Game Theoretical Models for Clustering and Resource Sharing in Macro-Femtocells Networks

by

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FOREWORD

This Ph.D. dissertation presents my research work realized between 2014 and 2019 at École de Technologie Supérieure, under the supervision of professors Zbigniew Dziong, Hadi Otrok and Rebeca Estrada. The objective of this research is to address the resource allocation problem in macro-femtocell networks. The proposed solutions for these problems are based on clustering techniques, coalitional game theory and evolutionary game theory.

This work resulted in a total of 3 journal papers and 1 conference paper, published or under peer review. This dissertation focuses on the content of the three journal papers, presented in Chapters 2, 3 and 4. The Introduction section presents background information on resource allocation in macro-femtocell networks, as well as the main problem statement, motivations and objectives of this research. A review of relevant literature on resource allocation, macro-femtocell networks, game theory and evolutionary game theory follows in Chapter 1. Chapter 5 draws a brief summary of contributions and highlights some recommendations for further research.

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I would give my special thanks to my grandparents Ida and Hugo, my parents Edgar and Senovia, my sisters Blanca and Camila, my brothers Yuri, Max, and Kevin. My gratitude is extended to my husband and my daughter for all their love and support. Many thanks to Camila and Amelia for teaching me that love can last forever.

This thesis is dedicated to my father Edgar Napoléon Rohoden Toledo.

Modèles théoriques de jeu pour le regroupement et le partage de ressources dans des réseaux macro-femtocellulaires

Katty Alexandra ROHODEN JARAMILLO

RÉSUMÉ

L'un des principaux défis des opérateurs de réseaux cellulaires est de conserver une bonne qualité de réseau pour leurs utilisateurs. Dans la plupart des cas, la qualité du réseau diminue dans les environnements intérieurs, ce qui oblige les utilisateurs à passer d'opérateur à un autre. Une solution prometteuse pour faire face à ce problème est le déploiement de femtocellules utilisées principalement à domicile pour améliorer la couverture du réseau mobile. En fait, la pénétration plus importante des téléphones mobiles et à large bande, ainsi que des nouvelles applications telles que la vidéoconférence et les jeux sur Internet, favorisent le marché des femtocellules. Cependant, le déploiement de femtocellules dans les réseaux de macrocellules existants est une tâche très difficile en raison de la grande complexité de l'allocation des ressources. Dans cette thèse, nous nous concentrons sur la proposition de plusieurs solutions pour résoudre le problème d'allocation de ressources dans les réseaux de macro-femtocellules pour un déploiement dense de femtocellules basé sur des techniques de clustering.

Les techniques de clustering sont utilisées pour réduire la complexité d'allocation de ressources des réseaux de femtocellules denses car les ressources sont allouées localement dans chaque cluster. En outre, un chef de cluster est responsable de l'allocation des ressources aux femtocellules au sein du cluster, ce qui évite les interférences à plusieurs niveaux. Les techniques de regroupement ont été largement utilisées pour l'allocation de ressources distribuées dans des réseaux hétérogènes grâce à l'utilisation de modèles de théorie des jeux. Dans ce travail, trois algorithmes d'allocation de ressources distribuées basés sur des jeux coopératifs et évolutifs sont proposés.

Dans la première partie, nous discutons du problème d'allocation des ressources pour le déploiement peu dense de femtocellules. À cette fin, un jeu de coalition est utilisé pour inciter les femtocellules à former des grappes. L'approche se décompose en: (*i*) un algorithme de sélection de station de base pour les utilisateurs publics, (*ii*) un algorithme de classification basé sur la théorie des jeux coopératifs et (*iii*) une allocation de ressources dans chaque groupe basée sur la technique Particle Swarm Optimization (PSO). En outre, un mécanisme de contrôle de interférence a permis aux femtocellules de quitter leur groupe actuel lorsque les niveaux de interférence sont supérieurs à un seuil de interférence.

Dans la deuxième partie, nous nous concentrons sur une allocation équitable des ressources pour les réseaux de macro-femtocellules. Nous développons un algorithme de clustering basé sur un jeu coopératif pour un réseau femtocell non dense. La valeur de Shapley est appliquée pour trouver la contribution marginale de chaque femtocellule à tous les groupes possibles de femtocellules, ce qui a permis de déterminer le montant raisonnable des ressources à allouer à chaque femtocellule dans un cluster. Cette solution est uniquement utilisée pour le déploiement de femtocellules non denses car la complexité du calcul de la valeur de Shapley augmente de manière significative avec un grand nombre de femtocellules. Des critères de stabilité basés sur le concept de cœur de la théorie des jeux sont utilisés pour trouver l'ensemble des clusters stables.

Enfin, l'analyse de l'allocation des ressources pour le déploiement de femtocellules denses est traitée dans un modèle de théorie de jeu évolutive (EGT). Il est supposé que l'EGT nécessite une rationalité limitée des joueurs, ce qui réduit la complexité et permet le déploiement dense de femtocellules. De plus, nous démontrons que l'ensemble des grappes formées avec EGT est stable au moyen de la dynamique du réplicateur. Le modèle proposé comprend également une analyse système pour les utilisateurs à mobilité réduite tels que les piétons et les cyclistes.

Mots-clés: techniques de regroupement, réseaux femtocell denses, la théorie des jeux, optimisation des essaims de particules, remplissage d'eau pondéré

Game Theoretical Models for Clustering and Resource Sharing in Macro-Femtocells Networks

Katty Alexandra ROHODEN JARAMILLO

ABSTRACT

One of the main challenges of cellular network operators is to keep a good network quality for their users. In most cases, network quality decreases in indoor environments causing users to switch from one operator to another. A promising solution to cope with this issue is the deployment of femtocells that are used mainly at homes to enhance the mobile network coverage. In fact, higher penetration of broadband and mobile phones with high requirements of new applications such as video conferencing and internet games are promoting femtocell market. However, the deployment of femtocells in existing macrocell networks is a very challenging task due to the high complexity of the resource allocation. In this thesis, we focus on proposing several solutions to address the resource allocation problem in macro-femtocell networks with dense deployment of femtocells based on clustering techniques.

Clustering techniques are used to reduce the resource allocation complexity of dense-femtocell networks since the resources are allocated locally within each cluster. Furthermore, a cluster head is responsible for the allocation of resources to femtocells within the cluster which avoids the co-tier interference. The clustering techniques have been widely used for distributed resource allocation in heterogeneous networks through the use of game theory models. In this work, three distributed resource allocation algorithms based on cooperative and evolutionary games are proposed.

In the first part, we discuss the resource allocation problem for the non-dense deployment of femtocells. Toward this goal, a coalitional game is used to incentive femtocells in the formation of clusters. The approach decomposes in: (*i*) a base station selection algorithm for public users, (*ii*) a clustering algorithm based on cooperative game theory and (*iii*) a resource allocation within each cluster based on the PSO technique. Besides, an interference control mechanism enabled femtocells to leave its current cluster when the interference levels are higher than an interference threshold.

In the second part, we focus on a fair allocation of resources for macro-femtocell networks. We develop a clustering algorithm based on a cooperative game for non-dense femtocell network. The Shapley value is applied to find the marginal contribution of every femtocell to all the possible groups of femtocells, thus, finding the fair amount of resources to be allocated to each femtocell within a cluster. This solution is only applied for non-dense femtocell deployment due to that the complexity of calculating the Shapley value increases significantly with a large number of femtocells. Stability criteria based on the ε-concept of game theory is utilized to find the set of stable clusters.

Finally, the analysis of the resource allocation for dense-femtocell deployment is addressed through an evolutionary game theory (EGT) model. It is assumed that EGT requires bounded rationality from players, this reduces the complexity and allows the dense deployment of femtocells. In addition, we demonstrate that the set of clusters formed with EGT are stable by means of the replicator dynamics. The proposed model also includes system analysis for users with low mobility such as pedestrians and cyclists.

Keywords: Clustering techniques, dense femtocell networks, game theory, particle swarm optimization, weighted water filling

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LIST OF ALGORITHMS

LIST OF ABREVIATIONS

3GPP	3rd Generation Partnership Project
4G	4th generation mobile network
5G	5th generation mobile network
BC-WWF	Balanced Cluster - Weighted Water Filling
BS	Base Station
BW	Bandwidth
CC-PSO	Centralized Clustering - Particle Swarm Optimization
CDMA	Code Division Multiple Access
CH	Cluster Head
CP	Cyclic Prefix
CPC	Cognitive Pilot Channel
CS	Coalition Structure
CSG	Closed Subscriber Group
dB	Decibel
DL	Downlink
DSL	Digital Subscriber Line
ED-WWF	Equal Distribution - Weighted Water Filling
EGT	Evolutionary Game Theory
eNB	Enhanced Node B

EPC	Evolved Packet Core
ESS	Evolutionary Stable Strategy
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
FC	Femtocell
FFR	Fractional Frequency Reuse
FT	Femto-Tier
GSM	Global System for Mobile Communication
GT	Game Theory
HNB	Home Node B
HeNB	Home Evolved Node B
HetNet	Heterogeneous Network
IEEE	Institute of Electrical and Electronics Engineers
IMS	IP Multimedia Subsystem
IoT	Internet of Things
ISI	Inter Symbol Interference
ITU	International Telecommunications Union
k-EGT	K-means-Evolutionary Game Theory
LBC	Load Balanced Cluster
LTE	Long Term Evolution
LP	Linear Programming

MC	Macrocell
MBS	Macro Base Station
MIMO	Multiple-Input Multiple-Output
MINLP	Mixed Integer Nonlinear Programming
mmWave	Millimeter Wave
MS	Mobile Station
MU	Mobile User
NP	Non-Polynomial
NTU	Nontransferable Utility
OFDMA	Orthogonal Frequency-Division Multiple Access
PL	Path Loss
PRB	Physical Resource Block
PSO	Particle Swarm Optimization
PSO-Dist	Particle Swarm Optimization - Distributed
PU	Public User
QoS	Quality of Service
RA	Resource Allocation
RAM	Resource Allocation Model
RAN	Radio Access Network
RB	Resource Block

RSSI	Received Signal Strength Indicator
SC	Subcarrier
SC-FDMA	Single Carrier-Frequency Division Multiple Access
SH-PSO	Shapley-Particle Swarm Optimization
SINR	Signal to Interference plus Noise Ratio
SU	Subscriber
TU	Transferable Utility
UDFN	Ultra Dense Femtocell Network
UE	User Equipment
UL	Uplink
UMTS	Universal Mobile Telecommunications System
WCDMA	Wideband Code Division Multiple Access
WiFi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access
WWF	Weighted Water Filling
WWF-Dist	Weighted Water Filling - Distributed

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

α_i^k	User i assigned to base station k
$\beta_i^{s,k}$	Subcarrier allocated to user i assigned in base station k
B_s	Bandwidth per subcarrier
C	Set of clusters
c_{max}	Maximum size achieved by a cluster
D_c	Requested data rate demand of cluster c
$D^{f,c}$	Requested data rate demand of femtocell f in cluster c
D_i	Data rate demand of mobile user i
d_{ik}	Distance from base station k to the user i
ϵ_f^c	Femtocell membership of the cluster c
f_c	Carrier frequency adopted by the macrocell (in MHz)
FC	Set of deployed femtocells
F^c	Set of femtocells per cluster c
γ_k^s	Spectral efficiency for subcarrier s in base station $k \in m, FC$
γ_f	Target subcarrier spectral efficiency in FC F
γ_{MC}	Target subcarrier spectral efficiency in MC
$I_i^{s,k}$	Perceived interference in subcarrier s allocated to user i in base station k
$I_{threshold}$	Interference threshold
MS	Set of mobile users

MS^c	Set of users for cluster c
$\mathcal{N}$	Set of players
N_0	Average thermal noise power
N_c	Number of clusters
N_f	Number of femtocells
N_s	Number of subcarriers
$N_{s-extra}^{f,c}$	Number of extra-subcarriers received by femtocell f in the cluster c
$\overline{N_s^f}$	Average number of subcarriers required by femtocells
N_s^{FT}	Number of subcarriers allocated to femto-tier
N_s^{PU}	Number of available subcarriers for public users
$N_{used,S}^{PU}$	Number of subcarriers used for public users in the coalition S
$N_{used,S}^{SU}$	Number of subcarriers used for subscribers in the coalition S
ω_k	Outdoor/indoor attenuation factor for base station k
$P_i^{s,k}$	Transmitted power in downlink transmission between base station k and the user i
P_k^{Total}	Total transmitted power in base station k
$P_k^{max,s}$	Maximum transmitted power per subcarrier in base station k
PL_i^k	Path loss for outdoor/indoor between base station k and user i
ϕ_i	Payoff of player i
r_k	Coverage radius of the base station $k \in m, FC$
R_{SU}^f	Sum of data rate of subscribers served by femtocell f

R_{PU}^{f}	Sum of data rate of public users served by base station $k \in m, FC$
$Ra_{SU}^{f,c}$	Data rate allocated to femtocell f in cluster c to serve SUs
$Ra_{PU}^{f,c}$	Data rate allocated to femtocell f in cluster c to serve PUs
S	Coalition or cluster
SC	Set of available subcarriers
SC_femto	Set of subcarriers for the femto-tier
SC_macro	Set of subcarriers for the macro-tier
SU	Set of subcarriers
$SINR_{i}^{s,k}$	Signal to interference plus noise ratio for the downlink between base station k and user i
$SINR_{k}^{max}$	Maximum signal to interference plus noise ratio for base station k
$v(C)$	Value of coalition c
U^c	Utility of cluster c
U^{FT}	Utility of femto-tier
U^N	Utility of macro-femtocell network
$x_{f,c}$	Individual payoff of FC f in cluster c

INTRODUCTION

Mobile communications play a vital role in daily life. According to Cisco's Global Mobile Data Traffic Forecast, 77.5 exabytes per month of mobile data traffic will be reached by 2022. In the same year, the average mobile network connection speed will be 28.5 Mbps. 4G connections will represent twice the 3G connections and 5G connections will be 2.6 times more than the average 4G connections. In this sense, it is clear the need of new technology to cope with the new requirements of mobile users such us new multimedia applications, higher data rates, and mobile connection anywhere at any time.

Long Term Evolution (LTE) is the leading Orthogonal Frequency-Division Multiple Access (OFDMA) wireless mobile broadband technology. It was published as part of the 3rd Generation Partnership Project (3GPP) Release 8 specifications in March 2009. In this release, the concept of new type base stations called Home Node B (HNB) was presented while the concept of Home Evolved Node B (HeNB) was presented in Release 9 of 3GPP. HeNBs, also known as femtocells, are plug-and-play cellular base stations that provide local broadband connectivity. Femtocells connect to the service providers network through the home broadband internet (such as cable).

Femtocells operate as low-power access points where its short range provides strengthened cellular signals for indoor mobile users. Including femtocells in the traditional macrocell creates a two-tier cellular network where both femtocell users and the service operator benefit from the deployment of femtocells. Mobile users will experience better signal quality while greater network capacity and spectral efficiency will be achieved by the service operators. Initially femtocells were planned to be deployed in residential areas, however, they also can be deployed in enterprises, campuses, and as hotspots. Despite all these benefits, femtocells are mostly deployed without prior planning which requires to have adequate schemes for resource allocation. In addition, the resource allocation in macro-femtocell networks can get worse with a dense deployment of femtocells and with the random mobility of users.

The purpose behind this research work is to address resource allocation for macro-femtocell networks under non-dense and dense femtocell deployment scenarios. The main goal is to improve the network throughput and increase the subscribers' satisfaction using game theory models to group femtocells into clusters with the lowest possible complexity.

Motivation

In recent years, mobile users have demanded adequate indoor coverage and good service quality, which also allows the operator to generate additional revenue and enhance subscriber loyalty. According to Cisco (2018), by 2022 there will be 4.8 billion of Internet users and 28.5 billion of devices and connections which will result in broadband speeds of 75.4 Mbps. However, in order to achieve these requirements, operators are still using base stations that are far away from the user which causes a degradation of the signal quality. This leads to the use of new solutions such as reduction of cell sizes, reusing spectrum, and enhancing spectral efficiency. Thus, to provide higher capacity to users, operators must upgrade their mobile networks. A promising technique is to deploy heterogeneous networks (HetNets) that combine macro base stations (MBSs) and small cells, e.g. femtocells. Some of the advantages of working with HetNets are that femtocells help to offload traffic from the macrocell networks, reduce poor reception at indoor and at cell-edge locations, and reduce power consumption at the mobile equipment.

Recently, considerably research has been addressed in the deployment of femtocells in the macrocell coverage area. The main issues tackled in a two-tier network are the spectrum allocation, Chandrasekhar & Andrews (2009a); Estrada, Jarray, Otrok, Dziong & Barada (2013a); Zhang, Zhang, Wu & Huang (2010), and the interference avoidance Chandrasekhar & Andrews (2009b); Poongup Lee, Taeyoung Lee, Jangkeun Jeong & Jitae Shin (2010). It is worth noting that centralized and distributed resource allocation solutions have been proposed for resource allocation in macro-femtocell networks. A centralized solution can optimize the global network resource allocation even though this requires sophisticated optimization techniques where the signaling load grows with the number of mobile users. On the other hand, in a distributed resource allocation solution, femtocells can make their own decisions such as cooperating in the formation of clusters, selecting a cluster head that is responsible for the allocation of resources, and reducing the interference caused to neighboring femtocells. In particular, game theory has been applied for the distributed resource allocation in macro-femtocell networks (Han, Li, Liu & Guan, 2016; Lin, Ni, Tian & Liu, 2015; P.Azadeh, M.Takht Fooladi, E.Zeinali Khosraghi & A.Masoud Rahmani, 2019; Rohoden, Estrada, Otrok & Dziong, 2019; Saha & Vesilo, 2018). Even though the game theory does not provide an optimal solution, there is a high reduction of the processing complexity due to the requirement of only incomplete information about the network.

Regarding the densely-deployed femtocells networks, the resource allocation problem becomes very complex and time-consuming. In this thesis, we consider application of game theory models to group femtocells in clusters and to solve the resource allocation within every cluster. Here are the main motivations for this approach:

- The resource allocation complexity of the centralized models can be reduced by means of clustering techniques. In particular, the clustering of femtocells allows the allocation of resources locally within each cluster which reduces complexity and execution times.
- Using cooperative games that encourage femtocells to work in hybrid access mode in order to grant service to public users and to form clusters can reduce the co-tier interference and increase the subscriber satisfaction.
- Evolutionary game theory can model and analyze the competitive decision making of a large number of players with different strategies that interact in a dynamic scenario, e.g. the femtocells are the players that interact among them in order to increase their payoff by means of stable cluster formation.

Problem Statement

The massive deployment of femtocells faces several issues in heterogeneous networks such as the fair and distributed resource allocation, mitigation of the interference, and keeping the stability of the network. In Figure 0.1, a heterogeneous network is shown, e.g. a macro-femtocell network. Along with these issues, there are several scenarios to be considered such as femtocells access modes, dense-deployment of femtocells, mobile users with low or high mobility, etc. In the following, the main issues addressed in this research work are explained.

1. Femtocells access modes: Most of the previous approaches propose a solution for femtocells working in closed access mode. This is not good for the network performance since the public users that are nearby the coverage area of femtocells are not granted the access to these femtocells. Thus, these public users will try to connect to the MBS resulting in a large increase of the cross-tier interference.
2. Lack of femtocell cluster formation algorithms: Cluster stability is a very important issue since it prevents the femtocells from abruptly changing from existing cluster to another one, which would lead to an unstable network.
3. Fair allocation of resources: A fair resource allocation allows femtocells to receive a higher number of subcarriers and thus increase the satisfaction of their subscribers.
4. Lack of rewarding methods: Rewarding methods that consider resources as a payment from the macrocell to encourage femtocells to form clusters and grant service to public users.
5. Mobility of public users: In a dense-femtocell network, the number of public users changing from one femtocell to another or from a femtocell to a macrocell or vice-versa increases with the users' mobility and this can cause instability in the network.

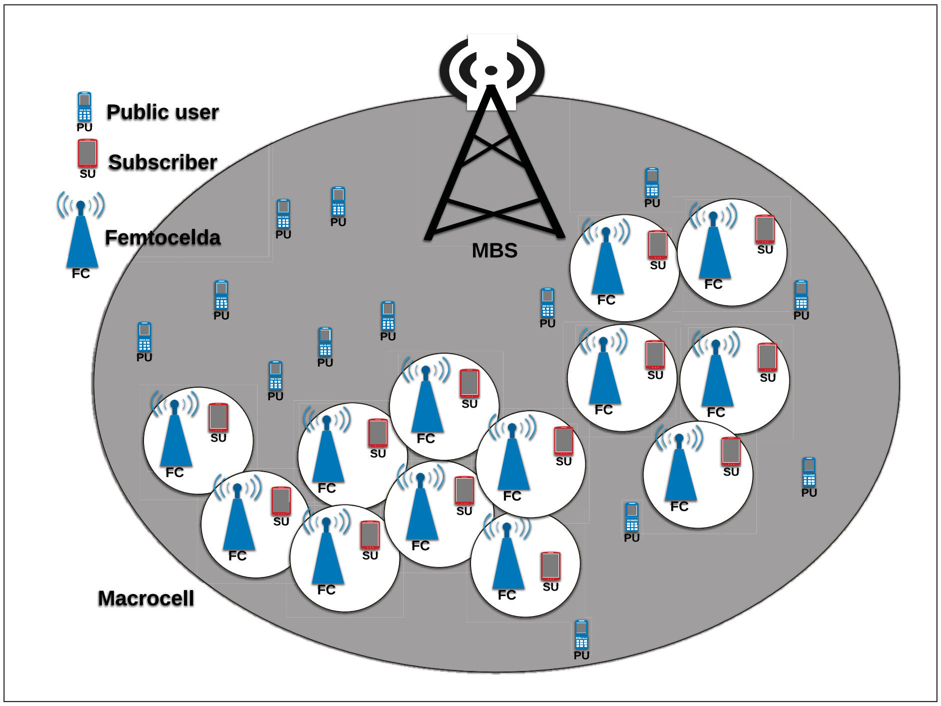

Figure 0.1 Macro-femtocell network

Objectives

The main objective of this work is to develop a distributed resource allocation framework for macro-femtocell networks for non-dense and dense femtocell deployment. To address the complex resource allocation problem, this thesis establishes the following main objectives:

- Develop a resource allocation model that maximizes the network throughput by means of bandwidth adaptation per tier.
- Develop a fair resource allocation model that improves femto-tier throughput by means of Shapley value and PSO algorithm while enhancing the satisfaction of femtocell subscribers.
- Develop a stable formation of clusters algorithm by means of coalitional and evolutionary games.

- Analyze the system performance when a mobility model is considered for public users in dense-femtocell networks.

Methodology

In this thesis, we use game theory to analyze the distributed allocation of resources in a macro-femtocell network. The resource allocation problem is tackled by reducing its complexity and allocating resources locally within clusters of femtocells. The clustering process is addressed using coalitional and evolutionary games resulting in three solutions illustrated in Fig. 0.2.

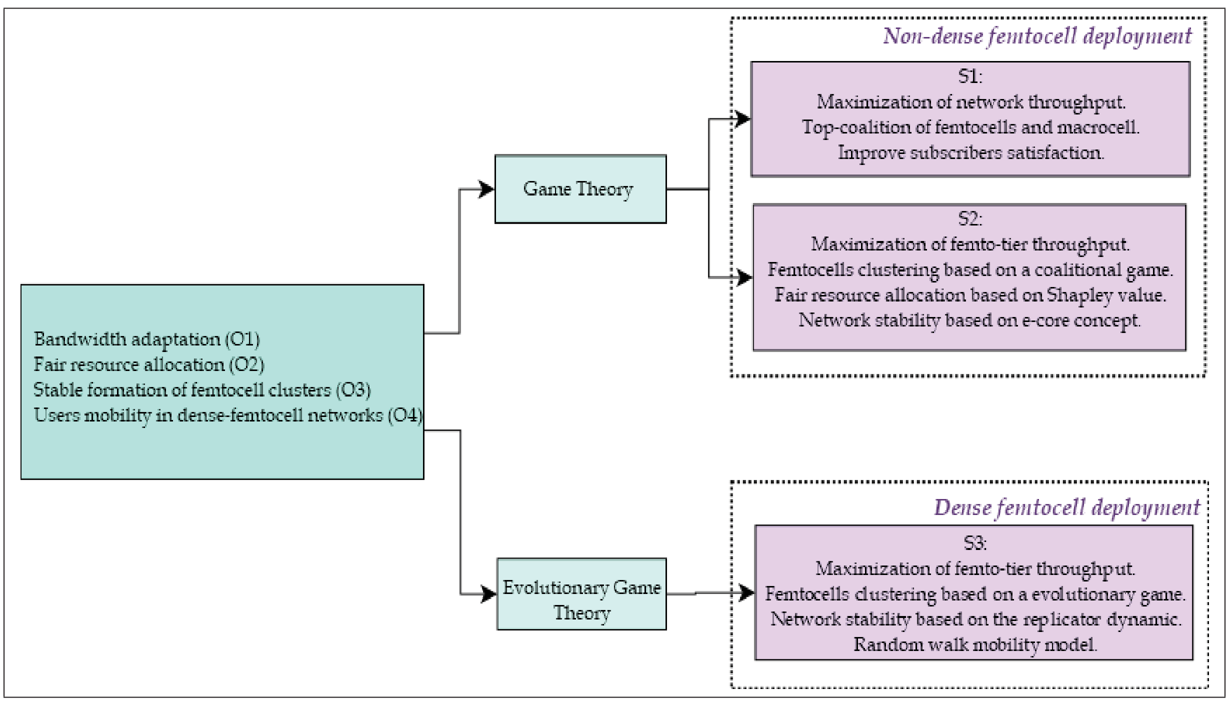

Figure 0.2 Methodology

In the first solution, we address the problem of resource allocation for downlink transmission in a macro-femtocell network under non-dense femtocell deployment, no stability demonstration, and no mobility analysis. This solution consists of the femtocell clustering and the optimal resource allocation. For the clustering of femtocells, we propose a coalitional game among the femtocells and the macrocell to determine the subcarrier distribution per tier. The cooperative game determines first a top-coalition formed by a set of femtocells and the macrocell such that the femtocells maximize their subscriber satisfaction and the network operator maximizes the satisfaction of the public users. The resource allocation algorithm is run locally within each cluster using the PSO technique which obtains a satisfying near-optimal solution.

The second solution focuses on the fairness of resource distribution among all femtocells by means of the Shapley value and the cluster stability by applying the e-core concept of the game theory. In the clustering process, femtocells are encouraged to join clusters through a rewarding method that allocates extra-subcarriers for their own subscribers. The stability is demonstrated by guaranteeing the highest achievable subscriber's satisfaction where any deviation from the current coalition would be harmful to the femtocell.

In the third solution, the clustering of femtocells is tackled using an evolutionary game where stability is demonstrated by applying the replicator dynamic. Moreover, the system performance is analyzed under a dense femtocell deployment where public users are mobile (such as pedestrians or cyclists).

In particular, the following elements are investigated and used throughout this research work:

- PSO as a near-optimal solution for resource allocation.
- Clustering techniques for complexity reduction of the resource allocation problem.
- Game theory for the motivation of femtocells to form clusters, the stability demonstration, and the fair allocation of resources.

Contributions and Novelty of the Thesis

This thesis work focuses on studying and developing solutions for the following macro-femtocell networks challenges: fair and distributed resource allocation, clustering of femtocells and network stability. The key contributions of the thesis are summarized as follows:

- Resource allocation model for no femtocell deployment that performs base station selection, bandwidth adaptation between tiers, and subcarrier allocation. In addition, subscriber satisfaction is enhanced and the inter-cluster interference is reduced.
- Fair allocation of resources using the Shapley value and PSO algorithm. Besides, a stability criteria based on the ε-core concept of game theory is defined for hybrid access femtocells.
- Application of an evolutionary game to form femtocells clusters in order to reduce the complexity of resource allocation in dense-femtocell networks. To guarantee the clusters' stability, we use the replicator dynamic of the evolutionary game theory and thus avoiding the reallocation of resources due to the constant changes in the cluster configuration. Furthermore, the system performance is analyzed applying the random walk mobility model for the public users.

Publications

The work presented in this thesis has led to the 3 journal and one conference publications.

Journals

Published

Rohoden, K., Estrada, R., Otrok, H. & Dziong, Z. (2018). Game theoretical framework for clustering and resource allocation in macro-femtocell networks. *Computer Networks*, 138, 164 - 176. doi: https://doi.org/10.1016/j.comnet.2018.03.035.

Rohoden, K., Estrada, R., Otrok, H. & Dziong, Z. (2019). Stable femtocells cluster formation and resource allocation based on cooperative game theory. *Computer Communications*, 134, 30 - 41. doi: https://doi.org/10.1016/j.comcom.2018.11.004.

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Conferences

Rohoden, K., Estrada, R., Otrok, H. & Dziong, Z. (2016). A coalitional game for femtocell clustering in OFDMA macro-femtocell networks. *NETWORKS Conference*, pp. 221 -226.

Thesis Outline

A literature review presenting the background of macro-femtocell networks considering the resource allocation is given in **Chapter 1**. This includes the basic concepts of LTE technology, femtocell networks, game theory, and evolutionary game theory. Then, **Chapter 2** introduces a first approach for the distributed resource allocation in macro-femtocell networks through the clustering of femtocells based on game theory. The work presented in this chapter corresponds to the paper “Game theoretical framework for clustering and resource allocation in macro-femtocell networks", which was submitted to the *Computer Networks* journal. In **Chapter 3**, we introduce the stability and fairness concept to the clustering of femtocells based on Game Theory through the use of the e-core concept and the Shapley value. This chapter corresponds to the paper entitled “Stable femtocells cluster formation and resource allocation based on cooperative game theory", submitted to the *Computer Communications* journal. In **Chapter 4**, we present a solution for the clustering of femtocells based on Evolutionary Game Theory that includes a mobile network with densely deployed femtocells. The content of this paper corresponds to the paper named “Evolutionary Game Theoretical Model for Stable Femtocells’ Clusters Formation", submitted to the *IEEE Access* journal. Finally, the conclusions section summarizes the main contributions of this thesis and the future research works.

CHAPTER 1

LITERATURE REVIEW

1.1 LTE Overview

LTE, proposed by the 3GPP is the long-term evolutionary access technology required to deal with the increasing data rate requirements of mobile users. In late 2004, the standardization of LTE was performed, then the features related to its functionality were presented in 2007, and by 2008 most protocols and performance specifications were finished. LTE its created to be the first all-Internet Protocol network technology for mobile systems. As a result, mobile networks design, deployment, and management will change considerably.

