Correlation-Aware Resource Allocation in Multi-Cell Networks

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***Abstract*—We propose a cross-layer strategy for resource allocation between spatially correlated sources in the uplink of multi-cell FDMA networks. Our objective is to find the optimum power and channel allocation to the different sources, in order to minimize the maximum distortion achieved in decoding any source data in the network. This problem is NP-hard and finding the optimal solution is not computationally feasible. We propose a three-step algorithm to be performed separately in each cell, which finds cross-layer resource allocation in simple steps. This method separates the problem into inter-cell resource management, grouping of sources for joint decoding, and intra-cell channel assignment. For each of these steps we propose methods that satisfy different design constraints and analyze them by simulations. We show that, while using correlation in compression and joint decoding can achieve 25% distortion reduction over independent decoding, the improvement grows to 37% when correlation is also utilized in resource allocation. This significant distortion reduction motivates further work in correlation-aware resource allocation. Overall, our solution is able to achieve a 60% decrease in 5 percentile distortion compared to independent allocation methods.**

***Index Terms*—Resource allocation, cellular networks, FDMA, correlated sensors, inter-cell interference.**

I. Introduction

We consider spatially correlated sources in a multi-cell Frequency Division Multiple Access (FDMA) network that transmit data to the base station of their cell, as depicted in Figure 1. Such a scenario exists for example in Wireless Sensor Networks (WSNs), where sensors measure various spatially correlated phenomena such as temperature, humidity, audio, video, etc. [1]. Since the early days of WSNs, the wireless infrastructure has vastly increased in geographic coverage and capabilities. Therefore we assume that the WSNs are deployed in a multi cell network infrastructure with a Medium Access Control (MAC) scheme similar to LTE of 3G, since large scale deployment of such infrastructure lowers the cost of WSNs.

Furthermore, we consider that the base station in the center of each cell contains a scheduler, which performs resource allocation with the aim of minimizing the maximum distortion in the reconstruction of data from any source in the global network. Distortion is an appropriate measure of quality for audio or video applications. Source distortion is commonly chosen as part of the utility function in multimedia transmission, as it defines the 'goodness' or the fidelity of the data representation at the source. Our goal in this work is to find a strategy to efficiently allocate resources to each sensor, while taking advantage of spatial correlation among the sources.

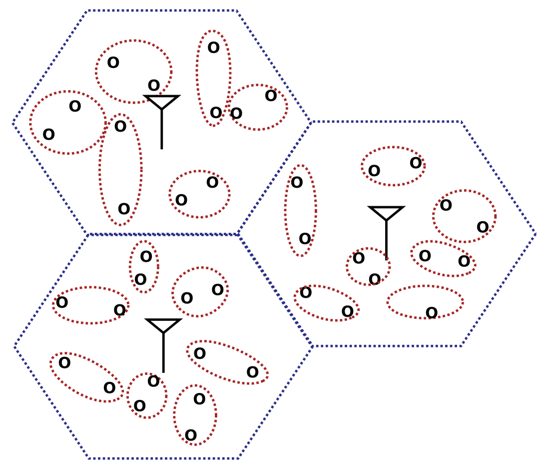

Fig. 1. Three neighboring cells with base stations in the center of each cell. The sensors are grouped in correlated groups of size 2 in this example.

The resource allocation problem for FDMA networks involves finding the channel and power assignment for sources in each cell, given the benefits and costs of this assignment (i.e., utility gain versus the interference with other sources). Even when sources are independent, optimal allocation of power and channels in an interfering network of users is a non-convex, mixed integer non-linear programming problem (MINLP). The independent allocation problem is strongly NP-hard when there are several channels to choose from [2]. Furthermore, for a non-trivial network size exhaustive solutions are not computationally feasible in a single scheduling period. Then, when considering correlated sources, the correlation characteristics of sources and their contribution to the performance of other sources in the network should be considered in the resource allocation scheme, which also adds to the complexity. Thus simplifications are necessary in practice for effective (but often suboptimal) resource allocation solutions.

We propose a constructive solution to the NP-hard resource allocation problem by splitting it into a set of simpler sub-problems. Our solution is based on a three-step approach: *i) Inter-cell resource management, ii) Source Grouping,* and *iii) Intra-cell Scheduling*. Such a separation of the overall resource allocation problem leads to an efficient solution with tractable complexity. First, we find the transmit power limits in each

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cell in the inter cell interference management step. For this, we use the Adaptive ICon interference coordination method [4]. ICon manages the inter-cell interference by concentrating the interference experienced by a cell base station in a designated frequency sub-band. This results in setting transmit power limits on each sub-band for the users of neighboring cells, and separates the global problem into smaller problems solvable in each cell, while adaptively managing the inter-cell interference. Adaptation is performed in order to balance the performance across the network. Second, in the Source Grouping (SG) step we split the set of sources in each cell into smaller groups to be jointly decoded. This takes advantage of spatial correlation with little increase in scheduler complexity. We compare the utility gain of larger group sizes and conclude that having two sources per group achieves most of the correlation gain. We propose a location-based adaptive SG method called Distance Outer-Priority (distance OP). This method finds the best grouping for the cell, while accounting for the interference to neighboring cells. Last, we use the parameters found in previous steps in order to allocate channels in the Intra-cell scheduling step using two novel scheduling methods. One scheme called Distortion Proportionally Fair (D-PF) is based on the popular Proportionally Fair method [5], modified in order to take the effects of correlation into account. The second scheduling method is a linear programming problem (OPT), which performs better than D-PF at the price of higher complexity.

