Radio resource allocation in 5G wireless networks

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M. MAAZ Bilal

Allocation des ressources radio dans les réseaux sans fil de la 5 G

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Titre : Allocation des ressources radio dans les réseaux sans fil de la 5 G.

Mots clés : ICIC; OFDMA; LTE; 5G; allocation de puissance; allocation des ressources;

Résumé : La communication mobile est considérée comme l'un des piliers des villes intelligentes, où les citoyens devraient pouvoir bénéficier des services de télécommunications partout et quand ils les souhaitent, d'une manière sûre et peu coûteuse. Cela est possible grâce à un déploiement dense des réseaux mobiles à large bande de dernière génération. Ce déploiement dense entraînera une consommation énergétique plus élevée et donc plus d'émissions de gaz et de pollution. Par conséquent, il est crucial d'un point de vue environnemental de réduire la consommation d'énergie. Dans le cadre de cette thèse, nous introduisons des méthodes dynamiques de gestion de ressources permettant d'augmenter le débit et l'efficacité énergétique, et réduisant ainsi la pollution. Ainsi, nous ciblons les réseaux multicellulaires verts où l'augmentation de l'efficacité énergétique doit tenir en compte de l'accroissement de la demande de débit par les utilisateurs mobiles. Cette augmentation, exponentielle en terme de débit, a poussé les opérateurs à utiliser la totalité du spectre fréquentiel dans toutes les cellules des réseaux mobiles de dernière génération. Par conséquence, l'interférence intercellulaire (ICI : Inter-Cell Interference) devient prépondérante et dégrade la performance des utilisateurs, en particulier ceux ayant de mauvaises conditions radios. Dans cette thèse, nous nous focalisons sur la technique du contrôle de puissance considérée comme une des méthodes clé de la coordination d'interférence les méthodes centralisées ayant recours à l'optimisation convexe alors que les méthodes décentralisées se basant sur la théorie des jeux non-coopératifs. Par ailleurs nous proposons ensuite une heuristique de contrôle de puissance qui a l'avantage d'être stable et basée sur des messages de signalisation déjà existant dans le système. Cette heuristique permet d'éviter le gaspillage de la bande passante par des signalisations intercellulaires et de réduire le ICI. De plus, le problème de contrôle de puissance a un impact important sur l'allocation des ressources radios et sur l'association des utilisateurs mobiles à une station de base. Ainsi, dans la deuxième partie de la thèse, nous avons formulé un problème globale englobant le contrôle de puissance, le contrôle d'allocation de ressources radios, et le contrôle de l'association des utilisateurs à une station de base, cela afin d'obtenir une solution globalement efficace. Ces trois sous problèmes sont traités itérativement jusqu'à convergence de la solution globale. En particulier nous proposons pour la problématique d'association des utilisateurs trois algorithmes: un algorithme centralisé, un algorithme semi-distribué et finalement un algorithme complètement distribué se basant sur l'apprentissage par renforcement. Par ailleurs, pour l'allocation de puissance, nous implémentons des solutions centralisées et des solutions distribuées. Les preuves de convergence des algorithmes ont été établies et les simulations approfondies ont permis d'évaluer et de comparer quantitativement

Intercellulaire (ICIC : Inter-Cell Interference Coordination), tout en mettant l'accent sur des méthodes efficaces énergétiquement. Nous formulons ce problème d'allocation de la puissance, sur le lien descendant en mettant en œuvre des méthodes centralisées et décentralisées:	les performances, l'efficacité énergétique et le temps de convergence des algorithmes proposés.

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Keywords : ICIC; OFDMA; LTE; 5G; power allocation; resource allocation;

Abstract : Mobile communication is considered as one of the building blocks of smart cities, where citizens should be able to benefit from telecommunications services, wherever they are, whenever they want, and in a secure and non-costly way. This can be done by dense deployment of the latest generation of mobile broadband networks. However, this dense deployment will lead to higher energy consumption, and thus more gas emission and pollution. Therefore, it is crucial from environmental point of view to propose solution reducing energy consumption. In this thesis, we introduce dynamic resource management methods that increase throughput and energy efficiency, and thus reduce pollution. In this framework, we are targeting green multi-cell networks where increased energy efficiency must take into account the increased demand of data by mobile users. This increase, which is exponential in terms of throughput, pushed operators to use the entire frequency spectrum in all cells of the latest generation of mobile networks. As a result, Inter-Cellular Interference (ICI) became preponderant and degraded the performance of users, particularly those with poor radio conditions. In this thesis, we focus on the techniques of power control on the downlink direction, which is considered as one of the key methods of Inter-Cell Interference Coordination (ICIC) while focusing on energy efficient methods. We propose centralized and decentralized methods for this problem of power allocation: centralized methods through convex optimization, and decentralized methods based on non-cooperative game theory. Furthermore, we propose a power control heuristic which has the advantage of being stable and based on signaling messages already existing in the system. The power control problem has a relevant impact on the allocation of radio resources and on the association of mobile users with their servicing Base Station. Therefore, in the second part of the thesis, we formulated a global problem encompassing power control, radio resources allocation, and control of users' association to a base station. These three sub-problems are treated iteratively until the convergence to the overall solution. In particular, we propose three algorithms for the user association problem: a centralized algorithm, a semi-distributed algorithm and finally a fully distributed algorithm based on reinforcement learning. In addition, for power allocation we implement centralized solutions and distributed solutions. The proof of convergence for the various algorithms is established and the in-depth simulations allow us to evaluate and compare quantitatively the performance, the energy efficiency, and the convergence time of the proposed algorithms.

À mes chers parents: Lotfi, Najia.

À ma famille.

À mon épouse: Hala.

À mes enfants :

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Book chapter

B. Maaz, K. Khawam, S. Lahoud, J. Nasreddine and S. Tohme, "Achieving Spectral and Energy Efficiencies in Smart Cities Multi-Cell Network," *Information Innovation Technology in Smart Cities, Springer Book-2017,* ISBN 978-981-10-1741-4.

Conferences papers

B. Maaz, K. Khawam, S. Lahoud, J. Nasreddine and S. Tohme, "Joint User Association, Power Control and Scheduling in Multi-Cell 5G Networks," *2017 IEEE Wireless Communications and Networking Conference (WCNC)*, San Francisco, CA, USA, 2017.

B. Maaz, K. Khawam, J. Nasreddine, S. Lahoud and S. Tohme, "Achieving Power and Energy Efficiency in Self-Organizing Networks," *2017 IEEE 14th Annual Consumer Communications & Networking Conference (CCNC)*, Las Vegas, NV, USA, 2017.

B. Maaz, K. Khawam, Y. Hayel, S. Lahoud, S. Martin and D. Quadri, "Joint user association, scheduling and power control in multi-cell networks," *2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, New York, NY, USA, 2016, pp. 1-7.

B. Maaz, K. Khawam and S. Tohme, "Achieving spectral and energy efficiencies in multi-cell networks," *2015 11th International Conference on Innovations in Information Technology (IIT)*, Dubai, 2015, pp. 98-103.

B. Maaz, K. Khawam, S. Tohme, S. Martin, S. Lahoud and J. Nasreddine, "Joint scheduling and power control in multi-cell networks for inter-cell interference coordination," *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, Abu Dhabi, 2015, pp. 778-785.

B. Maaz, K. Khawam, S. Tohme, S. Lahoud and J. Nasreddine, "Inter-cell interference coordination based on power control for self-organized 4G systems," *2015 Fifth International Conference on Digital Information and Communication Technology and its Applications (DICTAP)*, Beirut, 2015, pp. 149-154.

List of Figures

List of Abbreviations

3GPP	Third Generation Partnership Project
3G	Third Generation
4G	Fourth Generation
5G	Fifth Generation
BS	Base Station
BBU	Base Band Units
CoMP	Coordinated Multi-Point
CQI	Channel Quality Indicator
CRS	Cell specific Reference Signals
EE	Energy Efficiency
eIMTA	Enhanced Interference Mitigation and Traffic Adaptation
eNB	evolved Node B
FFR	Fractional Frequency Reuse
FRF	Frequency Reuse Factor
HPN	High Power Node
ICI	Inter-Cell Interference
ICIC	Inter-Cell Interference Coordination
IoT	Internet of Things
LPN	Low Power Node
LTE	Long Term Evolution
NE	Nash equilibriums

OFDMA	Orthogonal Frequency Division Multiple Access
OPG	Ordinal Potential games
PCG	Power Control Game
PF	proportional-fair
QoS	Quality of Service
RAT	Radio Access Technologies
RB	Resource Block
RE	Resource Element
RNTP	Relative Narrowband Transmit Power
RRM	Radio Resource Management
SE	Spectral Efficiency
SFR	Soft Frequency Reuse
SINR	Signal to Interference-plus-Noise Ratio
SISO	Single Input Single Output
SON	Self Organizing Networks
TTI	Transmit Time Interval
UE	User Equipment

Chapter 1

1. INTRODUCTION

1.1. Introduction

In recent years, it has been witnessed that the data traffic over cellular networks is growing up exponentially. In 2015, the global mobile data traffic is 3.7 exabytes ($3.7*10^6$ terabytes) per month [CIS16] which is nearly 2.5-fold from 2013 to 2015 [CIS13]. By 2020, this global mobile data traffic will increase 8.2 times to reach 30.6 exabytes per month [CIS16]. In additional to supporting this data traffic, 5G systems should be able to meet some goals [MET13] such as the growing of the user data rate (10 to 100 times higher than the existing networks), while guaranteeing more energy efficiency [MET15]. This exponential demand for higher data rates has put the current cellular wireless infrastructure under serious constraints. One effective means to satisfy this explosively data growth is to increase the existing spectral efficiency by densifying Base Stations (BSs) and increasing frequency reuse. Unfortunately, the later will increment inter cell interference, hindering the benefits of the adopted solution. Consequently, interference management is one of the most vital concerns of 5G networks that prone dense frequency reuse.

Several traditional Radio Resource Management (RRM) and power allocation are proposed in the literature, but may not be efficient in future mobile networks. Operators have to use approaches that reduce power consumption while ensuring high spectrum efficiency. To achieve that, an Inter-Cell interference Coordination (ICIC) based on radio resource allocation techniques [SAR09] and power control [JL03] should be designed to reduce energy consumption and inter-cell interference. In this thesis, we focus on the Orthogonal

Frequency Division Multiple Access (OFDMA) that is adopted as the access protocol for the 4G and 5G networks.

1.2 Orthogonal Frequency Division Multiple Access

The OFDMA scheme [STB09] is based on OFDM technology that subdivides the available bandwidth into a multitude of narrower mutually orthogonal subcarriers, which can carry independent information streams. The Figure 1.1 represents the time-frequency LTE type-1 frame structure. This frame has a length of 10 ms, and it is composed of 10 subframes of 1 ms each. Each subframe is divided into two slots of 0.5 ms. Each slot represents seven OFDM symbols in the normal cyclic prefix. A Resource Element (RE) is placed at the intersection of an OFDM symbol and a subcarrier, the subcarrier spacing is 15 kHz and there are seven OFDM symbols per slots. A Resource Block (RB) is defined as a group of resource elements corresponding to 12 subcarriers of 15 kHz or 180 kHz and a slot of 0.5 ms in the time domain.

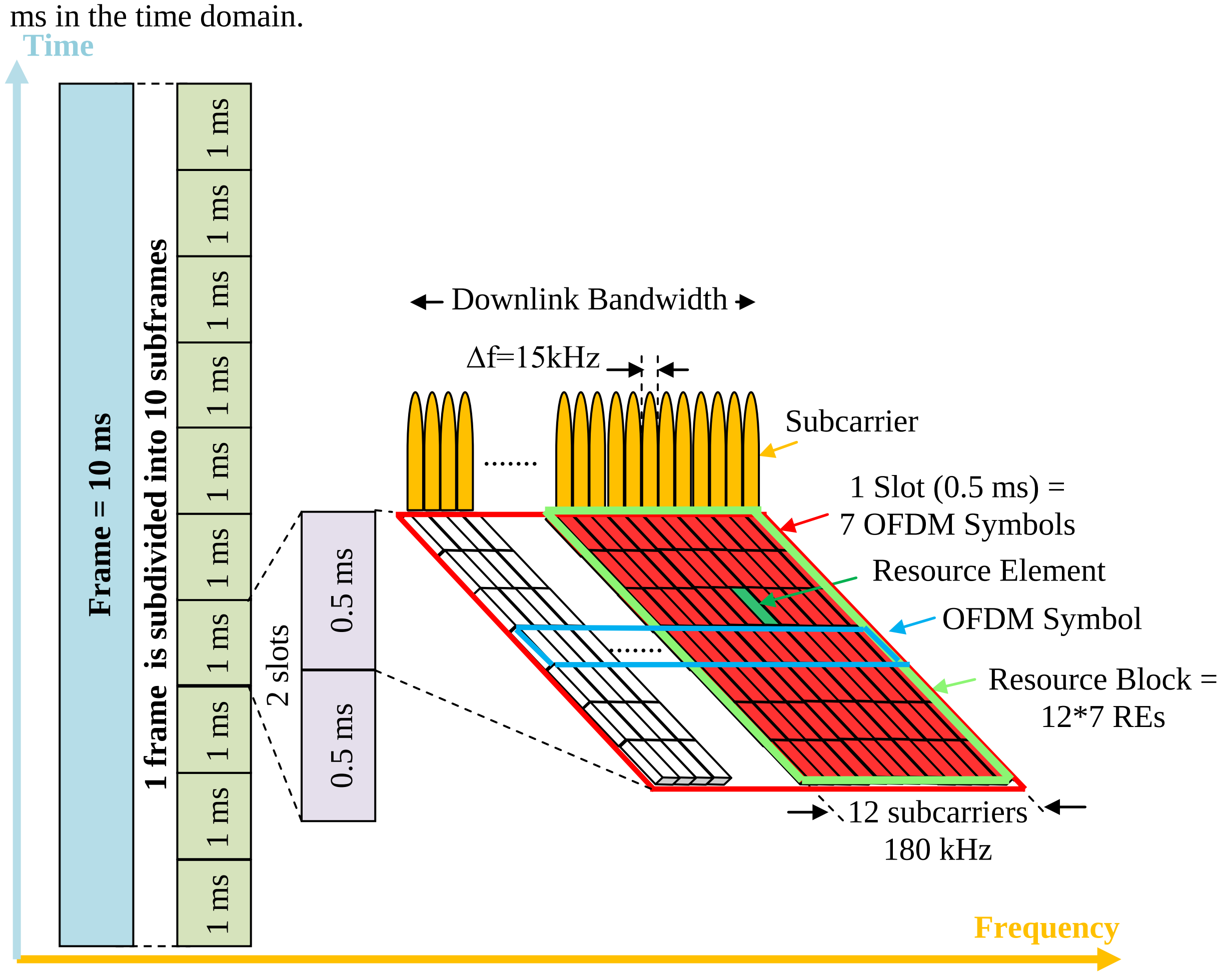


Figure 1.1 LTE-OFDMA downlink Frame and resource grid

In table 1, we represent the relation between the number of transmitted RBs and the channel bandwidths specified in LTE. We can see that the totality of RBs occupy around

77% of the channel bandwidth in the case of 1.4 MHz and 90% of this bandwidth in other cases.

TABLE I. RELATIONSHIP BETWEEN RBS NUMBER AND CHANNEL BANDWIDTHS

Channel bandwidth (MHz)	***Number of RBs***	***% of the channel bandwidth occupation***
1.4	***6***	***77.14***
3	***15***	***90***
5	***25***	***90***
10	***50***	***90***
15	***75***	***90***
20	***100***	***90***

The definition of a RB is important because it represents the smallest unit of transmission that is subject to scheduling. This scheduling as well as the power allocation are periodically performed by the schedulers every 1ms which is the Transmit Time Interval (TTI), where each RB is exclusively assigned to one UE in a given cell. In multiuser OFDMA networks [SL05], data is transmitted over independent orthogonal subcarriers, which eliminates the intra-cell interference. However, in the frequency reuse-1 model, the simultaneous use of the same RBs in neighboring cells, leads to ICI. This ICI strongly affecting the SINR of active Users Equipments (UEs), especially cell-edge UEs which degrade the total system throughput.

1.3 Inter Cell Interference Coordination ICIC

In the downlink, OFDMA allows assigning frequency sub-carriers to mobile users within each cell in an orthogonal manner. However, when the RB is used in neighboring cells, interference may occur and degrade the channel quality perceived by the UE, especially those UEs at the cell edge as shown in Figure 1.2.

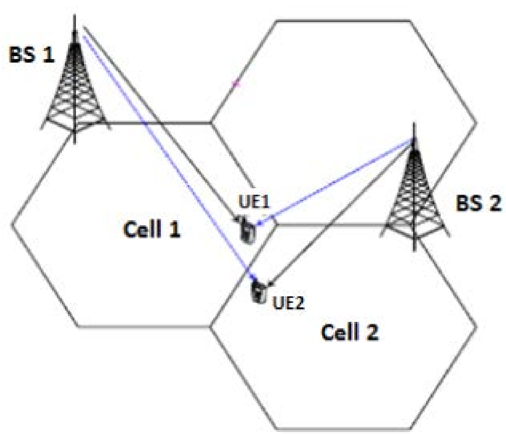


Figure 1.2 Cell edge Interference

Hence, efficient Inter-Cell Interference Coordination (ICIC) techniques are considered among the key building blocks of 5G networks. The ICI management is divided into two main categories, the static one where we manage statically the frequency distribution within each cell and the dynamic approaches where the ICI is mitigated through dynamic power control and resource allocation manner in order to achieve efficient inter-cell interference coordination.

1.3.1 Static ICIC

The Inter-Cell interference is one of the main factors limiting the capacity of mobile networks. In GSM networks, a number of adjacent cells are regrouped in a cluster, sharing the same operator bandwidth. In consequence, two neighboring cells don't use the same frequency, which reduces ICI. Although ICI within each cluster is eliminated, the spectral efficiency is drastically reduced. In the 3G-CDMA network, the ICI problems do not exist due to the cross-correlation between spreading codes.

In order to achieve a high spectral efficiency, 4G and beyond networks are deployed with a Frequency Reuse Factor (FRF) equal to one. In this case, as displayed in Figure 1.3, the whole frequency band is used in a cell and reused in each of the adjacent cells, resulting in high interference. The study in this thesis is based on frequency reuse-1 to maintain maximum spectral efficiency with dynamic power control and efficient resources allocation to reduce the harmful impact of resulting ICI.

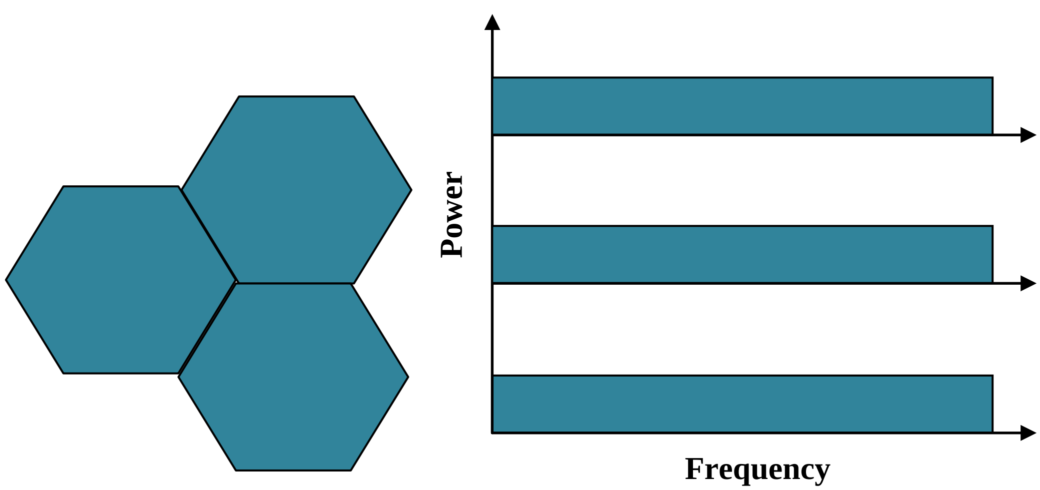


Figure 1.3 Frequency reuse-1 scheme

In the reminder of this section, we describe the static ICIC used in this thesis as state-of-the arts ICIC comparative benchmark. The first ICIC alternative is based on reusing-n frequencies by dividing the allocated band, and then the existing RBs, by a specific integer number of cells (n), and assigning each cell with a group of RBs and then repeating the assignment over and over. Figure 1.4 illustrates the frequency reuse-3, where each cell has one third of the available bandwidth, avoiding the existence of the same RBs in two neighboring cells, which decrements ICI to the detriment of spectral efficiency.

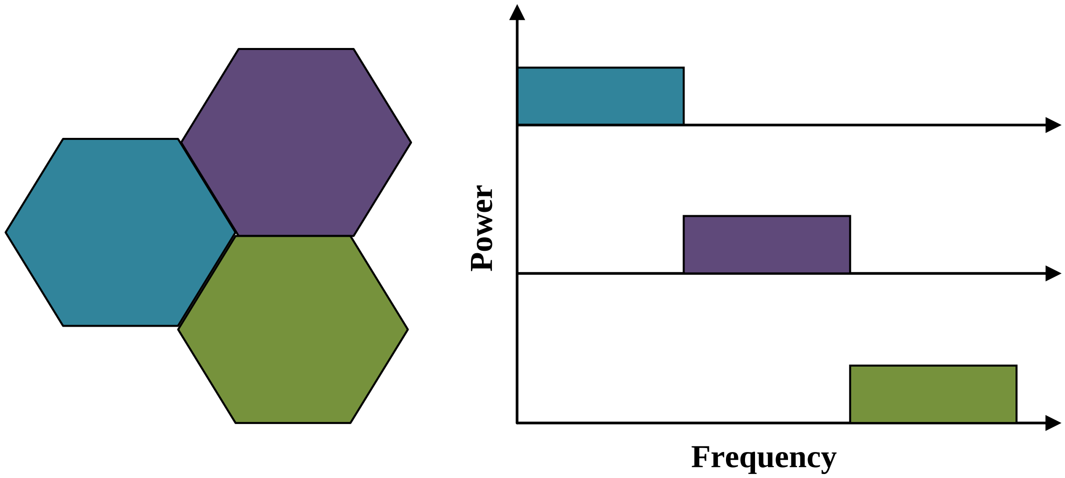


Figure 1.4 Frequency reuse 3 scheme

The second alternative is to proceed with the Fractional Frequency Reuse (FFR) [HA09], proposed as a static ICIC technique in OFDMA based networks. FFR divides the cell into 2 zones and sets restrictions on RB allocation between the different zones. FFR is portrayed in Figure 1.5, where a different frequency reuse fraction is applied in the edge zone (contains UEs close to the edge of each cell) and the same frequency fraction is applied in the center zone (contains UEs close to the base station).

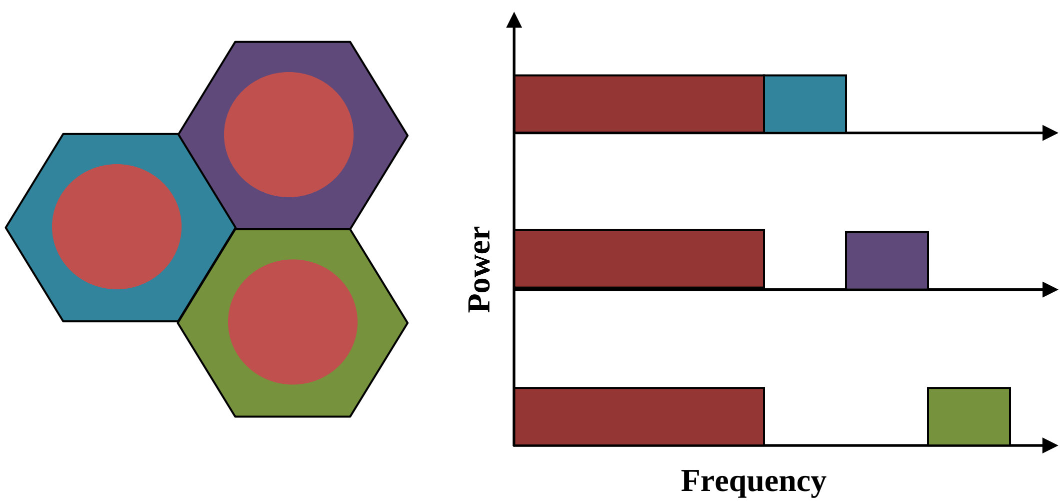


Figure 1.5 Fractional Frequency reuse scheme

In this approach, an edge UE is protected from interference by exclusive frequency allocation compared to all adjacent cells. A center UE is protected from interference owing to the large frequency reuse distance between the two center zones of adjacent cells. We find here the same disadvantage as for reuse-3 where a part of the spectral band is not allocated in each cell, which damages the spectral efficiency. The Soft Frequency Reuse SFR [YDH+10] is a common technique of ICIC where the totality of RBs are allocated in each cell, and where each cell implements a RRM and power control for used RBs. As shown in Figure 1.6, the center UEs are allocated RBs with less power (ratio 1/4) than the RBs allotted to edge users.

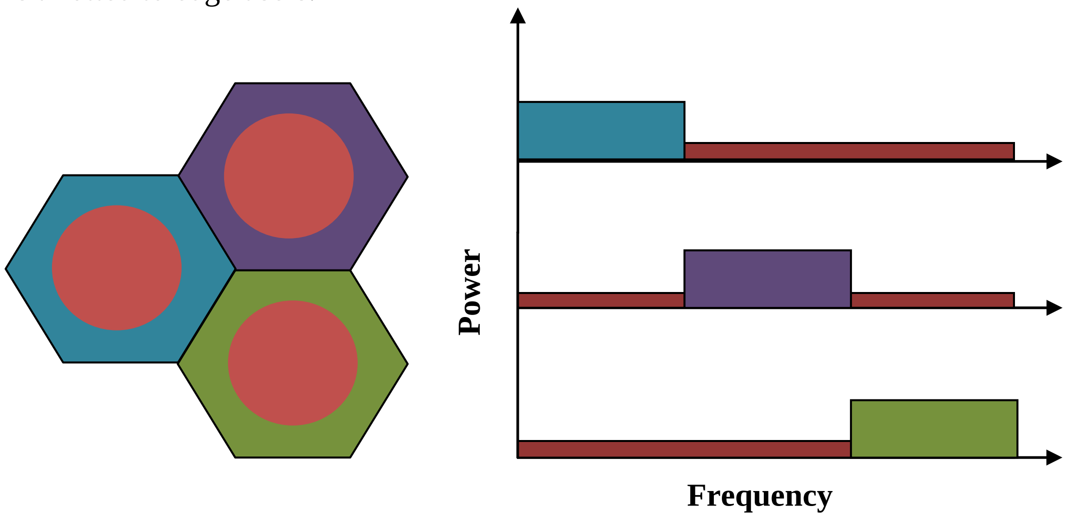


Figure 1.6 Soft Frequency Reuse scheme

Note that both FFR and SFR are statically implemented in each cell without any coordination between neighboring BSs, which is not adapted to realistic networks with dynamic UEs distribution and variable traffic, where a dynamic ICIC is desirable.

1.3.2 Dynamic ICIC

Unlike static frequency reuse schemes, the dynamic ICIC based on cell coordination schemes is well adapted to dynamic changes in the network. The dynamic ICIC has two main functionalities:

- Select which RB is allocated to an active UE each TTI.
- Tune the downlink power associated to each allocated RB.

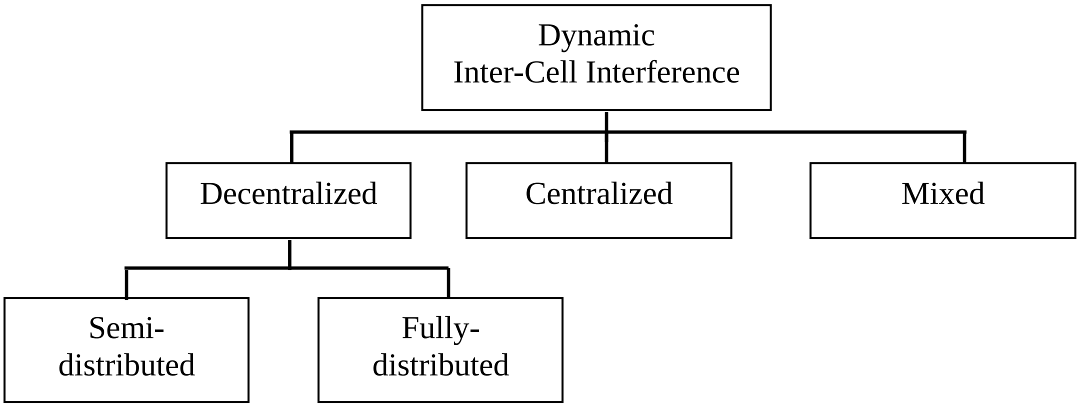


Figure 1.7 Dynamic ICIC classifications

Both RB and power allocation are operated in order to strike a good comprise between reducing ICI and increasing energy efficiency. The dynamic ICIC can be classified into three categories, decentralized, centralized and mixed ICIC technologies, as illustrated in figure 1.7.

- The decentralized ICIC, where each BS sets the ICIC parameters with or without any inter-Cell signaling data, which allows us to distinguish between two types of decentralized ICIC: the semi-distributed and the fully distributed ICIC.
    - The semi-distributed ICIC is based on the existence of inter-cell signaling exchange, through a dedicated signaling interface. The update reactivity on any proposed semi-distributed ICIC algorithm is directly related to the latency of the signaling interface.
        - In a LTE network, the inter-cell signaling is done through the X2 interface, as we can see in Figure 1.8.

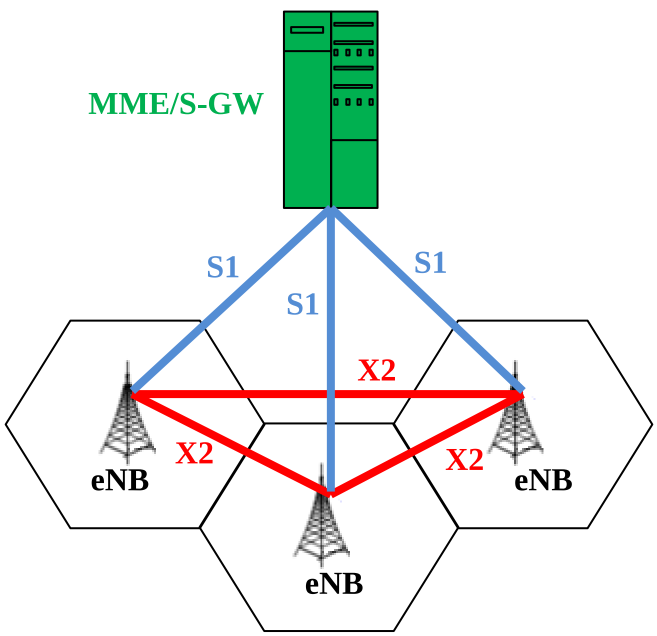


Figure 1.8 LTE signaling architecture

One of this signaling indicators, exchanged through the X2 interface is the Relative Narrowband Tx Power (RNTP) [3GP11] exchanged with a periodicity superior to 200 ms between the neighboring eNBs. The RNTP contains signaling information allowing a coordinate scheduling between neighboring eNBs in the downlink. This signaling information is relative to the RB transmission power: RNTP equals 0 if the transmission power will not exceed the RNTP threshold and equals 1 otherwise.

- The fully distributed ICIC is realized when the BSs optimize their resource parameters without inter-cell signaling. This ICIC scheme is based on intra-cell signaling, between UEs and the serving BS.
  - One of this intra-cell signaling indicators is the Channel Quality Indicator (CQI). This CQI is calculated every 1ms, based on pilots Cell specific Reference Signals (CRS) that are transmitted in every downlink sub-frame and in every RBs across the entire cell bandwidth independently of the individual UE allocation, as we see in Figure 1.9.

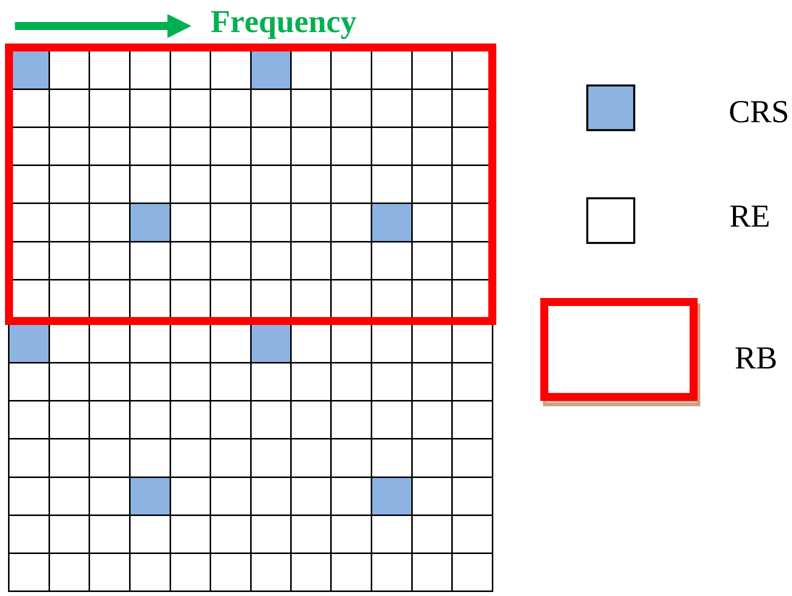


Figure 1.9 CRS in LTE downlink frame

The update reactivity on any proposed semi-distributed ICIC algorithm is directly related to the latency of the signaling interface. The update reactivity on any proposed fully distributed ICIC algorithm isn't related to the latency of the signaling interface.

- The centralized ICIC techniques require the existence of a central management entity that coordinate the entire network, as indicated in Figure 1.10, like the Coordinated Multi-point (CoMP) [3GP11] introduced in the LTE-A. It collects signaling information from all base stations related to channel quality and UE QoS. Then, it finds the optimal resource allocation between the existing base stations, and it also performs resource allocation among UEs. The centralized approach offers the optimal resource allocation solution at the cost of important processing load and large amount of signaling messages exchanged periodically between the BSs and the central controller.