1.1.1 LTE requirements

LTE systems should support peak data rates within a bandwidth of 20 MHz and a mobility up to 350 Km/h. Table 1.1 presents the basic requirements of LTE.

Table 1.1 LTE requirements

Requirements	**Downlink**	**Uplink**
Data transmission rate	> 100 Mbps	> 50 Mbps
Spectral efficiency	> 5 bps/Hz	> 2.5 bps/Hz
Cell spectral efficiency	2.1 bps/Hz/cell	> 1.0 bps/Hz/cell
Cell edge spectral efficiency	> 0.06 bps/Hz/user	> 0.03 bps/Hz/user
Broadcast spectral efficiency	1 bps/Hz	NA

1.1.2 LTE architecture

LTE architecture is characterized by the elimination of the circuit-switched domain and designed to support real-time IP-based services. The system of LTE is comprised of two networks: the Evolved UMTS Terrestrial Radio Access Network (E-UTRAN) and the Evolved Packet Core (EPC). As a result a non-hierarchical structure is obtained for increased scalability and efficiency.

E-UTRAN represents the access network which is characterized by Evolved-NodeBs (eNBs). eNBs support OFDMA, advanced antenna techniques, and perform functions such as handover and interference mitigation. Its main feature is the distributed functions into the eNBs and the integration of the X2 interfaces that allow direct communication between eNBs.

The core network, EPC, uses the IP Multimedia Subsystem (IMS) for delivery of packet-oriented multimedia services. The EPC is enabled to support interworking with several wireless access technologies.

1.1.3 LTE Multiple Access Technique

In the LTE E-UTRAN the transmission from eNB to the UE (user equipment) uses OFDMA, while the transmission from UE to the eNB is defined by the Single Carrier-Frequency Division Multiple Access (SC-FDMA). In LTE the resources are defined as Resource Blocks (RB) that represent the minimum unit that can be allocated. An RB contains 12 subcarriers and 7 OFDM symbols, it occupies 1 time slot and a bandwidth of 180 kHz.

With OFDMA the spectrum is divided into uniform orthogonal narrowband subcarriers where each subcarrier has a bandwidth of 15 KHz. A cyclic prefix (CP) is used to overcome the Inter Symbol Interference (ISI) and it is added at the beginning of each OFDM symbol as a guard symbol. There exist two types of CP, the first one known as the Normal CP that has 7 symbols per slot, and the second one named as Extended CP with 6 symbols per slot.

On the other hand, SC-FDMA is preferred for the uplink since it requires less power. In the SC-FDMA, there are 20 time slots per frame of 0.5 ms. Regarding the resource blocks, it has between 6 and 7 symbols with the CP and similar to OFDMA a bandwidth of 15 kHz per subcarrier with 12 subcarriers per RB.

1.1.4 LTE-Advanced

LTE-Advanced is the standard that evolved from LTE to improved performance. Among the proposed improvements are the transmission bandwidth up to 100 MHz in comparison with 20 MHz for LTE, and the peak spectral efficiency of 16 bits/s/Hz and 30 bits/s/Hz for the downlink and 8.1 bits/s/Hz and 16.1 bits/s/Hz for the uplink. Some of the main goals of the LTE-Advanced are the following:

- Heterogeneous networks, faster network deployment.
- Improved cell edge spectral efficiency to obtain better coverage.
- Wider bandwidth by carrier aggregation across bands.
- Higher peak user rate for ubiquitous and cost-effective broadband.

A major issue of LTE-Advanced is to achieve broader coverage and improve the spectral efficiency per unit area. The improvement of the spectral efficiency comes hand in hand with the well-known Heterogeneous Networks (HetNets). Basically, HetNets are systems with low power base stations and macrocells, e.g. macro-picocells, and macro-femtocells. Femtocells, also referred to as Home eNBs (HeNBs), are home base stations that connect to the EPC directly or through a gateway.

1.2 5G overview

5G is the 5th generation mobile network that will allow to interconnect and control machines, objects, and devices. Compared with the 4G LTE technology, 5G is expected to reach high speed (1 Gbps), low power, low latency, and to be used for massive Internet of Thing (IoT), tactile internet, and robotics. The main characteristics of 5G are presented in Table 1.2. 5G is being considered in telecommunication industria and academia as a solution to meet the 1000x

Table 1.2 5G technical specifications

Technical specifications	**Description**
Latency	< 1 ms
Data traffic	50 Exabytes/month (2021)
Peak data rates	20 Gbps
Number of mobile connections	11 billion (2021)
Channel bandwidth	100 MHz below 6 GHz, 400 MHz above 6 GHz
Frequency band	600 MHz-mmWave

wireless traffic volume increment in the next decade. The key technologies to achieve 5G targets are the following:

- Massive MIMO technology proposed to improve the spectrum efficiency.
- mmWave technology to extend the transmission bandwidth.
- Network densification to raise throughput and save energy consumption in cellular scenarios.

1.2.1 5G heterogeneous networks

The 5G cellular is considered as a multi-tier heterogeneous network where low power nodes will be deployed in the macrocell coverage area. This heterogeneity of different types of base stations, e.g. macrocells and small cells, improves the coverage area and the spectral efficiency. In Bhushan, Li, Malladi, Gilmore, Brenner, Damnjanovic, Sukhavasi, Patel & Geirhofer (2014), authors studies the network densification as the key mechanism for 5G evolution over the next decade. The key enabling technologies are presented in Hossain & Hasan (2015), the interference management is tackled in Hossain, Rasti, Tabassum & Abdelnasser (2014), and the energy efficient resource allocation is addressed in Wu, Yang, Li & Li (2015). In summary, according to Hossain & Hasan (2015), the main research challenges for the enabling technology heterogeneous multi-tier networks in 5G are interference management, adaptive power control, dynamic mode selection, offloading to underlay network, device discovery, and unified Medium Access Control (MAC) design.

1.3 Femtocells

As stated before, the concept of femtocell was proposed in LTE-Advanced as HeNB. Femtocells are low power, short range, and low-cost home base stations that operate in a licensed spectrum. Femtocells are connected to the mobile core network over a broadband connection, e.g. Digital Subscriber Line (DSL). Specifically, the data traffic is transported through the public internet while the voice traffic goes through the IMS network. According to Chandrasekhar, Andrews & Gatherer (2008), the main advantages of using femtocells are:

Coverage: The coverage of a mobile user served by a femtocell improves substantially due to the short distance between them. This also allows reducing the transmit power, increase the battery life of cellular equipment and improve the system capacity.

Reliability: When the traffic of mobile users is directed to the IP backhaul, the macrocell can improve the reception for mobile users.

Cost benefits: The operating and capital expenditures cost for networks' operator is reduced since that with the deployment of femtocells there is no need to install new macro base stations.

Despite all the benefits obtained from using femtocells, there are still several challenges such as the base station (BS) selection, resource allocation, power control and interference mitigation due to the dense deployment of femtocells and the access control mechanisms of femtocells.

1.3.1 Access Control Mechanisms

Femtocells make use of access control mechanisms to determine if public users (PUs), users served by the MBS, are allowed to access them or not. The access control categories are: closed access, open access, and hybrid access (Zhang, 2010).

In the closed access, just registered users can access the femtocell. In fact, there is a list of authorized users called Closed Subscriber Group (CSG), a concept that was introduced in the Release 8 and is basically used to restrict the access to the femtocell. Even though the femtocell resources are guaranteed to their subscribers, the interference generated by nearby mobile users affects the downlink communication of the subscribers. This interference is known as cross-tier interference and is caused by a mobile user that is not authorized to connect to the femtocell. Furthermore, unauthorized users can also be interfered by nearby femtocells in the downlink communication.

On the other hand, any user can connect to a femtocell that works in open access. With this access mode, the network capacity is improved even though the performance of the subscribers is reduced. In addition, the constant movement of outdoor mobile users increases the number of handovers between cells. Thus, signaling increases in the network resulting in traffic congestion over the backhaul connections.

The hybrid access is a trade-off between the closed access and open access to reduce interference and the handovers. Basically, the hybrid access combine two features: a preferential access for the CSG and a limited access for the non-subscribers. However, some important issues need to be considered under this mode such as time dependency, treatment of non-subscribers, and the use of the resources.

1.4 Resource Allocation Considerations for Macro-Femtocell Networks

A macro-femtocell network is a Heterogeneous Network comprised of femtocells deployed in the macrocell coverage area. HetNets were proposed by 3GPP in order to improve system capacity and enhance network coverage. According to Zhang (2010), femtocells are mostly deployed by users and not by the operator. They are also expected to configure itself automatically which means that the frequency planning of the femtocell network is not well elaborated.

Currently, the resource allocation is a problem that is widely studied in order to manage adequately the network resources and reduce the generated interference in a two-tier network. Authors in Kulkarni, Chin & Farnham (2010) refer to two approaches for the allocation of resources. The first approach, known as the dedicated channel, consists of dividing the spectrum between the femtocells and the macrocell. While in this approach, the cross-tier interference is eliminated, the spectrum utilization efficiency is reduced. In the second approach, the co-channel approach, the spectrum is shared between femtocells and the macrocell. Unlike the dedicated channel, this approach improves the spectrum utilization efficiency even though the cross-tier interference is not eliminated so it needs to be carefully managed. Following, some strategies to manage resources while mitigating interference are presented (Kulkarni *et al.*, 2010).

1.4.1 Transmit power control

In order to guarantee the service availability, the transmit power control has to be performed with cooperation of the femtocells involved. Some of the work related to the transmit power control in macro-femtocell networks have proposed a capacity analysis based on power control. For example: path loss and shadowing effects was addressed in Chandrasekhar & Andrews (2009b), an optimal distributed subchannel and power allocation based on Lagrangian dual method was presented in Zhang *et al.* (2010), and a power control scheme for co-channel deployment of femtocells was proposed in (Kurda, Yahiya, Yiltas-Kaplan & Kirci, 2015).

1.4.2 Random frequency use

Frequencies can be reallocated if the communication in a certain frequency receives severe interference or results in a bad performance. However, some concerns regarding the reallocation of frequencies need to be considered such as the availability of the resources especially in a dense deployment of femtocells. This will entail the necessity of a coordinated allocation of resources. An interference management scheme in LTE femtocell system is presented in Poongup Lee *et al.* (2010). The Fractional Frequency Reuse (FFR) is used to frequency allocation in the macrocell and femtocells chooses the sub-bands that are not being used by the macrocell. In Dalal, Li & Agrawal (2011), FFR is used to mitigate the interference among femtocells working in closed access mode. If femtocells detect a high level of interference the femtocell area is divided into cell-center and cell-edge areas where a different set of subcarriers is used in the cell-edge area.

1.4.3 Collaborative resource negotiation

This feature contemplates the negotiation of resource allocation among interfering femtocells. This negotiation can be either centralized or distributed. In the centralized approach, the operator is responsible for the whole resource management. However, keeping centralized network management would require a significant processing as the number of mobile users increases. In consequence, this approach is limited by possible delay and scalability issues. On the other hand, a distributed approach can reduce the complexity in resource management but stability is not guaranteed mainly due to the lack of planning in the deployment of femtocells. In order to find a trade-off between the centralized and the distributed approaches, a hybrid solution is proposed. A centralized spectrum allocation for two-tier networks in presented in Kim & Cho (2010) while in Chandrasekhar & Andrews (2009a) a decentralized spectrum allocation strategy is proposed as an alternative to centralized/coordinated frequency assignment in a two-tier network .

1.5 Game Theory

Game Theory (GT) is a set of mathematical tools used to analyze the social interactions among decision-makers, named from now on as players, that aim to obtain a fair and stable distribution of services. According to Von Neumann & Morgenstern (1953), the goal of game theory is to describe theories and models which represent the processes that occur between humans in social situations. Thus, resource allocation in wireless cellular networks is well-supported by game theory. The type of game applied for the resource allocation will depend on the networks' characteristics, applications, and the targets to be achieved.

According to Gilles (2010), in GT there are three forms to represent a game, which are indicated below:

The extensive form: This form is the most complete description of a game in game theory. It describes the sequential decision making process and the resulting outcomes.

The normal form: The normal form is characterized for containing only specific information such as the strategic interaction structure of the game. This allows the normal form mathematical structure to be much simpler than the extensive form.

The characteristic function form: This form requires much less information when compared with the normal and extensive forms. It only considers the payoffs that can be allocated to the coalitions of players in the game. This form is the preferred game form to represent a cooperative game with binding agreements.

In addition, there are two different high-level perspectives of GT: classical and evolutionary games.

1.5.1 Classical Games

In classical games, all the players are required to make rational choices among a set of strategies. A classical game is represented by $(\mathcal{N}, S, v)$ where:

- $\mathcal{N} = \{1, ..., N\}$ represents the set of players. It is worth noting that a player can be an individual or a group of individuals taking decisions. Moreover, players are assumed to be rational or bounded rational depending on the game.
- S is the set of strategies and is defined as $S = \{1, ..., S\}$. The strategies can consider a single action, multiple actions or probability distribution over multiple actions.

- v is the value function or payoff for player i. It is the reward that a player receives based on the strategies taken throughout the game. In fact, the payoff of a player depends on its own strategy and also on the strategies that are taken by all other players.

The prisoner's dilemma game

This game describes the situation where two prisoners A and B, suspected of committing a robbery, are taken into custody. Since both prisoners will be interrogated in separate rooms, each one must decide whether to confess or to lie. As can be shown in Table 1.3, both prisoners have the following choices: i) to confess, both go to jail for five years, ii) if both lie, both go to jail for one year, and iii) if one confesses and the other lies, the one that confesses obtains his freedom and the one that lies goes to jail for 20 years.

In order to analyze this game, it is assumed that prisoners cannot communicate and will make their decisions in a simultaneous manner. Consequently, each prisoner will analyze the best strategy given the other prisoner's possible strategies. If prisoner B confesses, he will get either five or zero years in jail. On the other hand, if prisoner B lies, he will get 20 or one year in jail. Since by confessing, prisoner B obtains fewer years in jail, it will choose to confess. The same procedure goes for prisoner A, thus, to confess is the dominant strategy. Then, the Nash equilibrium is (confess, confess) since this leads to the maximum utility for each prisoner.

Table 1.3 Prisoner's dilemma

<table>
<tr><th colspan="2" rowspan="2">Payoff matrix</th><th colspan="2">Prisoner B</th></tr>
<tr><th>Confess</th><th>Defeat</th></tr>
<tr><td rowspan="2">Prisoner A</td><td>Confess</td><td>5,5</td><td>0,20</td></tr>
<tr><td>Defeat</td><td>20,0</td><td>1,1</td></tr>
</table>

1.5.1.1 Cooperative games

Cooperative game is comprised of analytical tools that study the behavior of rational players when they cooperate. The main branch of cooperative game theory is focused on the formation of groups of players also known as coalitions. In this thesis, we will restrict our attention to coalitional game theory since our first contributions are based on forming coalitions of femtocells. Coalitional games are classified in three classes: canonical games, coalition formation games, and coalitional graph games, see e.g. Saad, Han, Debbah, Hjorungnes & Basar (2009). In Table 1.4, we describe the main characteristics of these classes.

Table 1.4 Coalitional games classes

Game class	**Features**
Canonical	The grand coalition, comprised of all players, is an optimal structure.
Coalition formation	The network structure depends on gains and costs from cooperation.
Coalitional graph	Players' interactions are ruled by a communication graph structure.

Coalitional Game Fundamentals

In coalitional games, the set of players that are denoted by $\mathcal{N} = \{1, \ldots, N\}$ seek to form cooperative groups, i.e. coalitions of femtocells. A fundamental concept in coalitional games is the value of the coalition C that represents the worth of a coalition in a game and is represented by v. Consequently, a coalitional game is defined by $(\mathcal{N}, v)$. It is worth noting that there exist coalitional games with and without transferable utility. A game with transferable utility (TU) implies that the total utility can be divided in any manner between the members of the coalition. Thus, the amount of utility that a player $i \in C$, a coalition member, receives from the division of $v(C)$ represents the payoff of the player i and is denoted by x_i. On the other hand, in games with nontransferable utility (NTU), the payoff that a player receives depends on the joint actions that players of the coalition S select.

Cooperative game theory has been widely used to solve the resource allocation problem in wireless cellular networks, see e.g. Saad *et al.* (2009); Yang, Fang & Xue (2012). Players form coalitions, within each coalition players acquire a cooperative behavior in order to maximize the value of the coalition and consequently improve their own benefit.

The Shapley value

The Shapley value is a unique payoff division $x(v) = \phi(\mathcal{N}, v)$ that divides the value of the coalition and that satifies the following axioms:

1. **Efficiency axiom:** $\sum_{i\in\mathcal{N}} \phi_i(v) = v(\mathcal{N})$
2. **Symmetry axiom:** $\phi_i(v) = \phi_j(v)$ if player i and player j are such that $v(C\cup\{i\}) = v(C\cup\{j\})$ for every coalition S not containing player i and player j.
3. **Dummy axiom:** $\phi_i(v) = 0$ if player i is such that $v(C) = v(S \cup \{i\})$ for every coalition C not containing player i.
4. **Additivity axiom:** If v_1 and v_2 are characteristic functions, then $\phi(v_1 + v_2) = \phi(v_1) + \phi(v_2)$.

Given a coalitional game $(\mathcal{N}, v)$, a coalition C, a set of players $\mathcal{N}$, an a value of coalition $v(C)$, the Shapley value of player i is given by

$$\phi_i = \sum_{C\subseteq\mathcal{N}\setminus i} \frac{|C|!(|\mathcal{N}| - |C| - 1)!}{|\mathcal{N}|!}[v(C \cup i) - v(C)] \tag{1.1}$$

where $[v(C \cup i) - v(C)]$ is the marginal contribution of every player i in a coalition C, the ways of positioning the players of C at the start of an ordering is represented by $|C|!$ and $(|\mathcal{N}| - |C| - 1)!$ defines the ways of positioning the remaining players at the end of an ordering. It is worth noting that in games with a large number of players the computational complexity of the Shapley value grows significantly. Since Shapley value gives a suitable fairness criteria for resource allocation, it has been used in several communication networks approaches, see e.g. Cai & Pooch (2004); Han & Poor (2009); Rohoden *et al.* (2019).

1.5.1.2 Non-cooperative games

Non-cooperative game studies the strategic choices resulting from the interactions among competing players. Thus, players are assumed to maximize their own utility without considering the effects of their choices on other players in the game. Therefore, the outcomes of the game depends on the strategies chosen by all players in the game. A fundamental concept in non-cooperative game is the Nash Equilibrium. It was named after John Forbes Nash and is defines as a set of strategies, one for each player, where no player has incentive to unilaterally change its strategy.

1.5.1.3 Stability

A set of actions is considered stable when no set of players would change their action given the opportunity. The solution concepts such as the Core, the Nash equilibrium and Stable sets have the property to be stable in some sense.

Stable sets

A coalitional structure is said to be stable if it satisfies two conditions, namely, internal and external stabilities. According to Stolwijk (2010), a strongly stable set $V \subset A$ is a set of imputations such that:

- **Internal stability:** $\nexists x, x'$ in V such that $x \succ x'$,

- **External stability:** $\forall y \in A \backslash V \exists x \in V$ such that $x \succ y$.

In the internal stability case, no player in a coalition has an incentive to leave its coalition and acts as a singleton since the payoff received by any player in the coalition is higher than the one received acting alone. In the external stability case, in a given partition, no player can improve its payoff by leaving its current coalition and joining another one.

Nash Equilibrium

A strategy set S^* is a pure strategy Nash equilibrium if for every player $i \in \mathcal{N}$,

$$x_i(S_i^*, S_{-i}^*) \geq x_i(S_i, S_{-i}^*) \quad for \quad all \quad S_i \in \mathcal{S} \tag{1.2}$$

Non-cooperative game has been utilized to address resource allocation problems in wireless networks where players are self-interested such as in Han, Ji & Ray Liu (2007); Lee, Tang, Huang, Chiang & Calderbank (2007).

The core concept

The core of a game is the set of payoff allocations such that no player could gain more than their current payoff by deviating and forming another coalition. Given the grand coalition $\mathcal{N}$, for a TU game, an imputation is a payoff vector if satisfies the following conditions:

- The payoff vector $x \in \mathbb{R}^N (N = |\mathcal{N}|)$ is group rational if $\sum_{i \in \mathcal{N}} x_i = v(\mathcal{N})$.
- The payoff vector x is individually rational if $x_i \geq v(i), \forall i \in \mathcal{N}$.

The core is the set of imputations where no coalition $C \subset \mathcal{N}$ has an incentive to deviate from the grand coalition and form a coalition C. Thus, the core guarantees that any payoff allocation x has at least an amount of utility equal to $v(C)$ for every $C \subset \mathcal{N}$. The core for a TU game is defined as

$$\{x : \sum_{i \in \mathcal{N}} x_i = v(\mathcal{N}) \quad and \quad \sum_{i \in C} x_i \geq v(C) \quad \forall C \subseteq \mathcal{N}\} \tag{1.3}$$

The ε-core concept

The ε-core concept is used when the core is empty and some approximately stable outcomes can be found. This concept relaxes the notion of the core by requiring that no member of a coalition would benefit significantly, or within a constant amount, ε, by deviating from its current coalition. Consequently, a coalition is stable if the following is true

$$\sum_{i \in c} x_i \geq v(c) - \varepsilon \tag{1.4}$$

1.5.2 Evolutionary Games

Evolutionary game theory (EGT) was proposed by John Maynard Smith who adapted the traditional game theory to the concept of evolution by natural selection. EGT is based on the study of the behavior of large populations of players who are repeatedly involved in strategic interactions. In addition, in EGT, the success of any of these players depends on how their behavior interact with the behavior of others.

An evolutionary game can be defined as $G = (\mathcal{N}, S, x^i(S_k)_{i \in \mathcal{N}, S_{k \in S}})$ where $\mathcal{N}$ is the set of players, which constitutes the population in an evolutionary game; S is the set of all strategies available to each player that is defined as $S = \{S_k\}$, and $x^i(S_k)$ is the player i payoff.

1.5.2.1 Stability in Evolutionary Games

In EGT, the evolutionary equilibrium (EE) is considered as the solution of the strategy adaptation process where no players have an incentive to change their strategy. In order to evaluate the stability of the evolutionary equilibrium, the following concepts have to be introduced.

Evolutionary Stable Strategy (ESS)

Evolutionary Stable Strategy is a stability concept that was also proposed by John Maynard Smith for populations of individuals sharing a common behavioral characteristic. ESS was presented for a monomorphic population, where every individual adopts the same strategy. Consider a player i using a strategy S_k and its expected payoff $x^i(S_k, \hat{S})$ considering that $\hat{S}$ is the strategy used by another player. Then, ESS for a monomorphic population is defined as

A strategy S^* is an ESS if and only if for all $S_k \neq S^*$ we have

$$x^i(S_k, S^*) \leq x^i(S^*, S^*) \tag{1.5}$$

$$x^i(S_k, S_k) < x^i(S^*, S_k) \quad \text{if} \quad x^i(S_k, S^*) = x^i(S^*, S^*) \tag{1.6}$$

where $x^i(S_k, S^*)$ refers to the payoff for the player using strategy S_k. Condition 1.5 implies that strategy S^* is the best response to itself. It defines the equilibrium condition while condition 1.6 defines the stability condition. The latter states that if a mutant strategy, S_k, is an alternative best response against the incumbent strategy, S^*, then the average payoff of S^* is higher than the average payoff of S_k.

ESS focuses on a static definition to capture the dynamic process of natural selection. However, models of natural selection are more likely to be dynamic, i.e. based on theories of dynamical systems and stochastic processes. In this sense, Taylor & Jonker (1978) defined the replicator dynamic that is the most important game dynamics studied in EGT.

Replicator Dynamics

Replicator dynamics studies the dynamic evolutionary games through a differential equation that determines the rate of growth of a specific strategy. An individual from a population is called replicator if it is able to replicate itself through the process of selection. Thus, a replicator with a higher payoff will replicate itself faster. This strategy adaptation process is modeled by using a set of ordinary differential equations called replicator dynamics Nowak (2006) defined as

$$\dot{p_c} = p_c[x_c - \bar{x}] \tag{1.7}$$

where $p_c = \frac{|c|}{N}$ represents the cluster c population share, x_c is the clusters' payoff c, and $\bar{x}$ is the average payoff in all clusters. According to the replicator dynamic, the population share of cluster c will increase if the payoff achieved in cluster c is higher than the average payoff, i.e. $x_c > \bar{x}$.

In Semasinghe, Hossain & Zhu (2015), the stability of the evolutionary equilibrium is performed by evaluating the eigenvalues of the Jacobian matrix that correspond to the replicator dynamics. The system is said to be stable if all eigenvalues have a negative real part. The Lyapunov stability concept has been considered in Lin *et al.* (2015) to find the evolutionary equilibrium stability. According to this concept, the stability of solutions of differential equations near to an equilibrium point are Lyapunov stable if they stay near the point forever.

1.6 State of art

This section presents the latest studies that address the resource allocation problem in femtocell networks. Specifically, works based on game theory and clustering techniques are presented. In Estrada, Otrok & Dziong (2016), a centralized clustering model is proposed. The centralized model, named as load balanced clustering (LBC) model, uses the WWF algorithm for the resource allocation. Furthermore, the LBC model proposes a femtocell power control to mitigate interference and to achieve a target SINR. A semi-distributed approach for femtocell clustering is presented in Qiu, Ding, Wu, Qian, Tsiftsis, Du & Sun (2016) where co-tier interference is mitigated. Basically, the approach proposes a clustering stage, an intra-cluster subchannel allocation, an inter-cluster interference resolution, and a power adjustment. In Li & Zhang (2018), the channel allocation problem is tackled by using a cluster topology for high-density networks. Based on the K-means algorithm, femtocells are divided into different clusters that can self-adapt to dynamic network topology. In Yang, Cao, Esmailpour & Wang (2018), the SDN-based hierarchical agglomerative clustering (SDN-HAC) model is proposed to group femtocells by using a suitable function based on the value of each cluster. In this model, femtocells are considered to work in closed access mode which allows them to increase their subscribers' satisfaction.

In the recent studies, game theory has been considered to address the main challenges of macro-femtocell networks such as resource allocation, offloading traffic, base station selection, and interference mitigation. For instance, authors in Lin *et al.* (2015) proposed a centralized scheme to group femtocells into clusters based on evolutionary game theory. In addition, a distributed fast power control game allows base stations to adjust their transmit power to reduce interference. In Saha & Vesilo (2018), a novel threshold pricing scheme is presented for offloading macro users to small cells. The authors modeled the behavioral dynamics of the macro users under two pricing strategies by means of evolutionary game. In P.Azadeh *et al.* (2019), an evolutionary game is used to modeled the BS allocation problem where the evolutionary equilibrium is the solution of the game. In Cao, Peng, Qi, Duan, Yuan & Wang (2018), a centralized user-centric merge-and-split rule based coalition formation game is proposed to estimate the inter-user interference. In addition, a resource allocation algorithm based on graph theory that eliminates intra-tier interference efficiently by allocating users who may severely interfere each other with orthogonal subchannels is presented. A distributed power and subcarrier allocation problem is formulated as an evolutionary game in Semasinghe *et al.* (2015). In particular, the strategy adaptation process of the femtocells is modeled by replicator dynamics and the evolutionary equilibrium is obtained as the solution.

CHAPTER 2

GAME THEORETICAL FRAMEWORK FOR CLUSTERING AND RESOURCE ALLOCATION IN MACRO-FEMTOCELL NETWORKS

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2.1 Abstract

We address the femtocell clustering together with the resource allocation in macro-femtocell networks. The clustering schemes allow the implementation of distributed approaches that can run locally within each cluster. Nevertheless, several limitations should be addressed for dense femtocell deployment, such as: lack of clustering schemes that encourage femtocells to grant service to public users and to become cluster members while guaranteeing their subscriber satisfaction, inefficient bandwidth usage due to the lack of bandwidth adaptation per tier when the cluster configuration changes, and lack of power control mechanisms to reduce interference. In this paper, we propose a distributed clustering model based on a cooperative game, where femtocells are encouraged to cooperate by forming clusters and rewarded with resources from macrocell. Our solution consists of: a cluster formation based on a coalitional game among femtocells and the macrocell to determine the subcarrier distribution per tier, a base station selection for public users and a resource allocation algorithm using Particle Swarm Optimization. We compare our solution with a centralized clustering approach and our cooperative clustering model using the well-known Weighted Water Filling resource allocation algorithm. Simulation results show that our proposal obtains throughput values similar to the

centralized approach, satisfies the service requirements for both types of users and reduces the interference in comparison with the benchmark models.

Keywords: Particle Swarm Optimization (PSO), Weighted Water Filling (WWF), Orthogonal Frequency Division Multiple Access (OFDMA), Clustering, Power Control, Game Theory.

2.2 Introduction

Femtocell (FC) technology has been used to solve the main limitations of the traditional cellular networks, such as: poor indoor coverage, degraded signal at cell-edge, offloading traffic and the inefficient use of spectrum. However, there are still several challenges such as base station (BS) selection, resource allocation, power control and interference mitigation due to the dense deployment of femtocells.

Femtocells are connected to the mobile core network by means of an internet backhaul (e.g. DSL connection) (Zhang, 2010). A femtocell supports all cellular standard protocols such as CDMA, GSM, WCDMA, LTE, WiMAX, and also all the protocols standardized by 3GPP, 3GPP2 and IEEE/WiMAX (Chandrasekhar *et al.*, 2008).

In a macro-femtocell network, mobile users are classified as public users (PUs) or subscribers (SUs). The public users are the traditional users of the wireless network while the FC subscribers are the authorized users that can connect to their own femtocells. Three access control modes are defined for the public users access to FCs. These are the closed, open and hybrid access modes (Zhang, 2010). In closed access mode, only FC subscribers can connect to their femtocells and these users get full benefit of their own FCs. However, the network capacity is limited and the interference caused by FCs to nearby macro users is increased. Open access mode allows any mobile user to use FCs, which requires a tight coordination between the macrocell (MC) and FCs. Hybrid access mode allows public users to access FCs but FCs reserve some resources for their own subscribers. Li, Yen & Sousa (2010); Valcarce, López-Pérez, Roche & Zhang (2009) demonstrated that the hybrid access mode outperforms the closed and the open access modes due to its ability to reduce the interference while guaranteeing the performance of their own subscribers.

