AMERICAN UNIVERSITY OF BEIRUT

DYNAMIC TIME DIVISION INTER-CELL INTERFERENCE COORDINATION AND RESOURCE ALLOCATION IN HETEROGENEOUS NETWORKS

by
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AN ABSTRACT OF THE THESIS OF

Youssef Ali Jaffal for Master of Engineering
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Title: Dynamic Time Division Inter-Cell Interference Coordination and Resource allocation in Heterogeneous Networks

Heterogeneous Networks are considered a promising solution to meet the exponentially increasing data demand. To make the best use of the small base stations added near the existing macro base stations, each user should be associated to the most appropriate base station, the base stations should cooperate to reduce the inter-cell interference, and each base station should allocate its resources (power and subcarriers) efficiently to its users. In this thesis we studied the time domain inter-cell interference coordination technique for the downlink of Long Term Evolution (LTE), which was proposed in 3GPP release 10. It consists of using the almost blank sub-frames to reduce the interference on the victim users. We proposed an efficient method to optimize the total network performance, and it is divided into two stages: the resource allocation and the cell association. The resource allocation problem for Orthogonal Frequency Division Multiplexing (OFDM) systems is a mixed integer non-linear programming problem and it is NP hard problem. We proposed to use the K-best branch and bound as a sub-optimal solution. The K-best branch and bound proved to have very low complexity at the cost of a slight reduction in the total data throughput. The cell association problem is also a mixed integer non-linear programming; we used the exhaustive search to find the optimal solution because it has a low complexity. We divided the users into three categories: pico cell center users, pico cell edge users, and macro cell users. We used the dynamic cell range expansion to determine the three groups. We proved by simulations that the muting rate of the almost blank sub-frames has an optimal solution, and we calculated the bias of the pico cell center users and the pico cell edge users using the equal average throughput and the maximum minimum rate methods respectively.

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LIST OF ABBREVIATIONS

3GPP	Third Generation Partnership Project
ABS	Almost Blank Sub-frames
BS	Base Station
CA	Carrier Aggregation
CRE	Cell Range Expansion
CSG	Closed subscriber group
CSI	Channel State Information
DL	Downlink
eICIC	enhanced Inter-Cell Interference Coordination
Het-Nets	Heterogeneous Networks
ICIC	Inter-Cell Interference Coordination
LTE	Long Term Evolution
MINLP	Mixed Integer Non-Linear Programming
OFDM	Orthogonal Frequency Division Multiplexing
QoS	Quality of Service
RSS	Received Signal Strength
SINR	Signal to Interference and Noise Ratio
TDM	Time Division Multiplexing
UE	User Equipment
UL	Uplink

CHAPTER I

INTRODUCTION

The existing cellular networks are facing an increasing traffic demand due to the increasing number of new developed devices and their data demanding applications. The deployment of Heterogeneous networks is one of the proposed solutions to face this increasing wireless data demand. The idea behind heterogeneous networks consists of overlaying the existing macro-cells with smaller cells (Pico-cells, femto-cells, WIFI routers…) in order to increase the data throughput for mobile user equipment (UE). Pico base stations (BS) and femto BS use the same spectrum used by the Macro BS, whereas the WIFI routers works on the unlicensed bands. The deployment of small cells in the vicinity of the existing macro-cells requires advanced resource allocation and interference coordination techniques.

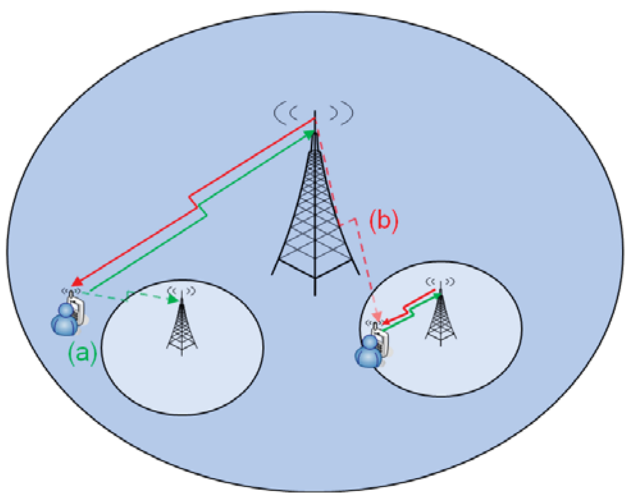

Figure 1: Inter-cell interference in Heterogeneous networks

Installing smaller LTE cells inside Macro cells introduces the issue of inter-cell interference, since those LTE cells share the same spectrum. According to [1] the main sources of interference in heterogeneous networks are:

1. Unplanned deployment: It is more probable that LTE femto BS and WIFI hotspots installed by users to be placed in a random manner, and not following an optimized deployment.
2. Closed subscriber group (CSG): when nonsubscribers UEs enter small cells restricted to subscribed users, they will not be connected to the nearest BS, and the macro-cell UE will transmit with high power causing high interference on the uplink (UL) of the GSC femto BS. Also the macro UEs will be receiving high power signals from the GSC cell, which will jam their Downlink (DL).
3. Power difference between nodes: Macro BSs use higher transmitting power compared to small cells, and thus UE preferring to connect to the cell providing the highest received signal strength (RSS) will be jamming the UL of the neighboring small cells.
4. Range expanded users: this comes as a solution for the power difference problem, where small BSs add a power offset to increase their RSS, in order to increase their coverage area, but the UE at the cell edge will suffer from low RSS at the DL.

Also the distribution of the available resources among different UEs is not a straight forward job, since there is a tradeoff between maximizing the overall capacity of the network and the fairness between the UEs. The resource allocation techniques focus on assigning the UEs to the existing cells and how each cell distributes its resources (power and resource blocks) among the UEs it is serving.

In heterogeneous networks the macro base stations ensure coverage and the smaller base stations provide more capacity. As the transmission power of the macro base station is the highest, most of the users will have the SINR from the macro base station higher than the SINR of the smaller base station. Higher SINR is preferred since it decreases the bit error rate and increases the capacity and the data throughput of the users. But the data rate provided for each user depends on the number of users served by the same base station, since they share the available power and bandwidth, and hence as the number of connected users increases the average data throughput will decrease. As a result, the cell association process should take into account both the SINR and the load on each base station.

CHAPTER II

LITERATURE REVIEW

2.1. State of the art on inter-cell interference coordination

ICIC between macro BSs and pico BSs can be handled through the X2 interface. And the coordination between the cellular BSs and the small cells installed by users should be handled through the internet, which introduces some delays that affect the performance of ICIC algorithms. The developed ICIC techniques in the literature can be grouped under four main categories: frequency-domain techniques, time-domain techniques, power-control techniques, and channel-coding techniques. The frequency-domain and time-domain techniques can be seen as inter-cell interference avoidance techniques, whereas power-control and channel coding techniques can be seen as interference cancellation techniques.

The time domain techniques consist of scheduling the transmissions of the neighboring cells in order to protect the transmitted signals. Such techniques require synchronization between the involved BSs. In the time division multiplexing ICIC (TDM-ICIC), the Macro BSs mutes some of their sub-frames periodically. Those sub-frames are called almost blank sub-frames (ABS). The pico BSs schedule the transmissions for their cell edge UEs in the ABS in order to reduce the interference from the macro BS. The power domain techniques consist of adjusting the transmission power for the neighboring BSs in order to reduce the impact of the interfering signals. And in the coding techniques, the BSs send some additional messages that enable the victim UEs to reduce the impact of the interfering signals through interference cancellation.

In [1] one time domain technique and four different power control techniques were compared, the four methods adjust the transmitted power of the small cells to reduce the interference on the macro UE, which decreases the capacity of the small cells. The time domain technique is based on scheduling the transmissions of the Macro UEs in the ABS of the femto BSs when the UEs enter the vicinity of the femto cells. The time domain technique maximizes throughput for Macro UEs, but it also minimizes the throughput of the small cell UEs. In [2] the performance of time domain multiplexing with cell range expansion is studied, where the macro BSs and the pico BSs get specific time slots for their transmissions, in order to avoid any interference from the macro-BS on the pico cell edge UEs. And in [3] the optimal muting rate of the ABS is studied in order to increase the throughput of the pico-cell without affecting the throughput of the macro-cell. In [4] a new TDM-LTE algorithm is proposed and simulated with and without traditional frequency domain ICIC, the inclusion of the frequency domain techniques enhances the performance of the TDM-LTE algorithm. In [5], a cell planning model is proposed for schemes with TDM-LTE and cell range expansion (CRE). In [6] an algorithm for resource allocation in TDM-LTE with CRE is proposed, it calculates the optimal power bias for the CRE and the optimal muting rate for the macro BSs.

A channel coding technique was proposed in [7], where the sent message contains two messages, a private message that can be decoded by the intended receiver only, and a common message that can be decoded by everyone. UEs decode and cancel the common messages, and then they treat the private messages of other UEs as noise. The results show that the proposed method improves the SINR and the average throughput of the UEs.

The frequency-domain techniques consist of assigning orthogonal subcarriers to the different neighboring UEs to avoid the inter-cell interference. One simple interference avoidance scheme is to assign orthogonal bands to the neighboring cells, which will avoid any inter-cell interference but with small throughput, where the frequency reuse factor is 3 (Fig 2.a). On the other side, using a frequency reuse factor of one will result in a high inter-cell interference for cell edge users.

