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Resource Allocation for Sources with Correlated Data

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To my parents for all their support.

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Acknowledgments

(Will be added before submission)

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Publications

D. Bandari, P. Frossard, and G. Pottie, "An Adaptive Cross-layer Resource Allocation Scheme for Correlated Wireless Video Sources." *in Proceedings of Wireless Communications and Networking Conference (WCNC)*, Cancun, Mexico, March 2011.

D. Bandari, G. Pottie, and P. Frossard, "ICon: Interference Concentration for Uplink in MultiCell OFDMA Networks." *in Proceedings of Wireless and Mobile Computing, Networking and Communications (WiMob)*, Shanghai, China, Oct. 2011.

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Abstract of the Dissertation

Resource Allocation for Sources with Correlated Data

by

Dorna Bandari

Doctor of Philosophy in Electrical Engineering

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Professor Gregory J. Pottie, Chair

When several nodes in a network share limited communication resources, the media access protocol is implemented in order to determine the allocation of resources to each node. This strategy is a key component in design of networks with high transmission efficiency. Additionally, when nodes observe and transmit correlated information, their correlation characteristics can be used in the media access protocol in order to increase the efficiency of the communication network.

This thesis studies the problem of cross-layer resource allocation for correlated sources. For several specific cases of single cell and multi-cell networks, novel and practicable solutions are proposed and verified with simulations.

First for the uplink transmission in a single cell, a Code Division Multiple Access (CDMA) network of correlated video sensors is considered. A novel cross-layer resource allocation strategy is proposed with the goal of maximizing the weighted average of all reconstructed video qualities. The algorithm finds the power and orthogonal code assignment to each sensor, using no communication among sensors and minimal communication between sources and the receiver. Compared with independent methods, the cross-layer correlation-aware resource

allocation achieves significant gain in average sensor video quality.

Secondly, a cross-layer resource allocation strategy is proposed for multi-cell Orthogonal Frequency Division Multiple Access (OFDMA) networks of general correlated sources. This method assumes a distance based correlation model among the sources. The goal is to find the power and orthogonal frequency sub-band assignment in order to minimize the maximum distortion achieved by any source in the network. The challenge in this case is to take both the inter-cell interference and the source correlation characteristics into consideration in the resource allocation strategy. Our proposed solution solves this large NP-hard problem in three simple, workable steps.

Additionally, this thesis contributes to the problem of resource allocation for general multi-cell OFDMA communication networks by introducing a novel inter-cell interference management scheme, called ICon. This method is based on concentrating the interference to a cell on a pre-determined frequency band, which is adapted in order to balance the performance across the network.

CHAPTER 1

Introduction

With high rate wireless communication becoming more commonly used in recent years, and the rise in the number of devices that share the same wireless medium, efficient use of system resources is gaining more importance. A key component of the design of an efficient multi-user system is the multiple access protocol, which consists of the algorithms and parameters that dictate the allocation of resources to users. Furthermore, when the system parameters are variable, adaptation in this resource allocation strategy can achieve significant gain over static methods. Therefore, it is desired to adaptively allocate resources to the users sharing the common medium, such that the utility chosen for the system is optimized. The broad objective of this thesis is to understand and develop algorithms for this problem in specific system settings.

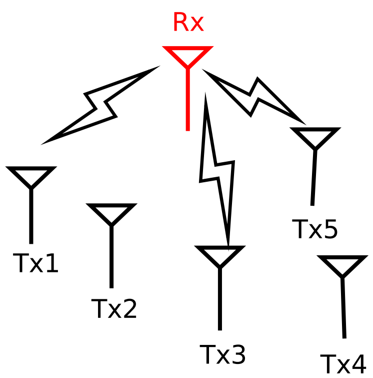


Figure 1.1: In multi-user networks many users share the common radio resources.

This chapter first defines and motivates the specific cases that were studied in this thesis. Then it lists the contributions and organization of this work.

1.1 Cases Considered

1.1.1 Correlation-aware Design

In some applications, such as Wireless Sensor Networks (WSNs) that measure temperature, humidity, audio and video, the sources capture and transmit correlated information. Correlation can be used in the Presentation layer of OSI (in coding) in order to increase the coding efficiency. Additionally, coding using correlation facilitates a trade-off of rates and distortions among the correlated users, characterized by the rate-distortion (R-D) region. This trade-off can be used in resource allocation in order to increase the transmission efficiency.

1.1.2 Multi-view Video Systems

Of the applications of correlation-aware resource management, an important one is resource allocation for multi-view video systems. As an example, an array of cameras capturing the same scene will have correlated footage, and correlation characteristics of the captured videos can be used in joint decoding, as well as in resource allocation when transmitting to a common receiver. The challenges in this case are to: 1) Assume and verify a model for the rate-distortion region for lossy joint coding of correlated videos. 2) Perform distributed resource allocation, since the rate-distortion characteristics of each camera vary in time and cannot be communicated with the receiver.

1.1.3 Cellular Systems

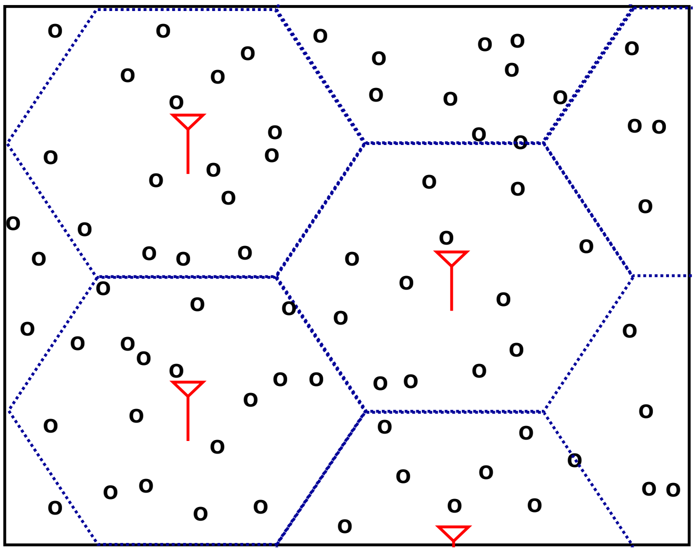


Figure 1.2: Cellular systems.

In recent years, higher data rates have been required from cellular systems, namely the mobile phone networks, as a result of a surge in mobile web devices. Multi-cell networks cover large geographical areas in order to ensure continuous coverage for these devices, and therefore reuse the spectrum at spatially separated areas. The resource allocation problem in this case should both address the inter-cell and intra-cell resource management. Inter-cell resource management is the strategy that determines how the resources are divided among the cells, which involves interference management, while intra-cell finds the resource allocation to users in a given cell. The optimal resource allocation in cellular networks is a large NP-hard problem, and requires heuristics based approximations and simplifications. We study the general adaptive resource allocation for multi-cell networks, as well as the case with correlated sources.

1.2 Contributions

The objective of this thesis is to study the problem of correlation-aware cross-layer resource allocation, and to propose practical solutions for this problem in various network settings. Our main contributions are as follows:

- A novel algorithm for correlation-aware resource allocation for video sensor networks using CDMA is proposed. The proposed end-to-end method works by using a simple correlated video decoding scheme, and models the resulting joint R-D function of the sources as a piecewise linear model.
- A novel adaptive interference management scheme is proposed for the uplink of multi-cell OFDMA networks. The interference to every cell is concentrated on a designated frequency band, which is easily adapted in order to balance the performance across the network.
- An original workable strategy is proposed for resource allocation for sources with correlated information in multi-cell OFDMA networks, taking into account both the inter-cell interference and correlation characteristics of source into account.

1.3 Organization

The remainder of this thesis is organized as follows. Chapter 2 presents some background technical information required to understand this thesis. Chapter 3 defines the resource allocation problem for multi-view video sources. Our solution is proposed in Section 3.3 and simulations presented in Section 3.4. Chapter

4 presents a solution for inter-cell resource management, namely, ICon. The solution is described in Section 4.3, and the simulation results are given in Section 4.5. Chapter 5 defines and solves the correlation-aware resource allocation for multi-cell networks. The solution is described in Section 5.4 and simulations are presented in Section 5.5. Chapter 6 concludes this thesis.

CHAPTER 2

Technical Background

This Chapter presents a number of topics required for understanding this research. We will briefly discuss and provide further references for convex optimization, multiple access protocols, resource allocation, and correlated source coding.

2.1 Convex Optimization

The significance of convex optimization is in its ability to solve large, practical engineering problems consistently, using efficient algorithms. In this Section we provide the general formulation of convex optimization problems, as well as describe the Lagrange dual decomposition method, appropriate for splitting a large global optimization problem into locally solvable problems. For further reading on the subject, please refer to [BV04].

2.1.1 General Formulation

A function, $f(x)$ is convex if its graph lies below the line which joins any two points of the graph. Figure 2.1 demonstrates a convex function of one variable.

Convex optimization studies the minimization of convex functions over constraints also defined by convex functions, i.e. over a convex set. Many communi-

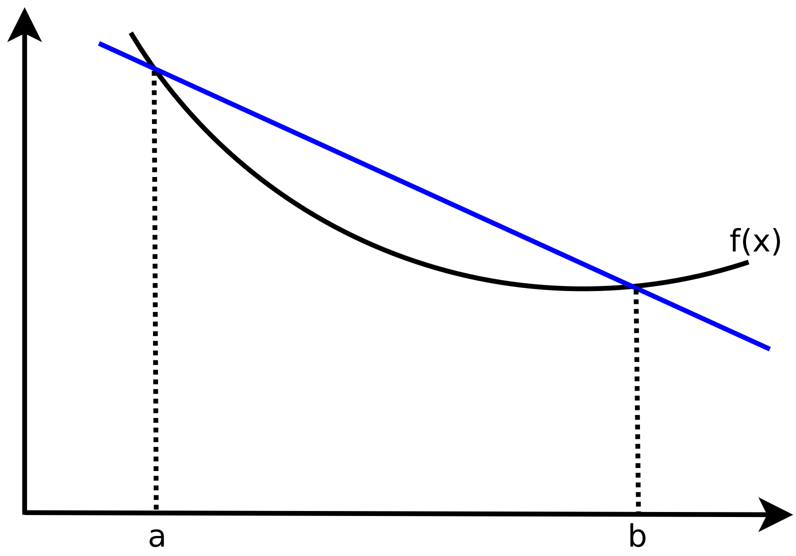


Figure 2.1: A convex function of one variable.

cations problems can be formulated in the following format:

$$
\begin{array}{lll}
\underset{x}{\text{Minimize}} & f_0(x) & \\
\text{Subject to} & f_i(x) \leq 0, & i = 1, ..., N \\
 & h_j(x) = 0, & j = 1, ..., M
\end{array}
$$

In the above, if $f_i(x)$ for $i = [0, ..., N]$ are convex functions, and $h_j(x) = 0$ for all $j = [1, ..., M]$ are affine functions of x, the problem is a convex optimization problem. A special case of convex optimization is Linear Programming, which is when all the above functions are affine.

Convex optimization problems can be solved efficiently using algorithms such as interior point methods, sub-gradient method, and in case of Linear Programming, the Simplex algorithm. Linear Programming can be solved in polynomial time using interior point methods, or in polynomial time average-case using the Simplex algorithm. Many software packages exist that perform convex optimization, we used the CVX package for Matlab [GB11].

2.1.2 Augmented Lagrangian Dual Decomposition Method

In large scale problems it sometimes occurs that the objective function is separable and solvable locally by smaller units, e.g. when the objective function is the sum of utilities of all the units. However some constraints, such as the limits on total available resources used by the units, couple the local problems. These constraints prevent the optimization problem from being separable, and solvable locally by each unit. The Augmented Lagrangian Dual Decomposition method can be used in such cases in order to enable a distributed solution, requiring only minimal coordination with a "coordinator" node. For further reading on the subject, please refer to [PC06].

2.2 Multiple Access Protocols

In multiuser systems, sources share common communication resources. The resources can be shared among the sources in a variety of ways. Namely, they can be divided along the time (time-division multiple access, TDMA), frequency (frequency-division multiple access, FDMA), and code (code-division multiple access, CDMA) axes. In this thesis we have utilized the FDMA and CDMA methods, and we briefly describe each method in this Section. For further reading on the subject, please refer to [Gol05].

2.2.1 CDMA

In order to share the same radio channel, users in a network can modulate their signal by different spreading codes. The spreading codes can be orthogonal or non-orthogonal. Orthogonal codes have zero cross-correlation, therefore a receiver can recover any of the signals by multiplying the received signal by the respective spreading code. Non-orthogonal codes have non-zero, small cross-correlation. In this case the receiver recovers the desired signal plus attenuated undesired signals. In systems with orthogonal CDMA, users do not cause interference to each other in the network. However they have to be synchronized. Users in systems that employ non-orthogonal codes on the other hand do not have strict synchronization requirements, but they cause interference to other users and therefore power control must be performed in order to limit the interference. In this thesis we only consider the orthogonal CDMA.

2.2.2 FDMA

In FDMA, users are each assigned a different frequency sub-band from the total bandwidth. The OFDMA technique implements this by assigning orthogonal subcarriers to each user. In this case, users do not interfere within the network. Since users may experience different channel conditions on different sub-bands, OFDMA can exploit multi-user diversity by enabling channel condition-aware channel allocation, which is not possible in techniques such as TDMA and CDMA.

2.3 Resource Allocation Problem

In multiuser systems, in addition to selecting an appropriate multiple access protocol for the given network, the allocation of the resources defined by the multiple access scheme to users should also be found. In resource allocation problems the issue is the assignment of limited communication resources to users. In this chapter we discuss the general formulation of the resource allocation problem and the case for multi-cell systems. For further reading on the subject, please refer to [ZQ01].

2.3.1 General Formulation

The aim of resource allocation is to assign limited communication resources to users, such that a pre-defined utility is maximized in the network. When channel conditions or transmission requirements of users change in time, the resource allocation must be performed adaptively. First, an appropriate utility function should be chosen for the system, and the relationship between the resource assignment to users and network utility should be derived. Given this relationship, the resources must be assigned such that the utility is optimized.

For example, for CDMA multiple access schemes, the following optimization problem finds the power and code assignment to each user such that the sum-rate of users is maximized, while resources are within the limits.

$$\begin{aligned} \underset{(p_i,k_i)}{\text{Maximize}} \quad & \sum_{i=1}^{N} R_i \\ s.t. \quad & p_i \leq P_{iMAX} \qquad\qquad \forall i \in [1:N] \\ & \sum_{i=1}^{N} k_i \leq K \end{aligned}$$

where p_i and k_i are the power and number of codes assigned to user i, and P_{iMAX} and K are the power and code resource limits. The relationship between the utility and the resources is given as follows,

$$R_i = k_i.B.log(1 + \beta_i.\frac{p_i.g_i}{N_0.B.k_i})$$

where B is the total available bandwidth and β_i is the SNR gap, which accounts for the difference between the theoretical achievable rate and the achievable rate in a real system. g_i is the channel gain for user i, and N_0 is the noise floor.

2.3.2 Multi-cell systems

In order to cover a large geographic area efficiently, infrastructure-based wireless networks can be divided into cells, each cell containing a base-station which is connected to the backbone wired network. This enables efficient use of resources by reusing frequency spectrum in geographically separated areas. However, the resource allocation task thus becomes more complicated, since orthogonal resource allocation across the whole network is no longer possible or efficient. Inter-cell interference management addresses the issue of resource allocation among interfering cells, and is part of the resource allocation problem for multi-cell systems.