The resource allocation problem for macro-femtocell networks was proved to be NP-hard due to the non-convexity of the signal-to-interference-plus-noise ratio(SINR) Ju, Liang, Li, Long & Yang (2015). In the literature, some centralized approaches have addressed different challenges such as interference mitigation Xue, Gong, Park, Park & Kim (2012) and resource allocation Estrada *et al.* (2013a) for non-dense FC deployment. Nevertheless, these solutions require global knowledge in real-time and long running times which make these approaches unfeasible for dense deployment.

The complexity of the resource allocation problem is still a very challenging issue for dense femtocell deployment. Recently, FC clustering schemes have attracted the attention of researchers in order to reduce this complexity. The main goal is to form FC groups that allow the implementation of distributed resource allocation approaches within each FC group. The majority of these approaches focuses on FCs deployed in the closed access mode (e.g. Mishra & Ram (2016)), despite the benefits of the hybrid access mode.

To the best of our knowledge, there are no related works that dynamically change the bandwidth allocated per tier taking into account the offloading traffic from macrocell and the cooperative femtocell networks. The main issues that need to be addressed when combining clustering and resource allocation for the hybrid access FCs are: 1) the bandwidth starvation in macrocell or cluster, 2) guarantees for the FC subscriber transmissions and 3) inter-cluster interference mitigation.

The limitations of the previous works can be summarized as follows:

- Lack of appropriate clustering schemes that encourage FCs to grant service to the public users while guaranteeing the quality of service of FC subscriber transmissions without depriving the macro user transmissions.

- Lack of dynamic bandwidth allocation per tier when the public user distribution changes with the cluster configuration.
- Lack of appropriate FC power control mechanisms to reduce not only co-tier interference but also inter-cluster interference.

To overcome these limitations, we propose a distributed clustering model using a game theoretical framework for cooperation between macrocell and femtocells that is able to determine the amount of MC resources (i.e. subcarriers) that can be allocated to the femto-tier without depriving macro user transmission of resources. Our cooperative game determines first the top-coalition C^* formed by a set of femtocells and the macrocell such that FCs maximize their subscribers satisfaction and the network operator maximizes the satisfaction of the public users. Then, other coalitions are formed using a fair portion of the allocated bandwidth to femto-tier. Finally, a distributed resource allocation algorithm is run locally within each cluster. The objective of this algorithm is to maximize the cluster throughput. We use Particle Swarm Optimization (PSO) technique for the resource allocation algorithm due to its ability to obtain a satisfying near-optimal solution while speeding up the optimization process.

2.2.1 Motivating Example

In this section, we use a motivating example to demonstrate that all entities of the macro-femtocell network (i.e. network, macrocell, femto-tier, clusters and femtocells) can effectively enhance their throughput by means of the clustering. Figure 2.1 shows a macrocell with eleven deployed femtocells ($FC_1, FC_2, ..FC_{11}$) represented by houses. Each FC is serving one subscriber (i.e. a total of 11 subscribers) and 17 public users are located within the FCs' vicinity. We assume equal demand for subscribers and the public users (e.g. 1 Mbps). The macrocell has 22 available channels for both tiers and each channel reaches a maximum data rate of 1 Mbps if it is not reused. Spectrum partitioning approach Ryoo, Joo & Bahk (2012) is assumed among tiers. This means that a dedicated number of subcarriers is allocated for each tier. The number of subcarriers allocated to the femto-tier should satisfy at least the average demand requested by FCs, $\overline{D^f_{SUE}}$, that is defined as the sum of FC's data rate demands divided by the FC number.

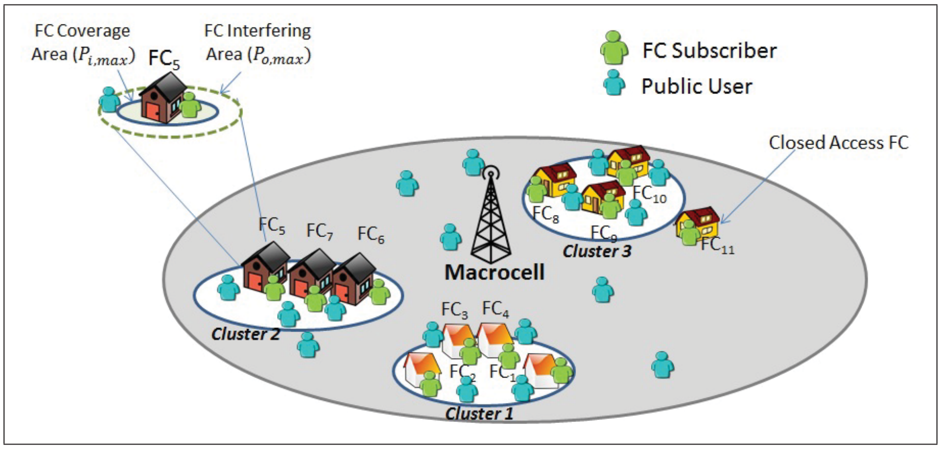


Figure 2.1 Network Model: $FC_1, FC_2, ..., FC_{10}$ work in the hybrid access mode and become cluster members, FC_{11} works in closed access mode

The network utility can be defined as the sum of all user data rates:

$$U^N = \sum_{i \in MS} \alpha_i^m R_i^m + U^{FT} \tag{2.1}$$

where the first term corresponds to the throughput delivered by macrocell m and the binary variable α_i^m indicates if user i is served by macrocell m. U^{FT} is the femto-tier utility, which is the sum of the data rates of the users served by FCs and is given by

$$U^{FT} = \sum_{c \in C} \sum_{f \in F^c} U^c + \sum_{f \in F^{sa}} R_{SU}^f \tag{2.2}$$

where F^c, F^{sa}, C are the sets of femtocells in coalition or cluster c, stand-alone femtocells, and clusters, respectively. The first term in Eq. (2.2) represents the sum of clusters' utilities, U^c, and the second term is sum of the stand-alone FCs' utilities. The cluster utility is estimated as the sum of data rate of both type of users being served by cluster members (i.e. $\sum_{f \in F^c}(R_{PU}^f + R_{SU}^f)$).

R_{PU}^f represents the sum of the data rate of public users being served by the femtocell f, i.e. $\sum_i^{PU} \alpha_i^f R_i^f$. R_{SU}^f corresponds to the sum of the data rate of the subscribers of femtocell f, i.e. $\sum_i^{SU} \alpha_i^f R_i^f$. R_i^f is the achievable data rate offered by femtocell f to user i and α_i^f is the binary variable indicating the allocation of user i to the femtocell f. Finally, FC's utility is given by

$$U^f = \begin{cases} \sum_{j \in PU} \alpha_j^f R_j^f + \sum_{i \in SU} \alpha_i^f R_i^f & f \text{ in a cluster} \\ \sum_{i \in SU} \alpha_i^f R_i^f & otherwise \end{cases} \tag{2.3}$$

Let's consider three scenarios: i) FCs work in closed access mode, ii) FCs work in hybrid access and they are cooperative forming clusters of equal size, and iii) FCs work in hybrid access but they form clusters of different size.

In the first scenario, each FC serves only its own subscriber because of its closed access mode. To reach the maximum data rate provided by a channel (i.e.1Mbps), dedicated channels are allocated to the users such that the cross-tier and co-tier interferences are avoided. Thus, the femto-tier needs 11 channels to satisfy the total demand required by subscribers while the macro-tier needs 17 Mbps (1 Mbps per PUs) to fulfill the PUs demand. However, the available channels are not enough to satisfy the total users' demand. To maximize the femto-tier throughput, the macrocell should allocated 11 channels to the femto-tier, grant access to 11 PUs and block 6 PUs. Table 2.1 summarizes the channel distribution per BSs and their respective utilities.

Table 2.1 Scenario with no coalition

BS	**Utility ($\mathbf{U^m}$, $\mathbf{U^f}$)**	**BS**	**Utility $\mathbf{U^f}$**	**BS**	**Utility $\mathbf{U^f}$**
m	11	FC_4	1	FC_8	1
FC_1	1	FC_5	1	FC_9	1
FC_2	1	FC_6	1	FC_{10}	1
FC_3	1	FC_7	1	FC_{11}	1
Femto-tier utility, U^{FT}: 11					
Total network utility U^N: 22					
Available channels: 0					

Table 2.2 shows the throughput values for the scenarios with coalition. In the second scenario, 9 FCs (FC_2, .., FC_{10}) choose to form three clusters of equal size while FC_1 and FC_{11} work in the

closed access mode. The macrocell rewards with one additional channel to each FC belonging to clusters. These two channels can reach the maximum data rate owing to the fact that the clusters are far from each other and the inter-cluster interference can be considered negligible. Each cluster reaches a utility of 6 Mbps and the femto-tier utility is 20 Mbps using only 6 channels. The femto tier serves 9 public users and 11 subscribers while the macrocell serves 8 public users. The macrocell and network utilities are equal to 8 Mbps and 28 Mbps respectively while keeping 8 available channels for new arriving users.

Table 2.2 Scenarios with coalition

(a) Equal size clusters

Cluster	**Utility ((U^{m}, U^{c})**	**F^{sa}**	**Utility U^{f}**
m	8		
$\{FC_2, FC_3, FC_4\}$	6	FC_1	1
$\{FC_5, FC_6, FC_7\}$	6	FC_{11}	1
$\{FC_8, FC_9, FC_{10}\}$	6		
Femto-tier utility, U^{FT}: 20			
Total network utility U^{N} :28			
Available channels : 8			

(b) Different size clusters

Cluster	**Utility (U^{m}, U^{c})**	**F^{sa}**	**Utility U^{f}**
m	7		
$\{FC_1, FC_2, FC_3, FC_4\}$	8	FC_{11}	1
$\{FC_5, FC_6, FC_7\}$	6		
$\{FC_8, FC_9, FC_{10}\}$	6		
Femto-tier utility, U^{FT}: 21			
Total network utility U^{N}: 28			
Available channels : 7			

Figure 2.1 depicts the third scenario where only femtocell FC_{11} is working alone and the remaining FCs form three clusters of different size. Table 2.2(b) summarizes the utility of the

network entities. The femto-tier utility is increased to 21 Mbps in comparison with the second scenario, the overall utility is the same while the number of available channels is lower than the scenario with cluster of equal size.

In summary, the coalitions allow the network to increase the throughput by means of rewarding FC with extra resources to grant service to PU and reduce the power consumption due to the proximity of the serving BSs. There is no gain for subscribers when their FCs become cluster members through the additional allocated channel but the the co-tier interference reduction. This motivates our work to investigate how to reward cooperative femtocells with additional resources from the unused channels in the network to improve the subscribers satisfaction. For example, three additional channels could be easily allocated to FC clusters in the second scenario and the FCs can increase the subscriber throughput to 2 Mbps and still keep some available channels for new arriving users.

2.2.2 Contributions

We propose a new framework that consists of three components: a distributed clustering model, a BS selection algorithm for public users, and a distributed resource allocation. In particular, our contribution is a model that provides:

- Bandwidth adaptation per tier based on the bandwidth allocated to a top coalition that maximizes the throughput of public users of the network.
- Enhanced subscriber satisfaction and reduction of the inter-cluster interference owing to the fact that FCs can choose to join or leave their current coalition depending on their SU satisfaction and the inter-cluster interference.
- Improved public user satisfaction by means of a BS selection algorithm, where each PU prefers to be connected to a FC, which is member of a cluster and provides higher data rate than the MC.
- Enhanced throughput per cluster by means of a cluster based resource allocation algorithm that maximizes its throughput using PSO technique.

Moreover, extensive simulations are carried out to perform a comparison between the proposed solution and two benchmark models: 1) its modified version using the same proposed distributed clustering scheme with a resource allocation algorithm based on the Weighted Water Filling (WWF) applied within each cluster, and 2) a centralized clustering model proposed in Estrada *et al.* (2016).

2.2.3 Organization

The rest of the paper is organized as follows: Section 2.3 presents an overview of related works. Section 4.4 describes the system model and problem formulation. Section 2.5 presents the components of the game theoretical framework for clustering and resource allocation as well as the benchmark models. Section 4.7 presents and analysis the numerical results obtained for the proposed and benchmark models. Finally, Section 2.7 concludes the paper.

2.3 Related work

To overcome the limitations of the traditional cellular networks, two technologies have been investigated: the integration of WiFi and cellular networks (i.e. heterogeneous wireless networks) and the deployment of femtocell networks (i.e. two tier cellular networks). Several approaches have focused on the design of integrated WiFi and cellular network such as mobility management and admission control Stevens-Navarro, Mohsenian-Rad & Wong (2008), QoS support for mobile users Mahindra, Viswanathan, Sundaresan, Arslan & Rangarajan (2014), efficient data offloading from the cellular to WiFi Lee, Yi, Chong & Jin (2013), and energy-efficient network management Luong, Nguyen, Le, Đào & Hossain (2016) to benefit from the heterogeneous wireless network.

Regarding the two-tier networks, several resource allocation approaches have been proposed in the literature. Some approaches perform bandwidth optimization Ko & Wei (2011), or power optimization Chandrasekhar & Andrews (2009b). Other approaches attempt to jointly optimize bandwidth and power for the femtocell network by means of maximizing of femtocells network throughput Zhang *et al.* (2010). For non-dense deployment, a dedicated number of subchannels can be assigned to each tier Lopez-Perez, Valcarce, de la Roche & Zhang (2009); Sundaresan & Rangarajan (2009) while for dense deployment, the spectrum should be shared among macrocell and femtocells and interference management schemes need to be implemented to enhance network throughput, such as: power control Chandrasekhar, Andrews, Muharemovict, Shen & Gatherer (2009), fractional spectrum reuse Dalal *et al.* (2011), soft spectrum reuse Jeong, Lee, Chung, Lee & Choo (2010) and dynamic or opportunistic spectrum reuse by means of the use of cognitive radiosNguyen & Le (2014).

We addressed the resource allocation problem for non-dense FC deployment using linear programming(LP) by means of a linear approximation of the signal-to-noise ratio Estrada, Jarray, Otrok & Dziong (2014b) or signal-to-interference-plus-noise ratio (Estrada *et al.*, 2013a). Due to the complexity of the LP solutions, we investigated alternative meta-heuristic models to find a satisfying near-to-optimal solution in less time such as genetic algorithm Marshoud, Otrok, Barada, Estrada, Jarray & Dziong (2012) or particle swarm optimization (PSO) (Estrada, Otrok & Dziong, 2013b). Moreover, we proposed a centralized meta-heuristic model to address the problem of joint clustering and resource allocation using PSO and demonstrated that the obtained results were close to our optimal solution for non-dense scenarios (Estrada *et al.*, 2016). The disadvantage of our prior solutions is that they employed centralized approaches either to solve the resource allocation or the clustering and therefore they are not suitable for dense deployment.

Recently, game theory has been proposed as a mechanism to implement distributed cluster based resource allocation algorithm such as in (Hatoum, Langar, Aitsaadi, Boutaba & Pujolle, 2014; Rohoden, Estrada, Otrok & Dziong, 2016; Zhang, Jiang, Li, Liu, Song & Dai, 2016). Abdelnasser, Hossain & Kim (2014) proposes a semi-distributed interference management scheme to group femtocells into clusters aiming at the minimization of the co-tier interference. In Hatoum *et al.* (2014), a resource allocation algorithm based on clustering and quality of service (QoS) for hybrid access mode is proposed. Their algorithm maximizes the number of satisfied FC subscribers while serving public users as best-effort service users. These approaches aim at the maximization of the femtocell network throughput. On the contrary, other approaches consider that femto users are the secondary users and they are served as best-effort service users in the network Ramamonjison & Bhargava (2015).

In Shih, Pang, Tsai & Chai (2015), an incentive mechanism to motivates FC owners to share their FC resources with public users is proposed. This mechanism is formulated using game theory where the network operator seeks to maximize its revenue by determining the revenue distribution among the FC owners, while the FC owners decide the amount of FC resources to share with public users. This approach assumed that femtocells have enough allocated resources to share with public users, which leads to an inefficient bandwidth usage if the public user density close to femtocell decreases.

2.4 System Model

We consider a network structure where femtocells are deployed within the macrocell coverage as shown in Figure 2.1. SC denote the set of available subcarriers in the network. To avoid the cross-tier interference, the set of subcarriers is split among the two tiers assuming the spectrum partitioning approach presented in Lopez-Perez *et al.* (2009); Sundaresan & Rangarajan (2009). The physical bandwidth of subcarrier s is denoted by B_s.

For OFDMA downlink (DL) transmissions Yang (2010), the Shannon's link capacity or spectral efficiency is given by

$$\gamma_k^s = log_2(1 + SINR_i^{s,k}) \tag{2.4}$$

where $SINR_i^{s,k}$ denotes Signal-to-interference-plus-noise ratio perceived by the mobile user i being served by femtocell k or a macrocell m. Since the spectrum partitioning approach among the tiers is assumed, the spectral efficiency γ_m^s for macro-users DL transmissions is only affected by the signal to noise ratio, which is given by:

$$SNR_i^{s,m} = \frac{P_i^{s,m}}{PL_i^{s,m} \times N_0}; i \in MS, s \in SC \tag{2.5}$$

For DL transmission in femto-tier, as the allocated subcarriers can be reused among the cluster, the inter-cluster interference is considered for the estimation of the SINR as follows:

$$SINR_i^{s,k} = \frac{\alpha_i^k P_i^{s,k}}{PL_i^{s,k} \times (N_0 + \sum\limits_{h \in \{C \setminus c\}} \sum\limits_{f \in \{F^h\}} I_i^{s,f})}; c \in C, k \in F^c, i \in MS \tag{2.6}$$

where $P_i^{s,k}$ is the transmitted power from serving BS k to user i in subcarrier s, $PL_i^{s,k}$ is the path loss due to the channel propagation models for outdoor and indoor environment, and $I_i^{s,k}$ represents the interference. The interference source is the inter-cluster interference and it is represented by the second term of the denominator in Eq. (4.1).

The propagation models used to estimate the path loss are similar to the ones presented in our previous work (Estrada *et al.*, 2013a) and are given as follows:

$$PL_i^{s,k}(dB) = \begin{cases} 10log_{10}(d_{ik}^{\omega_m}) + 30log_{10}(f_c) + 49, & k = m \\ 10log_{10}(d_{ik}^{\omega_f}) + 37, & k \in FC \end{cases} \tag{2.7}$$

where d_{ik} is the distance from BS k to user i that should be given in meters for FCs and kilometers for MC, fc is the carrier frequency adopted by the macrocell (in MHz), ω_k is the outdoor/indoor attenuation factor is assumed to be equal to 3.7 or 3 for outdoor and indoor environments, respectively, in accordance with the carrier frequency (ITU, 1997).

2.4.1 Problem formulation

The proposed model aims at maximization of the two-tier network throughput defined as the sum of achievable user data rates in the overlaid macrocell and FCs being grouped into disjoint clusters. Then, the objective function is formulated as

$$\max_{\epsilon,\alpha,\beta,\mathbf{P}} \sum_{i \in \{MS\}} \sum_{s \in \{SC\}} \alpha_i^m \beta_i^{s,m} \gamma_m^s + \sum_{c \in \{C\}} \sum_{i \in \{MS\}} \sum_{f \in \{FC\}} \sum_{s \in \{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} \gamma_f^s, \tag{2.8}$$

where ϵ is the vector of binary variables and ϵ_f^c defines the FC membership. α and β are the vectors that represent user base station association and bandwidth allocation per user, respectively. In other words, α is the vector composed of the binary variables, α_i^f, α_i^m described in Section 2.2.1 and β comprises binary variables $\beta_i^{s,f}$, that indicate if subcarrier s is allocated to user i in femtocell f.

This objective function is subject to the upper bound for transmitted power per BS:

$$\sum_{i \in MS} \sum_{s \in SC} \alpha_i^k P_i^{s,k} \leq P_k^{Total} \tag{2.9}$$

where vector P consists of power allocations per user $P_i^{s,k}$, $k \in \{m, FC\}$. MS and SC are the sets of mobile stations and subcarriers, respectively, C is the set of disjoint FC clusters, and γ_k^s is the spectral efficiency given in Eq. (2.4).

Exhaustive search could be applied to find the optimal cluster configuration, which means performing the joint BS selection and resource allocation over all possible cluster configurations. However, an exhaustive search would require long running times since the number of possible cluster configuration increases exponentially with the number of femtocells Bogart (2006).

In Estrada, Otrok & Dziong (2014a), we presented a centralized cluster formation that aims at balancing the traffic load of public users. The model attempts to find the best cluster configuration by means of the evaluation of the throughput after running the resource allocation algorithm. If the network throughput is enhanced and the interference level is reduced, then, the cluster configuration is kept as the new best cluster configuration.

2.4.2 Optimization of the cluster based resource allocation problem

Once the cluster are established, the goal of the resource allocation problem within each cluster is to maximize its throughput. Thus, the objective function for the cluster based resource allocation problem is given by

$$\max_{\boldsymbol{\epsilon},\boldsymbol{\alpha},\boldsymbol{\beta},\mathbf{P}} \sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} \gamma_f^s \tag{2.10}$$

subject to:

$$\sum_{k\in\{m,F^c\}} \sum_{s\in\{SC\}} \beta_i^{s,k} \leq 1 \quad ;i \in MS \tag{2.11}$$

$$\sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} \leq N_s - \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \alpha_i^m \beta_i^{s,m} \tag{2.12}$$

$$log_2\left(1 + SINR_i^{s,f}\right) \geq \alpha_i^f \beta_i^{s,f} \gamma_f \quad ;i \in MS, f \in \{F^c\}, s \in \{SC\}, \tag{2.13}$$

$$\sum_{k\in\{F^c\}} \alpha_i^k \leq 1 \quad ;i \in MS \tag{2.14}$$

$$B_s \times \sum_{s\in\{SC\}} \beta_i^{s,k} \gamma_k^s \geq \alpha_i^k \times D_i \quad ;i \in MS \tag{2.15}$$

Constraint (A I-2) is used to avoid the cross-tier interference, which means that a subcarrier being used in the macro-tier cannot be used in a cluster. We also assume orthogonal transmission among the users in a cluster to avoid the intra-cluster interference. Constraint (A I-3) indicates that the number of subcarriers allocated to cluster c (i.e. femto-tier) should be less or equal to the unused subcarriers in the macro-tier. Constraint (A I-4) guarantees that the spectral efficiency achieved by user i within a cluster is higher or equal than a target spectral efficiency. Finally, constraint (A I-5) indicates that one user can be assigned to only one BS and constraint (A I-6) establishes the lower bound for minimum data rate for public users, which is equal to the data rate that macrocell can offer to the user at any given instant. This optimization problem is solved using Particle Swarm Optimization (PSO) technique as described in Section 2.5.1.7.

2.4.3 Model Parameters

For sake of clarity, Table 2.3 summarizes the notation used in our model.

Table 2.3 Model Parameters

Name	Description
C	Set of clusters
SC	Set of available subcarriers
MS	Set of mobile users
FC	Set of deployed femtocells
PU	Set of public users
SU	Set of subscribers
S	Coalition or cluster
F^c, F^h	Set of FCs per cluster c or h
B_s	Bandwidth per subcarrier
N_s^{FT}	Number of subcarriers allocated to femto-tier
N_s	Number of subcarriers
$\overline{N_s^f}$	Average number of subcarriers required by FCs
$N_{used,S}^{PU}$	Number of subcarriers used for PU in the coalition S
$N_{used,S}^{SU}$	Number of subcarriers used for SU in the coalition S
N_s^{FT}	Number of subcarriers allocated to femto tier
P_k^{Total}	Total transmitted power in BS k
$P_k^{max,s}$	Maximum transmitted power per subcarrier in BS k
r_k	Coverage radius of the BS $k \in \{m, FC\}$
γ_k^s	Spectral efficiency fo subcarrier s in BS $k \in \{m, FC\}$
ω_k	Outdoor/indoor attenuation factor $k \in m \cup FC$
f_c	Carrier frequency adopted by the MC (in MHz)
N_0	Average Thermal Noise Power
U^c, U^{FT}, U^N	Utility of cluster c, femto-tier, and macro-femtocell network
D_i	Data rate demand of mobile user i
R_{SU}^f	sum of data rate of subscribers served by FC f
R_{PU}^k	sum of data rate of public users served by BS $k \in \{m, FC\}$
d_{ik}	Distance from BS k to the user i
α_i^k	User i is assigned to BS k
ϵ_f^c	Femtocell membership of the cluster c
$\beta_i^{s,k}$	Subcarrier allocated to user i in BS k
$P_i^{s,k}$	Transmitted Power in DL transmission between BS k and the user i

2.5 Game Theoretical Framework for Resource Allocation in Macro-femtocell networks

The proposed framework consists of: (i) BS selection for public users, (ii) clustering and (iii) resource allocation within each cluster. Figure 2.2 presents a flowchart of the proposed framework. Initially, each FC is consider a cluster or singleton coalition (i.e. $|C| = |FC|$) working in the closed access mode. This means that each FC serves only its own subscribers.

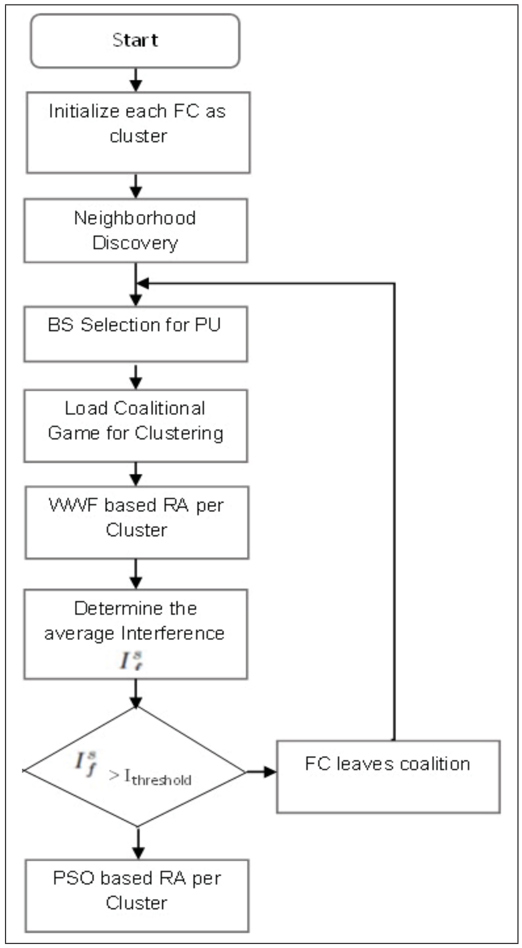


Figure 2.2 Game theoretical framework

2.5.1 Clustering

Here, we present our clustering approach based on the coalitional game theory. The classical coalitional games in characteristic form are based on the assumption that the value of a coalition can be computed independently of other coalitions. In our model, the situation is different because the utility of a coalition depends on the inter-cluster interference caused by other clusters due to the resource sharing. Note that we use the terms cluster and coalition interchangeably.

Our coalitional game is based on formation of a top-coalition, Banerjee, Konishi & Sönmez (2001). The top-coalition is the FC group that maximizes the sum of the data rate of public users in the two-tier network. This coalition allows our model to determine the bandwidth that should be used for both tiers. Then, other coalitions can be formed using a fair amount of bandwidth allocated for femto-tier, which depends on the PUs demand satisfied by each coalition.

2.5.1.1 Coalition Formation Game Fundamentals

Since coalitional game modeling is a natural way of doing clustering in a multi-agent environment and this paper addresses the FC clustering in a macro-femtocell network, we introduce the notions from coalitional game theory in this section.

Definition 1 - Game: A coalitional game is defined as the pair $(\mathcal{N}, v)$ where $\mathcal{N}$ is the set of players, and function v is defined for each coalition $C \subseteq \mathcal{N}$, $v(S)$ as a real number representing the utility that coalition S receives. This utility can be distributed in any arbitrary way among the players in the coalition.

Definition 2 - Preference Relation: A preference relation, denoted by $\succeq_i$, is a reflexive, complete and transitive binary relation on $\mathcal{S}_i = \{\mathcal{S} \in 2^{|\mathcal{N}|} : i \in \mathcal{S}\}$, where $\mathcal{S}, \mathcal{T} \in V$. The strict preference and the indifference relation are denoted by $\succ_i$ and $\sim_i$ respectively ($\mathcal{S} \succ_i \mathcal{T} \iff [\mathcal{S} \succeq_i \mathcal{T}$ and $\mathcal{T} \nsucceq_i \mathcal{S}]$ and $\mathcal{S} \sim_i \mathcal{T} \iff [\mathcal{S} \succeq_i \mathcal{T}$ and $\mathcal{T} \succeq_i \mathcal{S}]$).

Definition 3 - Partition: Partition $\pi := \mathcal{S}_\infty, ..., \mathcal{S}_{||} \in \pi(N)$ is a way of allocating the society of n players into disjoint non-empty coalitions $S_1, ..., S_k$ that defines a coalition structure (CS). Coalition structure $\pi = \{\mathcal{S}_1, \mathcal{S}_2, ..., \mathcal{S}_K\}$ is a partition of $\mathcal{N}$, where $K \leq |\mathcal{N}|$ is a positive integer and $C_k \neq \emptyset$ for any $k \in 1, 2, ...\mathcal{K}$. $\bigcup_{k=1}^{K} S_k = \mathcal{N}$, and $S_l \bigcap S_k = \emptyset$ for any $k, l \in 1, 2, ..., K$ and $k \neq l$. The collection of all coalition structures in $\mathcal{N}$ is denoted by $\Pi(\mathcal{N})$.

Definition 4 - Top coalition: Given a non-empty set of players $V \subseteq \mathcal{N}$, a non-empty subset $\mathcal{S} \subseteq V$ is a top-coalition of V if and only if $\mathcal{S} \succeq_i \mathcal{T}$ for any $i \in \mathcal{S}$ and any $\mathcal{T} \subseteq V$ with $i \in \mathcal{T}$. A coalition formation game satisfies the top-coalition property if and only if for any non-empty set of players $V \subseteq \mathcal{N}$, there exists a top-coalition of V Banerjee *et al.* (2001).

