$ $+5KQ$ $+3$	$+5(K(n_r+1)^2$ $+6KQ$ $+1$

In Table II we show the computational complexity required by each recursion associated with a parameter vector for the JPAIS-GBC algorithm, which is suitable for both the uplink and the downlink. A noticeable difference between the JPAIS-GBC with $G = K$ and $G = 1$ is that the latter is employed for each user, whereas the former is used for all the K users in the system. Since the computation of the inverse of $\hat{\boldsymbol{R}}[i]$ is common to all users for the uplink in our system, the JPAIS-GBC with $G = K$ is more efficient than the JPAIS-GBC with $G = 1$ computed for all the K users.

TABLE III

COMPUTATIONAL COMPLEXITY OF ALGORITHMS WITH INDIVIDUAL POWER CONSTRAINTS ($G = 1$).

Parameter	Number of operations per symbol	
	Additions	Multiplications
$\hat{\boldsymbol{w}}_k[i]$	$2(J)^2$ $+J$ $+1$	$3(J)^2$ $+5J$ $+1$
$\hat{\boldsymbol{a}}_k[i]$	$2(n_r+1)^2$ $+3(n_r+1)$ $+JL$ $+Q$ -3	$3(n_r+1)^2$ $+7(n_r+1)$ $+JL$ $+Q$ $+3$
$\hat{\boldsymbol{h}}_k[i]$	$2(Q)^2$ $+5MQ$ $-5(n_r+1)+3$	$6(Q)^2$ $+MQ$ $+4(n_r+1)+1$

The recursions employed for the proposed JPAIS-GBC with $G = K$ and the JPAIS-GBC with $G = 1$ are general and parts of them are used in the existing CIS and NIS algorithms.

Therefore, we can use them to describe the required computational complexity of the existing algorithms. In Table III we show the required recursions for the proposed and existing algorithms, whose complexity is detailed in Tables I and II.

TABLE IV
COMPUTATIONAL COMPLEXITY OF THE PROPOSED JPAIS AND EXISTING ALGORITHMS.

Algorithm	Recursions
JPAIS-GPC($G=K$) (Uplink)	$\hat{\boldsymbol{W}}[i]$, $\hat{\boldsymbol{a}}_T[i]$,$\hat{\boldsymbol{h}}_k[i]$
JPAIS-GBC ($G=1$) (Downlink)	$\hat{\boldsymbol{w}}_k[i]$, $\hat{\boldsymbol{a}}_k[i]$, $\hat{\boldsymbol{h}}_k[i]$
CIS (Uplink)	$\hat{\boldsymbol{W}}[i]$, $\hat{\boldsymbol{a}}_T[i]$ is fixed
CIS (Downlink)	$\hat{\boldsymbol{w}}_k[i]$, $\hat{\boldsymbol{a}}_k[i]$ is fixed
NCIS (Uplink)	$\hat{\boldsymbol{W}}[i]$ with $n_r=0$
NCIS (Downlink)	$\hat{\boldsymbol{w}}_k[i]$ with $n_r=0$

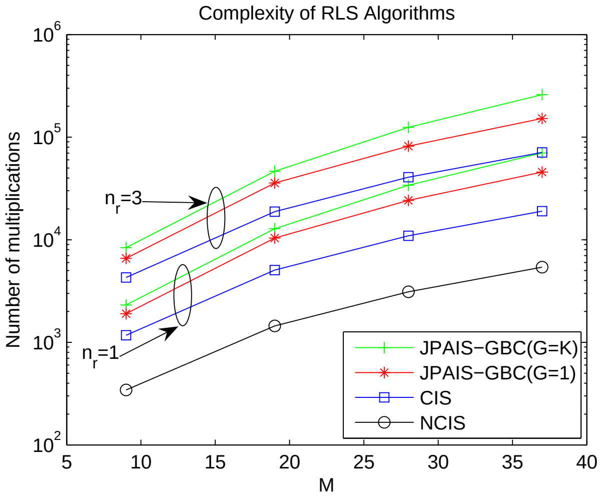

Fig. 3. Computational complexity in terms of the number of complex multiplications of the proposed and existing schemes for the uplink.