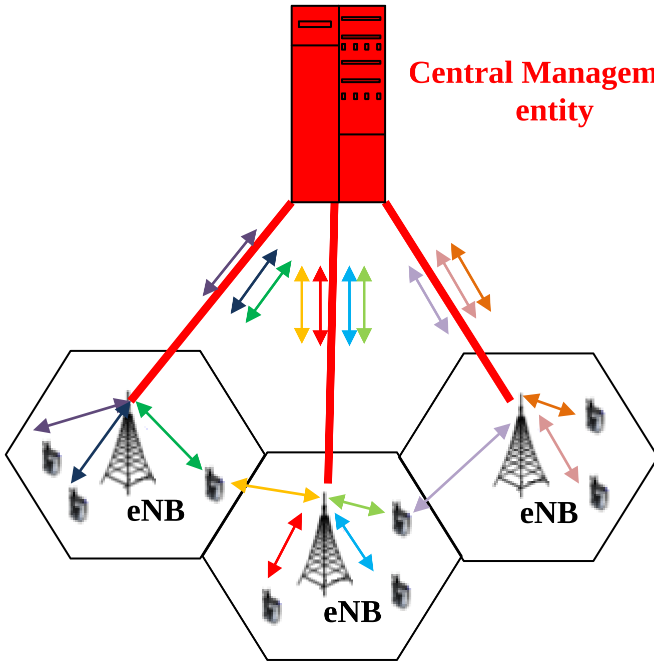


Figure 1.10 CoMP ICIC

- The mixed ICIC techniques, where some resource allocation parameters are optimized in a decentralized fashion and others are computed in a centralized fashion, in order to reach an optimal solution.

In this thesis, we investigated dynamic ICIC schemes, and we put forward centralized, decentralized and mixed ICIC approaches. The proposed approaches take into consideration both power control and scheduling. For global efficiency, we also considered user association in conjunction with ICIC.

1.3.2.1 Power control for ICIC

Power allocation has been widely used to maximize UE capacity and to minimize inter-cell interference. In [KHS11], a decentralized dynamic ICIC method allocates cell-edge bands dynamically by means of signaling messages through the X2 interface. The proposed dynamic ICIC method can autonomously optimize FFR parameters and thus increase throughput. In [SQ09], authors proposed an adaptive power control scheme to reduce inter-cell interference by applying a *Fair SINR* strategy, where power allocation is distributed among users in a way to obtain the same Signal-to-Interference and Noise Ratio (SINR) at the receiver. In [GGR+14], the proposed meta-heuristic-based downlink power allocation for LTE/LTE-A provides the required QoS by tuning the transmit power in each cell and minimizing the average inter-cell interference level. The authors in [YLI+14] proposed a distributed heuristic power control algorithm that aims at minimizing the total downlink power of an LTE system, where the impact of the power control algorithm on ICI and system performance is evaluated. The study in [MYY+12] is based on a relay node reference signal power control and multi-agent reinforcement learning algorithm. The relay node is modeled as an agent that learns an optimal policy of reference signal power control. The learning is achieved through interaction with the environment. The main goal of this method is to balance the load distribution of the SON network through dynamically changing its coverage area. In [WWC15], the authors proposed a distributed power control method for LTE uplink networks via a cooperative game to solve the energy efficiency problem. They used the Lagrange multipliers and presented an iterative algorithm to reach Nash equilibriums. Finally, the work in [SZP+14] presented a power allocation algorithm for adjusting the transmit power in each sub-band. The algorithm creates an efficient and dynamic SFR pattern for enhancing the performance of OFDMA downlink.

1.3.2.2 Joint power control and scheduling for ICIC

Joint power control and scheduling algorithms have been studied extensively in the literature. In the following, we investigate some of the most important works related to this approach. In [WSC12], semi-static ICIC and dynamic ICIC methods are discussed, and the problems facing conventional dynamic ICIC methods are analyzed and explored. Joint decision and multiple feedback schemes are proposed to enhance the system performances through appropriate selection of normal/mute transmitting status and accurate scheduling for dynamic ICIC. In [SV09], a semi-distributed neighboring gradient information based algorithm and a fully distributed heuristic based algorithm were proposed to automatically create soft FFR patterns in OFDMA based systems. The goal of the proposed algorithms is to adjust the transmit power of the different RBs by maximizing the overall network utility function. The work in [WKS+10] builds upon the work in [SV09] by extending the proposed algorithms for multi antenna OFDM systems with space division multiple access. In [KAL+14], the power level selection process of RBs is apprehended as a non-cooperative sub-modular game. In [GI10], the joint allocation of RBs and transmit power is investigated for the downlink transmission of OFDMA-based femtocells, modeled by an exact potential game. In [KC10], a joint sub-channel and binary power allocation algorithm is proposed, where only one transmitter is allowed to send signals on each sub-channel. In [WV11], various iterative schemes are proposed to centrally solve the problem of joint power allocation and scheduling in a coordinated OFDMA multi-cell network. The work in [ZZC+12] proposes several joint sub-channel and power allocation schemes for OFDMA femtocells based on Lagrangian dual relaxation. Finally, in [NKL14], an iterative approach is devised in which OFDM sub-channels and power levels of base stations are alternatively assigned and optimized at every step.

1.3.2.3 Joint power control and UE association for ICIC

The joint UE association (or alternately Base Stations election) and power control is a relevant problem in many wireless communications systems. However, despite its importance, is has remained largely unsolved, mainly due to its non-convex and combinatorial nature that makes the global optimal solution difficult to obtain. In OFDMA networks, several articles have addressed the subject of joint UE association and power control ([MBS+10]- [HL14] -[SY14]- [KFR14]- [QZW+13]). An intuitive idea is to optimize UE association and power levels in an iterative fashion, as suggested in ([MBS+10]-[SY14]). In [HL14], the authors propose an iterative method for power control and UE association: the power control is modeled as a non-cooperative game while the UE association relies on a signaling-based heuristic. The work in [SY14] considers a pricing-based UE association scheme for heterogeneous networks and proposes a distributed price update strategy based on a coordinate descent algorithm in the dual domain. The proposed UE association scheme is incorporated with power control and beam forming respectively and solved iteratively. The work in ([KFR14]-[QZW+13]) strives to obtain global optimality for the joint UE association and power control problem. In [KFR14], the joint problem is addressed by using duality theory, but only for a relaxed version of the problem where the discrete constraints are eliminated. Authors in [QZW+13] propose a novel algorithm based on Benders decomposition to solve the joint non-convex problem optimally. In [CKS13], a primal-dual infeasible interior point method has been applied to solve the problem of sum-rate maximization for the uplink. The original problem is solved in a two stage formulation by separating the UE association and power control variables and also by a single stage formulation where all variables are solved simultaneously. In [SHL12], the optimal settings for the UE association and power control that maximize the weighted sum rate are obtained under certain restricted conditions for the case where the number of UEs and BSs is the same. The work in [FOF11] formulates the joint serving cell selection and power allocation problem as an optimization task whose purpose is to maximize either the minimum user throughput or the multi-cell sum throughput. Heuristic solution approaches are proposed to solve these non-polynomial problems. In [CB10], the authors propose algorithms based on local measurements and do not require coordination among the wireless devices. They focus on the optimization of transmit power and of user association. The method is applicable to both joint and separate optimizations. The global utility minimized is linked to potential delay fairness. The distributed algorithm adaptively updates the system parameters and achieves global optimality by measuring SINR and interference. Finally, the work in [GWS+11] investigates the problem of Cell selection and resource allocation in heterogeneous wireless networks, by proposing a distributed cell selection and resource allocation mechanism, in which this processes are performed by UE independently. The problem is formulated as a two-tier game named as inter-cell game and intra-cell game, respectively. In the first tier, UEs select the best cell according to an optimal cell selection strategy derived from the expected payoff. In the second tier, UEs choose the proper radio resource in the serving cell to achieve maximum payoff.

1.4 Network Model

This thesis focuses on the downlink in a cellular OFDM based network model, suitable for LTE, LTEA and 5G networks. We consider permanent downlink traffic where each Base station (eNB or HPN) has persistent traffic towards its UEs. We also assume that all RBs are assigned on the downlink at each scheduling epoch. We introduce in this section the general framework we have used in this thesis.

1.4.1 The network model

In order to evaluate and validate our theoretic approach, our simulations are done in a cellular OFDMA based network model. We present hereafter the network framework:

1. We consider a cellular network comprising a set of eNBs denoted by J.
2. The time and frequency radio resources are grouped into time-frequency Resource Blocks (RB).
3. A RB is the smallest radio resource unit that can be scheduled to a User Equipment (UE).
4. Each RB consists of N_s OFDM symbols in the time dimension and N_f sub-carriers in the frequency dimension (in LTE N_s=7 and N_f=12).
5. The set of RBs is denoted by K, and the set of UEs is denoted by I.
6. Both eNBs and UEs have a SISO (Single Input Single Output) model, it is the transmission mode 1 as specified by 3GPP [3GP13].
7. We denote by $I(j)$ the set of UEs associated to eNB $j \in J$, in chapters 2-4, we consider a fixed cell assignment. In chapter 5, the UE association is considered as part of the optimization approach.

Symbols, variables and parameters used within this thesis are defined in Table 2

TABLE II. SYMBOLS, VARIABLES AND PARAMETERS IN THE DOCUMENT

$\boldsymbol{J}$	Set of eNBs.
$\boldsymbol{I}$	Total set of UEs.
$\boldsymbol{I(j)}$	Set of UEs associated to eNB *j*.
$\boldsymbol{K}$	Set of Resource blocks.
$\boldsymbol{K(j)}$	Set of RBs used by eNB *j*.
$\boldsymbol{N_0}$	Noise power.
$\boldsymbol{G_{ijk}}$	Channel power gain (UE *i* on RB *k* on eNB *j*).
$\boldsymbol{G_j}$	The antenna gain of eNB *j*.
$\boldsymbol{\pi_{jk}}$	Transmit power of eNB *j* on RB *k*.
$\boldsymbol{\rho_{ijk}}$	SINR of UE *i* associated eNB *j* served on RB *k*.
$\boldsymbol{p_j}$	Average consumed power by eNB *j*.
$\boldsymbol{d_{i,l}^{j}}$	The distance between eNB *l* and UE *i* served by eNB *j*.
$\boldsymbol{\alpha_{jk}}$	Interference impact of eNB *j* among other eNBs on RB *k*.
$\boldsymbol{\beta_{jk}}$	Interference impact of all eNBs on UEs served by eNB *j* on *RB k*.
$\boldsymbol{\theta_{ik}}$	Percentage of time UE *i* is associated with RB *k*.
$\boldsymbol{\tau_{ij}}$	The proportion of time that UE *i* is scheduled on the downlink by eNB *j*.
$\boldsymbol{\lambda_{ij}}$	The association variable given by what follows: $$\lambda_{ij} = \left\{ \begin{array}{l} 1 \text{ if UE } i \text{ is associated with eNB } j \\ 0 \text{ otherwise.} \end{array} \right\}.$$
$\boldsymbol{p_j^{max}}$	Maximum downlink transmission power per eNB.
$\boldsymbol{p_j^{min}}$	Minimum downlink transmission power per eNB.
$\boldsymbol{p_{min}}$	Minimum downlink transmission power per RB.
$\boldsymbol{p_{max}}$	Maximum downlink transmission power per RB.

1.4.2 Power Consumption Model

The power consumption of eNB $j \in J$ is modeled as a linear function [ABG+10] of the average transmit power per site as below:

$$p_j = \zeta_j^1 \pi_j + p_j^0. \tag{1.1}$$

where p_j and π_j denote the average consumed power by eNB *j* and its transmit power, respectively. The coefficient ζ_j^1 accounts for the power consumption that scales with the transmit power due to radio frequency amplifier and feeder losses while p_j^0 models the power consumed independently of the transmit power due to signal processing and site cooling.

The transmit power of each eNB is allocated to resource blocks serving the UEs in the network. The total transmit power of eNB *j* is the sum of the transmit power on each RB $k \in K$:

$$\pi_j = \sum_{k \in K} \pi_{jk}. \tag{1.2}$$

where π_{jk} is the transmit power of eNB *j* on RB *k*, hence, the total power consumed by any eNB *j* is given by:

$$P_j = \zeta_j^1 \sum_{k \in K} \pi_{jk} + p_j^0. \tag{1.3}$$

1.4.3 SINR Model

Given UE *i* served by eNB *j* ($i \in I(j)$), the signal-to-interference-plus-noise-ratio (SINR) of this UE when served on RB *k* is given by:

$$\rho_{ijk} = \frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}} \tag{1.4}$$

where G_{ijk} is the path gain of UE *i* towards eNB *j* on resource block *k* (computed as an average over the sub-carriers in the resource block), and N_0 is the noise power, which is, without loss of generality, assumed to be the same for all UEs on all resource blocks.

The defined framework presented in this section will be used for all the upcoming chapters; however some added aspects will be detailed for each contribution when necessary.

1.5 Thesis organization

In this work, we apply RRM in the ICIC context to achieve high performance according to two approaches: a centralized approach based on convex optimization suitable for CoMP *(Coordinated Multi-Point) solution where a central controller is the decision maker [3GP11].* and a distributed approach based on non-cooperative game theory suitable for SON (Self Organizing Networks). The remaining of this thesis is organized as follows. The work in chapter 2 introduces the Inter-Cell Interference Coordination based on power control for self-organized networks, where the power level selection of resource blocks (RBs) is portrayed as a sub-modular game. The PNE (Pure Nash Equilibrium) is attained based on a semi-distributed power control algorithm. The devised algorithm is compared to the centralized power control and to the max power policy. In chapter 3, we invest in the joint scheduling and power control algorithm in multi-cell networks for ICIC. In this thesis, our main objective is to enhance global system performances based on effective

ICIC schemes while keeping high energy efficiency. In order to attain this objective, we thoroughly evaluate, in chapter 4, our three proposed power control game based algorithms. The first power control algorithm optimizes spectral efficiency, while the other two algorithms are based on energy efficiency optimization. In chapter 5, we take into consideration the joint user association, power control and scheduling in multi-cell 5G networks. We address this multifaceted challenge according to the three broadly adopted approaches, early explained in this chapter:

1. the network-centric approach where power allocation and UE association are allocated efficiently in a centralized fashion;
2. the user-centric approach where fully distributed power allocation is devised and fully distributed UE association, based on Reinforcing learning, are used for reduced complexity;
3. the mixed approach where the UE association is solved in a decentralized fashion, based on a Best Response algorithm, whereas the power control is solved in a centralized fashion in order to reach an optimal solution of the joint optimization problem.

In all tackled approaches, the scheduling is solved in a centralized fashion. Finally, chapter 6 concludes the thesis, where we summarize the main contributions, and present future research directions.

Chapter 2

2. Inter-Cell Interference Coordination based on Power Control for self-organized Networks

Orthogonal Frequency Division Multiplexing (OFDMA) is accepted as the multiple access scheme for beyond 4G Systems as it provides resistance to inter-symbol and intra-cell interference. However, inter-cell interference, when dense frequency reutilization is used, can deteriorate the performance of UEs with bad channel quality, in particular at cell-edge UEs. This chapter addresses the problem of ICIC in the LTE downlink where the power level selection of resource blocks (RBs) is portrayed as a sub-modular game in the context of self-organizing networks. The existence of Nash equilibriums (NEs) for that type of games shows that stable power allocations can be reached by selfish eNBs. To attain these NEs, we propose a semi-distributed algorithm based on a best response algorithm. Based on local knowledge exchanged through the X2 interface in 4G networks [3GP08], each eNB will first select a pool of low interference RBs. Then, each eNB - to save energy - will make its best to fix the power level on these RBs achieving comparable performances in comparison with a policy serving active UEs with full power (deemed MAX Power Policy). In order to evaluate our proposal, we compare the obtained results to an optimal global CoMP solution where a central controller is the decision maker.

2.1 Introduction

Beyond 4G networks are designed to achieve high spectral efficiency by reusing the same frequency resource in each cell. However, this approach increases the inter-Cell Interference (ICI) and may degrade the channel quality especially for cell-edge UEs. In this chapter, we propose a method for Inter-Cell Interference Coordination (ICIC) to reduce ICI through efficient distributed power control. Power control does not only reduce the impact of interfering signals by lowering their power level (signals usually belonging to cell-center UEs), but it can increase the power level on resource blocks that suffer from bad radio conditions (usually RB allotted for cell-edge UEs).

Our work, in this chapter, belongs to the category of decentralized ICIC. Resorting to non-cooperative game theory is suitable to model the way eNBs compete in a distributed manner for limited resources. Devising an optimal power level selection scheme depends on the existence of Nash equilibriums (NE) for the present game. In this chapter, we prove that the model at hand is a sub-modular game (see [Top79], [Yao95]). Such games have always a NE and it can be attained using a greedy best response type algorithm, called algorithm 2.1. A comparison is made with a centralized CoMP system to assess the price of anarchy.

The chapter is organized as follows. The downlink data rate is introduced in section 2.2. In section 2.3, the power level selection scheme is presented as a non-cooperative sub-modular game. Further, a semi distributed learning algorithm based on a best response algorithm is proposed to reach the NE of the devised game. Section 2.4 presents the simulations results. The optimal CoMP approach is given in Section 2.5 with a comparison with our decentralized scheme. We conclude in Section 2.6.

2.2 Downlink Data Rate

We use the reference model presented in chapter 1, using the SINR presented in (1.4) and where the SINR observed at eNB *j* on RB *k* allocated to UE *i* can be expressed as:

$$\rho_{ijk} = \frac{G_j \,.\, \pi_{jk} \,.\, \left(\frac{1}{d_{ij}^{j}}\right)^{\beta}}{N_0 + \sum_{j' \neq j} G_{j'} \,.\, \pi_{j'k} \,.\, \left(\frac{1}{d_{ij'}^{j}}\right)^{\beta}} \tag{2.1}$$

where π_{jk} is the power transmitted by eNB j on RB k with $\pi_{jk} \in [P_{min}, P_{max}]$, and G_j represents the antenna gain of eNB *j* and β is the path-loss factor varying between 3 and 6.

It should be noted that $P_{min} \neq 0$ and our algorithm focuses on RBs already selected by the eNB. We denote by D_{ijk} the data rate achieved by UE i on RB k in eNB j given by what follows:

$$D_{ijk} = \frac{W}{E_b/N_o} . SINR_{ijk}$$

where W is the bandwidth per RB. Given a target error probability, it is necessary that $E_b/N_o \geq \gamma$, for some threshold γ which is UE specific.

Each cell will be logically divided into N_z concentric discs of radii R_z, $z=1,...,N_z$, and the area between two adjacent circles of radii R_{z-1} and R_z is called zone z. We denote by ρ_z the density of uniformly distributed mobile UEs in zone z. This UEs have the same radio conditions leading to the same γ_z and the same mean rate per zone D_{ijk} according to what follows:

$$D_{ijk} = \frac{\frac{W}{\gamma_z}\int_{R_{z-1}}^{R_z} \frac{\rho_z.2rdr}{r^\beta}. G_j . \pi_{jk}}{N_0 + \sum_{j' \neq j} G_{j'} . \pi_{j'k} . \left(\frac{1}{d_{ij'}^{j}}\right)^\beta} = \frac{\left(\frac{2.W.\rho_z}{(2-\beta)} \frac{R_z^{2-\beta} - R_{z-1}^{2-\beta}}{\gamma_z}\right). G_j . \pi_{jk}}{\sum_{j' \neq j} \pi_{j'k} . \frac{G_{j'}}{\left(\delta_{j,j'}^{z} . R_{cell}\right)^\beta} + N_0} \tag{2.2}$$

Where R_{cell} is the cell radius.

As for interference, we consider mainly for simplification the impact of eNB j' on eNB j by replacing $d_{i,j'}^{j}$ by $d_{z,j'}^{j} = \delta_{j,j'}^{z} . Rcell$ the distance between eNB j and eNB j' (the value of $\delta_{j,j'}^{z}$ depends on how far is eNB j' from zone z of eNB j).

We denote by T_{jkz} the data unit transmission time for UEs in zone z through RB k in eNB j. In fact, the latter is the inverse of the data rate perceived by the UE:

$$T_{jkz} = \frac{I_{jkz}}{\pi_{jk}} \tag{2.3}$$

where I_{jkz} is given by:

$$I_{jkz} = \frac{\sum_{\substack{j' \in J, \\ j' \neq j}} \pi_{j'k} . H_{j,j'}^{z} + N_0}{H_{j,z}} \tag{2.4}$$

while $H_{j,z} = \left(\frac{2.W.\rho_z}{(\beta-2)} \frac{R_{z-1}^{2-\beta} - R_z^{2-\beta}}{\gamma_z}\right). G_j$ captures distance dependent attenuation of power inside zone z and $H_{j,j'}^{z} = \frac{G_{j'}}{\left(\delta_{j,j'}^{z} . R_{cell}\right)^\beta}$ is the distance dependent attenuation of power between eNB j, j'.

We denote by N_z^j the pool of RBs used by UEs in zone z. eNB j will pay an amount α_z per power unit for the use of a given RB $k \in N_z^j$. This power unitary cost can decrease with the zone index to further protect UEs that are far away from the antenna; or it can increase to favor cell-center UEs in order to enhance overall performances. Furthermore, the price for the amount of allocated power depends on the traffic load per cell L_j to favor a group of cells in comparison with its neighbors if they experience momentarily a peak of traffic (for a short time due to a sudden incident or for a long time due to an organized event). Lowering the price paid for the power budget for such eNBs can enable them to increase relatively their transmitted power to better service their congested cells. Accordingly, the goal of the power control scheme proposed in this chapter is to minimize the following cost function in eNB j for RB k allotted to a UE in zone z:

$$c_{jkz} = \kappa . T_{jkz} + \alpha_z . (1 - L_j) . \pi_{jk} \text{, If RB } k \text{ is used in zone } z \quad (2.5)$$

$$0 \text{, If RB } k \text{ is not used in zone } z \quad (2.6)$$

where κ is a normalization factor.

2.3 Non-Cooperative Game For power Control

Non-Cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to power control. We define a multi-player game G between the J eNBs players. The eNBs are assumed to make their decisions without knowing the decision of each other.

The formulation of this non-cooperative game $G=\langle N,S,C \rangle$ can be described as follows:

- A finite set of players $J=(1,...,j)$ and a finite set of RBs $K=(1,...,k)$.
- For each eNB j, the space of strategies S_j is formed by the Cartesian product of each set of strategies $S_j=S_{j,1}\times...\times S_{j,k}$. An action of a eNB j is the amount of power π_{jk} sent on RB k and $S_{j,k}=[P_{min},P_{max}]$. A strategy profile $\pi=(\pi_1,...,\pi_J)$ specifies the strategies of all players and $S=S_1\times...\times S_J$ is the set of all strategies.
- A set of cost functions $C=(C_1(\pi),C_2(\pi), ... , C_j(\pi))$ that quantify players costs for a given strategy profile π where $C_j=(c_{j1z},c_{j2z},...,c_{jkz})$ is the cost of eNB j.

As the frequencies allocated to different RBs are orthogonal, minimization of cost c_{jkz} given in (2.5) on RB k is done independently of other RBs. Hence, we demote by π_{-jk} the strategies played by all eNBs on the RB k except eNB j.

2.3.1 The Nash Equilibrium

In a non-cooperative game, an efficient solution is obtained when all players adhere to a Nash Equilibrium (NE). A NE is a profile of strategies in which no player will profit from deviating its strategy unilaterally. Hence, it is a strategy profile where each player's strategy is a best response to other players' strategies.

$$c_{jkz}\left(\pi_{jk}, \pi_{-jk}\right) \leq c_{jkz}\left(\pi_{jk}^{'}, \pi_{-jk}\right) \quad (2.7)$$

$$\forall j \in J, \forall z \in N_z, \ \forall\, k \in N_z^j, \forall\, \pi_{jk}^{'} \in S_{j,k}$$

For every $j \in J$, in any zone and for all $k \in N_z^j$, c_{jkz} is convex w.r.t. π_{jk} and continuous w.r.t. $\pi_{jk}^{'}$. Hence, a Pure Nash equilibrium exists [Ros65].

Proposition 2.1: The Nash equilibrium is either the solution of the following system of *j* equations:

$$\pi_{jk}^{*} = \sqrt{\kappa.\frac{\sum_{\substack{j' \in J, \\ j' \neq j}} \pi_{j'k} \,.\, H_{j,j'}^{z} + N_0}{\alpha_z.\left(1 - L_j\right).H_{j,z}}} \tag{2.8}$$

$$\forall j \in J, \forall z \in N_z, \forall\, k \in N_z^j$$

or at the boundaries of the strategy space : $\pi_{jk} = \max(P_{min}, \min(p_{max}, \pi_{jk}^{*}))$

Proof of proposition 2.1:

Since the cost functions are convex, at the Nash equilibrium, the unilaterally minimum power levels are obtained by computing the partial derivative of the cost function of each eNB *j* on any of the used RB *k* in respect to its strategy π_{jk}, and by equating the result to zero:

$$\frac{\partial c_{jkz}}{\partial \pi_{jk}} = -\kappa \frac{\sum_{\substack{j' \in J, \\ j' \neq j}} \pi_{j'k} \,.\, H_{j,j'}^{z} + N_0}{\pi_{jk}^{2} \,.\, H_{j,z}} + \alpha_z.\left(1 - L_j\right) = 0$$

$$\forall j \in J, \forall z \in N_z, \ \forall\, k \in N_z^j.$$

We obtain a system of $|J|$ equations with $|J|$ unknowns given in (2.8). Unfortunately, the solution of the above system is not always feasible (not between P_{min} and P_{max}) as the set of actions is bounded. Furthermore, we need a distributed algorithm to attain the new NEs as the system evolves in time. In fact, a decentralized approach is adaptable to the system changes in dynamic scenarios while maintaining a low degree of system complexity. We turn to sub-modularity theory to obtain an algorithm that can attain Nash equilibriums.

2.3.2 Sub-modular Game

S-modularity was introduced into the game theory literature by [Top79] in 1979. S-modular games are of particular interest since they have Nash equilibriums, and there exists an upper and a lower bound on Nash strategies of each UE [OR00]. More importantly, these equilibriums can be attained by using a greedy best response type algorithm ([Top79],[Yao95]).

Definition 2.2: consider a game $G=\langle N,S,C\rangle$ with strategy spaces $S_j \subset \mathbb{R}^j$ for all $j \in J$ and for all $z \in N_z$, $k \in N_z^j$, G is sub-modular if for each j and k, S_{jk} is a sublattice[1] of $\mathbb{R}^j$, and $c_{jkz}(\pi_{jk}, \pi_{-jk})$ is sub-modular in π_{jk}.

Since S_{jk} is a single dimensional set, sub-modularity in π_{jk} is guaranteed. Also, in our work, since $\mathbb{R}^j = \mathbb{R}$ and $S_{j,k}=[P_{min},P_{max}]$ is a convex and compact subset, $S_{j,k}$ is a sublattice of $\mathbb{R}$.

Definition 2.3: If the utility function c_{jkz} is twice differentiable, it is sub-modular if: $\frac{\partial c_{jkz}(\pi_{jk},\pi_{-jk})}{\partial \pi_{jk} \partial \pi_{j'k}} \leq 0$ for all $j' \neq j \in J$, for all $k \in N_z^j$, for any zone z and for any feasible strategy. We need only to check whether the utility function c_{jkz} is sub-modular for every eNB j and every selected RB k which is straightforward as the following derivative is non-positive $\forall \pi \in S, j' \neq j$;

$$\frac{\partial c_{jkz}(\pi_{jk}, \pi_{-jk})}{\partial \pi_{jk} \partial \pi_{j'k}} = -\frac{H_{j,j'}^z}{\pi_{jk}^2 H_{j,z}}$$

Therefore, our game is indeed sub-modular.

2.3.3 Attaining the Nash Equilibrium

2.3.3.1.The Best Power Response

The Best response strategy of player j is the one that minimizes its cost given other players strategies. A best power response scheme consists of a sequence of rounds where each player j chooses the best response to the other players' strategies in the previous round. In the first round, the choice of each player is the best response based on its arbitrary belief about what the other player will choose. In some games, the sequence of strategies generated by best power response converges to a NE, regardless of the players' initial strategies. The S-modular games are part of those games.

To reach the NE, the work in [AA03] proposes the following greedy best response algorithm built on an algorithm called algorithm I in [Top79], [Yao95]: there are T infinite increasing sequences T_t^j for $t \in T$ and $j=1,...,J$. Player j uses at time T_k^j the best response policy (a feasible one) to the policies used by all other players just before T_k^j. This scheme includes in particular parallel updates (when T_t^j does not depend on t). Once this UE updates its strategy, the strategies of one or more other UEs need not be feasible anymore.

Any eNB j strives to find, for the pool of selected RBs in any zone z, the following optimal power level:

$$\pi_{jk}^* = \arg min_{\pi_{jk}} c_{jkz}(\pi_{jk}, \pi_{-jk})$$

[1] A is sublattice of $\mathbb{R}^j$ if a and $a' \in A$ imply $a \wedge a' \in A$ and $a \vee a' \in A$

for $\pi_{jk} \in [P_{min}, P_{max}]$. By definition π_{jk}^{*} is a best response of eNB *j* to the other eNBs strategies on RB *k*.

2.3.3.2 Distributed Learning of NE

In a real environment, a best response type algorithm as the one proposed in ([Yao95], [Top79]) cannot be practically applied as every eNB *j* needs to know the policy of all other eNBs π_{-jk} on every used RB *k*, which necessitates expensive signaling. Fortunately, we can easily render our algorithm distributed by making use of signaling information already present in the downlink of an LTE system. In fact, π_{-jk} (or equivalently $\pi_{j'k}, \forall j' \neq j$) only intervene in the total interference I_{jkz} endured on RB *k* in zone *z* of eNB *j* in equation (2.4). In practice mobile UEs sent every TTI, for the attributed RB *k*, the CQI (Channel Quality Indicator) indicating the channel quality and interference. This CQI is calculated based on pilots CRS (Cell specific Reference Signals) that are transmitted in every downlink sub-frame and in every RBs across the entire cell bandwidth independently of the individual UE allocation. However, the eNBs should update their transmission powers on selected RBs sequentially in a predefined round robin fashion that need to be set once and for all.

We present in appendix A the flowchart of the BR Algorithm deemed BPR, which is a power control scheme under the distributed best-response algorithm. In LTE, for example, the RNTP (Relative Narrow-band Transmit Power) indicator (received every 200*TTI through the X2 interface) advertises on which RBs a neighboring eNB will use full power. This information is necessary for the ICIC mechanism to lower the impact of inter-cell interference by avoiding an eNB *j* from allocating some RBs and selecting properly the pool of favorable RBs deemed N_z^j. Hence, it is fundamental that our BPR algorithm converges before the exchange of new RNTP messages. At the system start, any eNB *j* allocates in parallel all selected RB $k \in N_z^j$ with an initial random power $\pi_{jk}(0)$ to a given mobile UE in zone $z \in N_z$ as advocated by the scheduler.

2.4 Simulation results

We consider 9 hexagonal cells where each cell is surrounded with 6 others. The physical layer parameters are based in the 3GPP technical specifications TS 36.942. These parameters are shown in table 1.

We set x_{jk} for any eNB *j* on RB *k* belongs to *{0.1,0.2,0.35,0.5,0.6,0.7,0.85,1} and* $L_j=0$*.* We conducted in this chapter preliminary simulations in a Matlab simulator where only two zones with same area size are taken into account: cell-center zone located at a distance smaller than R_1*=0.7Km* and cell-edge zone located between R_1 *and* R_2*=*R_{cell}*=1 Km*, Various power unitary costs *(α1,α2)* were tested.

TABLE I. PHYSICAL LAYER PARAMETERS

Channel bandwidth	5Mhz	***Number of RBs***	25
User Noise Figure	7.0 dB	***Time subframe***	1 ms
Sub-channel bandwidth	180 Khz	***Thermal noise***	-104.5 dBm
Mean antenna gain[a]	12 dBi	P_0	10 W
Receiver noise floor N_0	-97.5 dBm	***Transmission power***[b]	43 dBm
Antenna configuration	1-transmit, 1-receive SISO		

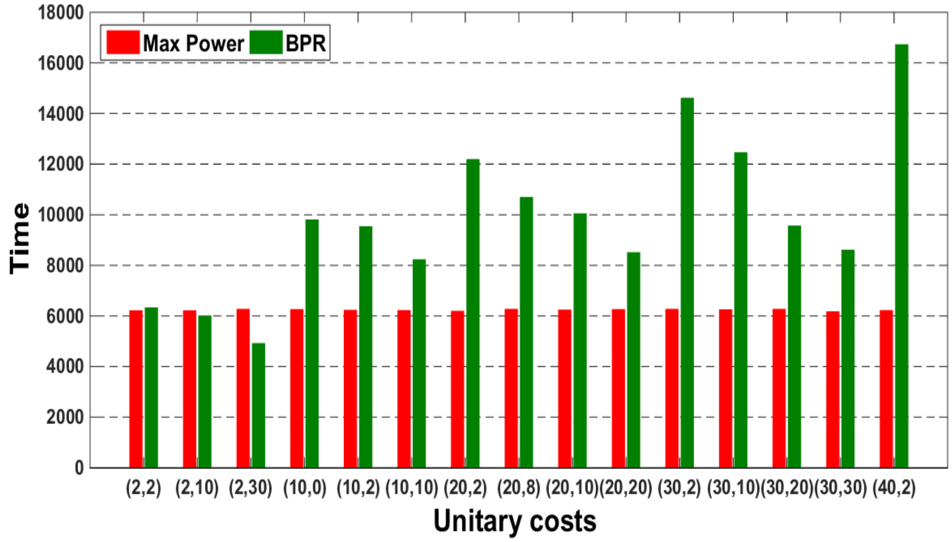
a. urban zones (900 Mhz)

b. according to TS 36.814 corresponding to 20 Watts

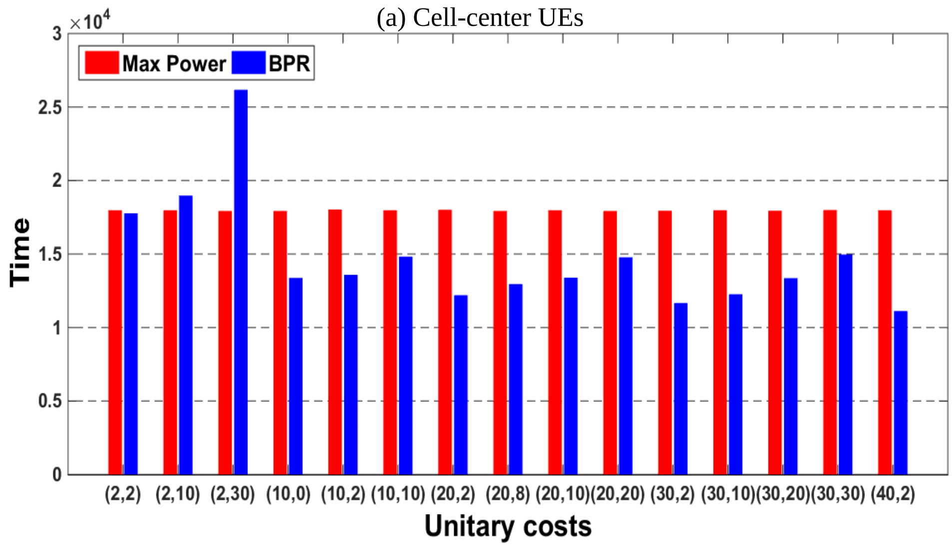
For each scenario, 25 simulations were run where in each cell a random number of UEs is chosen in each zone corresponding to a snapshot of the network rate. For each simulation instance, the same pool of RBs per zone is given for the three policies: our devised BPR algorithm, Max Power policy where full power P_0 is used on all RBs and Random policy where power levels are set at random. For every simulation, 100 runs of Random policy were made.