We demonstrate in simulations that our proposed scheme presents a constructive and simple solution to the computationally infeasible optimum resource allocation problem. Finally, the rate-distortion performance is superior to resource allocation methods that do not consider correlation in the optimization.

The paper is organized as follows. In Section II we discuss related work. We formulate the problem in Section III, and our three phased solution in Section IV. We present the results of our simulations in Section V and conclusions in Section VI.

II. Related Work

Resource allocation implies finding joint power and channel allocation to multiple sources in the same cellular network. Common approaches are based on decoupling the inter-cell and intra-cell resource management problems. For inter-cell resource management, Fractional Frequency Reuse (FFR) and Soft Frequency Reuse (SFR) [6] [7] have been proposed by the cellular industry. In these methods, a *power profile* is assigned to every cell, which sets transmit power limits on each frequency sub-band for Orthogonal FDMA (OFDMA). The neighboring cells are assigned complementary power profiles in order to shape the inter-cell interference. These power profiles are based on heuristics. For intra-cell scheduling, the scheduler in each cell usually performs channel allocation independently using a method such as Proportionally Fair scheduling [5]. Unfortunately, their performance is not better in general than the frequency Reuse 1 scheme [8], which simply permits the use of every frequency band at the same transmit power limit in every cell. In order to improve on these solutions, we proposed Adaptive ICon in [4]. Adaptive ICon is an adaptive inter-cell interference management method based on concentrating the interference to a cell on a particular sub-band. This is achieved by requiring the neighboring cells to respect an *interference power profile* set by the cell. The method achieves significant improvement over FFR and SFR schemes. Another interesting inter-cell interference management method called *inverted reuse* is proposed in [9]; it is also based on concentrating the interference experienced by a cell on a specific frequency band by setting transmit power limits for its neighboring cells.

Spatial correlation in resource allocation has been studied mainly in the field of WSNs. Early methods use an 802.11-like MAC, and save power by enabling periodic sleep-wake cycles for wireless sensors, with algorithms such as S-MAC [11] and P-MAC [12]. A later method is Correlation-based Collaborative Medium Access Control (CC-MAC) [13], which takes advantage of spatial correlation by finding a subset of sensors to transmit their data while data from the other sensors is omitted. Here we rather use the data from every sensor, while minimizing the maximum distortion in the network.

In multi-hop WSNs, spatial correlation is used in combining routing and rate allocation with data compression [14] [15] [16] [17]. In [18], routing is combined with rate allocation using Wyner-Ziv (WZ) distributed source coding [19]. It is shown that routing and rate optimization can be decoupled and optimized separately, when the cost function is a weighted sum of rates. As for our solution in multi-cell networks, correlation is exploited by a joint decoder in order to reduce the overall resource utilization.

III. Resource Allocation Problem

Recall that we consider a 2-D multi-cell network with FDMA multiple access scheme. The sources sense spatially correlated information. They transmit their observations to the base station of their cell, using medium access parameters determined by the scheduler located in the cell base station.

A. Resources

In FDMA the bandwidth is split into frequency sub-bands and a subset of these sub-bands is assigned to each user. In the multi-cell scenario, users from different cells interfere if they are assigned to the same channel. The MAC problem consists of allocating the power per channel and channels among users. Each of the independent orthogonal channels are assumed to be Gaussian and interference is considered to be equivalent to noise with respect to channel capacity. The following rate is achieved for source s_i in cell *k* according to Gaussian channel capacity [20]:

$$R_i = \sum_{c=1}^{C} a_{i,c} B_c \log_2\left(1 + \frac{p_{i,c} \cdot g_{i,k}}{N_0 . B_c + \sum_{u \in U_k} P^I_{ukc}}\right) \quad (1)$$

where $a_{i,c}$ is the binary value specifying channel allocation and $p_{i,c}$ the transmit power of source s_i on channel *c*, $g_{i,k}$ is the channel gain from source s_i to receiver of cell *k*, and B_c is the bandwidth of channel *c*. N_0 is the noise power, U_k is the set of neighboring cells of cell k. P^I_{ukc} is the received interference power from cell *u* to cell *k* on channel *c*; namely, $P^I_{ukc} = \sum_{s_j \in X_u} a_{j,c} . p_{j,c} . g_{j,k}$, where X_u is the set of all the sources in cell u.

B. Rate-Distortion Region

The rate-distortion (R-D) function is a characteristic of the coding scheme. In the general case of lossy distributed coding, the R-D region is not yet known. However, for distributed coding in the limit of *high resolution*, the R-D region is known to be similar to the rate region given by lossless Slepian-Wolf coding [3]. When the sources $\boldsymbol{S}$ in the set $\boldsymbol{G}$ in cell *k* are decoded jointly, the R-D region for this set is then given by:

$$\forall \boldsymbol{S} \subseteq \boldsymbol{G}:$$
$$\sum_{s_i \in \boldsymbol{S}} R_i \geq h_2(\boldsymbol{S}|\boldsymbol{G}\backslash\boldsymbol{S}) - \frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}\prod_{s_i\in\boldsymbol{S}} D_i\right) \quad (2)$$

where $h(.)$ is the differential entropy, and D_i is the squared error distortion of source s_i. This is an outer bound for the general coding case; it becomes tighter as the resolution increases. In this work we do not provide an optimal distributed encoding scheme. We rather assume that perfect decoding can be achieved, and that the above bound can be reached by proper coding.