2.4 Correlated Sources

When sources gather and aim to transmit correlated information, correlation should be used in both the coding and resource allocation in order to increase the efficiency of the system. This occurs in wireless sensor networks (WSNs) where sensors on a field measure various parameters such as temperature, humidity, audio or video. In this work we have considered an array of video sensors capturing the same scene from different angles, as well as general WSNs. In this section we discuss the joint coding basics and the rate-distortion region.

2.4.1 Joint Rate-Distortion Region

When sources capture and transmit correlated data, correlation can be used in joint coding in the Presentation layer (of OSI layers) in order to increase the coding efficiency. The coding scheme can provide the relationship between the compression rate and the distortion caused to the data after reconstruction. This relationship is characterized by the rate-distortion (R-D) bound.

For general sources, in this work we assume that the coding is performed using lossy joint Distributed Source Coding (DSC). DSC is used for compression of correlated sources that do not communicate [XLC04]. In the case of DSC, this region is defined jointly for all the sources involved. The bound was found by Wyner and Ziv for lossy joint coding of correlated sources, known as the Wyner-Ziv (WZ) bound [WZ76] [ZB99]. For two correlated users, it is given as follows:

$$\begin{aligned}
&R_1 \geq h_2(X_1|X_2) - \frac{1}{2}\log_2(2\pi e D_1) \\
&R_2 \geq h_2(X_2|X_1) - \frac{1}{2}\log_2(2\pi e D_2) \\
&R_1 + R_2 \geq h_2(X1, X_2) - \frac{1}{2}\log_2\Big((2\pi e)^2 D_1 D_2\Big)
\end{aligned}$$

For multi-view video systems, we have used a simple joint decoding, which is based on replacing dropped frames of a video by corresponding frames from a correlated neighbor. This way, when resources are scarce, a video source can drop its frames, and thus decrease its required transmission rate, without its video quality being severely degraded. This is a simple scheme for using correlation in coding. For this simple joint video coding scheme we model the R-D bound of a sensor as a piecewise linear function of distortions of the correlated neighbors, as demonstrated in Chapter 3.

CHAPTER 3

Correlation used in resource allocation for single-cell networks

3.1 Introduction

In this chapter we consider a scenario where several cameras capture a live event and stream it simultaneously to a base station. The applications are live coverage of concerts, conferences, or political events. With free-view and multi-view video becoming more popular, and with limited resources in wireless transmission, we expect an increased demand for more efficient streaming of correlated videos.

We consider the scenario of N video sources transmitting correlated video streams through a shared wireless channel to a common base station, before delivery to the decoder. In this work we consider a regular H.264 video encoder and a simple decoder which uses correlation between sources for concealment of missing frames. The goal is to maximize the weighted sum of received video qualities given the resource constraints. The decoder may use source correlation to decode the N videos in case of insufficient bandwidth or loss, as shown in Figure 3.1. We consider Code Division Multiple Access (CDMA) as the MAC scheme, however the methods developed in this paper can be applied to other access schemes. We formulate an optimization problem that selects the best code, power assignment, and packet selection at each wireless source, with minimal feedback from the base station.

We introduce a piecewise linear model for the quality of each video decoded using correlated information and show the validity of the model for a two node case. This model enables us to split the global optimization problem into separate problems that are solved at each station, and to iteratively converge to the global optimum using updates from the base station. We apply a cross-layer algorithm for the sources to find their individual optimum MAC parameters and packet scheduling with minimal information exchange with the base station.

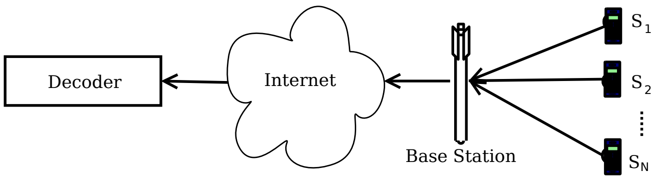


Figure 3.1: General framework: N sources stream live video to the base station on a shared bottleneck channel, before it is forwarded to the decoder.

When transmitting dependent videos, it is desirable to use correlation characteristics to increase communication efficiency. An area of research that considers correlated video streams is multiview video coding (MVC). In MVC multiple cameras capture the same scene from different views, producing correlated video sequences that are encoded jointly in order to increase the overall compression performance [WW00], at the price of inter-camera communication. Alternatively, distributed coding techniques have been proposed for the independent encoding of correlated camera sources; the complexity is shifted to the joint decoder that exploits the inter-view correlation for effective reconstruction [YR10]. DSC has been studied jointly with the resource allocation problem in [KSS10]. However, the resource allocation method does not take advantage of the developments in cross-layer design.

In general, the wireless resource allocation for correlated video sources has not been studied extensively in the literature. In the area of multimedia communication for independent sources, it has been thoroughly demonstrated that there is significant benefit in using cross-layer design as compared to traditional layered design for live video transmissions [SRK03] [DN05]. The works in [SBA10] and [SL05] propose optimal solutions for a utility-based cross-layer resource allocation. These methods however consider downlink communications, which does not present the same challenges as uplink, in particular the fact that each sources' individual constraints (e.g., power) also needs to be considered.

Among uplink optimum resource allocation solutions, the following three papers are most related to our work. In [HSB07] an uplink OFDM system is considered and a utility-based objective function is optimized, although not specific to video sources. In [SS08] optimal resource allocation is performed for uplink transmission of video sources; specifically algorithms are developed to assign MAC resources to each video source in a centralized manner, optimizing overal received quality. In [Cha06] optimum rate allocation and packet scheduling for video sources is found for uplink tranmission, with the objective of maximizing the overall video quality. However the individual MAC parameters are not found, which does not allow for adaptation to changes in availability of individual resources. None of the works explicitly consider the sources' correlation in the rate allocation problem.

The rest of the sections of this chapter are as follows. In Section 3.2 we introduce the framework of our proposed method and formulate the problem. In Section 3.3 we discuss the piecewise linear model and give details on the optimization solution. In Section 3.4 we present simulations for validation of the piecewise linear quality model, as well as overall resource allocation results.

3.2 Problem Settings

3.2.1 Framework

We consider the transmission of N correlated video sources through one common base station. We consider that the sources have no possibility to precisely adapt the video encoding to the actual transmission conditions, so that the rate allocation problem becomes equivalent to a packet scheduling optimization. A joint decoder reconstructs each of the views. It uses the inter-view correlation information to compensate missing information due to frames that have been lost or dropped. We consider here a very simple concealment strategy where missing frames are replaced by the corresponding data in the most correlated views. Note that the error concealment can be chosen differently without affecting the resource allocation framework proposed in this chapter.

Our objective is to maximize the weighted sum of qualities of all received videos. In case of concealment we model the quality of each video as the weighted sum of qualities of its neighbours, where the weights depend on video characteristics, correlation between sources, and packet loss probability. Then the global optimization problem is split into local optimization problems solved at each source, and the global optimum is reached iteratively by using updates from the base station. As we choose CDMA as the Multiple Access scheme, the variables to be found are the optimum code and power assignment and packet scheduling for each individual source.

3.2.2 Problem Formulation

First, we note that the transmission rate can be written as a function of the MAC parameters. In a Gaussian multiple-access channel, the achievable rate for user i

in terms of CDMA parameters is given by [Gol05],

$$R_i = k_i.B.log(1 + \zeta_i.\frac{p_i}{k_i}), \tag{3.1}$$

where p_i is the power allocated to user i and k_i is the number of orthogonal codes assigned to it. B is the total available bandwidth, and $\zeta_i = \beta_i \frac{g_i}{N_0.B}$. The parameter β_i is called the SNR gap, which accounts for the difference between the theoretical achievable rate and the achievable rate in a real system. g_i is the channel gain for user i, and N_0 is the noise floor. We name $\frac{N_0.B}{g_i}$ the *Normalized Noise* for user i.

The resource allocation problem consists in finding the optimal code choice, power assignment and packet selection at each of the CDMA sources, so that the overall quality is maximized. The problem can be formulated as follows.

$$\begin{aligned} \underset{(p_i,k_i)}{\text{Minimize}} \quad & -Q_T(\boldsymbol{R}) && \\ s.t. \quad & p_i \leq P_{iMAX} && \forall i \in [1:N] \\ & \sum_{i=1}^{N} k_i \leq K && \\ & \sum_{i=1}^{N} p_i \leq P_T && \end{aligned} \tag{3.2}$$

$Q_T(R)$ represents the objective function, with the aggregate decoding quality. It is a function of $\boldsymbol{R}$, the vector of rates of each source as given by Eq (5.1). P_{iMAX} is the maximum power for source i, K is the total number of available codes, and P_T is the total power that can be used by the network. In the next section we propose a solution to optimize this problem with a simple iterative algorithm.

3.3 Optimal Resource Allocation

3.3.1 Aggregate Utility Model

In general, the quality of a decoded video stream, when decoded using correlation irrespective of the decoding scheme, is a function of its own data rate as well as data rates of videos that are correlated to it. When the rates are denoted by the vector $\boldsymbol{R}$, the quality of video i becomes

$$Q_i^c(\boldsymbol{R}) = f(R_1, R_2, R_3, ...) \tag{3.3}$$

A concave, monotonically increasing quality-rate function can be constructed for any video stream. When the stream is pre-encoded, rate adaptation can be achieved by packet filtering. A packet ordering algorithm such as one proposed in [CF05] can be used to order the frames so that the least important packets are dropped first when resources become scarce.

That being said, our resource allocation method does not require all nodes to order their frames, and if complexity is strictly constrained, each node can choose to use a known model for its Q-R function. Of course, using a model results in a sub-optimal solution. One such function is given in [SFL00]. Whether a known model is used or an optimum algorithm utilized, the resulting quality-rate function is bijective. Therefore we can replace the rate in equation (3.3) by the quality from the estimated Q-R function, formulating the decoding quality as a function of quality of the correlated video sequences, i.e.,

$$Q_i^c(\boldsymbol{R}) = f(Q_1(R_1), Q_2(R_2), Q_3(R_3), ...)$$

We now propose a simple piecewise first order approximation of the above function in the decoder, with a linear combination of qualities:

$$Q_i^c(\boldsymbol{R}) = \sum_{j=1}^{N} \alpha_{ij}^m . Q_j(R_j) + \delta_i^m, \quad \boldsymbol{Q}_N \in C_m^N. \tag{3.4}$$

$\boldsymbol{Q}_N$ is the array of quality-rate functions, i.e. $[Q_1(R_1)...\text{-}Q_N(R_N)]$. The model parameters, α_{ij}^ms and δ_i^ms are estimated for the range of values of $\boldsymbol{Q}_N$ that belong to the N dimensional space C_m^N. In this work C_m^Ns are constructed by partitioning the range of possible values for qualities of each video into 2dB sections. Therefore any value for the array of qualities, $\boldsymbol{Q}_N$, belongs to one such space.

The model parameters are initially calculated at the decoder by decoding videos in two ways; regular decoding, which results in videos with qualities $\boldsymbol{Q}_N$, and correlated decoding, which is used to find values for $Q_i^c(\boldsymbol{R})$s. Then, for each range of video quality values, C_m^N, the model parameters, $\boldsymbol{\alpha}^m$ and $\boldsymbol{\delta}^m$, are found by fitting the video quality values to the model from Equation (3.4), using LMS.

Depending on the correlation level and the qualities of the correlated videos, it is possible for the correlated decoding method to decrease the quality of a decoded video when compared to regular decoding, i.e., for some i and some m,

$$Q_i^c(\boldsymbol{R}) < Q_i(R_i), \quad \boldsymbol{Q}_N \in C_m^N.$$

To ensure that we always decode using the method that achieves the higher decoded quality, the decoder can simply set the model parameters to a row of the identity matrix in such cases.

$$\text{if } \sum_{j=1}^{N} \alpha_{ij}^m . Q_j(R_j) + \delta_i^m < Q_i(R_i), \text{ set } \begin{cases} \alpha_{ii}^m = 1, \\ \alpha_{ij}^m = 0, \ \forall j \neq i \\ \delta_i^m = 0. \end{cases}$$

The aggregate quality of the network finally becomes

$$
\begin{aligned}
Q_T(\boldsymbol{R}) &= \sum_{i=1}^{N} \gamma_i . Q_i^c(\boldsymbol{R}) \\
&= \sum_{j=1}^{N} \left(\sum_{i=1}^{N} \gamma_i . \alpha_{ij}^m . Q_j(R_j) \right) + \sum_{i=1}^{N} \delta_i^m . \gamma_i \\
&= \sum_{j=1}^{N} \eta_j . Q_j(R_j) + \delta_j^m . \gamma_j, \qquad (3.5)
\end{aligned}
$$

where $\eta_j = \sum_{i=1}^{N} \gamma_i . \alpha_{ij}^m$ and γ_i is a parameter set by network administrators as a measure of relative importance of each video stream in the aggregate quality function. It can be shown that the above is a concave function of p_i and k_i [BV04], which makes (3.2) a convex optimization problem with linear constraints.

3.3.2 Optimization Solution

In order to solve the optimization problem presented in Section 5.3 we first formulate it as an unconstrained optimization problem. The Lagrangian cost function is given by

$$
L(\boldsymbol{k}, \boldsymbol{p}, \boldsymbol{\lambda}, \nu, \omega) = -Q_T(\boldsymbol{R}) + \boldsymbol{\lambda}.[\boldsymbol{p} - \boldsymbol{P_{MAX}}]^T + \nu.(\sum_{i=1}^{N} k_i - K) + \omega.(\sum_{i=1}^{N} p_i - P_T),
$$

where $\boldsymbol{\lambda} = [\lambda_1 \lambda_2 ... \lambda_N]$, ν and ω are the dual variables, $\boldsymbol{p} = [p_1, p_2, ..., p_N]$ is the vector of power assignments, $\boldsymbol{k} = [k_1, k_2, ..., k_N]$ is the vector of number of codes assigned to each user, and $\boldsymbol{P_{MAX}} = [P_{1MAX}, P_{2MAX}, ..., P_{NMAX}]^T$ is the vector of power limits of each user. K is the total number of codes, and P_T is the maximum total power allowed in the network. Then taking the infimum over $\boldsymbol{k}$ and $\boldsymbol{p}$ will result in the Lagrange dual function,

$$
g(\boldsymbol{\lambda}, \nu, \omega) = \inf_{\boldsymbol{k}, \boldsymbol{p}} (L(\boldsymbol{k}, \boldsymbol{p}, \boldsymbol{\lambda}, \nu, \omega))
$$

In this problem strong duality holds, therefore solving the Lagrange dual function will solve the primal problem. To solve the unconstrained concave dual problem, the partial derivatives of Lagrangian function with respect to $\boldsymbol{p}$ and $\boldsymbol{k}$ are set to zero. For each station we get the following two equations,

$$B.\eta_i.\left[\log(1+\zeta_i.\frac{p_i}{k_i})-\frac{p_i.\zeta_i}{(k_i+p_i.\zeta_i).\ln(10)}\right].\frac{dQ^{(i)}(R_i)}{dR_i}=\nu \tag{3.6}$$

$$\frac{B.\eta_i.\zeta_i}{\ln(10)}.[\frac{k_i}{k_i+p_i.\zeta_i}].\frac{dQ^{(i)}(R_i)}{dR_i}=\lambda_i+\omega \tag{3.7}$$

Once the above two equations are solved for p_i and k_i in each station, the dual optimal variables can be found iteratively using the sub-gradient method. Starting from $\boldsymbol{\lambda}^0, \omega^0, \nu^0$, repeat,

$$\lambda_i^{k+1}=(\lambda_i^k+\theta.(p_i^*-P_{iMAX}))^+ \tag{3.8}$$

$$\nu^{k+1}=(\nu^k+\delta.(\sum_{i=1}^{N}k_i^*-K))^+ \tag{3.9}$$

$$\omega^{k+1}=(\omega^k+\varepsilon.(\sum_{i=1}^{N}p_i^*-P_T))^+. \tag{3.10}$$

$\theta, \delta,$ and ε are small constants, and $(x)^+$ is 0 for $x \leq 0$ and x otherwise. Since source nodes do not have access to information about other stations' power and code assignment, the variables ν^{k+1} and ω^{k+1} have to be computed at the base station or the receiver. Their value is periodically broadcasted back to the stations. Algorithm 1 describes this method.