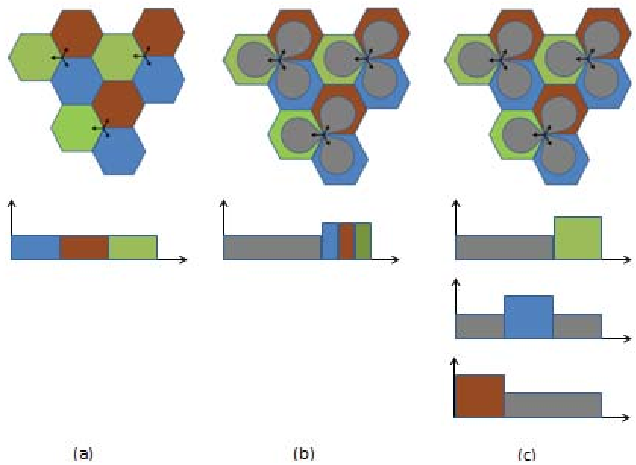

Figure 2: Static frequency domain ICIC, (a) reuse factor 3, (b) partial frequency reuse, (c) soft frequency reuse

Another approach is to divide the cell area into two parts, the cell central area and the cell edge area. Users in the central area can use the same subcarriers used for users in the central area of neighboring cells, whereas cell edge users must use different subcarriers than those used for cell edge users in the neighboring cells. In such fractional frequency reuse schemes the reuse factor is between 1 and 3. The fractional frequency reuse techniques proved to have better performance compared to the schemes where the reuse factor is 1 or 3 [8], [9].There are two main fractional frequency reuse schemes in the literature, the partial frequency reuse (fig1.b) and the soft frequency reuse (Fig 2.c). The performance of those schemes depends on the power allocated for the cell edge and cell center UEs, on the fraction of the bandwidth allocated to the cell edge users, and on the traffic distribution in the cell. In [10] the soft and partial reuse schemes are compared, the soft reuse schemes have shown to have higher overall throughput. In [11] the effect of different traffic loads on the throughput of the cell edge and cell center UEs is studied. In [12] the author proposed to use a frequency reuse factor-4 in the soft frequency reuse scheme for femto-cell systems to improve the performance of the cell edge UEs.

The frequency domain ICIC techniques described above are considered as static techniques. The schemes where the BSs adapt the bandwidth and power allocated to the cell edge users are considered as semi-static techniques, such semi-static schemes have better performance compared to the static schemes [13],[14]. The Static and semi-static ICIC cannot be applied to the new networks, because the random placement of small cells installed by users will make any static frequency planning difficult. Whereas the dynamic ICIC can operate based on the interference information from other cells. Dynamic frequency domain ICIC consists of dynamic power and subcarriers allocations for the UEs. Dynamic ICIC schemes proved to have better performance compared to the static and semi-static ICIC schemes [15]-[16]. In [17] the authors proposed a dynamic ICIC method where the neighboring cells take the decision jointly based on the feedback from the UEs. In [16] a dynamic ICIC taking into consideration the distribution of the UEs is proposed.

Frequency domain ICIC based on carrier aggregation (CA) enhances the overall UEs' throughput. In such techniques, each BS is assigned a portion of the bandwidth, with the ability to share some subcarriers of the neighboring cells when low interference is guaranteed. In [18], a frequency domain ICIC based on CA for femto-cell scenario was proposed. In [19] a dynamic carrier selection algorithm with interference coordination is proposed.

2.2. State of the art on resource allocation

The resource allocation techniques try to maximize the overall capacity of the network in addition to guarantying acceptable QoS for all the UEs. Given the existing BSs and UEs, and given the constraints on the total bandwidth and the total transmission power, a resource allocation algorithm tries to assign the different users to the suitable BSs, to allocate the appropriate subcarriers and transmission power for each UE, and to use a scheduler that guaranty some fairness among the users and to maximize the overall throughput.

First, to select the most suitable BS to serve a given UE, the selection can be obtained by calculating the score of the existing cell. This score depends on some attributes (bandwidth, delay, load, UE's mobility, received power…), and each attribute will have its specific weight based on the application requirement. The score of each cell is a combination of the attributes and their weights, and it can be calculated by two methods: Simple additive weighted or multiplicative exponential weighted [20]. In [21], a resource allocation algorithm in het-nets together with cell selection was proposed. It consists of prioritizing the cells based on the location of the UE; the close small cells are assigned high weights for subscribed UE and medium weight for unsubscribed UE, whereas the cellular cells are the lowest weighted BSs. To simplify the optimization problem, the authors approximated the log terms by linear operations and then used a mixed-integer linear programing way to get the optimal resource allocation solution. In [22] the authors assigned different weights to the cells based on their coverage area, and they suggested keeping the high speed users at the macro layer, because high speed users are expected to stay short time durations inside the small cells.

Second, the BS tries to schedule the transmissions for its assigned UEs targeting fairness among UEs together with maximized throughput. A scheduler seeking the maximization of the throughput favorites the cell center UEs which results in poor throughput for the cell edge UEs. On the other hand, seeking good throughput for the cell edge UEs having bad conditions will decrease the throughput of the cell-center UEs and the overall throughput of the cell. Thus the scheduler tries to assign acceptable throughput for the cell edge UEs with a minimal impact on the overall cell throughput. There are several scheduling algorithm proposed in the literature, the throughput of the proportional fair algorithm is estimated in [23], the proportional fair scheduler assigns resources to the UEs based on the current data demand and on the past allocated resources. The proportional fair scheduler is widely investigated in the literature. In [24] the authors proposed a pruning scheduler that avoids scheduling resources for users with weak SNR, the idea behind this pruning scheduler is that users with weak SNR will have a high block error rate, and scheduling resources for a considerable number of UEs with weak SNR decreases the network throughput.

Third, the BS distributes the available subcarriers among the selected users and assigns different power levels for each subcarrier. To achieve the maximal overall throughput, the subcarriers and power levels should be assigned in a manner that maximizes the Shannon capacity equation:

$$C = \sum_{i=0}^{N} b_i \times \sum_{k=0}^{M} log_2(1 + SINR_{i,k}) \tag{1}$$

Where the total number of OFDM subcarriers is N, b_i corresponds to the bandwidth of the i^{th} subcarrier, M is the total number of users, and $SINR_{i,k}$ corresponds to the signal to interference and noise ratio of the k^{th} user at the i^{th} subcarrier. Suboptimal solutions are used to guaranty some fairness in the network, since in the optimal solution the UEs suffering from high power losses may not get any resources. Also suboptimal solutions are used to reduce the complexity of resource distribution process. Several low-complexity resource allocation techniques are investigated in the literature [25], [26]…

2.3. System Model

We consider a group of *M* neighboring LTE macro cells, and each macro cell contains P_m LTE pico cells in its vicinity. In addition, we consider a group of *K* users distributed randomly on the map. We assume there are K_m UEs served by the m^{th} Macro BS, and K_{pc} UEs served by the p^{th} pico BS and located in its center area, and K_{pe} UEs served by the p^{th} pico BS and located in its cell edge area. We assume that we have a total of *N* subcarriers allocated for downlink data transmission.

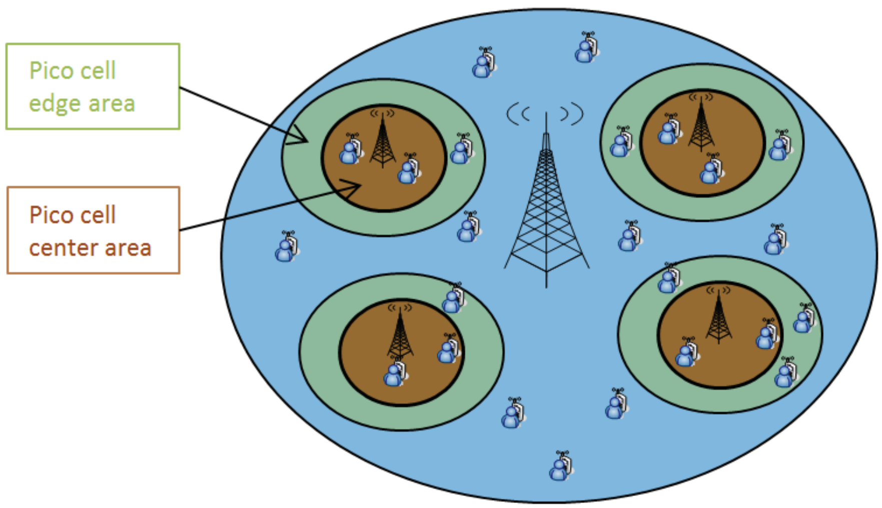

Figure 3: Het-Net with one Macro BS and several Pico BSs and UEs

We assume a full traffic scenario; all users are always demanding data as much as the network can provide. Since the coordination between the macro BSs and the pico BSs is handled using the X2 interface, we assume that the macro BSs and pico BSs are synchronized. In this thesis, the studied ICIC technique is the time domain technique (usage of ABS), where the macro BS mutes its sub-frames periodically to enhance the pico cell edge UEs' throughput. This technique was first introduced in 3GPP release 10.

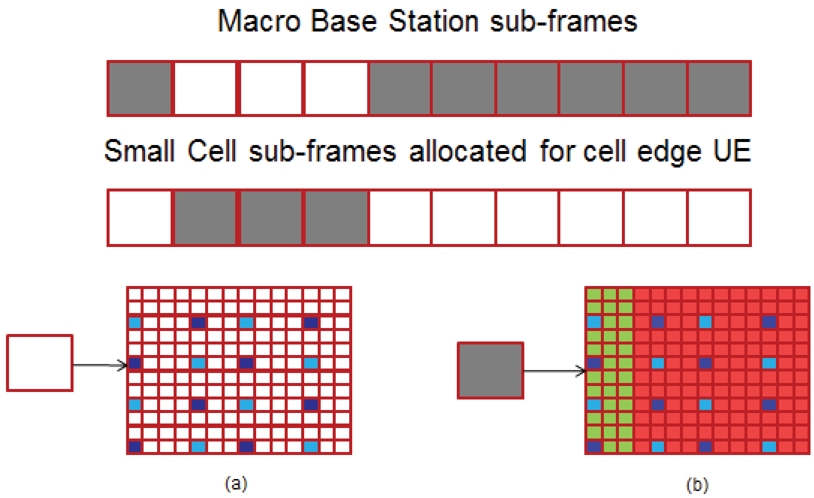

Figure 4: ABS Configuration, (a) blanked Sub-frame, (b) used Sub-frame

We assume that the macro cell UEs receives data in the non ABSs, the pico cell edge UEs receive data only during the ABSs, and the pico center cell UEs can receive data in any sub-frame. We assume that the pico cell edge UEs can cancel the effect of the pilots that Macro BSs send during the ABSs. We assume that there is no inter-cell interference between the pico BSs.