We model the observations at the sources as joint Gaussian random variables. For the correlation model we use an exponential distance-based correlation model [21]. The entropy is then given by,

$$h_2(\boldsymbol{S}) = \frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}|\Sigma|\right) \quad (3)$$

where $|\Sigma|$ is the determinant of the covariance matrix of the sources, with elements of the matrix given as: $\sigma_{ij}^2 = \sigma^2.e^{(\frac{-d_{ij}}{\theta})}$. σ^2 is the variance of the sources. d_{ij} is the distance between sources s_i and s_j, and θ is the correlation model parameter. This model can be replaced without significantly changing our resource allocation methodology so long as correlation decreases with distance.

The set of sources, $\boldsymbol{G}$, that are decoded jointly can include between 1 source and all the sources in a cell. Increasing the size of joint decoding groups increases the complexity in decoding and scheduling. Also, we later show that increasing the group size has diminishing returns. Therefore we assume that sources are decoded in small groups.

C. Problem Formulation

The optimization problem is to minimize the maximum distortion, subject to resource constraints. Assuming there are N sources in the network and X_k is the set of all sources in cell *k*, the resource allocation problem is given as follows.

Problem 1:

$$\underset{\boldsymbol{a},\boldsymbol{p},\boldsymbol{G}}{\text{Minimize}} \quad \max_i(D_i) \quad (4)$$
$$\begin{aligned} s.t. \quad & \sum_{s_i\in\boldsymbol{S}} R_i \geq -\frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}\prod_{s_i\in\boldsymbol{S}} D_i\right) \\ & \quad + h_2(\boldsymbol{S}|\boldsymbol{G}_k^j\backslash\boldsymbol{S}), \qquad \forall \boldsymbol{S}\subseteq\boldsymbol{G}_k^j, \forall j, \boldsymbol{G}_k, k \\ & \sum_{s_i\in X_k} a_{i,c} = 1, \qquad \forall c, k \\ & P_{MIN} \leq p_{i,c} \leq P_{MAX}, \qquad \forall i, c \end{aligned}$$

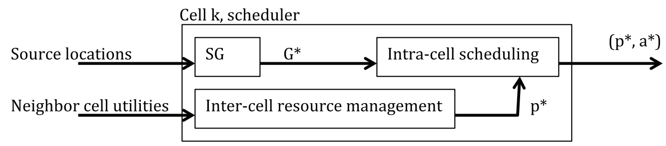

Fig. 2. Scheduler in the base stations.

where R_i is given in Eq. (1). P_{MIN} and P_{MAX} are the transmit power limits. $\boldsymbol{G}_k$ is the source grouping, i.e., set of all the correlated sets in cell *k*, and $\boldsymbol{G}_k^j$ is the j^{th} correlated set in this cell. Parameter $\boldsymbol{S}$ is a possible subset of the correlated set $\boldsymbol{G}_k^j$. The aim is to find the optimum resource allocation vectors $\boldsymbol{a}^*$ and $\boldsymbol{p}^*$; and the source grouping, $\boldsymbol{G}^* = [\boldsymbol{G}_1^*, ..., \boldsymbol{G}_K^*]$. This problem is NP-hard for $C > 1$ based on similar arguments as those given in [2]. We therefore propose in the next section to decompose this problem into three smaller problems that can be solved efficiently.

IV. Three-Step Solution

We separate the resource allocation problem into three steps, as demonstrated in Figure 2, each performed in the scheduler, located in the base station of every cell. The steps are called Inter-cell resource management, Source Grouping (SG), and Intra-cell Scheduling.

A. Approximate Solution

The Inter-cell resource management finds the transmit power limits for each user on each sub-band, given the location of the sources on the field and the performance of the neighboring cells. We use Adaptive ICon [4] for this step. The ICon parameters are adapted in order to balance the utility (i.e., maximum distortion) across the network by increasing or decreasing interference limits of a cell depending on its utility relative to neighbors. The utility achieved in a cell and its neighbors is communicated among the base-stations.

In the Source Grouping (SG) step, the sources are grouped together for joint decoding. We consider correlated groups of one, two, and three sources. We propose a distance-based SG, which also takes the potential added interference of the sources into consideration when finding correlated groups. The intra-cell scheduling step allocates channels to users, given the power and source grouping found in the previous steps. Given that schedulers can have different computational capacity, we propose two methods with different complexities/benefits: 1) a very simple method called D-PF, similar to the common Proportionally Fair (PF) scheduling [5], and modified to take correlation into account, 2) a more complex, but still polynomial time solvable linear programming method, which is a relaxed version of the integer programming scheduling problem.

Each step is performed at different time scales, depending on the design choices. Typically the inter-cell resource management is performed infrequently, since it requires feedback from the decoder. Source grouping is performed whenever sources are moved, or once nodes are added or removed. The intra-cell scheduling is performed often, with a frequency depending on the choice (and therefore complexity) of the scheduling algorithm. We detail each of the subproblems below.