At each source, the system of equations, (3.6) and (3.7) is solved by defining a new variable, $X_i = (1+\frac{p_i}{k_i}.\zeta_i)$, and dividing the two equations in order to eliminate $\frac{dQ^{(i)}(R_i)}{dR_i}$. After rearranging, we get the following:

$$X_i.(\log(X_i)-\frac{1}{\ln 10})=\frac{\nu.\zeta_i}{(\lambda_i+\omega).\ln 10}-\frac{1}{\ln 10}. \tag{3.11}$$

There is always a unique solution for X_i. This can be solved by a simple table look up at each source. Once X_i is found, each station finds its own optimum

Algorithm 1: Optimal Resource Allocation

Input: Constraints: $K, P_T, \boldsymbol{P}_{MAX}$; Channel parameters: $B, \boldsymbol{\eta}, \boldsymbol{\zeta}$; C_m^Ns found by 2dB partitions of video quality values.

Initialization: $\nu^0 = \omega^0 = 0.5, \lambda_i^0 = 0.5 \quad \forall i,\ k = 0,$ flag $= 0, \boldsymbol{\alpha}^n = I_{N\times N} \quad \forall n, andm = 0.$

Repeat:

At each source, i**:**

1) Capture and encode W_k video frames.
2) Arrange frames in the order of contribution to video quality, or assume a model for the Q-R plot, as in Section 3.3.1.
3) Using ν^k, ω^k and λ_i^k find p_i^*, k_i^* and optionally the optimum set of frames to transmit by solving Equations (3.11) through (3.13).
4) Transmit the optimum set of frames using MAC parameters, p_i^*, k_i^*.
5) Update λ_i^{k+1} using Equation (3.8).

At base station:

6) Receive video frames from all sources, forward to the decoder.
7) Find ν^{k+1} and ω^{k+1} using (3.9) and (3.10).
8) Broadcast ν^{k+1} and ω^{k+1}, and if flag $= 1$, $\boldsymbol{\alpha}^m$.

At the decoder:

In the initial phase: Find $\boldsymbol{\alpha}^m$ parameters using method described in Section 3.3.1.

Otherwise:

9) Using the rate vector, $[R_1 ... R_N]$, calculate the quality vector, $[Q_1(R_1), ... Q_N(R_N)]$.
10) Find m' such that $[Q_1(R_1), ... Q_N(R_N)] \in C_{m'}^N$. If $m' \neq m$, then $m = m'$ and flag $= 1$.
11) Decode the videos, with error concealment method depending on values of $\boldsymbol{\alpha}^m$.

$\frac{dQ^{(i)}(R_i)}{dR_i}$ using Equation (3.7). Then, using its corresponding Q-R function, the station finds the rate at which the slope of Q-R plot matches the found $\frac{dQ^{(i)}(R_i)}{dR_i}$, which is its optimum rate, R_i. If a packet ordering algorithm was used to create the Q-R function, the station also simultaneously finds its packet selection. The following equations are finally solved to determine the parameters p_i and k_i:

$$k_i = \frac{R_i}{B.log(X_i)} \tag{3.12}$$

$$p_i = \frac{(X_i - 1).k_i}{\zeta_i}. \tag{3.13}$$

This method has low complexity for sources and the base station, i.e. a few operations per iteration. A packet ordering algorithm can be used at a source, with complexity depending on the choice of the user. Alternatively a user can use a known Q-R model as given in [SFL00]. At the decoder only the initial phase has added complexity compared to decoding of independent sources. In the initial phase each frame is decoded twice, and LMS is used to find the correlation parameters. The overall number of iterations for the algorithm convergence is as the sub-gradient method, $1/\epsilon_T^2$, where ϵ_T is the distance to the optimum.

3.4 Simulations

3.4.1 Simulation Setup

Simulations are performed using Matlab and a modified version of the H.264 reference software [JVT10]. We simulate the performance for videos from two sets of correlated sequences, BreakDancing and BookArrival [pro][MSR]. In each case a network with one receiver and three transmitting video sources is considered, with two correlated sources, and one source which does not use correlated decoding. We encode each video using H.264, creating a stream of RTP packets.

Table 3.1: Channel parameters in simulations

Parameter	Values
Max Power per user	10W
Bandwidth	40 kHz
Max total power	20 W
β (SNR gap) for each user	0.9

Each video packet consists of exactly one video frame. The GoP size is 5, with one I and 4 P frames. The frame rate is set to 5 fps. For decoding we use the H.264 [JVT10] decoder that has been modified to replace lost frames with either the corresponding frames from a correlated neighbour, or the previous frame in the same sequence, depending on the algorithm input. The wireless channel is Gaussian, with the channel parameters given in Table 3.1. We vary the number of orthogonal codes in order to vary the normalized rate.

3.4.2 Correlated Video Model Validation

To verify the piecewise linear quality model for correlated decoding of Eq (3.4), we use two sets of video sequences, BreakDancing [MSR] and Book Arrival sequences [pro]. The aim is to construct a plot relating changes in the quality of a video decoded using correlated error concealment, i.e., $Q_1^c(R_1, R_2)$, to qualities of videos that are used in the decoding, $Q_1(R_1)$ and $Q_2(R_2)$, as defined in Section 3.3.1. We remove frames from each video at random. We then decode the sequence using two methods. The first is frame replacement with the previous frame; this gives the values $Q_i(R_i)$. The second is frame replacement with corresponding frames from the correlated video source, which gives values of $Q_1^c(R_1, R_2)$. Figure 3.2

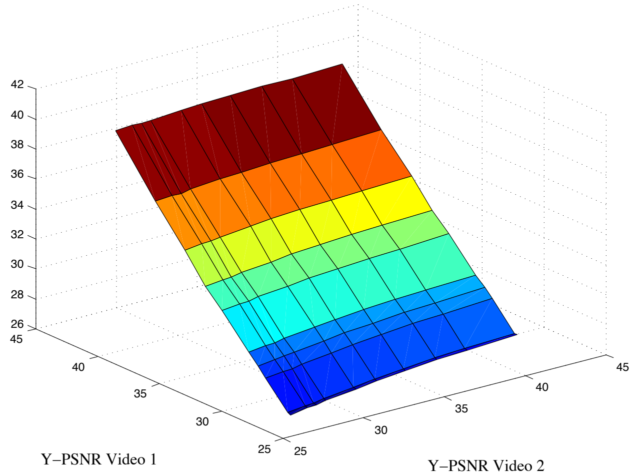


Figure 3.2: Breakdancing sequence.

demonstrates this 3D function for the BreakDancing sequence set, averaged in order to smooth the function. To visualize it better we project the 3D function on both axes in Figures 3.3 and 3.4.

We model the found $Q_1^c(R_1, R_2)$ function as a piecewise linear approximation of $Q_1(R_1)$ and $Q_2(R_2)$. We create the C_m^2 spaces by partitioning the possible values of quality vector $[Q_1(R_1),\ Q_2(R_2)]$ into 2dB by 2dB sections. For each range we use LMS to find the respective model parameter matrix, $\boldsymbol{\alpha}^m$. The MSE of the model is found to be 0.43 dB for video sequence sets of BreakDancing, and 0.88 dB for the Book Arrival sequence sets, as given in Table 3.2.

The gain from using correlated decoding versus regular decoding can be observed in Figure 3.3. We observe that when $Q_1(R_1)$ is on average 27 dB and the average $Q_2(R_2)$ is 40 dB we get about 1dB gain from using correlated decoding. We should point out that this gain is from decoding only, and does not include gains from the correlated resource allocation.

Table 3.2: MSE values of the piecewise linear model.

Sequence	C_m^2 size	MSE
BreakDancing	$2dB \times 2dB$	0.43 dB
Book Arrival	$2dB \times 2dB$	0.88 dB

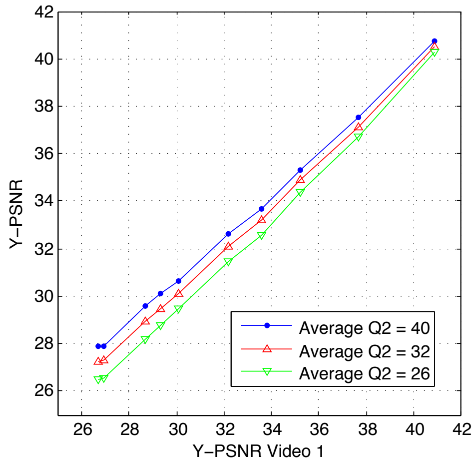


Figure 3.3: Breakdancing sequence.

3.4.3 Resource Allocation Performance

We compare the performance of three algorithms. One is our proposed correlated resource allocation scheme described in Algorithm 1. The second also uses our algorithm but the correlation parameter matrix is set to $I_{N\times N}$, which makes it an optimal resource allocation scheme for independent sources. We use this comparison to demonstrate the utility gain solely due to use of correlation. We refer to this algorithm as No-Correlation (NC). The third algorithm is a basic resource allocation, where code and power are divided equally among the nodes, but sources optimally order the frames as in the previous two schemes. We refer to this algorithm as the Basic method.

We plot average quality of videos in terms of Y-PSNR versus the normalized

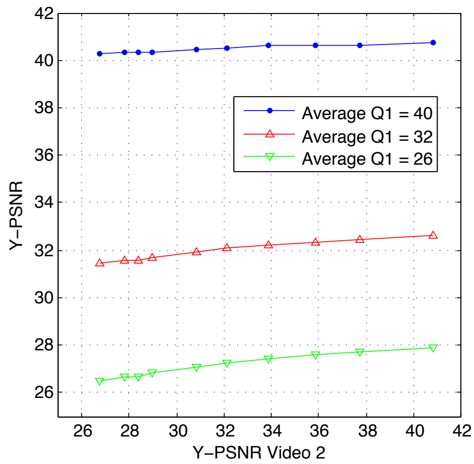
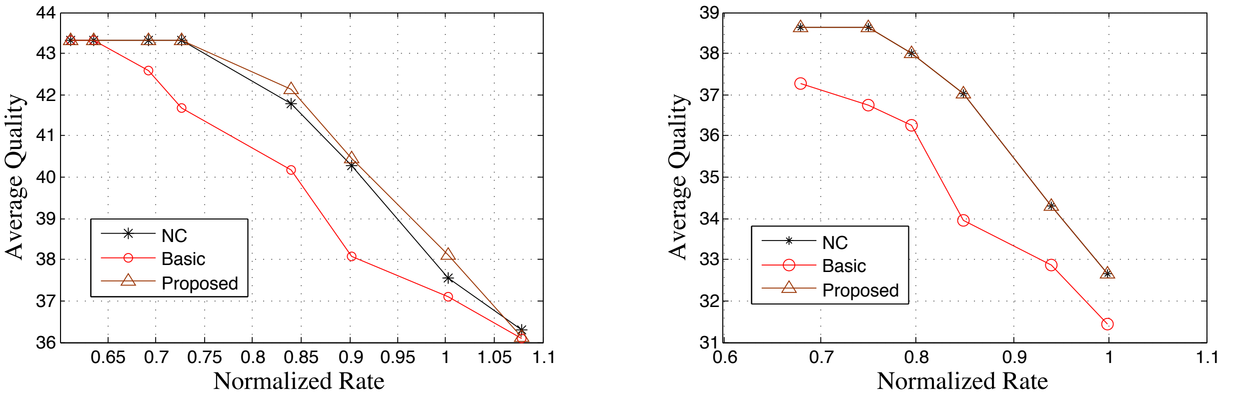


Figure 3.4: Breakdancing sequence.

rate. The normalized rate is calculated by dividing the total load by the channel capacity. We consider two cases for channel conditions. In the first case the two correlated sources experience 23 and 17 dBm *Normalized Noise*, as defined in Eq. 5.1, and the uncorrelated source has normalized noise of of 23 dBm. The resulting performance for each video sequence set is given in Figures 3.5(a) and 3.5(b). We observe that the proposed algorithm has up to 0.5 dB higher average Y-PSNR than the NC method for the BreakDancing sequences, and at worst case it performs equally well. For the BookArrival sequence our proposed method has the same performance as the NC.

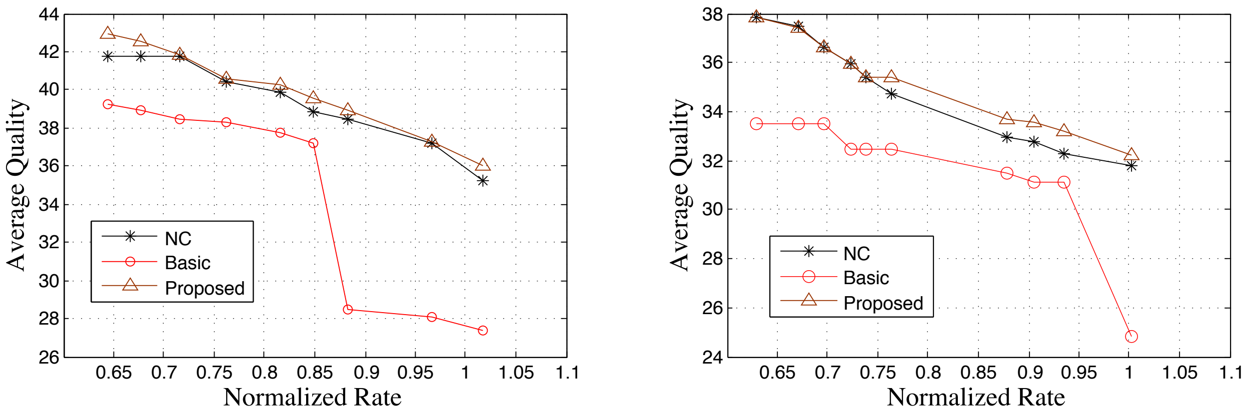
We then consider the normalized noise of 27 dBm and 17 dBm for the correlated sources and 20 dBm for the independent source. The results are presented in Figures 3.6(a) and 3.6(b). In this case for both videos we see gain, up to 1.75 dB in average video quality, in our proposed method compared with the NC method. The basic method performs poorly since the quality found for the user with the worst channel drops to zero when normalized rate is at 0.87 for BreakDancing and at 1 for BookArrival sequence sets.



(a) BreakDancing

(b) BookArrival

Figure 3.5: Average quality for 3 sources, Normalized Noise power (dBm) = [23, 17, 23].



(a) BreakDancing

(b) BookArrival

Figure 3.6: Average quality for 3 sources, Normalized Noise power (dBm) = [27, 17, 20].

3.5 Conclusion

In this chapter we propose a method to find the optimum resource allocation for uplink transmission of correlated video sources, such that the total received video quality is maximized. We develop a model for relating the quality of a video decoded using correlation to quality-rate characteristic functions of videos that are used in its decoding. Based on this model, we formulate an optimization problem and develop an algorithm to solve it with little information exchange with the base station. From the simulations we observe that even with a simple correlated error concealment scheme, our proposed resource allocation method results in up to 1.75 dB gain over the optimum resource allocation with independent decoding, which provides a lower-bound on the performance of our algorithm. The small additional complexity at the decoder resides in the estimation of the source correlation parameters, which is generally only performed once in a static setting.