In this model, we aim at maximizing the overall throughput with acceptable fairness between the UEs. We define the following variables to derive the resource allocation problem:

1. α_m is the fraction of time scheduled for ABS in the m^{th}Macro cell.
2. $Pt_{m,k,i}$ is the power transmitted by the m^{th}Macro BS to the k^{th} UE on the i^{th} subcarrier.
3. $Pt_{p,k,i}$ is the power transmitted by the p^{th}Pico BS to the k^{th} UE on the i^{th} subcarrier.
4. $Pl_{m,k,i}$ is the power that the signals on the i^{th} subcarrier loses on the path from the m^{th} macro BS to the k^{th} UE.

5. $Pl_{p,k,i}$ is the power that the signals on the i^{th} subcarrier loses on the path from the m^{th} macro BS to the k^{th} UE.
6. $Pr_{m,k,i}$ is the received power by the k^{th} UE on the i^{th} subcarrier from the m^{th} macro BS.
7. $Pr_{m,p,k,i}$ is the received power by the k^{th} UE on the i^{th} subcarrier from the p^{th} pico BS located in the m^{th} macro cell.
8. The signal to interference and noise ratio for the k^{th} UE on the i^{th} subcarrier, and served by the m^{th} Macro BS is given by:

$$SINR_{i,k,m} = \frac{Pr_{m,k,i}}{\sum_{l\neq m}^{M} Pr_{l,k,i} + \sum_{m=1}^{M}\sum_{l=1}^{P_m} Pr_{l,k,i} + N_0} \tag{2}$$

9. The signal to interference and noise ratio for the k^{th} UE on the i^{th} subcarrier, and served by the p^{th} pico BS is given by:

$$SINR_{i,k,p,m} = \frac{Pr_{m,p,k,i}}{\sum_{l=1}^{M} Pr_{l,k,i} + \sum_{n\neq m}^{M}\sum_{l=1}^{P_n} Pr_{l,k,i} + N_0} \tag{3}$$

10. The overall throughput for the pico cells center UEs is:

$$C_{Pc} = \sum_{m=1}^{M}\sum_{p=1}^{P_m}\sum_{i=1}^{N} b_i \sum_{k=1}^{K_{pc}} log_2(1 + SINR_{i,k,p,m}) \tag{4}$$

11. The overall throughput for the pico cells edge UEs is:

$$C_{Pe} = \sum_{m=1}^{M}(1-\alpha_m)\sum_{p=1}^{P_m}\sum_{i=1}^{N} b_i \sum_{k=1}^{K_{pe}} log_2(1 + SINR_{i,k,p,m}) \tag{5}$$

12. The overall throughput for the Macro cells center UEs is:

$$C_M = \sum_{m=1}^{M} \alpha_m \sum_{i=1}^{N} b_i \sum_{k=1}^{K_m} log_2(1 + SINR_{i,k,m}) \tag{6}$$

Then the total achievable capacity in this scenario is $C_{total} = C_{pc} + C_{Pe} + C_M$

$$C_{total} = \sum_{m=1}^{M} \sum_{p=1}^{P_m} \sum_{i=1}^{N} b_i \sum_{k=1}^{K_{pc}} log_2(1$$

$$+ \frac{Pr_{m,p,k,i}}{\sum_{l=1}^{M} Pr_{l,k,i} + \sum_{n\neq m}^{M} \sum_{l=1}^{P_n} Pr_{l,k,i} + \sum_{l\neq p}^{P_m} Pr_{l,k,i} + N_0})$$

$$+ \sum_{m=1}^{M} (1 \tag{7}$$

$$- \alpha_m) \sum_{p=1}^{P_m} \sum_{i=1}^{N} b_i \sum_{k=1}^{K_{pe}} log_2(1 + \frac{Pr_{m,p,k,i}}{\sum_{l=1}^{M} Pr_{l,k,i} + N_0})$$

$$+ \sum_{m=1}^{M} \alpha_m \sum_{i=1}^{N} b_i \sum_{k=1}^{K_m} log_2(1 + \frac{Pr_{m,k,i}}{\sum_{l\neq m}^{M} Pr_{l,k,i} + N_0})$$

Equation (7) has the following constraints:

1. $\sum_{k}^{Km} \sum_{i}^{N} Pt_{m,k,i} \leq P_{Macro\_total}$: the total transmit power per macro BSs limit.
2. $\sum_{k}^{Kpe} \sum_{i}^{N} Pt_{m,k,i} + \sum_{k}^{Kpc} \sum_{i}^{N} Pt_{m,k,i} \leq P_{Pico\_total}$: the total transmit power per pico BSs limit for all m=1,..M.
3. $0 < \alpha_m < 1$

The maximization problem for equation (7) is a mixed integer non-linear programming (MINLP) problem and it is NP hard. Our goal is to find the optimal values for the transmitted power per base station, the best distribution of the available resource blocks among the users, the cell association, and the muting rate.

In this thesis we solve the problem in two steps: resource allocation and cell association. By solving the resource allocation problem we determine the optimal distribution of resource blocks among the UEs and the optimal transmission powers. And by solving the cell association problem we classify the users (Macro UEs, Cell Center Pico UEs, or Cell Edge UEs) and we find the optimal muting rate for the ABSs.

CHAPTER III

RESOURCE ALLOCATION IN OFDM

The Orthogonal Frequency Division Multiplexing (OFDM) consists of dividing the bandwidth into carriers for wireless data transmission. This technique is robust against fading and it is used in the 4th generation of mobile telecommunications (LTE). In Frequency division multiple Access systems different OFDM sub-channels are assigned to different users, and the resource allocation consists of distributing the subcarriers and allocating different power levels either to maximize the total data throughput given the constraint on the total transmission power or to minimize the total transmission power for a given data throughput. In this thesis we maximize the total throughput given the total transmission power constraint.

3.1. Single-User downlink resource allocation

The power allocation problem has the well-known water-filling solution. Consider the downlink of a multiuser OFDM network that consists of one base station serving one user with the downlink bandwidth divided into N sub-channels. We assume that the user experiences different channel conditions on the different resource blocks, and we assume perfect channel state information (CSI) at the base station.

The channel to noise ratio for the user on the j^{th} subcarrier is given by

$$\gamma_j = \frac{h^2{}_j}{N_j} \tag{8}$$

Where h_j is the channel gain and N_j is the noise level. Let p_j to be the transmitted power on the j^{th} subcarrier and B to be the bandwidth of the resource block. Based on the Shannon capacity equation, the total capacity for the downlink is given by

$$C = \sum_{j=1}^{N} B \times log_2(1 + \frac{p_j \times \gamma_j}{B}) \tag{9}$$

Let P_{max} to be maximum transmission power for the base station, then

$$\sum_{j=1}^{N} p_j \leq P_{max} \tag{10}$$

Since our goal is to maximize the total capacity described by equation (3), the resource allocation will have the same solution as the following optimization problem, since the constants can be removed for simplicity, and let $\sigma_j = \frac{B}{\gamma_j}$.

$$\begin{gathered} Minimize - \sum_{j=1}^{N} log_2(\sigma_j + p_j) \\ subject\ to \begin{cases} \sum_{j=1}^{N} p_j \leq P_{max} \\ p_j \geq 0, \ \ for\ j = 1, \ldots, N \end{cases} \end{gathered} \tag{11}$$

This problem is a convex optimization problem because of the following:

- The objective function is concave because it is a linear combination of convex functions.
- The two constraints are convex.

Then the Lagrangian can be derived as follows:

$$L = \sum_{j=1}^{N} -log_2(\sigma_j + p_j) + \mu(P_{max} - \sum_{j=1}^{N} p_j) + \sum_{j=1}^{N} \lambda_j p_j \tag{12}$$

And the optimal power allocation is the root of the derivative of the Lagrangian, then

$$\frac{\partial L}{\partial p_j} = -\frac{1}{\sigma_j + p_j^*} + \mu^* - \lambda_j^* = 0 \tag{13}$$

And then

$$p_j^* = \begin{cases} \frac{1}{\mu^*} - \sigma_j \; if \; \mu^* < \frac{1}{\sigma_j} \\ 0 \; if \; \mu^* \geq \frac{1}{\sigma_j} \end{cases} \tag{14}$$

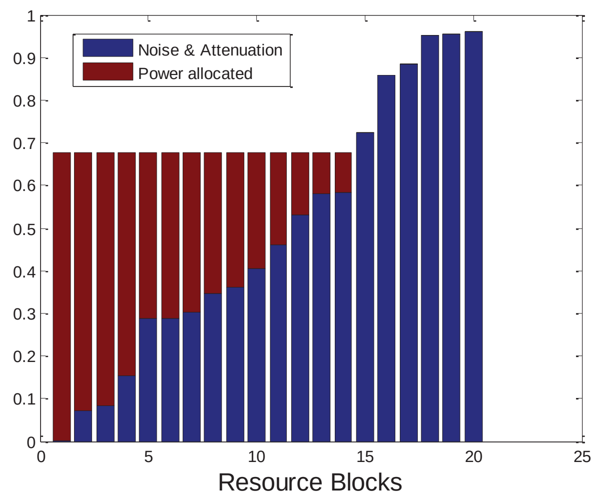

Figure 5: Water-filling Solution

Fig.5 illustrates the water-filling solution. And $\frac{1}{\mu^*}$ is the water level that should be calculated or estimated. As shown in Fig.5, some resource blocks are not used (no power is allocated), so we introduce R_{min} to be the minimum acceptable rate for each resource block, and the optimization problem becomes:

$$Minimize - \sum_{j=1}^{N} log_2(\sigma_j + p_j)$$

$$subject\ to \begin{cases} \sum_{j=1}^{N} p_j \leq P_{max} \\ B \times log_2\left(1 + \frac{p_i \times \gamma_i}{B}\right) \geq R_{min} \\ \forall\, i = 1, \ldots, K \\ p_j \geq 0,\ \ for\ j = 1, \ldots, N \end{cases} \tag{15}$$

This problem is also convex since the additional constraint is convex. This problem can be solved by two steps:

1. Assign the minimum required power that achieves the minimum rate

$$P_{min_j} = (2^{\frac{R_{min}}{B}} - 1) \times \frac{B}{\gamma_i} \tag{16}$$

2. Allocate the remaining available power by using the water-filling solution.

Fig.6 shows the effect of adding the minimum rate constraint; all the resource blocks are used.