B. Inter-Cell Resource Management

In this step, we find a rule for allocating resources among interfering cells. If no rule is chosen, the Inter-cell resource management is effectively a Reuse 1 scheme, i.e. all resources are used in all cells. We rather propose to use the Adaptive ICon algorithm [4] for inter-cell resource management.

ICon is an inter-cell resource management method based on defining Interference Power Profiles (IPPs). The IPP defines a limit to received interference on each frequency sub-band, which the neighboring cells are obliged to meet. Adaptation of ICon can be performed efficiently, with minimal inter-cell communication. Namely, for each user i in cell k using channel c, the following inequalities must hold: $p_{i,c}.g_{i,u} \leq I_u(c)\ \forall u$, where $I_u(c)$ is the value of IPP of cell u for channel c, and $g_{i,u}$ is the channel gain from user i to base station of cell u. This value is known at the user if we assume channel reciprocity; it can be transmitted to the base station of cell k. The maximum transmit power that does not violate any of the neighbors' IPP is thus determined as $p_{i,c}^{max} = \min_{u,u\neq k} \frac{I_u(c)}{g_{i,u}}$. These transmit power limits control the interference in the network. Namely, a cell scheduler respecting these limits can perform its scheduling independently, without penalizing the other cells.

Going back to the optimization problem given in Eq. (4) and separating the problem to be solved independently in each cell, we find that the objective function in each cell is decreasing in $\boldsymbol{p}$. In other words, when assigned channel c, the user i should transmit at maximum power within its own transmit power limits, $p_{i,c}^* = max(min(p_{i,c}^{max}, P_{MAX}), P_{MIN})$. We thus know the maximum rate for each user on each channel. From Eq. (1), we can write the rate of user i on channel c as

$$R_{i,c}^* = B_c \log_2\left(1 + \frac{p_{i,c}^*.g_{i,k}}{N_0.B_c + P_{kc}^I}\right) \tag{5}$$

where P_{kc}^I is the total interference that the base station of cell k measures on channel c. We can update the optimization problem of Eq. (4) by fixing the power, and thus the rate per channel, to the value defined by inter-cell resource management. In every cell k we have,

Problem 2:

$$\underset{\boldsymbol{a},\boldsymbol{G}_k}{\text{Minimize}} \quad \max_{s_i \in X_k}(D_i) \tag{6}$$

$$\begin{aligned} s.t. \quad & \sum_{s_i\in\boldsymbol{S}}\sum_{c=1}^{C} a_{i,c}R_{i,c}^* \geq -\frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}\prod_{s_i\in\boldsymbol{S}} D_i\right) \\ & \qquad + h_2(\boldsymbol{S}|\boldsymbol{G}_k^j\backslash\boldsymbol{S}), \qquad \forall \boldsymbol{S}\subseteq \boldsymbol{G}_k^j, \forall j, \boldsymbol{G}_k \\ & \sum_{s_i\in X_k} a_{i,c} = 1 \qquad \forall c \end{aligned}$$

The variables now are the channel allocation matrix $\boldsymbol{a}^*$ and the optimum grouping $\boldsymbol{G}^*$. In the next step we find $\boldsymbol{G}^*$, which simplifies the scheduling further.

C. Grouping of Correlated Sources

In order to take advantage of correlation in our framework where sources are encoded independently, we need to make use of joint decoding. The number of sources that are jointly decoded can theoretically be as many as all the sources in a cell; the benefits of exploiting correlation increase with the number of jointly decoded sources. However, increasing the group size beyond two or three sources per group does not offer significant benefits in terms of distortion. Using Eq. (2), we illustrate this point by finding the approximate decrease in total distortion as a result of joint decoding of N correlated sources. For this short illustration, we assume equal distortion in all sources; the minimum distortion is given by:

$$\Delta_{indep} \geq -\sum_{i=1}^{N} R_i + \sum_{i=1}^{N} h_2(Xi) - \frac{N}{2}\log_2(2\pi e), \qquad |\mathbf{G}| = 1$$

$$\Delta_{corr} \geq -\sum_{i=1}^{N} R_i + h_2(\mathbf{G}) - \frac{N}{2}\log_2(2\pi e), \qquad |\mathbf{G}| = N$$

We define $\Delta = 1/2\log_2\prod_N D_i$ to simplify the notation. The overall benefit in log distortion will then be found as:

$$\delta\Delta = \left[\sum_{i=1}^{N} h_2(Xi) - h_2(\mathbf{G})\right]. \tag{7}$$

If all users have equal distortion levels, each user's distortion is decreased by $\frac{\delta\Delta}{N}$ as a result of joint decoding. Using the entropy given by Eq. (3), and with equal distances between sources, diminishing returns of set sizes can be shown. Since large sets increase the Slepian-Wolf decoder complexity, as well as intra-cell scheduling complexity, we consider grouping of only two or three nodes per set.

Grouping affects the performance in two ways, directly and indirectly. The direct effect refers to the performance that a cell achieves as a result of jointly decoding the groups of sources. Specifically, the correlation levels of sources that are grouped together and the channel rate that each source achieves affect the utility in the cell. On the other hand, the indirect effect refers to the impact of the particular grouping method on the cross-layer resource allocation strategy, and therefore on the interference levels in the network.