In Fig. 3, we illustrate the required computational complexity for the proposed and existing schemes for different number of relays (n_r). The curves show that the proposed JPAIS-GBC with $G=K$ and JPAIS-GBC with $G=1$ are more complex than the CIS scheme and the NCIS. This is due to the fact that the power allocation and channel estimation recursions are employed. However, we will show in the next section that this additional required complexity (which is modest) can significantly improve the performance of the system.

B. Feedback Channel Requirements

The JPAIS algorithms presented so far for cross-layer design require feedback signalling in order to allocate the power levels across the relays. In order to illustrate how these requirements are addressed, we can refer to Fig. 4 which depicts the structure for both the data and feedback packets. The data packet comprises a number of allocated bits for training ($N_{\rm tr}$), for synchronization and control ($N_{\rm sync}$) and the transmitted data ($N_{\rm data}$). The feedback packet requires the transmission of the power allocation vector $\boldsymbol{a}_T$ for the case of the JPAIS-GBC algorithm with $G=K$, whereas it requires the transmission of $\boldsymbol{a}_k$ for each user for JPAIS-GBC with $G=1$. A typical number of bits n_b required to quantize each coefficient of the vectors $\boldsymbol{a}_T$ and $\boldsymbol{a}_k$ via scalar quantization is $n_b = 4$ bits. More efficient schemes employing vector quantization [48], [49] and that take into account correlations between the coefficients are also possible.

For the uplink (or multiple-access channel), the base station (or access point) needs to feedback the power levels across the links to the K destination users in the system. With the JPAIS-GBC with $G=K$ algorithm, the parameter vector $\boldsymbol{a}_T$ with $(n_r+1)Kn_b$ bits/packet must be broadcasted to the K users. For the JPAIS-GBC algorithm with $G=1$, a parameter vector $\boldsymbol{a}_k$ with $(n_r+1)n_b$ bits/packet must be broadcasted to each user in the systems. In terms of feedback, the JPAIS-GBC algorithm with $G=1$ is more flexible and may require less feedback bits if there is no need for a constant update of the power levels for all K users.

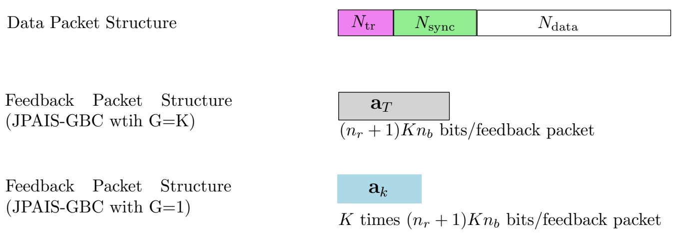

Fig. 4. Proposed structure of the data and feedback packets.

For the downlink (or broadcast channel), the K users must feedback the power levels across the links to the base station. With the JPAIS-GBC algorithm with $G=K$, the parameter vector $\boldsymbol{a}_T$ with $(n_r+1)Kn_b$ bits/packet must be computed by each user and transmitted to the base station, which uses the $\boldsymbol{a}_T$ vector coming from each user. An algorithm for data fusion or a simple averaging procedure can be used. For the JPAIS-GBC algorithm with $G=1$, a parameter vector $\boldsymbol{a}_k$ with $(n_r+1)n_b$ bits/packet must be transmitted from each user to the base station. In terms of feedback, the JPAIS-GBC algorithm with $G=1$ requires significantly less feedback bits than the JPAIS-GBC with $G=K$ in this scenario.

The MIMO TDS and RS scheme can be interpreted as a 1-bit power allocation scheme and therefore achieves performance improvements whilst utilizing the minimum number of feedback bits per antenna. Consequently, the feedback requirements per update of a cooperative MIMO system using TDS and RS is given by the total number of relay transmit antennas n_rK. This minimal feedback allows optimization of the system whilst maintaining the capacity of the system with regards to the transmission of useful data.