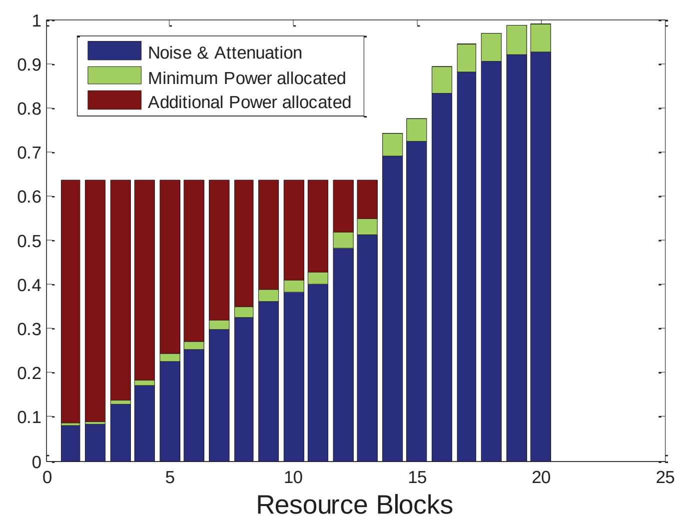

Figure 6: Water-filling with Minimum Rate Constraint

3.2. Multi-User downlink resource allocation

The resource allocation problem for the multiuser downlink is a Mixed Integer Non-Linear Programming problem (MINLP), and this problem is considered as NP hard problem. The Branch and Bound technique [27] and the Outer Approximation Algorithm [28] are used to search for the optimal solution for MINLP problems, but their complexity increases exponentially with the number of variables. In the literature, different methods were proposed for resource allocation in OFDM; the authors in [29]-[31] used different game theoretical approaches to maximize the total throughput taking into account the issue of fairness between the different users. In [32] the authors used the genetic algorithm and the particle swarm optimization.

In this thesis we propose the k-best branch and bound method for multiuser downlink resource allocation for OFDM. The proposed algorithm is evaluated in terms of computational complexity and average user throughput; it reduces the computational complexity tremendously at the cost of a slight reduction in the average user throughput.

3.2.1. Problem Formulation

Consider the downlink of a multiuser OFDM network that consists of one base station serving *M* users with the downlink bandwidth divided into *N* sub-channels. We assume that each user experiences different channel conditions on the different sub-channels, and we assume perfect channel state information (CSI) at the base station. The channel to noise ratio for the i^{th} user on the j^{th} subcarrier is given by

$$\gamma_{i,j} = \frac{h^2{}_{i,j}}{N_{i,j}} \qquad (17)$$

Where $h_{i,j}$ is the channel gain on the j^{th} subcarrier for the i^{th} user, and $N_{i,j}$ is the noise level on the j^{th} subcarrier for the i^{th} user. Let $p_{i,j}$ to be the transmitted power to the i^{th} user on the j^{th} subcarrier, and $\alpha_{i,j}$ to be a binary indicator that indicates whether the j^{th} subcarrier is allocated to the i^{th} user or not. Since each subcarrier cannot be allocated to more than one user, the following constraint must be satisfied

$$\forall\, j = 1, \ldots, N;\ \sum_{i=1}^{M} \alpha_{i,j} \leq 1 \tag{18}$$

Based on the Shannon capacity equation, the total capacity for the downlink is given by

$$C = \sum_{i=1}^{M} \sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2(1 + \frac{p_{i,j} \times \gamma_{i,j}}{B}) \tag{19}$$

Let P_{max} to be maximum transmission power for the base station, then

$$\sum_{i=1}^{M} \sum_{j=1}^{N} p_{i,j} \leq P_{max} \tag{20}$$

To insure fairness between the different users, let R_{min} to be the minimum acceptable rate for each user, then

$$\sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2\left(1 + \frac{p_{i,j} \times \gamma_{i,j}}{B}\right) \geq R_{min} \qquad \forall\, i = 1, \ldots, K \tag{21}$$

Since our goal is to maximize the total capacity described by equation (3), the resource allocation becomes an optimization problem as follows:

$$Maximize \sum_{i=1}^{M}\sum_{j=1}^{N}\alpha_{i,j}\times B\times log_2\left(1+\frac{p_{i,j}\times\gamma_{i,j}}{B}\right)$$

$$subject\ to\begin{cases}\alpha_{i,j}\in\{0,1\}\\ \sum_{i=1}^{M}\alpha_{i,j}\leq 1\\ \sum_{i=1}^{M}\sum_{j=1}^{N}p_{i,j}\leq P_{max}\\ \sum_{j=1}^{N}\alpha_{i,j}\times B\times log_2\left(1+\frac{p_{i,j}\times\gamma_{i,j}}{B}\right)\geq\ R_{min}\end{cases} \tag{22}$$

In addition, the base station should allocate to its users approximately the same number of resource blocks. The problem is how to allocate the resource blocks if some users prefer to have the same resource block. This problem has no closed form solution and it is a mixed integer non-linear programming problem and it is NP hard.

3.2.2. Proposed Solution

MINLP problems are usually solved by using branch and bound algorithm or by the outer approximation algorithm. In this thesis we focused on the branch and bound technique, and we proposed the K-best branch and bound algorithm to calculate a sub-optimal solution with acceptable computational complexity.

3.2.2.1. <u>Branch and Bound</u>

The branch and bound technique consists of two interacting parts, a tree search that solves the combinatorial problem, and a solver for the NLP part. Fig.7 describes the branch and bound algorithm.

Branch and bound always finds the optimal solution and it does not necessarily require a complete tree search, because the tree may get pruned due to:

1. Infeasible node is reached.
2. The upper bound at a node is less than the achieved lower bound.

When such nodes are reached then there is no need to process their sub-trees.

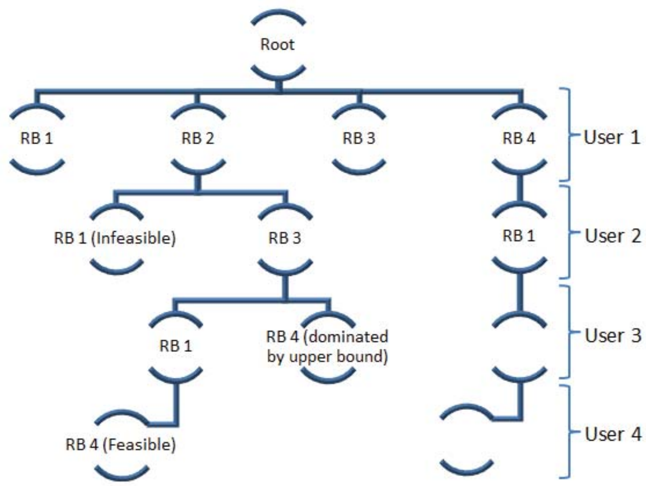

Figure 7: Branch and Bound Tree

The NLP part is solved by using the water-filling solution with prior minimum power allocation; it consists of allocating first the minimum amount of power that satisfies the minimum rate constraint, and then distribute the remaining power by using the water-filling algorithm. The computational complexity of the branch and bound is not fixed, since it depends on the pruned branches, but in the worst case scenario, the branch and bound may lead to a complete tree search which increases exponentially with number of users and subcarriers.

3.2.2.2. K-Best Branch and Bound

This is a modified version of the branch and bound technique; it consists of restricting the search to *K* survival paths in the tree. The operation of the algorithm is shown in Algorithm 1.

Initialize: K empty paths with zero achieved throughput
Iterate Over the Users: • For each path create N child • Calculate the achieved capacity of the resulting $K \times N$ paths Select the best K paths having the highest achieved throughput
Select the path with the highest achieved throughput

Algorithm 1: K-best Branch and Bound Algorithm

From the described algorithm, it can be deduced that the computational complexity of the K-best branch and bound increases linearly with number of users and subcarriers, and that this algorithm does not necessary find the optimal solution.

3.2.3. Simulation Results

The simulation parameters are shown in Table.1. The simulations are done for the branch and bound algorithm and for the K-best branch and bound algorithm with different *K* values.

Parameter	Value
Maximum transmission power	46 dbm
Number of Users	8
Noise spectral density	-174.0 dbm/Hz
Pathloss model	120+ 36 log(d), d in Km
Bandwidth of one RB	180 KHz
User distribution	i.i.d.