In Figure 2.1, we depict the total transfer time per zone $T_z = \sum_{j=1}^{J} \sum_{k=1}^{K} T_{jkz}$ for cell-center and cell-edge UEs as a function of various power unitary costs *(α1,α2)* for BPR and Max Power Policy. In most scenarios, we aimed at favoring cell-edge UEs by lowering the power unitary cost in comparison to that of cell-center UEs. We notice as expected that the improvement in one zone as compared to the Max Power policy is obtained at the expense of performance degradation of the other zone. This fact is highlighted in the lowest sub-figure where the relative deviation $100 * (T_z^{BPR} - T_z^{MaxPower})/T_z^{BPR}$ is displayed. Further, we see that the improvement in one zone does not strictly depend on how low its power unitary cost is but on how low it is relatively to the other zone: despite the fact that no power unitary cost is inflected on cell-edge UEs in scenario (10,0), the total transfer time is greater than that for scenarios (20,2), (30,2) or (40,2).

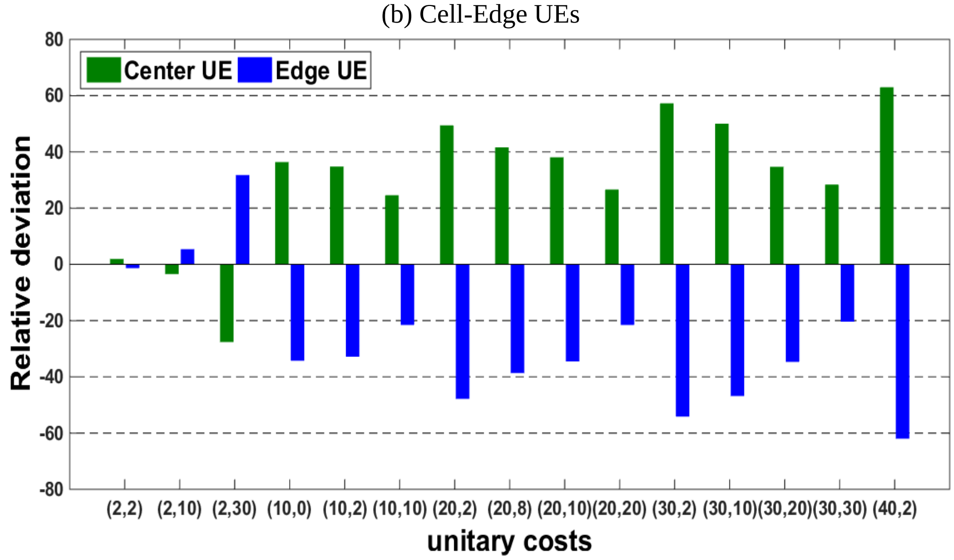
In Figure 2.2, we depict the system transfer time: $T = \sum_{z=1}^{2} \sum_{i=1}^{n} \sum_{k=1}^{m} T_{i,k,z}$ as a function of power unitary cost for BPR, Max power policy and random policy. Except for (2,30) and (40,2) where there is a large discrepancy between the power unitary cost of one zone in comparison with the other, the performances of BPR and Max Power policy are equivalent for all other scenarios.



(a) Cell-center UEs



(b) Cell-Edge UEs



(c) Relative Deviation

Figure 2.1 Transfer Time per zone for BPR vs. Max Power Policy

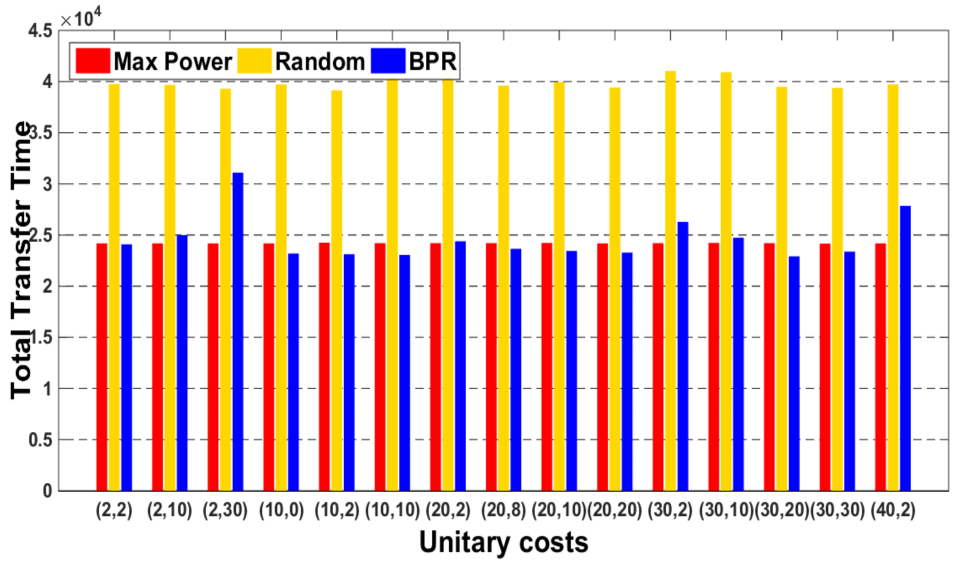


Figure 2.2 Total Transfer Time for BPR vs. Max Power Policy and Random policy

However, BPR permits a considerable power economy in comparison with Max Power policy as we can see in Figure 2.3 where the relative deviation between the total power in BPR and the Max Power policy is displayed as a function of power unitary cost. We can see that the best performances are reached when the same (high) power unitary cost is assigned for both zones in scenarios (20,20) and (30,30) where power economy vary from 72% till 82% while the total transfer time is slightly lower than that in the Max Power policy. In Figure 2.4, we report the mean convergence time as a function of power unitary cost. We note that BPR attains NE faster than 120 TTI and hence before the exchange of new RNTP messages.

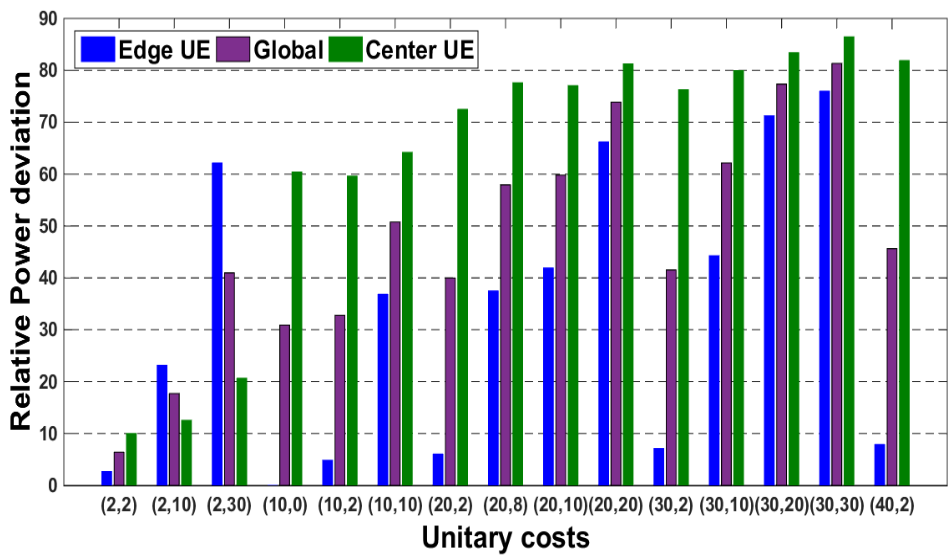


Figure 2.3 Power Economy

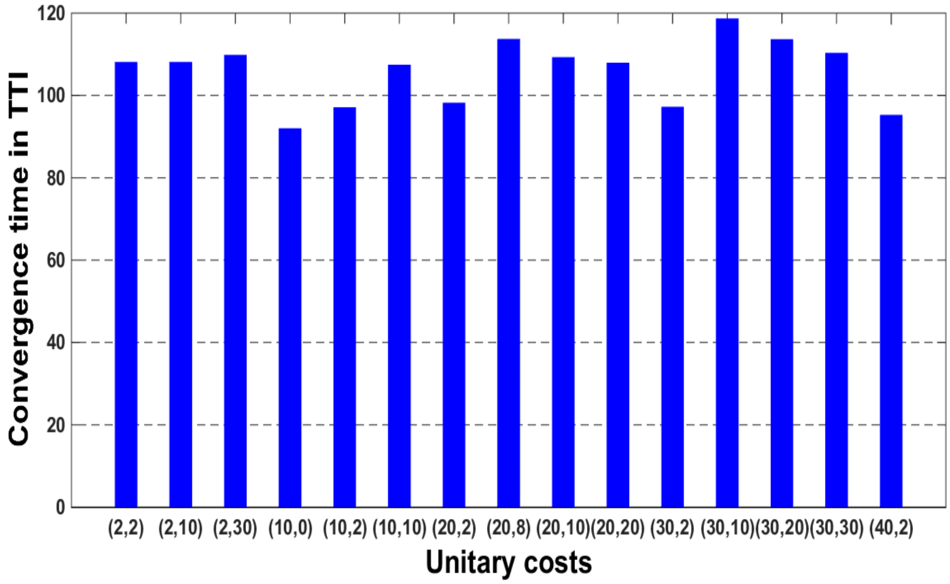


Figure 2.4 Convergence Time

2.5 The CoMP Optimization Scenario

In this section, we quantify the loss in efficiency suffered when a distributed scheme is adopted rather than a centralized CoMP optimization.

2.5.1 Optimal Centralized Approach

Unlike the distributed SON (Self Organizing Networks) approach where precedence is given to the interests of each individual eNB, power control may be performed in a way that favors the overall system performance. We do so by introducing a centralized CoMP approach, where a central controller assigns the power levels of each eNB in order to minimize the total network cost.

The obtained optimizations problem is a non-linear convex problem subject to $0 \leq x_{j,k} \leq 1$

$$minimize\colon \sum_{j,z} \left(\frac{I_{j,k,z}}{x_{j,k}} + \alpha_z . P_0 . x_{j,k} \right)$$

2.5.2 Simulation Results

In Figure 2.5, we illustrate the mean time necessary to send a data unit for all UEs as a function of the system load for the optimal policy, our algorithm based on Best Power Response and Max Power policy. We see that the performances of BPR and the Optimal policy are equivalent while we notice an expected improvement in comparison with the Max Power approach that resorts to full power allocation.

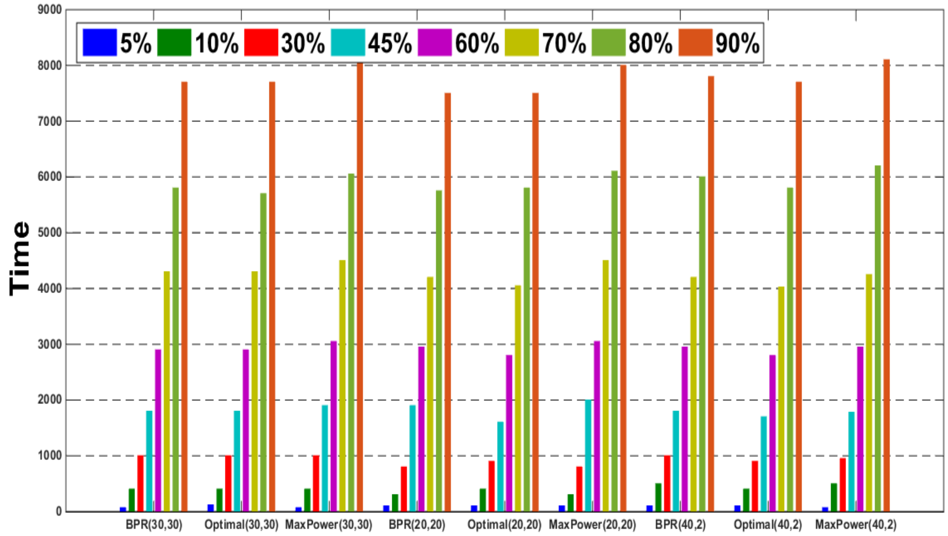
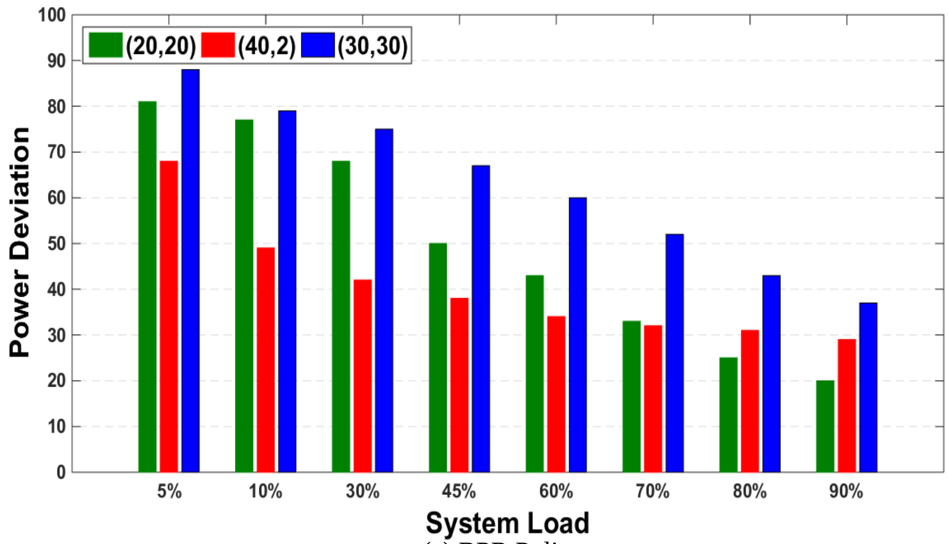
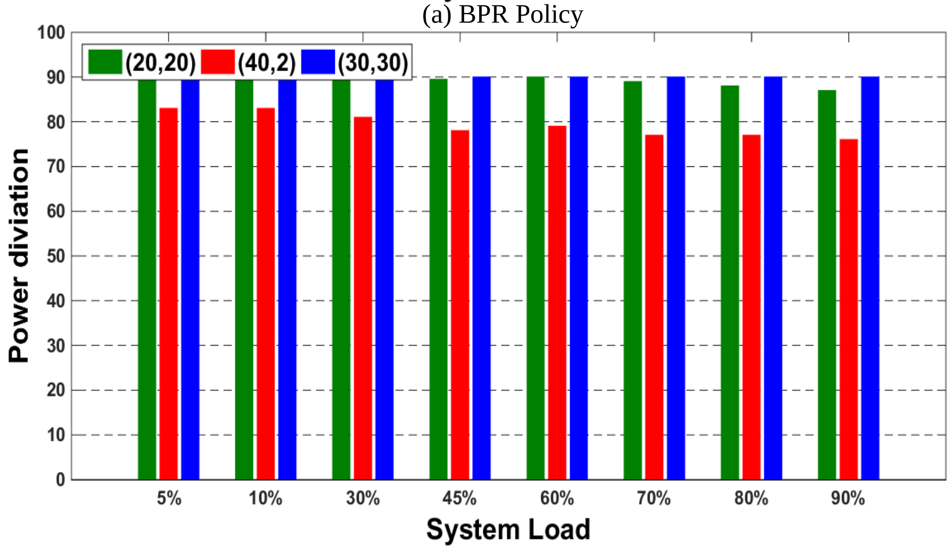


Figure 2.5 Global Transfer Time for BPR, Max Power and Optimal policies



(a) BPR Policy



(b) Optimal Policy

Figure 2.6 Power Economy for BPR and Optimal policies

However, the power economy made in the optimal approach as compared to BPR tempers its benefits as we can see from Figure 2.6, where the relative deviation between the total power in BPR (respectively in the Optimal policy) and the MAX Power policy is displayed as a function of power unitary cost. It is obvious that the optimal policy saves up much more power than the decentralized approach even in high load; whereas, the power economy in BPR withers slowly as load increases. Nevertheless, the slight discrepancy between the global transfer time in BPR and the Optimal policy which is the primary goal sought for and the low degree of system complexity of the decentralized approach makes it still an attractive solution.

2.6 conclusion

In this chapter, the power levels are astutely set as part of beyond 4G ICIC process. We proposed a game based on a semi distributed algorithm to reach NEs in a time coherent with the signaling time. Numerical simulations assessed the good performances of the proposed approach in comparison with a policy that services active UEs with full power. More importantly, considerable power economy can be realized.

Chapter 3

3. Joint Scheduling and Power Control in Multi-Cell Networks for Inter-Cell Interference Coordination

The focus of this chapter is targeted towards multi-cell dense OFDMA networks, which are composed of multiple eNB co-existing in the same operating area and sharing the available radio resources. In such scenarios, momentous emphasis is given towards the techniques that take Inter-Cell Interference (ICI) into account while allocating the scarce radio resources. In this context, we propose solutions for the problem of joint power control and scheduling in the framework of Inter-Cell Interference Coordination (ICIC) in the downlink of LTE OFDMA-based multi-cell systems. Two approaches are adopted to allocate system resources in order to achieve high performance: a centralized approach based on convex optimization and a semi-distributed approach based on non-cooperative game theory. The centralized approach needs a central controller to optimally allocate resources like in LTE CoMP (Coordinated Multipoint). In the semi-distributed approach, eNBs coordinate among each other for efficient resource allocation based on local knowledge conveyed by the X2 interface. It turns out that despite the lower complexity of the semi-distributed approach and its inherent adaptability, there is only a slight discrepancy of results among both approaches, which makes the distributed approach much more promising, in particular as a procedure of SON (Self Organized Network).

3.1 Introduction

In this chapter, we formulate the joint scheduling and power allocation problem for multi-cell OFDMA-based networks. We prove that the original problem is separable into two independent optimization problems: a scheduling problem and a power allocation problem. Our objective is to strike a good balance between fairness and efficiency through maximizing the achievable Signal-to-Interference and Noise Ratio (SINR). In particular, the power allocation problem is initially solved in a centralized way; the resulting optimization problem is rendered convex through geometric transformation. Then, a semi-distributed version is presented and casted as a non-cooperative game where each eNB tries to optimize locally its own performances and communicates its power level to its neighbors until convergence.

This chapter is organized as follows. Section 3.2 introduces the network utility function. Section 3.3 presents the power level selection scheme as a non-cooperative game for the semi-distributed approach. Section 3.4 presents the simulations results. Section 3.5 concludes the chapter with a summary of the findings works.

3.2 Utility function Model

We use the reference model of Section 1.4 presented in chapter 1 and we denote by θ_{ik} the percentage of time UE *i* is scheduled on resource block *k*. We consider the below global utility function for the system:

$$U(\theta,\pi) = \sum_{j\in J} \sum_{i\in I(j)} \sum_{k\in K} \log\left(\theta_{ik}\rho_{ijk}\right), \qquad with\ 0 \le \theta_{ik} \le 1. \tag{3.1}$$

The above utility function ensures that the deviation between the highest and lowest throughput over all UEs is as small as possible. This will provide fairness in the system using a mathematically tractable optimization problem.

The utility function presented in (3.1) is linearly separable into two different optimization problems: a scheduling problem $U(\theta)$, that computes the percentage of time UE *i* is served on each RB *k* by eNB *j*, and a power allocation problem$U(\pi)$:

$$U(\theta,\pi) = U(\theta) + U(\pi),$$

where $U(\theta)$ and $U(\pi)$ are given by what follows:

$$U(\theta) = \sum_{j\in J} \sum_{i\in I(j)} \sum_{k\in K} \log(\theta_{ik}), \qquad with\ 0 \le \theta_{ik} \le 1. \tag{3.2a}$$

$$U(\pi) = \sum_{j\in J} \sum_{i\in I(j)} \sum_{k\in K} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j'\neq j} \pi_{j'k} G_{ij'k}}\right) \tag{3.2b}$$

3.2.1. The Scheduling Problem

Based on (3.2a), the utility function of the scheduling problem is independent of j and hence can be solved locally by each eNB j:

$$U(\theta) = \sum_{\mathrm{j}\in \mathrm{J}} \sum_{i\in I(j)} \sum_{k\in K} \log(\theta_{ik}) = |J|. \sum_{i\in I(j)} \sum_{k\in K} \log(\theta_{ik}).$$

Accordingly, the scheduling problem per cell can be written as the following optimization problem $\left(\widehat{\mathrm{P}}_{\mathrm{sched}}\right)$:

$$\underset{\theta}{\text{maximize}}\ U_j(\theta) = \sum_{i\in I(j)} \sum_{k\in K} \log(\theta_{ik}), \tag{3.3a}$$

$$\text{Subject to :}\quad \sum_{i\in I(j)} \theta_{ik} \leq 1, \qquad \forall k \in K. \tag{3.3b}$$

$$\sum_{k\in K} \theta_{ik} \leq 1, \qquad \forall i \in I(j). \tag{3.3c}$$

$$0 \leq \theta_{ik} \leq 1, \qquad \forall i \in I(j), \forall k \in K. \tag{3.3d}$$

Proposition 3.1:

The optimal solution of the per scheduling problem is given by:

$$\theta_{i,k}^{*} = \begin{Bmatrix} \dfrac{1}{|I(j)|}, if\ |K| \leq |I(j)| \\ \dfrac{1}{|K|}, otherwise \end{Bmatrix}, \quad \forall i \in I(j), \forall k \in K. \tag{3.4}$$

Proof of proposition 3.1:

In problem (3.3), constraints (3.3b) give $\sum_{k\in K} \sum_{i\in I(j)} \theta_{ik} \leq K$ and constraints (3.3c) give $\sum_{i\in I(j)} \sum_{k\in K} \theta_{ik} \leq |I(j)|$. Further, the objective function in (3.3a) can be written as:

$$U_j(\theta) = \log\left(\prod_{i\in I(j),k\in K} \theta_{ik}\right). \tag{3.5}$$

Hence, we define a new scheduling problem less constrained than the initial one as follows:

$$\underset{\theta}{\text{maximize}}\ U_j(\theta) = \log\left(\prod_{i\in I(j),k\in K} \theta_{ik}\right) \tag{3.6a}$$

$$\text{Subject to:}\quad \sum_{i\in I(j)} \sum_{k\in K} \theta_{ik} \leq \min\big(K, |I(j)|\big) \tag{3.6b}$$

$$0 \leq \theta_{ik} \leq 1, \qquad \forall i \in I(j), \forall k \in K. \tag{3.6c}$$

As the objective function is non-decreasing, the optimal point must lie on equality constraint in (3.6b). Consequently, the sum of the θ_{ik} variables is constant and given by $\sum_{i\in I(j)} \sum_{k\in K} \theta_{ik} = \min\big(K, |I(j)|\big)$. Hence, the product of these variables is maximized when they are the same, i.e. for:

$$\theta_{ik} = \frac{\min(K, |I(j)|)}{K.|I(j)|}, \forall i \in I, \forall j \in J$$

This solution obeys the constraints of the original scheduling problem (3.3) but that it might not be an optimal solution for the latter. Let us suppose that $|\mathrm{I(j)}| \geq |\mathrm{K}|$ and θ^* is a solution vector for problem $(\widehat{\mathrm{P}}_1)$ given by $\forall \mathrm{i} \in \mathrm{I(j)}, \forall \mathrm{k} \in \mathrm{K}, \theta^*_{\mathrm{ik}} = \frac{1}{|\mathrm{I(j)}|}$. θ^* is a feasible solution for problem $(\widehat{\mathrm{P}}_1)$ as it satisfies the constraints (3.3b) and (3.3c). Particularly, (3.3b) becomes an equality and (3.3b) is satisfied because $\sum_{k\in K} \theta_{ik} = \frac{|\mathrm{K}|}{|\mathrm{I(j)}|} \leq 1$. Let us demonstrate by contradiction that θ^* is an optimal solution for problem $(\widehat{\mathrm{P}}_1)$. For any other solution of problem $(\widehat{\mathrm{P}}_1)$, suppose that $\exists i' \in \mathrm{I(j)}$, $\theta_{\mathrm{i'k}} = \frac{1}{|\mathrm{I(j)}|} + \epsilon$. Then, to satisfy the constraints (3.3b), we should have $\exists i'' \in \mathrm{I(j)}, \theta_{\mathrm{i''k}} = \frac{1}{|\mathrm{I(j)}|} - \epsilon$. The objective of such solution is lower that of $\theta^*$and the optimality of $\theta^*$is proved.

3.2.2. The Centralized Power Control Problem

Based on (3.2b), the power control problem can be written as the following optimization problem $P(\pi)$:

$$\underset{\pi}{\text{maximize}}\ U(\pi) = \sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j'\neq j} \pi_{j'k} G_{ij'k}}\right). \tag{3.7a}$$

$$\text{Subject to:} \quad \sum_{k\in K} \pi_{jk} \leq p_j^{max}, \qquad \forall j \in J. \tag{3.7b}$$

$$\pi_{jk} \geq p_j^{min}, \qquad \forall j \in J, \forall k \in K. \tag{3.7c}$$

Problem (3.7) is a non-linear and non-convex optimization problem. However, it can be transformed into a convex optimization problem in the form of geometric programming by performing a variable change $\hat{\pi}_{jk} = \log(\pi_{jk})$ and defining $\widehat{N}_0 = \log(N_0)$ and $\widehat{G}_{ijk} = \log(G_{ijk})$.

The resulting optimization problem deemed $P(\hat{\pi})$ is given by what follows:

$$\underset{\hat{\pi}}{\text{maximize}}\ U_j(\hat{\pi}) = \sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K} (\hat{\pi}_{jk} + \widehat{G}_{ijk}) \tag{3.8a}$$

$$+ \sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K}\left(-log\left(\exp(\widehat{N}_0) + \sum_{j'\neq j} \exp(\hat{\pi}_{j'k} + \widehat{G}_{ij'k})\right)\right).$$

$$\text{Subject to:} \quad \log\left(\sum_{k\in K} \exp(\hat{\pi}_{jk})\right) - log(p_j^{max}) \leq 0. \tag{3.8b}$$

$$-\hat{\pi}_{jk} + \log(p_j^{min}) < 0, \qquad \forall j \in J, \forall k \in K. \tag{3.8c}$$

Proposition 3.2:

The resulting optimization problem $P(\hat{\pi})$ is convex and hence can be very efficiently solved for global optimality even with a large number of UEs.

Proof of proposition 3.2

We will prove that the resulting optimization problem (3.8) P($\hat{\pi}$) is convex; the first term of the objective is a linear function, thus concave (and convex). The second term contains log-sum-exp expressions which are convex. The opposite of the sum of convex functions being concave, this completes the proof of the concavity of the objective function. As for the new constraints: constraints (3.8b) are convex by virtue of the properties of the log-sum-exp functions and (3.8c) are linear functions and hence convex.

3.3 Distributed Power Control

We have solved the problem $P(\pi)$, which is a convex problem, in a centralized fashion. In general, central entities performing the task of interference coordination with global knowledge should be avoided as they easily become bottlenecks in the network. Therefore, our work strives to obtain a semi-distributed scheme that exploits the existence of X2 interface between neighboring eNBs in LTE.

Any optimum π^* of the centralized convex problem (3.8) must satisfy the Karush Kuhn Tucker (KKT) conditions, *i.e.*, there exist unique Lagrange multipliers $\forall j \in J$ such that:

$$\frac{\partial U_j(\hat{\pi})}{\partial \hat{\pi}_{jk}} + \sum_{l \neq j} \frac{\partial U_{lk}(\hat{\pi})}{\partial \hat{\pi}_{jk}} = \mu_j - \lambda_j^k; \qquad \forall k \in K. \qquad (3.9a)$$

$$\mu_j . \left(\log\left(P_j^{max}\right) - \log\left(\sum_{k \in K} \exp\left(\hat{\pi}_{jk}\right) \right) \right) = 0. \qquad (3.9b)$$

$$\lambda_j^k . \left(\hat{\pi}_{jk} - \log\left(p_j^{min}\right)\right) = 0; \qquad \forall k \in K. \qquad (3.9c)$$

$$\mu_j \geq 0; \qquad \forall k \in K. \qquad (3.9d)$$

$$\lambda_j^k \geq 0; \qquad \forall k \in K. \qquad (3.9e)$$

where

$$U_{jk} = \sum_{i \in I(j)} log \left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}} \right)$$

.

We come back to the solution space in π instead of $\hat{\pi}$. In particular, we have what follows:

$$\frac{\partial U_{jk}(\pi)}{\partial \pi_{jk}} = \frac{\partial \hat{\pi}_{jk}}{\partial \pi_{jk}} \frac{\partial U_{jk}(\hat{\pi})}{\partial \hat{\pi}_{jk}} = \frac{1}{\pi_{jk}} \frac{\partial U_{jk}(\hat{\pi})}{\partial \hat{\pi}_{jk}}.$$

Accordingly, we obtain the following set of equations:

$$\pi_{jk} . \left(\frac{\partial U_{jk}(\pi)}{\partial \pi_{jk}} + \sum_{l \neq j} \frac{\partial U_{lk}(\pi)}{\partial \pi_{jk}} \right) = \mu_j - \lambda_j^k; \qquad \forall k \in K. \tag{3.10a}$$

$$\mu_j . \left(P_j^{max} - \sum_{k \in K} \pi_{jk} \right) = 0. \tag{3.10b}$$

$$\lambda_j^k . \left(\pi_{jk} - p_j^{min} \right) = 0; \qquad \forall k \in K. \tag{3.10c}$$

$$\mu_j \geq 0; \qquad \forall k \in K. \tag{3.10d}$$

$$\lambda_j^k \geq 0; \qquad \forall k \in K. \tag{3.10e}$$

Using the KKT conditions, we give a decomposition of the original problem into $|J|$ subproblems. Following [HBH06], we define the interference impact I_{ijk} for UE *i* associated to eNB *j* on RB *k* such as:

$$I_{ijk}(\pi_{-j}) = \sum_{l \neq j} \pi_{lk} G_{ilk} + N_0, \qquad \forall i \in I(j). \tag{3.11}$$

Further, we define the derivative relative to the interference impact of $U_{ijk} = log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right)$ as follows: $\frac{\partial U_{ijk}}{\partial I_{ijk}} = \frac{-1}{I_{ijk}}$.

using (3.11), condition (3.10a) can be written as:

$$\pi_{jk} \frac{\partial U_{jk}}{\partial \pi_{jk}} - \sum_{l \neq j} \sum_{i \in I(l)} \pi_{jk} \frac{G_{ijk}}{I_{ijk}} = \mu_j - \lambda_j^k. \qquad \forall k \in K, \forall j \in J. \tag{3.12}$$

Given fixed interference and fixing the power profile of any eNB except eNB *j*, it can be seen that (3.12) and conditions (3.10b)-(3.10e) are the KKT conditions of the following optimization sub-problems $\forall j \in J$:

$$\underset{\pi_j}{\text{maximize}}\, V_j(\pi_j, \pi_{-j}) = \sum_{k \in K} \pi_{jk} U_{jk} - \sum_{k \in K} \int U_{jk}\, d\pi_{jk} - \sum_{k \in K} \pi_{jk}^2 \alpha_{jk} = \sum_{k \in K} \pi_{jk} \left(|I(j)| - \pi_{jk} \alpha_{jk} \right). \tag{3.13}$$

Subject to:

$$\sum_{k \in K} \pi_{jk} \leq p_j^{max},$$

$$\pi_{jk} \geq p_j^{min}, \qquad \forall k \in K.$$

where α_{jk} is the interference impact of eNB *j* on other eNBs $l \neq j$, and given by:

$$\alpha_{jk} = \frac{1}{2} \sum_{\substack{l \in J \\ l \neq j}} \sum_{i \in I(l)} \frac{G_{ijk}}{\left(\sum_{\substack{j' \in J \\ j' \neq l}} \pi_{j'k} G_{ij'k} + N_0 \right)}. \tag{3.14}$$

Resorting to non-cooperative game theory is quite suitable to model the way eNBs compete in a distributed manner for limited resources. Devising an optimal power level selection scheme depends on the existence of Nash equilibriums for the present game which will be explored in what follows.

3.3.1 Non-Cooperative Game for power allocation

Non-cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to power allocation modeling. Here, eNBs are the decision makers or players of the game. We define a multi-player game *G* between the |J| eNBs which are assumed to make their decisions without knowing the decisions of each other.