CHAPTER 4

ICon: Multi-cell OFDMA based resource allocation using interference concentration

4.1 Introduction

The aim in this chapter is to allocate resources to users for uplink transmission in a 2-D multi-cell OFDMA network, maximizing minimum rate achieved by any user. The solution can be directly applied to improving cell edge user performance in OFDMA based networks such as Long Term Evolution (LTE) of 3G [3GP06] and WiMAX [20006].

The problem of joint optimum channel and power assignment to interfering sources is NP-hard, and a non-convex mixed integer programming problem [LZ08]. The only way to find the global optimum is exhaustive search, namely, for each possible channel assignment, the optimum power allocation has to be found. Therefore further simplification of the problem is required.

One approach is to allow each user to independently find its own allocation, while taking the interference it causes to others as a cost, which can be communicated between the neighbors. This idea has been used in many of the game theoretic resource allocation methods [HJR04] [HBH06]. However the solution the system reaches at equilibrium is unlikely to be the global optimum, and in fact may be far from it [HL09]. However, for ad hoc communication this approach might be the only option.

When the network has a known, fixed structure however, a better approach is to exploit this knowledge in order to simplify the problem. For example, for cellular networks this approach will be as follows. A predetermined Inter-Cell Interference Coordination (ICIC) rule can be found for the given network parameters, i.e., cell size, transmit powers, cell load, etc. The ICIC determines the inter-cell resource management [3GP06]. Then each cell can independently schedule its users, for example using frame by frame Proportionally Fair (PF) scheduling [WOG05], while following the inter-cell interference rules.

In this chapter we are proposing a two phase solution: the ICIC adaptation phase (i.e. *Interference Concentration* (ICon)) and intra-cell scheduling phase. At each iteration of ICon, inter-cell resource management is found, given the performance achieved in each cell in the previous iteration. Then, having fixed the inter-cell resource management, the intra-cell scheduling problem becomes a linear programming problem for which fast and simple solutions exist[BV04].

The idea behind the two phase approach is that when the inter-cell resource management rule is found and optimized using communication theory and experiments, the solution space of the original NP-hard problem is limited to the most reasonable options. And although global optimality is not guaranteed in this method either, it greatly reduces the problem size and complexity.

- We first propose ICon, a novel inter-cell resource management method based on defining *Interference Power Profiles* (IPPs) for cells. The IPP defines a limit to received interference on each sub-band, which the neighboring cells are obliged to meet. An example is given in Figure 5.4. The idea is that if the high interference causing users from all neighboring cells are concentrated on the same band, the bandwidth will be used more efficiently.

- In order to balance performance across cells, ICon is made adaptable. At each ICIC adaptation time, cells broadcast the average utility they achieved in the previous period (e.g. over the X2 interface in LTE). Then each cell updates the IPP it imposes on its neighbors, given its performance relative to theirs. Each cell loosens its IPP requirements for neighbors that have worse performance than itself, and tightens it for neighbors that perform better.

- In the Intra-cell scheduling phase each cell finds the transmit power limits for each user on each sub-band such that none of its neighbors' IPPs is violated. This is easily done using channel gains between each user and the neighboring base stations (BSs), which is available at each user given pilots from neighboring BSs, assuming channel reciprocity holds (available in LTE for use in hand-off). Once the maximum transmit powers are found for each user on each sub-band, a linear optimization problem can be solved by each base station in order to allocate channels to its users, maximizing the minimum rate in the cell. This can be updated frequently since linear optimization problems are efficiently solved.

Our contributions in this chapter are twofold. First is that we propose a novel inter-cell interference management scheme based on interference concentration (i.e. ICon). ICon outperforms the common ICIC methods in cell edge user performance, it is simple to implement, easily adaptable, and can be applied to all OFDMA-based networks. Secondly, we combine ICon with inter-cell resource optimization and propose a two phase solution that adaptively improves the global performance of the network.

The rest of the chapter is as follows. Related work will be presented in Section 4.2. We define the optimization problem we aim to solve in Section 4.3 and propose our ICIC and intra-cell scheduling method. In Section 4.4 we propose the adaptive ICIC method. The simulations are reported in Section 4.5.

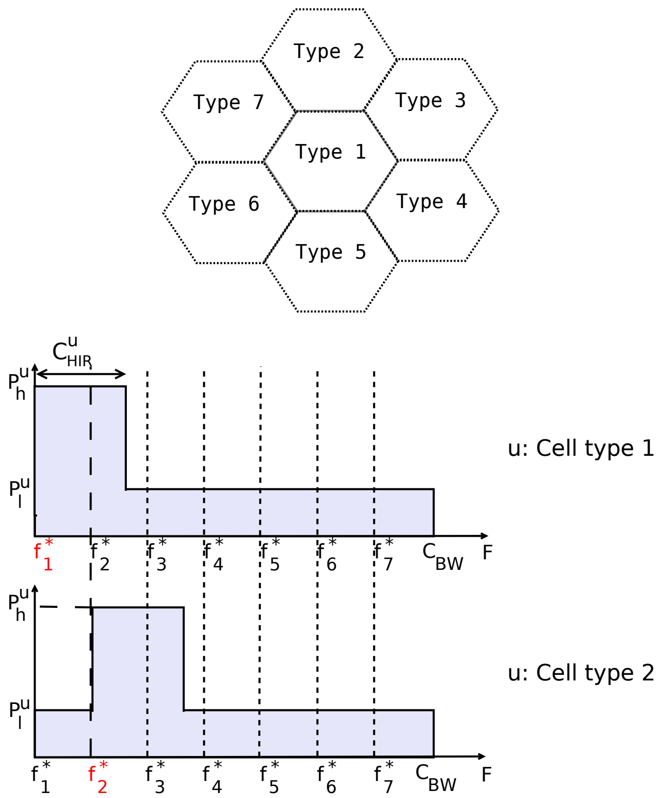


Figure 4.1: An example of Interference Power Profiles (IPPs) set by ICon method for cell types 1 and 2 in a hexagonal cellular network.

4.2 Related Work

An example of a common ICIC method is Fractional Frequency Reuse (FFR) [Hal83] [Gen04]. In FFR, the bandwidth is partitioned into two sections each with a different reuse factor. Commonly one partition has frequency reuse of 1 and the rest reuse of 3. The partition with reuse 1 is employed for users in the inner circle of each cell which cause little interference to other cells. On the other hand the bordering users of each cell are assigned the reuse 3 bands, which are not used in any of the first tier neighbors of the cell. The performance of this method depends on the level of interference coupling between cells. In low coupling, FFR would only cause low spectral efficiency and not much gain compared with reuse 1. Additionally, since part of the spectrum is used with reuse of 3, spectral efficiency is low and the peak rate is less than that of reuse 1 [Sim07] [EBF08] [NAS10] [RSV10].

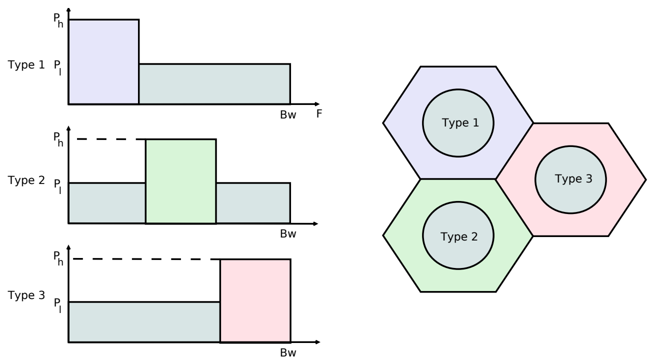


Figure 4.2: Transmit power profiles for each cell type in a hexagonal cellular network, using SFR. The colored section of each cell only has access to the parts of the spectrum with the matching color, the inner sections of cells have access to the whole spectrum.

Another common ICIC method is Soft Frequency Reuse (SFR). In this method frequency is reused in every cell, however each cell is assigned a transmit power profile, with complementary patterns across neighboring cells, as shown in Figure 4.2 [Hua05] [EBF08].

An interesting ICIC method which was recently proposed is the *inverted reuse* scheme [GKW10], [HTR10]. In inverted reuse, users are restricted to a given *transmit power profile*, if they are found to be sufficiently close to a given cell. To find sufficiently close users, a threshold is used for the path loss difference between the serving BS and the neighboring BS. Since all users in all cells neighboring a cell will be given the same power profile, the received interference at the cell will be concentrated as given by that power profile. Our proposed ICIC scheme uses a similar idea as the inverted reuse, that is to shape the interference of a cell. However, we directly define an interference power profile (IPP) for each cell which allows for more direct and intuitive adaptation.

The work in [FSC10] also uses the idea of assigning *interference profiles* for uplink ICIC using Overload Indicators (OIs) defined by 3gpp for LTE of 3G. Fixed interference profiles similar to transmit power profiles in SFR are assigned to cells. This work requires each cell to identify the high interference users in the nearby cells, and therefore requires more processing and inter-cell communication.

For inter-cell resource allocation, Proportionally Fair (PF) scheduling is a common method for LTE. This method is simple to implement and can be modified to achieve different levels of fairness [WOG05]. Additionally for single cell OFDM networks, the optimal allocation of power per subband per user is found to be a convex optimization problem [LZ08], solvable in polynomial time.

4.3 Optimization Problem

We consider a 2-D multi-cell network with OFDMA multiple access scheme. Users in each cell are allocated resources by the scheduler located in the cell base station for uplink communication. The resources to assign are power and channel allocation to each user. Each of the independent orthogonal channels are assumed to be Gaussian and interference is considered to be equivalent to noise in terms of channel capacity. The variables to find are each user's transmit power spectral density for each channel, $p_{i,c}$ and channel assignment, $a_{i,c}$ which is a binary array.

We assume no intra cell interference. The following rate is achieved for user i in cell k:

$$R_{i,k} = \sum_{c=1}^{C} a_{i,c}.B_c. \log_2 \left(1 + \frac{p_{i,c}.g_{ik}}{N_0.B_c + \sum_{u=1,u\neq k}^{K} P_{ukc}^I}\right), \tag{4.1}$$

where g_{ik} is the channel gain from user i to receiver of cell k, B_c is the bandwidth of channel c. N_0 is the noise power and P_{ukc}^I is the received interference power from cell u to cell k on channel c. Namely, $P_{ukc}^I = \sum_{j\in X_u} a_{j,c}.p_{j,c}.g_{jk}$.

$$\begin{aligned} \underset{\boldsymbol{a},\boldsymbol{p}}{\text{Maximize}} \quad & \min_{i,k}(R_{i,k}) & \\ & \sum_{i\in k} a_{i,c} = 1, \quad a_{i,c} \in \{0,1\} & \forall k \\ & P_{MIN} \leq p_{i,k} \leq P_{MAX}, & \forall i,k \end{aligned} \tag{4.2}$$

where $R_{i,k}$ is given as Eq. (5.1). This problem is NP-hard for $(C > 1)$ [LZ08]. NP hardness of (4.2) means that optimality of any solution cannot be guaranteed unless with exhaustive search over all possible solutions. Therefore we can only use intuition and solutions that are experimentally proven to be effective to simplify the problem.

To do this, we first devise a new inter-cell interference coordination method, ICon, in order to decouple the inter-cell resource allocation problem from the intra-cell scheduling. The intra-cell scheduling problem will consist of assigning maximum allowed power to users without violating the IPPs set by ICon, and solving a linear optimization problem in order to assign subbands to users. ICon can then be adapted in order to increase the overall network utility.

4.3.1 ICon

Each cell is given an IPP which neighboring cells are required to respect, as shown in Figure 5.4. High Interference Region (HIR) is the section of frequency band that allows high levels of interference for each cell, as shown in the figure. We assume P_h is set to allow maximum transmit power for bordering cells on the HIR. Depending on the type of each cell, the HIR starts at a given subband, f_i^*. There are two design parameters for the IPP,

$$P_l^u : \text{Interference power limit on low interference sub-bands}$$

and

$$C_{HIR}^u : \text{Number of sub-bands in HIR.}$$

These parameters are assumed to be known if the network structure is known. Then, for each channel and each user, the maximum power that does not violate any of the neighbors' Interference Profile (IPP) should be found.

$$p_{i,c}^{max} = \min(\min_{u,u \neq k} \frac{I_u(c)}{g_{iu}}, P_{MAX}) \tag{4.3}$$

where $I_u(c)$ is the value of IPP of cell u at channel c, and g_{iu} is the channel gain from user i to base station of cell u. This can be found by the user from pilots from neighboring base stations, if we assume channel reciprocity, and can be transmitted to BS of cell k (this information is also available in the UEs in cellular networks for handover).

The number of sub-bands in HIR, i.e. C_{HIR}^u, can be as high as C_{BW}, meaning that equal high interference is allowed on all bands, or can be very small, concentrating all the interference on a small band. Furthermore, since C_{HIR}^u can be set individually for each cell (or modified adaptively as proposed in Section 4.4) our IPP can easily be adapted given the load in each cell. This is in contrast with FFR and SFR where the frequency divisions are generally not modifiable, although the load on each frequency section can be set individually in each cell. Additionally, ICon essentially merely imposes transmit power limits for users on different subbands based on their location in the cell. Therefore resource allocation to users can be performed independently, unlike FFR and SFR where users are assigned to bands depending on their location.

4.3.2 Channel and Power Assignment in Each Cell

In this section we find the power assignment and channel allocation for cell k. In each cell the the scheduler is located at the base station. In the previous section, we fixed the maximum interference levels on each channel in each cell, given by the IPP of a cell. We now approximate Problem (4.2) by assuming P^I_{ukc} to be constant during a scheduling period. This approximation results in Problem (4.2) becoming separable and solved in each cell. Then if $a_{i,c}$ is relaxed to be real valued, (i.e. the optimization problem will be solved every T frame lengths, and the $a_{i,c}$ will be rounded), Problem (4.2) becomes separable into the following optimization problems in each cell k:

$$\begin{aligned}
\underset{\boldsymbol{a},\boldsymbol{p}}{\text{Maximize}}\quad & t && (4.4)\\
& t \leq \sum_{c=1}^{C} a_{i,c}.B_c.\log_2\left(1+\frac{p_{i,c}.g_{ik}}{N_0.B_c+P^I_{kc}}\right) && \forall i\\
& \sum_{i\in k} a_{i,c} = T, \quad 0 \leq a_{i,c} \leq T\\
& P_{MIN} \leq p_{i,k} \leq p^{max}_{i,c}, && \forall i
\end{aligned}$$

where P^I_{kc} is the total interference power received at cell k at subband c. We can further simplify the problem by noting that the optimum transmit power for this modified problem is simply the maximum transmit power allowed for each user, i.e. $p^*_{i,c} = p^{max}_{i,c}$. Then the problem becomes a linear programming problem in $\boldsymbol{a}$:

$$\begin{aligned}
&\underset{\boldsymbol{a}}{\text{Maximize}} \quad t && (4.5)\\
&t \leq \sum_{c=1}^{C} a_{i,c}.B_c.\log_2\left(1 + \frac{p^{max}_{i,c}.g_{ik}}{N_0.B_c + P^I_{kc}}\right) \qquad \forall i\\
&\sum_{i\in k} a_{i,c} = T, \quad 0 \leq a_{i,c} \leq T
\end{aligned}$$

which has efficient solutions [BV04]. In the simulations we solve the optimization problem once every 10 frames, i.e. T = 10.

There are two issues with problem (4.5). One is that since all cells are solving this problem separately, P^I_{kc} is not going to be constant during the scheduling period. Second, is that even if the interference is constant in a scheduling period, optimizing the resources individually in each cell does not guarantee convergence to the global optimum.