2.5.1.2 Coalitional Game for FC Clustering

In our coalitional game, the set of players includes the subset of available FCs and MC (i.e. $\mathcal{N} = \{FC\} \cup m$) and the function v is defined for each coalition S or FC cluster FC^c is given by

$$v(S) = \begin{cases} \dfrac{\sum\limits_{k\in S} \frac{R^f_{PU}}{\gamma_f}}{\frac{R^m_{PU}}{\gamma_m} + \sum\limits_{k\in S} \frac{R^f_{PU}}{\gamma_f}} \times (N_s - \overline{N^f_s}) & |S| \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{2.16}$$

where $\overline{N^f_s}$ is the initial number of subcarriers allocated for FC subscribers transmission as the average number of subcarriers required per femtocells, which is given by:

$$\overline{N^f_s} = \frac{\sum\limits_{f\in\{FC\}} R^f_{SU}/\gamma_f}{|FC| \times B_s} \tag{2.17}$$

where B_s is the bandwidth per subcarrier. Femtocells in stand alone mode are allowed to reuse this set of subcarriers. Note that a coalition S is equivalent to the definition of cluster F^c given in Section 2.2.1. From now on, we will use S instead of the set F^c.

The utility in Eq. (2.16) represents the resources gained by the coalition and should be divided between the coalition members (i.e. FCs and MC). The top coalition is the one that maximizes v(S) for the macrocell and the set of FCs in the coalition S. The information available at each decision point of the game is the set of candidate FCs and their demand. We assume that each femtocell is able to collect the needed information about the corresponding data rate demand of nearby PU and neighboring FCs by means of the cognitive pilot channel mechanism 5 (2009).

We use the same idea as the dynamic coalition formation proposed in Arnold & Schwalbe (2002), where the payoff of each player in a characteristic form is not defined. The characteristic function provides a worth for the coalition, and each player claims a share of this worth. If the claims can be met, each player gets it, otherwise, each player gets the worth it would get if it were to form a single coalition. We assume fair subcarrier allocation between the coalition members. Therefore, the payoff of any player (MC and FCs) $k \in S$ is

$$\phi_k(S) = \begin{cases} \frac{b \times v(S)}{(|S|-1)} & k \in S \backslash m \\ (1-b)v(S) & k = m \end{cases} \tag{2.18}$$

where b is a value between [0, 1] that represents the portion of the available subcarriers used by the femto-tier. The number of available subcarriers for public users can be determined as:

$$N_s^{PU} = (N_s - \overline{N_s^f}) \tag{2.19}$$

The first step of the coalition formation process is to determine the top-coalition that maximizes the sum of the PU data rates, guaranteeing their subscribers satisfaction and avoiding the starvation of resource in the macrocell. It is assumed that the macrocell is the major player and takes precedence over the other players (femtocells) because the wireless resources belong to the mobile operator. Therefore, public users served by FCs in coalitions can use the unused subcarriers in the macrocell, which is given as $\frac{b \times N_s^{PU}}{|FC|}$.

At each step (i.e. each time new public users arrive), the available actions for the femtocells in stand alone mode are to stay as singleton coalition or to join any established coalition that maximizes its payoff without depriving the utilities of the coalition and the coalition members. The available actions for the femtocells in a coalition are either to stay or leave the current coalition. If the average perceived interference per subcarrier is higher than the interference threshold, then, the femtocell decides to leave the coalition and acts in the stand-alone mode.

Within a coalition, the femtocell payoff corresponds to the extra resources for their own subscribers based on the offloaded traffic from the macrocell. Thus, the payoff received by FCs depends on the sum of public user data rates (i.e. $\sum_i^{PU} \alpha_i^f R_i^f$). FC subscribers can access the initial number of allocated subcarriers per femtocell $\overline{N_s^f}$ plus the remaining resources that public users did not use in the coalition S, $\lambda_f \times (b \times N_s^{PU} - N_{used,c}^{PU})$. The parameter λ_f considers the data rate granted to the public user by femtocell f in the coalition S and is given by:

$$\lambda_f = \frac{\sum_{i \in PU} \alpha_i^f R_i^f}{\sum_{f \in S} \sum_{i \in PU} \alpha_i^f R_i^f} \tag{2.20}$$

It is important to notice that FCs choosing to stay in the closed access mode can increase their throughput if their neighboring FCs become members of a cluster due to the inter-cluster interference reduction. This is owing to the fact that number of FCs sharing the initial number of subcarriers allocated to the femto tier is reduced. To mitigate the inter-cluster interference, we propose to perform power control using two different maximum transmitted power thresholds per FC in order to reach the target spectral efficiency for the users. One threshold for users inside the FC coverage area, $P^f_{i,max}$, and another threshold for users in the interfering area of the femtocell, $P^f_{o,max}$, as shown in Figure 2.1.

2.5.1.3 Coalition Formation Algorithm

The proposed strategy aims to find the best partition of players, containing a top-coalition S^* of femtocells and the macrocell and several coalitions of femtocells (S_j). Note that the top-coalition is the one that maximizes the sum of achievable data rate of public users in the network. This allow the model to determine the bandwidth allocated to macro-tier and the femto-tier cluster. Top-coalition S^* may change over time when new public users arrive or depart. The coalition formation is described in Algorithm 2.1. The complexity of Algorithm 2.1 is evaluated by simulations in Section 2.6.4 in terms of the running time required by the clustering scheme.

2.5.1.4 Cluster head selection

The cluster head is responsible for the clustering formation. This means that the cluster head is responsible for searching femtocells working in stand-alone mode and invite them to join the cluster such that the inter-cluster interference can be reduced. If the invitations are accepted, more resources from the macrocell can be granted to the cluster. Therefore, our model selects the femtocell with the highest number of neighbors outside of its coalition as a cluster head, Algorithm 2.1 Coalition formation algorithm

Input: *Each FC is a cluster, i.e.* $|FC| = |C|$. *Each FC computes its payoff* $\phi_i(C, \pi_N)$.
Output: *top-coalition* $S*$, *coalitions of femtocells* S_j
Neighbor Discovery
for $f \in C$ **do**
    f collects RSSI of neighboring FCs using measurement reports from its active users.
    Each FC f keeps a list of neighboring FCs, $Neighbor^f$.
end
Coalition Formation
Step 1 - Base Station Selection
Run Algorithm 2.2
Step 2 - Coalition Formation
for *each* $f \in F^{sa}$ **do**
    for *each* $j \in Neighbor^f$ *that are CH* **do**
        Coalition S_j computes its throughput gain using Algorithm 2.3.
        if $\phi_i^*(S_j \cup f) \geq \phi_i^*(S_j)$, S_j *sends the estimated throughput for* f *being a member of the coalition* **then**
            $S_f^* \leftarrow max_j R_f^{SU,S_j}$ $S_f^* \leftarrow S_f^* \cup f$ $F^{sa} \leftarrow F^{sa} \backslash f$
        end
    end
end
Step 3 - Top Coalition Selection
for *each* $S_j \in \pi_N$ **do**
    Run Algorithm 2.3 (WWF based resource allocation algorithm) $TC \leftarrow max_{j \in N}(R_{S_j}^{PU} + R_m^{PU})$
    $N_s^{FT} = N_{used,S_j}^{PU} + N_{used,S_j}^{SU} + \overline{N_s^f}$
end
Step 4 - Cluster Head Selection
for *each* $S_j \in \pi_N$ **do**
    $CH \leftarrow max_{f \in S_j} |Neighbor^f \cap F^{sa}|$.
end
Step 5: Cluster based Resource Allocation
for *each* $S_j \in \pi_N$ **do**
    Run Algorithm 2.4 (PSO based resource allocation algorithm)
end
Step 6 - Interference Control per FC
for *each* $S_j \in \pi_N$ **do**
    for *each* $f \in S_j$ **do**
        f computes I_f^s using Eq. (2.30)
        if $I_f^s > I_{threshold}$ *Eq. (2.31)* **then**
            f leaves the coalition S_j ($S_j \leftarrow S_j \backslash f$ $F^{sa} \leftarrow F^{sa} \cup f$
        end
    end
end

which is responsible of sending the invitations to the nearby stand alone FCs. Moreover, the cluster head is also responsible of the resource allocation.

The required information exchange among the cluster head and other femtocells can be done via the wired backhaul link. For convenience, we assume that the wired backhaul communication meets the tight demands for reliable and low latency communication to avoid a negative impact on the proposed framework. However, this issue can be investigated as a future work and is out of the scope of this paper.

2.5.1.5 BS selection for public users

Public users can be close to several FCs that belong to different clusters and our objective is to select the BS that can allocate the highest data rate. Thus, the required information for this selection is the data rate demands of public users and the link rate conditions between the surrounding FCs and the MC. First, each public user sends its data rate demand to each nearby FC that in turn sends this information to its cluster head. Second, the cluster head processes the WWF based resource allocation algorithm and returns to FCs the estimated subcarriers allocation for the users and then each FC returns the achievable data rate to the public user. Finally, each public user sorts the possible data rates in descending order and sends a request to the femtocell with the highest data rate. If the BS with the highest data rate has no available capacity (in terms of number of connected users), the public user sends the request to the next BS in its list. This procedure for BS selection for public users is described formally in Algorithm 2.2.

2.5.1.6 WWF based resource allocation per cluster

WWF is an algorithm that fairly allocates bandwidth based on users' data rate demands Ko & Wei (2011). In this case the users are sorted in ascending order according to their data rate demands. The weights used in the proposed WWF based algorithm are given by

$$w_i = \frac{D_i}{\sum_{f\in\{S\}} \sum_{i\in\{MS\}} \alpha_i^f D_i} \tag{2.21}$$

Then, pieces of bandwidth are allocated sequentially to the users in several rounds until the available bandwidth is exhausted or the last user data rate demand is satisfied. The WWF based resource allocation is presented in Algorithm 2.3. Since the PSO approach takes longer computation time than the WWF approach, we propose to apply the pre-processing of the offered

Algorithm 2.2 BS Selection for public users

Input: *PU set of public users, FC set of femtocell, m represents macrocell, user locations* (X_i, Y_i)*, FC locations* (X_f, Y_f)*, Demands*(D_i)
Output: (A_i^j) *BS selection*
Sort PU in decreasing order by their weighted demand (D_i)
for *each* $i \in MS$ **do**
    Determine the set of neighboring FC_{user} with higher link rate than the macrocell.
    if $FC_{user}! = 0$ **then**
        Sort FC_{user} in decreasing order by: link rate, available capacity, available resource in its cluster, available number of FC to be connected to the cluster. Assign user to the first femtocell f in the ordered list. $\alpha_i^f \leftarrow 1$;
        Increase the number of public users on FCs. $N_{PU}^f \leftarrow N_{PU}^f + 1$;
        Reduce the available capacity of femtocell f.
    else
        Assign user to the macrocell.
        $\alpha_i^m \leftarrow 1$;
    end
end

data rate for public users within a cluster using WWF algorithm. Then, once the BS selection for the public users is finally made, the final resource allocation is carried out using the PSO based resource allocation, which is described in section 2.5.1.7. For the comparison purposes, we also run simulations using this algorithm as the final resource allocation within each cluster.

2.5.1.7 PSO based resource allocation per cluster

We propose the Particle Swarm Optimization technique for solving the optimization problem, defined by Eqs. (A I-1)-(A I-6) presented in Section 2.4.2, since this technique has been proven to obtain a satisfying near-optimal solution while speeding up the optimization process.

PSO is a population-based search approach that requires information sharing among the population members to enhance the search process by using a combination of deterministic and probabilistic rules. PSO algorithm uses two vectors that determine the position and velocity of each particle n at each iteration k. These two vectors are updated based on the memory gained by

Algorithm 2.3 WWF Algorithm per cluster

```
Input: Bandwidth assigned to femto-tier (B_f^m), set of users assigned to femtocell in cluster
    f ∈ S (MS^S)
Output: Data Rate and resources allocated per user (T_i^c), (B_MS^f, P_MS^f).
Sort MS^c according to the bandwidth required divided by the total required bandwidth;
while i ∈ MS^S do
    b_i^wwf ← min( (b_i^required − b_i^(k−1)) / w_i^f , (B_f^m − Σ_{k=1}^{i−1} Σ_{j=k}^{MS^f} b_j) / (Σ_{j=i}^{MS^f} w_j^f) );
    for j = i → |MS^S| do
        while b_i is not satisfied and B_f and P^f are not exhausted do
            b_j^k ← b_j^(k−1) + w_j^f b_i^wwf;
        end
    end
    p_i^f ← min( SNR_th^f N_0 PL_i^f , min(P_f^max, P_f^res) );
end
Calculate the data rate using Shannon Law's Capacity, T_i^S
```

each particle. The position x_n^{k+1} and velocity v_n^{k+1} of a particle n at each iteration k are updated as follows:

$$x_n^{k+1} = x_n^k + \delta_t v_n^k, \tag{2.22}$$

$$v_n^{k+1} = \omega v_n^k + c_1 r_1 (p_k^{local} - x_n^k) + c_2 r_2 (p_k^{global} - x_n^k), \tag{2.23}$$

where δ_t is the time step value typically considered as unity (Perez & Behdinan, 2007), p_k^{local} and p_k^{global} are the best ever position of particle n and the best global position of the entire swarm so far, and r_1 and r_2 represent random numbers from interval [0,1]. Moreover, parameters ω, c_1 and c_2 are the configuration parameters that determine the PSO convergence behavior. The first term of Eq. (2.23) corresponds to the inertia of particle i which is used to control the exploration abilities of the swarm. Large inertia values produce higher velocity updates allowing the algorithm to explore the search space globally. Conversely, small inertia values force the velocity to concentrate in a local region of the search space. The second and third terms of Eq. (2.23) are associated with cognitive knowledge that each particle has experienced and the social interactions among particles respectively Bratton & Kennedy (2007). The convergence of PSO is guaranteed if the following two stability conditions are met:

$$0 \leq (c_1 + c_2) \leq 4 \quad \text{and} \quad \frac{c_1 + c_2}{2} - 1 \leq \omega \leq 1 \tag{2.24}$$

In order to apply the PSO technique to our optimization problem, we define vectors **b** and **P** to represent the location of each particle n in our search space. These vectors represent the allocated bandwidth and transmitted power per user, respectively. The dimension of each vector is equal to the cardinality of the set mobile users in the vicinity of cluster, i.e. $|MS^S|$. We use two different velocity vectors (v_b, v_p) to update the particle location in each iteration and they are updated using Eq. (2.23).

PSO algorithm is formulated as an unconstrained optimizer. One way to accommodate constraints is to augment the objective function with penalties proportional to the degree of constraint infeasibility. The main concern with this method is that the quality of the solution depends directly on the value of the specified scaling parameters. For that reason, we use a parameter-less scheme, where penalties are based on the average of the objective function and the level of violation of each constraint during each iteration Perez & Behdinan (2007). Therefore, penalty coefficients are determined as

$$cp_l = |\overline{f(x)}| \frac{\overline{g_l(x)}}{\sum_{j=1}^{CP} [\overline{g(x)}]^2}, \tag{2.25}$$

where $\overline{f(x)}$ is the average objective function, $\overline{g(x)}$ is the average level of l_{th} constraint violation over the current population and CP is the number of constraints (Perez & Behdinan, 2007). Then, the fitness function is defined by

$$f^*(x) = \begin{cases} f(x_n^k), & \text{if } x_n^k \text{ is feasible} \\ f(x_n^k) + \sum_{l=1}^{CP} cp_l \widehat{g}(x_n^k), & \text{otherwise} \end{cases} \tag{2.26}$$

and $\widehat{g}(x_n^k)$ is determined as

$$\widehat{g}(x_n^k) = \max\left(0, [g_j(x_n^k)]\right). \tag{2.27}$$

Accordingly, the average of the fitness function for any population is approximately equal to $\overline{f(x)} + |\overline{f(x)}|$.

The PSO parameter-less scheme is used to solve minimization problems and our objective is to maximize the cluster throughput. Therefore, we need to convert our maximization problem into a minimization problem. There are several techniques for such conversion Chvatal (1983). We use a simple one, in which the original objective function defined by Eq. (A I-1) is subtracted from a large number Q so the objective function for our PSO based resource allocation (RA) model is determined as follows:

$$f_{RA}(\mathbf{b,P}) = Q - \sum_{i\in\{MS\}} \sum_{\in\{m,FC\}} \alpha_i^k b_i log_2(1 + SINR_i^{s,f}) \tag{2.28}$$

where Q is a large number (at least twice of the maximum throughput that can be achieved in a cluster). The binary parameter α_i^k is the user-base station association and is equal to 1 if $bs_n(i)$ is equal to k and 0 otherwise as already described in section 2.5.1.5. Following the PSO parameter-less scheme, the fitness function of our PSO based resource allocation model is defined by

$$f_{RA}^*(x) = \begin{cases} f_{RA}(\mathbf{b,P}), & \text{for feasible solutions} \\ f_{RA}(\mathbf{b,P}) + \sum_{l=1}^{CP} k_l \widehat{g}(\mathbf{b,P}), & \text{otherwise} \end{cases} \tag{2.29}$$

where constraints (A I-2)-(A I-6) are included in $\sum_{l=1}^{CP} k_l \widehat{g}(\mathbf{b,P})$ to penalize unfeasible solutions. Algorithm 2.4 presents the PSO based resource allocation executed at the cluster head that knows the allocated bandwidth per cluster and pre-fixed BS selection per user. Our PSO based resource allocation algorithm executed by each cluster head is presented in Algorithm 2.4.

Algorithm 2.4 PSO based resource allocation algorithm

Input: *MS User Locations* (x_i, y_i)*, set of FC member of the cluster* (x_f, y_f)*, users demands* (D_i)*, BS selection per user* (bs_i)*, bandwidth per cluster* (B_c)*.*
Output: *Bandwidth and power allocation per user* (b_i, P_i).
for *each* $i \in MS$ **do**
  $b_i^{max} \leftarrow \frac{D_i}{\gamma_f}$;
  $P_i^{max} \leftarrow \min(P_f^{max}, SINR_k^{max} \times (N_o + I_{th}) \times PL_i^f)$;
end
Generate initial swarm with the particle positions and velocities as follows;
$\mathbf{b} \leftarrow \mathbf{r_1}.\mathbf{b^{max}}$;
$\mathbf{P} \leftarrow \mathbf{P^{min}} + \mathbf{r_2}.(\mathbf{P^{max}} - \mathbf{P^{min}})$;
$\mathbf{v_b} \leftarrow \mathbf{r_3}.\mathbf{b^{max}}$;
$\mathbf{v_P} \leftarrow \mathbf{P^{min}} + \mathbf{r_4}.(\mathbf{P^{max}} - \mathbf{P^{min}})$;
Evaluate Fitness Function;
Determine first global best of the swarm;
while $k \leq MaxIteration$ **do**
  Update Position;
  Evaluate Fitness Function;
  Determine best local for each particle;
  Determine best global in the swarm and update the best global;
  Update velocity;
end

2.5.1.8 Interference control mechanism

Since the proposed solution is distributed, the interference received by femtocells in a cluster cannot be estimated before the resource allocation. Therefore, we propose an interference mitigation mechanism that allows FCs to leave its current coalition when the interference levels given by

$$I_i^{s,k} = \sum_{f \in \{F^c \backslash k\}} \sum_{j \in \{MS \backslash i\}} \sum_{s \in \{SC\}} \frac{\beta_j^{s,f} P_j^{s,f}}{PL_i^f}, \quad k \in S \tag{2.30}$$

are higher than the interference threshold denoted as $I_{threshold}$. This interference threshold is estimated as the average interference level received by the subscribers being served by femtocells when all the femtocells work in the closed access mode:

$$I_{threshold} = \frac{1}{|FC|} \sum_{f \in \{FC\}} \sum_{i \in \{MS\}} \sum_{s \in \{SC\}} \alpha_i^f I_i^{s,f} \tag{2.31}$$

2.5.2 Benchmark models

In order to assess performance of our proposal, we use two benchmark models. The first benchmark model (BC-WWF) is a centralized clustering approach using a WWF resource allocation algorithm within each cluster. BC-WWF model corresponds to our previous work, presented in (Estrada *et al.*, 2014a). This approach attempts to balance the traffic load of the public users among the clusters without causing the bandwidth starvation at the macro-tier. The model consists of three components: (1) a centralized BS selection procedure that ensures that the traffic load of public users is fairly balanced among the FC clusters, (2) a WWF based resource allocation within each cluster that maximizes the cluster throughput and avoids co-tier interference, (3) a cluster formation algorithm to mitigate the co-tier interference and to balance the number of FC per cluster. This model tries to merge stand-alone FCs with the cluster that has the highest available capacity in terms of available subcarriers guaranteeing QoS subscriber transmission without exceeding the maximum number of FCs per cluster allowed in a given period of time. The second benchmark model (WWF-Dist) is a modified version of the solution proposed in this paper and it consists of our distributed clustering model combined with the WWF resource allocation algorithm, instead of the PSO based resource allocation model, within each cluster.

2.6 Simulation Results

We consider a single hexagonal macrocell with 10 femtocells and high density public users located near the femtocells. The hybrid access policy is adopted for FC if it is in a coalition; otherwise it works in the closed access mode. For each FC, we set two values of maximum transmit power, $P^f_{o,max}$ and $P^f_{i,max}$, that are used for users in the surrounding of the FC house or inside the FC house, respectively. Transmissions are affected by the distance dependent path loss according to the 3GPP specifications 3rd Generation Partnership Project (2011) and the external FC house wall loss attenuation of 3 dB. The number of available subcarriers is 256 and each one has a bandwidth of 15 KHz. We consider the spectrum partitioning approach, in which different sets of subcarriers are allocated to the macro-tier and the femto-tier to avoid the cross-tier interference. All relevant network and environment parameters are described in Table 2.4.

Table 2.4 Parameter settings

Network Configuration		
Name	**Description**	**Value**
N_s	Number of Subcarriers	256
P_m^{Total}	Transmitted power per MC	60 dBm
P_f^{Total}	Transmitted power per FC	10 dBm
r_m, r_f	Macrocells and femtocell radius	500 m, 20 m
θ_f, θ_m	Attenuation factor of indoor and outdoor	3, 3.7
γ_m, γ_f	Spectral efficiency for MC or FC	(2, 4), 6
W_l	Wall loss penetration	-3 dB
f_c	Carrier frequency	2300 MHz
N_0	Noise	-174 dBm/Hz
$\|SU\|$	Number of subscribers per FC	1
$\|PU\|$	Number of public users	5-60
FC	Number of deployed femtocells	10
PSO Parameters		
Name	**Description**	**Value**
c_1	Cognitive knowledge parameter	2.0
c_2	Social interactions parameter	1.5
ω	Inertia	0.85

The simulations are executed for different number of public users (increasing from 10 to 60 with 5 user increment) and with 10 FCs deployed within an area of 240x80 meters as illustrated in Figure 2.1. The public users are randomly located within FCs' vicinity.

The proposed approach motivates FCs to cooperate and become member of a cluster by means of the allocation of extra subcarriers. To show well this feature, we consider only one subscriber per FC with random data rate demand (128 kbps - 1 Mbps) in the following analysis. With more subscribers per FC, more resources would be required to satisfy the subscriber data rate demands and less public users can be connected to FCs, as it was shown in our prior work (Estrada *et al.*, 2016).

2.6.1 Analysis of the proposed coalition formation

In this section, we illustrate how the number of FC subcarriers is increased when FCs cooperate and form a top-coalition and several other coalitions. First we focus on the top-coalition and its dynamic adaptation caused by new PUs arrivals. This dynamic adaptation is illustrated in Figure 2.3 where the number of subcarriers allocated to femtocells forming the top-coalition is shown. Initially, the considered three femtocells, FC_3, FC_2 and FC_9, work in the stand-alone mode and share the same subcarriers allocated to the femto-tier, $\overline{N_s^f}$. Note that the number of subcarriers allocated for FC_3 in the stand-alone mode is lower than the number of subcarriers allocated to FC_2 and FC_9 because the data rate demanded by FC_3's subscriber is lower than the average data rate demand $\overline{D_{SUE}^f}$.

Figure 2.3 shows the resulting top-coalition is formed by FC_2, FC_3 and FC_9 at time 5. Note that the top-coalition may change with the arrivals of new PUs. In this particular scenario, a top coalition was formed before at time 2 by FC_1 and FC_6 which can be observed in Figure 2.4a when the subscribers' satisfaction increases to 100%. However, at time 3, FC_2 and FC_3 form the top-coalition that maximizes the public users achievable data rate. In this case, FC_2 receives extra-subcarriers for its subscriber transmission and FC_3 keeps the same number of subcarriers because its subscriber satisfaction was already 100% as shown in Figure 2.5a. FC_3's subscriber data rate is enhanced by the reduction of the co-tier interference caused previously by FC_2. At time 5, FC_9 joins the top-coalition and is awarded with additional subcarriers for its subscriber transmission. Moreover, the subscriber satisfactions for femtocells FC_2 and FC_9 are improved because of the extra-subcarriers obtained from the macrocell and the reduction of the co-tier

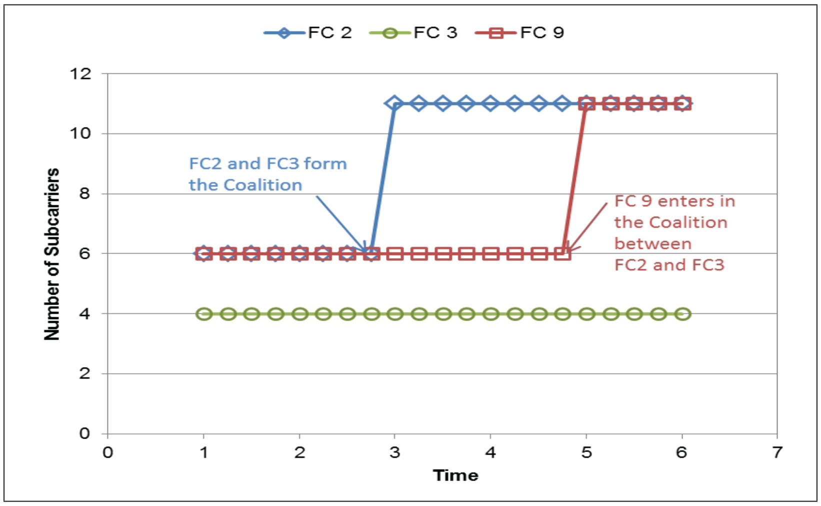
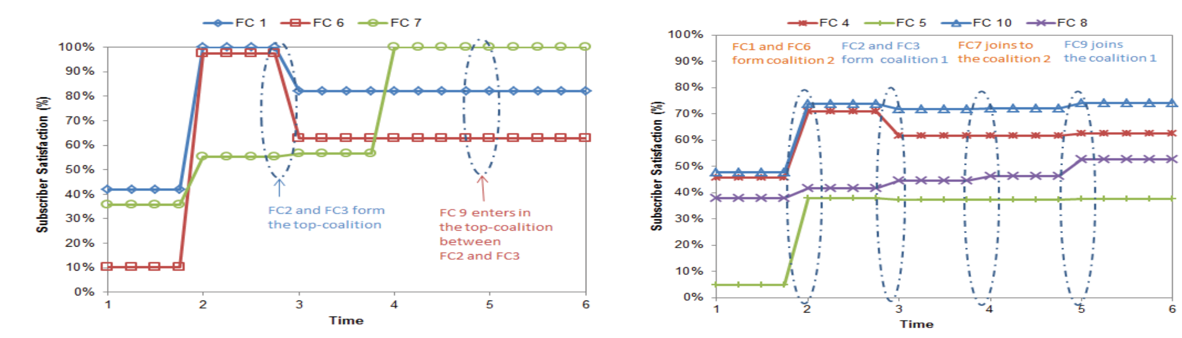


Figure 2.3 Subcarriers allocated for subscriber transmissions in FCs forming the top-coalition

interference caused previously by FC_3. The total number of subcarriers allocated to the final top-coalition for subscribers transmissions is 26.

Since our model is distributed, we analyze the subscriber satisfactions when the coalitions add new femtocells. Figures 2.4a and 2.4b depict the subscriber satisfactions for coalition 2 with femtocells FC_1, FC_6, and FC_7 and for stand-alone FCs, respectively. We denote the points where the top-coalition changes in both figures. Figure 2.4b shows that stand-alone femtocells are affected when the changes occur in the coalitions. It can be observed that most of the changes in coalitions can effectively enhance the subscribers satisfaction when compared to their initial subscriber satisfactions, even for the stand-alone FCs.

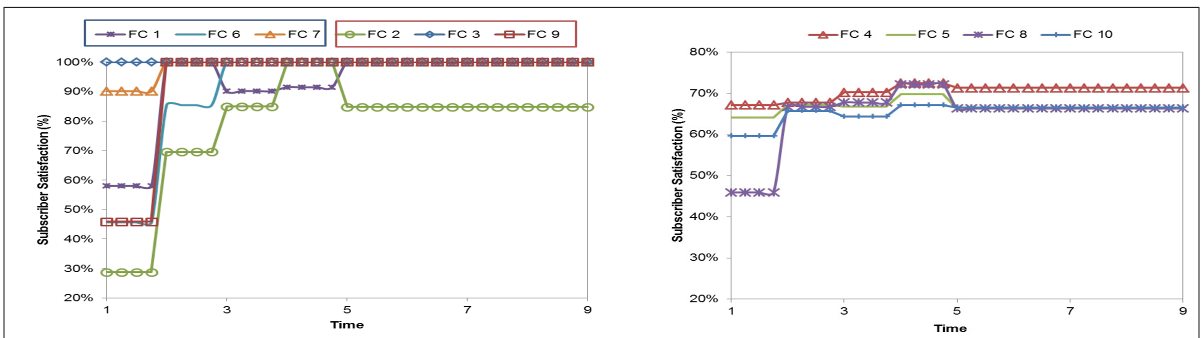
It can be noticed that the subscriber satisfactions are also affected by the formation of other coalitions in the network. For example, Figure 2.4a shows that subscribers transmission in FC_6 is severely affected when FC_2 and FC_3 form the top-coalition. To avoid this problem, we propose to implement a splitting mechanism for FCs that have joined any coalition. The idea is that each member of a coalition evaluates its interference level. If the interference value is higher than the average value per FC in the coalition, then, the FC chooses to stay in the stand-alone mode and considers joining other coalitions.



a) FC in coalition 2 b) Stand-alone FCs

Figure 2.4 Subscribers Satisfaction in FCs belonging to coalition 2 and in stand-alone FCs

Figure 2.5a presents the subscribers satisfactions for the FCs in coalition, where the mentioned above preference for leaving a coalition is applied if a FC senses high interference levels in a given period of time. In this figure, the legends are separated to indicate femtocells in the same coalition. After period 5, we can see that subscriber satisfaction is 100% for almost all FC except for FC_2. After period 5, the satisfaction of FC_2 decreases to 85%. This is owing to the fact that other coalitions cause interference to the top-coalition due to the resources sharing. However, this satisfaction value is still higher than the ones obtained by the subscribers in stand-alone mode FCs that are depicted in 2.5b or its initial subscriber satisfaction (i.e. 30 %).



a) FC in coalitions b) Stand-alone FCs

Figure 2.5 Subscribers Satisfaction in FCs belonging to the coalitions and stand-alone FC

In summary, the top-coalition C^* is determined as the subset of femtocells, S, and the macrocell that achieve the maximum sum of data rate for public users without starving the MC resources.