The formulation of this non-cooperative game $G=\langle N,S,V\rangle$ can be described as follows:

- A finite set of eNBs J=(1,...,|J|) and a finite set of RBs K=(1,...,|K|).
- For each eNB *j*, the space of pure strategies S_j is as follows:

$$S_j = \left\{ \begin{array}{c} \pi_j \in R^{|K|} such\ as \\ \pi_{jk} \geq p_j^{min}, \\ \sum_{k \in K} \pi_{jk} \leq p_j^{max}, \forall k \in K \end{array} \right\}$$

- An action of an eNB *j* is the amount of power $\pi_{j,k}$ sent on RB *k*. The strategy chosen by eNB *j* is then $\pi_j = \left(\pi_{j,1}, \ldots, \pi_{j,k}\right)$. A strategy profile $\pi = (\pi_1, \ldots, \pi_{|J|})$ specifies the strategies of all players and $S = S_1 \times \ldots \times S_{|J|}$ is the set of all strategies.
- A set of utility functions $V=(V_1(\pi), V_2(\pi),\ldots, V_{|J|}(\pi))$ that quantify players' utility for a given strategy profile π where the utility function V_j of a given eNB *j* is as follows:

$$V_j\left(\pi_j, \pi_{-j}\right) = \sum_{k \in K} \left(\sum_{i \in I(j)} |I| \pi_{jk} - \alpha_{jk} \pi_{jk}^2 \right)$$

Note that, the first term of the new utility function $V_j\left(\pi_j, \pi_{-j}\right)$ is a non-decreasing function in π_{jk} while the second term $-\alpha_{jk}\pi_{jk}^2$ is decreasing in π_{jk} which permits to strike a good balance between spectral efficiency and energy efficiency. Hence, the higher is the interference harm inflected by eNB *j* on neighboring eNBs on a given RB *k*, the lower will be the chosen power amount π_{jk}. This will restrain selfish eNBs from transmitting at the maximum allowable power per RB.

Furthermore, as $V_j\left(\pi_j, \pi_{-j}\right)$ is concave w.r.t. π_j and continuous w.r.t. $\pi_y, y \neq j$, Pure Nash equilibriums exist according to [Ros65]. We turn to S-modularity theory [Top79] to obtain an algorithm that can attain the Nash equilibriums of the game $G=\langle N,S,V\rangle$.

3.3.2 The Super-modular Power Control Game

S-modularity was introduced into the game theory literature by [Top79] in 1979. S-modular games are of particular interest since they have Nash equilibriums, and there exists an upper and a lower bound on Nash strategies of each UE [AA03]. More importantly, these equilibriums can be attained by using a greedy best response type algorithm.

Definition 3.1: consider a game $G=\langle N,S,V\rangle$ with strategy spaces $S_j \subset \mathbb{R}^K$ for all $j \in J$ and $k \in K$, G is super-modular if for each j, S_j is a sublattice of $\mathbb{R}^K$, and $V_j(\pi_j, \pi_{-j})$ is a super-modular function. Since S_j is a convex and compact subset of $\mathbb{R}^K$, it is a sublattice of $\mathbb{R}^K$.

Definition 3.2: If the utility function $V_j(\pi_j, \pi_{-j})$ is twice differentiable, it is super-modular if: $\frac{\partial V_j(\pi_j,\pi_{-j})}{\partial \pi_{j,k} \partial \pi_{y,k}} \geq 0$ for all $y \neq j \in J$, for all $k \in K$ and for any feasible strategy. We need only to check whether the utility function is super-modular for any eNB j and any RB which is straightforward as the following derivative is positive:

$$\frac{\partial V_j(\pi_j, \pi_{-j})}{\partial \pi_{j,k} \partial \pi_{y,k}} = \sum_{\substack{l \in J \\ l \neq j}} \sum_{i \in I(l)} \frac{G_{ijk}\, \pi_{jk}\, G_{iyk}}{\left(\sum_{\substack{j' \in J \\ j' \neq l}} \pi_{j'k} G_{ij'k} + N_0 \right)^2} \geq 0 \qquad (3.15)$$

Therefore, our game is indeed super-modular.

3.3.3 Attaining the Nash Equilibrium

The Best response strategy of player j is the one that maximizes its utility given other players strategies. A best power response scheme consists of a sequence of rounds; each eNB j chooses the best response to the other eNBs strategies in the previous round. In some games, the sequence of strategies generated by best power response converges to a NE, regardless of the players' initial strategies. S-modular games are part of those games.

Hence, the main idea behind the best power response is for each eNB j to iteratively solve the optimization problem in (3.13) given the current interference impact and power profile of the other eNBs and then to recalculate the corresponding interference impact until convergence. Formally, we summarize this as follows:

1. Each eNB j chooses an initial power profile π_j satisfying the power constraint.
2. Using (3.14), each eNB j calculates the interference price vector α_j given the current power profile and announces it to other eNBs.
3. At each time t, one eNB j is randomly selected to maximize its payoff function $V_j(\pi_j, \pi_{-j})$ and update its power profile, given the other eNBs power profiles π_{-j} and price vectors, i.e.:

$$\pi_j(t+1) = arg \max_{\pi_j} V_j(\pi_j, \pi_{-j}(t)) \quad (3.16)$$

Finding the best response strategy comes down to obtaining the optimal solution of (3.13). To compute the optimal power solution π_j for any eNB j, we have recourse to the Lagrangian method. Accordingly, we write the Lagrangian of problem (3.13) as follows:

$$L(\pi_j, \beta, \gamma_1, \dots, \gamma_k) = \sum_{k\in K} \pi_{jk}\left(|I(j)| - \pi_{jk}\alpha_{jk}\right) + \beta\left(P_j^{max} - \sum_{k\in K}\pi_{jk}\right) + \sum_{k\in K}\gamma_k\left(\pi_{jk} - p_j^{min}\right). \quad (3.17)$$

where $\beta \geq 0$ and $\gamma_k \geq 0, \forall k \in K$ are the Lagrangian multipliers.

The dual problem in (3.17) is as follows:

$$\min_{\substack{\beta\geq 0\\ \gamma_1\dots\gamma_k\geq 0}} g(\beta, \gamma_1 \dots \gamma_k) = \min_{\substack{\beta\geq 0\\ \gamma_1\dots\gamma_k\geq 0}} \max_{\pi_j} L(\pi_j, \beta, \gamma_1 \dots \gamma_k) \quad (3.18)$$

As $L(\pi_j, \beta, \gamma_1, \dots, \gamma_k)$ is a standard concave function, each eNB j derives the optimal power levels by seeking zero points of the derivatives of $L(\pi_j, \beta, \gamma_1, \dots, \gamma_k)$. The power-allocation equations are:

$$|I(j)| - 2\alpha_{jk}\pi_{jk} = \beta + \gamma_k. \quad (3.19)$$

Accordingly, we obtain:

$$\pi_{j,k}(t) = \frac{|I(j)| - \beta(t) - \gamma_k(t)}{2.\alpha_{jk}(t)}. \quad (3.20)$$

Finally, to obtain the required power levels, we use a gradient method to update the dual variables β and $\gamma_k, \forall k \in K$since $g(\beta, \gamma_1, \dots, \gamma_k)$ is differentiable:

$$\frac{\partial g(\beta, \gamma_1, \dots, \gamma_k)}{\partial \beta} = P_j^{max} - \sum_{k\in K}\pi_{jk} \quad (3.21)$$

$$\frac{\partial g(\beta, \gamma_1, \dots, \gamma_k)}{\partial \gamma_k} = \pi_{jk} - p_j^{min}.$$

Hence, *β and γ_k variables are updated* $\forall k \in K$ *as follows:*

$$\beta(t) = \max\left(0, \beta(t-1) - \delta_t\left(P_j^{max} - \sum_{k\in K}\pi_{jk}(t-1)\right)\right) \quad (3.22)$$

$$\gamma_k(t) = \max\left(0, \gamma_k(t-1) - \delta_t\left(\pi_{jk}(t-1) - p_j^{min}\right)\right)$$

where δ_t is a suitably small step size.

3.4 Simulation results

We consider a network with hexagonal cells, where the physical layer parameters are based on 3GPP technical specifications TS 36.942 [3GP14]. These parameters and the simulation parameters are displayed in Table 1.

In this chapter, we conducted preliminary simulations in a Matlab simulator, where various scenarios were tested to assess the performances of the two power control schemes.

TABLE I. PHYSICAL LAYER AND SIMULATION PARAMETERS

Channel bandwidth (MHz)	5	*Number of RBs*	25
Thermal noise (dBm)	-174	*Time subframe TTI (ms)*	1
Max power/eNB (dBm)	43	*Min Power/RB (dBm)*	15
Number UE/eNB	8	*Number eNBs*	9
Antenna configuration	1-transmit, 1-receive SISO (Single Input Single Output)		

For each approach, 25 simulations were run where in each cell a predefined number of UEs is selected. The mean performance are obtained with the confidence interval of 95%. Users' positions were uniformly distributed uniformly in the cells. For each simulation instance, the same pool of RBs, UEs and pathloss matrix are given for both algorithms (Centralized and Semi-distributed).

3.4.1 Performance Evaluation

In Figure 3.1, we depict the histogram of the SINR for the centralized approach vs. the semi-distributed algorithm.

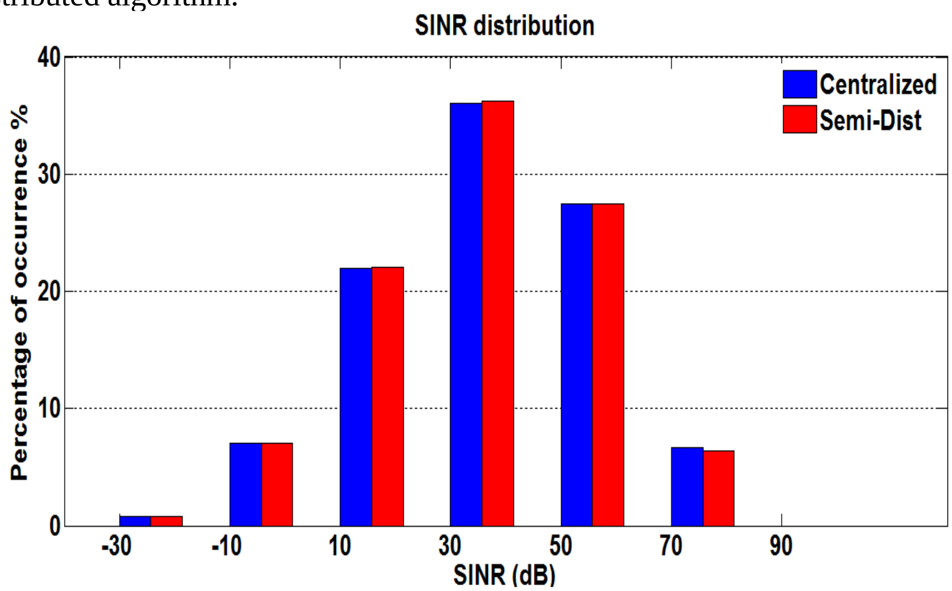


Figure 3.1 Percentage of SINR distribution occurrences for centralized vs. semi-distributed algorithms

As we can see, the SINR distribution is equivalent for both approaches for which more than 91% of the SINR is greater than 10 dB. More importantly, we see that both approaches have almost similar performances, which favor the semi-distributed approach owing to its lower complexity.

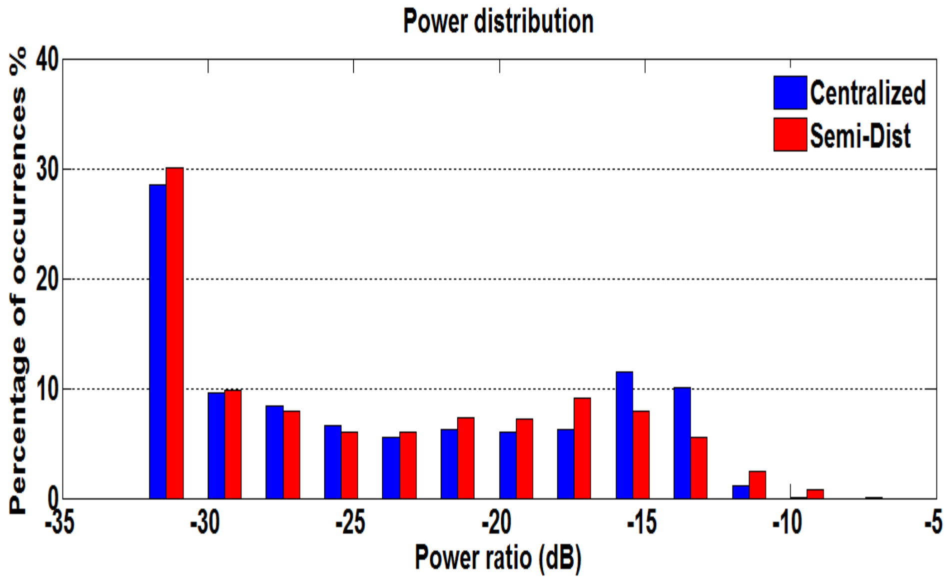


Figure 3.2 Percentage of power ratio distribution occurrences for centralized vs. semi-distributed algorithms

In Figure 3.2, we depict the histogram of the power ratio, defined as π_{jk}/P^{j}_{max}, for both approaches. For the semi-distributed strategy, we display the power distribution after convergence. Here, we see the discrepancy in the power distribution between both strategies. For the semi-distributed approach, more than 90% of power ratio is less than (-14 dB). Indeed, the existence of the power cost $-\pi^2_{jk}\alpha_{jk}$ in the utility function (3.11), diminishes the selfishness of eNBs that are tempted to transmit at full power on all RBs.

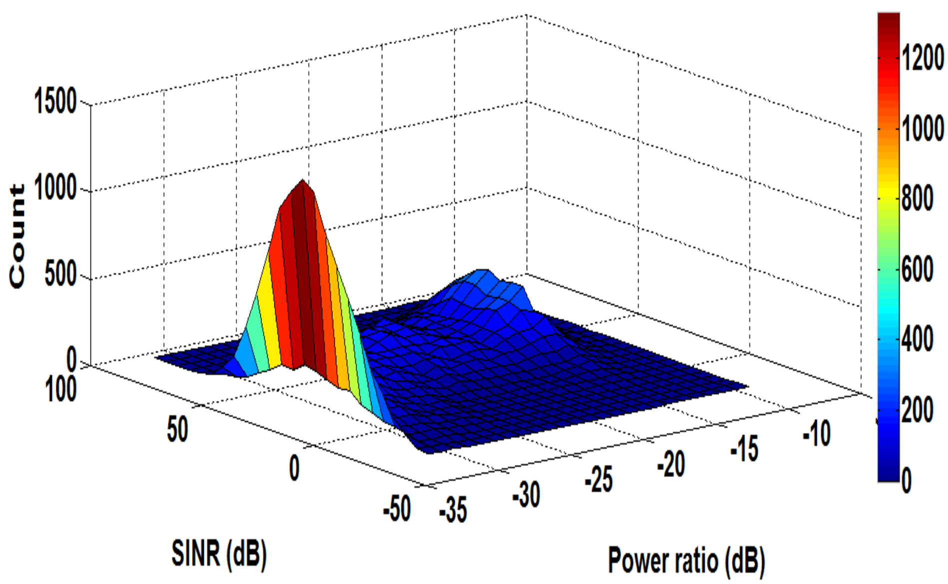


Figure 3.3 Occurences of SINR as function of power ratio for centralized algorithm

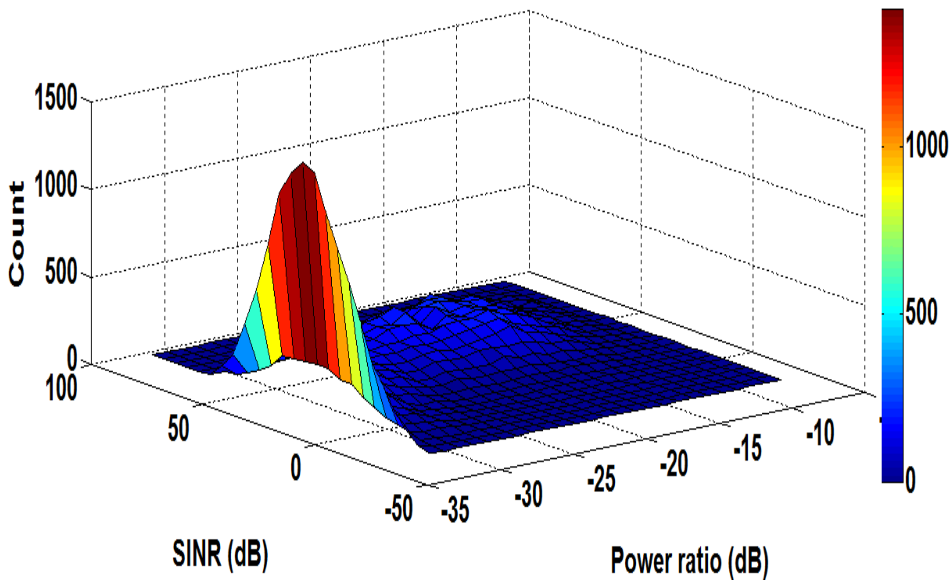


Figure 3.4 Occurrences of SINR as function of power ratio for semi-distributed algorithm

Moreover, we can see that more than 30% of the power in the semi-distributed scenarios is around the minimum power level p_j^{min}. The highest SINR occurrences are obtained for power ratio levels ranging between -30 and -27 dB which is illustrated in Figure 3.3 and 3.4.We can see that the occurrences count of high SINR values is high for power level interval ranging between -30 and -27dB and -18 and -13 dB for the centralized approach. However, the same SINR occurrences' values are concentrated only on the power interval ranging between -30 and -27 dB for the semi-distributed approach.

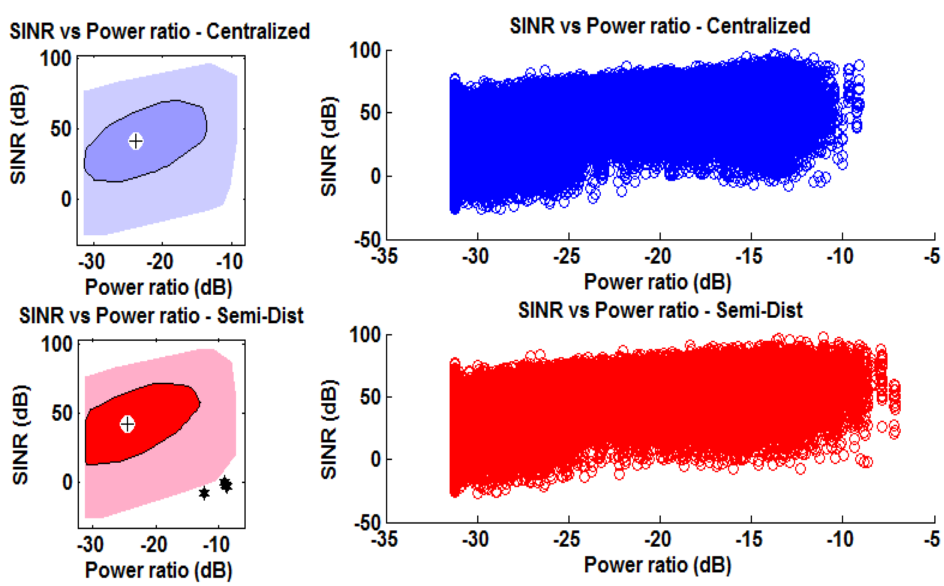


Figure 3.5 SINR and power ratio as a function of pathloss for centralized vs. semi distributed algorithms

In Figure 3.5, we can see again the minor difference in SINR performances and power distribution between both approaches. Furthermore, the mean value of SINR, ranging between 30 and 40 dB, is obtained in the centralized approach for an average power value smaller than that of the semi-distributed scenario. Still, both power control schemes permit a considerable power economy in comparison with the Max Power policy, that uses full power P^j_{max} for each eNB, as we can see in Figure 3.6 where the power economy percentage for all eNBs vary from 53 to 77 % in comparison with the Max power policy.

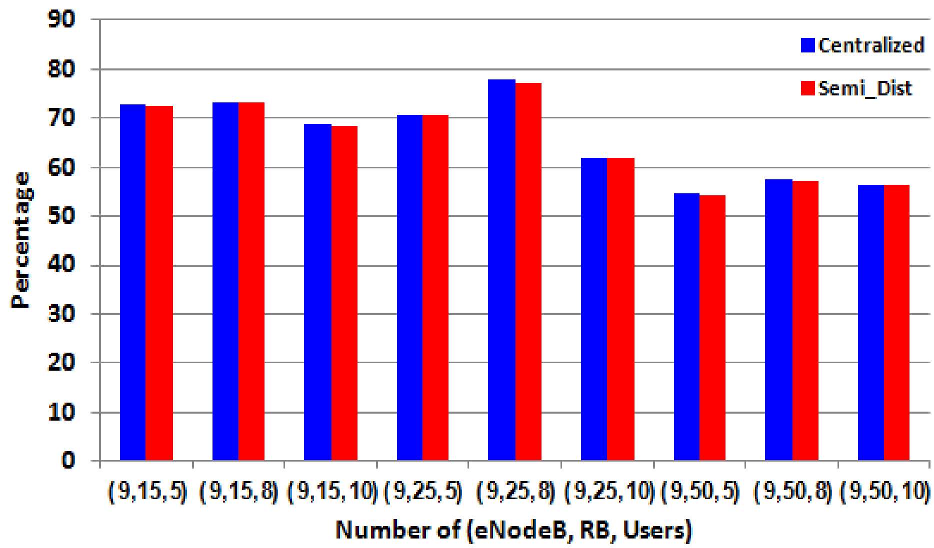


Figure 3.6 Percentage of power economy as a function of the number of eNB, RB and users for centralized vs semi-distributed algorithms

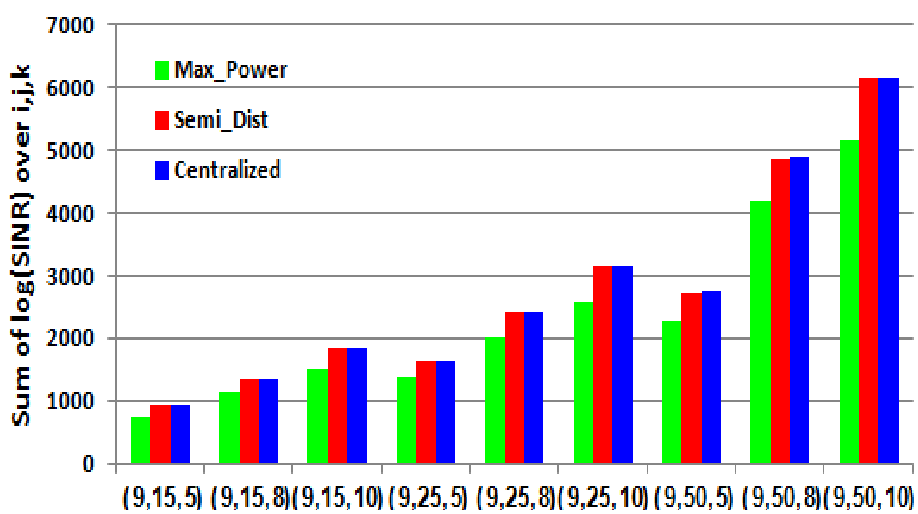


Figure 3.7 The Sum of log(SINR) as function of the number of eNB, RB and users for centralized, semi-distributed vs Max power algorithms

We can see the similarity of power economy efficiency between the centralized algorithm and the semi-distributed algorithm. This power economy is obtained while maintaining good performances as we can see in Figure 3.7 where the utility function in (3.7a) is depicted as a function of the number of eNBs, RBs and UEs for the centralized, the semi-distributed and Max Power algorithms.

3.4.2 Convergence Time

In Figure 3.8, we report the mean convergence time per eNB of the semi-distributed algorithm for various scenarios. We note that each eNB attains the NE within 52 to 92 iterations. At each iteration, one eNB is randomly selected to maximize its payoff function given in (3.13). The iteration period is equal one TTI (Transmit Time Interval), which equals 1ms in LTE.

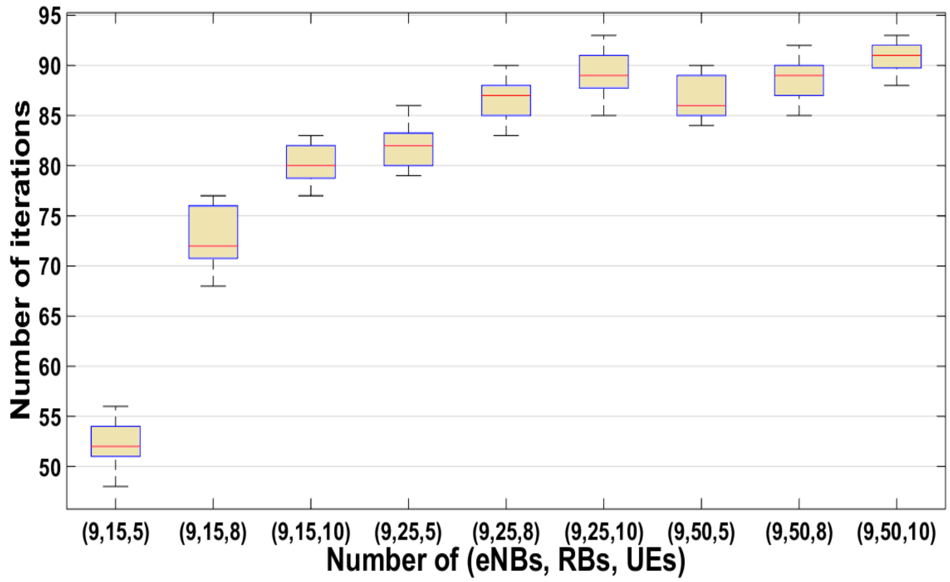


Figure 3.8 Total convergence time by eNB as function of the number of eNB, RB and users for semi-distributed algorithm

We noted during the extensive simulations conducted, that the power levels attain 90% of the values reached at convergence in less than 25 iterations. We can see that in Figure 3.9, where we represented the power distribution of 25 RBs for an eNB selected randomly and for which convergence time was equal to 87 iterations.

Low convergence time in conjunction with high performances is an undeniable asset for our semi-distributed schemes. This result is corroborated in Figure 3.10 where we show that the utility function attains nearly its optimal value at 25 iterations. Hence, the fast convergence time, the near optimal results and the lower complexity degree of the semi-distributed approach makes it a very attractive solution.

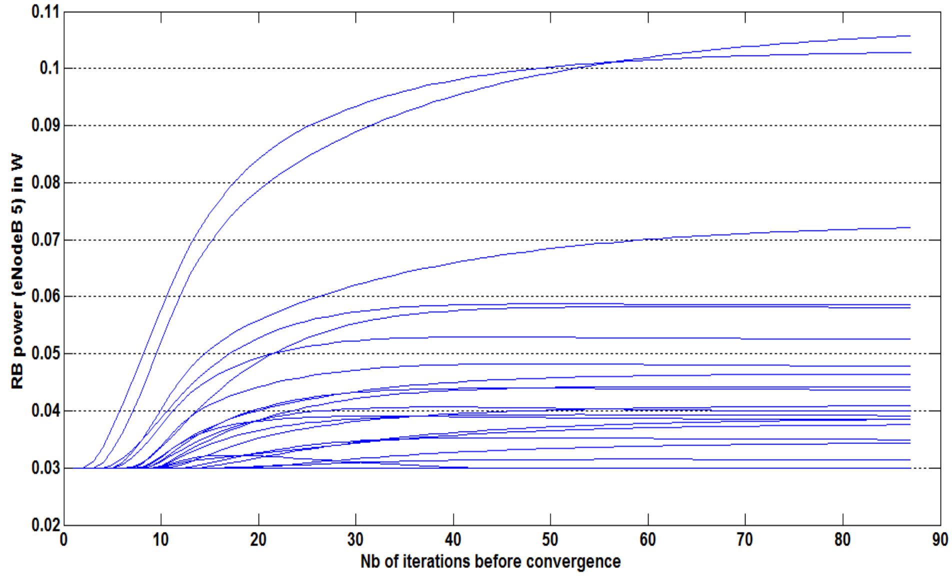


Figure 3.9 Power distribution by RBs before reaching convergence for semi-distributed algorithm

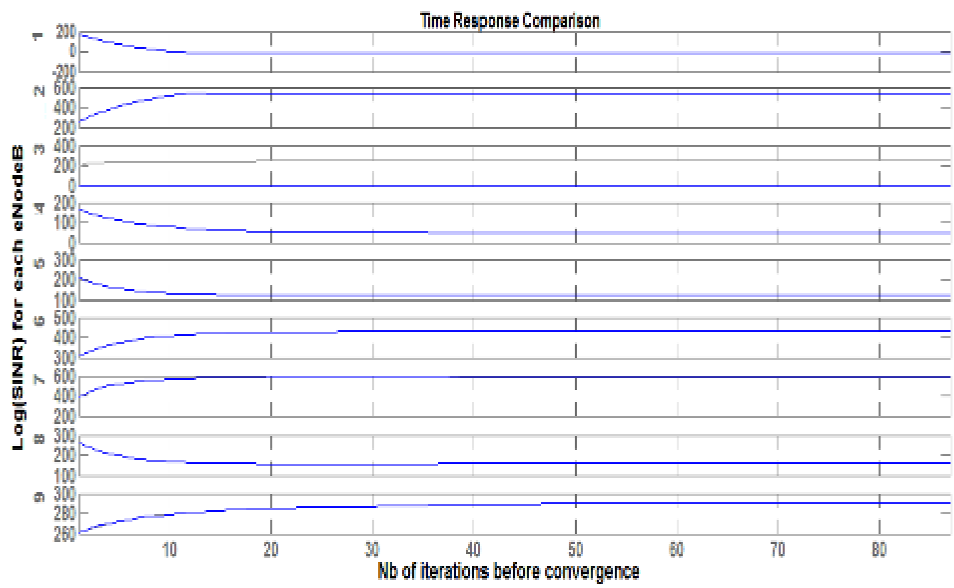


Figure 3.10 log(SINR) distribution by eNB before reaching convergence for semi-distributed algorithm

3.5 Conclusion

In this chapter, a joint scheduling and power control scheme is proposed as part of the LTE Inter cell Interference coordination process. The original problem is decoupled into a scheduling scheme and a power control scheme. We showed that, for the scheduling problem, proportional fairness has led to temporal fairness. The latter fairness is applied in a global fashion by a central controller. However, we still need to explore other fairness criteria taking into consideration the user's requirements. As for the power control problem, a non-cooperative game resulted in a semi-distributed algorithm that astutely and efficiently set the power levels with relatively low convergence time. Numerical simulations assessed the good performances of the proposed approach in comparison with the optimal centralized approach. The complexity of the Best Response convergence time will be investigated in a future work, to evaluate its NP-hardness .

Chapter 4

4. Achieving Power and Energy Efficiency in SON

The target of this chapter is to propose a practical low-complexity power allocation algorithm that strikes a good balance between Spectral Efficiency (SE) and power saving for the downlink of interference-limited cellular networks. Because abundant interference usually results from dense frequency reuse and high power transmission, power optimization schemes are critical to interference management in wireless systems. Powerful power optimization schemes can be efficiently implemented in the framework of Self-Organizing Network (SON). In this context, we resort to non-cooperative game theory to devise three distributed power allocation schemes. By only considering SE, our first Power Control Game (PCG) algorithm, deemed SE-PCG, provides high SE but push autonomous eNBs into consuming all available power. To address this shortcoming and enhance Energy Efficiency (EE), we put forward an enhanced version of PCG algorithm, deemed EE-PCG, which inflicts a penalty on power consumption. The EE-PCG is divided into two power allocation schemes, the first one described as semi-distributed (SD) algorithm based on Best Response dynamics deemed SD-EE-PCG. The second one is a fully-distributed (FD) algorithm, deemed FD-EE-PCG. The originality of the fully distributed scheme lies in deriving the power penalty through a signaling-free heuristic. We have analyzed the three proposed algorithms through extensive numerical simulations and compared them with the state-of-the-art approaches. The results have shown that our algorithms outperform the latter.

4.1 Introduction

Energy consumption in mobile communication systems has shown continuous growth during the last decade. In [KVP+13], it was reported that 3% of the world-wide energy is consumed by the information and communication technology infrastructures. In addition, energy costs represent 50% of operators' operating expenses [HBTM12]. Hence, operators have to use approaches that reduce power consumption while keeping Spectrum Efficiency (SE) at high levels. In order to do so, radio resource management techniques should be designed astutely to reduce energy consumption and inter-cell interference (ICI). This chapter addresses the problem of Inter-Cell Interference Coordination (ICIC) through power control in the downlink of cellular OFDMA-based systems. The power level selection process of resource blocks (RBs) is applied as a non-cooperative game. The latter is suitable for the decentralized context of Self Organizing Networks (SON) [HZZ+10], where network elements dynamically allocate radio resources in a distributed fashion.

In this chapter, we favor dynamic ICIC and stress on distributed schemes suitable for SON. For that, we formulate three distributed ICIC power allocation algorithms in order to maximize system throughput. In addition, we prove that the model at hand is a super-modular game [Top79] for all algorithms. Such games have always a Nash Equilibrium (NE) that can be suitably attained using best response dynamics.

In the first algorithm, deemed *SE-PCG*, each eNB optimizes its own performances locally. However, the available power will be unduly wasted due to the selfishness of eNBs. The second scheme, deemed *SD-EE-PCG*, is a semi distributed power allocation method that makes profit from the X2 interface between neighboring eNBs. The third scheme, deemed *FD-EE-PCG*, is a fully distributed power allocation method where each eNB optimizes its performance while accounting for power consumption. For that, UEs send a power cost metric to their servicing eNB, so that they can set the appropriate transmission power. The existence of a power cost in the utility function of the *SD-EE-PCG* and *FD-EE-PCG* diminishes the greediness of eNBs that are no longer tempted to transmit at full power on all RBs. In addition to power economy of the EE-PCG algorithms, the *FD-EE-PCG* operates without any inter-cell signaling.

The rest of this chapter is organized as follows. Section 4.2 describes the problem formulation, which is followed by Section 4.3, where the power allocation is presented as a non-cooperative game. In Section 4.4, we present the SE-PCG algorithm, while we explain the semi and fully distributed EE-PCG algorithms in Section 4.5. Subsequently, the performance of the proposed approaches, as well as the comparison with some of the state-of-the art approaches, are presented in Section 4.6. Finally, we conclude in Section 4.7.