To circumvent these issues we propose the following. First, we define average interference, $\bar{P}^I_{kc}$ as an average of the previous N_T scheduling periods which updates as follows:

$$\bar{P}^I_{kc}(t) = (\frac{1}{N_T}).P^I_{kc}(t) + (1 - \frac{1}{N_T}).\bar{P}^I_{kc}(t-1)$$

This will be slow changing in one scheduling period. We use this value instead of the instantaneous $P^I_{kc}(t)$ to estimate the achievable rate in the next scheduling period. Secondly, by setting an interference power profile (IPP) for each cell in the ICIC phase, we steer the problem towards better global solutions, although global optimality is not guaranteed.

4.4 Adaptation of ICon

We define an IPP in each cell to impose on each of its neighbors, and initially set all equal to the IPP found for the given network structure for the particular cell type. Modifiable attributes of the internal IPP are as explained in Section 4.3.1 and shown in Figure 5.5.

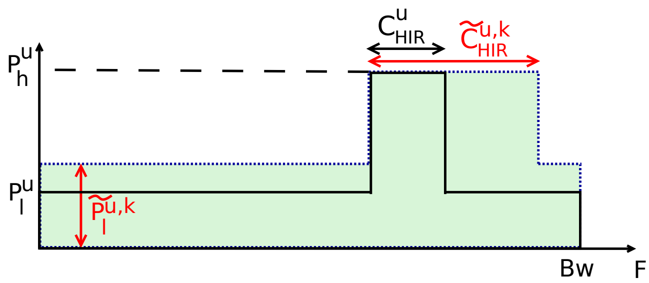


Figure 4.3: Interference Power Profile (IPP) for cell u. Green curve is the IPP that cell k has to respect for cell u.

At ICIC adaptation time, all cells broadcast the average utility they achieved in the previous period (e.g. on X2 channel in LTE). Then each cell k updates the C^u_{HIR} for the IPP it imposes on its neighbor u as follows,

$$\widetilde{C}^{u,k}_{HIR}(t+1) = \max\left\{\widetilde{C}^{u,k}_{HIR}(t) + \alpha.\left(\frac{U^u(t) - U^k(t)}{(U^u(t) + U^k(t))/2}\right).C_{Bw}, C^u_{HIR}\right\}$$

and the low interference power limit, $\widetilde{P}^u_l$ is updated by,

$$\widetilde{P}^{u,k}_l(t+1) = \max\left\{\widetilde{P}^{u,k}_l(t) + \beta.\left(\frac{U^u(t) - U^k(t)}{(U^u(t) + U^k(t))/2}\right).P^u_h, P^u_l\right\}$$

where $U^k(t)$ is the utility achieved in cell k at time t. For our problem, $U^k(t) = \min_i(R_{i,k})$. α and β are step size values for the updates, and are in the range $[0,1]$. The larger the step size, the faster the convergence but the more the possibility of having to backtrack. Also, the larger step size value for a given parameter, the more adaptable that parameter will be. For example, a designer may choose to only adapt the $\widetilde{P}_l$s and not the $\widetilde{C}_{HIR}$s, and vice versa by setting α or β to zero. Step sizes can also be adaptive, and vary depending on the range of each parameter. Finally, the modified parameters need to be communicated to neighboring base-stations.

Table 4.1: Simulation parameters

Parameter	Values
Number of cells	19, with wrap around
Users per cell for adaptive method	19-21, uniformly distributed
Site to site distance (m)	130
Bandwidth	10 MHz
Number of subbands	63
Max Power per user per band	250mW/63
Path loss model (dB)	$30 \log_{10} R$, R in (m).
Fractional power control	$\alpha = 1$, Γ differs.
IoT	ICon=10, Reuse1=13 (dB)
PF scheduling parameters	a = 3.5
FFR reuse 1 band /total band	$\eta = 45/63$
SFR parameters	$p_l/p_h = 1/10$, $\gamma = 6$ dB
PF Scheduling at every:	1 frame (1ms)
Optimal Scheduling at every:	10 frames (10ms)
Step sizes for adaptive ICon	$\alpha = \beta = 0.2$

4.5 Simulations

We provide Monte Carlo simulations for a 19 cell hexagonal 2-D cellular network, similar to one given in micro case for LTE [3GP06]. We use wrap around in order

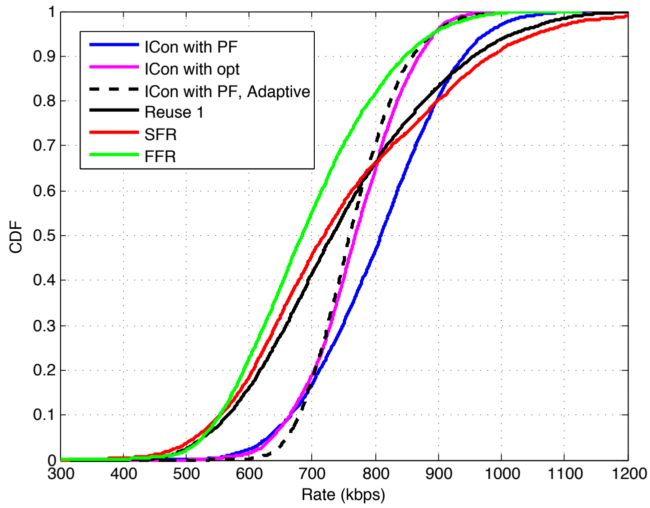


Figure 4.4: CDF of achieved rates in a cell using various inter-cell interference coordination and scheduling schemes.

Table 4.2: 5 percentile rate, ICon with PF, with IoT=10 db in low interference region.

Rate(Kbps)	$P_l = P_h/20$	$P_h/10$	$P_h/4$	$P_h/2$
$C_{HIR} = 9$	429.50	487.00	568.00	491.00
18	439.50	488.00	558.50	483.00
27	458.50	535.00	545.50	496.50
36	538.50	**632.00**	539.00	476.00
54	625.50	577.00	510.00	487.50

to avoid boundary inconsistencies. Simulation parameters are given in Table 5.1. We simulate several common ICIC and resource allocation methods: Reuse 1, SFR, and FFR, all with fractional power control and using proportionally fair scheduling, with parameters given in Table 5.1. We simulate our ICIC method,

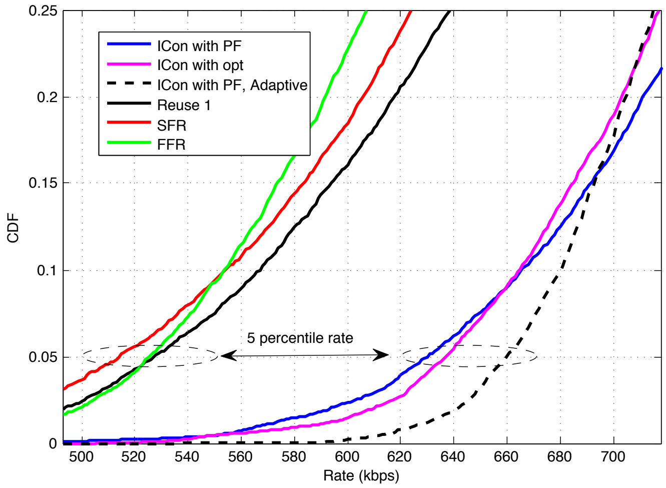


Figure 4.5: Close-up of Fig. 4.4 demonstrating the five percentile rate achieved in each of the methods.

ICon, with proportionally fair intra-cell scheduling, and with optimum intra-cell scheduling given in Section 4.3.2. We perform simulations for 4 cell sizes, with site to site distance ranging from 32.5 (m) to 260 (m).

First, to find the P_l and C_{HIR} parameters for ICon, we find the 5 percentile rate achieved using a range of P_l and C_{HIR} values. An example is given in Table 4.2, which demonstrates this for site to site distance of 130 (m). In this case $P_l = P_h/10$ and $C_{HIR} = 36$ achieves the highest 5 percentile rate.

Figure 4.4 demonstrates the CDFs of rates achieved by users in each scheme for site to site distance of 130 m, and Figure 5.10 is the closeup of the 5 percentile region of the curves. Given these parameters, Reuse 1, SFR, and FFR achieve similar 5 percentile rates, but FFR performs worse than SFR and Reuse 1 for high rate users. ICon with both optimal and PF scheduling methods achieve higher 5 percentile rate than other methods, with 18% for ICon with PF and 20% for ICon with optimal scheduling. Additionally, we observe that the optimal scheduling does not achieve a much higher performance compared with PF, only about 1%

gain in rate. The reason for this is that the approximation of interference in the next scheduling time as the average of the past is not accurate. Furthermore, optimal scheduling is done once every 10 frames, whereas PF is at every frame, which decreases the accuracy of interference prediction.

Lastly, we demonstrate the adaptation of ICon in Figure 4.6. Initially we run the simulations with static ICon with parameters as above, until the rates settle to fixed values. Then we start the adaptation algorithm. We plot the five percentile rate versus the number of iterations of the adaptive method. From the first iteration, the 5 percentile rate is instantly increased by 18 Kbps, and eventually converges to a 5% gain over static ICon. This demonstrates both rapid convergence and performance gain over the static case.

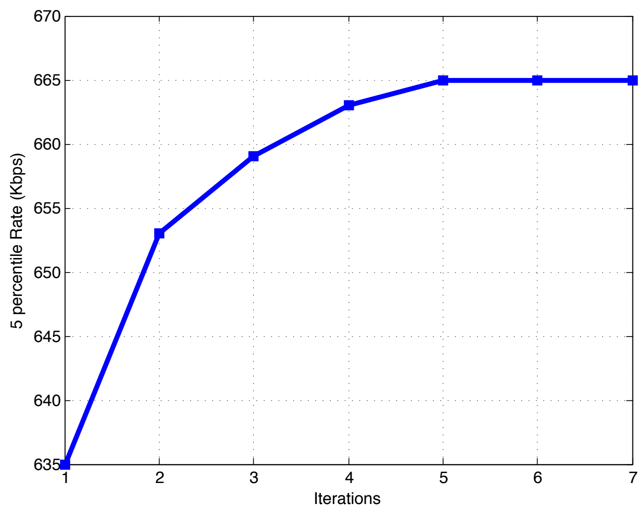


Figure 4.6: Evolution of 5 percentile rate when the ICon adaptation is allowed. ICon with PF scheduling for site to site = 130 m, users per cell: 19-21, uniformly distributed.

4.6 Conclusion

In this work we propose a new inter-cell interference management method (ICon) for OFDMA based networks, such as LTE of 3G and WiMAX. ICon is based on setting interference power limits on each subband for each cell, requiring the neighboring cells to respect the imposed limits. Our simulations show that ICon achieves up to 18% gain over reuse 1 for the 5 percentile rate in a typical cellular network. ICon is easily and rapidly adapted to the performance obtained by each cell, which results in balancing of the performance over the whole network.

We also propose a two phase solution to the NP-hard problem of resource allocation in multicell OFDMA-based networks. First, ICon performs inter-cell resource management, updating interference power limits for each cell. Second, the intra-cell optimal scheduling assigns resources in each cell while meeting the constraints imposed by ICon. The optimal intra-cell scheduling is found to be a linear optimization problem for which efficient solutions exist. Static ICon with optimal scheduling performs 20% better than reuse 1 in terms of 5 percentile rate, and the adaptive method adds an additional 5% gain over this value.

CHAPTER 5

Correlation used in resource allocation for Multi-cell networks

5.1 Introduction

In this chapter we examine a scenario where sources in a multi-cell Orthogonal Frequency Division Multiple Access (OFDMA) network are spatially correlated, and aim to transmit their data to the base station of their cell. An example is shown in Figure 5.1, where the sources are scattered on a field which is divided into three hexagonal cells. The base station in the center of each cell contains a scheduler which is tasked with performing the resource allocation with the aim of minimizing the maximum individual distortion achieved in the global network after data reconstruction. Our goal is to find a strategy to allocate resources to each source, while taking advantage of spatial correlation among the sources.

The scenario we consider in this work readily applies to Wireless Sensor Networks (WSNs), where sensors are scattered on a field, measuring various spatially correlated phenomena such as temperature, humidity, audio, video, etc. [ASS02]. Since much of the surface area of interest for WSN applications is now covered by cellular networks, it is more accessible for some WSNs to simply use this existing communication infrastructure. Therefore in this work we assume a multi cell network with a Medium Access Control (MAC) scheme similar to LTE of 3G and WiMAX.

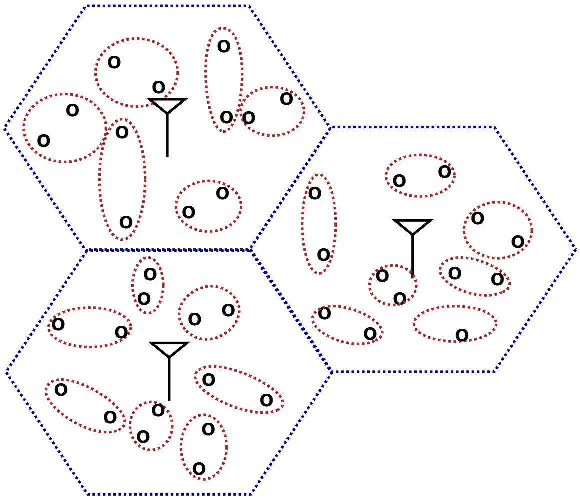


Figure 5.1: 3 neighboring cells shown, with base stations in the center of each cell. Sources are grouped in correlated groups of size 2.

The resource allocation problem for OFDMA 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 to others). 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 the number of channels is more than 1 [LZ08]. Furthermore, for a non-trivial network size exhaustive solutions are not computationally feasible in a single scheduling period. Therefore further simplifications and approximations are needed.

Furthermore, adding correlation to the design only makes this problem more complex. In order to take advantage of correlation in resource allocation, we first need to assume a model for the rate-distortion region of sources coded with lossy distributed source coding. This rate-distortion region is not known for the general quantization resolution of the sources. However in the limit of high resolution the region is known, as given in [ZB99]. In fact, this bound is an outer limit to the general rate-distortion region, which tightens as the resolution increases. We therefore assume this model for the rate-distortion region in our resource allocation scheme. However, given the R-D region, now the distortion must also be allocated among the correlated sources. Additionally, 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. Lastly, another design question arises from this and should be addressed, which is whether all the correlated sources should be jointly decoded or the sources should be split into smaller groups, and what are the costs and benefits of different group sizes.

In this chapter we present a three step approach for the problem of resource allocation for spatially correlated sources. Namely, the three steps are called *Inter-cell resource management, Source Grouping,* and *Intra-cell Scheduling.*

First, we find transmit power limits in each cell in the inter cell interference management step. For this, we use the Adaptive ICon interference coordination method of the prior chapter. 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, and requires that at each adaptation time the decoder transmits the utility achieved in the cell, as well as its surrounding cells.

Secondly, in the Source Grouping (SG) step we split the set of sources in each cell to smaller groups to be jointly decoded. This is done in order to take most advantage of spatial correlation without high increase in complexity in the decoder and scheduler. We compare the utility gain of larger group sizes and conclude that having two sources per group achieves much of the achievable 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.

Lastly, we use the parameters found in previous steps in order to find the channel and distortion allocation 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 [WOG05], modified in order to take the effects of correlation into account. The second scheduling method is a linear programming problem (OPT) which simultaneously finds channel and distortion allocation for each source. OPT performs better than D-PF at the price of higher complexity.

In the simulations we demonstrate that our proposed scheme presents a constructive, simple solution to the computationally infeasible optimum resource allocation problem, superior to the existing uncorrelated resource allocation methods.