Then, other FCs form coalitions using a portion of the allocated bandwidth to the top-coalition while the FC subscriber satisfaction is guaranteed and inter-cluster interference is minimized.

2.6.2 Network Throughput

Here, we present a comparison between the proposed distributed clustering model, that uses the PSO based distributed resource allocation model, (PSO-Dist) and the WWF based resource allocation algorithms (WWF-Dist) within each cluster. We also include the simulation results of our centralized clustering approach (CC-PSO) (Estrada *et al.*, 2016). Figure 2.6 presents the overall network throughput using the three models. It can be observed that the centralized clustering approach and PSO-Dist model give similar throughput values for more than 30 users in the network. For less than 30 users, the WWF-Dist and CC-PSO models present similar throughput values while PSO-Dist enhances the network throughput. As stated in subsection 2.5.1.3, a FC that perceives an interference higher than the interference threshold can decide to leave its current coalition and go back to work in the closed access mode. This can be seen in Figure 2.6, where some throughput fluctuations exist for the PSO-Dist model. These fluctuations reflect the fact that a femtocell belongs to a coalition temporarily but leaves it taking into account the received interference level.

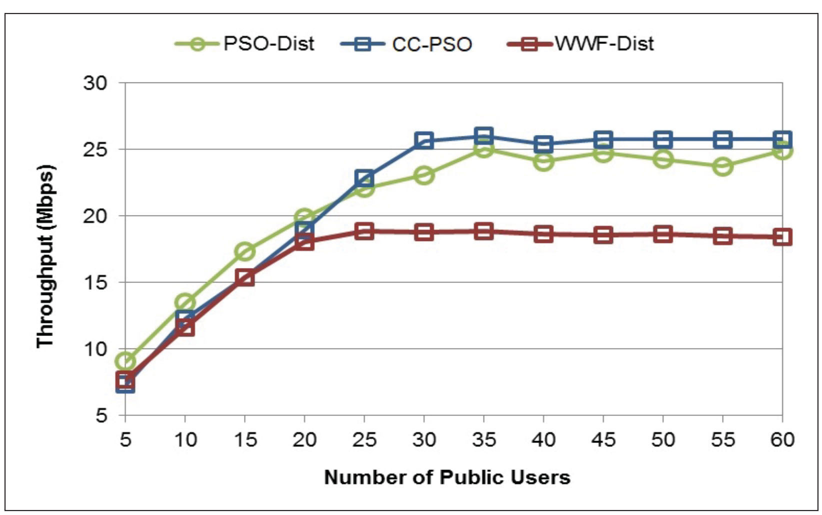
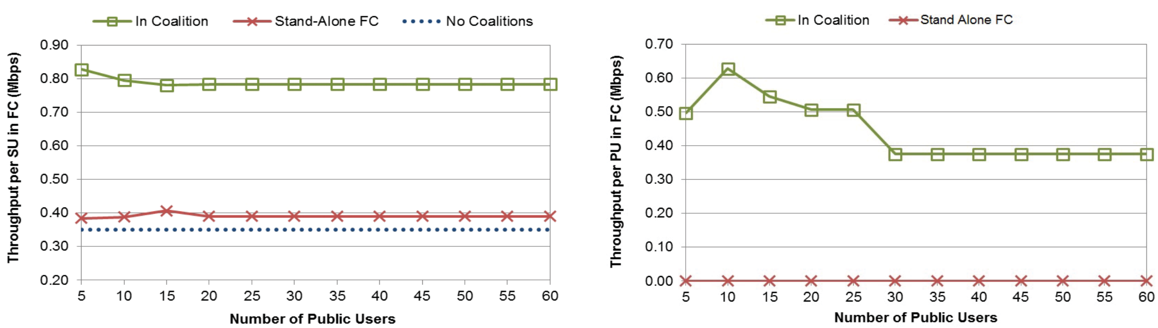


Figure 2.6 Network throughput

2.6.3 FC performance metrics analysis

Some femtocell performance metrics are analyzed in this section. In particular the average throughput per type of user (i.e. public user or subscriber) and the average interference per subcarrier are presented for both types of femtocells: the ones that form coalitions and the stand-alone femtocells. Figures 2.7a and 2.7b show the average throughput of FC subscribers and the public users being served by femtocells in coalition and in the stand-alone mode (i.e. the closed access mode).



a) Average Throughput per FC subscriber

b) Average Throughput per public user in femto-tier

Figure 2.7 Impact of FC coalition over average throughput per user

These results show that the FC subscribers in a coalition can reach higher throughput than the subscribers served by stand-alone FCs. This is due to two main features: 1) stand-alone FCs work in the closed access mode and they do not get extra resources from macrocell since they do not grant access to public users and 2) the interference in stand-alone FCs is higher than in FCs that form coalitions. The second feature is illustrated in Figure 2.8. In summary, the simulation results show that the proposed approach finds the top-coalition while guaranteeing the minimum level of FC subscriber satisfaction, which is determined by the subscriber satisfaction in a femtocell working in the closed access mode.

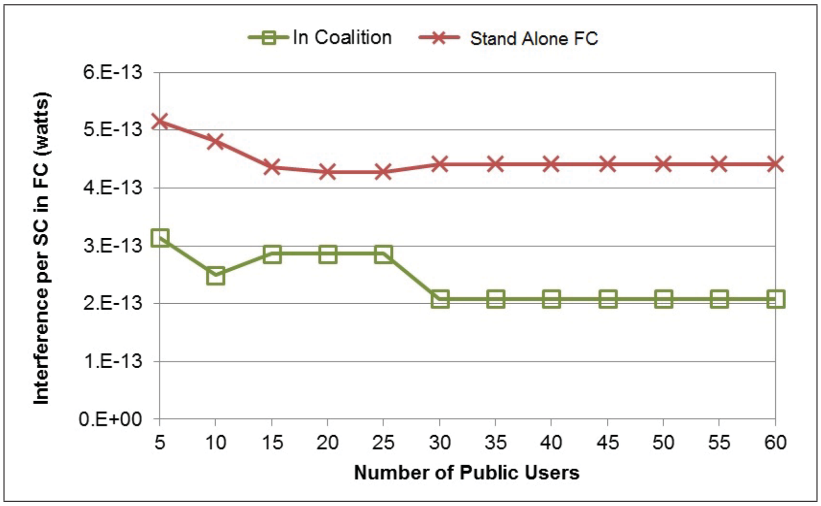


Figure 2.8 Average Interference per subcarrier

2.6.4 Complexity

Table 2.5 presents the running times for different number of femtocells and nearby PUs. First and second column represent the number of femtocells and number of public users close to their vicinity. The third column corresponds to the time spent on the clustering formation. We assume that one subscriber is located inside each FC and three public users are located in the FC vicinity, which gives high density of the nearby PUs. We can see that the running time increases as the number of FC increases.

Table 2.5 Running time for different FC number and high density of PU

FC Number	PU Number	Clustering Time (sec)
10	30	1.81
20	60	6.48
30	90	18.48
40	120	39.78
50	150	89.78

Nevertheless, we propose a distributed clustering scheme, which means that the model can select disjoint set of FCs in different areas and solve the problem for the top coalition in each area. Then, the model selects the one that maximizes the public users data rate in each respective sector among all the top coalitions. If we consider that each sector has 10 FC and that the clustering problem per sector can be solve in parallel, then, the running time with high PU density is 1.81 sec.

For the case of one sector with 10 FCs, Table 2.6 presents the running times for different public users density. First column represents the number of public users, the second column corresponds to the time spent on the clustering formation and the third column indicates the average running time of the model for resource allocation within a cluster.

Table 2.6 Running time

PU	Time (sec)	
Number	Clustering	Cluster based RAM
10	1.81	1.75
20	2.22	2.65
30	1.62	2.87
40	0	0

In the initial step, the clustering running time is measured for the initial coalition formation when 10 public users arrive to the FC vicinity, then, at the next step (i.e. 10 new PUs arrive), the running time corresponds to the process of joining the stand alone femtocells to the already established clusters from the previous step, and so on. We can see that after 30 users the running time of the clustering scheme and resource allocation algorithm becomes 0. This means that for more than 30 public users close to FC vicinity, neither the clusters can increase their utility by admitting new femtocells nor the FCs can get extra resources to increase their subscriber satisfactions and the users can keep the allocated resources from previous step. Finally, it can be observed that the running time for the resource allocation algorithm is increased when more users are assigned to each coalition.

2.7 Conclusions

We propose a game theoretical framework for clustering and resource allocation in macro-femtocell networks. The proposed solution consists of the FC coalition formation model aiming at maximization of the sum of public user data rate and the Particle Swarm Optimization based resource allocation algorithm that is executed locally by the cluster head within each cluster. For simplicity, we select the cluster head as the femtocell with the highest number of neighbors outside of its coalition. The proposed model is able to determine the best serving BS and the bandwidth and power allocation for each user taking into account its data rate demand, location and FC proximity. Our solution was compared with the centralized clustering model. The comparison showed that the proposed approach presents similar values of network throughput without reducing the subscribers satisfaction by means of rewarding FCs with extra resources for their subscriber transmission. In the tested scenarios, the subscriber satisfaction is at least 85% for the femtocells belonging to a coalition while for the stand-alone FCs it is 60%. Moreover, the proposed solution reduces the inter-cluster interference and allows efficient bandwidth usage. As future work, we propose to investigate other evolutionary computational techniques for the resource allocation within a cluster to reduce further the computational time, the evaluation of other cluster head selection techniques, and the incorporation of inter-cluster interference models.

CHAPTER 3

STABLE FEMTOCELLS CLUSTER FORMATION AND RESOURCE ALLOCATION BASED ON COOPERATIVE GAME THEORY

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3.1 Abstract

In this paper, we address the problem of forming stable groups of femtocells that can reduce the complexity of the resource management and enhance the subscribers' satisfaction while guaranteeing the service to nearby public users. In a macro-femtocell network, the resource management becomes a very challenging task as the number of deployed femtocells increases. Several strategies of clustering have been proposed to allocate resources in a distributed manner. However, forming stable clusters of femtocells is yet to be addressed. We propose a distributed cluster-based resource allocation framework that consists of three components: 1) a base station selection algorithm for public users that guarantees them a high data rate, 2) a coalition game, where femtocells are grouped into stable clusters to reduce the resource allocation complexity, and 3) a fair resource allocation using the Shapley value to compute the payoff of each cluster member based on Particle Swarm Optimization algorithm. The ε-core concept from game theory is used as the stability criteria to form the clusters. A performance comparison is carried out between the proposed solution and two benchmark models: a centralized approach and a distributed approach with non-stable group formation. Simulation results show that our framework indeed increases the network throughput, provides higher subscribers satisfaction,

and higher Jain fairness index for the distribution of resources among the existing users in the femto-tier.

Keywords: Clustering, PSO, OFDMA, Game Theory, Femtocell Networks.

3.2 Introduction

According to Cisco (2017), global mobile data traffic will increase approximately sevenfold between 2016 and 2021. One promising solution for achieving this goal is network densification. Accordingly, the mobile broadband network has introduced a heterogeneous network model, which consists of macrocells and femtocells (also known as small cells). In fact, it is expected that the next generation of wireless networks will be dominated by densely deployed femtocell networks, also referred to as ultra-dense femtocell networks (UDFNs). Femtocells (FCs) are home base stations that are deployed inside the coverage area of a macrocell (MC). Their purpose is to increase the coverage in dead zones for indoor environments and provide better system capacity. It should be noticed that femtocells are mostly deployed by end users without prior planning. As a result, interference can increase dramatically if the resources are not adequately managed among neighboring femtocells. In addition, interference depends on the access control mechanisms for femtocells.

Access control mechanisms are used to determine if public users are allowed to access a nearby femtocell or not. There are three access control categories: closed access, open access and hybrid access (Zhang, 2010). In the closed access case, the public users cannot access the nearby FCs and the FC subscribers get full benefit of their own FC but this approach limits the network bandwidth utilization and increases the interference to nearby public users, which is known as a dead-zone problem. The open access category allows any user to benefit from FCs services. However, this approach requires tight coordination between FCs and their macrocell that may result in traffic congestion over the backhaul connections. In the hybrid access case, a public user can access a nearby FC but some capacity of this FC is reserved for this FC subscriber.

This approach can combine the benefits and overcome the limitations of the two previous access control categories. Due to this potential, in this paper we focus on the hybrid access control.

A macro-femtocell network can be implemented using spectrum partitioning Ko & Wei (2011) or spectrum sharing Cheng, Ao, Tseng & Chen (2012) between tiers. Spectrum sharing approaches allow femtocells to share the same set of subcarriers with the macrocell. On the other hand, spectrum partitioning approaches divide the set of subcarriers into two disjoint sets to be used by the macro-tier and the femto-tier. Nevertheless, the resource allocation problem is a very challenging task for dense femtocell networks. Currently, several approaches have been proposed to solve the clustering together with the resource allocation such as (Bezzina, Ayari, Langar & Saidane, 2016; Qiu *et al.*, 2016). In Qiu *et al.* (2016), interfering femtocells are grouped into clusters while the subchannel allocation is performed by a cluster head, the femtocell with the highest degree of interfering neighbors. In Bezzina *et al.* (2016), the clustering is performed based on femtocells positions. Specifically, the K-means algorithm executes an iterative, data-partitioning algorithm based on a given cluster size and cluster number. Then, the resource allocation takes into account QoS requirements and cross-tier interference.

The majority of the previous cluster-based resource allocation approaches do not consider neither the stability of the clusters nor the fair allocation of resources. The cluster stability assures that the cluster configuration is not constantly changing over the time. Thus, the number of unnecessary handovers of public users changing their serving femtocell can be reduced. Moreover, there is no need to perform a constant resource reallocation due to the cluster configuration changes.

The main limitations of the prior related work can be summarized as follows:

1. The majority of approaches focus on clustering schemes for femtocells that work in closed access mode (Bezzina *et al.*, 2016; Chandrasekhar & Andrews, 2009a). Those approaches are not suitable for femtocells working in hybrid access mode and thus the access to nearby public users would not be guaranteed.

2. Lack of cluster formation methods that ensure the formation of stable clusters. Cluster stability is important since it prevents the femtocells from abruptly changing the existing cluster for another one, which leads to an unstable network.
3. Most of the resource management approaches do not ensure a fair allocation of resources (Han *et al.*, 2016; Kim & Cho, 2010). A fair resource allocation allows for the cooperative femtocells to receive a higher number of subcarriers in comparison with the non-cooperative femtocells.
4. Lack of rewarding methods that consider resources as a payment from the macrocell to encourage femtocells to form clusters and grant service to public users.

To overcome the above limitations, we propose a distributed resource allocation framework that maximizes the femto-tier throughput while enhancing the satisfaction of femtocell subscribers. The proposed solution focuses on the fairness of the resource distribution among all femtocells by means of the Shapley value and the cluster stability by applying the e-core concept of the game theory. Previously, we addressed a resource distribution in Rohoden *et al.* (2016) using an equal distribution of the resources among FCs within a cluster. However, this method does not guarantee the same subscriber satisfaction for the cooperative femtocells. The main differences between the current work and our prior work (Rohoden *et al.*, 2016) are the methods used to reward the cooperative femtocells and in the applied stability criteria.

The proposed solution comprises three stages. In the first stage, a Base Station (BS) selection algorithm is used to assign public users to BSs that provide them with high data rates. The second stage executes a cluster formation, in which a coalitional game is carried out to group femtocells into stable clusters. This stage includes the cluster head selection. Finally, in the third stage, a resource allocation algorithm based on the Shapley value and Particle Swarm Optimization (PSO) is implemented. In this stage, the cluster heads run locally the resource allocation algorithm within their respective clusters.

In brief, the main contribution of this paper is a framework that is able to:

- Form stable clusters while enhancing the subscriber's satisfaction using the ε-core concept of game theory.
- Allocate resources fairly among the cluster members using the Shapley value and PSO algorithm.

The remainder of this paper is organized as follows. Section 3.3 presents the related work where clustering for macro-femtocell networks is emphasized. Section 3.4 describes the system model, problem formulation and model parameters. Section 3.5 explains the components of the proposed model for clustering and resource allocation. This section also covers the performance metrics and the benchmark models. Section 3.6 presents the metrics used to validate our proposal. Section 3.7 provides simulation results. Finally, conclusions are drawn in Section 3.8.

3.3 Related work

This section presents the latest studies that address the resource allocation problem in femtocell networks. Specifically, works based on game theory and clustering techniques are presented. In general, the resource allocation problem for heterogeneous cellular networks has been widely investigated. For instance, authors in Kim & Cho (2010) proposed a centralized resource allocation framework. The aim was to maximize the system capacity for dense indoor mobile communication systems by jointly allocating power and subchannels. A physical resource block (PRB) allocation with improved QoS (Quality of Service) by avoiding co-channel and co-tiered interference is proposed in (Liang, Chung, Ni, Chen, Zhang & Kuo, 2012). Chandrasekhar & Andrews (2009a) analyzes an optimal decentralized spectrum allocation policy for two-tier networks. The approach is optimal in terms of area spectral efficiency while guaranteeing that MC and FC users obtain a prescribed data rate. A framework to allocate differentiated resources to users was developed in Lopez-Perez *et al.* (2009) by considering different users' requirements.

Game theory has been considered to solve the problem of resource allocation in a macro-femtocell network. In Nazir, Bennis, Ghaboosi, MacKenzie & Latva-aho (2010), an evolutionary game is proposed to adjust the FC transmitted power to mitigate the cross-tier interference by means of FC cooperation with the MC. Thus, FCs are allowed to reuse the less interfered MC channels although their subscribers' satisfaction is not guaranteed. In Han *et al.* (2016), the MC and the FCs maximize their capacity by playing a multiple-leader multiple-follower Stackelberg game under a distributed algorithm for downlink power allocation. In Pantisano, Bennis, Saad, Debbah & Latva-aho (2013) a distributed algorithm for the formation of stable femtocells coalitions is proposed to suppress intra-tier interference using interference alignment. Power control in a two-tier Orthogonal Frequency Division Multiple Access (OFDMA) femtocell network is proposed in (Deng, Zhang, Song, Han, Yang & Jiao, 2012) to mitigate the co-tier and cross-tier interference. Further, an auction game is formulated between the MC and the FC users in order to minimize the total power radiated by the FC base station.

Recently, cluster-based approaches have been studied to solve the complexity of resource allocation and interference management in densely deployed femtocells. In Bezzina *et al.* (2016), a semi-centralized scheme based on clustering for joint power control and resource allocation is proposed, the problem of cross-tier and co-tier interference is tackled based on a closed access mode scenario. A centralized meta-heuristic model and a semi-distributed interference management scheme are proposed in (Estrada *et al.*, 2016) and (Abdelnasser *et al.*, 2014), respectively, to address the problem of joint clustering and resource allocation. In Zhang *et al.* (2016), a resource allocation algorithm is proposed based on FCs clustering and a femto user mobility model to guarantee the mobile service quality. Kurda *et al.* (2015) presents a power control scheme for co-channel deployment of cluster of femtocells in the macrocell area. Qiu *et al.* (2016) presents a hierarchical resource allocation framework for small cell networks. Their proposal is comprised of small cells clustering, a cluster head election to carry out intra-cluster subchannels allocation, and a distributed learning-base coordination mechanism to tackle the inter-cluster interference.

Table 3.1 Literature review summary of the resource allocation in macro-femtocell networks

Techniques	Scheme	Advantages	Shortcomings
Resource allocation	- decentralized (Chandrasekhar & Andrews, 2009a) - decentralized (Han *et al.*, 2016) - decentralized (Rohoden *et al.*, 2016) - decentralized (Rohoden, Estrada, Otrok & Dziong, 2018) - centralized (Estrada *et al.*, 2016)	- Optimal in terms of Area Spectral Efficiency, considers QoS requirements. - Considers Stackelberg equilibrium, reduces algorithm costs. - Cluster-based, increases SUs satisfaction, guarantees service to PUs, manages stability. - Finds the top-coalition formed by femtocells and macrocell, PSO-based resource allocation. - Uses PSO, manages hybrid access mode, serving BS selection.	- FCs operate in closed access mode. - Prioritizes MC over FCs. - Fairness not considered, high clustering computation time. - Fairness not considered. - No cluster stability, high complexity.
Power control	- decentralized (Nazir *et al.*, 2010) - hybrid scheme (Kurda *et al.*, 2015)	- FC cooperation with MC, reuse MC channels. - Minimizes FC power consumption, guarantees user's QoS.	- FC subscriber satisfaction not guaranteed, FC access policy not defined. - Manages CSG, no cluster stability.
Interference management	- centralized Liang *et al.* (2012) - decentralized (Pantisano *et al.*, 2013)	- Considers QoS, manages co-channel and co-tiered interference, improves resource efficiency. - Interference alignment technique, stability based on recursive core.	- Manages closed subscriber group. - Wired backhaul constraints.
Joint schemes	- centralized (Kim & Cho, 2010) - decentralized Deng *et al.* (2012) - semi-centralized (Bezzina *et al.*, 2016) - partially-distributed (Qiu *et al.*, 2016)	- Allocating power and subchannel, maximizes the system capacity. - Guarantees FC throughput requirements, low computational complexity. - Considers cluster members' QoS requirements, alleviates cross-tier interference. - Mitigates co-tier interference, reduce network complexity, manages graph coloring.	- Poor power allocation, additional complexity, problem of fairness. - Low femtocell density, no incentives to FC users. - No resource allocation for MC users, closed FC access, no cluster stability. - Manages CSG, no cluster stability, no incentive to FCs.

3.4 System Model

We consider a macro-femtocell network with several femtocells, FCs, deployed under the coverage area of a macrocell, MC, as illustrated in Figure 3.1. Let $F = \{f_1, f_2, \dots f_{N_f}\}$ be the set of FCs where the f_i is the i-th femtocell of the considered macrocell and $|F| = N_f$. The set of available subcarriers is denoted as $SC = \{s_1, s_2, \dots, s_{N_s}\}$ where s_i denotes a subcarrier. Furthermore, SC is partitioned into two disjoint sets, SC_{macro} and SC_{femto}, in such a way that their intersection is the empty set and their union is SC. These two disjoint sets represent the set of subcarriers for the macro-tier and the femto-tier, respectively. Each subcarrier, s_i, has a bandwidth denoted by B_s.

We assume that each femtocell can grant service to one subscriber since in this case FCs are more likely to obtain more resources than in the case of FCs having multiple subscribers, as it was demonstrated in our prior work (Estrada *et al.*, 2016). It is assumed that femtocells work in the hybrid access mode allowing to grant service to nearby public users as well as their own subscribers. The demanded data rate for subscribers and public users is assumed to be random.

The resource allocation complexity in the considered macro-femtocell network is addressed by grouping femtocells into clusters. For example, in Figure 3.1, the femtocells f_5, f_6, f_7 and f_8 are forming a cluster. Within this cluster, the interference among FCs is controlled by allocating resources in an orthogonal fashion. However, in the same figure, there are some femtocells that do not belong to any cluster, i.e. f_1, f_2, f_3, f_4, f_8 and f_{10}. Since these femtocells use the same set of subcarriers, it can cause interference among them, for example, FC_1 causes interference to f_3's subscriber, SU_3. This interference can be avoided if femtocells form clusters and a designated femtocell, within each cluster, coordinates the allocation of resources, e.g. a cluster head.

Our model proposes an algorithm for the formation of femtocell clusters and the allocation of resources locally within each cluster. The set of clusters is defined as $C = \{c_1, c_2, \dots, c_{N_c}\}$. The total amount of clusters $|C| = N_c$.

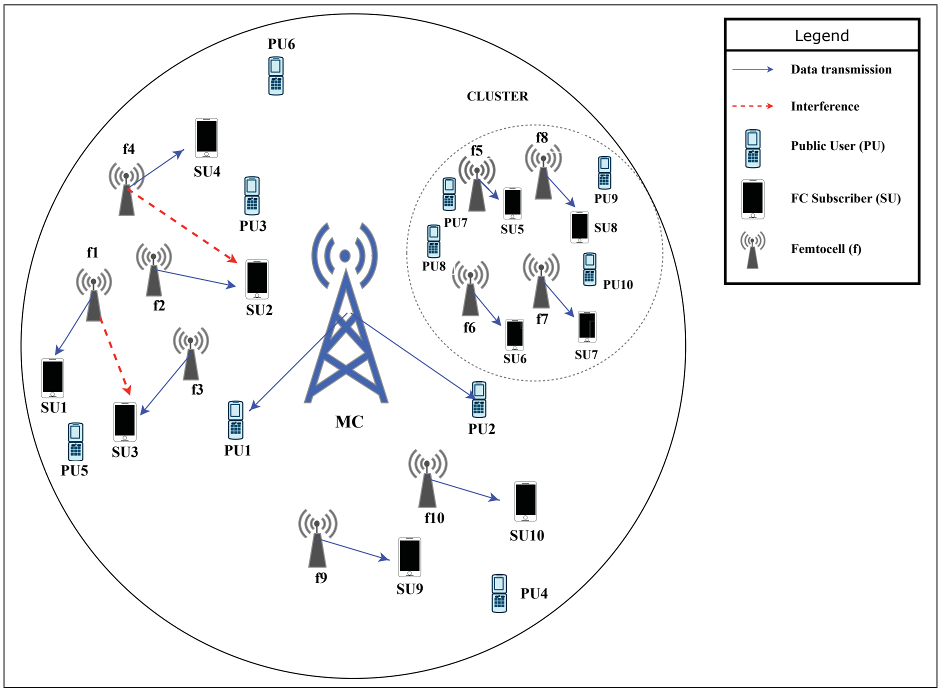


Figure 3.1 Topology of the macro-femtocell network

3.4.1 Problem formulation

Our goal is to maximize the femto-tier throughput, estimated as the sum of the achievable data rates of the users served by the femtocells forming clusters in the network. The objective function is defined as:

$$\max_{\boldsymbol{\epsilon},\boldsymbol{\alpha},\boldsymbol{\beta},\mathbf{P},\mathbf{C}} \sum_{c\in\{C\}} \sum_{f\in\{F\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} log_2(1 + SINR_i^{s,f}) \tag{3.1}$$

where P consists of power allocations $P_i^{s,f}$ per user i served by femtocell f in the frequency s. MS, SC and C are the sets of mobile stations, subcarriers, and clusters, respectively, F is the set of femtocells, ϵ is the vector of binary variables, ϵ_f^c, that defines membership of femtocell f in cluster c. α and β are the vectors that represent user base station association and bandwidth allocation per user, respectively. These two parameters are indicator functions and their values are either 1 or 0. In other words, α is composed of binary variables, α_i^f, that determines if user i is served by femtocell f while β comprises binary variables $\beta_i^{s,f}$, that indicates if subcarrier s is allocated to user i in femtocell f. $SINR$ perceived by mobile user i being served by femtocell f in subcarrier s is assumed to be given by

$$SINR_i^{s,f} = \frac{\alpha_i^f P_i^{s,f}}{PL_i^{s,f} \times (N_0 + \sum\limits_{h \in \{C \setminus c\}} \sum\limits_{f \in \{F^h\}} I_i^{s,f})}; c \in C, f \in F^c, i \in MS \tag{3.2}$$

where $P_i^{s,f}$ is the transmitted power from serving BS f to user i in subcarrier s, $PL_i^{s,f}$ is the path loss due to the channel propagation models for indoor environment, and $I_i^{s,f}$ represents the co-tier interference. In our model, the interference source for the femto-tier is the inter-cluster interference that is represented by the second term of the denominator in Eq. (3.2).

The propagation model used to estimate the SINR ratio is similar to the one presented in our previous work (Estrada *et al.*, 2013a), and is given by:

$$PL_i^{s,k}(dB) = 10log_{10}(d_{ik}^{\omega_f}) + 37, k \in F \tag{3.3}$$

where d_{ik} is the distance from BS k to user i (that should be given in meters) and ω_f is the indoor attenuation factor assumed to be equal to 3, in accordance with the carrier frequency used for femtocells (ITU, 1997).

Eq. (3.1) formulates the maximization of the femto-tier throughput in a centralized manner that creates a Mixed Integer Nonlinear Programming (MINLP) problem with continuous and discrete variables and nonlinear functions. This problem was proved to be intractable in Abdelnasser *et al.* (2014) owing to the fact that the computational complexity increases as the FC number increases. In addition, the computational complexity is a function of the number of possible cluster configurations that can be formed. In Abdelnasser *et al.* (2014), the authors determined that the potential number of cluster configurations is given by the Stirling number of the second kind (Bell number), which grows exponentially with the number of femtocells and the complexity is given as $O(f^f)$. Therefore, in order to reduce the complexity, we propose to decompose the maximization problem into two sub-problems: the clustering sub-problem that forms the clusters and the resource allocation within each cluster sub-problem that maximizes each cluster throughput. It is important to underline that our approach finds a satisfying near-to-optimal solution within each cluster.

The clustering sub-problem is solved by using a coalitional game in partition form where femtocells are considered the players of the game. In this game, femtocells are divided into disjoint clusters using Algorithm 3.2. The goal of the clustering is to distribute the resource allocation per cluster and improve femtocells' performance. In particular, the femtocells cooperate in the formation of clusters to increase their data rate and reduce the co-tier interference. In addition, every cooperative femtocell will grant service to nearby public users. As a consequence, cooperative femtocells receive extra-subcarriers for their subscribers which in turn increase the throughput of the cluster. Thus, the increase of the networks' throughput is guaranteed by the increase of every cluster's throughput. In addition, our solution focuses on forming stable clusters. To tackle this task, we use a stability criterion based on the e-core concept of game theory. Thus, when stability is maintained, the solution that maximizes the throughput of each cluster is equivalent to maximizing the sum of the throughputs of all clusters, since the clusters do not change constantly.