VI. SIMULATIONS

In this section, we illustrate with Monte-Carlo simulations the performance of the cross-layer algorithms described in this chapter. Specifically, we assess the performance in terms of the bit error ratio (BER) of the JPAIS scheme and adaptive algorithms with group-based power constraints (GBC). The JPAIS scheme and algorithms are compared with schemes without cooperation (NCIS) and with cooperation (CIS) [26] using an equal power allocation across the relays (the power allocation in the JPAIS scheme is disabled). We also assess the proposed algorithms for transmit diversity selection and relay selection (Iterative TDS with RS) are presented and comparisons drawn against the optimal exhaustive solutions (Exhaustive TDS with RS), the unmodified system (No TDS), and the direct transmission (Non-Cooperative).

A. DS-CDMA System

A DS-CDMA network with randomly generated spreading codes and a processing gain $N = 16$ is considered. The fading channels are generated considering a random power delay profile with gains taken from a complex Gaussian variable with unit variance and mean zero, $L = 5$ paths spaced by one chip, and are normalized for unit power. The power constraint parameter $P_{A,k}$ is set for each user so that the designer can control the SNR (SNR $= P_{A,k}/\sigma^2$) and $P_T = P_G + (K - G)P_{A,k}$, whereas it follows a log-normal distribution for the users with associated standard deviation equal to 3 dB. The DF cooperative protocol is adopted and all the relays and the destination terminal use either linear MMSE, which have full channel and noise variance knowledge, or adaptive receivers. The receivers are adjusted with the proposed RALS with 2 iterations for the JPAIS scheme, and with RLS algorithms for the NCIS and CIS schemes. We employ packets with 1500 QPSK symbols and average the curves over 1000 runs. For the adaptive receivers, we provide training sequences with $N_{\rm tr} = 200$ symbols placed at the preamble of the packets. After the training sequence, the adaptive receivers are switched to decision-directed mode.

The first experiment depicted in Fig. 5 shows the BER performance of the proposed JPAIS scheme and algorithms against the NCIS and CIS schemes with $n_r = 2$ relays. The JPAIS scheme is considered with the group-based power constraints (JPAIS-GBC). All techniques employ MMSE or RLS-type algorithms for estimation of the channels, the receive filters and the power allocation for each user. The results show that as the group size G is increased the proposed JPAIS scheme and algorithms converge to approximately the same level of the cooperative JPAIS-MMSE scheme reported in [28], which employs $G = K$ for power allocation, and has full knowledge of the channel and the noise variance.

The proposed JPAIS-GBC scheme is then compared with a non-cooperative approach (NCIS) and a cooperative scheme with equal power allocation (CIS) across the relays for $n_r = 1, 2$ relays. The results shown in Fig. 6 illustrate the performance improvement achieved by the JPAIS scheme and algorithms, which significantly outperform the CIS and the NCIS techniques. As the number of relays is increased so is the performance, reflecting the exploitation of the spatial diversity. In the scenario studied, the proposed JPAIS-GBC with $G = 3$ 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. The curves indicate that the GBC for power allocation with only a few users is able to attain a performance close to the JPAIS-GBC with $G = K$ users, while requiring a lower complexity and less network signalling. A comprehensive study of the signalling requirements will be considered in a future work.

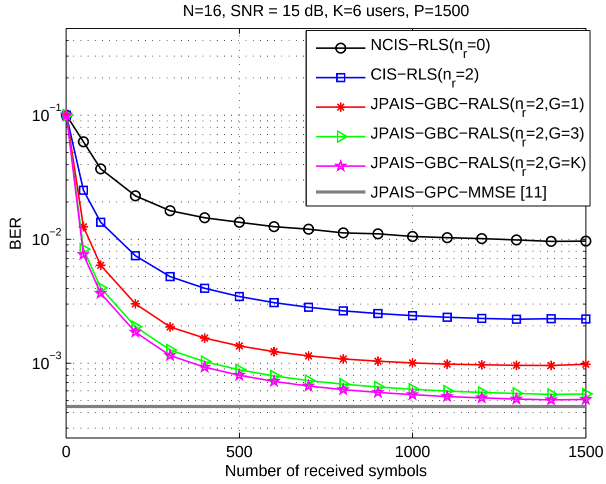

Fig. 5. BER performance versus number of symbols. Parameters: AF protocol, $\lambda_T = \lambda_k = 0.025$ (for MMSE schemes), $\alpha = 0.998$, $\hat{\boldsymbol{R}}^{-1}_{\mathcal{S},k}[i] = 0.01\boldsymbol{I}$ and $\hat{\boldsymbol{R}}^{-1}[i] = 0.01\boldsymbol{I}$.