The direct effect of a particular grouping of sources can be estimated using the rate-distortion region given in Eq. (2), if the data rates of the sources are fixed. However, the rate allocation depends on the source grouping strategy, as well as the inter-cell interference. Even if it cannot be used directly in our framework, the analysis of Eq. (2) still provides a few valuable lessons that we use in constructing our grouping methods. One is that the direct benefit of joint decoding is larger when sources are grouped such that the intra-group correlation is maximized. Additionally, the channel quality for sources in a group affect the final correlation gain. As an example, if a source is jointly decoded with sources that have very low data rates, the benefit achieved by exploiting the correlation is small, even if the correlation is high within the group.

Additionally, recall that we must also take the indirect effects of grouping into account. The indirect effects of grouping are difficult to predict, especially since the prediction requires

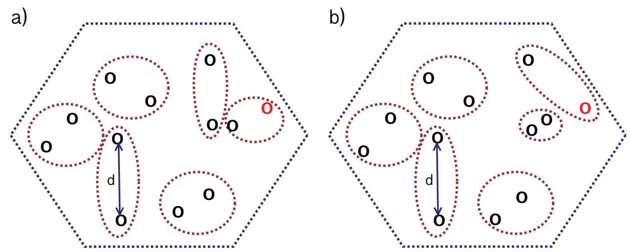

Fig. 3. (a) Result of the distance based grouping method without outer priority (OP); (b) groups resulting from distance based method with OP. The effects of OP can be seen by observing the change of grouping that occurs around the source drawn in red.

knowledge of the load in nearby cells. In Figure 3 we illustrate two source grouping methods, one which only considers the direct effects of SG and another that also considers the indirect effects by prioritizing the outer-cell, high interference users.

We propose two methods for source grouping. These are simple, constructive solutions to an NP-hard problem that cannot be solved optimally in real time. Each of these methods is appropriate for different problem settings. The first method is a distortion-based grouping with outer priority (Distortion OP), which can be used for static networks, where sources are not added or removed, and channel conditions can be assumed constant. The second method is a distance-based grouping with outer priority (Distance OP) which is an adaptive method appropriate for non-static networks. This method does not use the R-D region to find the grouping, and simply uses the fact that the correlation likely decreases with distance between sources.

Distortion-based grouping with OP: The system initially performs independent resource allocation and decoding until performance is stable. Then we pick a random source from N outer-most sources in the cell and compute its expected performance if it is paired with any of the other sources in the cell using conditions in (2). We choose the pairing that results in the lowest distortion and remove the pair from the set. We repeat the process until no node remains and we measure the resulting distortion in the cell. The process is repeated T times with different initializations, and we finally keep the grouping with lowest distortion.

Distance based grouping with OP: Given that the location of sensors is known, we first pick a source at random from the N outer-most sources in the cell. We pair it with its closest neighbor and remove the pair from the set. We repeat the process until no nodes remain and calculate the sum of inter-group distances in the cell. We repeat the method T times and choose the source grouping that achieves the lowest sum of inter-group distances.

When this step is performed, the scheduler of cell k has an updated source grouping (i.e., $\boldsymbol{G_k^*}$ in Eq. (6)).

D. Intra-Cell Scheduling

In the previous phases of the three-step strategy we have determined $\boldsymbol{p}^*$ and $\boldsymbol{G}^*$, i.e., power value and source grouping. In this last step we find $\boldsymbol{a}^*$, namely the channel allocation for each user in a given scheduling period.

We propose two solutions for this phase with different complexity and performance. For schedulers with low computational capacity, we propose the Distortion Proportionally Fair algorithm (D-PF). This solution is similar to the Proportionally Fair (PF) scheduling method [5]; it is however modified to use distortion as utility instead of rate, and to take the correlation effects into account. D-PF scheduling can be performed for every transmission frame. The second solution, OPT, is appropriate for schedulers that are capable of solving a linear programming scheduling problem at every scheduling period. OPT is a relaxed optimal assignment of channels, i.e., the relaxed version of Problem 2 given in (6). This method is solvable in polynomial time. We present below both intra-cell scheduling algorithms in more detail.

D-PF scheduling: With the common PF scheduling, the user that maximizes the following ratio is assigned channel c at each frame [5]:

$$i = \underset{j}{\operatorname{argmax}} \left(\frac{R^*_{j,c}}{\overline{R}_j^{\alpha}} \right) \quad \Rightarrow \quad a^*_{i,c} = 1 \text{ and } a^*_{j,c} = 0, \forall j \neq i.$$

$R^*_{i,c}$ is the possible rate achieved for user i on channel c is given by Eq. (5). $\overline{R}_j$ is the exponentially averaged rate of user j over the previous N_T frames, given as

$$\overline{R}_j(t-1) = (\frac{1}{N_T}).\sum_{c=1}^{C} R^*_{j,c}(t-1) + (1 - \frac{1}{N_T}).\overline{R}_j(t-2).$$

The parameter α is used to vary the trade-off between fairness and sum-rate maximization. The PF scheduling method is simple, yet performs almost the same as relaxed optimal channel allocation for independent sources, as we demonstrated in [4]. However, for correlated sources it is not sufficient to maximize the above ratio, since it ignores the effects of joint decoding.