Table 1: Simulation Parameters for Resource Allocation

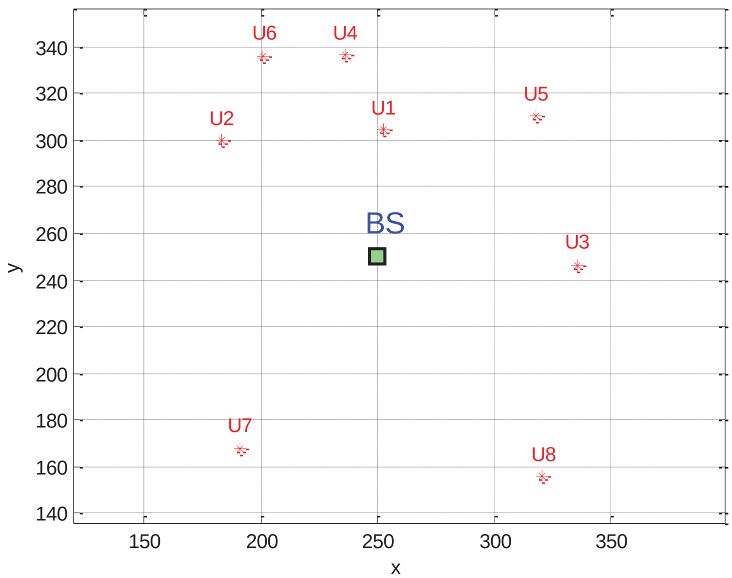

Figure 8: Schematic of the studied cell

Fig.8 shows the distribution of the users around the BS. The assigned names are based on the increasing order of the distances between the UE and the base station (i.e. U1 is the nearest UE to the base station). The performance of the k-best branch and bound algorithm depends on the order of users. In the following we show the performance of the K-best branch and bound with two different orders of users:

1. “K-best Inc”: this algorithm starts with the users having the best channel conditions; it gives higher priority for those users.
2. “K-best Dec”: this algorithm starts with the users having the worst channel conditions, and it gives them higher priorities.

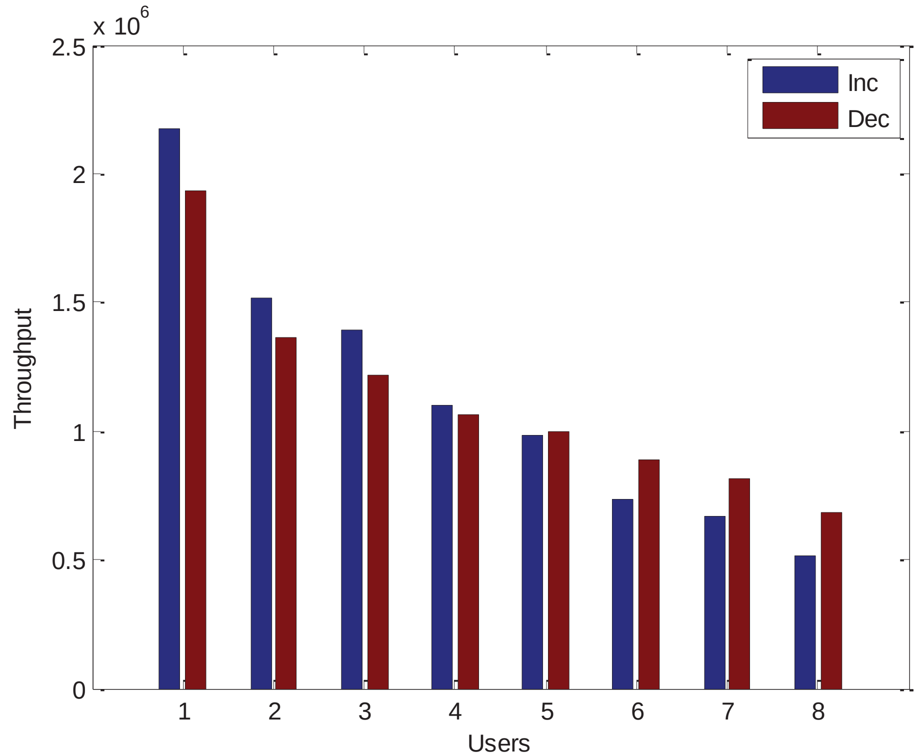

Figure 9: Average throughput for the different users

Fig.9 shows the average user throughput when using the two different orders. By comparing the results for both algorithms, we notice that cell center users enjoy higher throughput when the “K-best Inc” algorithm is used, and the cell edge users enjoy higher throughput when the “K-best Dec” algorithm is applied. In total the “K-best Inc” algorithm achieves better total throughput (9.0911 Mbps compared to 8.957 Mbps for the “K-best Dec” algorithm), but the “K-best Dec” algorithm achieves higher minimum throughput as shown in Fig.9.

In the following we compare the k-best branch and bound with the branch and bound algorithm in terms of computational complexity and achieved total downlink throughput.

3.2.3.1. Computational Complexity

Fig. 10 shows the computational complexity in terms of the consumed time for each algorithm. The complexity of the branch and bound algorithm clearly increases exponentially with the number of subcarriers, whereas the complexity of the k-best algorithm increases linearly with the number of subcarriers for the different values of *K*. Decreasing the value of *k* decreases the consumed time. The value of "*K*" in Fig.10 is equal to the number of channels.

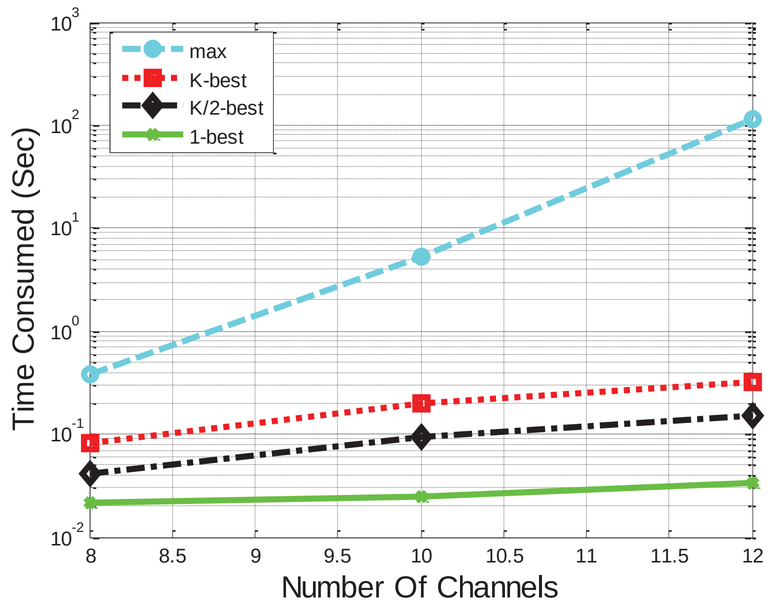

Figure 10: Time consumed by each algorithm

3.2.3.2. Total Downlink Throughput

The simulation results for the total downlink throughput are shown in fig. 10. The branch and bound algorithm achieves the maximum throughput and the K-best branch and bound has a slight reduction compared to the branch and bound (0-30 Kbits/sec). Also it is shown in the figure that decreasing the value of *"K"* has considerable impact on the average user throughput (around 30-50 Kbits/sec for *K*/2 best, and 80-90

Kbits/sec for the 1-best branch and bound).

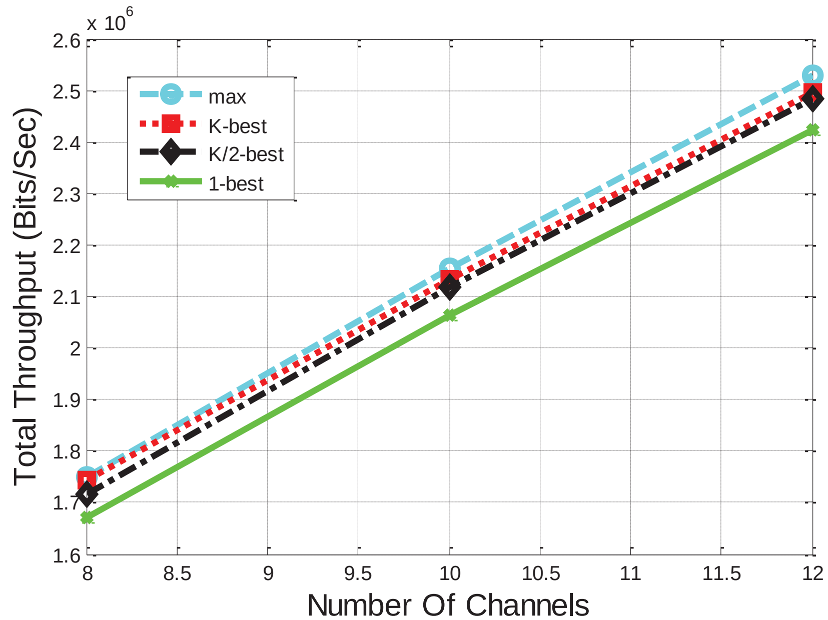

Figure 11: Average throughput for different algorithms

Based on the obtained results, *"K"* must be set to the maximum possible value (i.e. to the number of subcarriers), because most of the gain in the complexity is achieved by any value of "*K*", and decreasing it reduces the achieved throughput significantly.

CHAPTER IV

CELL ASSOCIATION IN HET-NETS

One candidate solution for cell association is to use cell range expansion (CRE); it consists of offloading some users to small cells even if they have lower received signal strength by adding a bias to the SINR of the small cells. The CRE can be static or dynamic; the static CRE uses a constant SINR bias whereas the dynamic CRE uses a variable SINR bias based on the distribution of the users. The dynamic CRE has better performance since it adapts to the changes in the network.