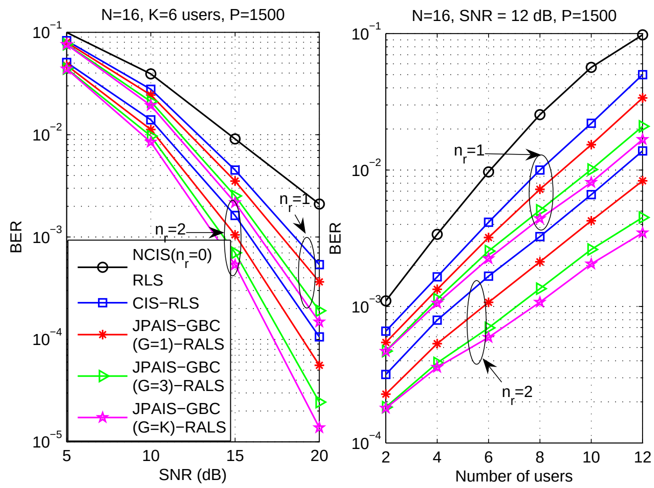

Fig. 6. BER performance versus SNR and number of users for the optimal linear MMSE detectors. Parameters: AF protocol, $\alpha = 0.998$, $\hat{\boldsymbol{R}}^{-1}_{\mathcal{S},k}[i] = 0.01\boldsymbol{I}$ and $\hat{\boldsymbol{R}}^{-1}[i] = 0.01\boldsymbol{I}$.

The next experiment considers the average BER performance against the normalized fading rate f_dT (cycles/symbol), as depicted in Fig. 7. The idea is to illustrate a situation where the channel changes within a packet and the system transmits the power allocation vectors computed by the proposed JPAIS algorithms via a feedback channel. In this scenario, the JPAIS algorithms compute the parameters of the receiver and the power allocation vector, which is transmitted only once to the mobile users. This leads to a situation in which the power allocation becomes outdated. The results show that the gains of the proposed JPAIS algorithms decrease gradually as the f_dT is increased to the BER level of the existing CIS algorithms for both $n_r = 2$ and $n_r = 4$ relays, indicating that the power allocation is no longer able to provide performance advantages. This problem requires the deployment of a frequent update of the power allocation via feedback channels.

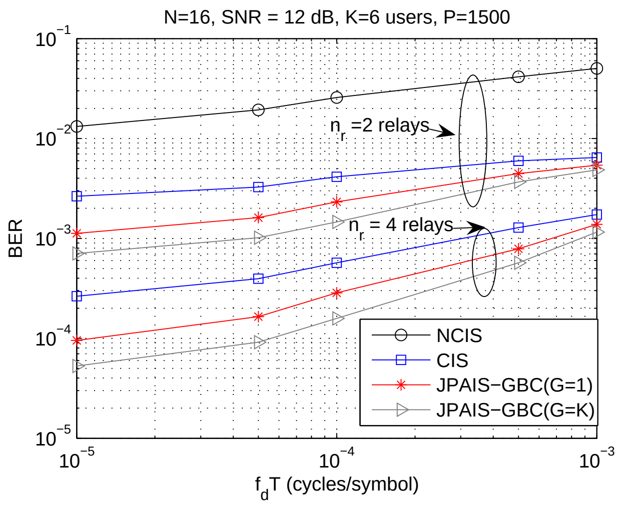

Fig. 7. BER performance versus f_dT for the AF protocol. The parameters of the adaptive algorithms are optimized for each f_dT.