4.2 Problem formulation

We use the reference model of Section 1.4 presented in chapter 1 and we assume a proportional fairness service provided by each eNB on each resource block. In a decentralized system, every eNBj ∈ J will strive to maximize its own utility function given by what follows [Kel97]:

$$\begin{aligned} U_j(\pi) &= \sum_{i \in I(j)} \frac{g(|I(j)|)}{|I(j)|} \sum_{k \in K} \log(\rho_{ijk}) \\ &= \sum_{i \in I(j)} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right). \end{aligned} \tag{4.1}$$

where $|I(j)|$ is the cardinality of set $I(j)$, $g(|I(j)|)=\sum_{s=1}^{|I(j)|} 1/s$, as we consider the PF scheduler with a fast varying fading channel (Rayleigh fading) [BP03].

In the following sections, we will provide three algorithms maximizing the above mentioned utility function based on distributed approaches.

4.3 Non-Cooperative game for Power Allocation

4.3.1 Game Formulation

Non-Cooperative game theory models the interaction between players competing for a common resource. Hence, it is well adapted to power allocation modeling. Here, eNBs are the decision makers or players of the game.

We define a multi-player game G between the eNBs. The eNBs are assumed to make their decisions without knowing the decisions of each other in order to eliminate the need of exchanged information.

The formulation of this non-cooperative game $G=\langle J, S, U\rangle$ can be described as follows:

- A finite set of eNBs $J = (1, ..., |J|)$ and a finite set of RBs $K = (1, ..., |K|)$.
- For each eNB j, the space of pure strategies S_j is as follows:

$$S_j = \left\{ \begin{matrix} \pi_j \in \mathbb{R}^{|K|} \, such\ as\ \pi_{jk} \geq p_j^{min}\ and \\ \sum_{k \in K} \pi_{jk} \leq p_j^{max}, \forall k \in K \end{matrix} \right\}$$

- An action of an eNB j is the amount of power π_{jk} sent on RB k. The strategy chosen by eNB j is then $\pi_j = (\pi_{j1}, \ldots, \pi_{jk})$. A strategy profile $\pi = (\pi_1, \ldots, \pi_{|J|})$ specifies the strategies of all players and $S = S_1 \times \ldots \times S_{|J|}$ is the set of all strategies.
- A set of utility functions $U=(U_1(\pi), U_2(\pi),\ldots, U_{|J|}(\pi))$ that quantify player's utilities for a given strategy profile π.

4.3.2 The Nash Equilibrium

In a non-cooperative game, an efficient solution is obtained when all players adhere to a Nash Equilibrium (NE) [Ros65]. A NE is a profile of strategies in which no player will profit from deviating its strategy unilaterally. Hence, it is a strategy profile where each player's strategy is an optimal response to other players' strategies.

$$U_j(\pi_j, \pi_{-j}) \leq U_j(\pi_j^{'}, \pi_{-j}), \qquad \forall i \in N, \forall \pi_j^{'} \in S_j. \qquad (4.2)$$

where π_{-j} denotes the vector of strategies played by all other eNBs except eNB j.

4.3.3 Super-Modular Games

According to [Top79], a game is super-modular if for any eNB $j \in J$:

- The strategy space S_j is a compact sub-lattice of $\mathbb{R}^k$.
- The objective function U_j is super-modular, i.e., if $\forall l \in J - \{j\}$ and $\forall \pi_j \in S_j$:

$$\frac{\partial U_j}{\partial \pi_l \partial \pi_j} \geq 0.$$

In [Top79], it was proven that, in super-modular game, if we start with a feasible policy, the sequence of best responses monotonically converges to an NE; it monotonically increases in all components in the case of maximization in a super-modular game.

4.4 Spectral Efficiency Power Control Game

For our first power Control game, *SE-PCG*, every eNB $j \in J$ strives to improve selfishly its own utility function:

$$U_j(\pi_j, \pi_{-j}) = \frac{g(|I(j)|)}{|I(j)|} \sum_{i \in I(j)} \sum_{k \in K} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right).$$

For every j, U_j is concave w.r.t.π_j and continuous w.r.t. π_l, $l \neq j$. Hence, a NE exists. Furthermore, the game is super-modular. In fact, the strategy space S_j is a compact convex set of $\mathbb{R}^k$, while the objective function of any eNB j is super-modular:

$$\frac{\partial U_j}{\partial \pi_l \partial \pi_j} = 0, \forall l \in J - \{j\}.$$

As we are in presence of a super-modular game, we know that Best Response algorithm permits attaining the NEs [Top79]. Accordingly, at each iteration t, eNB j strives to find, in parallel for all RBs $k \in K$, the following optimal power level as a response to $\pi_{-j}(t-1)$:

$$U_j(\pi_j, \pi_{-j}) \leq U_j(\pi_j^{'}, \pi_{-j}), \qquad \forall i \in N, \forall \pi_j^{'} \in S_j \tag{4.3}$$

which can be computed by solving the following optimization problem:

$$\underset{\pi_j}{\text{maximize}}\, U_j(\pi_j, \pi_{-j}) \quad = \frac{g(|I(j)|)}{|I(j)|} \sum_{i \in I(j)} \sum_{k \in K} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j^{'} \neq j} \pi_{j^{'}k} G_{ij^{'}k}}\right) \tag{4.4a}$$

$$\text{subject to:} \qquad \sum_{k \in K} \pi_{jk} \leq p_j^{max}, \tag{4.4b}$$

$$\pi_{jk} \geq p^{min}, \qquad \forall k \in K. \tag{4.4c}$$

4.4.1 The Power Expression at Equilibrium

The optimum power π^* of the convex problem (4.4) must satisfy the Karush Kuhn Trucker (KKT) conditions, i.e., there exists a unique Lagrange multiplier $\beta \geq 0$ such that:

$$\nabla_{\pi_{jk}}(U_j) + \beta . \nabla_{\pi_{jk}}\left(f_j(\pi_j)\right) = 0, \qquad \forall k \in K, \tag{4.5a}$$

$$\beta . f_j(\pi_j) = 0, \tag{4.5b}$$

$$p^{min} \leq \pi_{jk}, \qquad \forall k \in K. \tag{4.5c}$$

where $f_j(\pi_j) = p_j^{max} - \sum_{k \in K} \pi_{jk}$. Thus, according to (4.5a), the power allocation is given by:

$$\pi_{j,k} = \sqrt{\frac{g(|I(j)|)}{\beta}}, \qquad \forall k \in K. \tag{4.6}$$

Note that all power levels for a given eNB j are equal at equilibrium. Finally, to obtain the power levels that are sought for, we have recourse to (4.5b): as $\beta > 0$, we have that $\sum_{k \in K} \pi_{jk} = p_j^{max}$ at optimality and hence, by virtue of the equality among the power components, we have $\pi_{jk} = \frac{p_j^{max}}{k}, \forall k \in K$. Hence, we deduce the following:

$$\pi_{jk} = \max\left(p^{min}, \frac{p_j^{max}}{K}\right), \qquad \forall k \in K, \forall j \in J. \tag{4.7}$$

4.5 Energy Efficiency Power Control Game

We have proposed in Section 4.4 a game theory-based power allocation method, but the proposed algorithm suffers from an important shortcoming. In fact, it drives eNBs to consume all available power as shown in (4.7). In this section, we propose two EE-PCG:

1. The first one described as semi-distributed (SD) algorithm based on Best Response dynamics deemed SD-EE-PCG,
2. The second one is a fully-distributed (FD) algorithm, deemed FD-EE-PCG.

4.5.1 SD-EE-PCG

4.5.1.1 Ordinal Potential Game

Ordinal Potential games (OPG) [MS96] form a special class of normal form games where the unilateral change of one UE strategy π_j to $\pi_j^{'}$ results in a change of its utility function that is paralleled by a change of a so-called potential function $\emptyset: S^n \rightarrow \mathbb{R}$ as follows:

$$U_j\left(\pi_j, \pi_{-j}\right) > U_j\left(\pi_j^{'}, \pi_{-j}\right) \leftrightarrow \emptyset\left(\pi_j, \pi_{-j}\right) > \emptyset\left(\pi_j^{'}, \pi_{-j}\right)$$

An OPG admits at least one PNE which is essential in the present context.

Proposition 4.1 *The game G is an ordinal potential game and we propose the following potential function which maps a profile* $\pi = (\pi_1, \dots, \pi_n)$ *to a real:*

$$\emptyset(\pi) = \sum_{j \in J} \sum_{k \in K} \log \frac{G_{jk}\, \pi_{j,k}}{\sum_{\substack{j' \in J \\ j' \neq j}} \pi_{j',k} G_{j'k} + N_0} \tag{4.8}$$

Proof of proposition 4.1: The proof is given in the appendix B

As the strategy space is convex and $\emptyset$ is continuously differentiable on the strategy space, then every NE of the power control game is a stationary point [ET94] of $\emptyset$. Furthermore, as the potential function is concave, every NE of the game is a maximum point of $\emptyset$. Hence, $\pi^*$is a NE of the game G if and only if:

$$\pi^* \in \arg\max_{\pi} \emptyset(\pi)$$

We deduce that obtaining the NE boils down to solving the following optimization problem *P(π):*

$$\underset{\pi}{\text{maximize}}\, U(\pi) \quad = \sum_{j \in J} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \sum_{i \in I(j)} \log\left(\rho_{ijk}\right) \tag{4.9a}$$

$$= \sum_{j \in J} \sum_{i \in I(j)} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right).$$

Subject to:

$$\sum_{k \in K} \pi_{jk} \leq p_i^{max}, \qquad \forall j \in J. \tag{4.9b}$$

$$p_j^{min} \leq \pi_{jk}, \qquad \forall j \in J, \forall k \in K. \tag{4.9c}$$

This centralized power control problem (4.9) is non-linear and apparently difficult, non-convex optimization problem. However, it can be transformed into a convex optimization problem in the form of geometric programming by performing a variable change $\hat{\pi}_{jk} = \log(\pi_{jk})$ and defining $\hat{N}_0 = \log(N_0)$ and $\hat{G}_{ijk} = \log(G_{ijk})$.

The resulting optimization problem deemed $P(\hat{\pi})$ is given by the following:

$$P(\hat{\pi}): \underset{\pi}{\text{maximize}}\ \mathrm{U_j}(\hat{\pi}), \text{ with } \mathrm{U_j}(\hat{\pi}) = \tag{4.10a}$$

$$\sum_{j \in J} \sum_{i \in I(j)} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \left(\log(\pi_{jk}) + \log(G_{ijk}) - \log\left(N_0 + \sum\nolimits_{j' \neq j} \pi_{j'k} G_{ij'k}\right)\right) =$$

$$\sum_{j \in J} \sum_{i \in I(j)} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \left(\hat{\pi}_{jk} + \hat{G}_{ijk} - \log\left(N_0 + \sum_{j' \neq j} \exp(\log(\pi_{j'k} G_{ij'k}))\right)\right) =$$

$$\sum_{j \in J} \sum_{i \in I(j)} \sum_{k \in K} \frac{g(|I(j)|)}{|I(j)|} \left(\hat{\pi}_{jk} + \hat{G}_{ijk} - \log\left(\exp(\hat{N}_0) + \sum_{j' \neq j} exp(\hat{\pi}_{j'k} + \hat{G}_{ij'k})\right)\right).$$

Subject to

$$\log\left(\sum_{k \in K} \exp(\hat{\pi}_{jk})\right) - \log(p_j^{max}) \leq 0, \qquad \forall j \in J, k \in K. \tag{4.10b}$$

$$-\hat{\pi}_{jk} + \log(p_j^{min}) \leq 0, \qquad \forall j \in J, k \in K. \tag{4.10c}$$

Proposition 4.2 The resulting optimization problem $\boldsymbol{P}(\hat{\boldsymbol{\pi}})$ is convex and hence can be efficiently solved for global optimality even with a large number of UEs.

Proof of proposition 4.2:

The first term of the objective is a linear function, thus concave (and convex). The second term contains log-sum-exp expression which is convex. The opposite of the sum of convex functions being concave, this completes the proof of the concavity of the objective function. As for the new constraints: constraints (4.10b) are convex by virtue of the properties of the log-sum-exp functions and (4.10c) are linear function and hence convex.

We have established that finding the NE of the game G is equivalent to finding:

$$\pi^* = arg\max_{\pi} \emptyset(\pi) \tag{4.11}$$

which is convex problem and can be solved in a centralized fashion. However, in our context with selfish eNBs, we should seek for distributed algorithms that make profit from the X2 interface between neighboring eNBs in LTE.

Any local optimum π^* of the centralized convex problem (4.10) must satisfy the KKT conditions, i.e. there exist unique Lagrange multipliers $\forall j \in J$ such that:

$$\frac{\partial U_j(\hat{\pi})}{\partial \hat{\pi}_{jk}} + \sum_{l \neq j} \frac{\partial U_l(\hat{\pi})}{\partial \hat{\pi}_{jk}} = \mu_j - \lambda_j^k, \qquad \forall k \in K. \tag{4.12a}$$

$$\mu_j . \left(\log\left(P_j^{max}\right) - \log\left(\sum_{k \in K} \exp\left(\hat{\pi}_{jk}\right) \right) \right) = 0. \tag{4.12b}$$

$$\lambda_j^k . \left(\hat{\pi}_{jk} - \log\left(p_j^{min}\right)\right) = 0; \qquad \forall k \in K. \tag{4.12c}$$

$$\mu_j \geq 0 \; and \lambda_j^k \geq 0; \qquad \forall k \in K. \tag{4.12d}$$

We come back to the solution space in π instead of $\hat{\pi}$. In particular, we have what follows:

$$\frac{\partial U_j(\pi)}{\partial \pi_{jk}} = \frac{\partial \hat{\pi}_{jk}}{\partial \pi_{jk}} \frac{\partial U_j(\hat{\pi})}{\partial \hat{\pi}_{jk}} = \frac{1}{\pi_{jk}} \frac{\partial U_j(\hat{\pi})}{\partial \hat{\pi}_{jk}}.$$

Accordingly, we obtain the following set of equations:

$$\pi_{jk} . \left(\frac{\partial U_j(\pi)}{\partial \pi_{jk}} + \sum_{l \neq j} \frac{\partial U_{lk}(\pi)}{\partial \pi_{jk}} \right) = \mu_j - \lambda_j^k, \qquad \forall k \in K. \tag{4.13a}$$

$$\mu_j . \left(P_j^{max} - \sum_{k \in K} \pi_{jk} \right) = 0. \tag{4.13b}$$

$$\lambda_j^k . \left(\pi_{jk} - p_j^{min}\right) = 0, \qquad \forall k \in K, \tag{4.13c}$$

$$\mu_j \geq 0 \; and \lambda_j^k \geq 0, \qquad \forall k \in K. \tag{4.13d}$$

Using the KKT conditions, we give a decomposition of the original problem into $|J|$subproblems. Following [HBH06] we define the interference impact I_{ijk} for UE *i* associated to eNB *j* on RB *k* such as:

$$I_{ijk}\left(\pi_{-j}\right) = \sum_{l\neq j} \pi_{lk} G_{ilk} + N_0;\ \forall i \in I(j). \tag{4.14}$$

Further, we define the derivative of $U_{ijk} = \frac{g(|I(j)|)}{|I(j)|} log\left(\frac{\pi_{jk} G_{ijk}}{N_0+\sum_{j'\neq j}\pi_{j'k}G_{ij'k}}\right)$ relative to the interference impact as follows:

$$\frac{\partial U_{ijk}}{\partial I_{ijk}} = \frac{g(|I(j)|)}{|I(j)|}\frac{-1}{I_{ijk}}.$$

Using (4.14), condition (4.13a) can be re-written as:

$$\pi_{jk}\left(\frac{\partial U_{jk}}{\partial \pi_{jk}} - \sum_{l\neq j}\sum_{k\in K}\sum_{i\in I(l)}\frac{g(|I(j)|)}{|I(j)|}\frac{G_{ijk}}{I_{ijk}}\right) = \mu_j - \lambda_j^k;\ \forall k \in K, \forall j \in J. \tag{4.15}$$

Given fixed interference and fixing the power profile of any eNB except eNB *j*, it can be seen that (4.15) and conditions (4.13b)-(4.13d) are the KKT conditions of the following optimization sub-problems $\forall j \in J$:

$$\underset{\pi_j}{\text{maximize}}\, V_j\left(\pi_j, \pi_{-j}\right) = \tag{4.16a}$$

$$\sum_{k\in K}\sum_{i\in I(j)}\frac{g(|I(j)|)}{|I(j)|} log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j'\neq j}\pi_{j'k}G_{ij'k}}\right) - \sum_{k\in K}\pi_{jk}\,\alpha_{jk}.$$

$$\text{Subject to: } \sum_{k\in K}\pi_{jk} \leq p_j^{max}, p_j^{min} \leq \pi_{jk};\qquad \forall k \in K. \tag{4.16b}$$

Where α_{jk} is the interference impact on RB *k* of eNB *j* on other eNBs, and given by:

$$\alpha_{jk} = \sum_{\substack{l\in J\\ l\neq j}}\sum_{i\in I(l)}\frac{g(|I(j)|)}{|I(j)|}\frac{G_{ijk}}{\left(\sum_{\substack{j'\in J\\ j'\neq l}}\pi_{j'k}G_{ij'k} + N_0\right)}. \tag{4.17}$$

However, we choose to replace α_{jk} by $\bar{\alpha}_{jk} = \frac{\alpha_{jk}}{|J|}$, which is the mean interference impact on RB *k* inflicted by eNB *j* on other eNBs. Hence, we formulate a new non-cooperative game $G^{'}=\langle J, S, \bar{V}\rangle$, where:

$$\bar{V}_j\left(\pi_j, \pi_{-j}\right) = \sum_{k\in K}\left(\sum_{i\in I(j)} U_{ijk} - \bar{\alpha}_{jk}\,\pi_{jk}\right);\qquad \forall j \in J. \tag{4.18}$$

The first term of the new utility function$\sum_{i\in I(j)} U_{ijk}$ is a non-decreasing function in π_{jk} while the second term $-\bar{\alpha}_{jk}\pi_{jk}$ is decreasing in π_{jk}, which permits to strike a good balance between spectral efficiency and energy efficiency. Hence, the higher is the mean interference harm inflected on neighboring eNBs on a given RB *k*, the lower will be the chosen power amount π_{jk}.

For every $j, \bar{V}_j$ is concave w.r.t. π_j and continuous w.r.t. $\pi_l,\ l \neq j$. Hence, a Nash Equilibrium (NE) exists [Ros65]. Furthermore, the game at hand is super-modular. In fact, the strategy space S_j is obviously a compact convex set of $\mathbb{R}^k$, while the objective function of any eNB *j* is super-modular [Top79]:

$$\frac{\partial \bar{V}_{jk}}{\partial \pi_{lk} \partial \pi_{jk}} = \sum_{\substack{s \in J \\ s \neq \{j,l\}}} \sum_{i \in I(s)} \frac{g(|I(s)|)}{|J||I(s)|} \frac{G_{ijk}\, G_{ilk}}{\left(\sum_{j' \in J, j' \neq s} \pi_{j'k} G_{ij'k} + N_0\right)^2} \left(1 - \frac{G_{ijk}\, \pi_{jk}}{\left(\sum_{j' \in J, j' \neq s} \pi_{j'k} G_{ij'k} + N_0\right)}\right) \geq 0.$$

$\forall l \in J - \{j\}$ and $\forall k \in K$, as we can fairly assume with at least 6 neighboring eNBs for any eNB *s* that:

$$\frac{G_{ijk}\, \pi_{jk}}{\left(\sum_{j' \in J, j' \neq s} \pi_{j'k} G_{ij'k} + N_0\right)} < 1.$$

As we proved that we are in presence of a super-modular game, we know that a Best response algorithm enables attaining the NEs. The main idea behind this algorithm is for each eNB *j* to iteratively solve the optimization problem in (4.16) given the current interference impact and power profile of the other eNBs and then to recalculate the corresponding interference impact until convergence. Formally, we summarize this as follows:

1. Each eNB *j* chooses an initial power profile π_j satisfying the power constraint.
2. Using (4.17), each eNB *j* calculates the mean interference price vector $\bar{\alpha}_j$ given the current power profile and announces it to other eNBs.
3. At each time *t*, one eNB *j* is randomly selected to maximize its payoff function $\bar{V}_j\left(\pi_j, \pi_{-j}\right)$ and update its power profile, given the other eNBs power profiles π_{-j} and price vectors:

$$\pi_j(t+1) = arg\, \max_{\pi_j \in S_j} \bar{V}_j(\pi_j, \pi_{-j}(t)).$$

4.5.1.2The Power Expression at Equilibrium

We begin by solving the unconstrained convex optimization problem $\max_{\pi_j} \bar{V}_j\left(\pi_j, \pi_{-j}\right)$. Then, to obey the bounding constraints on power levels, any eNBs *j* must do locally a projection step in order to get back to the feasible region defined by S_j. The optimal values of the unconstrained problem are either on the boundaries of the strategy space or resulting from the following derivation $\forall j \in J, \forall k \in K$:

$$\frac{\partial \bar{V}_j\left(\pi_j, \pi_{-j}\right)}{\partial \pi_{jk}} = 0 \Rightarrow \tag{4.19a}$$

$$\pi_{jk}^2 . \left(\sum_{l\neq j}\sum_{i\in I(l)} G_{ijk}^2 \, C_l B_{jl}\right) + \pi_{jk} . \left(\sum_{l\neq j}\sum_{i\in I(l)} G_{ijk} \, A_{ik} \, C_l\left(2B_{jl} - 1\right)\right) + \sum_{j\neq j}\sum_{i\in I(l)} C_l A_{ik}^2 = 0 \tag{4.19b}$$

where $C_l = \frac{g(|I(j)|)}{|J||I(j)|}$, $B_{jl} = \frac{g(|I(j)|)}{g(|I(l)|)} and A_{ik} = \left(\sum_{\substack{j'\in J \\ j'\neq\{j,l\}}} \pi_{j'k} G_{ij'k} + N_0\right)$.

Consequently, π_{jk} is the solution of the second degree equation in (4.19b). After obtaining the various Sπ_{jk}, the projection algorithm 4.1 is run by every eNB *j* at each iteration as follows:

Algorithm 4.1 Projection algorithm for eNB *j*

Procedure POWER**P**ROJECTION (π_j)
S(K) ←**S**ORT**IND**ECREASING**O**RDER(K)
for all $k \in s(K)$**do**
if $\pi_{jk} < p_j^{min}$ **then**
$$\pi_{jk}^p \leftarrow P_j^{min}$$
end if
end for
if $\pi_j \not\forall S_j$ **then**
$$\rho(k) \leftarrow \pi_{jk} + \frac{1}{k} \times \left(P_j^{max} - \sum_{i\in s(K), i\leq k} \pi_{ji}\right) \forall k \in s(K) \text{and } \pi_{jk} > P_j^{min}$$
$$\rho^* \leftarrow \underset{k\in s(K)}{\operatorname{argmax}}\{v(k)\}$$
$$\lambda \leftarrow \frac{1}{\rho^*} \times \left(P_j^{max} - \sum_{i\in s(K), i\leq k} \pi_{ji}\right)$$
for all k ∈S(K) **do**
if $\pi_{jk} > p_j^{min}$ **then**
$$\boldsymbol{\pi_{j,k}^p} \leftarrow max\left\{\pi_{jk} - \lambda . p_j^{min}\right\}$$
end if
end for
end if
Return $\boldsymbol{\pi_j^p} = \left(\boldsymbol{\pi_{j,k}^p}, \forall k \in K\right)$
end procedure

4.5.2Fully-Distributed EE-PCG

In this section, we introduce a penalty on power consumption proportional to the interference harm inflicted by eNB *j* on its neighboring eNBs. Accordingly, we propose a simple heuristic to evaluate such a penalty that we deem β_{jk} and we formulate another non-cooperative game $G^{"} = \langle J, S, W \rangle$, where:

$$W_j(\pi_j, \pi_{-j}) = \sum_{k \in K} (U_{jk} - \beta_{jk} \pi_{jk}), \forall j \in J.$$

For every *j*, W_j is concave w.r.t. π_j and continuous w.r.t.$\pi_l, l \neq j$. Hence, a NE exists [Ros65]. Furthermore, the game is super-modular. In fact, the strategy space S_j is a compact convex set of $\mathbb{R}^k$, while the objective function of any eNB *j* is super-modular:

$$\frac{\partial W_j}{\partial \pi_l \partial \pi_j} = 0, \forall l \in J - \{j\}.$$

Thus, we know that a Best Response algorithm permits attaining the NEs. Accordingly, at each iteration *t*, eNB *j* strives to find, in parallel for all RBs $k \in K$, the following optimal power level as a response to $\pi_{-j}(t-1)$:

$$\pi_j^*(t) = arg \max_{\pi_j} W_j(\pi_j, \pi_{-j}), s.t. \pi_j^* \in S_j. \quad (4.20)$$

which corresponds to the following optimization problem:

$$\max_{\pi_j} W_j(\pi_j, \pi_{-j}) = \sum_{k \in K} (U_{jk} - \beta_{jk} \pi_{jk}) \quad (4.21a)$$

Subject to:

$$\sum_{k \in K} \pi_{jk} \leq p_j^{max}, \quad \forall k \in K, \forall j \in J, \quad (4.22b)$$

$$\pi_{jk} \geq p^{min}, \quad \forall k \in K. \quad (4.23c)$$

4.5.2.1 The Power Expression at Equilibrium

Let us write the Lagrangian of problem (4.23) as follows:

$$L(\pi_j, \gamma) = \sum_{=k \in K} \sum_{i \in I(j)} \frac{g(|I(j)|)}{|I(j)|} log\left(\frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right)$$
$$- \sum_{k \in K} \pi_{jk} \beta_{jk} + \gamma \left(p_j^{max} - \sum_{k \in K} \pi_{jk}(t)\right). \quad (4.24)$$

where$\gamma \geq 0$ is the Lagrangian multiplier. The dual problem in (4.24) may be expressed as follows:

$$min_{\gamma \geq 0} h(\gamma) = min_{\gamma \geq 0} max_{\pi_j} L(\pi_j, \gamma) \quad (4.25)$$

As $L(\pi_j, \gamma)$ is a standard concave function, each eNB *j* derives the optimal power levels by seeking zero points of the derivatives of $L(\pi_j, \gamma)$. Accordingly, we obtain:

$$\pi_{jk}(t) = \frac{g(|I(j)|)}{\gamma(t) + \beta(t)}, \forall k \in K \tag{4.26}$$

Recall that β_{jk} is a constant evaluated according to a simple heuristic that will be explained in the next subsection. Note that the higher the interference harm β_{jk} is, the lower the power allocated on that particular RB *k* will be.

Finally, to obtain the power level that is sought for, we use a gradient method to update the dual variable γsince h(γ)is differentiable:

$$\frac{\partial h(\gamma)}{\partial \gamma} = p_j^{max} - \sum_{k \in K} \pi_{jk}(t) \tag{4.27}$$

Hence, γ is updated as follows:

$$max\left(0, \gamma(t-1) - \delta_t\left(p_j^{max} - \sum_{k \in K} \pi_{jk}(t-1)\right)\right) \tag{4.28}$$

whereδ_t is a suitably small step size.

4.5.2.3 Heuristic to assess power penalty

Our proposed power penalty is based on an inter-cell signaling-free heuristic. In our proposed *EE-PCG* algorithm, we consider that, at each iteration, any eNB *j* decides to optimize the power allocation using equation (4.21). We assume that the power penalty β_{jk} existing in equation (4.21) will be the average interference impact of eNB *j* on other eNBs and it is reflected by the interference impact of all other neighboring eNBs to eNB *j*. Accordingly, the value of the power penalty cost β_{jk} is given by:

$$\beta_{jk} = \frac{1}{|K|.|J|.|I(j)|} \frac{g(|I(j)|)}{|I(j)|} \sum_{i \in I(j)} \sum_{\substack{l \in J \\ l \neq j}} S_{ilk}. \tag{4.29}$$

We assume that S_{ilk} reflects the interference level inflected by eNB *j* on a given neighboring cell served by eNB *l*. This S_{ilk} represents the SINR received by UE *i*, $i \in I(j)$, from neighboring eNB *l*, $l \in J, l \neq j$. Note that the power penalty is computed per RB, per eNB, and per UE and reflects the proportional fairness gain. The value of S_{ilk} is given by:

$$S_{ilk} = \frac{G_{ilk}\pi_{lk}}{\left(\sum_{\substack{l' \in J \\ l' \neq l}} \pi_{l'k} G_{il'k} + N_0\right)} \tag{4.30}$$

S_{ilk} is practically measured in a real environment by any UE and used, for instance, for the handover process. All UEs served by eNB *j* transmit the value of S_{ilk} periodically to eNB

j. When an eNB receives a new value of S_{ilk} from the served UEs, it starts the *FD-EE-PCG* algorithm. First of all, eNB j computes β_{jk} using (4.29), and starts optimization using the current π_{jk} as initial power value.

Each eNB adapts the signal transmission in the downlink without any Inter-cell signaling. The eNB repeats this adaptation process, at each iteration, until convergence. The Flowchart, illustrated in appendix B, represents the *FD-EE-PCG* algorithm process.

4.6 Performance evaluation

4.6.1 Simulation parameters

We consider a Bandwidth of 5 Mhz with 25 RBs in a 9 hexagonal cells network, the number of UE ranging from 4 to 14 per eNB uniformly distributed in any cell. Further, we consider the following parameters listed in the 3GPP technical specifications TS 36.942 [3GP14]: the mean antenna gain in urban zones is 12 dBi (900 MHz). Transmission power is 43 dBm (according to TS 36.814) which corresponds to 20 Watts (on the downlink). The eNBs have a frequency reuse of 1, with W = 180 KHz. As for noise, we consider the following parameters: UE noise figure 7.0 dB, thermal noise −104.5 dBm which gives a receiver noise floor of $N_0 = -97.5$ dBm.

In this chapter, we conducted preliminary simulations in a Matlab simulator, where various scenarios were tested to assess the performances of the power control schemes.

For each approach, 25 simulations were run, where in each cell a predefined number of UEs is selected. The mean performance are obtained with the confidence interval of 95%. Users' positions were uniformly distributed in the cells. For each simulation instance, the same pool of RBs, UEs and pathloss matrix are given for all algorithms.

4.6.2 Global performance

In Figure 4.1, we can see the similarity of power economy efficiency between the semi-distributed algorithm and the fully-distributed algorithm.

Both EE-PCG permit a considerable power economy in comparison with the SE-PCG, that uses full power P_j^{max} for each eNB, as we can see in Figure 4.1 where the relative power economy percentage of the SD-EE-PCG vs SE-PCG, for all eNBs, vary from 55 to 65 %, which is a sensible power economy. Concerning the FD-EE-PCG, we note that the relative power economy percentage, varying from 89 to 93 % in comparison with the SD-PCG, which is a significant power economy. In fact, the existence of the power costs in the utility function (4.16) and (4.21) diminishes the selfishness of eNBs that are tempted to transmit at full power on all RBs.

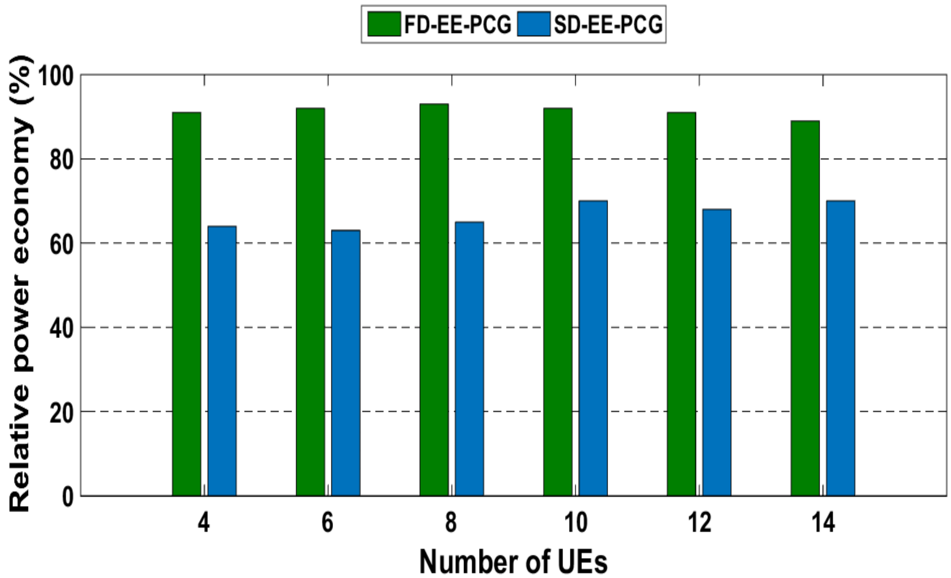


Figure 4.1 Percentage of Power economy of FD-EE-PCG and SD-EE-PCG vs SE-PCG

This power economy is obtained while maintaining good performances as we can see in Figure 4.2 where the total Throughput is depicted as a function of the number of UEs for the FD-EE-PCG, SD-EE-PCG and the SE-PCG approaches.

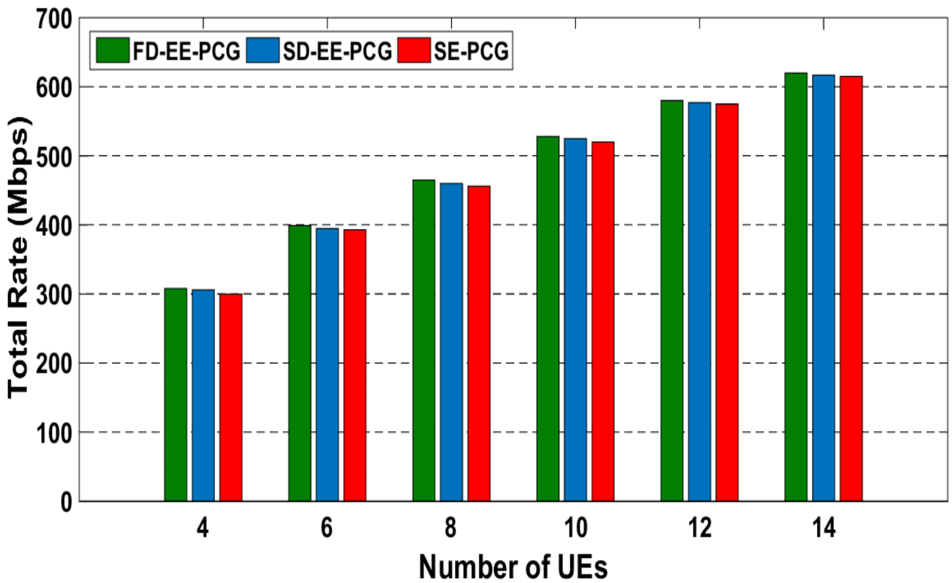


Figure 4.2 Total Throughput of the proposed algorithms as function of number of UEs

4.6.3 SD-EE-PCG performance evaluation

In Figure4.3, we report the mean convergence time per eNBs for the SD-EE-PCG for various scenarios. We note that each eNBs attains in average the NE within 19 to 27 iterations. At each iteration, one eNB is randomly selected to maximize its payoff function given in (4.16). The iteration period coincides with one TTI (Transmit Time Interval), which equals 1ms in LTE.