On the other hand, the resource allocation-subproblem, that maximizes the throughput within a cluster, is solved for every user within a cluster using Algorithm 3.3 that is based on PSO. In this case, within each cluster, the femtocell with highest number of neighbors is elected as the cluster head. The cluster head is responsible for the resource allocation among all the members of the cluster and the objective function of the resource allocation sub-problem is formulated as follows:

$$\max_{\boldsymbol{\alpha},\boldsymbol{\beta},\mathbf{P}} \sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \alpha_i^f \beta_i^{s,f} log_2(1 + SINR_i^{s,f}) \tag{3.4}$$

3.4.1.1 Model Constraints

Our objective function 3.4 is subject to the following constraints:

- Constraint (3.5) is used to avoid the cross-tier interference, which means that a subcarrier being used in the macro-tier is not used by any cluster in the femto-tier. Furthermore, subcarriers cannot be reused within a cluster but they can be reused in different clusters.

$$\sum_{k\in\{MC,F^c\}} \sum_{s\in\{SC\}} \beta_i^{s,k} \leq 1 \quad ; i \in MS \tag{3.5}$$

- Upper bound for the allocated subcarriers to the cluster c (i.e. femto-tier).

$$\sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \alpha_i^f \beta_i^{s,f} \leq N_s - \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \alpha_i^{MC} \beta_i^{s,MC} \tag{3.6}$$

- Spectral efficiency achieved by mobile user i within a cluster is higher or equal to a target spectral efficiency. Here, γ_f represents the target spectral efficiency in FC f.

$$log_2\left(1 + SINR_i^{s,f}\right) \geq \alpha_i^f \beta_i^{s,f} \gamma_f \quad ; i \in MS, f \in \{F^c\}, s \in \{SC\}, \tag{3.7}$$

- One user can be assigned to only one base station.

$$\sum_{k\in\{MC,F^c\}} \alpha_i^k \leq 1 \quad ; i \in MS \tag{3.8}$$

- Lower bound for minimum data rate for public users, which is equal to the data rate that macrocell can offer to the user at a given instant.

$$B_s \times \sum_{s\in\{SC\}} \beta_i^{s,k} \gamma_k^s \geq \alpha_i^k \times D_i \quad ; i \in MS \tag{3.9}$$

3.4.1.2 Model Parameters

The parameters of the proposed model are detailed in Table 3.2. These parameters are classified into: system, input, and output parameters. The system parameters describe the network features while the input parameters specify the users' requirements and locations. Output parameters are the set of stable clusters, the set of femtocell-cluster membership, and the bandwidth and power resources allocated to all users.

The proposed solution consists of three stages: (1) a BS selection for PUs, (2) a cluster formation based on a coalitional game, and (3) a distributed fair resource allocation algorithm.

Table 3.2 Model Parameters

System Parameters	
Name	**Description**
C	Set of clusters
c_{max}	Maximum size achieved by a cluster
SC	Set of available subcarriers
MS	Set of mobile users
F	Set of deployed femtocells
F^c	Set of FCs per cluster c or h
B_s	Bandwidth per subcarrier
BW_c	Bandwidth reserved for the clusters formation
N_f	Number of femtocells
N_c	Number of clusters
N_s	Number of subcarriers
$\overline{N_s^f}$	Average number of subcarriers required per femtocells
$N_{s-extra}^{f,c}$	Number of extra-subcarriers received by FC f in the cluster c
P_k^{Total}	Total transmitted power in BS k
$P_k^{max,s}$	Maximum transmitted power per subcarrier in BS k
P_f^{max}	Total transmitted power in femtocells
r_{MC}, r_f	Radii in macrocell and femtocells
θ_f, θ_{MC}	Attenuation factor of indoor and outdoor environments
$\gamma_{MC}^s, \gamma_f^s$	Subcarrier s spectral efficiency in MC and in FC f, respectively
γ_{MC}, γ_f	Target subcarrier spectral efficiency in MC and in FC f, respectively
ω_k	Outdoor/indoor attenuation factor $k \in MC, FC$
f_c	Carrier frequency adopted by the MC (in MHz)
N_0	Average Thermal Noise Power
$v(c)$	Value of the cluster c in terms of subcarriers
$x_{f,c}$	Individual payoff of FC f in cluster c
Input Parameters	
R_{SU}^f	Subscriber data rate demands in FC f
R_{PU}^f	PU data rate demands in FC f
D_i	Requested data rate demand of mobile user i
D_c	Requested data rate demand of cluster c
$D^{f,c}$	Requested data rate demand of femtocell f in cluster c
d_{if}	Distance from FC f to the mobile user i
d_{iMC}	Distance from MC to the mobile user i
Output Parameters	
α_i^k	User i is assigned to BS k
ϵ_f^c	Femtocell membership of the cluster c
$\beta_i^{s,k}$	Subcarrier allocated to user i in BS k
$P_i^{s,k}$	Transmitted Power in DL transmission between BS k and the user i
$Ra_{SU}^{f,c}$	Data rate allocated to femtocell f in cluster c to serve SUs
$Ra_{PU}^{f,c}$	Data rate allocated to femtocell f in cluster c to serve PUs

3.5 Stable Cluster Formation and Resource Allocation Framework

In this section, we describe the proposed framework that performs: (1) a BS selection for PUs based on their requested data rate and their proximity towards the FCs, (2) a cluster formation algorithm based on a coalitional game where cooperative FCs are rewarded with extra-subcarriers and the clusters stability is analyzed using the ε-core concept, and (3) a fair resource allocation within each cluster based on the Shapley value and the PSO algorithm.

In the following sections we describe the algorithms used to implement the three stages of the proposed framework.

3.5.1 Base station selection for public users

The objective of the base station selection procedure is to select the femtocell that can grant service to nearby public users. For this, the public users are sorted in a descending manner by their demanded data rate and in ascending manner by their distance towards FCs, considering that each FC can be a cluster or belongs to a cluster. In this approach, the resource allocation uses two algorithms, the WWF algorithm and the PSO algorithm. The WWF algorithm (Rohoden *et al.*, 2016) is used to determine the possible offered data rate for every public user in the base station selection stage, while the PSO algorithm is used in the final allocation of resources per cluster. While PSO could be also used in the base station selection stage, we opted for the WWF algorithm since it reduces the computation times as was demonstrated in (Estrada *et al.*, 2016). Each public user is assigned to the femtocell that provides higher data rate than the macrocell with available capacity. Then, the femtocell updates its capacity for the next public user in the list. Otherwise, the public user is assigned to the macrocell. The base station selection procedure is repeated until all PUs are assigned to base stations. The base station selection for public users is described in Algorithm 3.1.

Algorithm 3.1 BS selection algorithm

Input: *Set of users MS, cluster set C, user locations (X_i, Y_i), FC locations (X_f, Y_f), Demands(D_i)*
Output: α_i^k *BS selection,* MS^c *Set of users for each cluster*
Sort set MS in decreasing order by demanded data rate (D_u);
for *each* $u \in MS$ **do**
    Determine the set of clusters that can possibly serve the public users $Cluster_i$.
    for *each* $c \in Cluster_i$ **do**
        Determine the possible offered data rate using WWF based resource allocation algorithm.
    end
    Select the set of Cluster that satisfied the data rate higher than the macrocell, $Cluster_i^*$
    Sort the Cluster set, $Cluster_i^*$, in decreasing order by offered data rate
    for *each* $c \in Cluster_i^*$ **do**
        if *Femtocell f belonging to cluster c has capacity* **then**
            Assign the user to the femtocell in the cluster in the ordered list, $\alpha_i^f = 1$.
            Increase the number of femto or public users served by FCs depending on its type.
            Reduce the available capacity of femtocell f.
            Break
        end
    end
    if *user u was not assigned to any cluster* **then**
        Assign user to the macrocell, $\alpha_i^{MC} = 1$.
    end
end

3.5.2 Clustering

In this section, the clustering stage is presented. Clustering techniques allow reducing the resource allocation complexity of a dense femtocell network. In addition, the co-tier interference is avoided since the set of subcarriers allocated to FCs in a cluster is managed by a cluster head. That is, the cluster head allocates different subcarriers to all FCs within a cluster. The clusters created by the proposed algorithm are stable, i.e., no FCs would gain from changing the cluster allocation. The stability conditions for each possible cluster are presented in Section 3.5.2.2.3.

3.5.2.1 Coalition Formation Game Fundamentals

In order to solve the clustering problem, we propose a coalitional game with Transferable Utility (TU) where FCs are the players. In the proposed coalitional game, FCs are encouraged to cooperate in the formation of clusters while improving their own performance by increasing their SUs satisfaction and granting service to some nearby PUs. From now on the groups of FCs are named as clusters or coalitions interchangeably.

Definition 1 - Game: A coalitional game with transferable utility is defined as the pair $(\mathcal{N}, v)$ where $\mathcal{N} = \{F\}$ is the set of players that includes the subset of available FCs, and function v is defined for each coalition $c \subseteq \mathcal{N}$, $v(c)$ as a real number representing the utility that coalition c receives, also known as the value of a coalition. This utility can be distributed in any arbitrary way among the FCs belonging to the coalition. The proposed coalitional game is in partition form as $v(c)$ depends on how the FCs are organized outside c since FCs in a coalition experience interference from FCs outside the coalition c.

Note that in our approach we assume that each femtocell is able to collect the needed information about the corresponding data rate demand of nearby public users and neighboring femtocells. For example, this can be done by means of the cognitive pilot channel (CPC) mechanism (5, 2009).

Definition 2 - Preference Relation: The preference relation is a standard way to model player preferences. Let X be the set of outcomes elements with common elements x, y, z. The relation on X represents the relative merits of any two outcomes for the player with respect to some criterion. The following notations denote strict and weak preferences. We denote $x \succ y$ whenever x is strictly preferred to y and $x \succeq y$ whenever x is weakly preferred to y. The indifference relation is denoted by $x \sim y$ which means that the player is indifferent between x and y Slantchev (2012).

Definition 3 - Shapley Value: Given a coalitional game $(\mathcal{N}, v)$, a coalition c, a set of players $\mathcal{N}$, an a value of coalition $v(c)$, the Shapley value of player i is given by

$$\phi_i = \sum_{c \subseteq \mathcal{N} \setminus i} \frac{|c|!(|\mathcal{N}| - |c| - 1)!}{|\mathcal{N}|!} [v(c \cup i) - v(c)] \tag{3.10}$$

Definition 4 - Stability: A set of actions is considered stable when no set of players would change their action given the opportunity. In fact, a coalitional structure is said to be stable if it satisfies two conditions, namely, internal and external stabilities. In the internal stability case, no player in a coalition has an incentive to leave its coalition and acts as a singleton since the payoff received by any player in the coalition is higher than the one received acting alone. In the external stability case, in a given partition, no player can improve its payoff by leaving its current coalition and joining another one Niyato, Wang, Saad, Han & Hjørungnes (2011).

Definition 5 - Core: The core of a game is the set of all stable allocations. A vector $x \in \mathbb{R}^{\mathcal{N}}$ is a core allocation of the cooperative game $(\mathcal{N}, v)$ if for every coalition:

$$\sum_{i \in c} x_i \geq v(c) \tag{3.11}$$

If the core for a set of payoff vectors exists, it means that no subset of players c' could increase their payoff by deviating from their current coalition. However, as the number of players increases the computation of the core becomes intractable since its computation turns into a combinatorial problem Asl, Bentahar, Otrok & Mizouni (2015). Furthermore, considering that there is a possibility of not finding a distribution of payoffs that assures the stability of coalitions, we use the ε-core concept Asl *et al.* (2015). This concept relaxes the notion of the core by requiring that no member of a coalition would benefit significantly, or within a constant amount, ε, by deviating from its current coalition. Consequently, a coalition is stable if the following is true

$$\sum_{i \in c} x_i \geq v(c) - \varepsilon \tag{3.12}$$

In addition, the minimun value of ε guarantees that the ε-core is not empty. We use the least-core of a game to find the minimum amount of ε since the least-core minimizes the incentive of a femtocell to drop out of its current coalition.

3.5.2.2 Coalition Formation Algorithm

In order to motivate cooperation among femtocells, we propose to reward cooperative FCs with extra-resources (i.e. extra-subcarriers). A cooperative femtocell is defined as the femtocell that joins into coalitions and grants service to nearby PUs. We assume that femtocells are aware of their surrounding PUs and their demanded data rates. Note that in the proposed coalition game $(\mathcal{N}, v)$, the coalition c_i is ε-core stable and the value of an empty coalition is 0, $v(\emptyset) = 0$. Our distributed coalition formation algorithm is presented in Algorithm 3.2.

3.5.2.2.1 Value Function and Payoff

The value function, $v(c)$, of a coalition is determined by the sum of data rates demanded by PUs within a coalition, which constitutes the coalition demand, D_c. Since the coalitional game has a transferable utility, $v(c)$ is a real number and it can be transferable among the members of the coalition and is defined as:

$$v(c) = \begin{cases} \frac{|F^c| \times BW_c}{c_{max} \times B_s}, & D_c > \frac{\gamma_f \times |F^c| \times BW_c}{c_{max}} \\ \frac{D_c}{\gamma_f \times B_s}, & otherwise \end{cases} \tag{3.13}$$

where $|F^c|$, c_{max}, BW_c, and D_c represent the size of a coalition, the maximum size achieved by a coalition, the reserved bandwidth for the formation of coalitions, and the demand of the coalition, respectively. γ_f is the spectral efficiency for FCs and B_s is the bandwidth per subcarrier.

We define the individual payoff of an FC f in coalition c as:

$$x_{f,c} = \frac{Ra_{SU}^{f,c} - R_{SU}^{f}}{\gamma_f \times B_s} \tag{3.14}$$

where $Ra_{SU}^{f,c}$ and R_{SU}^{f} are the allocated and requested data rate of subscriber served by FC f, respectively.

3.5.2.2.2 Femtocell Rewarding Method

As already mentioned, to encourage femtocells to join any cluster, we propose a rewarding method based on the allocation of extra-subcarriers for their own subscribers.

In particular, the subcarriers allocated for PUs and SUs served by femtocells within a cluster are provided by offloading traffic from the macrocell. Data offloading is a solution that reduces network congestion by moving mobile data traffic from a congested Radio Access Network (RAN) to a RAN with available capacity Ren, Chen, Chang & Chen (2016). The data rate allocated to femtocell f within coalition c to serve PUs is based on PU data rate demands in FC f, R_{PU}^{f}, and is defined as:

$$Ra_{PU}^{f,c} = \frac{R_{PU}^{f}}{D^{f,c}} \times (N_{s-extra}^{f,c} \times \gamma_f \times B_s) \tag{3.15}$$

while the allocated data rate to a femtocell f in coalition c to serve their subscribers is given by:

$$Ra_{SU}^{f,c} = \frac{R_{SU}^{f}}{D^{f,c}} \times ((N_{s-extra}^{f,c} + \overline{N_s^f}) \times \gamma_f \times B_s) \tag{3.16}$$

where $\overline{N_s^f}$ represents the average number of subcarriers required per femtocells, $D^{f,c}$ is the requested data rate demand of femtocell f in coalition c, and $N_{s-extra}^{f,c}$ is the number of extra-subcarriers received by femtocell f in coalition c and is determined by the following equation:

$$N_{s-extra}^{f,c} = \frac{\phi_f \times v(c)}{\sum_{i \in c} \phi_i} \tag{3.17}$$

where ϕ_f represents the Shapley value of femtocell f, that is determined from Eq. (3.10).

3.5.2.2.3 Stability Analysis

In our proposal, femtocells cooperate in the formation of coalitions as long as their subscribers achieve the highest available satisfaction. Consequently, we should guarantee that the subscriber's satisfaction will be kept during all the clustering process. It can be stated that by guaranteeing the highest achievable subscriber's satisfaction, any deviation from the current coalition would be harmful to the femtocell.Also, it is assumed that the mobile users have low mobility so they would not frequently switch from the femto-tier to the macro-tier and viceversa. This assumption makes possible to have stable clusters. Moreover, a stability condition is used to maintain a stable coalition formation.

The stability condition is based on the ε-core concept of game theory, which is defined by Eq. (3.12). The use of the ε-core concept states that femtocells get a minimal amount of ε by deviating from the coalition while keeping the ε-core of the game non-empty. The minimum value of ε for which the ε-core is not empty is defined by the least-core of the game. To find the least-core value, ε, the relative ε-core is applied since it states that no coalition would benefit more than $\varepsilon \times v(c)$ by deviating Zick, Polukarov & Jennings (2013). In order to get the least core value for the considered scenario, we run the clustering stage varying ε from 0 to 1 and showed the results in Figure 3.2. For ε values of 0.1 or less, there are seven femtocells in stable coalitions thus 70% of the femtocells in coalition have a non-empty core. While for ε values equal or higher than 0.2 ten deployed femtocells are within stable coalitions. Consequently, we conclude that a gain of 20% of $v(c)$ is enough to join all femtocells in stable coalitions while guaranteeing the non-emptiness of the ε-core.

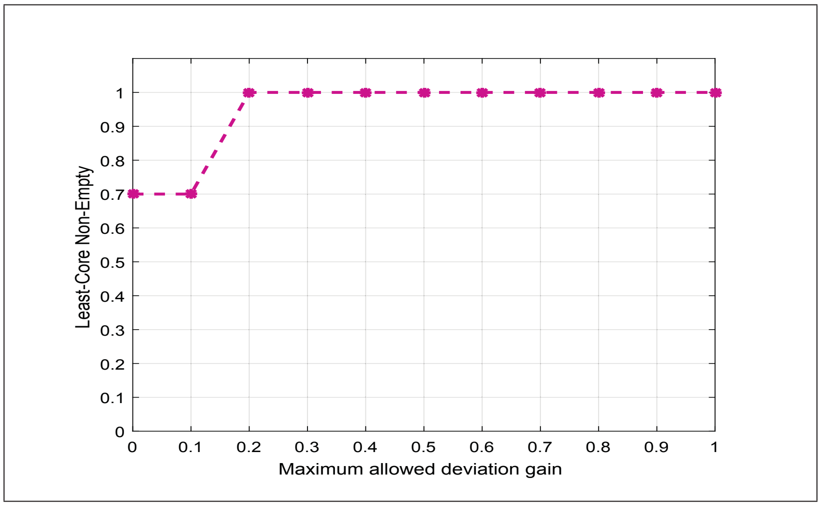


Figure 3.2 Analysis of ε-core set to find the least-core value

Thus, based on the ε-core analysis a coalition formed by cooperative femtocells is said to be stable if $\mathbb{S} = 1$, otherwise it is not stable:

$$\mathbb{S} = \begin{cases} 1, & \min x_{f,c} > 0 \\ & \min N^{f,c}_{s-extra} \neq 0 \\ & \sum_{f \in F^c} N^{f,c}_{s-extra} \geq v(c) - \varepsilon \\ 0, & otherwise \end{cases} \tag{3.18}$$

3.5.2.3 Cluster head selection

The cluster head is responsible for managing the clustering of femtocells and the resource allocation per cluster. For convenience, the proposed cluster head selection is similar to Hatoum, Aitsaadi, Langar, Boutaba & Pujolle (2011); Qiu *et al.* (2016), where the selected cluster head is the femtocell with the highest number of neighboring femtocells. By doing so, the cluster head is able to communicate with stand-alone femtocells and to invite them to join the coalition. Moreover, a cluster head should be aware of the amount of resources needed for the new members of the coalition, considering that these resources are taken from the macrocell.

Algorithm 3.2 Coalition formation algorithm

Input: *Initially, each FC is a cluster, so there are totally $|FC|$ clusters and all femtocells are in the stand-alone (SA) mode.*
Output: ϵ_f^c, $\beta_i^{s,k}$, $P_i^{s,k}$, $Ra_{SU}^{f,c}$, $Ra_{PU}^{f,c}$
Step 1 - Neighbor Discovery
for $f \in F^{sa}$ **do**
    Collects RSSI of the neighboring FCs from each of its own active mobile users.
    Based on the collected RSSIs, each FC f discovers the neighbor FC j and keeps a list of neighboring FCs, $Neighbor^f$.
    Form initial clusters by joining each FC f with its neighboring femtocells, C_{ini}.
end
Step 2 - Cluster Head Selection
for *each coalition* C_{ini} **do**
    $CH = max_{f \in F^c} |Neighbor^f - Neighbor^f \cap F^c|$.
end
Step 3 - Coalition Formation
for *each coalition* C_{ini} **do**
    Compute the value of the coalition, $v(C_{ini})$, based on the demanded data rate of PUs served by FCs within the coalition C_{ini}.
    for *each* $f \in C_{ini}$ **do**
        Calculate the extra-subcarriers per femtocell f.
        Calculate the payoff per femtocell f, ϕ_f, based on the received extra-subcarriers, use Eq. (3.10).
    end
    Evaluate the stability by applying the Eq. (3.11).
    Determine the set of stable coalitions, C_s, by verifying the conditions in 3.18.
end
Step 4: Resource Allocation per Cluster
for *each coalition* $C_s \in \pi_N$ **do**
    Determine the set of users for the current coalition C_s.
    Run the PSO based resource allocation algorithm for the mobile users in the coalition.
end

3.5.3 PSO based resource allocation per cluster

PSO is a technique that has been studied for the resource allocation in OFDMA macrocell systems (Gheitanchi, Ali & Stipidis, 2007) and in LTE systems (Su, Wang & Liu, 2012). In Estrada *et al.* (2013b), it was demonstrated that the resource allocation based on PSO requires between 100 to 1000 iterations to converge to a solution. In fact, PSO has been demonstrated to speed up the optimization process and find a satisfying near-optimal solution (Bratton & Kennedy, 2007). The implementation of PSO requires relatively small number of code lines since it is based on simple operations. In particular, it takes only one operation to update the velocity and position to coordinate and control the particles movements. Since no overlapping and mutation calculations are involved, PSO demands less time to find solutions when compared to genetic algorithms (Alkayal, 2018).

PSO is considered as a meta-heuristic global optimization method where the set of candidate solutions to the optimization problem is defined as a swarm of particles. These particles move through the search space defining trajectories that are driven by the best solution that they individually have found and the best solution that any particle in their neighborhood has found Bratton & Kennedy (2007); Marini & Walczak (2015).

PSO algorithm uses two vectors that determine the position and velocity of each particle n at each iteration k. These two vectors are updated based on the memory gained by each particle. The position x_n^{k+1} and velocity v_n^{k+1} of a particle n at each iteration k are updated as follows:

$$x_n^{k+1} = x_n^k + \delta_t v_n^k, \tag{3.19}$$

$$v_n^{k+1} = \omega v_n^k + c_1 r_1 (p_k^{local} - x_n^k) + c_2 r_2 (p_k^{global} - x_n^k), \tag{3.20}$$

where δ_t is the time step value typically considered as unity (Perez & Behdinan, 2007), p_k^{local} and p_k^{global} are the best ever position of particle n and the best global position of the entire swarm so far, and r_1 and r_2 represent random numbers from interval [0,1].

Moreover, parameters ω, c_1 and c_2 are the configuration parameters that determine the PSO convergence behavior. The first term of Eq. (3.20) corresponds to the inertia of particle i which is used to control the exploration abilities of the swarm. Large inertia values produce higher velocity updates allowing the algorithm to explore the search space globally. Conversely, small inertia values force the velocity to concentrate in a local region of the search space. The second and third terms of Eq. (3.20) are associated with cognitive knowledge that each particle has experienced and the social interactions among particles respectively (Bratton & Kennedy, 2007). The convergence of PSO is guaranteed if the following two stability conditions are met:

$$0 \leq (c_1 + c_2) \leq 4 \quad \text{and} \quad \frac{c_1 + c_2}{2} - 1 \leq \omega \leq 1 \tag{3.21}$$

In order to apply the PSO technique to our optimization problem, we define vectors **b** and **P** to represent the location of each particle n in our search space. These vectors represent the allocated bandwidth and transmitted power per user, respectively. The dimension of each vector is equal to the cardinality of the set mobile users in the vicinity of the cluster, i.e. $|MS^c|$. We use two different velocity vectors (v_b, v_p) to update the particle location in each iteration and they are updated using Eq. (3.20).

PSO parameter-less scheme is used to solve minimization problems and our objective is to maximize the cluster throughput. Therefore, we need to convert our maximization problem into a minimization problem. We use a simple technique, in which the original objective function defined by Eq. (3.4) is subtracted from a large number Q so the objective function for our PSO based resource allocation (RA) model is determined as follows:

$$f_{RA}(\mathbf{b},\mathbf{P}) = Q - \sum_{i \in \{MS\}} \sum_{f \in \{F\}} \alpha_i^f b_i log_2(1 + SINR_i^{s,f}) \tag{3.22}$$

where Q is a large number (at least twice of the maximum throughput that can be achieved in a cluster) in order to guarantee the maximization of the cluster throughput. Following the PSO parameter-less scheme, the fitness function of our PSO based resource allocation model is defined by

$$f_{RA}^*(x) = \begin{cases} f_{RA}(\mathbf{b},\mathbf{P}), & \text{for feasible solutions} \\ f_{RA}(\mathbf{b},\mathbf{P}) + \sum_{l=1}^{CP} k_l \widehat{g}(\mathbf{b},\mathbf{P}), & \text{otherwise} \end{cases} \tag{3.23}$$

where constraints (3.5)-(3.9) are included in $\sum_{l=1}^{CP} k_l \widehat{g}(\mathbf{b,P})$ to penalize unfeasible solutions. Algorithm 3.3 presents the PSO algorithm executed at the cluster head that knows the allocated bandwidth per cluster and BS selection per user.

Algorithm 3.3 Resource allocation algorithm based on PSO

Input: *MS Locations* (x_i, y_i), *Set of FC member of the cluster* (F^c), *Users Demands* (D_i), *BS selection per user* (α_i^f), *Bandwidth per cluster* (BW_c).
Output: *Bandwidth and power allocation per user* (b_i, P_i).
for *each* $i \in MS$ **do**
    $b_i^{max} = \frac{D_i}{\gamma_f}$
    $P_i^{max} = \min(P_f^{max}, SINR_k^{max} \times (N_o + I_{th}) \times PL_i^f)$
end
Generate initial swarm with the particle positions and velocities as follows
$\mathbf{b} = \mathbf{r_1}.\mathbf{b^{max}}$
$\mathbf{P} = \mathbf{P^{min}} + \mathbf{r_2}.(\mathbf{P^{max}} - \mathbf{P^{min}})$
$\mathbf{v_b} = \mathbf{r_3}.\mathbf{b^{max}}$
$\mathbf{v_P} = \mathbf{P^{min}} + \mathbf{r_4}.(\mathbf{P^{max}} - \mathbf{P^{min}})$
Evaluate Fitness Function
Determine first global best of the swarm
while $k \leq MaxIteration$ **do**
    Update Position.
    Evaluate Fitness Function.
    Determine best local for each particle.
    Determine best global in the swarm and update the best global.
    Update velocity.
end

3.5.4 Benchmark models

We compare our model with two benchmark models, namely a centralized clustering model and a distributed clustering model. The centralized model, named as load balanced clustering (LBC) model, uses the WWF algorithm for the resource allocation. Furthermore, the LBC model proposes a femtocell power control to mitigate interference and to achieve a target SINR (Estrada *et al.*, 2016). The distributed model (ED-WWF) works with the WWF algorithm which is performed locally within each cluster. Besides, this model allocates resources in an equal distribution manner (Rohoden *et al.*, 2016). These models apply the same BS selection for public users as well as our proposed model. The main difference of the proposed model is the fair resource allocation per cluster and the analysis of stability executed during the clustering process.

3.6 Performance metrics

The following metrics were used to evaluate the performance of our model:

1. **Throughput:** It is defined as the sum of the achievable data rates of the users served by the femtocells and the macrocell. The throughput achieved by the network is based on Shannon's Law Capacity:

$$T = \sum_{i \in \{MS\}} \sum_{j \in \{MC,F\}} \alpha_i^j \beta_i^j log_2(1 + SINR_i^j) \tag{3.24}$$

2. **Subscriber satisfaction:** It is given by the ratio between the sum of achieved subscribers' data rates and the demanded subscribers' data rates:

$$S_{SU} = \frac{\sum_{i \in \{SU\}} \sum_{j \in \{F\}} \alpha_i^j \beta_i^j \gamma_f}{\sum_{i \in \{SU\}} D_i} \tag{3.25}$$

3. **Jain's fairness index:** It is used to measure how fairly the resources are distributed among the mobile users Jain, Chiu & Hawe (1998). It is expressed as:

$$J_{index} = \frac{(\sum_{i \in \{MS\}} Th_i)^2}{(|MS| \times \sum_{i \in \{MS\}} Th_i^2)} \tag{3.26}$$

   where $|MS|$ is the total number of mobile users, and Th is the throughput of user i.

3.7 Simulation Results

In this section, we show the performance of the proposed model in terms of subscribers' satisfaction, public users' throughput, network throughput, Jain's fairness index, and running times for the clustering process. In addition, we compare these results with the two benchmark models described in Section 3.5.4.

Table 3.3 presents the system parameters for the network configuration and the PSO parameters. We perform our simulations using MATLAB R2018a running on a Lenovo computer with an Intel(R) Core(TM) i7-7500 processor and RAM of 8.00 GB. In the simulated scenario the number of PUs varies from 10 to 60 with increments of five users. 10 femtocells are deployed in an area of 500×500 m. One subscriber is assigned to each FC with variable demand from 128 Kbps to 1 Mbps. The available spectrum is split between the macro-tier and femto-tier to avoid the cross-tier interference. Additionally, a dedicated number of macrocell subcarriers is used for the PUs served by femtocells in coalitions and for giving extra-subcarriers to femtocells subscribers, $BW_c = b \times Bs \times Ns$, where b is a value between $[0, 1]$ that represents the portion of available subcarriers used by the femto-tier. From the analysis of Section 3.5.2.2, we set the epsilon value to 0.2 in order to evaluate the stability of the coalitional game.

The simulation results are obtained by running the experiments several times and then averaging them for use in the following analysis. First, we analyze the network performance by comparing the network throughput of the three models. Then, we analyze the subscribers' satisfaction resulting from the proposed model and compare it with the benchmark models. We also present a subscriber satisfaction analysis per coalition for 20 PUs and 40 PUs for the proposed model and the LBC model. A fairness performance comparison is done for the SH-PSO and LBC models. Finally, we analyze the models' complexity by computing the running times of the clustering phase of the distributed models.

3.7.1 Network performance analysis

In this subsection, we compare the network performances of the SH-PSO, LBC, and ED-WWF models. Figure 3.3 shows the network throughput as a function of the number of PUs varying from 10 to 60. As can be seen, the highest throughput is achieved by the proposed model.