Therefore, we first define $D^*_{i,c}$ as the possible distortion achieved by user i if scheduled on channel c, and D^*_j as the possible distortion achieved by its correlated group members, i.e., for $j \in \boldsymbol{G}$ and $j \neq i$. In order to find these values, we must use conditions of Eq. set (2) for the group of correlated sources $\boldsymbol{G}$ that i belongs to. These conditions require the knowledge of the values of possible data rate that the source i achieves if assigned channel c in the next scheduling period, as well as the data rates of its correlated group members, which are therefore *not* assigned channel c. We assume that, for every channel c, $R_i = R^*_{i,c}$, and $R_j = 0$ for $j \in \boldsymbol{G}$ and $j \neq i$. Given these possible data rates, then we can use the conditions in Eq. (2) to find $D^*_{i,c}$ and D^*_j.

We finally propose the Distortion Proportionally Fair algorithm (D-PF), which uses the following condition for scheduling user l to channel c:

$$l = \underset{i}{\operatorname{argmin}} \left(\frac{D^*_{i,c}}{\overline{D}_i^{\alpha}} . \prod_{j \in \boldsymbol{G}^*(i)} \frac{D^*_j}{\overline{D}_j^{\alpha}} \right) \quad \Rightarrow \quad a^*_{l,c} = 1 \text{ and}$$
$$a^*_{i,c} = 0, \forall i \neq l$$

where $\overline{D}_j$ is the exponentially averaged distortion of user j over the previous N_T frames, given as

$$\overline{D}_j(t-1) = (\frac{1}{N_T}).D^*_j(t-1) + (1 - \frac{1}{N_T}).\overline{D}_j(t-2) \quad (8)$$

The distortion $D_j^*(t-1)$ is found at the previous scheduling period after the channel assignment matrix $\boldsymbol{a}^*$ is determined, using the conditions in (2) with rates equal to $R_i = \sum_{c=1}^{C} a_{i,c}^*.R_{i,c}^*$. The output is a matrix $\boldsymbol{a}^*$, which is transmitted to the sources at every scheduling period. The above conditions can be readily generalized to more than two correlated sources per decoding group, with the conditions in Eq. (2) solved for decreasing the maximum distortion.

OPT scheduling: Here, each cell finds the scheduling matrix $\boldsymbol{a}^*$ by minimizing the maximum distortion in the cell, with $\boldsymbol{p}^*$ and $\boldsymbol{G}^*$ given in the previous steps. For this, we use Problem 2 in Eq. (6) and relax it to become a linear programming problem. Namely, the values of $\boldsymbol{a}$ are relaxed to be real valued, allowing for time-sharing of each channel between sources. We perform OPT scheduling once every T frames and the real valued vector $\tilde{\boldsymbol{a}}$ is rounded to achieve the corresponding resolution. The problem for cell k is:

Problem 3:

$$\begin{aligned} \underset{\tilde{\boldsymbol{a}}}{\text{Minimize}} \quad & \max_i(\Delta_i + \overline{\Delta}_i) \\ & \sum_{s_i\in S}\sum_{c=1}^{C} \tilde{a}_{i,c}R_{i,c}^* \geq -\frac{|S|}{2}\log_2(2\pi e) + \sum_{s_i\in S}\Delta_i \\ & \quad + h_2(\boldsymbol{S}|\boldsymbol{G}_k^j\backslash\boldsymbol{S}), \qquad \forall \boldsymbol{S}\subseteq \boldsymbol{G}_k^j, \forall j, \boldsymbol{G}_k^* \\ & \sum_{i\in k}\tilde{a}_{i,c} = T, \qquad \forall c \\ & 0 \leq \tilde{a}_{i,c} \leq T, \qquad \forall i, \forall c. \end{aligned}$$

$\overline{\Delta}_i$ is $\log_{10}\overline{D}_i$, given by Eq. (8) and $R_{i,c}^*$ is given by Eq. (5). This is a linear programming problem in $\tilde{\boldsymbol{a}}$, solvable in polynomial time using a method such as the simplex algorithm [22]. After this problem is solved, the matrix $\boldsymbol{a}$ is found by rounding $\tilde{\boldsymbol{a}}$ such that each channel c is assigned to a single source in every transmission frame for the following scheduling period. As in the case of D-PF, the matrix $\boldsymbol{a}$ is transmitted to sources, determining the channel allocation in the following scheduling period.

E. Complexity

We now discuss the complexity of the proposed method. Our correlation-aware resource allocation method barely increases the complexity from the commonly available independent resource allocation schemes. However, complexity of the joint decoder must also be taken into account when considering using correlation in the design.