The users associated to small base stations are divided into two categories, cell center user and cell edge users. As the cell edge users experience higher interference compared to the cell center users, the enhanced inter-cell interference coordination (eICIC) techniques were proposed by 3GPP, the eICIC can be in frequency domain or in time domain. In this thesis we focus on the time domain eICIC, which consists of using the almost blank sub-frames (ABS); the macro base station mutes its power periodically to reduce the interference on the pico cell edge users.

4.1. System Model

Consider the downlink of a multiuser OFDM network that consists of one macro base station, P pico base stations, serving K users with the downlink bandwidth divided into N sub-channels. Assume that K_1 users are connected to the macro base station, and $K_{2,p}$ users are connected to the p^{th} pico base station. The users are associated based on the CRE with a bias 'b_p'. And we assume perfect channel state information (CSI) at the base station.

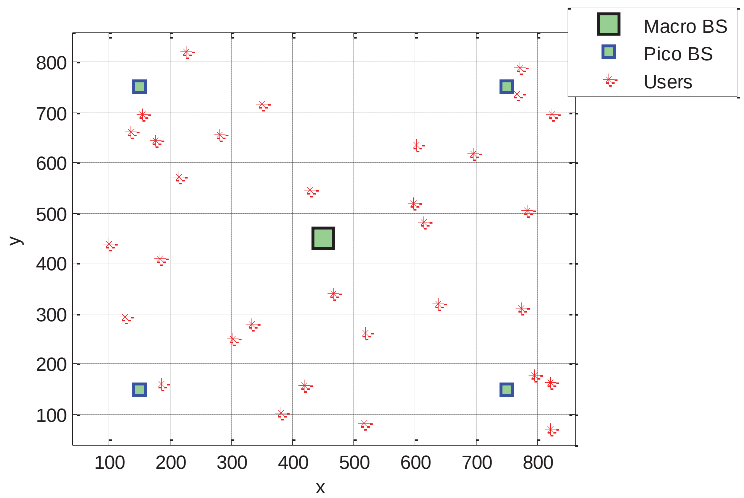

Figure 12: Schematic of the studied area

4.1.1. Cell Association without blanking (with interference)

In this scenario, the Macro BS and the Pico BS transmit on the same frequencies, and then the optimal transmission power of one BS depends on the transmission of the other BS. Since the optimization problem becomes non-convex, we decided that each BS allocates its resources assuming that the other BS is using equal power transmission. Let $p_{i,j}$ to be the transmitted power to the i^{th} user on the j^{th} subcarrier, $\alpha_{i,j}$ to be a binary indicator that indicates whether the j^{th} subcarrier is allocated to the i^{th} user or not, $\sigma_N$is the noise power, P_P to be the total transmission for the Macro BS, P_M to be the total transmission for the Pico BS, $h_{1,i,j}$ is the channel gain on the j^{th} resource block between the i^{th} user and the Macro BS, and $h_{2,i,j}$ is the channel gain on the j^{th} resource block between the i^{th} user and the Pico BS. Based on the Shannon capacity equation, the average capacity for the downlink for the macro bases station is given by

$$CM = \sum_{i=1}^{K_1}\sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2(1 + \frac{p_{i,j} \times {h_{1,i,j}}^2}{B \times \left(\frac{P_P \times {h_{2,i,j}}^2}{N \times B} + \sigma_N\right)}) \tag{23}$$

The average capacity for the downlink for the p^{th} pico base station is given by

$$CP_p = \sum_{i=1}^{K_{2,p}}\sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2(1 + \frac{p_{i,j} \times {h_{2,i,j}}^2}{B \times \left(\frac{P_M \times {h_{1,i,j}}^2}{N \times B} + \sigma_N\right)}) \tag{24}$$

Our goal is to select the optimal SINR bias for CRE that achieves the maximum average throughput with fairness between the users.

4.1.2. Cell Association with ABS

We assume no inter-cell interference since the pico base stations transmits when the macro base station mutes its transmission power. Let τ to be the muting rate used by the macro base station. Based on the Shannon capacity equation, the average capacity for the downlink for the macro bases station is given by

$$CM = (1 - \tau) \times \sum_{i=1}^{K_1}\sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2(1 + \frac{p_{i,j} \times {h_{1,i,j}}^2}{B \times \sigma_N}) \tag{25}$$

The average capacity for the downlink for the p^{th} pico base station is given by

$$CP_p = \tau \times \sum_{i=1}^{K_{2,p}}\sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2(1 + \frac{p_{i,j} \times {h_{2,i,j}}^2}{B \times \sigma_N}) \tag{26}$$

The SINR bias used at each pico base station determines the number of its associated users. As in the previous scenario, our goal is to select the optimal SINR bias and muting rate that achieve the maximum average throughput with fairness between the users.

4.1.3. Combined Scenario

In this scenario we combine the two scenarios described in the previous sections, as described in chapter 3 we divide the users into three different groups: Macro UEs, cell center Pico UEs, and cell edge Pico UEs. The Macro BS sends data to its UEs during its specified time slot, the Pico BS transmits to its cell edge UEs when the Macro BS mutes its sub-frames, and the Pico BS transmits to its cell center UEs all the time.

In this scenario, our goal is to find the optimal muting rates and the optimal SINR biases for CRE that determine the Pico cell center and Pico cell edge UEs. The optimal muting rate and the optimal biases should achieve the maximum total throughput with acceptable fairness between the users.

4.2. Problem Formulation

For the three different scenarios, our goal is to achieve maximum total throughput with acceptable fairness between the different UEs. Our solution consists of finding the bias for CRE in each case and assigning the users to the appropriate BS. And then each BS allocates its resources (resource blocks and power) using the k-best branch and bound. The load on each base station is defined as the percentage of UEs assigned to it.

In this thesis we exploit two possible methods that assure acceptable fairness. The first method consists of minimizing the difference between the average throughputs for the different base stations, and the second method aims at maximizing the minimum throughput for all the UEs.

4.2.1. *Equal Average Throughput*

The average throughput per base station is defined as follows:

$$C_{avg} = \frac{1}{K}\sum_{i=1}^{K}\sum_{j=1}^{N}\alpha_{i,j} \times B \times log_2\left(1 + \frac{p_{i,j} \times \gamma_{i,j}}{B}\right) \tag{27}$$

Where K is the number of the users connected to the base station, N is the number of subcarriers, $\alpha_{i,j}$ is the binary indicator that indicates whether the j^{th} subcarrier is allocated to the i^{th} user or not, B is the bandwidth of the resource block, $\gamma_{i,j}$ is the channel to noise ratio for the i^{th} user on the j^{th} resource block, and $p_{i,j}$ is the transmitted power on the j^{th} resource block for the i^{th} user. Each base station uses the k-best branch and bound to allocate the power and resource blocks to its UEs, then the variables for this problem are the number of UEs associated to each base station, and they depend on the SINR bias used for CRE. The optimization problem is defined as follows

$$\min_{K_m, K_p} (C_{m_{avg}} - C_{p_{avg}})^2 \tag{28}$$

Where $C_{m_{avg}}$ is the average throughput for the Macro UEs, $C_{p_{avg}}$ is the average throughput for the Pico UEs, K_m is the number of Macro UEs, and K_p is the number of Pico UEs. The optimization problem is MINLP, but with low complexity (increases linearly with the number of users) so we do an exhaustive search to find the optimal SINR bias values.

4.2.2. *Maximizing minimum Throughput*

Since we are using the k-best branch and bound for resource allocation at each base station, the cell center users get higher data rates than the cell edge users. And as the number of users connected to a base station increases, the data rate per user decreases because the limited resources (power and frequencies) are shared with more users. Then increasing the SINR bias for CRE decreases the data rates for the pico users and increases the data rates for the macro users, and vice versa.

Our goal is to find the cell association that maximizes the minimum throughput, i.e. the users are connected to the base station that provides them with higher data rates. The throughput for the i^{th} user is defined by:

$$C_i = \sum_{j=1}^{N} \alpha_{i,j} \times B \times log_2\left(1 + \frac{p_{i,j} \times \gamma_{i,j}}{B}\right) \tag{29}$$

And the optimization problem is defined by:

$$\underset{K_m, K_p}{\text{Maximize}}(\text{Min}(C_{m_i}, C_{p_j})) \tag{30}$$

Here C_{m_i} is the throughput of the i^{th} macro user, and C_{p_j} is the throughput of the j^{th} pico user. This problem is MINLP but with low complexity, so as in the previous problem we do an exhaustive search for the optimal cell association.

4.3. Simulations results

We did the simulations for a static scenario (no mobility models) where the users are independent and identically distributed. And we calculate the optimal values of the variables dynamically. We iterate over 4000 iterations and we present the average values of the calculated variables. The simulation parameters are listed in the following table:

Parameter	Value
Macro BS Maximum transmission power	40 Watts
Pico BS Maximum transmission power	1 Watts
Number of Macro BSs	1
Number of Pico BSs	4
Number of Users	32
Noise spectral density	-174.0 dbm/Hz
Macro Path-loss model	128.1+ 37.6 log10(d), d in Km
Pico Path-loss model	140.7+ 36.7 log10(d), d in Km
Bandwidth of one RB	180 KHz
Number of RBs	4, 8, 12
Fading model	Rayleigh flat fading
User distribution	i.i.d.

Table 2: Simulation Parameters for Cell Association

4.3.1. Cell Association without blanking (with interference)

Each base station allocates its resources using the k-best branch and bound algorithm. The simulations are performed with different number of resource blocks. The simulations show that for each number of RBs an optimal bias exists for each Pico BS. The optimal bias depends on the load on each BS; it is the value that achieves balance between average throughputs of the different base stations.