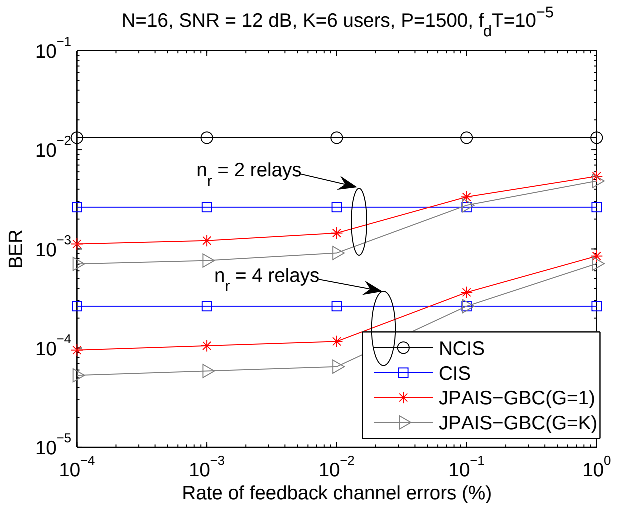

Fig. 8. BER performance versus f_dT for the AF protocol. The parameters of the adaptive algorithms are optimized for each f_dT.

The last experiment, shown in Fig. 8, illustrates the averaged BER performance versus the percentage of errors in the feedback channel for an uplink scenario. Specifically, the feedback packet structure is employed and each coefficient is quantized with 4 bits. Each feedback packet is constructed with a sequence of binary data (0s and 1s) and is transmitted over a binary symmetric channel (BSC) with an associated probability of error P_e. We then evaluate the BER of the proposed JPAIS and the existing algorithms against several values of the P_e. The results show that the proposed JPAIS algorithms obtain significant gains over the existing CIS algorithm for values of $P_e < 0.1\%$. As we increase the rate of feedback errors, the performance of the proposed JPAIS becomes worse than the CIS algorithms. This suggests the use of error-control coding techniques to keep the level of errors in the feedback channel below a certain value.

B. MIMO System

In this part, simulations of the proposed algorithms (Iterative TDS with RS) are presented and comparisons drawn against the optimal exhaustive solutions (Exhaustive TDS with RS), the unmodified system where all antennas are active (No TDS), and the direct transmission (Non-Cooperative). Plots of the schemes with TDS only (Exhaustive TDS, Iterative TDS) are also included to illustrate the performance improvement obtained by RS. Equal power allocation is maintained in each phase so that the total transmit bit power of the relays is unity. RLS channel estimation (CE) is used where all auxiliary matrices are initialized as identity matrices and estimation matrices are zero matrices, and the exponential forgetting factor is 0.9. Each simulation is averaged over 1000 packets ($N_{\rm p}$), each with training sequences of 200 symbols.

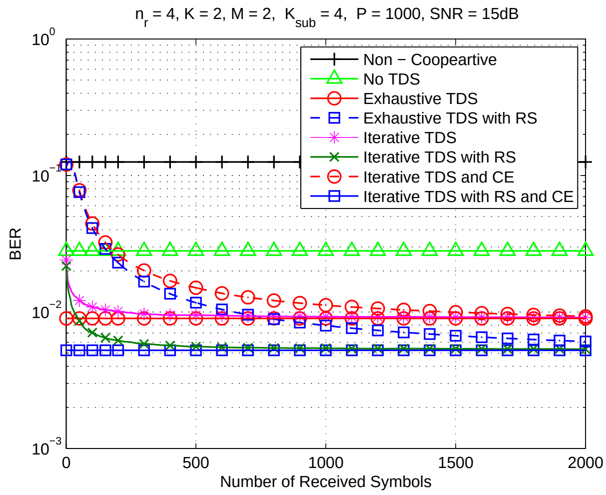

Fig. 9. Cooperative DF MIMO BER performance versus the number of received symbols.

Fig. 9 gives the BER convergence performance of the proposed algorithms. The iterative TDS with RS algorithm converges to the optimal BER as does TDS with RS and CE, albeit in a delayed fashion due to the CE. The TDS with RS scheme exhibits quicker convergence and lower steady state BER. These results and the interdependence between elements of the algorithm confirm that both the RS and TDS portions of the algorithm converge to their exhaustive solutions.