As discussed in Section IV-A, each step of the proposed algorithm may be performed at different time scales, so we will discuss each step separately. Inter-cell resource allocation period involves the inter-cell resource allocation step, which has a $O(n)$ complexity for n sources in a cell. The SG step has a complexity of $O(n^2)$ for grouping of n sources, in Distance based grouping. The Distortion based grouping can only be performed once in the beginning of the transmission, so it should not be counted in the computational complexity of the online algorithm. In the Intra-cell scheduling step, PF and D-PF have a complexity of $O(cn)$, where c is the number of channels and n is the number of sources. OPT scheduling is a convex optimization problem and is polynomial time solvable,

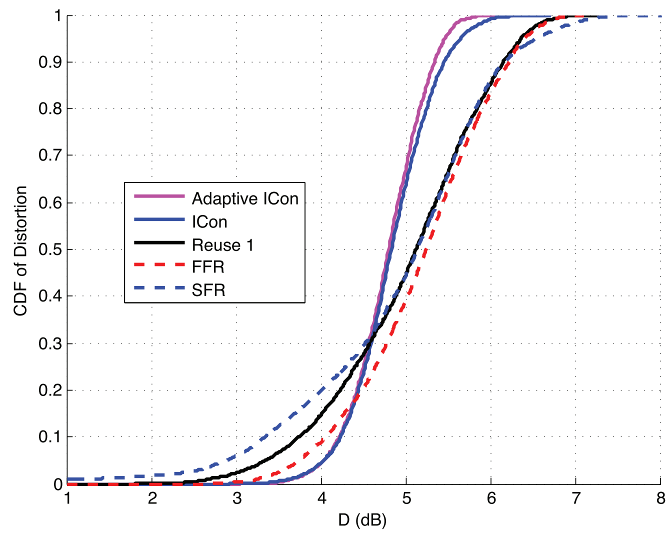

Fig. 4. Distortion of various inter-cell resource management methods.

but the exact complexity depends on the solver used by the scheduler [22].

V. Results

We simulate a 19-cell hexagonal 2-D cellular network, with wrap around in order to avoid boundary inconsistencies. In each instance of the problem, 18 sources are placed randomly with uniform distribution in every cell. Simulation parameters are chosen in accordance with the micro test case in LTE [4]. The observations at the sources are modeled as joint Gaussian random variables with $\sigma^2 = 10$ and $mean = 0$, and correlation parameter $\theta = 100$, as described in Eq. 3. We use the Cumulative Density Function (CDF) of the distortion values and rates achieved by all sources in order to demonstrate the performance of different resource allocation algorithms. This metric illustrates the performance of all the sources in every cell, from the highest performing ones to the most disadvantaged. Since our aim is to minimize the maximum distortion achieved in the network, the parameter we look for is the performance of 5 percentile worst performing users (95 percentile distortion).

In order to compare the inter-cell resource management methods, we simulate FFR, SFR, Reuse 1, static ICon, and Adaptive ICon schemes. In this step we do not use correlation, since we would like to isolate the effects of inter-cell resource management methods. We compare the CDFs of distortions in Figure 4. We observe that using our static ICon inter-cell interference management method compared with Reuse 1, FFR, and SFR, the 95 percentile distortion is decreased by 0.75 dB. FFR, SFR and Reuse 1 perform similarly, with Reuse 1 having a slight advantage. With little communication between base-stations of neighboring cells and Adaptive ICon, this gain is increased to 1 dB.

We now add correlation to the resource allocation method in order to compare source grouping methods. We use D-PF for intra-cell allocation for all methods in this part of the analysis. We first compare in Figure 5 the two grouping methods proposed in Section IV-C, namely distance OP and distortion OP for groups of two sources. We also show the

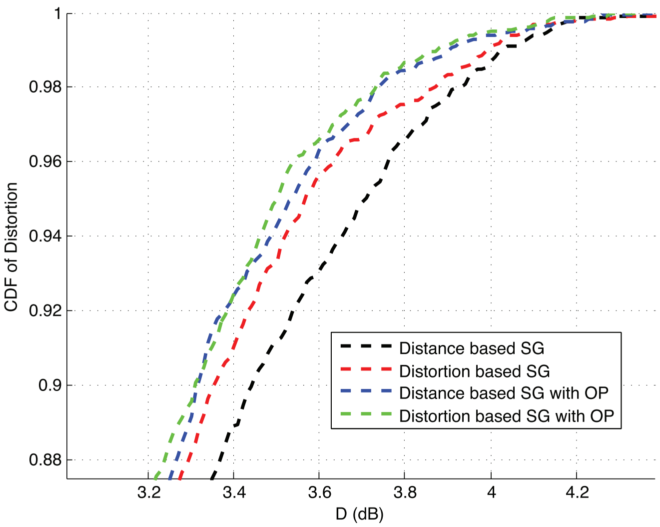

Fig. 5. Comparison of the grouping methods (two sources per group).

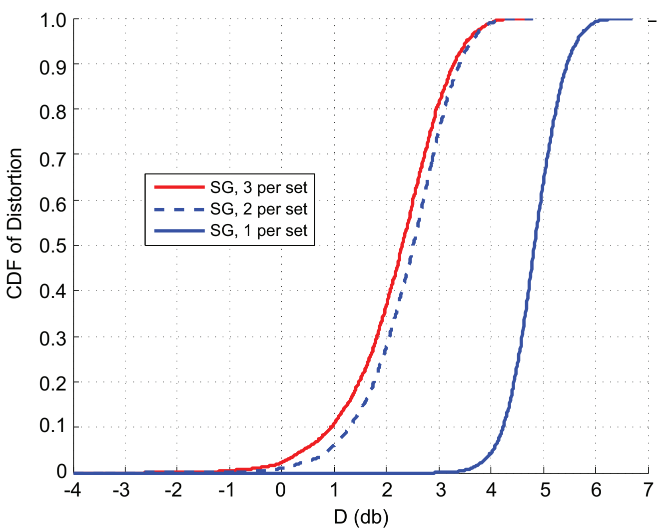

Fig. 6. Influence of the size of the groups in the resource allocation scheme.