Fig.13 shows how we get the optimal cell association with equal average throughput, as shown in the figure, the Pico average throughput decreases when the number of connected users to the Pico BS increases, and the Macro average throughput increases when the number of connected users to the Pico BS increases (i.e. number of users connected to the Macro BS decreases). The optimal cell association is defined by the point of intersection between the two lines (i.e. equal average throughput).

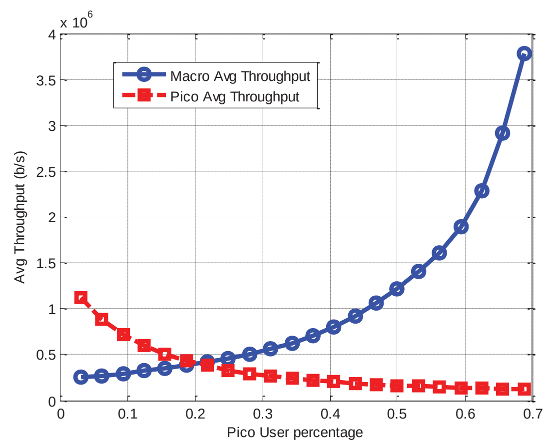

Figure 13: Average throughputs with respect the to load on the Pico BSs

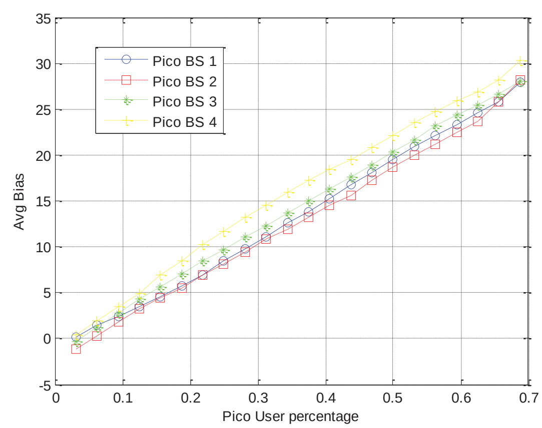

Figure 14: The relation between the SINR bias and the load on the Pico BSs

As shown in fig.14, the optimal bias depends on the load on the Pico BSs, and it is calculated based on the optimal Pico BS load calculated determined in Fig.13. Fig.15 shows the throughput per user, where the users are sorted based on their distances with respect to the pico and macro base stations (User number 1 is the nearest one to the pico BS, and User number 8 is the nearest one to the Macro BS). Without loss of generality, in this case the first three users are connected to the Pico BS and the rest are connected to the macro BS, and as the number users per BS decreases the minimum rate for this BS increases. In the problem of maximizing the minimum throughput, we search for the cell association that achieves balance between the minimum rates for the macro BS and the pico BSs.

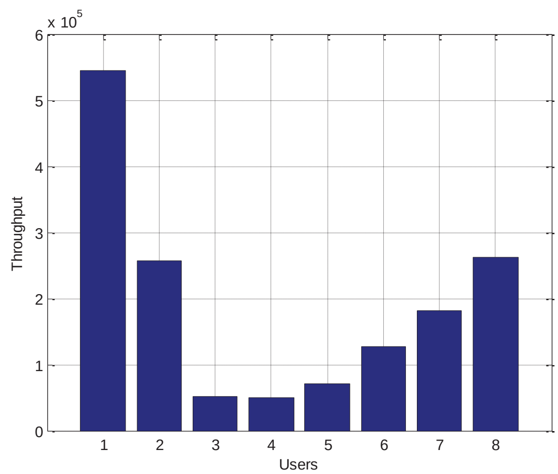

Figure 15: Throughput per user, Maximization of Minimum Rate

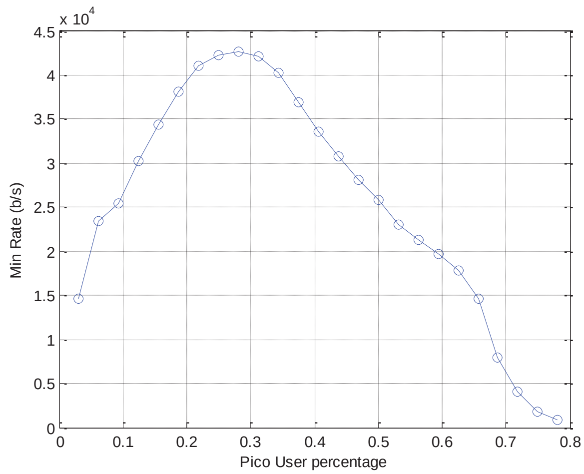

Figure 16: Optimal User association by maximizing the minimum rate

Fig.16 shows that an optimal value for the minimum exists and it defines the appropriate cell load (which defines the optimal bias for CRE). With a low number of UEs connected to the Pico BS, a large number of the UEs will be connected to the Macro BS, and then some macro UEs will suffer from very low rates (as shown in Fig.16 at low values of Pico User percentage). And the same happens when a large number of users are connected to the Pico BS; some Pico UEs will suffer from very low rates (as shown in Fig.16 at high values of Pico User percentage). So the optimal value should be a medial value that decreases the load on both the macro and pico BSs.

The optimal SINR bias for CRE is calculated based on the optimal load on the Pico BS. And Fig.17 shows the optimal SINR biases calculated by each method for different number of resource blocks. We notice from Fig.17 that the optimal SINR bias for the maximum minmum rate method is higher than the optimal SINR bias calculated by the equal average throughput method. This is expected because the Macro BS has higher power resources compared to the Pico BSs, then the Macro BS can serve additional UEs with very low data rate whithout a great effect on the average thoughput, but the average throughput for the pico BS will be much more affected when additional UEs are served with low data rates. From Fig.17 we notice that the SINR bias for CRE decreases with the increase in the number of RBs, and it is almost constant when using the equal average method.

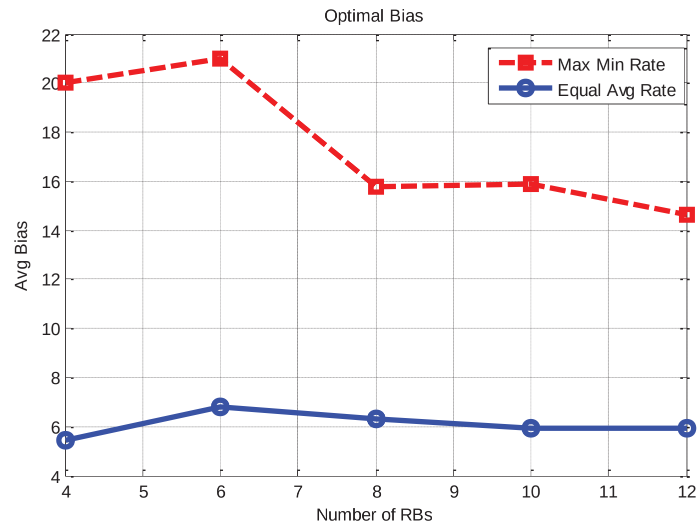

Figure 17: Optimal Biases, without blanking

4.3.2. Cell Association with ABS

The simulations show that for each number of channels an optimal bias and an optimal muting rate exist for each Pico BS. The optimal bias for CRE at each base station depends on the muting rate; it is the value that achieves balance between average throughputs of the different base stations.

Fig.18 and Fig.19 show that an optimal muting rate exists for both methods (equal average throughput and maximizing minimum rate). When using a low value for the muting rate, the available resources (power and resource blocks) will be rarely used at the Pico BSs, which decreases both the total average throughput and the minimum rate for the Pico UEs, and this pushes the UEs to be served by the Macro BS, and then the total average throughput and the minimum rate for the Macro UEs also decreases. Also when using high values for the muting rates, the available resources at the Macro BS will be rarely used, and then both the minimum rate and the average throughput for the Macro UEs will decrease, which pushes the UEs to be connected to the Pico BSs, and then the total average throughput and the minimum rate for the Pico UEs will also decrease. So the optimal value should be a medial value that increases the usage of the available resources at each BS, and achieves balance on the load for the different BSs.

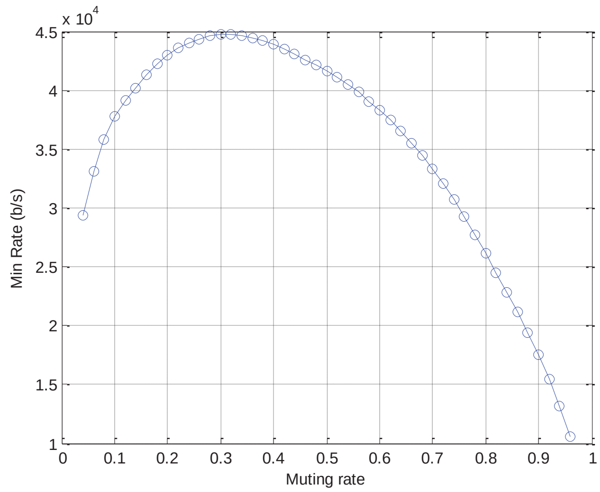

Figure 18: Optimal muting rate by maximizing the minimum rate

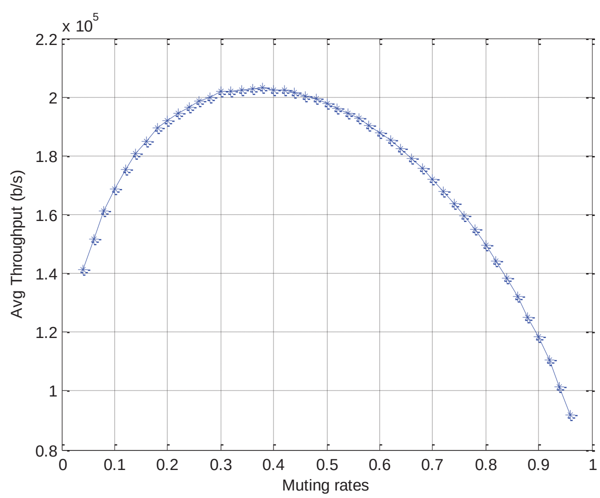

Figure 19: Optimal muting rate by using equal average throughput

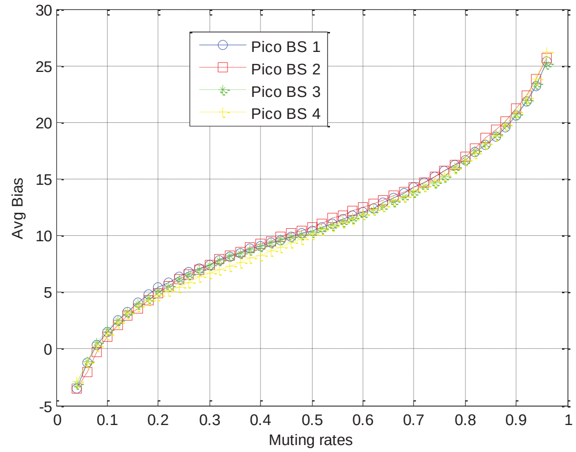

Figure 20: The relation between the muting rates and the bias for equal average throughput method