We noted during the extensive simulations conducted, that the power levels attain 90% of the values reached at convergence in less than 8 iterations. We represented in Figure 4.4 the power distribution of 25 RBs for an eNB selected randomly and for which convergence time was equal to 22 iterations. Low convergence time in conjunction with high performances is an undeniable asset for distributed schemes.

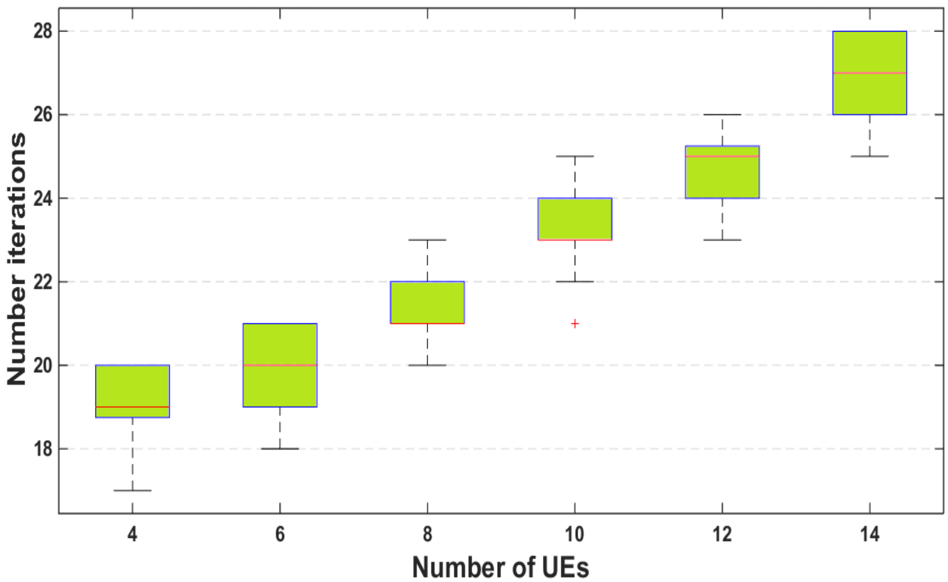


Figure 4.3 Total convergence time as a function of the number of users for the SD-EE-PCG

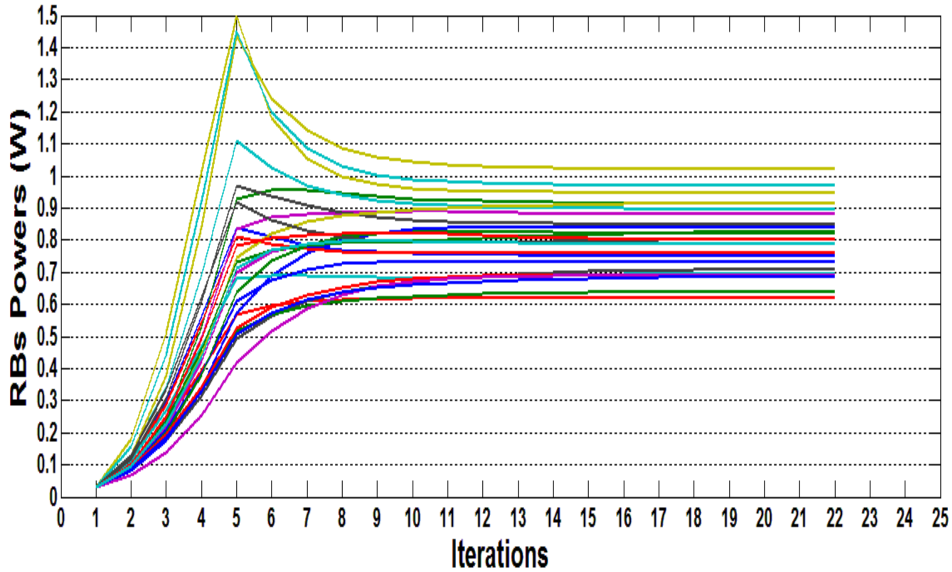


Figure 4.4 Power distribution by RBs before reaching convergence for SD-EE-PCG

Distributed algorithms can adapt to fast changes of network state though it is difficult to avoid converging to local optimum. It turns out that even though the distributed game results are sub-optimal, the low degree of system complexity and the inherent adaptability make the semi-distributed approach promising especially for dynamic scenarios. The fast convergence time, the near optimal results and the lower complexity degree of the semi-distributed approach makes it a very attractive solution.

4.6.4 FD-EE-PCG performance evaluation

In Figure 4.5, we report the mean convergence time per eNB of the FD-EE-PCG algorithm for various scenarios. We note that each eNB attains, in average, the NE within 60 to 72 iterations as shown in Figure 4.5. At each iteration, all eNBs try to maximize their payoff function given in (4.21). Note that convergence is faster when increasing the number of UEs because the power penalty cost estimation is more accurate.

Moreover, we noted during the extensive simulations conducted, for the FD-EE-PCG, that the power levels attain 90% of the values reached at convergence in less than 20 iterations, which is relatively fast.

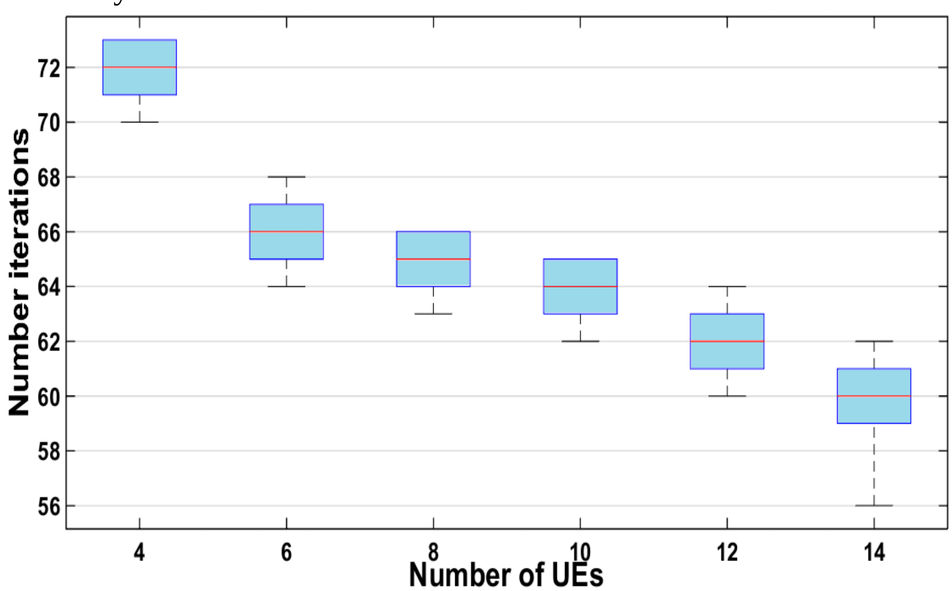


Figure 4.5 Mean convergence time as a function of the number of UEs for FD-EE-PCG algorithm.

We represent in Figure 4.6 the power distribution on the 25 RBs for an eNB selected randomly and for which convergence time was equal to 64 iterations. At t=0, we set the power value $\frac{P_j^{max}}{K}$ for each RBs. The latter high power level will increase the power penalty due to the resulting high level of interference. This increase in β_{jk} forces the eNBs to decrement drastically, at the first iteration, their power values to P^{min}. Lowering the power allocation will decrease the power penalty, which will drive again eNBs to increase back their power level, as seen in Figure 4.6. This behavior is reproduced by increasing and decreasing β_{jk} alternately, until we reach a stable power allocation.

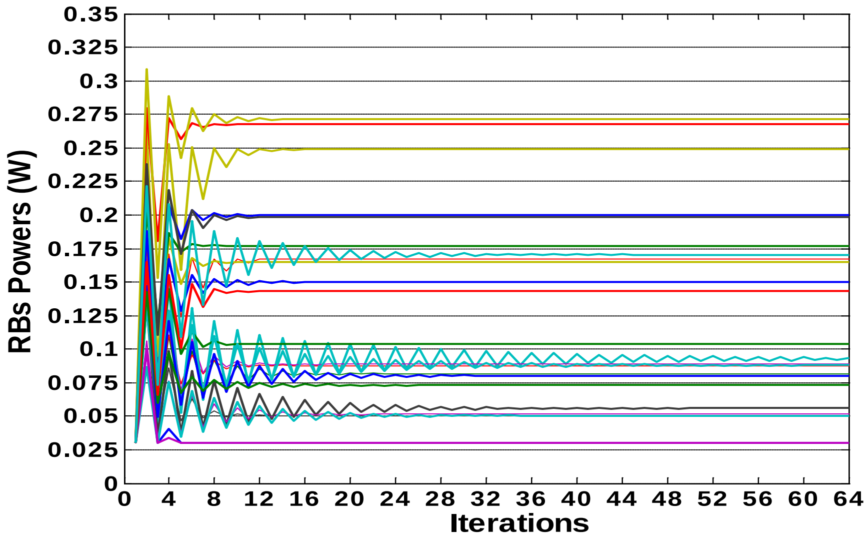


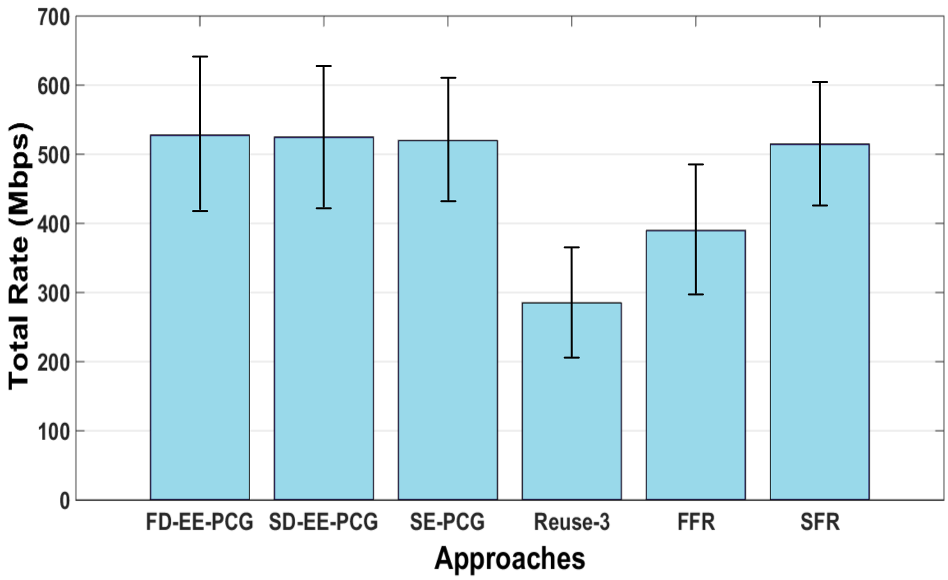
Figure 4.6 Power distributionon RBs before reaching convergence for FD-EE-PCG algorithm.

The low convergence time in conjunction with high performance is an incontestable asset for the SON context. As it can be seen from the results, the FD-EE-PCG can provide better efficiency than the SE-PCG algorithm with much reduced consumed power. Moreover the fully distributed power penalty cost estimation is well adapted to the SON context and is considered as an advantage of the FD-EE-PCG compared to the SD-EE-PCG.

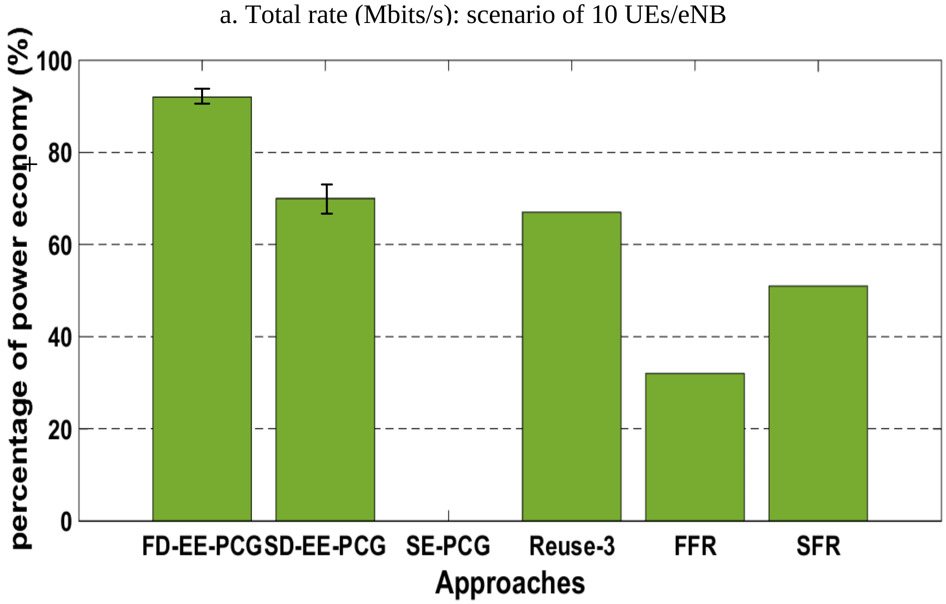
4.6.4 Comparison with state of the art approaches

However, we still need to assess the performance of our devised schemes with state-of-the-art approaches such as the frequency reuse-3 model, FFR and SFR techniques, presented in chapter 1. The simulation results include 95% confidence interval.

Accordingly, we display in Figure 4.7(a) the total rate of our SE-PCG, SD-EE-PCG and FD-EE-PCG algorithms in addition to the above mentioned standard techniques. We can clearly see from the portrayed results that our dynamic ICIC schemes provide higher rates than the state-of-the-art ICIC techniques. In particular, the FD-EE-PCG and SD-EE-PCG approaches satisfied UEs needs better than static ICIC with quantified transmission power levels and static resource allocation. Theses good performances of the EE-PCG family are obtained while maintaining a high power saving in comparison with SE-PCG and state-of-the-art approaches as portrayed in Figure 4.7(b)



a. Total rate (Mbits/s): scenario of 10 UEs/eNB



b. Power saving percentage relative to Max power policy (serving all RBs with maximum power)

Figure 4.7 Comparison with state-of-the-art approaches

4.7 Conclusion

In this chapter, we proposed three distributed ICIC power control games for the downlink of a SON OFDMA-based network. We demonstrated that all algorithms provide a significant performance improvement in comparison with the state-of-the art approaches. The first algorithm, SE-PCG, provides high spectral efficiency, but push autonomous eNBs into consuming all available power. The second group of algorithms, based on EE-PCG, reduces power wastage without degrading system performance owing to a power penalty cost. For the SD-EE-PCG, the penalty cost is estimated via an inter-cell signaling based one X2 signaling. Contrariwise, the penalty cost is estimated via an inter-cell signaling free heuristic that enables our energy efficient algorithm to astutely adjust the downlink transmission power according to UE feedbacks.

This SD-EE-PCG and the FD-EE-PCG algorithms judiciously and efficiently set the power levels with relatively low convergence time. Numerical simulations assessed the good performances of the EE-PCG approaches in comparison with the SE-PCG approach. More importantly, considerable power economy and signaling optimization can be realized.

Chapter 5

5. Joint User Association, Power Control And Scheduling in Multi-Cell 5G Networks

The focus of this chapter is targeted towards multi-cell 5G networks composed of High Power Nodes (HPNs) and of simplified Low Power Nodes (LPNs) *co-existing in the same operating area and sharing the scarce radio resources. Consequently, this chapter focuses on Inter-Cell Interference Coordination (ICIC) based on multi-resource management techniques that take into account UE association to cells. Beside UE association, this chapter takes also power control and scheduling into consideration. The complex problem of jointly optimizing UE association, power control, and scheduling is still largely unsolved. This is mainly due to its non-convex nature, which makes the global optimal solution difficult to obtain. We address this multifaceted challenge according to the three broadly adopted approaches in wireless networks: the network-centric approach where power allocation and UE association are allocated efficiently in a centralized fashion; the user-centric approach where fully distributed power allocation and fully distributed UE association, based on Reinforcing learning, are used for reduced complexity; the mixed approach where the UE association is solved in a distributed fashion, based on Best Response algorithm and the power control is solved in a centralized fashion in order to reach an optimal solution of the joint optimization problem. In all over approaches, the scheduling is solved in a centralized fashion. We have analyzed the three proposed approaches through extensive numerical simulations in order to evaluate the performances* *of the UE association schemes, and compared the global performance of the joint optimization problem in term of efficiency and complexity.*

5.1 Introduction

5G networks are currently facing significant challenges in terms of signaling load. Compared to its predecessors, 5G requires a significantly higher signaling load per subscriber. While a portion of this new signaling is required for new services and new device types, the majority of the signaling burden is related to mobility and paging. This increase is in part due to architectural changes such as heterogeneous networks and greater node density. Consequently, one of the objectives of 5G networks is to enhance the capabilities of HPNs and simplify LPNs through offloading some of their functions to a *signal processing cloud* connected through high-speed optical fibers. The signal processing cloud is, in fact, a pool of Base Band Units (BBUs). For a simplified architecture, all control signaling and system broadcasting information are delivered by HPNs to UEs.

This chapter addresses the issue of UE association to HPNs in 5G networks. Further, as multiple HPNs use the same radio resources in a given operating area, ensuing interference harms radio transmissions and degrades the performances. Hence, a certain degree of coordination between the HPNs belonging to the same baseband unit (BBU) pool is required to minimize the interference level through power control.

We consider Orthogonal Frequency Division Multiple Access (OFDMA) as the multi access scheme for the downlink. As the same Resource Block (RB) is used in neighboring cells, interference may occur and degrade the channel quality of serviced UEs. Hence, efficient Inter-Cell Interference Coordination (ICIC) techniques [DSZ12] are still-considered among the key building blocks of 5G networks, in particular, ICIC through power control. Multi-Resource management based on joint power allocation, scheduling and UE association is a primary key to achieve good global performance.

Accordingly, the aim of this chapter is threefold:

1. UE association to HPNs:
    - Decide the UE association to the adequate HPN for the signaling plan; this decision is operated in a centralized fashion by the advanced cloud computing processing techniques in the BBU pool.
    - Decide the UE association to the adequate HPN for the data plan; this decision is operated by UEs in a distributed fashion.
2. Interference mitigation among HPNs through power control:

- The joint HPN/UE association and HPN power control is solved in an iterative fashion until convergence involving the following steps:
    - Fixing the association of UEs, the power levels are cooperatively updated by HPNs, in centralized or decentralized fashion.
    - Fixing the HPN power allocation, the association of UEs to each HPNs is again done by solving the resulting optimization problem for UE association.
3. Fair scheduling of resources among UEs.

We propose a unified framework to study the interplay of UE association and HPN power allocation, in conjunction with fair scheduling. For that, we strive to optimize a network utility function that ensures proportional fairness among all served UEs.
In this chapter, we show that proportional fairness among UEs boils down to time fairness in section 5.3.1. The ensuing joint UE association and power control in section 5.3.2 is solved according to the network-centric approach, the user-centric approach, and the mixed approach.

1. In the network-centric approach, we resort to centralized schemes for UE association and power control. In particular, we have recourse to an iterative optimization approach involving the following steps:
    - For a fixed UE association, the HPN power levels are updated by computing the resulting non-convex optimization problem for power control; the latter is rendered convex through geometric transformation. Such a solution allows multiple cells to coordinate to alleviate inter-cell interference and improve the overall network utility.
    - For a fixed power allocation, the assignment of UEs to each HPN is again done in a centralized fashion by computing the resulting optimization problem for UE association.

    The above two steps will be iterated to reach a local optimal solution of the joint optimization problem. Such centralized schemes are stable but are highly computational. In fact, they require a central controller that collects information from HPNs and UEs, optimizes parameters, and sends signaling messages back to HPNs and UEs, which can be cumbersome. However, it is particularly suited for the UE association to the control plane. As for the data plane, it requires more frequent updates and it is better handled in a distributed fashion by the end-user, as described in the user-centric approach and the mixed approach.

2. In the user-centric approach, the UE association and power control schemes are portrayed as non-cooperative games that can lead to a substantial complexity reduction. In our case, HPNs and UEs optimize their local parameters by making use of signaling messages already present in the network. Notably, a fully distributed algorithm for the UE association scheme based on reinforcement learning will be applied by UEs to attain the Nash Equilibriums (NEs) of the game. User-centric schemes can adapt to fast changes of network state at the cost of reduced efficiency.
3. In the mixed approach, the power control is solved in centralized fashion, described in subsection 5.4.1. In this approach for a fixed UE association, the power levels are updated by computing the resulting non-convex optimization problem for power control. Such solution allows multiple cells to coordinate with the objective of alleviating inter-cell interference, and improving overall network utility. The UE association utility function, described in section 5.6.2, is solved according to distributed approach where the UE association scheme for the data plane is portrayed as non-cooperative game. In our case, UEs optimize their local parameters by using signaling messages already present in the network. A distributed algorithm for the UE association scheme based on Best-response algorithm will be applied by UEs to attain the Nash Equilibriums (NE) of the game.

The rest of this chapter is organized as follows. The utility function model is presented in Section 5.2. The problem formulation is explained in Section 5.3. The network-centric approach is explained in section 5.4. The user-centric approach is detailed in section 5.5. In section 5.6 the mixed approach is presented. Extensive simulations and performance evaluations are displayed in Section 5.7 proving the relevance of our devised schemes. Conclusion is given in Section 5.8.

5.2 Utility Function Model

We use the reference model presented in chapter 1, and we focus on the HPN power allocation, scheduling, and UE association. Conventional UE association uses the max-SINR rule. It is evident from a network utility maximization perspective that max-SINR is inappropriate as it may deprive bad channel quality UEs from accessing radio resources. We assume that there is a mapping function *f()* that maps the Signal-to-interference-plus-noise-ration (SINR) of UE i associated to HPN j and allocated RB k (ρ_{ijk}) to its corresponding bit rate r_{ijk} (bit/s), i.e., r_{ijk} =*f*(ρ_{ijk}).

Therefore, in this chapter, we consider the network utility maximization problem under proportional fairness. Hence, we privilege users' interest by using the proportional equity incarnated by the logarithmic function [Kel97]. To reach this objective we maximize $\sum_{i\in I}\log(r_i)$ where r_i is the mean bit rate of UE i:

$$r_i = \sum_{j\in J} \lambda_{ij}\tau_{ij} \sum_{k\in K(j)} f(\rho_{ijk}), \tag{5.1}$$

with τ_{ij} the proportion of time that UE i is scheduled on the downlink by HPN j and λ_{ij} is the association variable:

$$\lambda_{ij} = \left\{ \begin{array}{l} 1\ if\ UE\ i\ is\ associated\ with\ HPN\ j \\ 0\ otherwise. \end{array} \right\}. \tag{5.2}$$

Hence, the joint multi-resource management problem based on power control, UE association and proportional fair scheduling is defined as:

$$\underset{\lambda,\tau,\pi}{\text{maximize}} \quad \sum_{i\in I} \log\left(\sum_{j\in J} \lambda_{ij}\tau_{ij} \sum_{k\in K(j)} f(\rho_{ijk})\right), \tag{5.3a}$$

$$\text{subject to:} \quad \sum_{j\in J}\lambda_{ij} = 1, \qquad \forall i\in I, \tag{5.3b}$$

$$\sum_{i\in I(j)}\tau_{ij} = 1, \qquad \forall j\in j, \tag{5.3c}$$

$$\sum_{k\in K(j)}\pi_{jk} \le P_j^{max}, \qquad \forall j\in J, \tag{5.3d}$$

$$\lambda_{ij} \in \{0,1\}, \qquad \forall i\in I, \forall j\in J, \tag{5.3e}$$

$$0 \le \tau_{ij} \le 1, \qquad \forall i\in I, \forall j\in J, \tag{5.3f}$$

$$\pi_{jk} \ge P_j^{min}, \qquad \forall j\in J, \forall k\in K(j). \tag{5.3g}$$

Constraint (5.3c) ensures that a UE is served at most 100% of the time by a given HPN. Constraints (5.3d-5.3g) guarantee the maximum total power consumed per HPN and the minimum power allocated per RB respectively. The utility function in (5.3a) can be re-written as:

$$\begin{aligned} U &= \sum_{i\in I} \log\left(\sum_{j\in J} \lambda_{ij}\tau_{ij} \sum_{k\in K(j)} f(\rho_{ijk})\right) \\ &= \sum_{i\in I}\sum_{j\in J}\lambda_{ij}\log(\tau_{ij}) + \sum_{i\in I}\sum_{j\in J}\lambda_{ij}\log(r_{ij}). \end{aligned} \tag{5.4}$$

Where $r_{ij} = \sum_{k\in K(j)} f(\rho_{ijk})$ represents the mean bit rate obtained by UE i connected to HPN j.

In this chapter, we consider that the function *f()* is the identity function. Accordingly, the utility formulation is technology-agnostic: the mapping between the throughput and the

SINR of each UE can be derived in respect to the appropriate coding and modulation scheme in wireless networks. Inevitably, improving this network utility amounts to improving the UE throughput.

5.3 Problem Formulation

We show that proportional fairness among UEs boils down to time fairness in Section 5.3.1. The resulting joint UE association and power control problems will be presented in Section 5.3.2.

5.3.1 The Scheduling Problem

The utility function in (5.4) contains in its first term the per cell scheduling problem that we intend to solve in this section by computing τ_{ij}.

Assuming that UE i has chosen HPN l (i.e. $\lambda_{il} = 1$; $\lambda_{ij} = 0, \forall j \neq l$), we have what follows:

$$\sum_{i \in I, j \in J} \lambda_{ij} \log(\tau_{ij}) = \sum_{i \in I(l)} \log(\tau_{il}). \tag{5.5}$$

where *I(l)* is the set of UEs associated to HPN *l*. Consequently, the scheduling problem for HPN *l* is as follows:

$$\underset{\tau}{\text{maximize}} \quad \sum_{i \in I(l)} \log(\tau_{il}), \tag{5.6a}$$

$$\text{subject to} \quad \sum_{i \in I(l)} \tau_{il} = 1, \qquad \forall l \in J, \tag{5.6b}$$

$$0 \leq \tau_{il} \leq 1, \qquad \forall i \in I(l), \forall l \in J. \tag{5.6c}$$

***Proposition 5.1*:**

The optimal solution of the scheduling problem is given by what follows:

$$\tau_{il}^* = 1/|I(l)|, \forall l \in J, \forall i \in I(l). \tag{5.7}$$

Proof of proposition 5.1:

Problem (5.6) is a convex optimization as the utility function (5.6a) is concave (sum of concave functions) and all constraints are linear. Let us express the KKT conditions that provide a first-order optimality condition for the problem:

$$-1/\tau_{il} + \mu_l = 0, \qquad \forall l \in J, \forall i \in I(l), \tag{5.8a}$$

$$\sum_{i \in I(l)} \tau_{il} \leq 1, \qquad \forall l \in J, \qquad (5.8b)$$

$$\mu_l \left(\sum_{i \in I(l)} \tau_{il} - 1 \right) = 0, \qquad \forall l \in J. \qquad (5.8c)$$

From constraints (5.8a), we know that $\mu_l \neq 0$, otherwise $1/\tau_{il} = 0$ which is not possible. Hence, we deduce from constraint (5.8c) that $\sum_{i \in I(l)} \tau_{il} = 1$. Furthermore, the utility function in (5.6a) can be re-written as:

$$\log \left(\prod_{i \in I(l)} \tau_{il} \right). \qquad (5.9)$$

As the sum of the τ_{il} variables is constant, the product of these variables is maximized for $\tau_{il} = \frac{1}{|I(l)|}, \forall l \in J, \forall i \in I(l)$.

5.3.2 The Joint UE Association and Power Control Problem

As $\tau_{ij} = \frac{1}{|I(j)|} = \frac{1}{\sum_{i \in I(j)} \lambda_{ij}}, \forall j \in J$, the utility function in (5.5) can be re-written such as:

$$U = \sum_{i \in I} \log \left(\sum_{j \in J} \frac{\lambda_{ij}}{\sum_{i' \in I(j)} \lambda_{i'j}} \sum_{k \in K(j)} \rho_{ijk} \right). \qquad (5.10)$$

As the λ_{ij} variables are binary and $\sum_{j \in J} \lambda_{ij} = 1$ for all UEs, there exists only one HPN j for which $\lambda_{ij} = 1$ ($\lambda_{ij'} = 0,\ \forall j' \neq j \in J$). Hence, the utility function can be re-casted as:

$$U = \sum_{i \in I} \sum_{j \in J} \lambda_{ij} \log \left(\frac{\sum_{k \in K(j)} \rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}} \right). \qquad (5.11)$$

Given Jensen's inequality and the concavity of the log function, we have:

$$\log \left(\frac{\sum_{k \in K(j)} \frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}}}{|K(j)|} \right) \geq \frac{\sum_{k \in K(j)} \log \left(\frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}} \right)}{|K(j)|}$$

Thus, the utility function can be re-casted as follows: $U =$

$$\sum_{i \in I} \sum_{j \in J} \lambda_{ij} \log \left(\sum_{k \in K(j)} \frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}} \right) \geq \sum_{i \in I} \sum_{j \in J} \sum_{k \in K(j)} \lambda_{ij} \log \left(\frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}} \right) \qquad (5.12)$$

We denote by $\overline{U}$ the lower bound on the utility function, given by:

$$\bar{U} = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K(j)} \lambda_{ij} \log\left(\frac{\rho_{ijk}}{1+\sum_{i'\neq i}\lambda_{i'j}}\right). \tag{5.13}$$

Henceforward, we adopt this newly defined utility function $\bar{U}$. The resulting joint UE association and power control will be solved according to a network-centric approach in Section 5.4, to a user-centric approach in Section 5.5 and according to a mixed approach in Section 5.6.

5.4 The Network-Centric Approach

In the network-centric approach, we resort to a centralized power control scheme presented in Section 5.4.1 and to a centralized UE association scheme presented in Section 5.4.2. Both schemes will be run iteratively until convergence. Convergence to a local optimum is guaranteed as, at each iteration, both the power control scheme and the UE association scheme monotonically improve the value of the utility function.

5.4.1 Centralized Power Control

Fixing the UE association, the corresponding Power Control (PC) problem is given by:

$$\underset{\pi}{\text{maximize}}\, U^{PC}(\pi) = \sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K(j)} \log\left(\frac{1}{n_j}\times\frac{\pi_{jk}G_{ijk}}{N_0+\sum_{j'\neq j}\pi_{j'k}G_{ij'k}}\right). \tag{5.14a}$$

$$\text{subject to:} \quad \sum_{k\in K(j)} \pi_{jk} \leq P_j^{max}, \qquad \forall j\in J, \tag{5.14b}$$

$$\pi_{jk} \geq P_j^{min}, \qquad \forall j\in J, \forall k\in K(j). \tag{5.14c}$$

where n_j is the number of UEs associated to HPN j, i.e. $|I(j)|$.

Problem (5.14) is a non-convex optimization problem. However, it can be rendered convex through geometric programming by performing a variable change $\hat{\pi}_{jk} = \log(\pi_{jk})$ and defining the following $\hat{N}_0 = \log(N_0)$, $\hat{G}_{ijk} = \log\left(G_{ijk}\right)$ and $\hat{n}_j = \log(n_j)$. The resulting optimization problem deemed $P(\hat{\pi})$ is given by the following:

$$\underset{\pi}{\text{maximize}}\, U^{PC}(\hat{\pi}) = \tag{5.15a}$$

$$\sum_{j\in J}\sum_{i\in I(j)}\sum_{k\in K(j)} (\hat{\pi}_{jk}+\hat{G}_{ijk} - \log(\exp(\hat{N}_0)+\sum_{j'\neq j}\exp(\hat{\pi}_{j'k}+\hat{G}_{ij'k}))) - \sum_{j\in J} K.n_j.\hat{n}_j$$

$$\text{subject to:} \quad \log\left(\sum_{k\in Kj)}\exp\left(\hat{\pi}_{jk}\right)\right) - log\left(p_j^{max}\right) \leq 0. \tag{5.15b}$$

$$-\hat{\pi}_{jk} + \log(p_j^{min}) < 0, \qquad \forall j\in J, \forall k\in K(j). \tag{5.15c}$$

Proposition 5.2: The optimization problem $P(\hat{\pi})$ is convex.

Proof of proposition 5.2:

The first part of the utility function is linear thus concave. The second part includes the log-sum-exp expressions which are convex and hence their opposite is concave. Further, the new constraints in (5.15b) are convex owing to the properties of the log-sum-exp expression, while the constraints in (5.15c) are linear and hence convex.

5.4.2 Centralized UE Association

For fixed power levels, The UE Association (UA) problem is given by:

$$\underset{\lambda}{\text{maximize}}\, U^{UA}(\pi) = \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\lambda_{ij}\,\log\left(\frac{\rho_{ijk}}{n_j}\right) \tag{5.16a}$$

subject to:

$$\sum_{j\in J}\lambda_{ij} = 1, \qquad \forall i \in I, \tag{5.16b}$$

$$\lambda_{ij} \in \{0,1\}, \qquad \forall i \in I(j), \tag{5.16c}$$

$$n_j = \sum_{i\in I}\lambda_{ij} \qquad \forall j \in J. \tag{5.16d}$$

The problem in (5.16) is combinatorial due to the binary variable $\lambda_{ij}, \forall j \in J, \forall i \in I$ and the complexity of the brute force algorithm (in $O(|J|^{|I|})$) is exponential in the number of UEs. A workaround is to allow UEs to be associated to more than one HPNs, i.e., the UE association becomes a load balancing scheme.