This Chapter is organized as follows. In Section 5.2 we discuss the related work. We formulate the problem in Section 5.3, and propose our three phased solution in Section 5.4. Then each step of the proposed solution is discussed in Sections 5.4.1, 5.4.2, and 5.4.3. We present results of our simulations in Section 5.5.

5.2 Related Work

Resource allocation in this work refers to finding joint power and channel allocation to sources subject to the limitations in the resources. For this problem in cellular networks, 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) [Hal83] [Hua05] 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 OFDMA. The neighboring cells are assigned complimentary power profiles in order to shape the inter-cell interference. These power profiles are based on heuristics. Usually for intra-cell scheduling, the scheduler in each cell performs channel allocation independently, using a method such as Proportionally Fair scheduling [WOG05]. Although these methods are a promising step towards simultaneous power and channel allocation, their performance is not generally better than the frequency Reuse 1 scheme [EBF08], which simply allows 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 [BPF11]. 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* was proposed in [GKW10], which 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.

On the other hand, the use of spatial correlation in resource allocation has been studied mainly in the field of WSNs. In most WSN applications, energy saving communication is a priority [RM04]. Well-known early power saving methods involve using 802.11-like MAC, and saving power by enabling periodic sleep-wake cycles for wireless sensors, such as S-MAC [YHE02] and P-MAC[ZRS05]. Later [VA06] proposed Correlation-based Collaborative Medium Access Control (CC-MAC), which takes advantage of spatial correlation among sensors by finding a subset of sensors to transmit their data while data from the rest is omitted. In this work we aim to use the data from every sensor, while minimizing the maximum distortion in the network.

A different, but related problem is studied in multi-hop WSNs, where spatial correlation is utilized in combining routing and rate allocation with data compression [PKG04] [LR09] [WPW09] [MRB11]. In [CB06] the authors propose a method for lossy transmission of data, combining routing with rate and distortion allocation using Wyner-Ziv (WZ) [WZ76] distributed lossy source coding. They find that routing and rate and distortion optimization can be decoupled and optimized separately, when the cost function is a weighted sum of rates. Although this is a different problem than what we are considering in this work, the ideas developed in this area are similar to our approach to the joint power and channel allocation problem for correlated sources.

To the best of our knowledge there is no work that proposes solutions for the joint power and channel allocation using spatial correlation in multi-cell networks.

5.3 Problem Formulation

We consider a 2-D multi-cell network with OFDMA multiple access scheme. Sources observe spatially correlated information, and transmit their observation to the base station of their cell, using medium access parameters determined by the scheduler, which is located in the cell base station. Figure 5.2 gives an overview of the system.

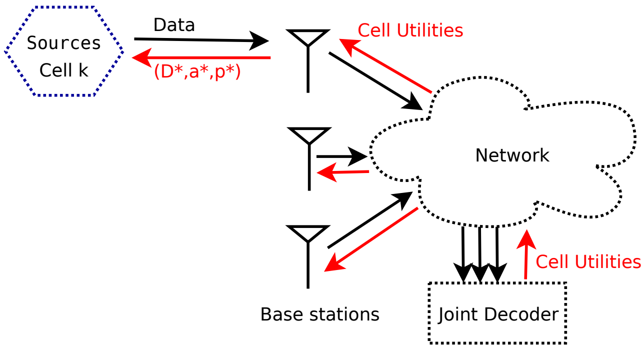


Figure 5.2: System overview.

5.3.1 Resources

In OFDMA, bandwidth is split into orthogonal frequency sub-bands and a subset of these sub-bands is assigned to each user. In the multi cell scenario, since users from different cells interfere if assigned to the same channel, transmission power per channel for each user is also a determining factor in network performance. Therefore the MAC problem consists of finding power per channel and orthogonal channel allocation to the users. Each of the independent orthogonal channels are assumed to be Gaussian and interference is considered to be equivalent to noise in terms of channel capacity. The following rate is achieved for user i in cell k according to Gaussian channel capacity [CT91]:

$$R_{i,k} = \sum_{c=1}^{C} a_{i,c} BW_c \log_2 \left(1 + \frac{p_{i,c} . g_{ik}}{N_0 . BW_c + \sum_{u=1, u \neq k}^{K} P_{ukc}^{I}} \right) \tag{5.1}$$

where $a_{i,c}$ is the binary value specifying channel allocation and $p_{i,c}$ the transmit power of user i on channel c, g_{ik} is the channel gain from user i to receiver of cell k, and BW_c is the bandwidth of channel c. N_0 is the noise power and P^I_{ukc} is the received interference power from cell u to cell k on channel c. Namely, $P^I_{ukc} = \sum_{j \in X_u} a_{j,c}.p_{j,c}.g_{jk}$.

5.3.2 Rate-Distortion Region

Now we must relate the rate available to a source to distortion caused to its observation after its data is reconstructed. This is achieved by rate-distortion (R-D) function, which is a characteristic of the coding scheme. For the general lossy distributed coding, the R-D region is not yet known. However, for distributed coding in the limit of *high resolution*, i.e. as the quantization resolution increases, the R-D region is known [ZB99], and is similar to the rate region given by lossless Slepian-Wolf coding [SW73]. When sources in set $\boldsymbol{G}$ are decoded jointly, the R-D region for this set in the limit of high resolution is given by:

$$\begin{aligned} &\forall \boldsymbol{S} \subseteq \boldsymbol{G}: \\ &\sum_{i \in \boldsymbol{S}} R_{i,k} \geq h_2(\boldsymbol{S} | \boldsymbol{G} \backslash \boldsymbol{S}) - \frac{1}{2} \log_2 \left((2\pi e)^{|\boldsymbol{S}|} \prod_{i \in \boldsymbol{S}} D_{i,k} \right) \end{aligned} \tag{5.2}$$

where $h(.)$ is the differential entropy, and D_{ik} is the squared error distortion of source i. This is an outer bound for the general resolution coding case, and becomes tighter as resolution increases, thus increasing the accuracy of the model. Therefore we find this model appropriate for use in resource allocation. However it can be replaced depending on the coding scheme without changing our resource allocation methodology.

The R-D region allows for various feasible values of distortion for a given rate vector. Therefore for a fixed rate vector, the distortion vector that would minimize the maximum distortion should be found. Namely, the distortion vector is also a variable that must be assigned by the scheduler, which in the above model would translate to quantization levels of the encoder. We now explain how $\boldsymbol{G}$ and $h(.)$ are found.

The set of sources that are decoded jointly, i.e. $\boldsymbol{G}$ in the above bound, can include from only 1 source which results in independent coding, up to all the sources in a cell, which results in taking full advantage of correlation. However, 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 in terms of decrease in achieved distortions. Therefore we assume that sources are decoded in smaller groups, namely we perform simulations for groups of size one, two, and three. In this case, the choice of sources that are grouped together in the same joint decoding group is an important factor in the resulting distortion levels of sources. We propose an algorithm for the grouping in Section 5.4.2.

Additionally, in the R-D region given in Eq. (5.2), the source entropies must be found. In order to find the entropies we need to model the sources as joint random variables with some known distribution, with a distance based correlation model. The choice of the distribution and the correlation model does not affect our analysis, however in the simulations we use the following example. The observations at the sources are modeled as joint Gaussian random variables, which is commonly used in WSNs to simplify the analysis. For the correlation model we use an exponential distance based correlation model [BDS01]. The entropy in this example is given by,

$$h_2(\boldsymbol{S}) = \frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}|\Sigma|\right) \tag{5.3}$$

where $|\Sigma|$ is the determinant of the covariance matrix with elements given as below, when σ^2 is the variance of the sources:

$$\sigma_{ij}^2 = \sigma^2 . e^{(\frac{-d_{ij}}{\theta})} \tag{5.4}$$

These are not assumptions of this method, but only examples that we consider in our simulations. The only requirement for the correlation model is that correlation must decrease with distance.

5.3.3 Optimization Problem

The optimization problem is to minimize the maximum distortion found in the global network, subject to resource constraints and the R-D region. It is given as follows.

Problem 1:

$$\begin{aligned}
\underset{\boldsymbol{a},\boldsymbol{p},\boldsymbol{D}}{\text{Minimize}} \quad & \max_{i,k}(D_{i,k}) && (5.5)\\
s.t. \quad & \sum_{i \in \boldsymbol{S}} R_{i,k} \geq -\frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}\prod_{i\in \boldsymbol{S}} D_{i,k}\right) + h_2(\boldsymbol{S}|\boldsymbol{G}\backslash\boldsymbol{S}), && \\
& && \forall \boldsymbol{S} \subseteq \boldsymbol{G}, \forall \boldsymbol{G} \subseteq \boldsymbol{X}^k, \forall k\\
& \sum_{i \in k} a_{i,c} = 1 && \forall k\\
& P_{MIN} \leq p_{i,k} \leq P_{MAX}, && \forall i,k
\end{aligned}$$

where $R_{i,k}$ is given as Eq. (5.1), and $\boldsymbol{X}^k$ is the set of all sources in cell k. The parameters are the resource allocation vectors, $\boldsymbol{a}$ and $\boldsymbol{p}$, as well as the source grouping for each cell, $\boldsymbol{G}$, such that $\cup \boldsymbol{G} = \boldsymbol{X}^k$ and $|\boldsymbol{G}|$ is small. This problem is NP-hard for $C > 1$ based on similar arguments given in [LZ08]. We therefore propose in the next section to decompose this problem into three smaller steps which can be solved efficiently.

5.4 Proposed Three Phase Solution

We separate the scheduling problem into three steps, as demonstrated in Figure 5.3. The three steps are performed in the scheduler, located in the base station of every cell. The steps are called Inter-cell resource management, Source Grouping, and Intra-cell Scheduling.

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 performance of the neighboring cells. We use Adaptive ICon [BPF11] for this step, which is based on concentrating the interference to a cell on a portion of the bandwidth. The ICon parameters are adapted in order to balance the utility across the cellular network by increasing or decreasing interference limits of a cell depending on its utility relative to its neighbors. The utility achieved in the cell and its neighbors is communicated by the decoder.

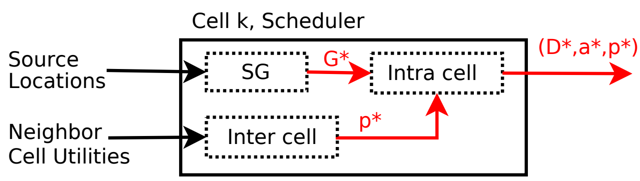


Figure 5.3: Scheduler in the base stations.

In Source Grouping (SG) step, the sources are grouped together for joint decoding (which is then used in the intra-cell scheduling step). We examine having correlated groups of one, two, and three. 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 involves allocating channels and distortion 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 [WOG05] 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. As an example, in our simulations the inter-cell resource management is performed infrequently, once every 100 frames, 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, either once every frame or once every 10 frames, depending on the choice (and therefore complexity) of the scheduling algorithm.

5.4.1 Inter-Cell Resource Management

In this step, we find a rule to allocate 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. FFR and SFR could also be used in this step. We propose to use Adaptive ICon which we presented in the prior chapter, which improves on the Reuse 1, FFR, and SFR schemes for the worst performing users, as we will demonstrate in the simulations.

ICon is an inter-cell resource management method based on defining Interference Power Profiles (IPPs) [BPF11]. The IPP defines a limit to received interference on each frequency subband, which the neighboring cells are obliged to meet. An example is given in Figure 5.4. This is a heuristics-based method, based on the intuition that if the strong interferers in all neighboring cells are concentrated on the same subband, the bandwidth will be used more efficiently. The design parameters are P_h^u and C_{HIR}^u, respectively the maximum received interference and width of the *high interference region* for cell u. We assume that these parameters are known for a given network structure, and are later adapted in order to balance the interference across the cells. Adaptation of ICon can be performed efficiently, requiring minimal inter-cell communication.

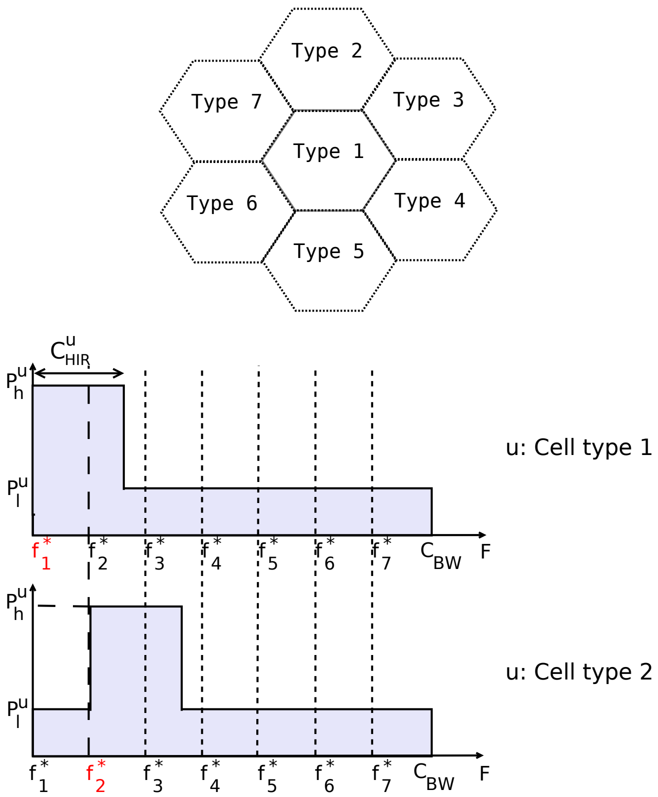


Figure 5.4: An example of Interference Power Profiles (IPPs) set by ICon method for cell types 1 and 2 in a hexagonal cellular network.

We initially set all the IPPs equal to the IPP found for the given network structure for the particular cell type. Modifiable attributes of the internal IPP are shown in Figure 5.5.

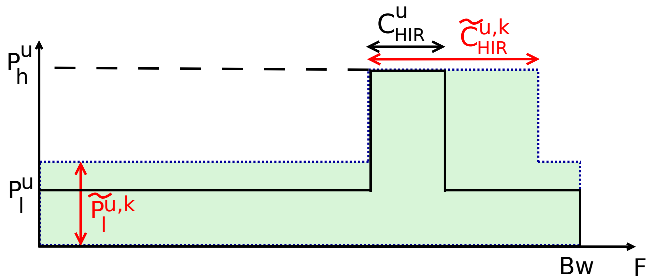


Figure 5.5: Interference Power Profile (IPP) for cell u. Green curve is the IPP that cell k has to respect for cell u.

At each Inter-cell adaptation time, the decoder sends the utility achieved by each cell and its neighbors in the previous period to the cell base station. Then each cell updates the the IPP it imposes on each of its neighbors. This way two neighbors with different utilities are assigned different IPPs. The new, neighbor-specific parameters are given as follows, for cell k IPP to its neighbor u,

$$\widetilde{C}^{u,k}_{HIR}(t+1) = \max\left\{\widetilde{C}^{u,k}_{HIR}(t) - \alpha.\left(\frac{U^u(t) - U^k(t)}{(U^u(t) + U^k(t))/2}\right).C_{Bw}, C^u_{HIR}\right\}$$

and the low interference power limit, $\widetilde{P}^u_l$ is updated by,

$$\widetilde{P}^{u,k}_l(t+1) = \max\left\{\widetilde{P}^{u,k}_l(t) - \beta.\left(\frac{U^u(t) - U^k(t)}{(U^u(t) + U^k(t))/2}\right).P^u_h, P^u_l\right\}$$

where $U^k(t)$ is the utility achieved in cell k at time t. For this problem, $U^k(t) = \max_i(D_{i,k})$. α and β are step size values for the updates, and are in the range $[0, 1]$. The above updates should be transmitted to the base station of each neighboring cell. This amount of inter-cell communication is practical, for example in Long Term Evolution of 3G networks, it is allowed on the X2 communication channel.