Fig.20 shows the relation between the muting rates and the SINR biases for CRE. The optimal muting rates calculated previously determine the appropriate SINR bias for each method (for the equal average throughput and for the maximum minimum rate method).

Fig.21 shows the optimal SINR biases for both methods with different number of RBs. We notice from Fig.21 that the optimal SINR bias for the maximum minmum rate method is higher than the optimal SINR bias calculated by the equal average throughput method. This is expected because the Macro BS has higher power resources compared to the Pico BSs, so adding more UEs with low data rates will have higher effect on the average throughput for the Pico BS compared to the average throughput of the mcaro cell.

Fig.22 shows the optimal muting rates for both methods with different number of RBs. The equal average throughput method achieves higher muting rates compared to the maximum minimum rate method; the optimal muting rates are related with the optimal SINR biases and the load on the macro and pico BSs.

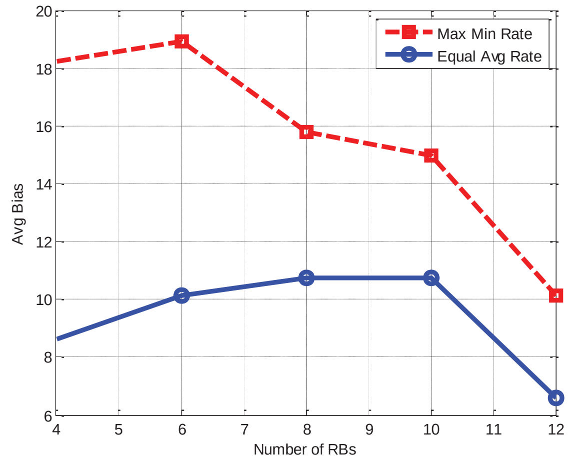

Figure 21: Optimal Biases for CRE for the scenario with ABS

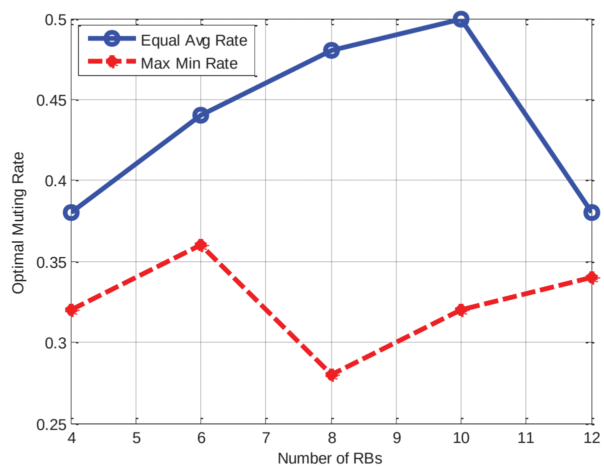

Figure 22: Optimal muting rates for ABS

4.3.3. Combined Scenario

The time domain ICIC was proposed to protect the cell edge users, so in thesis we propose to use the maximum minimum rate method to calculate the optimal bias for the cell edge area. And concerning the optimal bias for the cell center users, since all the cell center users will have acceptable throughput, we propose to use the equal average throughput because this method have higher total throughput compared to the maximum minimum rate method.

Fig. 23 shows the optimal biases for the cell edge and cell center areas when using different number of resource blocks. The cell edge area has an optimal SINR bias of 15.62 db on average, and the cell center area has an optimal SINR bias of 6 db on average. The optimal SINR bias for the maximum minmum rate method is higher than the optimal SINR bias calculated by the equal average throughput method and the results are consistent with the results in Fig.17 and Fig.21. Also we notice that the SINR bias for CRE decreases with the increase in the number of RBs, and it is almost constant when using the equal average method.

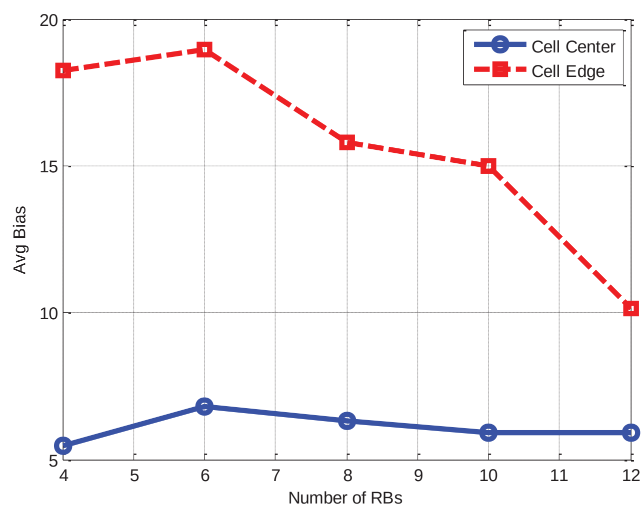

Figure 23: Optimal biases for the combined scenario

Based on the calculated average SINR biases for CRE, we can determine the different UEs classes; as shown in Fig.24 we divide the area into three different areas: Pico cell center users, Pico cell edge users, and macro users. In Fig.24 the Pico cell center areas are in the corners, the Pico cell edge areas are the areas in between the green and pink colored lines, and the Macro cell area is the area inside the pink colored polygon.

We notice that the Pico cell edge border is almost in the middle between the Pico BS and the Macro BS, although the Macro BS has higher transmission power. This can be explained by the following: when using the K-best branch and bound, the furthest UEs gets only the minimum rate used by the water-filling algorithm with minimum rate constraint, then the UEs in the middle between the Macro BS and the Pico BS get almost the same rate from both BSs, which is the minimum rate set by the water-filling algorithm. But when we use the equal average throughput, the area of the Macro cell is much higher than the area of the Pico cell.

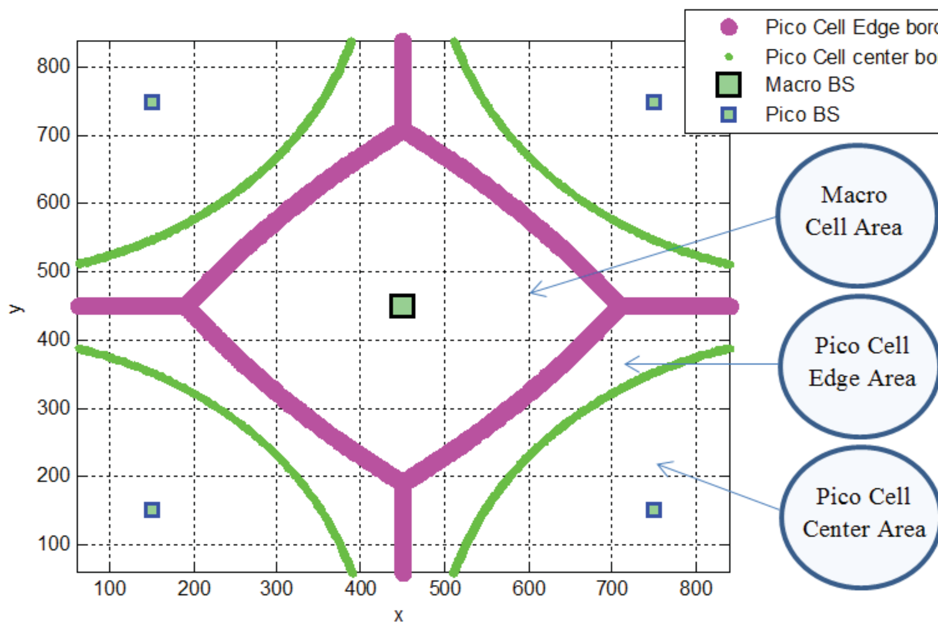

Figure 24: Schematic of the three different areas

CHAPTER V

CONCLUSION

In this thesis we studied the time domain ICIC for heterogeneous networks, which consists of using the Almost blank sub-frames. First we proposed to use the k-best branch and bound as a sub-optimal solution for resource allocation in OFDM systems. The simulations results showed that the proposed solution reduces the complexity tremendously at the cost of a slight reduction in the total achievable throughput. Second, we solved the problem of cell association using two different methods: the equal average throughput and the maximum minimum rate per user. The simulation results showed that there exists an optimal solution for the muting rate of ABS, and the optimal biases were calculated dynamically. We used the equal average throughput method to calculate the bias for the cell center users, and we used the maximum minimum rate method to calculate the bias for the cell edge users. To solve the cell association problem we used the exhaustive search because its complexity increases linearly with the number of users, which is considered to be an acceptable complexity.

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