Table 3.3 Parameter Settings

Network Configuration		
Name	**Description**	**Value**
N_s	Number of Subcarriers	256
P_{MC}^{Total}	Transmitted power per MC	60 dBm
P_f^{Total}	Transmitted power per FC f	10 dBm
r_{MC}, r_f	Macrocells and femtocell radius	500 m, 20 m
θ_f, θ_{MC}	Attenuation factor of indoor and outdoor	3, 3.7
γ_{MC}, γ_f	Spectral efficiency for MC or FC f	(2, 4), 6
W_l	Wall loss penetration	-3 dB
f_c	Carrier frequency	2300 MHz
N_0	Noise	-174 dBm/Hz
$\|SU\|$	Number of subscribers per FC f	1
$\|PU\|$	Number of public users	5-60
N_f	Number of deployed femtocells	10
PSO Parameters		
Name	**Description**	**Value**
c_1	Cognitive knowledge parameter	2.0
c_2	Social interactions parameter	1.5
ω	Inertia	0.85

In this particular scenario, starting from 30 PUs the SH-PSO model throughput gain is in the range from 25% to 35% compared to LBC model and from 21% to 34% compared to ED-WWF model. Note that starting from 30 PUs the network throughput for the SH-PSO model rises considerably in comparison with the two benchmark models. This increase in the network throughput is due to the fact that in this range of PU numbers all femtocells are within coalitions. Consequently, the users served by femtocells suffer less interference resulting in higher data rates. This also implies that all the subscribers within coalitions increase their throughput since they receive extra-resources and more public users are being served by femtocells in a coalition.

It is important to underline that in the centralized LBC model the traffic load is balanced among the clusters in order to have the same cluster sizes. In our model, the clusters have different sizes

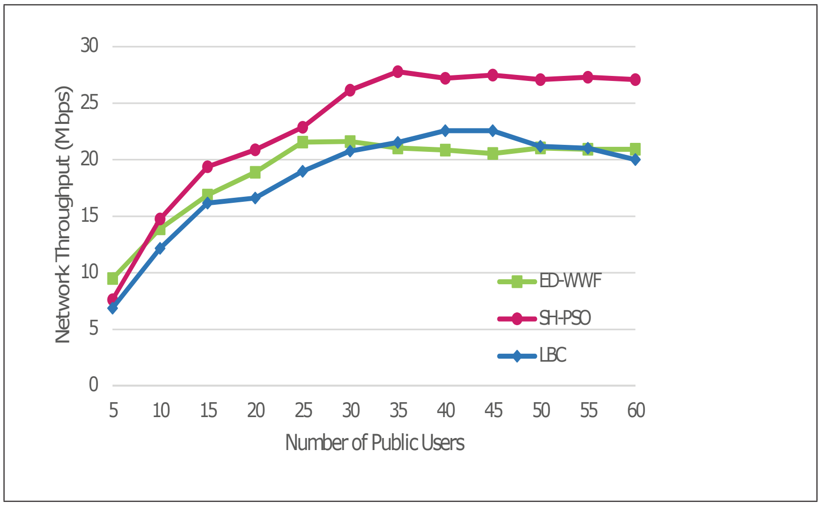


Figure 3.3 Network throughput for SH-PSO, LBC, and ED-WWF models

depending on the achievable stability. This allows increasing the network throughput since more nearby public users can improve their performance by being served by femtocells in a coalition.

3.7.2 Subscribers performance analysis

Here, we analyze the satisfaction of subscribers served by femtocells forming coalitions. We define the subscriber satisfaction as the relation between the assigned data rates and the demanded data rates, see Eq. (3.25). As can be seen from Figure 3.4, the distributed models SH-PSO and ED-WWF give higher satisfaction for subscribers within coalitions in comparison with the centralized model.

In particular, our proposal allows having 100% subscribers' satisfaction starting from 30 PUs due to the fair resource allocation method based on the Shapley value. At the beginning of the clustering phase, with 5 PUs, only 5 femtocells cooperate in the formation of coalitions and the other 5 FCs prefer to work in stand-alone mode causing interference to the femtocells in a coalition resulting in satisfaction below 100%. Nevertheless, starting from 30 PUs more femtocells are joining coalitions, which allows to increase the subscriber satisfaction to 100%. In Figure 3.5, we show the performance of the coalitions in terms of SU satisfaction. The SUs

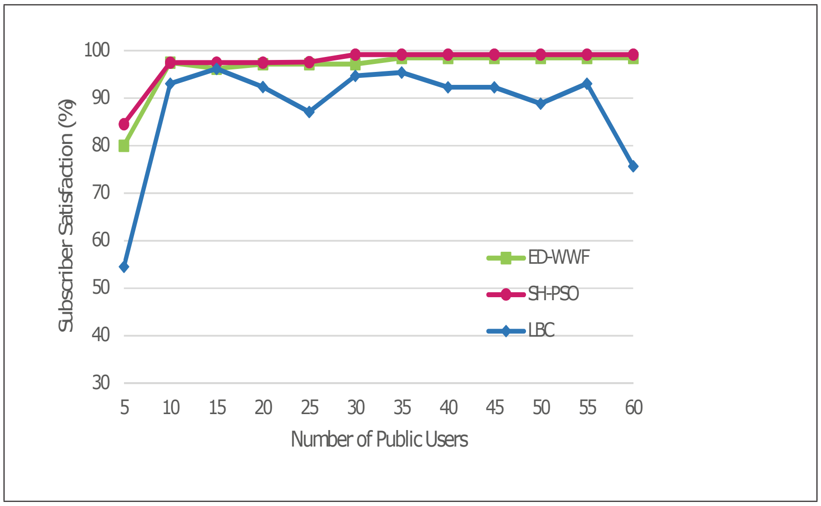


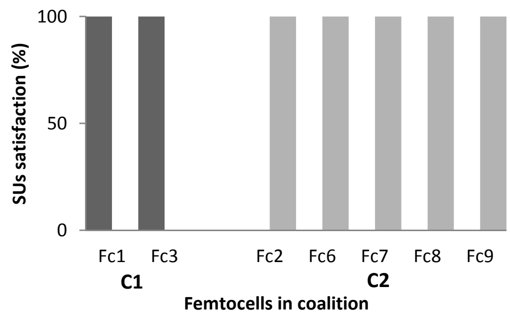
Figure 3.4 Subscribers' satisfaction for SH-PSO, LBC, and ED-WWF models

satisfaction is shown specifically for two cases, namely 20 PUs and 40 PUs. For the case of 20 PUs, we can observe that in the proposed model two coalitions are formed, $c_1 = \{F_{c1}, F_{c3}\}$ and $c_2 = \{F_{c2}, F_{c6}, F_{c7}, F_{c8}, F_{c9}\}$. Then, for the case of 40 PUs, femtocells F_{c4}, F_{c5} and F_{c10} form a third coalition, c_3. All the SUs served by the FCs within these three coalitions have 100% SU satisfaction, as can be seen in Figures 3.5a and 3.5b. This is owing to the fact that the cooperative femtocells are rewarded with extra-subcarriers.

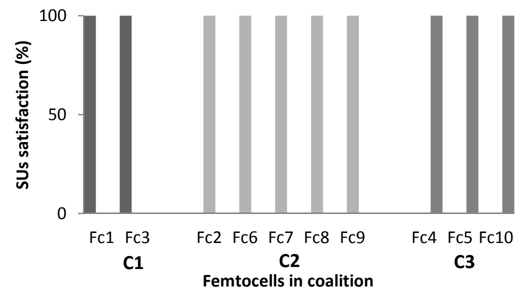
Figures 3.5c and 3.5d present the subscriber satisfaction for 20 PUs and 40 PUs, respectively, for the LBC model. It can be observed that with our proposal more femtocells are in coalition, for both 20 PUs and 40 PUs. In addition, with 20 PUs, the LBC model allows only the subscribers served by F_{c1} to obtain 100% satisfaction, unlike the case of 40 PUs, where all FCs in coalition except F_{c6} obtain a 100% of satisfaction. This is owing to the fact that the proposed model uses a fair resource allocation based on Shapley value for the cooperative femtocells.

3.7.3 Public users performance analysis

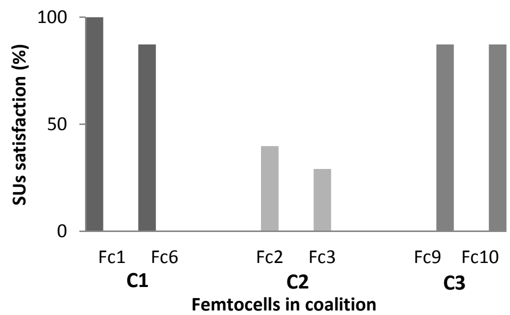
In this subsection, we compare the total PUs throughput, estimated as the sum of the public users data rates, for the SH-PSO and ED-WWF models and the particular case with no coalitions.



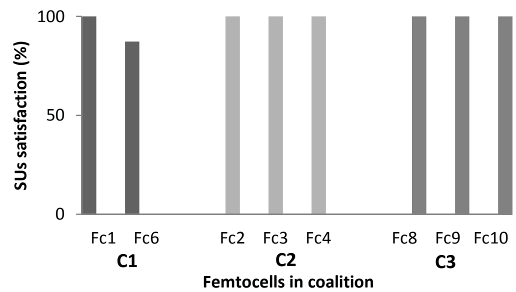
a) SUs satisfaction using SH-PSO model for 20 PUs.



b) SUs satisfaction using SH-PSO model for 40 PUs.



c) SUs satisfaction using LBC model for 20 PUs.



d) SUs satisfaction using LBC model for 40 PUs.

Figure 3.5 Subscriber satisfaction per coalition for the proposed and the LBC models

Figure 3.6 shows that for the SH-PSO and ED-WWF models the PUs throughput is higher in comparison with the no-coalition model. Namely, starting from 30 PUs the SH-PSO model throughput gain is in the range from 38% to 83% and the ED-WWF model throughput gain is in the range from 16% to 44% when compared to the no coalition model. This is because the PUs that cannot be served by the macrocell are being served by nearby femtocells. Note that the SH-PSO model outperforms the no coalition model for more than 15 PUs. This implies that in the no coalition model the first 15 PUs are better served by the macrocell. It can be noticed that in the no coalition model the PUs throughput does not increase when the number of public users increases. This is due to the low link rate conditions among the PUs and the macrocell. In scenarios with coalitions of femtocells, the link rate conditions are improved due to the proximity between FCs and PUs and therefore PUs improve their throughput.

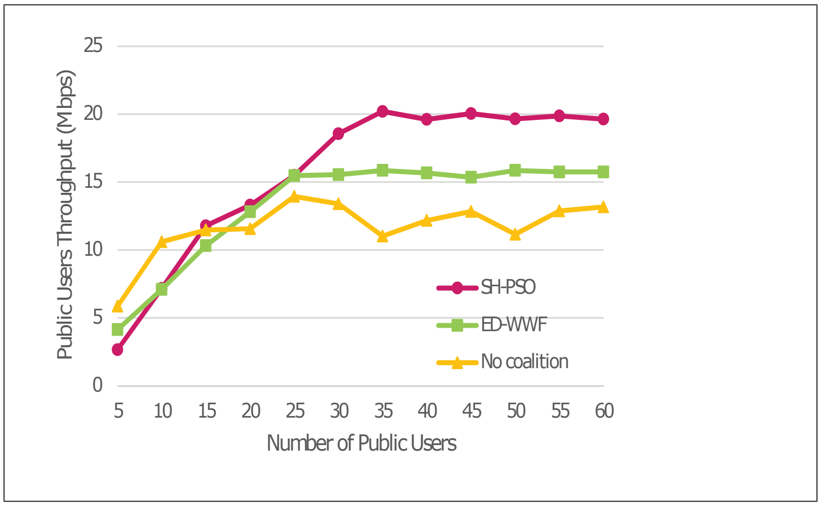


Figure 3.6 Public users' throughput for SH-PSO, ED-WWF, and no-coalition model

3.7.4 Mobile users performance analysis

Here, we analyze the performance of mobile users within a cluster. For this purpose, we show the satisfaction of subscribers and public users that are within the cluster 2, $c_2 = \{F_{c2}, F_{c6}, F_{c7}, F_{c8}, F_{c9}\}$. In this cluster there are 4 subscribers and 9 public users giving a total of 13 mobile users. From Figure 3.7, it can be observed that all mobile users achieve similar satisfaction demonstrating that our solution performs a fair allocation of resources. In particular, the subscribers achieve the highest satisfaction of 100% demonstrating the fair allocation of extra-resources. Moreover, the public users served by femtocells in coalition have a good performance in terms of the achieved satisfaction.

3.7.5 Jain's Fairness Index

We used the Jain's fairness index (Jain *et al.*, 1998) to measure the fairness in the resulting distribution of resources among the users in the femto-tier. From Figure 3.8 we see that the resource allocation using the Shapley value yields better fairness than the centralized resource allocation. This comes from a fair resource allocation applied per coalition in the Shapley value case. Note that the minimum index for the LBC model is 61% while for the SH-PSO model is 70%.

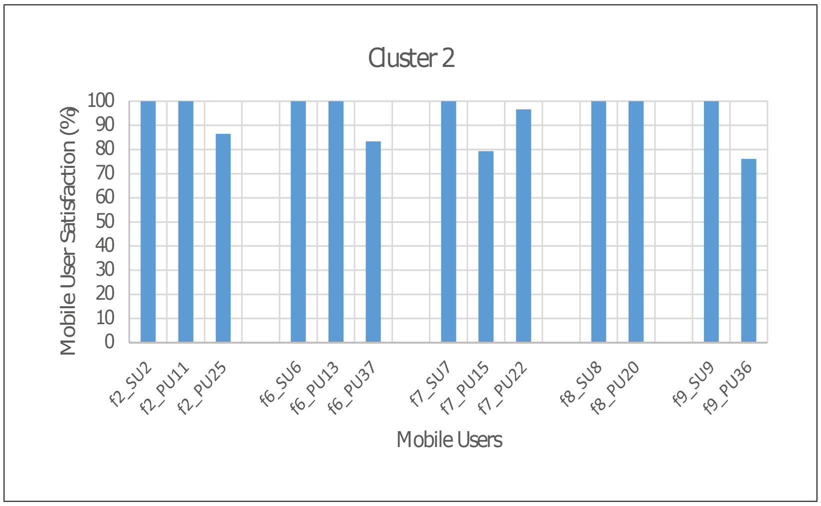


Figure 3.7 Mobile users' satisfaction for SH-PSO model

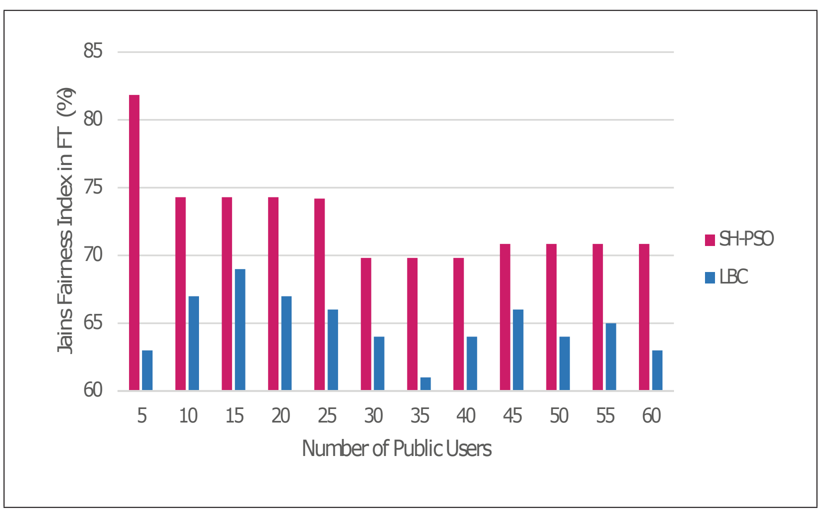


Figure 3.8 Jain's fairness index for users in the femto-tier

3.7.6 Complexity

Table 3.4 reports the computation time associated with the clustering process of the proposed model and the ED-WWF model for different public users density. The first column represents the number of PUs, the second column corresponds to the clustering time using the SH-PSO model, and the third column shows the clustering time of the ED-WWF model.

Note that the running times are significant only for the cases with 10 and 30 PUs. This follows from the fact that only in these cases there is formation of new coalition. In the remaining cases no coalition can increase their utility by admitting stand-alone femtocells and no femtocell can obtain extra-resources to improve the satisfaction of its subscribers so the running time is negligible.

Table 3.4 Running time for the clustering component

PUs	Clustering time (sec)	
Number	SH-PSO	ED-WWF
10	0.241	1.015
20	0	0
30	0.075	0.953
40	0	0
50	0	0

3.8 Conclusions

In this work, a coalitional game to form stable coalitions of femtocells that enhances femto-tier throughput and subscribers' satisfaction is proposed. Femtocells are motivated to join a coalition by the payoff that they receive in terms of extra-subcarriers allocated to their own subscribers. This work also defines stability criteria for hybrid access femtocells and demonstrates that the formed coalitions lie in the ε-core of the proposed game. Moreover, resources are fairly allocated among cooperative femtocells using the Shapley value. Simulations results demonstrate that the proposed model improves the network throughput compared to the benchmark models, and the gain is up to 26% in the considered scenarios. Further, the simulation results show that the subscriber satisfaction increases by rewarding cooperative femtocells. Moreover, with our proposal, the public users' throughput gain is in the range from 60% to 90% compared to the no coalition model. Fairness in the distribution of resources among the femto-tier users is also evaluated with the Jain's Fairness index. The results obtained with the SH-PSO model present a better fairness than the centralized resource allocation model.

CHAPTER 4

EVOLUTIONARY GAME THEORETICAL MODEL FOR STABLE FEMTOCELLS' CLUSTERS FORMATION

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4.1 Abstract

Femtocell deployment is one of the key solutions to achieve the high data rate of the fifth generation mobile communication. Nevertheless, dense femtocell networks face several challenging tasks such as interference control and resource management. In this paper, we address the problem of resource allocation for dense femtocell networks by forming stable clusters using an evolutionary game where femtocells learn from the environment and make their decisions considering the achieved payoff. In order to guarantee the cluster stability, we use the replicator dynamic that finds the evolutionary equilibrium of the evolutionary game. In addition, Particle Swarm Optimization (PSO) is used for the resource allocation algorithm that runs locally within each cluster owing to the fact that PSO has been proved to find a satisfying near-optimal solution while having the advantage of speeding up the optimization process. We run simulations for non-dense and dense femtocell networks taking into account two scenarios: fixed public users and public users that keep mobility such as pedestrians or cyclists. Simulation results show that the proposed solution is able to enhance the network throughput, to provide higher subscribers satisfaction, and to reduce the co-tier interference in dense femtocell networks.

Keywords: Clustering, dense femtocell networks, evolutionary game theory, PSO, replicator dynamics.

4.2 Introduction

Fifth generation mobile communication (5G) has three targets to achieve: high data rates, low latency, and wide connectivity. These targets can be addressed by key technologies, such as heterogeneous networks (HetNets), massive multiple-input multiple-output (MIMO), and millimeter wave (mmWave) techniques Liu, Wang, Chen, Elkashlan, Wong, Schober & Hanzo (2016). HetNets, that comprise macrocells and small cells such as femtocells, are a cost-effective solution to tackle the increasing demand for network capacity. However, with increasing number of mobile users with random velocities In HetNets, attention should be drawn to the fact that the users will tend to move from one base station to another more frequently. In addition, the resources in each tier should be properly allocated considering that the number of femtocells will eventually increase.

The deployment of femtocells (FCs) in the macrocell coverage area is a promising and efficient solution owing to the fact that frequency bands can be reused between the macrocell and the femtocells. Furthermore, femtocells increase the coverage area in dead zones of indoor environments, consume less energy than macro base stations (MBSs), and improve the system capacity when the number of femtocells increases. However, it should be noticed that femtocells are mostly deployed by end users without prior planning, which generates interference among femtocells also known as co-tier interference. The co-tier interference can be increased dramatically if the resources are not adequately managed within neighboring femtocells. Another type of interference, produced between tiers, is known as the cross-tier interference, where femtocell subscribers can be interfered by public users (PUs), that are not subscribed to nearby femtocells because they are unauthorized to connect to these femtocell or because these femtocells have no available capacity. The public users can also be interfered by nearby femtocells in the downlink communication.

Femtocell access control mechanisms are used to determine if public users are authorized to access this femtocell or not. The access control categories are: closed, open, and hybrid (Zhang, 2010). In the closed access case, the public users cannot access the nearby femtocells but they can generate interference that affects the downlink communication of the subscribers. The open access category allows any user to benefit from FCs' services. This approach requires tight coordination between FCs and their macrocell that may result in traffic congestion over the backhaul connections. In the hybrid access case, a public user can access a nearby FC but some capacity of this FC is reserved for its FC's subscribers. This approach can combine the benefits of the two previous access control categories and overcome their limitations. Due to this potential, in this paper we consider the hybrid access control.

The underlying challenges for resource allocation in HetNets have been already treated in several existing research Bezzina *et al.* (2016); Deng, Li, Chen, Zeng, Wang, Zhou & Choi (2018); Liu, Zhang, Chan, Li & Guan (2019); Qiu *et al.* (2016); Rohoden *et al.* (2018); Yu, Han & Li (2018); Zeng, Li, Xiao, Havyarimana & Bai (2018); Zheng, Cai, Liu, Xu, Duan & Shen (2014); Zheng, Wu, Zhang, Zhou, Cai & Shen (2017). Nevertheless, there are still some outstanding issues related to stability, complexity and payoffs of the femtocell cluster based solutions. In this paper we address these issues by proposing a resource allocation solution on femtocell clustering that uses an evolutionary game enabling femtocells to switch clusters to obtain a higher payoff. This evolutionary game considers a scenario with dense-femtocell deployment and a random walk mobility model. Initially, a set of femtocell clusters is formed using the K-means algorithm. Then, public users are allocated to nearby femtocells depending on their demanded data rate. This allows to determine the payoff of every cluster and consequently the average payoff of all clusters. At this point, our evolutionary game determines the set of stable clusters by using the replicator dynamic, i.e. set of clusters with a payoff similar to the average payoff. Finally, a distributed resource allocation algorithm will run locally within every cluster using the Particle Swarm Optimization (PSO) technique.

4.2.1 Motivational Scenario

In game theory, it is often assumed that all players have knowledge of all network information at every moment. In this case, each user has to exchange large amounts of information, which makes game theory not suitable for large-scale networks. To cope with this issue, one can apply the evolutionary game theory where it is assumed that players have bounded rationality, which reduced the complexity and makes it suitable for densely-deployed femtocell networks. These characteristics allow players to adapt their strategy to obtain a higher payoff by replication. In addition, strategies that are more fruitful dominate over time which leads to evolutionary equilibrium.

Motivated by the characteristics of EGT presented in the previous paragraph, we propose a model that provides stable clusters by means of the replicator dynamic. This is the main contribution of this work that also constitutes the main difference when compared to the Load-Balanced Clustering (LBC) model (Estrada *et al.*, 2016), which is used as a benchmark model. The LBC model proposed the grouping of femtocells into clusters of similar size with no guarantee of stability as can be seen in the example illustrated in Table 4.1. The table shows the payoff per cluster and the average payoff of all clusters obtained with the LBC model. According to the replicator dynamic, the stability is achieved when all formed clusters tend to have payoffs equal to the average payoff of all clusters (Taylor & Jonker, 1978) but Table 4.1 shows that the LBC model does not reach this condition. In particular the payoff of the fourth cluster is always below the average payoff (see the highlighted column in Table 4.1). In contrast, our model uses the replicator dynamic as the stability criteria that is explained in Section 4.5.2.

4.2.2 Contribution

In our previous work Rohoden *et al.* (2019), a stable cluster formation of femtocells was proposed based on a coalitional game and the e-core concept stability criteria where neither mobility and dense femtocell deployment were considered. Thus, the main goal of this work is to maximize the throughput of the femto-tier by means of a cluster based resource allocation approach for

Table 4.1 Payoff per cluster for 10 femtocells using the LBC model

Iterations	**Payoff per cluster c**					
	$\mathbf{c_1}$	$\mathbf{c_2}$	$\mathbf{c_3}$	$\mathbf{c_4}$	$\mathbf{c_5}$	**Avg. payoff**
1	2.09	1.02	2.22	1.01	1.99	1.88
2	1.99	2.37	2.58	1.11	2.03	2.13
3	2.89	2.62	1.70	1.41	1.57	1.97
4	2.38	2.27	1.81	0.96	2.11	1.97
5	2.83	2.37	1.87	1.21	2.14	2.13
6	3.06	2.47	2.32	1.16	1.72	2.18
7	2.23	2.27	1.93	1.06	2.14	1.99
8	2.39	2.57	1.85	1.26	2.21	2.08
9	2.47	2.47	2.13	1.41	1.58	1.99
10	2.44	2.52	1.54	1.16	2.27	1.99

dense femtocell networks using an evolutionary game to form stable clusters. To the best of our knowledge, the majority of the previous cluster based resource allocation approaches do not guarantee the stability of the clusters in dense femtocell networks. The main contributions of this work are:

- Application of an evolutionary game to form femtocells clusters that reduces the complexity of resource allocation in dense-femtocell networks, in such a way that the resource allocation algorithm based on the PSO technique can run locally within each cluster.
- Use of the replicator dynamic of the evolutionary game theory to guarantee the clusters' stability and to avoid the reallocation of resources due to the constant changes in the cluster configuration.
- Analysis of the system performance when a mobility model is considered for public users in dense-femtocell networks.

The rest of this paper is organized as follows. Section 4.3 describes the related work. The system model, problem formulation, and user mobility are presented in Section 4.4. Section 4.5 details the fundamentals concepts of the evolutionary game theory, the replicator dynamic, and the stability concept. The main components of the proposed model for clustering and resource allocation, and the benchmark models are explained in Section 4.6. The simulation results are discussed in Section 4.7. Finally, Section 4.8 concludes the work.

4.3 Related work

To solve the resource allocation in a macro-femtocell network, several approaches that work with clustering techniques have been proposed. In Bezzina *et al.* (2016), the clustering is performed based on femtocells positions. Specifically, the K-means algorithm executes an iterative data-partitioning algorithm based on a given cluster size and cluster number. Then, the resource allocation takes into account QoS requirements and cross-tier interference. In Qiu *et al.* (2016), interfering femtocells are grouped into clusters while the subchannel allocation is performed by a cluster head, the femtocell with the highest degree of interfering neighbors. In Li & Zhang (2018), the channel allocation problem is performed by using the cluster topology for high density networks. In this case, based on the K-means algorithm, femtocells are divided into different clusters that can self-adapt to a dynamic network topology.

Recently, the resource allocation problem has been tackled by game theory and evolutionary game theory models. In Yu *et al.* (2018), a robust Stackelberg game that aims to achieve robust equilibrium is proposed for the resource allocation considering the macro-base stations demanded capacity. In Cao *et al.* (2018) a centralized user-centric merge-and-split rule based coalition formation game is proposed to estimate interuser interference. Interference management based on hierarchically joint user scheduling and power control is proposed in Sun, Wang, Sun & Zhang (2018) to alleviate co-channel interference. Further, a Stackelberg game is formulated between macro base station and femtocell base stations in order to determine the optimal transmission power.

An evolutionary game is proposed to develop an energy efficient subcarrier allocation method. The authors consider the height of base station's antenna and secondary users, the total data transmission rate limit, total power consumption constraint and power consumption constraint on a single carrier Zhang, Chen, Cui & Zhang (2018). In Feng, Song, Han, Dusit & Zhao (2013), EGT is applied to cell selection in two-tier femtocell networks with different access methods and coverage area. In Lin *et al.* (2015), a centralized evolutionary game theoretic framework is proposed to form balanced femtocell clusters based on a distributed power control, a bankruptcy channel allocation, and an evolutionary clustering. In Saha & Vesilo (2018), a novel threshold pricing scheme is presented for offloading macro users to small cells. Based on an evolutionary game model, the behavioral dynamics of the macro users under two pricing strategies is analyzed. Distributed resource allocation is addressed with EGT in Semasinghe *et al.* (2015). The authors proposed two game models based on the achievable signal-to-interference-plus-noise ratio (SINR) and data rate. In P.Azadeh *et al.* (2019), BS allocation problem is modeled as an evolutionary game with QoS guarantee. In addition, a distributed learning-based algorithm is proposed to demonstrate the convergence to the evolutionary equilibrium.

The main limitations of the prior related work can be summarized as follows:

1. Most of the previous approaches propose a solution for femtocells working in closed access mode (Bezzina *et al.*, 2016; Chandrasekhar & Andrews, 2009a). This is not suitable for public users that are nearby the coverage area of femtocells since the access to these femtocells is not granted. Thus, public users will try to connect to the MBS resulting in a large increase of the cross-tier interference.
2. Lack of femtocell cluster formation algorithms that guarantee the stability of the clusters. Cluster stability is a very important issue since it prevents the femtocells from abruptly changing from existing cluster to another one, which would lead to an unstable network.
3. Not taking into account the mobility of public users in the resource allocation approaches for dense femtocell networks. In a dense-femtocell network, the number of public users changing from one femtocell to another or from a femtocell to a macrocell or vice-versa increases with the users' mobility and this can cause instability in the network.

To overcome the above limitations, we propose a distributed resource allocation framework that maximizes the femto-tier throughput while enhancing the satisfaction of femtocell subscribers.

The proposed solution focuses on the clustering of femtocells based on an evolutionary game model where stability is achieved by using the replicator dynamic. The main reason for using EGT is the reduced amount of information that would be exchanged among femtocells which makes it suitable for dense femtocell networks.

We previously addressed the resource allocation in macro-femtocell networks in Rohoden *et al.* (2016) using an equal distribution of the resources among femtocells within a cluster. However, this method does not guarantee the same subscriber satisfaction for the cooperative femtocells. Our latest work, Rohoden *et al.* (2019), tackled the resource allocation issue with a coalitional game that groups femtocells into clusters. In addition, Shapley value was used to guarantee the fairness distribution of resources and stability was demonstrated by means of the e-core concept. The main differences between the current work and our prior works, Rohoden *et al.* (2016) and Rohoden *et al.* (2019), are the evolutionary game used to group femtocells into clusters and the stability criteria based on the replicator dynamic. In addition, the present work analyzes scenarios with and without mobility for public users by means of a mobility model to assign random speed to the public users. It is also worth noting that our proposal evaluates the system performance in a dense femtocell network.