Now given the IPPs of the neighboring cells, each cell finds the maximum allowed power for each of its sources. Namely, for each user i in cell k and each channel c, the following inequalities must hold:

$$p_{i,c}.g_{iu} \leq I_u(c) \qquad \forall u \tag{5.6}$$

where $I_u(c)$ is the value of IPP of cell u at channel c, and g_{iu} 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 and can be transmitted to BS of cell k. So the maximum transmit power that does not violate any of the neighbors' IPP is found as follows.

$$p_{i,c}^{max} = \min_{u,u \neq k} \frac{I_u(c)}{g_{iu}} \tag{5.7}$$

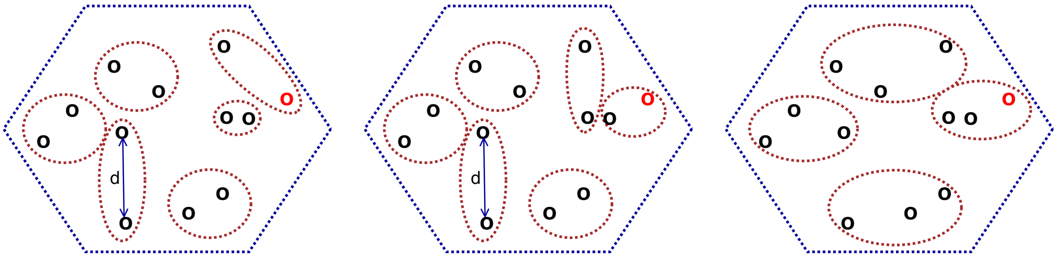
These transmit power limits, set in the inter-cell resource management step, control and limit the interference in the network. Namely, a cell scheduler respecting these limits can independently perform its scheduling. Going back to the optimization problem given in Eq (5.6) and separating the problem to be solved in independently in each cell, we find that the objective functions are decreasing in $\boldsymbol{p}$. In other words, given the independent scheduling problem, if allocated channel c, user i should transmit at maximum power within its own transmit power limits.

$$p_{i,c}^{*} = max(min(p_{i,c}^{max}, P_{MAX}), P_{MIN}) \tag{5.8}$$

i.e., for cell k, no other power assignment can achieve higher utility within the problem constraints. We now know the maximum (and optimum) rate for each user on each channel (note that this will be achieved *if* user i is assigned to channel c):

$$R_{i,c}^{*} = BW_c \log_2 \left(1 + \frac{p_{i,c}^{*}.g_{ik}}{N_0.BW_c + P_{kc}^{I}}\right) \tag{5.9}$$

where P_{kc}^{I} is the total interference that the base station of cell k measures on channel c. Updating the optimization problem we get the following scheduling



(a) 2 per set, distance based without OP. (b) 2 per set, distance based with OP. (c) 3 users per set, distance based with OP

Figure 5.6: Example of output of grouping algorithms. (a) is the result of the distance based grouping method without outer priority (OP), while (b) is the 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. (c) demonstrates the grouping results from the three per set distance based with OP method.

problem for cell k.

Problem 2:

$$\underset{\boldsymbol{a},\boldsymbol{D}}{\text{Minimize}} \quad \max_{i}(D_{i,k}) \tag{5.10}$$

$$s.t. \quad \sum_{i\in\boldsymbol{S}}\sum_{c=1}^{C} a_{i,c}R^*_{i,c} \geq -\frac{1}{2}\log_2\left((2\pi e)^{|\boldsymbol{S}|}\prod_{i\in\boldsymbol{S}} D_{i,k}\right) + h_2(\boldsymbol{S}|\boldsymbol{G}\backslash\boldsymbol{S}),$$

$$\forall\boldsymbol{S}\subseteq\boldsymbol{G}, \forall\boldsymbol{G}\subseteq\boldsymbol{X}^k$$

$$\sum_{i\in k} a_{i,c} = 1$$

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

5.4.2 Grouping of Correlated Sources

In order to take advantage of correlation in this problem setting, sources need to be decoded jointly. The number of sources that are jointly decoded can theoretically be as many as all the sources in a cell, and as little as two sources per decoding group, with correlation benefits increasing with more sources decoded jointly. However, as we will show in this section, increasing the group size beyond two or three sources per group does not offer significant benefits in terms of distortion. Additionally, complexities of both decoding and cross layer scheduling increase with the number of sources involved in joint decoding. Therefore in this work we assume that only a small number of sources can be decoded jointly, i.e. two or three. Initially, we assume the size of groups is set and fixed. Given this fixed group size, in this step the scheduler has to find which sources are grouped together and jointly decoded.

Grouping affects the performance in two ways, directly and indirectly. The direct effect refers to the performance a cell achieves as a result of jointly decoding the given groups of sources together. Specifically, the correlation levels of sources that are grouped together and the channel rate each source achieves affect the utility of the cell after the particular groups of sources are decoded jointly. 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, which results in change in the utility achieved in each cell.

The indirect effect of grouping is difficult to predict, especially since it involves knowledge of the load in nearby cells. However, the direct effect of a particular grouping of sources can be found using the rate-distortion region given in Eq (5.2), if data rates of the sources are assumed fixed. In order to simplify the analysis, we demonstrate this effect for a group of two correlated sources. The joint rate-distortion region is given by the following three inequalities:

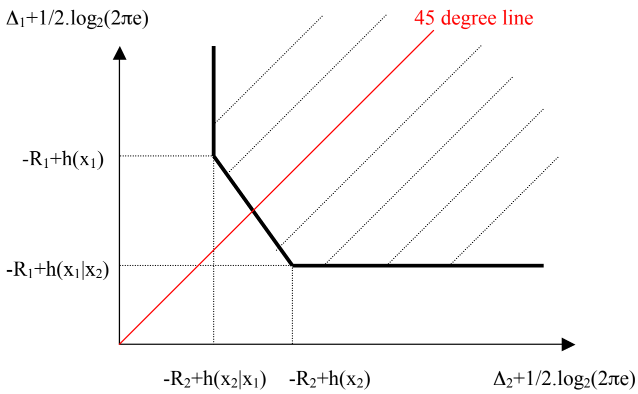


Figure 5.7: Trade-off of distortions for two correlated users.

$$R_1 \geq h_2(X_1|X_2) - \frac{1}{2}\log_2(2\pi e D_1)$$
$$R_2 \geq h_2(X_2|X_1) - \frac{1}{2}\log_2(2\pi e D_2)$$
$$R_1 + R_2 \geq h_2(X1, X_2) - \frac{1}{2}\log_2\left((2\pi e)^2 D_1 D_2\right)$$

We define $\Delta_i = 1/2\log_2 D_i$ to simplify the notation. For fixed rates, Δ_i values are bounded by:

$$\Delta_1 \geq -R_1 + h_2(X_1|X_2) - \frac{1}{2}\log_2(2\pi e) \tag{5.11}$$
$$\Delta_2 \geq -R_2 + h_2(X_2|X_1) - \frac{1}{2}\log_2(2\pi e)$$
$$\Delta_1 + \Delta_2 \geq -R_1 - R_2 + h_2(X1, X_2) - \log_2(2\pi e)$$

This region is demonstrated in Figure 5.7. When the aim is to minimize the maximum distortion, the following conditions determine the outcome of assigning distortion to users:

$$if \quad -R_i + h_2(X_i|X_j) \geq -R_j + h_2(X_j) \tag{5.12}$$
$$\text{then } \Delta_i = -R_i + h_2(X_i|X_j) - \frac{1}{2}\log_2(2\pi e)$$
$$\text{and } \Delta_j = -R_i + h_2(X_j) - \frac{1}{2}\log_2(2\pi e)$$

for i=1, j = 2, and vice versa. If neither condition is met, then the distortions will be equal:

$$\Delta_1 = \frac{1}{2}\left[-R_1 - R_2 + h_2(X1, X_2) - \log_2(2\pi e)\right]$$
$$\Delta_2 = \Delta_1. \tag{5.13}$$

Conditions (5.12) and (5.13) can be directly observed in Figure 5.7, by intersecting the R-D region with the line $\Delta_1 = \Delta_2$, which is the line that minimizes the maximum Δ_i. Note that in each of the above conditions one of the three inequalities given in Eq. (5.11) is met with equality. This applies to higher number of users per set as well [ZB99].

However, these conditions cannot be used to exactly predict the achieved distortion in a cell as a result of a particular source grouping. The reason is that the assumption of fixed data rates for sources is not realistic in a cross-layer resource allocation strategy, since the rate assigned to each source is affected by the source grouping method. Additionally, the above conditions only consider the *direct* effect of grouping on distortion, and ignore the effects of the particular grouping on the resource allocation, and therefore the interference in the network, and the resulting change in distortion of the sources in each cell. Therefore, an exhaustive solution cannot find the optimum source grouping using the above conditions, and is not computationally feasible in a reasonable timeline. However, from the above we learn 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 of sources in a group affect the final correlation gain of a source. As an example, if a source is jointly decoded with sources that have very low data rates, the correlation benefit it achieves is small, even if correlation level is high among the group.

Additionally, we must take the indirect effects of grouping into account. For this, we compare two source groupings that achieve the same direct correlated utility benefits, one which results in less need for transmission by a source located in the outer region of a cell. The grouping that results in less need for outer-user transmission results in lower interference levels in the network, and therefore less need for neighboring cells to increase their transmission power, thus achieving lower distortion in the network. Figure 5.6 demonstrates an example with two source groupings, one which takes the indirect effect into account and one that does not.

For source grouping, we propose two constructive, simple solutions to an NP-hard problem that cannot be solved exhaustively in real time. Each method is appropriate for a different problem setting. The first is 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.

Distortion based grouping with OP: Initially perform independent decoding until system performance is stable. Once performance stabilizes, pick a random source from N outer-most sources in the cell (we choose N=3 in simulations) and compute its projected performance if it is paired with any of the other sources in the cell, using conditions in (5.12) and (5.13). Choose the pairing which results in the lowest projected distortion for the chosen source and remove the pair from the set. Repeat until no nodes remain. Find the projected distortion in the cell if this grouping is used. Repeat the method T times and choose the source grouping that achieves the lowest projected distortion in the cell (T is chosen to be 10 in our simulations).

The second method is 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 decreases with distance between cells.

Distance based grouping with OP: Pick a random source from three outer-most sources in the cell and pair it with its closest neighbor and remove the pair from the set. Repeat until no nodes remain. Calculate sum of inter-group distances in the cell if this grouping is used. Repeat the method 10 times and choose the source grouping that achieves the lowest sum of inter-group distances.

When grouping is performed on more than two sources, the *tradable* log distortion is:

$$\delta\Delta = \left[h_2(\mathbf{S}) - \sum_{X_i \in \mathbf{S}} h_2(Xi) \right] \qquad |\mathbf{S}| = N. \tag{5.14}$$

If all users have equal independent distortion levels, each users' distortion is decreased by $\frac{\delta\Delta}{N}$ as a result of joint decoding, when the aim is to minimize the maximum distortion. We plot this value for various set sizes, with entropy given by Eq (5.3), covariance matrix given by Eq (5.4), and with distances assumed equal (although even for a 3 dimensional space this is only possible for up to five nodes). Figure 5.8 demonstrates the diminishing returns of set size. Additionally having large sets increases the Slepian-Wolf decoder complexity, as well as intra-cell scheduling complexity. Therefore we generally consider grouping of only a small number of sources and we compare performance of two and three nodes per set in the simulation section.

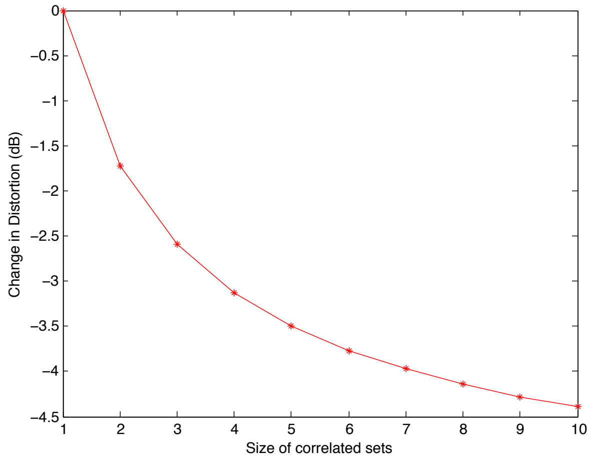


Figure 5.8: Diminishing returns of increasing correlated set size on distortion.

When this step is performed, the scheduler of cell k has an updated source grouping (i.e. $\boldsymbol{G}^*$ in Eq. (5.10)). Given this value and $\boldsymbol{p}^*$ found in the previous step, the intra-cell scheduling unit now can find the channel allocation.

5.4.3 Intra-Cell Scheduling

In the previous phases of the three step strategy we found $\boldsymbol{p}^*$ and $\boldsymbol{G}^*$, power and source grouping. In this last step we find $\boldsymbol{a}^*$ and $\boldsymbol{D}^*$, namely the channel and distortion allocation to each user for the frames in the given scheduling period.

We propose two solutions for this phase, with different complexities and performances. For schedulers with low computational capacity, we propose Distortion Proportionally Fair (D-PF). This solution is similar to the proportionally fair (PF) scheduling method [WOG05], modified to use distortion as utility instead of rate, and to take correlation effects into account. D-PF scheduling can be performed at every frame, similar to how PF is commonly used. As we will later show in the simulations, D-PF achieves better performance that PF, as a result of accounting for correlation in resource allocation.

The second solution we propose is called OPT, and is for schedulers with higher computational capacity, specifically ones that are capable of solving a linear programming scheduling problem at every scheduling period. OPT is a relaxed optimal assignment of channels and distortions, i.e. the relaxed version of Problem 2 given in (5.10). This problem is polynomial time solvable. Additionally, in the simulations we show that performing OPT scheduling once every ten frames still achieves better performance than the D-PF.

5.4.3.1 D-PF scheduling

With the common proportionally fair scheduling, at each frame the user which maximizes the following ratio is assigned channel c [WOG05]:

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

$R^*_{i,c}$ is the possible rate achieved for user i on channel c is given by Eq (5.9) and α is a parameter used to vary the trade-off between fairness and sum-rate maximization. $\overline{R}_j$ is the exponentially averaged rate of user j at time *t-1*, given by the following at time t by,

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

This scheduling method is simple, yet performs almost the same as relaxed optimal channel allocation for independent sources, as we demonstrated in [BPF11]. However, for correlated sources it is not sufficient to maximize the above ratio, since the effects of joint decoding are ignored.

For this, we first define $D^*_{i,c}$ as the possible distortion achieved by user i if scheduled on channel c. In order to find this value, we must use conditions (5.12) and (5.13) in Section 5.4.2, given the source grouping found in the previous step of the algorithm. These conditions require the knowledge of the values of possible data rate that 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 c, $R_i = R^*_{i,c}$, and $R_j = 0$ for $j \in \boldsymbol{G}^*(i)$ and $j \neq i$. Given these possible data rates, then we can use the conditions (5.12) and (5.13) to find $D_{i,c}$ and D_j.