The relaxed problem, that we deem *optimal load balancing*, is convex (for $0 \leq \lambda_{ij} \leq 1$,) and provides an upper bound to the original problem in (5.16). However, in a practical system, it is much more difficult to implement a load balancing algorithm that allows costly recurrent shifts between HPNs than a UE association algorithm (single HPN selection). Thus, we adopt a rounding method to revert back to the original UE association problem and we deem it *centralized UE Association*.

5.5 The User-Centric Approach

In the user-centric approach, we resort to a distributed power control scheme presented in Section 5.5.1 and to a distributed UE association scheme presented in Section 5.5.2. In particular, in the distributed UE association scheme, a fully distributed algorithm based on reinforcement learning will be run by UEs.

5.5.1 Distributed Power Control

For the distributed power control scheme, HPNs are the decision makers of the game. We define a multi-player game G_{PC} between the $|J|$ HPNs. The HPNs are assumed to make their decisions without knowing the decisions of each other.

The formulation of this non-cooperative game $G_{PC} = \langle \mathrm{J}, \mathrm{S}, \mathrm{U}^{\mathrm{PC}} \rangle$ can be described as follows:

- A finite set of HPNs $J=\{1,...,|J|\}$.
- For each HPN j, the space of pure strategies Sj is:

  $$\mathrm{S_j} = \{\vec{\pi}_j \in \mathbb{R}^{|\mathrm{K}|} \text{such as } p_j^{min} \leq \pi_{jk} \text{ and } \sum_{k \in K(j)} \pi_{jk} \leq p_j^{max}\}.$$

  An action of an HPN j is the amount of power π_{jk} sent on RB k. The strategy chosen by HPN j is then $\vec{\pi}_j = (\pi_{j1}, \dots, \pi_{jk})$. A strategy profile $\pi = (\pi_1, \dots, \pi_{|J|})$ specifies the strategies of all players and $\mathrm{S} = \mathrm{S}_1 \times \dots \times \mathrm{S}_{|\mathrm{J}|}$ is the set of all strategies.
- A set of utility functions

  $$\mathrm{U}^{\mathrm{PC}} = \left(\mathrm{U}_1^{\mathrm{PC}}(\pi), \mathrm{U}_2^{\mathrm{PC}}(\pi), \dots, \mathrm{U}_{|\mathrm{J}|}^{\mathrm{PC}}(\pi)\right)$$

  that quantify players' utility for a given strategy profile π, where the utility function of any HPN j is given by:

$$U_{\mathrm{j}}^{PC} = \sum_{k \in K(j), i \in I(j)} \log\left(\frac{1}{n_j} \times \frac{\pi_{jk} G_{ijk}}{N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k}}\right) \tag{5.17}$$
$$= |I(j)| \sum_{k \in K(j)} \log(\pi_{jk}) + \sum_{k \in K(j), i \in I(j)} \log\left(\frac{G_{ijk}}{n_j (N_0 + \sum_{j' \neq j} \pi_{j'k} G_{ij'k})}\right)$$

For every j, U_j^{PC} is concave w.r.t. π_j and continuous w.r.t. $\pi_l, l \neq j$. Hence, a NE exists [Ros65].

Note that we are only interested in the first part of the utility function that we call $U_j^{\overline{PC}}$ (the second part being independent of π_j) and given by what follows:

$$U_j^{\overline{PC}} = |I(j)| \sum_{k \in K(j)} \log(\pi_{jk}) = |I(j)| \log \prod_{k \in K(j)} \pi_{jk}.$$

Consequently, the NE is the solution of the following optimization problem:

$$\underset{\pi}{\text{maximize}}\, U_j^{\overline{PC}}(\pi_j) = \log \prod_{k \in K(j)} \pi_{jk} \tag{5.18a}$$

subject to:

$$\sum_{k \in K(j)} \pi_{jk} \leq P_j^{max}, \tag{5.18b}$$

$$\pi_{jk} \geq P_j^{min}, \qquad \forall k \in K(j). \tag{5.18c}$$

As the utility function is strictly increasing, constraint (5.18 b) boils down to $\sum_{k\in K(j)} \pi_{jk} = P_j^{max}$. Since we need to maximize a product of variables whose sum is constant, the highest possible value for these variables π_{jk} is attained when they get the same value and hence $K \times \pi_{jk} = P_j^{max}$. Finally, owing to constraints (5.18c), the optimal power allocation is:

$$\pi_{jk} = \max\left(\frac{P_j^{max}}{K}, P_j^{min}\right), \forall k \in K(j).$$

5.5.2 Distributed UE Association

We also propose to solve the distributed UE association problem by having recourse to non-cooperative game theory. Non-Cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to model the HPN selection by selfish UEs. We define a multiplayer game G_{UA} between the $|I|$ UEs, assumed to make their decisions without knowing the decisions of each other.

The formulation of this non-cooperative game $G_{UA} = \langle I, S, \mathrm{U}^{\mathrm{UA}} \rangle$ can be described as follows:

- A finite set of UEs $I=\{1,...,|I|\}$.
- The space of pure strategies S formed by the Cartesian product of each set of pure strategies $\mathrm{S} = \mathrm{S}_1 \times \mathrm{S}_2 \times ... \times \mathrm{S}_{|\mathrm{I}|}$, where the strategy space of any UE i is $\mathrm{S}_{\mathrm{i}} = \left\{HPN_j^i, HPN_{j'}^i\right\}$ with $j, j' \in J$.
    - If the UE i is finally associated with HPN_j^i (this is an outcome of the pure strategies played by UE i), then $\lambda_{ij} = 1$, else $\lambda_{ij'} = 1$.
    - We denote by $a_i \in S_i$ the action taken by UE i.
- A set of utility functions

  $$\mathrm{U}^{\mathrm{UA}} = \left(\mathrm{U}_1^{\mathrm{UA}}(\lambda), \mathrm{U}_2^{\mathrm{UA}}(\lambda), \dots, \mathrm{U}_{|I|}^{\mathrm{UA}}(\lambda)\right)$$

  That quantify UEs' utility for a given strategy profile λ, where the utility function of any UE i is given by:

  $$U^{\mathrm{UA}} = \sum_{j\in J}\sum_{k\in K} \lambda_{ij} \log\left(\frac{\rho_{ijk}}{1 + \sum_{i' \neq i} \lambda_{i'j}}\right) \qquad (5.19)$$

Note that interestingly, the utility depends of the outcome implied by the action taken by each individual UE. Then, we have $U_i(\boldsymbol{a})$, where $\boldsymbol{a} = (a_1, \dots, a_I)$ is the action vector of all UEs. The game G_{UA} is an unweighted crowding game as it is a normal-form game in which the UEs share a common set of actions and the payoff a particular UE i receives for choosing a particular action (selecting one of the available HPNs) is player specific and a non-increasing function of the total number of UEs choosing that same action. Unweighted crowding games have PNE (Pure NE). Furthermore, when players have only two strategies (choosing between HPN_j^i and $HPN_{j'}^i$ for any UE i), the game has the Finite Improvement Path (FIP[2]) property. In fact, according to the optimal UE association as investigated in the performance evaluation Section 5.7, the large majority of UEs will be only associated to a single HPN and very few UEs will load balance their traffic among two HPNs solely. Hence, in the distributed approach, it is largely enough to give each UE a choice among the two best received HPNs (i.e. two strategies per UE).

5.5.2.1. Sub-strategic congestion games

We consider a game with $|I|$ = n players that share a common set of R strategies. This game is very specific as for each strategy $r \in R$ there exists a set of sub-strategies $J(r)$. Each player determines a strategy $r \in R$ but its payoff depends on the sub-strategies of all players.The sub-strategy of player i, which is the action taken by each player, is a result of a mapping $a_i(r) \in \{1, \dots, J(r)\}$ from the common strategy set R to the sub-strategies set $J(r)$ for a given strategy r. In our context, the strategy is the choice of the two best detected HPNs and the sub strategy is the specific HPN to be associated with. Then, the mapping function is the best HPN decision process.

A vector of strategy $\sigma = (\sigma_1, \dots, \sigma_n)$ is a Nash equilibrium if for all player i and strategy r:

$$U_{i\sigma_i}\left(n_{a_i(\sigma_i)}\right) \geq U_{ir}\left(n_{a_i(r)} + 1\right),$$

where for all strategy r, for all sub-strategy $j \in J(r)$ we have: $n_j = |\{1 \leq i \leq n | a_i(\sigma_i) = j\}|$ is the number of players that take the sub-strategy j.

5.5.2.2. The Learning-based algorithm

We demote by P_i the mixed strategy that gives the probability that UE i selects HPN_j^i, i.e. $p_i = \mathbb{P}(a_i = HPN_j^i)$.

We describe a Reinforcement Learning (RL) algorithm [SPT94] in algorithm 5.1 that converges to the PNE for this type of game. The convergence of the algorithm is ensured by the existence of a potential function as the game possesses the FIP property [Mil98]. We present in appendix C the flowchart of the RL algorithm, deemed *fully-distributed* UE association.

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[2] A path is any sequence of strategy profiles in which each strategy profile differs from the preceding one in only one coordinate. When the unique player that deviates in each step strictly decreases its cost, the path is called an improvement path. Hence, an improvement path is generated by myopic players. A finite congestion game has the finite improvement path property (FIP) if every improvement path is finite [MS96].

Algorithm 5.1: RL algorithm for UE Association

1) Initialization: set t=0 and each UE i defines a probability p_i^0.
2) Each UE determines an initial action $a_i(t)$. Then, we get the action vector $\boldsymbol{a}(t) = \left(a_1(t), \dots, a_{|I|}(t)\right)$.
3) Each UE i determines its HPN j depending on its own action $a_i(t)$ and receives its utility $U_i(t) = U_i(\boldsymbol{a}(t))$.
4) Each UE i normalizes its utility as $\widetilde{U}_i(t) \coloneqq \frac{U_i(t)}{U_i^{max}}$, where U_i^{max} is the maximal utility realized by UE i.
5) Each UE i updates its decision probability as:

$$p_i(t+1) = p_i(t) + \frac{1}{t}\left(\mathbb{1}_{a_i(t)=HPN_j^i} - p_i(t)\right)\widetilde{U}_i(t).$$

6) Set $t \leftarrow t+1$ and go to step 2 (until satisfying termination criterion).

5.5.2.3.The semi-distributed association algorithm

We use the work in [YRC+13] as a reliable comparison for our work. In fact, the work in [YRC+13] turns to the Lagrangian dual decomposition method whereby a Lagrange multiplier μ is introduced to solve the UE association problem. The resolution of the centralized problem gives a compound algorithm, described in algorithm 5.2, operated on both UE and HPNs and necessitating weighty signaling among them.

Algorithm 5.2: Semi-distributed UE Association

Initialization: set t=0 and $\mu_j\ (0), \forall\, j \in J$ equals to some non negative value.

1) Each UE $i \in I$ determines HPN j^* which satisfies what follows:

$$j^* = \arg\max_j \left(\sum_{k\in K(j)} \log\left(\rho_{ijk}\right) - \mu_j\,(t)\right)$$

2) Each HPN updates the value of n_j and μ_j and announces the latter to the system, according to the following steps:
   a) The value of n_j is updated as follows:

$$n_j\,(t+1) = \exp \mu_j\,(t) - 1$$

   b) The Lagrange prices are updated as follows:

$$\mu_j\,(t+1) = \mu_j\,(t) - \delta(t).\left(n_j\,(t) - \sum_{i\in I} \lambda_{ij}\right)$$

   Where $\delta(t)$ is a suitably small step size

3) set$t \leftarrow t+1$ and go to step 1 (until satisfying termination criterion).

We deem the latter scheme *semi-distributed* UE Association and use it as a benchmark for the fully-distributed UE Association and for the centralized UE association.

5.6 The Mixed approach

In the mixed approach, the ensuing joint UE association and power control, in the utility function $\overline{U}$ (5.13) will be solved according to a centralized power control described in 5.4.1 and a decentralized UE association approach based on Best Response algorithm. The game defined in section 5.5.2 has the Finite Improvement Path (FIP) property [MS96] and hence a Best-Response algorithm permits attaining the PNE of the game. In fact, according to the optimal UE association as investigated in the performance evaluation Section 5.7, the large majority of UEs will be only associated to a single HPN and very few UEs will load balance their traffic among two HPNs solely. Hence, in this decentralized approach, deemed *distributed approach*, it is largely enough to give each UE a choice among the two strategies denoted $(\lambda_i, 1-\lambda_i)$. Accordingly, the utility function in (5.19) can be re-written as:

$$\begin{aligned} U_i^{\mathrm{UA}} &= \lambda_i \ \log\left(\frac{\rho_{ij}}{1+\sum_{i'\neq i}\lambda_{i'}}\right) + (1-\lambda_i)\ \log\left(\frac{\rho_{ij'}}{|I|-\sum_{i'\neq i}\lambda_{i'}}\right) \\ &= \lambda_i \ \log\left(\frac{\rho_{ij}/(1+\sum_{i'\neq i}\lambda_{i'})}{\rho_{ij'}/(|I|-\sum_{i'\neq i}\lambda_{i'})}\right) + \log\left(\frac{\rho_{ij'}}{|I|-\sum_{i'\neq i}\lambda_{i'}}\right) \end{aligned} \tag{5.20}$$

where $\rho_{ij} = \prod_{k\in K}\rho_{ijk}$. Note that the second term in (5.20) is independent of the player strategy and does not intervene in the strategy updates given in algorithm 5.3. Further at each round of the Best-response algorithm, each UE *i* favors the HPN that endows it with the higher mean rate.

Algorithm 5.3: BR algorithm for UE association

1) Initialization: set t=0 and each UE *i* defines an initial strategy $\theta_i(0)$.

2) For each UE *i*, *i*={1,...,|I|}, do if:

$$\frac{\rho_{ij}}{1+\sum_{i'\neq i}\lambda_{i'}} > \frac{\rho_{ij'}}{|I|-\sum_{i'\neq i}\lambda_{i'}}$$

Then UE *i* associates with $HPN_j^i(\lambda_i(t)=1)$.

Else, UE i associates with $HPN_{j'}^i(\lambda_i(t)=0)$.

3) Set$t \leftarrow t+1$ and go to step 2

(until satisfying termination criterion : $\lambda_i(t+1)=\lambda_i(t)$ for all $i\in I$).

5.7 Performance Evaluation

We consider a bandwidth of 5 MHz with 25 RBs in a network of 9 hexagonal cells and a number of UE ranging from 4 to 14 per HPN uniformly distributed in any cell. The mean performance are obtained with the confidence interval of 95%. Further, we consider the following parameters listed in the 3GPP technical specifications TS 36.942: the mean antenna gain in urban zones is 12 dBi (900 MHz). Transmission power is 43 dBm (according to TS 36.814) that corresponds to 20 Watts (on the downlink). The HPNs have a frequency reuse of 1, with the bandwidth W = 180 KHz. As for noise, we consider the following: user noise Figure 7.0 dB, thermal noise −104.5 dBm which gives a receiver noise floor of $P_N = -97.5$ dBm.

5.7.1 UE Association Schemes

We begin by comparing the UE association schemes based on 25 simulations for each scenario with a random level for power allocation (the same power allocation is set for all UE association schemes). We portray in Figure 5.1, the total rate using the Shannon capacity:

$$\sum_{i \in I} \sum_{j \in J} \sum_{k \in K(j)} \frac{\lambda_{ij}}{1 + \sum_{i' \neq i} \lambda_{i'j}} W|K| \log_2 (1 + \rho_{ijk})$$

The results after rounding (deemed centralized UE Association) are almost the same as the global optimum obtained by the relaxed problem (deemed optimal Load balancing), which shows the effectiveness of the rounding scheme. This occurs because in the optimal load balancing scheme, UEs have always a strong preference towards one of the HPNs as shown in Figure 5.2.

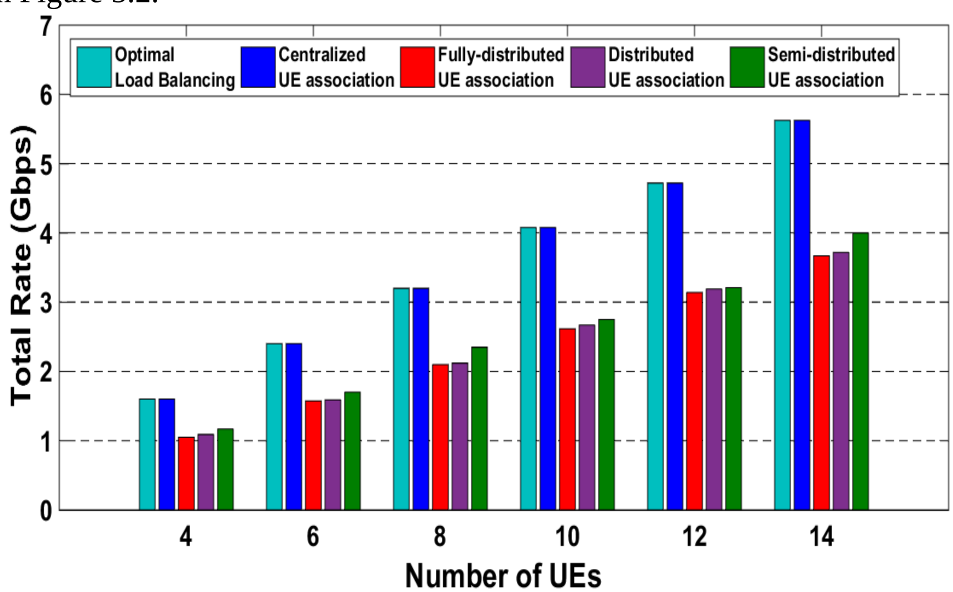


Figure 5.1 Performance of all proposed UE Association schemes

In fact, more than 98% of UEs are associated with exclusively a single HPN, the remaining UEs (less than 2%) are associated with solely two HPNs (best detected).

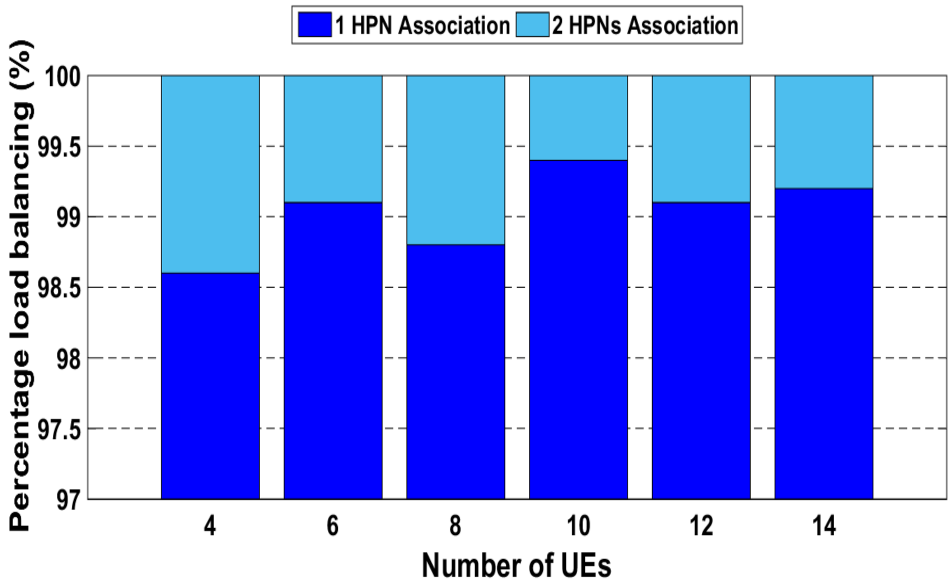


Figure 5.2 Percentage of Load Balancing

Therefore, and as stated earlier, it is relevant for the decentralized UE Association to choose among only two HPNs (best detected). Furthermore, for the decentralized UE association scheme, extensive simulations show that the results obtained according to the reinforcement learning algorithm 1 match those obtained by the best-response algorithm. In what follows, the user-centric approach is performed using the reinforcement learning algorithm that is fully distributed, where as the decentralized UE association in the mixed approach is run using the best-response algorithm. As expected, the optimal and centralized schemes perform better than the decentralized algorithms: the fully-distributed, distributed and semi-distributed UE association algorithm.

More importantly, we can see in Figure 5.1 the low discrepancy between the total mean rate realized by the semi-distributed UE association and the fully-distributed UE association, running according to the reinforcement learning algorithm (5.1). Hence, to distinguish the performance of these two UE Association schemes, we need to assess the complexity of the both algorithms. The dual algorithm (5.2) of the semi-distributed UE association provides sub-optimal performances with relatively high complexity: at each iteration, each HPN j broadcasts its μ_j, and each UE reports its association to the selected HPN. Hence, the amount of information to be exchanged is $s.(|J|+|I|)$, where s is the mean number of iteration displayed in Figure 5.3 This amounts to approximately 120 messages exchanged for a dozen of UEs per HPN.

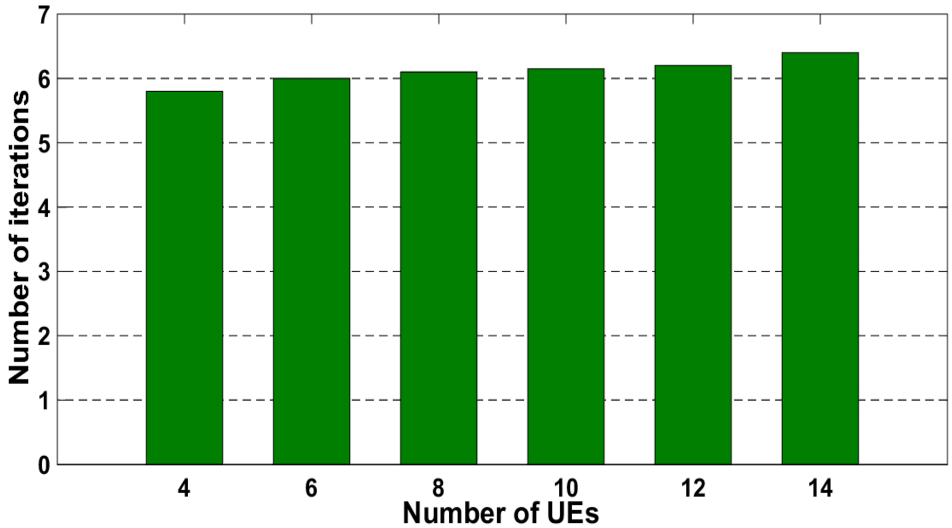
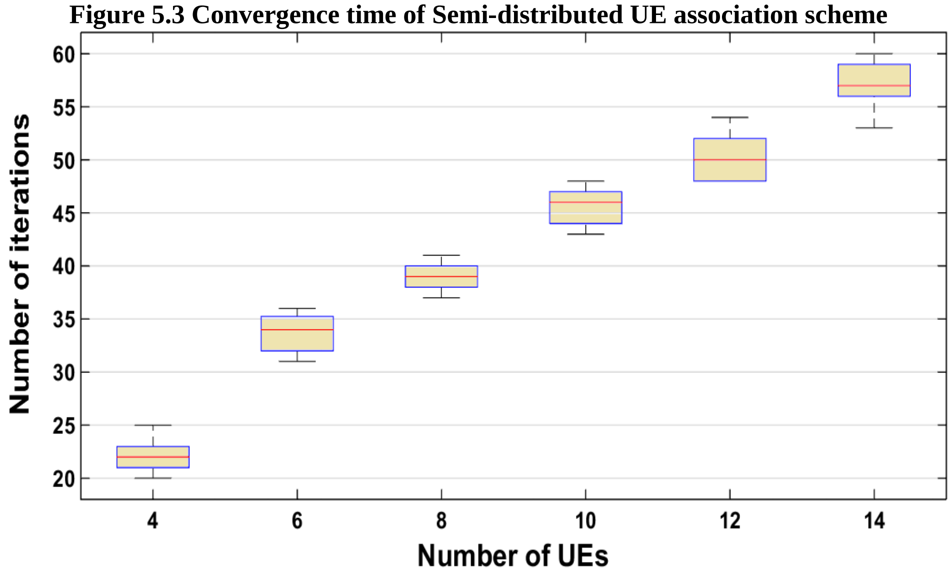
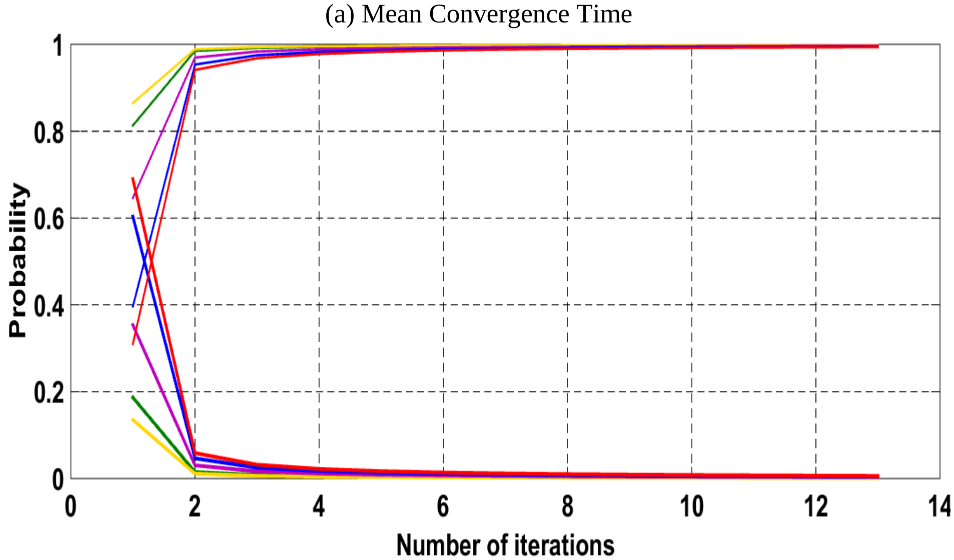


Figure 5.3 Convergence time of Semi-distributed UE association scheme



(a) Mean Convergence Time



(b) Strategy Updates

Figure 5.3 Convergence time of fully-distributed UE association scheme

In Figure 5.4, we display the convergence time to NE for the fully-distributed UE association algorithm, and note that the mean number of iterations until convergence for the fully-distributed scheme is reasonably low as shown in Figure 5.4(a). Moreover, we depict in Figure 5.4(b), the probabilities (p_i, 1− p_i) to choose one of the best detected HPN for UE $i \in I$, as a function of the number of iterations for 5 UEs chosen randomly among the 10 active UEs (for HPN 3 in the considered scenario). We can see that the UEs strategies converge to either 0 or 1 opting for one single HPN among the 2 best received HPNs. More importantly, we see that the convergence is relatively fast. Hence, the HPN that will be ultimately selected by any UE is clearly designated (around 3 iterations in the displayed results and after a mean of 5 iterations for the considered scenario) much earlier before convergence (a mean time of 46 iterations). We recorded this behavior through the extensive simulations we performed.

5.7.2 Global Performances

5.7.2.1 Global performance of the Network-centric approach

In this subsection, we evaluate the performances of the network centric approach where the centralized power control given in section 5.4 and the centralized UE Association (assessed in the previous subsection) will be run iteratively until convergence.

We have already ruled out the *semi-distributed* UE Association scheme, from the network-centric approach, as its suboptimal performances are further weighed down by its relative complexity.

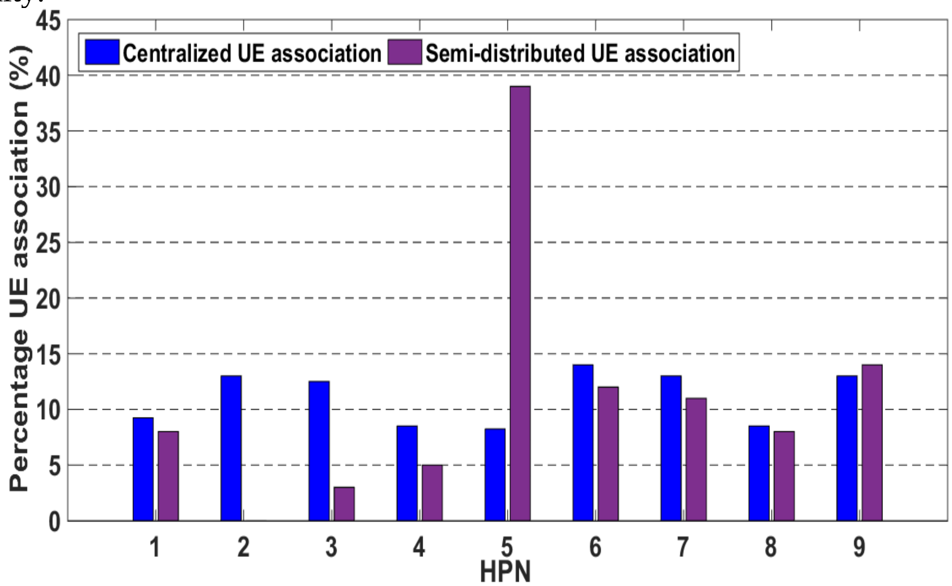


Figure 5.4 Convergence time of Distributed UE Association scheme

This sub-optimality is further exacerbated when the UE association is coupled with optimal power control as shown in Figure 5.5 where the UEs distribution is displayed (for the scenario with 10 UEs per HPN).

In fact, we see that the centralized UE association schemes equilibrates uniformly the UE load among the various HPN, whereas the *semi-distributed* UE association generates a notable imbalance: HPN5 (the central HPN) is overly crowded (almost 40% of total load) while some HPNs are lightly loaded (in particular, HPN 2 is empty). This loss of balance is due to the power level chosen by the centralized power control scheme: the convex optimization will invariably give the highest power level to the HPN that suffers from the highest interference (which is obviously the central HPN). Consequently, the UEs attached to the central HPN will enjoy the highest SINR levels. Thus, since the HPN selection in the *semi-distributed* UE Association, as described in algorithm 5.2, is driven by the SINR values perceived by UEs and is almost oblivious to the HPN load, the central HPN will always attract a lot of UEs which will deteriorate global performances.

5.7.2.2. Global performance of the User-centric approach

We begin by comparing the global performances of our fully-distributed UE association scheme and the semi-distributed association scheme given in Section 5.5.2 and 5.5.3 and the one-shot distributed power control scheme given in section 5.5.1.

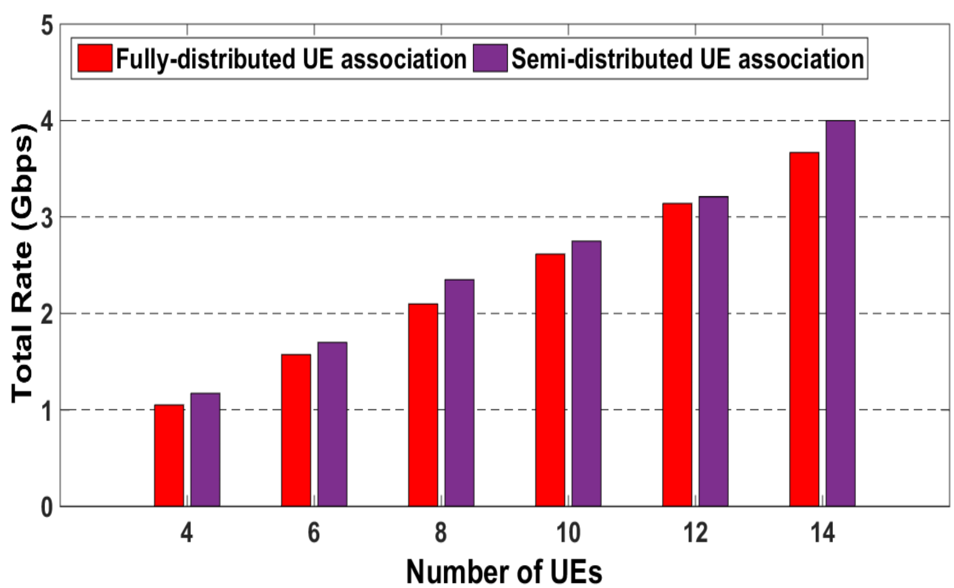


Figure 5.5 Performance evaluation of fully-distributed vs. semi-distributed UE Association schemes in user-centric approach

We portray in Figure 5.6 the total rate using the Shannon capacity, the performance of both UE association schemes are equivalent in terms of convergence time, as seen in subsection 5.7.1, and equivalent in terms of mean rate as we can show in Figure 5.6, which is a definite argument in favor of the fully-distributed UE association algorithm. The latter relies only on signaling already present in beyond 4G wireless networks. In fact, a served UE measures its channel quality based on pilots, i.e. Cell Specific Reference Signals (CRS) that are spread across the whole band and enables the UE to infer its SINR on each attributed RBs. In the semi-distributed scheme, the SINR values (actually the CQI (Channel Quality Indicator) values) need to be sent repeatedly from UEs to HPNs which incurs delays and erroneous estimations

The extensive simulation results prove the significance of the devised fully-distributed UE association scheme. In particular, we note that it combines a low degree of system complexity and good performances comparing to the semi-distributed scheme.

5.7.2.3 Global performance of user-centric vs network-centric approach

In this subsection, we evaluate the performance of the user-centric approach compared to the network-centric approach, after ruling out the semi-distributed UE association, as proved in subsection 5.7.2.1 and 5.7.2.2.

Here, we evaluate the performance of the global algorithm:

- The network-centric approach based on the *centralized* power control and the *centralized* UE association, given in Section 5.4, will be run iteratively until convergence.
- The user-centric approach based on the fully-distributed UE association given in Section 5.5.2 and the one-shot distributed power control scheme given in Section 5.5.1.

The UEs distribution is displayed in Figure 5.7 for the scenario with 10 UEs per HPN. We can see that the centralized and fully-distributed UE association schemes equilibrate uniformly the UE load among the various HPN.