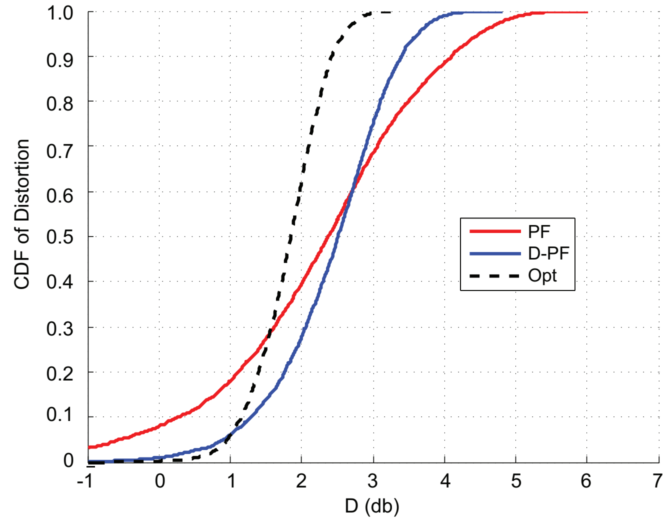

Fig. 7. Comparison of CDF of distortion in D-PF, PF, and OPT scheduling.

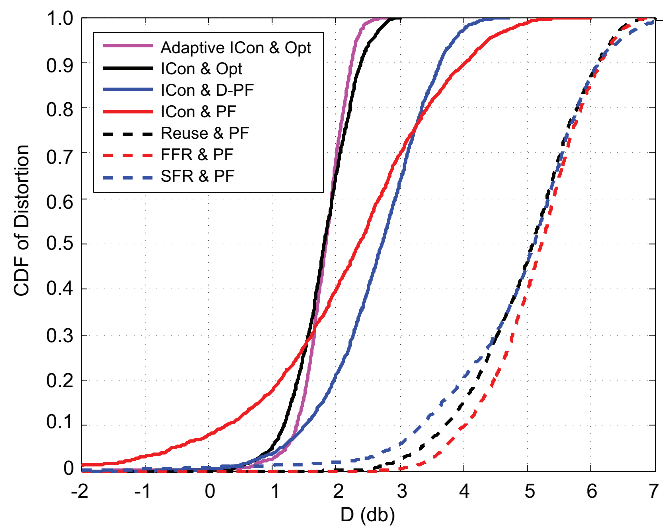

Fig. 8. Comparison of our resource allocation methods with SFR, FFR, and reuse 1.

effects of using outer priority in the grouping algorithm. We find that distortion OP performs slightly better than distance OP, however distortion OP cannot be used adaptively. We also compare the effects of the group size in Figure 6. Increasing the size from one user per group (i.e., independent decoding and independent resource allocation) to two users per group decreases the 95 percentile distortion by 2 dB (37%). As expected, there is almost no difference in performance when we increase the group size from two to three sources.

We then compare the intra-cell scheduling methods, namely, PF, D-PF, and OPT, with inter-cell method given by static ICon and 2-source grouping with Distance OP for all comparisons. The results are shown in Figure 7, where the correlation is used in joint decoding, but not in resource allocation. The comparison of the PF curve with the independent decoding and resource allocation case, demonstrated in Figure 6 in the case of 1 source per group, highlights the benefits of exploiting correlation, achieving 1.25 dB (or 25%) decrease in 95 percentile distortion. On the other hand, comparison of D-PF with PF highlights the added benefits of correlation-aware resource allocation, achieving an additional 0.75 dB decrease in distortion, adding up to 37% loss in distortion. Using OPT scheduling instead of D-PF increases this distortion loss further, adding up to 1.75 dB over PF scheduling, for a total of 50% loss over the independent case.

Finally we show in Figure 8 the overall performance of the three-step strategy, with Adaptive ICon, Distance OP source grouping (two sources per group), and optimal intra-cell scheduling. We compare to Reuse 1, FFR and SFR with PF scheduling. Overall, we demonstrate that our method can achieve a large improvement with almost a 4 dB (60%) decrease in distortion for 5 percentile users compared to common LTE methods.

VI. Conclusion

We have considered the problem of resource allocation between spatially correlated sources in FDMA multi-cell networks. This is an NP-hard problem for which exhaustive solutions are not computationally feasible in practice. We proposed a cross-layer solution that performs effective but suboptimal resource allocation in three simple steps. We evaluated our design choices in simulations by comparing various methods for each step of the algorithm, and we showed considerable gain over methods that do not exploit correlation. Additionally, we showed that while there is significant benefit in using correlation in joint decoding, adding even a simple correlation-aware resource allocation improves this performance by a large amount. We plan to extend this work by characterizing the effects of uncertainty in correlation and source models on resource allocation performance.

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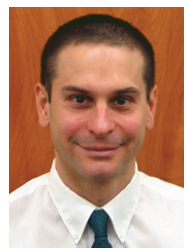

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