We now propose D-PF, which uses the following condition for scheduling user l to channel c:

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

where $\overline{D}_j$ is the exponentially averaged distortion of user j at time *t-1*, given by the following at time t:

$$\overline{D}_j(t) = (\frac{1}{N_T}).D^*_j(t) + (1 - \frac{1}{N_T}).\overline{D}_j(t-1) \tag{5.15}$$

And $D^*_j(t)$ is found at each scheduling period after the channel assignment matrix ($\boldsymbol{a}^*$) is found, using the conditions (5.12) and (5.13) with rates equal to $R_i = \sum_{c=1}^{C} a^*_{i,c}.R^*_{i,c}$. The output of this method is then the matrix $\boldsymbol{a}^*$ and vector $\boldsymbol{D}^*$, which are 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 (5.12) and (5.13) replaced by the inequality set 5.2, solved for decreasing the maximum distortion.

5.4.3.2 OPT scheduling

Each cell finds the scheduling matrix, $\boldsymbol{a}^*$, and distortion vector, $\boldsymbol{D}^*$ by minimizing the maximum distortion in the cell. For this, we use Problem 2 given in (5.10), 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 users. Specifically, we perform OPT scheduling once every 10 frames and the real valued vector, $\tilde{\boldsymbol{a}}$, is rounded to achieve that resolution. The problem becomes the following:

Problem 3:

$$\underset{\tilde{\boldsymbol{a}},\boldsymbol{\Delta}}{\text{Minimize}} \quad \max_i(\Delta_i + \overline{\Delta}_i)$$

$$\sum_{i \in S} \sum_{c=1}^{C} \tilde{a}_{i,c} R^*_{i,c} \geq h_2(\boldsymbol{S}|\boldsymbol{G}^* \backslash \boldsymbol{S}) + \sum_{i \in S} \Delta_i - \frac{|S|}{2} \log_2(2\pi e)\,, \qquad \forall \boldsymbol{S} \subseteq \boldsymbol{G}^*, \forall \boldsymbol{G}^* \subseteq \boldsymbol{X}_k$$

$$\sum_{i \in k} \tilde{a}_{i,c} = 10, \quad 0 \leq \tilde{a}_{i,c} \leq 10 \qquad \forall i, \forall c.$$

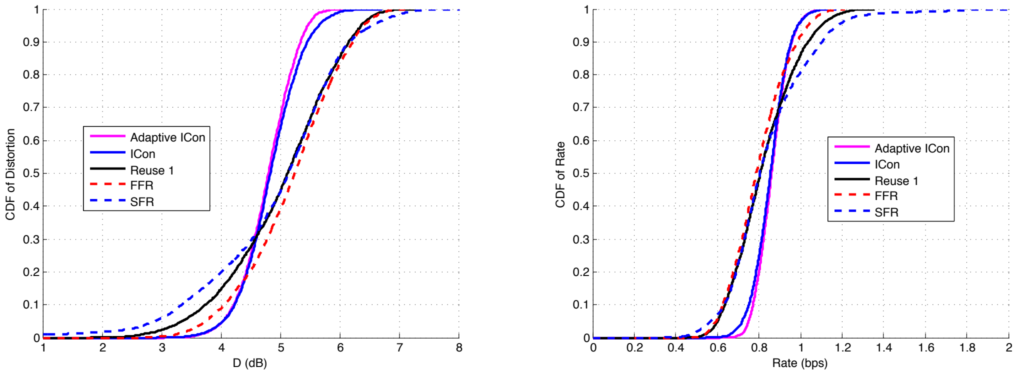
$\overline{\Delta}_i$ is $\log_{10} \overline{D}_i$, given by Eq (5.15), and $R^*_{i,c}$ is given by Eq (5.9). This is a linear programming problem in $\tilde{\boldsymbol{a}}$ and $\boldsymbol{\Delta}$, solvable in polynomial time using a method such as the Simplex algorithm [BV04]. After this problem is solved, matrix $\boldsymbol{a}$ is found by rounding $\tilde{\boldsymbol{a}}$ such that each c is assigned to a single source in every frames in the following scheduling period. Then $\boldsymbol{D}$ is found using the conditions (5.12) and (5.13) with rates equal to $R_i = \sum_{c=1}^{C} a^*_{i,c}.R^*_{i,c}$. As with the case of D-PF, the matrix $\boldsymbol{a}$ and vector $\boldsymbol{D}$ are then transmitted to users, determining the resource and distortion allocation in the following scheduling period. We compare these two scheduling methods in the simulations section.

5.5 Simulations

We simulate a 19 cell hexagonal 2-D cellular network, comparable to one given for the micro test case for LTE [3GP06], with wrap around in order to avoid boundary inconsistencies. In each instance of the problem, 18 sources are placed with uniform distribution in every cell. Simulation parameters are given in Table 5.1. We use CDF of distortion values and rates achieved by sources in order to demonstrate the performance of different algorithms. Since the aim in this work is to minimize the maximum distortion achieved in the network, the parameter we look for is the performance of 5 percentile worst performing users (5 percentile rate and 95 percentile distortion). We begin by comparing performance of various methods for each step of the three step algorithm, in order to justify the choices we have made in the proposed scheme. Later we will compare the overall performance gain of utilizing correlation in resource allocation using our proposed scheme, versus independent allocation of resources. Finally, we demonstrate convergence of the proposed algorithm.

In order to compare 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 and rates achieved by sources, as shown in Figures 5.9(a) and 5.9(b), with 5 percentile distortion details shown in Figure 5.10. 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, as we expected. With little base station communication between neighboring cells, using Adaptive ICon, this gain is increased to 1 dB.

We now add correlation to resource allocation in order to compare source grouping methods in Figure 5.12. We use D-PF for intra-cell allocation, and use that for all methods in this step. We first the two grouping methods we proposed in Figure 5.12(a), namely distance OP and distortion OP. We also show the effects



(a) Comparison of distortion of various inter-cell resource management methods.

(b) Comparison of rate of various inter-cell resource management methods.

Figure 5.9: Inter-cell scheduling methods.

of using outer priority in this plot. We find that distortion OP performs slightly better than distance OP, however distortion OP cannot be used adaptively, and thus is not appropriate for some applications. We also compare the effects of group size in Figure 5.12(b). Increasing set size from one user per group (i.e. independent decoding) to two decreases the 95 percentile distortion by 2 dB. However, there is almost no difference in this value when we increase the group size from two to three sources, which is expected as explained in Section 5.4.2.

We compare the intra-cell scheduling methods, namely, PF, D-PF, and OPT, with the inter-cell method given by static ICon and source grouping of 2 per set distance OP for all comparisons. Results are demonstrated in Figure 5.11. We observe that using correlation in resource allocation, even with a simple method, i.e. D-PF compared with PF, decreases the 95 percentile distortion by 0.75 dB. Using OPT scheduling decreases this performance metric by 1 dB more over the D-PF, adding up to 1.75 dB over PF scheduling. This is a large gain, which is feasible if the scheduler has the computational capacity to perform OPT, as discussed in Section 5.4.3.

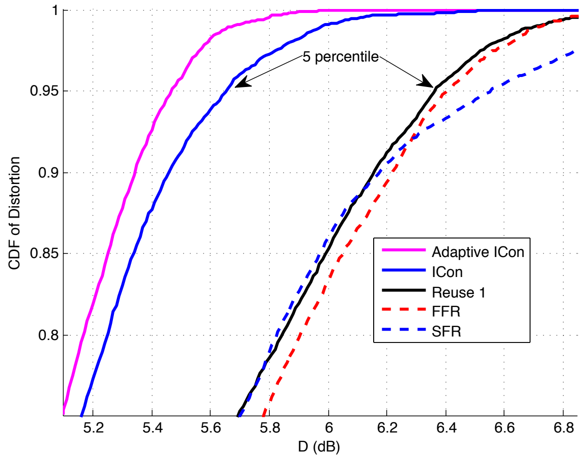


Figure 5.10: Closeup of distortion CDF of inter-cell resource management methods..

In Figure 5.13(a) we demonstrate the overall performance of the three phased strategy, with adaptive ICon, two users per set distance based with OP source grouping, and optimal intra-cell scheduling, with a baseline method, namely Reuse 1 without spatial correlation and PF scheduling, common in cellular networks. Overall, we demonstrate that this method achieves a large improvement of almost a 4 dB (60%) decrease in distortion for 5 percentile users.

Finally we show the convergence behavior of the three step algorithm in Figure 5.13(b). Each iteration shown in the Figure is 1 iteration of adaptive ICon (inter-cell resource management step), which in our simulations is equal to 100 intra-cell scheduling periods. This demonstrates that ICon adaptation converges almost fully after one inter-cell resource management period.

5.6 Conclusion

In this work we consider the problem of resource allocation to spatially correlated sources in OFDMA multi-cell networks, which is an NP-hard problem for which

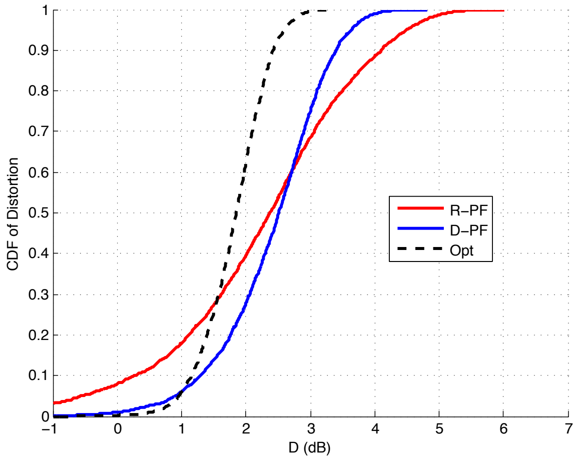
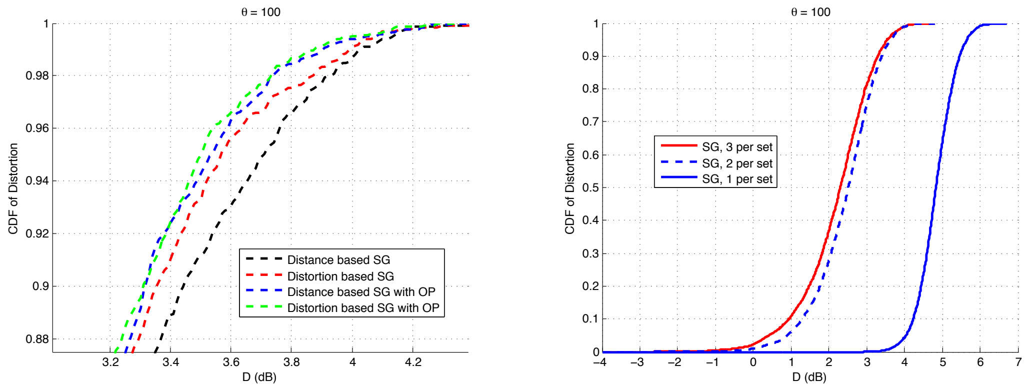


Figure 5.11: Comparison of distortion CDF in D-PF vs R-PF vs OPT scheduling.



(a) 2 per set, distance vs distortion based, with/without outer priority.

(b) 2 vs 3 nodes per set.

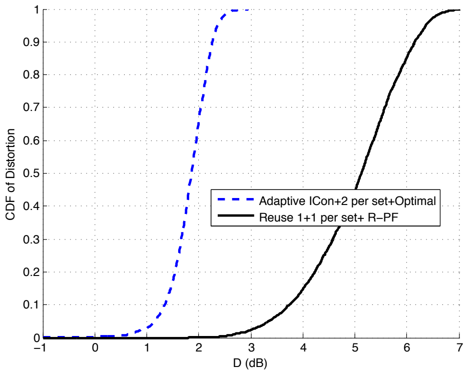
Figure 5.12: Source grouping methods.

exhaustive solutions are not computationally feasible in one scheduling period. We propose a cross-layer solution that performs resource and distortion allocation to sources in three simple, practical steps.

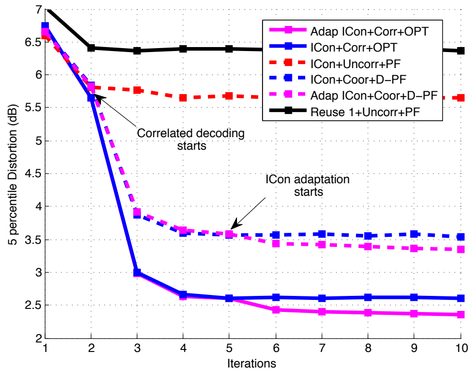
The design parameters are power per channel per source, and the grouping of sources to be decoded jointly. We find each of these parameters in one step of a three step approach. Namely, we find power per channel per user in the

Table 5.1: Simulation parameters

Parameter	Values
Number of cells	19, with wrap around
Users per cell	18, uniformly distributed
Site to site distance (m)	130
Bandwidth	10 Hz
Number of subbands	63
Max Power per user per band	$250\text{mW}/63 \times 10^{-6}$
Path loss model (dB)	$30 \log_{10} R$, R in (m).
Fractional power control	$\alpha = 1$, Γ differs.
IoT	ICon=10, Reuse1=13 (dB)
PF scheduling parameters	a = 3.5
FFR reuse 1 band/total band	$\eta = 45/63$
SFR parameters	$p_l/p_h = 1/10$, $\gamma = 6$ dB
PF Scheduling at every:	1 frame
Optimal Scheduling at every:	10 frames
Step sizes for adaptive ICon	$\alpha = \beta = 0.2$
Gaussian sources mean and var	σ^2=10, mean = 0
Correlation parameter	θ= 100



(a) Comparison of proposed method v baseline.



(b) Convergence of adaptive method.

Figure 5.13: Intra-cell scheduling methods.

inter-cell resource management step, grouping of sources for joint decoding in the source grouping step, and the channel and distortion allocation to each user in the intra-cell scheduling step.

We justify our design choices in the simulations by comparing various methods for each step of the algorithm. Overall, the performance gain over base-line, non-correlated method is a 4 dB (i.e. 60%) decrease in distortion of the worst performing sources.

CHAPTER 6

Concluding Remarks

In this work we proposed workable algorithms for adaptive resource allocation for correlated sources in specific systems, namely, for single cell multi-view video systems, and multi-cell networks with general correlated sources. Additionally, we proposed an inter-cell interference management for multi-cell systems.

First, we proposed an adaptive resource allocation scheme for multi-view video sources. This case was considered in order to demonstrate the benefits of correlation-aware resource allocation in an end to end system design. We used a simple joint decoding scheme based on the common H.264 standard, and modeled the boundary of the R-D region as a piecewise linear function. We showed that even with a simplistic coding scheme which achieves little gain over independent coding, the correlation-aware resource allocation achieves much gain over independent resource allocation. A more sophisticated joint decoding scheme and R-D region associated with it could be used in our proposed method, which would lead to higher gains.

We then considered resource allocation in multi-cell OFDMA networks. The challenge here is to manage the inter-cell interference. We proposed a heuristics based method called ICon, which sets interference power limits on each subband for each cell, concentrating the interference to a cell on a designated band. This allows for more efficient use of the bandwidth compared to the common inter-cell interference methods such as FFR and SFR. In order to balance the performance across the cells, the high interference band for each cell is rapidly and efficiently adapted. This method can easily be utilized in Long Term Evolution of 3G networks.

Finally we studied the problem of resource allocation to spatially correlated sources in OFDMA multi-cell networks. This is an NP-hard problem for which exhaustive solutions are not computationally feasible in a single scheduling period. For this problem we proposed a location based, three step cross-layer resource allocation algorithm, which takes both inter-cell interference and correlation characteristics of sources into consideration. Our method achieves significant gain over independent resource allocation with little increase in complexity.

By studying different instances of the resource allocation problem, in this thesis we demonstrated that for networks of correlated sources, the correlation-aware resource allocation (RA) problem achieves much gain over independent methods. In each case we proposed practical RA schemes. An interesting future research direction of this work is to characterize the effects of uncertainty in the correlation model and the high-resolution R-D bound on the performance of the correlation-aware RA.

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