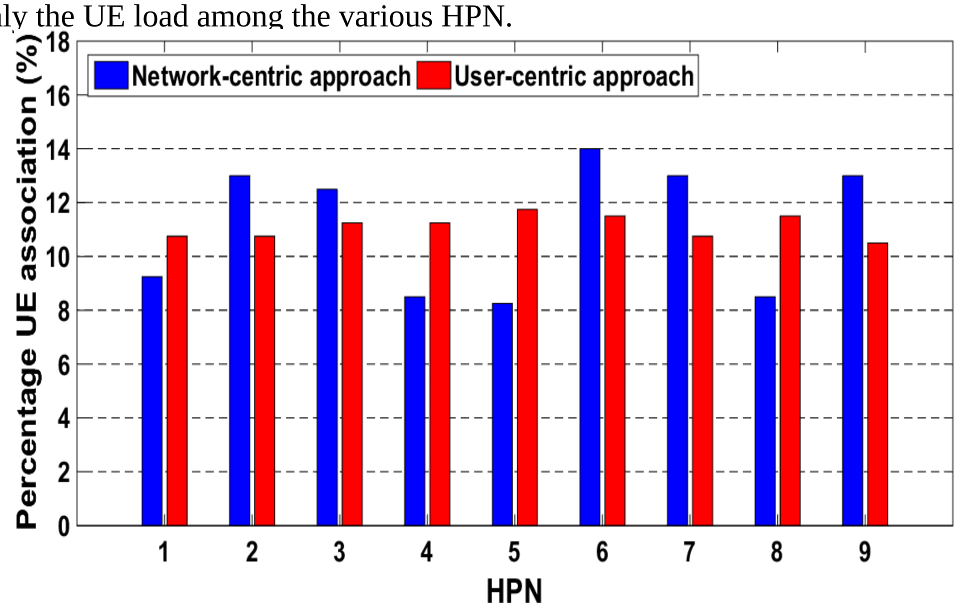
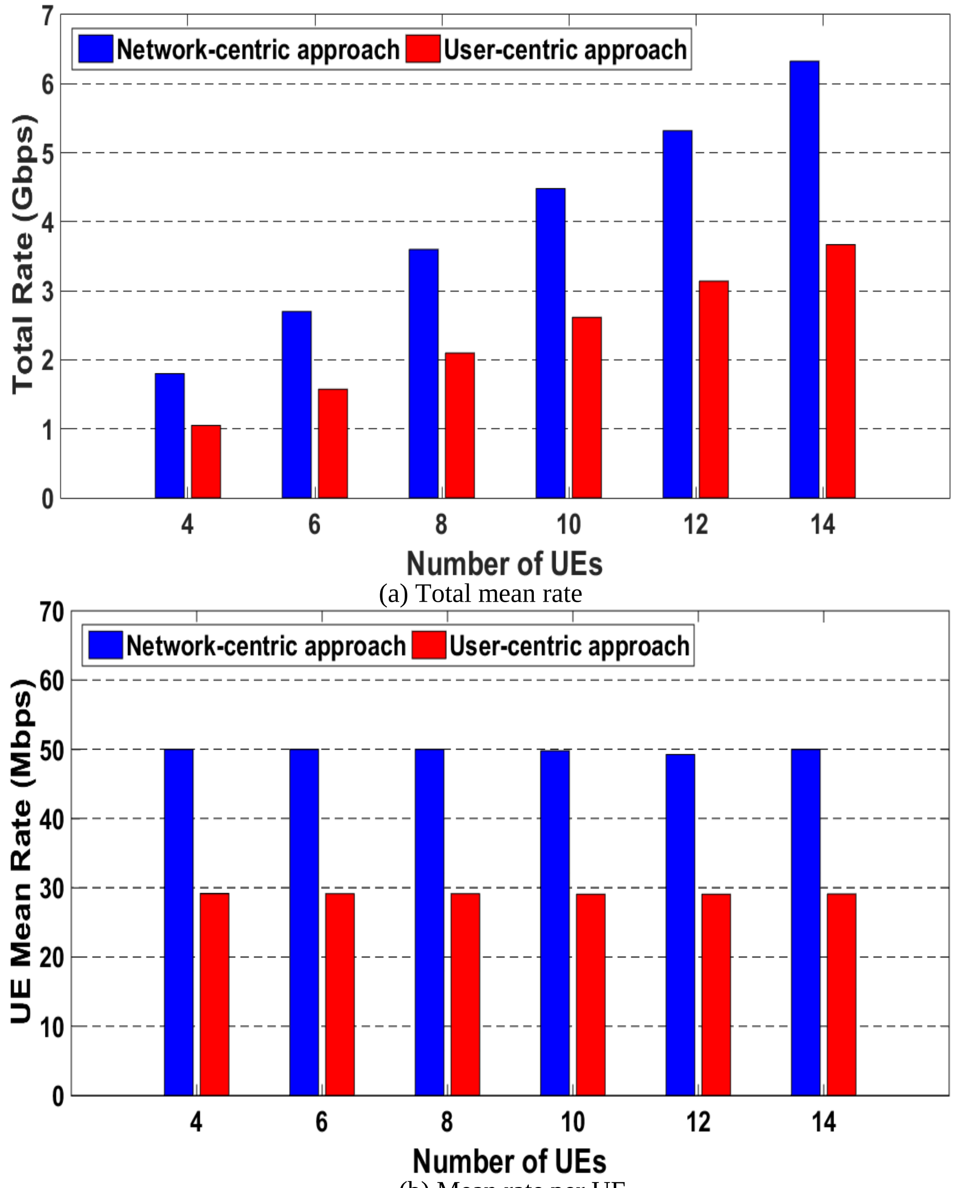


Figure 5.6 Percentage of UE Association for network-centric and user-centric approaches

In Figure 5.8, we compare the global performance of the UE association and power control schemes for the network-centric and user-centric approaches. We display the total mean rate and the mean rate per UE as a function of the number of UEs, where we note some dissimilarity among the performance of both approaches. This discrepancy in results is expected as the complexity and the signaling reduction in the user-centric approach is obtained at the cost of lower efficiency.

The local optimal solution is attained by recurring to the network-centric approach. In order to attain an optimal solution, we propose the mixed approach explained in section 5.6, where the HPN is the power control decision maker, where as the UEs decide which HPN to associate to. We compare these two optimal solutions in subsection 5.7.2.4.



(a) Total mean rate

(b) Mean rate per UE

Figure 5.7 Global performances of network-centric vs. user-centric approaches

5.7.2.4 Global performance of the optimal solutions

In this section, we evaluate the performance of the network-centric approach and the mixed approach of the global algorithm, where:

- The scheduling, the centralized HPN power allocation and the centralized UE association will be run iteratively until convergence to a local optimal solution.
- The scheduling, the centralized HPN power allocation and the distributed UE association, based on Best Response algorithm, will be run iteratively until convergence to a local optimal solution.

The UEs distribution is displayed in Figure 5.9, for the scenario with 10 UEs per HPN, where we see that the centralized and distributed UE association schemes equilibrate uniformly the UE load among the various HPNs.

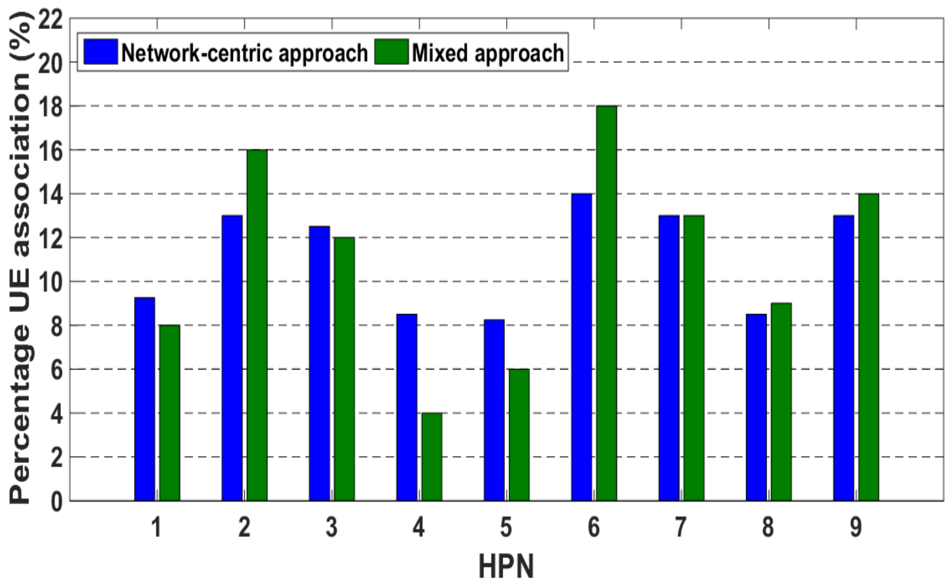


Figure 5.8 Percentage of UE association for network-centric and mixed approaches

In Figure 5.10, we compare the global performance of the HPN power control and the UE association for the network-centric and mixed approaches. We display the total mean rate as a function of the number of UEs, where we note a very low discrepancy among both approaches.

However, due to their selfish behavior, the mixed scheme consumes around 20% more power than the network-centric scheme, as we can see in Figure 5.11, where we illustrated the relative power economy of the network-centric approach in comparison with the mixed approach. One more definite argument in favor of the mixed approach is the very fast global convergence (around 4 iterations). Furthermore, note that the signaling messages necessary for the distributed UE Association algorithm are already present in actual wireless networks. Hence, the mixed approach is a good comprise between complexity, efficiency in comparison with the network-approach, and in term of efficiency and power economy in comparison with the user-centric approach, where the HPNs consumed the maximum power P_j^{max} .

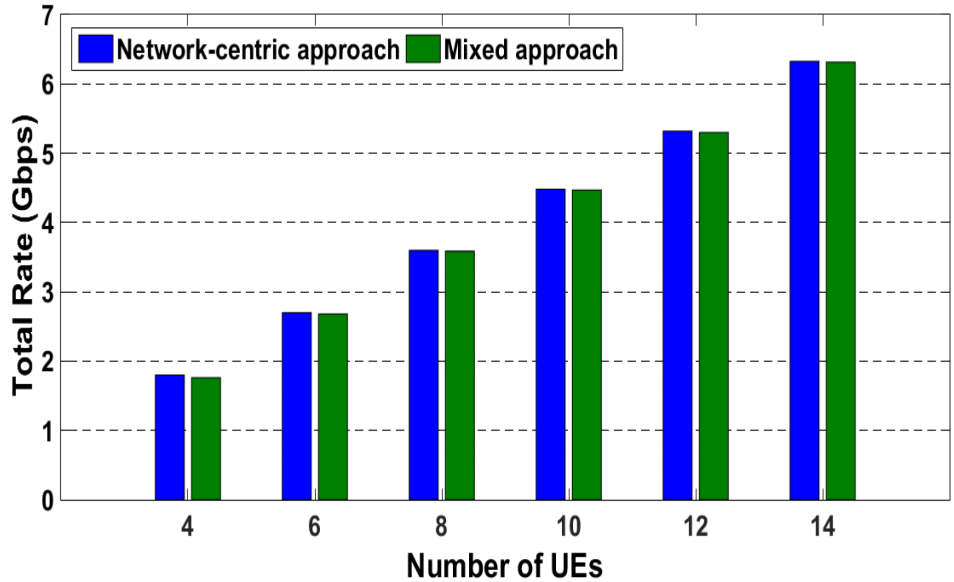


Figure 5.9 Global performances of network-centric and mixed approaches

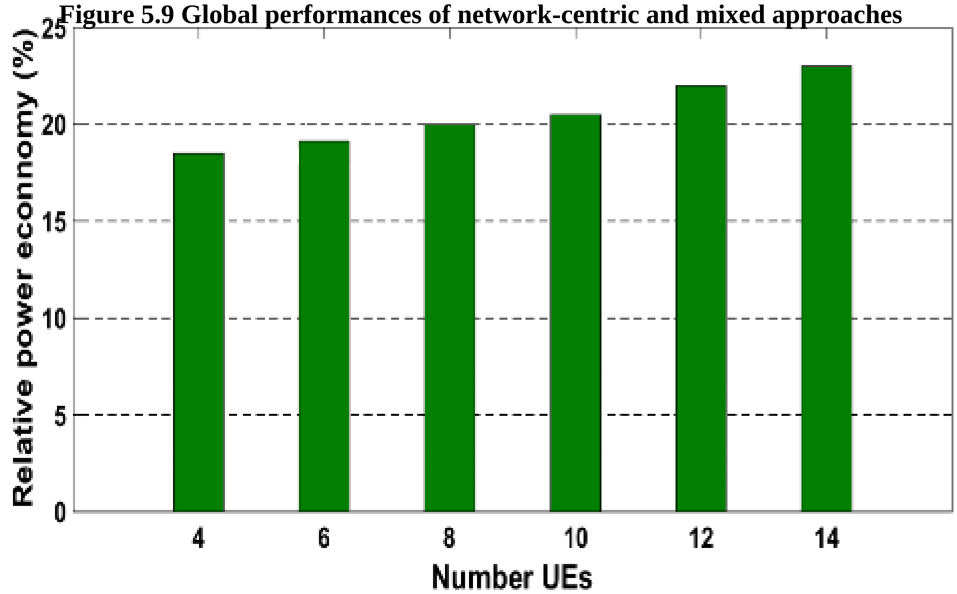


Figure 5.10 Relative power economy of the network-centric vs. the mixed approaches

5.8 Conclusion

The joint resource and power allocation problem is a challenging problem for present and future wireless networks. Several papers tackle this arduous task but rarely in a multi-cell network that accounts for the harmful impact of interference. In this chapter, we formulate the joint multi-cell scheduling, UE association and power allocation problem for 5G networks, where the objective is to maximize system throughput while guaranteeing fairness among UEs. We propose three approaches, the network-centric approach where the power control is addressed in a centralized fashion and the UE association is addressed in a centralized fashion by having recourse to convex optimization; the user-centric approach, where the power control is presented in a decentralized fashion by means of non-cooperative game theory and the UE association is addressed in a fully-distributed fashion based on *Reinforcing Learning* algorithm; the *Mixed* approach where the HPN is the power control decision maker, and each UE selects the serving HPN in a distributed fashion based on a Best Response algorithm. Extensive simulation results prove the significance of the user-centric schemes and the mixed schemes. In particular, the user-centric schemes operated without any inter-cell signaling and showed relatively good performances in comparison with the network-centric approach that are dependent on a central controller. The mixed schemes combine a low degree of system complexity and good performances in comparison with the network-centric schemes but with greater power consumption. These approaches are well adapted to the UE association for the adequate HPN for the signaling plan and for the data plan in 5G networks.

Chapter 6

6. GENERAL CONCLUSION

This chapter presents the general conclusion of the different work described in this thesis report. We summarize the main contributions in Section 6.1, and we give future directions and topics in Section 6.2, related to the 5G resource allocation, where our contributions can be exploited in an efficient way.

6.1 Summary of Contribution

The exponentially growing demand for mobile broadband communications has made the dense deployment of cellular networks with aggressive frequency reuse a crucial need. However, this dense deployment will lead to higher energy consumption. Therefore, it is crucial from environmental point of view to reduce the energy consumption. However, Inter-Cell Interference caused by this simultaneous usage of the same spectrum in different cells, reduces system throughput and network capacity, and has a negative impact especially on cell-edge UE performance. In this context, the focus of this thesis is to introduce dynamic radio resource management methods that increase system throughput and energy efficiency, and thus reduce pollution and unduly energy consumption.

Our first contribution addresses the problem of Inter-Cell Interference Coordination (ICIC) in beyond 4G downlink networks where the power level selection of resource blocks is portrayed as a non-cooperative game in the context of self-organizing networks (SON). The existence of Nash Equilibriums for the devised games shows that stable power allocations can be reached by selfish eNodeBs (eNBs). We have proposed a semi-distributed algorithm based on best response dynamics to attain these NEs in a relatively fast way as shown by the extensive simulations. Using the signaling messages already present in the downlink of LTE, each eNB will first select a pool of low interference Radio Blocks (RBs), and then it will make its best to fix the power level on these RBs. Simulation results have shown that this method can achieve comparable performance with respect to a policy serving active users with full power (MAX Power Policy).

In the second contribution, we have proposed solutions for the problem of joint power control and scheduling in the framework of ICIC in the downlink of OFDMA-based multi-cell systems. The original problem is decoupled into a scheduling scheme and a power control scheme. We have shown that, for the scheduling problem, proportional fairness has led to temporal fairness. As for the power control problem, two approaches have been adopted to achieve high performance: a centralized approach and a semi-distributed approach. For the centralized approach, the resulting optimization problem is rendered convex through geometric transformation. In the semi-distributed approach based on non-cooperative game, each eNB tries to optimize locally its own performance and communicates its power level to its neighbors until convergence.

In the third contribution, we have focused on SON OFDMA-based network, in order to achieve energy efficiency. We have proposed three distributed ICIC power control games for the downlink scenario. We demonstrated that all algorithms provide a significant performance improvement with respect to the state-of-the art approaches. The first algorithm provides high spectral efficiency, but pushes autonomous eNBs into consuming all available power. The remaining algorithms provide high energy efficiency and reduces power wastage without degrading system performance owing to a power penalty cost. This penalty cost is estimated by two methods one based on inter-cell X2 signaling and the other is based on inter-cell signaling-free heuristic that enables our energy efficient algorithm to astutely adjust the downlink transmission power according to UE feedbacks.

In the last contribution, we have formulated a global problem comprising: users association, power control and radio resources allocation in order to obtain a globally efficient solution. These three sub-problems are treated iteratively until the overall solution converges. In particular, we have proposed three algorithms for the user association problem: a centralized algorithm, a semi-distributed algorithm, and finally a fully distributed algorithm based on reinforcement learning. In addition, for power allocation we have implemented centralized and distributed solutions. We have solved the global problem in the following fashions: the user-centric, the network-centric, and a mixed approach where the power control can be delegated to the cloud in a 5G network, while the radio resource allocation and scheduling can be managed locally in the eNB, and the eNB selection can be delegated to the UEs to be managed locally in a decentralized fashion.

6.2 Future Directions

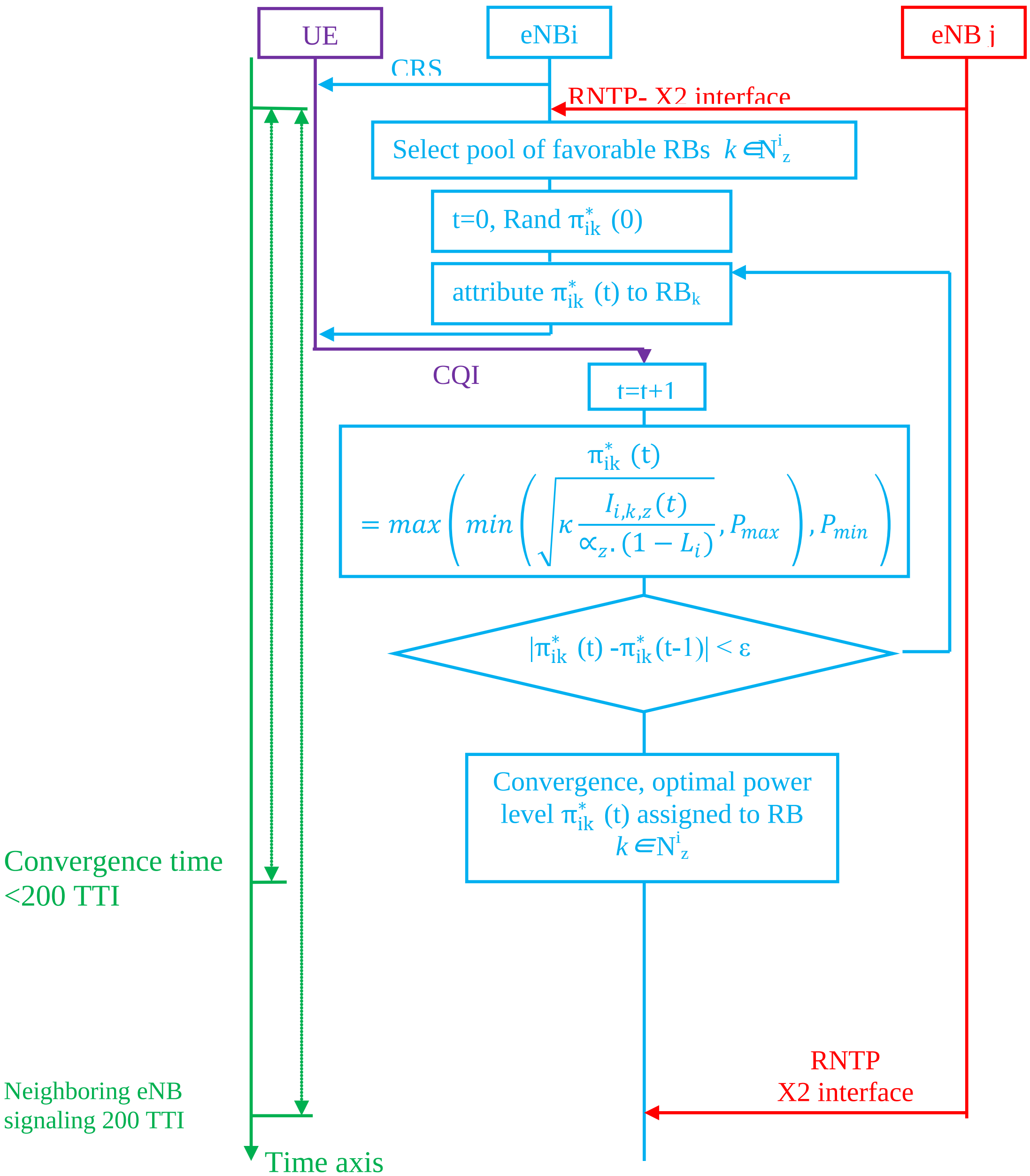
In this thesis, we have investigated the challenging problem of dynamic resource allocation in present and future cellular networks. Our contribution have provided proficient solutions for power allocation, UE association and scheduling while *maintaining a good balance between spectral and energy efficiency*. However, the growing proliferation of mobile devices, the surge in internet traffic together with the rapid evolution toward smart cities and Internet of things are pushing towards more challenging research topics, such as the increased heterogeneity and new radio technologies. In fact, the integration of heterogeneous wireless environment consisting of multiple Radio Access Technologies (RATs) are proliferating within 5G networks. The optimization and the dynamic resource allocation of heterogeneous cellular networks is one of these challenges to tackle in future research issues. Our current contribution can be easily extended to include the co-existence of multi-RAT and multi-tiers like macro cells and femtocells in the same area. In this case, our proposed joint user association, scheduling and power control detailed in chapter 5, can be recast in the heterogeneous scenario, where RAT user selection process is done before power control allocation. This new joint problem can take into consideration the maximization of the system throughput, the energy economy and the spectral efficiency. In this context also appear the problem of small cells where time division duplex can be used to support traffic asymmetry between uplink and downlink. So, our focus will be on enhanced interference mitigation and traffic adaptation (eIMTA), and especially on clustering-based models.

With the deployment of Internet of Things (IoT), uplink traffic will drastically increase. Therefore, uplink resource allocation will become also a crucial problem to solve. Specifically, our research will focus on the UE-base station association in uplink, which can be different than the downlink as it is proposed for 5G networks to provide more flexibility. In general, in the downlink, the UE is associated to the best coverage eNB with the highest received signal strength, which favors the choice of macro cell serving with the highest transmitting power. Consequently, the macro cell will attract more UEs which degrade its capacity and resource availability. The serving macro cell in the downlink may be not ideal for uplink traffic. It is interesting to study the improvement of the downlink/uplink decoupling on throughput efficiency and power economy.

Finally, as our main objective in this thesis was to provide methods and approaches to have *greener* mobile systems we are starting a work on designing multiple power sources for base stations, i.e. power lines and solar panels. Our focus will be also for special cases, where the power is cut in periodic way, i.e. mostly 12 hours per day. Therefore, the operators use generator most of the time, and thus generate more CO_2 and air pollution in addition to their need to higher cost.

Appendix A

A.1 Flowchart for BPR Power Control Algorithm



APPENDIX B

B.1 Proof of proposition 4.1

We will prove that if π and π' are two profiles which only differ on the strategy of one BS l, then $U_l(\pi_l,\pi_{-l}) - U_l(\pi_l^{'},\pi_{-l}) > 0$ if and only if $\emptyset(\pi_l,\pi_{-l}) - \emptyset(\pi_l^{'},\pi_{-l}) > 0$. We assume that $U_l(\pi_l,\pi_{-l}) - U_l(\pi_l^{'},\pi_{-l}) > 0$ which gives the following:

$$\sum_{k\in K}\log\left(\frac{\pi_{l,k}G_{lk}}{\sum_{\substack{j\in J\\ j\neq l}}\pi_{j,k}G_{jk} + N_0}\right) + \sum_{k\in K}\log\left(\frac{\sum_{\substack{j\in J\\ j\neq l}}\pi_{j,k}G_{jk} + N_0}{\pi_{l,k}^{'}G_{lk}}\right) > 0$$

.

$$\sum_{k\in K}\log\frac{\pi_{l,k}}{\pi_{l,k}^{'}} > 0 \Rightarrow \prod_{k\in K}\pi_{l,k} > \prod_{k\in K}\pi_{l,k}^{'} \qquad \text{(B.1)}$$

As for potential function, we have the following $\emptyset(\pi) - \emptyset(\pi^{'})$

$$= \sum_{\substack{j\in J\\ j\neq l}}\sum_{k\in K}\log\frac{\pi_{j,k}G_{jk}\left(\sum_{\substack{j\in J\\ j^{'}\in J}}\pi_{j^{'},k}^{'}G_{j^{'}k} + N_0\right)}{\pi_{j,k}^{'}G_{jk}\left(\sum_{\substack{j^{'}\in J\\ j^{'}\neq j}}\pi_{j^{'},k}G_{j^{'}k} + N_0\right)} + \sum_{k\in K}\log\frac{\pi_{l,k}G_{lk}\left(\sum_{\substack{j^{'}\in J\\ j^{'}\neq J}}\pi_{j^{'},k}G_{j^{'}k} + N_0\right)}{\pi_{l,k}^{'}G_{lk}\left(\sum_{\substack{j^{'}\in J\\ j^{'}\neq J}}\pi_{j^{'},k}G_{j^{'}k} + N_0\right)}$$

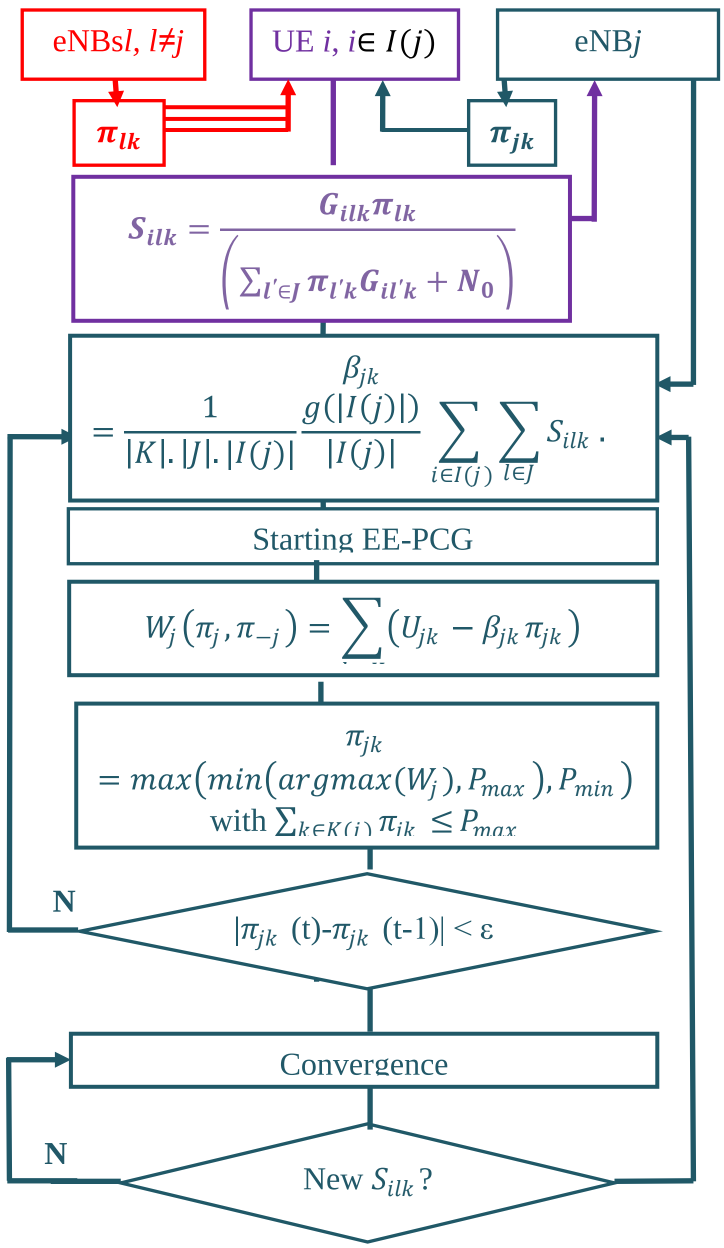
$$= \sum_{\substack{j\in J\\ j\neq l}}\sum_{k\in K}\log\frac{\sum_{\substack{j^{'}\in J\\ j^{'}\neq j\\ j^{'}\neq l}}\pi_{j^{'},k}G_{j^{'}k} + N_0 + \pi_{l,k}^{'}G_{lk}}{\sum_{\substack{j^{'}\in J\\ j^{'}\neq j\\ j^{'}\neq l}}\pi_{j^{'},k}G_{j^{'}k} + N_0 + \pi_{l,k}G_{lk}} + \sum_{k\in K}\log\frac{\pi_{l,k}}{\pi_{l,k}^{'}}$$

$$= \sum_{\substack{j\in J\\ j\neq l}}\sum_{k\in K}\log\frac{K_{j,k} + \pi_{l,k}^{'}}{K_{j,k} + \pi_{l,k}} + \sum_{k\in K}\log\frac{\pi_{l,k}}{\pi_{l,k}^{'}} = \sum_{k\in K}\left(\log\prod_{\substack{j\in J\\ j\neq l}}\frac{K_{j,k} + \pi_{l,k}^{'}}{K_{j,k} + \pi_{l,k}} + \log\frac{\pi_{l,k}}{\pi_{l,k}^{'}}\right)$$

$$= \sum_{\substack{j\in J\\ j\neq l}}\left(\log\prod_{k\in K}\frac{\left(\pi_{l,k} + \frac{\pi_{l,k}\pi_{l,k}^{'}}{K_{j,k}}\right)}{\pi_{l,k}^{'} + \frac{\pi_{l,k}\pi_{l,k}^{'}}{K_{j,k}}}\right) > 0$$

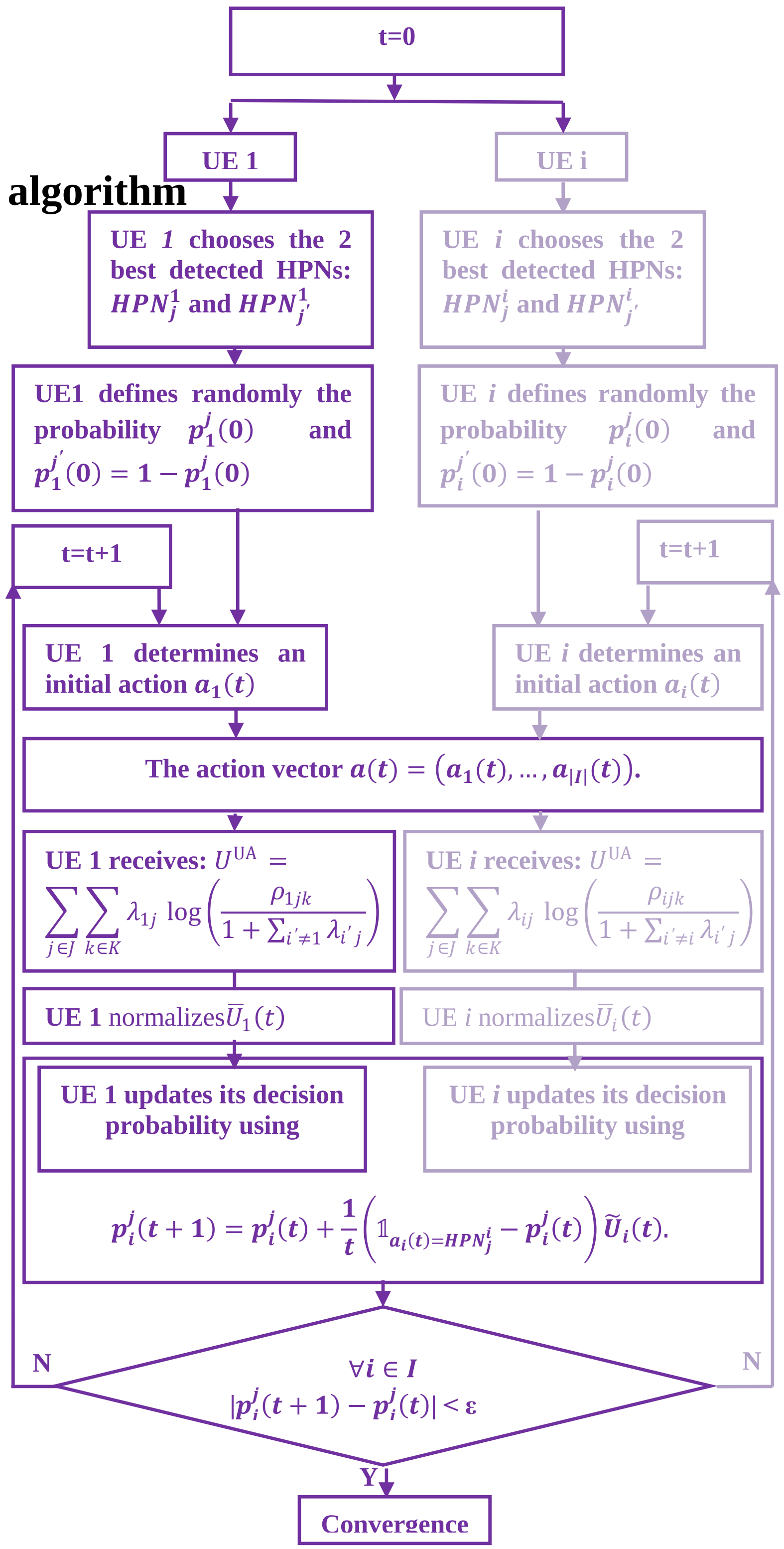
where $K_{j,k} = (\sum_{\substack{j' \in J \\ j' \neq j \\ j' \neq l}} \pi_{j',k} G_{j'k} + N_0) / G_{lk} > 0$. The positivity is obtained in virtue of inequality (B.1).

B.2 the *FD-EE-PCG* algorithm process.



APPENDIX C

C.1 The flowchart of the RL algorithm



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