Fig. 10 shows the BER versus SNR performance of the proposed and conventional algorithms. Increased diversity has been achieved without sacrificing multiplexing gain and illustrates that although the maximum available diversity advantage decreases from $M(n_r+1)$ to $M(K_{sub}/K+1)$ with RS with TDS because fewer antennas are active, the actual diversity achieved has increased. These diversity effects can be attributed to the removal of poor paths and therefore a lower probability of first phase and second phase channel mismatch but also the increase in transmit power over the remaining paths. The largest gains in diversity are present in the $15-25$dB region and begin to diminish above this region because relay decoding becomes increasingly reliable and lower power paths become more viable for transmission.

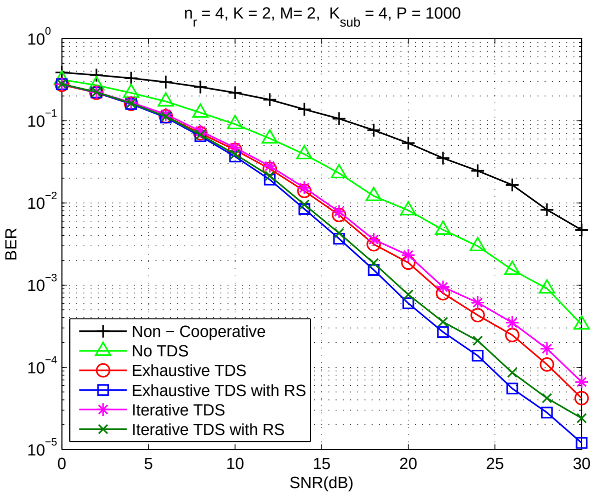

Fig. 10. Cooperative FD MIMO BER performance versus SNR.

VII. Extensions and Suggestions for Future Work

The algorithms for joint resource allocation and interference mitigation described in this chapter are quite general and can be employed in a variety of wireless communication systems that are equipped with cooperative techniques. These include orthogonal-frequency-division-multiplexing (OFDM) [51], single-carrier systems with frequency-domain equalisation (SC-FDE) [52] and ultra-wide band (UWB) systems [53].

Possible extensions include the incorporation of more advanced interference mitigation strategies than linear schemes. These include nonlinear detection techniques such as successive interference cancellation [11], [38], decision feedback strategies [37], [39] and sphere decoders [23]. The detection algorithms could also be considered with space-time coding schemes [9], [10], channel coding and iterative processing approaches [39], [55].

Another complementary set of techniques comprises algorithms for adaptive parameter estimation. These methods are fundamental to estimate key parameters such as channel gains, amplitudes and receive filters, whilst keeping the complexity low and being able to track variations of the environment. Amongst the adaptive parameter estimation techniques, a designer can choose between supervised and blind approaches [46]. Blind techniques [56]- [61] are appealing as they can increase the spectral efficiency of wireless systems. This is especially relevant for cooperative systems as they require extra signalling for cross-layer design. Supervised adaptive algorithms usually rely on training sequences that are sent at the beginning of each data packet [62], [63]. One fundamental issue in the choice of the adaptive parameter estimation algorithm is the speed of convergence and the tracking performance. The literature suggests that reduced-rank algorithms [40]- [45], [65]–[67] are very attractive choices when fast training and accurate tracking are important issues.

VIII. Concluding Remarks

We have presented in this work joint iterative power allocation and interference mitigation techniques for DS-CDMA and MIMO networks which employ multiple hops and the AF and DF cooperation protocols. A joint constrained optimization framework and algorithms that consider the allocation of power levels across the relays subject to group power constraints and the design of linear receivers for interference suppression were proposed. A scheme for joint transmit diversity optimisation and relay selection along with linear interference suppression has also been detailed and applied to MIMO systems. A study of the requirements of the proposed and existing algorithms in terms of computational complexity and feedback channels has also been conducted. The results of simulations have shown that the proposed algorithms obtain significant gains in performance and capacity over existing non-cooperative and cooperative schemes.

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