4.4 System model

We consider the downlink transmission of an OFDMA macro-femtocell network with several femtocells, FCs, deployed under the coverage area of a macrocell, MC, as illustrated in Fig. 4.1. Let $F = \{F_1, F_2, ..., F_f, ..., N_F\}$ be the set of femtocells and $|F| = N_F$. The set of available subcarriers is denoted as $SC = \{S_1, S_2, ..., S_s, ..., N_S\}$ and B_s denotes the bandwidth of each subcarrier. In order to eliminate the cross-tier interference, SC is partitioned into two disjoint sets, SC_{macro} and SC_{femto}, in such a way that their intersection is the empty set and their union is SC. These two disjoint sets represent the set of subcarriers for the macro-tier and the femto-tier, respectively.

For convenience, in this paper we assume that each femtocell can grant service to one subscriber so the femtocell obtains more resources from the macrocell than in the case of FCs having multiple subscribers. However, it should be underlined that our approach is still valid for the cases with more than one subscriber per femtocell. It is assumed also that femtocells use the hybrid access mode allowing them to grant service to nearby public users. The demanded data rate for subscribers and public users is randomly generated.

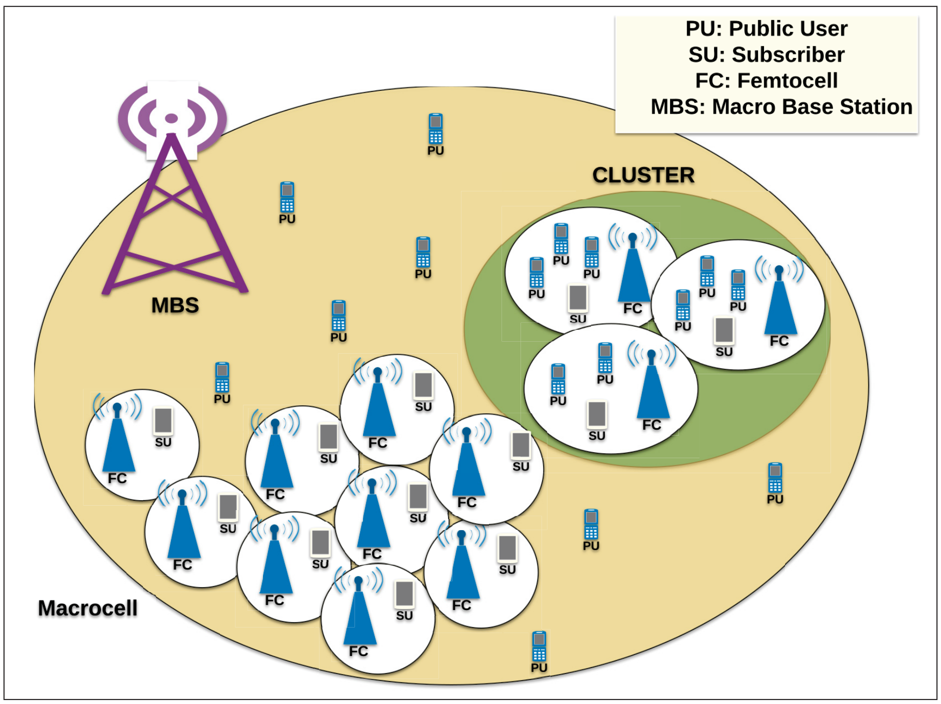


Figure 4.1 Example of a dense macro-femtocell network with 3 femtocells forming a cluster and 9 stand-alone femtocells. SU and PU represent the subscribers and public users, respectively

4.4.1 Problem formulation

In this work, we focus on the resource allocation for subscribers and public users served by femtocells within a cluster. In the proposed scenario, femtocells join a cluster through a clustering algorithm based on evolutionary game theory. A set of subcarriers are allocated to each cluster and they can be reused among different clusters. The set of clusters and mobile users are represented by $C = \{C_1, C_2, ..., C_c, ..., N_C\}$ and $MU = \{U_1, U_2, ..., U_u, ..., N_U\}$, respectively. In addition, the set of femtocells within a cluster c is denoted as F^c.

The SINR at mobile user u being served by femtocell f for the subcarrier s is given by

$$SINR_u^{f,s} = \frac{\alpha_u^f P_u^{f,s}}{PL_u^{f,s} \times (\sigma + \sum\limits_{h \in \{C \backslash c\}} \sum\limits_{f \in \{F^h\}} I_u^{f,s})}; f \in F^c, u \in MU \tag{4.1}$$

where $P_u^{f,s}$ is the transmitted power from femtocell f to user u in subcarrier s, $PL_u^{f,s}$ is the path loss, $I_u^{f,s}$ represents the interference generated for users within clusters h, and σ is the noise power. In our model, the interference source for the femto-tier is the inter-cluster interference that is represented by the second term of the denominator in Eq. (4.1).

The propagation model used to estimate the SINR ratio is similar to the one presented in our previous work Estrada *et al.* (2013a), and is given by:

$$PL_u^{f,s}(dB) = 10log_{10}(d_{uf}) + 37 \tag{4.2}$$

where d_{uf} is the distance (in meters) from user u to femtocell f in accordance with the carrier frequency used for femtocells ITU (1997).

The achievable data rate of mobile user u served by a femtocell f in subcarrier s is represented by

$$R_u^{f,s} = \alpha_u^f \cdot \beta_u^{f,s} \cdot Bs \cdot log_2(1 + SINR_u^{f,s}) \tag{4.3}$$

where α and β are the binary variables that represent user base station association and subcarrier allocation per user, respectively. In other words, α_u^f determines if user u is served by femtocell f while $\beta_u^{f,s}$ indicates if subcarrier s is allocated to user u in femtocell f.

In Abdelnasser *et al.* (2014), the authors determined that the potential number of clusters is given by the Stirling number of the second kind (Bell number), which grows exponentially with the number of femtocells where the complexity is defined as $O(f^f)$. To reduce the complexity, we decompose the maximization problem into two sub-problems: the clustering sub-problem that forms the femtocell groups and the resource allocation sub-problem that maximizes the throughput of each cluster. It is worth noting that our approach finds a satisfying near-to-optimal solution within each cluster through the use of the PSO algorithm that is used for the resource allocation.

The clustering sub-problem is solved by using an evolutionary game where the femtocells are considered as players of the game. In this game, the femtocells' allocation evolve towards balanced clusters with payoffs close to the average payoff using Algorithm 4.1. The goal of the clustering is to allocate resources within each cluster, to improve the femtocells' performance, and to reduce the inter-cluster interference. As result, the femtocells increase their subscriber's rate owing to the fact that they receive more subcarriers by granting access to nearby public users. Thus, the increase of the network' throughput is guaranteed by the increase of every cluster's throughput. In addition, our solution focuses on forming stable clusters. To accomplish this task, we use a stability criterion based on the replicator dynamic of the evolutionary game theory. Therefore, when stability is reached, the solution that maximizes the throughput of each cluster is equivalent to maximizing the sum of the throughputs of all clusters, since the clusters do not change constantly.

On the other hand, the resource allocation-subproblem, that considers the maximization of the throughput within a cluster c formed by the subset of femtocells F^c, is run by each cluster head using Algorithm 4.2. The cluster head is the femtocell with the highest number of neighboring femtocells and it is responsible for the resource allocation among all the members of the cluster.

The objective function is formulated as follows:

$$\begin{aligned}
\max_{\alpha,\beta,\mathbf{P}} \quad & \sum_{u\in MU}\sum_{f\in F^c}\sum_{s\in SC}\alpha_u^f\cdot\beta_u^{f,s}\cdot Bs\cdot log_2(1+SINR_u^{f,s}) \\
\text{subject to} \quad & C1:\sum_{f\in\{F^c\}}\sum_{s\in\{SC\}}\beta_u^{f,s}\leq 1; u\in MU, \\
& C2:\sum_{f\in\{F^c\}}\sum_{u\in\{MU\}}\sum_{s\in\{SC\}}\alpha_u^f\beta_u^{f,s}\leq \\
& N_S-\sum_{u\in\{MU\}}\sum_{s\in\{SC\}}\alpha_u^{MC}\beta_u^{MC,s} \\
, \quad & C3: log_2\left(1+SINR_u^{f,s}\right)\geq\alpha_u^f\beta_u^{f,s}\gamma_f; \\
& u\in MU, f\in\{F^c\}, s\in\{SC\}, \\
& C4:\sum_{f\in\{F^c\}}\alpha_u^f\leq 1; u\in MU, \\
& C5: B_s\times\sum_{s\in\{SC\}}\beta_u^{f,s}\gamma_f^s\geq\alpha_u^f\times D_u; u\in MU.
\end{aligned} \tag{4.4}$$

Constraint C1 guarantees that a subcarrier being used in the macro-tier is not used by any cluster in the femto-tier. Constraint C2 represents the upper bound for the subcarriers allocated to the cluster c. Constraint C3 provides that the spectral efficiency achieved by a mobile user u within a cluster has to be higher or equal to a target spectral efficiency (γ_f). Constraint C4 guarantees that one user is assigned to only one base station. Constraint C5 defines the lower bound for minimum data rate for mobile users.

In order to reduce the resource allocation complexity for macro-femtocell networks, we propose to use cluster formation techniques. The optimal cluster configuration can be found by applying an exhaustive search. However, an exhaustive search would require long running times since the number of possible cluster configuration increases as the numbers of femtocells increase. The total number of disjoint clusters of femtocells can be derived using the Stirling Partition number

C.S. K. Bogart (2006), which is given by

$$C^{total} = \sum_{j=1}^{|F|} \frac{1}{j!} \sum_{i=0}^{j} (-1)^{j-i} \binom{j}{i} i^{|F|} \tag{4.5}$$

4.4.2 User Mobility

The mobility of public users is modeled using the Random Walk Mobility model. Random Walk was proposed to mimic the movement behavior of mobile nodes which are considered to move in an unexpected way. It is a memoryless model where the information of the previous velocity and direction is not retained Roy (2010).

The main characteristics of Random Walk Mobility are summarized as follows:

- The speed and direction of the nodes are changed each time interval and it has zero pause time.
- Speed $v(t)$ is chosen from previously defined ranges $[V_{min}, V_{max}]$ by each node which follow a uniform distribution or Gaussian distribution.
- The direction $\theta(t)$ is also chosen by each node from the ranges $[0, 2\pi]$.
- Every movement is made either in constant time interval t or in constant distance traveled d.
- During time t, the node moves with the velocity vector $[v(t)\cos(\theta(t)), v(t)\sin(\theta(t))]$.

According to Zhang, Wen, Wang, Zheng & Sun (2010), the users velocities are classified as low (from 0 to 15 km/h), medium (from 15 to 30 km/h), and high (above 30 km/h). In the present work, we considered low velocities for the public users.

4.4.3 Model Parameters

Table 4.2 presents the basic parameters used in the proposed model. The parameters are classified into three categories: system, input, and output parameters. The system parameters describe the network features. The users' requirements and locations are presented as the input parameters. The output parameters are the set of stable clusters and the bandwidth and power allocated to all users.

Table 4.2 Model Parameters of the k-EGT model

System Parameters	
Symbol	**Description**
C	Set of clusters
SC	Set of available subcarriers
MU	Set of mobile users
F	Set of deployed femtocells
F^c	Set of FCs in cluster c
B_s	Bandwidth per subcarrier
BW_c	Bandwidth reserved for the clusters formation
N_F	Number of femtocells
N_C	Number of clusters
N_S	Number of subcarriers
P_f^{total}	Total transmitted power in femtocell f
r_{MC}, r_f	Radio in macrocell and femtocells
γ_f^s	Subcarrier s spectral efficiency in femtocell f
γ_f	Target subcarrier spectral efficiency in femtocell f
f_c	Carrier frequency adopted by the MC (in MHz)
σ	Average thermal noise power
$x_{f,c}$	Individual payoff of FC f in cluster c
$v(t)$	Users' velocity
Input Parameters	
R_{SU}^f	Subscriber data rate demands in FC f
R_{PU}^f	PU data rate demands in FC f
D_u	Requested data rate demand of mobile user u
d_{uf}	Distance from mobile user u to FC f
$\alpha_u^M C$	User u assigned to MC
$\beta_u^{MC,s}$	Subcarriers s allocated to user u in MC
Output Parameters	
α_u^f	User u is assigned to BS f
$\beta_u^{f,s}$	Subcarrier s allocated to user u infemtocell f
$P_u^{f,s}$	Transmitted power in DL transmission betweenfemtocell f and user u
$R_u^{f,s}$	Data rate allocated to MU u served by femtocell f in subcarrier s

4.5 Evolutionary game theory fundamentals

Evolutionary game theory was proposed by John Maynard Smith who adapted the traditional game theory to the concept of evolution by natural selection. In brief, evolutionary game theory models the behavior of large populations of individuals with bounded rationality. In traditional game theory, the strategies are fixed while in evolutionary game theory strategies evolve. In our case, the populations of individuals corresponds to the population of femtocells. In particular, the femtocells observe the behavior of other femtocells and make decisions based on their payoff and the average payoff of all other femtocells. Therefore, femtocells will be tempted to choose those strategies that give better payoffs. In this manner, those strategies will predominate with time.

Definition 1 - Evolutionary Game: An evolutionary game can be defined as $G=(F,S,\pi^f(S_k)_{f\in F,S_{k\in S}})$ where F is the set of players (femtocells in our case), which constitutes the population in an evolutionary game; S is the set of all strategies available to each player that is defined as $S = \{S_k\} = \{a_1, a_2\}$ where actions a_1 and a_2 refer to staying in the femtocell current cluster and to switching to another cluster, respectively, and $\pi^f(S_k)$ is the femtocell f payoff, at time $t+1$, obtained by using strategy k at time t.

Payoff function: The payoff of femtocell f is defined as

$$\pi^f = \sum_{u\in MU} \sum_{s\in SC} \alpha_u^f R_u^{f,s} \tag{4.6}$$

where α_u^f is the binary variable that determines if user u is served by femtocell f and $R_u^{f,s}$ is the allocated data rate of mobile user u served by a femtocell f in subcarrier s. The main goal of a femtocell is to maximize its throughput represented as payoff, Eq. (4.6). Thus, evolutionary game theory allows a femtocell to leave the current cluster and choose another cluster that increases its payoff. As a result, the femtocell cluster allocations evolve to balanced clusters where femtocells tend to have payoffs equal to the average payoff of the whole population. The average payoff of all clusters is defined as

$$\bar{\pi} = \frac{\sum_{c \in C} \pi_c}{|C|} \tag{4.7}$$

where $|C|$ is the total number of clusters and π_c is the payoff of cluster c defined as

$$\pi_c = \sum_{f \in F^c} \pi^f \tag{4.8}$$

4.5.1 Evolutionary Stable Strategy (ESS)

Evolutionary Stable Strategy is a stability concept that was also proposed by John Maynard Smith for populations of individuals sharing a common behavioral characteristic. ESS was presented for a monomorphic population, where every individual adopts the same strategy. According to Saha & Vesilo (2018), ESS makes the following assumptions:

- Players choose their strategies from identical sets.
- The payoff to a player choosing a particular strategy against a competitor choosing another strategy is the same regardless of the characteristics of the players.
- Players cannot condition their choice of strategies based on any characteristics of players.

Consider player f using a strategy S_k and its expected payoff $\pi^f(S_k, \hat{S})$ considering that $\hat{S}$ is the strategy used by another player. Then, ESS for a monomorphic population is defined as

Definition 2 - Evolutionary Stable Strategy: A strategy S^* is an ESS if and only if for all $S_k \neq S^*$ we have

$$\pi^f(S_k, S^*) \leq \pi^f(S^*, S^*) \tag{4.9}$$

$$\pi^f(S_k, S_k) < \pi^f(S^*, S_k) \quad \text{if} \quad \pi^f(S_k, S^*) = \pi^f(S^*, S^*) \tag{4.10}$$

where $\pi^f(S_k, S^*)$ refers to the payoff for the player using strategy S_k. Condition 4.9 implies that strategy S^* is the best response to itself. It defines the equilibrium condition while condition

4.10 defines the stability condition. The latter states that if a mutant strategy, S_k, is an alternative best response against the incumbent strategy, S^*, then the average payoff of S^* is higher than the average payoff of S_k.

ESS focuses on a static definition to capture the dynamic process of natural selection. However, models of natural selection are more likely to be dynamic, i.e. based on theories of dynamical systems and stochastic processes. In this sense, Taylor & Jonker (1978) defined the replicator dynamic that is the most important game dynamics studied in EGT.

4.5.2 Replicator Dynamics and Stability Definition

Replicator dynamics studies the dynamic evolutionary games through a differential equation that determines the rate of growth of a specific strategy. An individual from a population is called replicator if it is able to replicate itself through the process of selection. Thus, a replicator with a higher payoff will replicate itself faster. This strategy adaptation process is modeled by using a set of ordinary differential equations called replicator dynamics (Nowak, 2006) defined as

$$\dot{x}_c(t+1) = x_c(t)[\pi_c - \bar{\pi}] \tag{4.11}$$

where $x_c(t) = \frac{|F^c|}{N_F}$ represents the cluster c population share at iteration t, π_c is the payoff of cluster c, and $\bar{\pi}$ is the average femtocell payoff in all clusters.

The replicator dynamics consider the payoff of cluster c, π_c, and the average payoff $\bar{\pi}$ of all clusters. Thus, in order to evaluate the replicator dynamic, each femtocell within cluster c observes its payoff and compares it with the average payoff of all clusters. If its payoff is less than the average payoff of the femtocells in cluster c, it will select a_2 strategy and move out to another cluster. According to the replicator dynamics, the population share or the proportion of femtocells choosing strategy a_2 (leaving the cluster) will increase if the payoff is higher than the average payoff. In addition, the replicator dynamics are used to evaluate the cluster stability. Thus, when the replicator dynamics are equal to zero, $\dot{x}_c(t+1) = 0$, the clusters' stability is achieved since the payoff of each cluster is similar to the average payoff of all clusters, i.e. $\pi_c = \bar{\pi}$.

Consequently, no femtocell will change its strategy and move out of its current cluster since its payoff is equal to the average payoff of all the population.

According to Zhu, Hossain & Niyato (2014), the replicator dynamics gives the connection between the dynamic evolutionary equilibrium (EE) and the ESS. Consequently, the ESS of our evolutionary game can be derived by finding the EE of the replicator dynamics. In the replicator dynamics, there exist the boundary EE and the interior EE. The boundary EE is given when a population share $x_{c_k} = 1$ and thus $x_{c_j} = 0$ for all $j \neq\in S$. On the other hand, the interior EE corresponds to $x^*_{c_k} \in (0, 1), \forall k \in S$. According to our work, $x^*_{c_k}$ is an interior EE of the replicator dynamics. The demonstration is that the payoffs achieved by femtocells within clusters are similar to que average payoff of all clusters. Thus, it is demonstrated that the payoff obtained is strictly higher than the payoff obtained when femtocells decide to keep in the clusters where their payoff is lower than the average payoff. This solution is considered as the Nash equilibrium and since any strict Nash equilibrium corresponds to an ESS Hofbauer & Sigmund (2003), it is demonstrated that our approach can reach the ESS.

4.6 Femtocell clustering based on evolutionary game theory

In this section, the k-EGT framework is presented for the clustering of femtocells in a macro-femtocell network. Initially femtocells are clustered using the K-means algorithm Jain (2010). In addition, the resource allocation is performed within every cluster using a PSO algorithm.

4.6.1 k-EGT framework

The k-EGT framework consists of an initial formation of clusters using the K-means algorithm, an evolutionary game to balance clusters based on the cluster payoffs and a resource allocation carried out using the PSO algorithm. In Table 4.3, we describe the components of the proposed k-EGT framework. Furthermore, a flow diagram showing the k-EGT framework components is presented in Figure 4.2. Specifically, the steps to form evolved clusters of femtocells are

- Initial formation of clusters using the K-means algorithm.
- Evolutionary clustering where femtocells choose to switch clusters or not.
- Distributed resource allocation using the PSO algorithm within every evolved and stable cluster.

Table 4.3 Components of the proposed k-EGT framework

Components	**Description**
Players	Set of femtocells is $F = \{F_1, F_2, ..., F_f, ..., N_F\}$.
Set of Strategies	Femtocells will decide either to switch or not to a new cluster depending on the achieved payoff of their current clusters. The set of possible strategies for each femtocell $S = \{S_k\} = \{a_1, a_2\}$ is defined by possible actions, where a_1 and a_2 refers to staying in the femtocell's current cluster and to switching to another cluster, respectively.
Population Share	The set of femtocells constitutes the population in our k-EGT model. Thus, a portion of the femtocells will join a cluster by choosing the a_2 action while the rest of femtocells will remain in their current clusters by choosing a_1 action. Consequently, the population share of cluster c is given by $x_c(t) = \frac{\lvert F^c \rvert}{N_F}$, where $\lvert F^c \rvert$ represents the number of femtocells within cluster c and N_F is the total number of femtocells.
Payoff function	The payoff of a cluster depends on the throughput achieved for all femtocells within the cluster as explained in Section 4.5.

4.6.2 k-EGT clustering algorithm

This section describes the femtocell clustering using the k-EGT model that is used in Algorithm 4.1. The clustering approach is used to reduce the complexity of the resource allocation in a two-tier network. As already assumed in Section 4.4, the resources are split between macro-tier and femto-tier in order to eliminate the cross-tier interference. Concerning the co-tier interference, it is reduced by clustering since each cluster head optimizes locally the resource allocations.

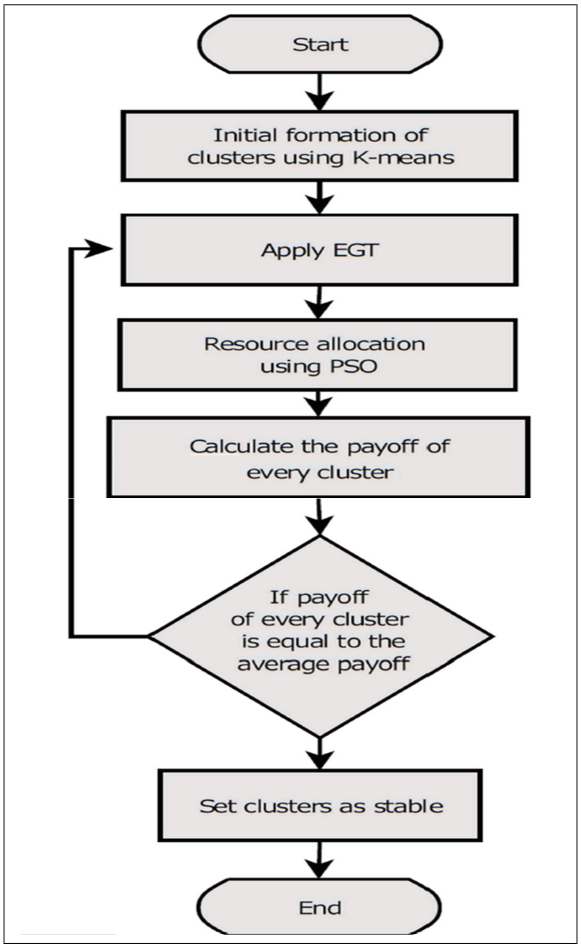


Figure 4.2 Flow diagram of the evolutionary game framework denominated as k-EGT model

To group femtocells into clusters, an initial clustering process is made using the K-means algorithm. The first step of K-means algorithm is to arbitrarily select an initial femtocell partition among N_c clusters. This initial partitioning is based on location points chosen randomly within the femtocells area coverage. These location points, also known as centroids, are treated as cluster centers. Then, each femtocell is allocated to the cluster whose centroid is closest to the femtocell. Then the centroid locations are adjusted based on the current allocation of femtocells to clusters and the allocation process is repeated.

The proposed k-EGT model illustrated in Fig. 4.2 is performed to balance the formed clusters towards stable clusters. To do that, femtocells within clusters with payoffs smaller than the average payoff ($\pi_c < \bar{\pi}$) leave their current clusters and join clusters with payoff larger than the average payoff. This also avoids having overcrowded clusters.The femtocells that leave their current cluster need to choose a cluster from the set of clusters with payoff larger than the average payoff. Consequently, any cluster with $\pi_c > \bar{\pi}$ can be chosen and the selection of a particular cluster is done with probability (Lin *et al.*, 2015) defined as

$$p_c = \frac{\dot{x_c} - x_c}{\sum(\forall h)(\dot{x_h} - x_h)}; \pi_c > \bar{\pi}, \pi_h > \bar{\pi} \tag{4.12}$$

4.6.3 Resource Allocation based on Particle Swarm Optimization

According to our model, a specific amount of the macrocell bandwidth is dedicated to the formation of the femtocell clusters. Consequently, the total number of available subcarriers (Ns) is divided into macro-tier subcarriers and femto-tier subcarriers which eliminates the cross-tier interference. When the clusters are established, the cluster head of every cluster receives information of the corresponding subcarriers for its cluster. Then, the cluster head performs an orthogonal allocation of subcarriers to every femtocell within the cluster based on the PSO algorithm, this orthogonal allocation reduces the intra-cluster interference.

In our previous work, Estrada *et al.* (2016), we demonstrated that a Particle Swarm Optimization (PSO) algorithm gives a satisfying near-optimal solution and speeds up the optimization process. Therefore in our evolutionary approach, the resource allocation within each cluster is based on a PSO based algorithm. PSO has been already used for the resource allocation in OFDMA macrocell systems Gheitanchi *et al.* (2007) and in LTE systems Su *et al.* (2012). In Estrada *et al.* (2013b), it was demonstrated that the resource allocation based on PSO requires between 100 to 1000 iterations to converge to a solution. The implementation of PSO requires relatively small number of code lines due to the use of simple operations. In particular, it takes only one operation to update the velocity and position to coordinate and control the particles movements.

Algorithm 4.1 Evolutionary clustering algorithm

Input: *Initially, clusters are formed using the K-means algorithm. So there are totally N_c clusters.*
Output: *Set of stable clusters, $\beta_u^{f,s}$, $P_u^{f,s}$, R_{SU}^{f}, R_{PU}^{f}*
Step 1 - Cluster Head Selection
for *each cluster $c \in C$* **do**
    Determine the members of the cluster c.
    for *each member of the cluster c* **do**
        Calculate the number of neighbors.
    end
    Select the member that has the maximum number of neighbors as cluster head of cluster c .
end
Step 2 - Evolutionary Cluster Formation
for *each cluster $c \in C$* **do**
    Compute the payoff of the cluster, π_c, based on the demanded data rate of PUs served by FCs within the cluster.
    Compute the average payoff of all the clusters acording to (4.7).
    Evaluate the stability by applying (4.11).
    Determine the set of stable clusters by verifying that the payoff of every cluster is equal than the average payoff.
end
Step 4: Resource Allocation per Cluster
for *each cluster $c \in C$* **do**
    Determine the set of users for the current cluster c.
    Run the PSO based resource allocation algorithm for the mobile users in the cluster.
end

In this technique, no overlapping and mutation calculations are involved. In addition, PSO demands less time to find solutions when compared to genetic algorithms Alkayal (2018).

The PSO algorithm simulates the social behavior of animals living in swarms Kennedy & Eberhart (1995). It initializes with a population of particles where each particle stands for a candidate solution to a problem. PSO has three main attributes: the position in the search space l, the current velocity v, and the best position ever found by the particle during the search process. In order to determine the position and velocity of each particle n at each iteration t, PSO algorithm uses two vectors that are updated based on the memory gained by each particle. Thus, the position l_n^{t+1} and velocity v_n^{t+1} of a particle n at each iteration t are updated as follows:

$$l_n^{t+1} = l_n^t + \delta_t v_n^t, \tag{4.13}$$

$$v_n^{t+1} = \omega v_n^t + d_1 r_1 (p_t^{local} - l_n^t) + d_2 r_2 (p_t^{global} - l_n^t) \tag{4.14}$$

where δ_t is the time step value typically considered as unity (Perez & Behdinan, 2007), p_t^{local} and p_t^{global} are the best ever position of particle n and the best global position of the entire swarm so far, and r_1 and r_2 represent random numbers from interval [0,1]. Moreover, parameters ω, d_1 and d_2 are the configuration parameters that determine the PSO convergence behavior, the values of these parameters are indicated in Table 4.4.
The applied PSO algorithm, Algorithm 4.2, is executed by the cluster head that allocates the bandwidth within each cluster. The selection of the cluster head is based on the maximum number of neighbors that a cluster member has, see Algorithm 4.1.

4.6.4 Benchmark models

We compare our model with four benchmark models. The first one, SH-PSO, is a distributed clustering model that was presented in Rohoden *et al.* (2019). This model employs the PSO algorithm that is performed locally within each cluster. In this model the resources are allocated in a fair manner since the Shapley value is used. The second benchmark model, named as load balanced clustering (LBC) model, is a centralized model that was presented in Estrada *et al.* (2016). It uses the Weighted Water Filling (WWF) algorithm for the resource allocation. Furthermore, the LBC model proposes a femtocell power control to mitigate interference and to achieve a target SINR. The third one, PSO-Dist, proposes a distributed clustering model based on a cooperative game, where femtocells are encouraged to form clusters while being rewarded with resources from the macrocell Rohoden *et al.* (2018). The fourth model named SDN-HAC tackles the femtocell clustering by using a suitable function based on the value of each cluster. In this model, femtocells are considered to work in closed access mode, thus, femtocells only give service to their subscribers Yang *et al.* (2018). The main difference between the proposed

Algorithm 4.2 Resource allocation algorithm

Input: *MU Locations* (l_u, y_u), *Set of femtocell members of the cluster* (F^c), *users demands* (D_u), *BS selection per user* (α_u^f), *bandwidth per cluster* (BW_c).
Output: *Bandwidth and power allocation per user* (b_u, P_u).
for *each* $u \in MU$ **do**
  $b_u^{max} = \frac{D_u}{\gamma_f}$;
  $P_u^{max} = \min(P_u^{max}, SINR_f^{max} \times (\sigma + I_{th}) \times PL_u^f)$;
end
Generate initial swarm with the particle positions and velocities as follows;
$\mathbf{b} = \mathbf{r_1}.\mathbf{b^{max}}$;
$\mathbf{P} = \mathbf{P^{min}} + \mathbf{r_2}.(\mathbf{P^{max}} - \mathbf{P^{min}})$;
$\mathbf{v_b} = \mathbf{r_3}.\mathbf{b^{max}}$;
$\mathbf{v_P} = \mathbf{P^{min}} + \mathbf{r_4}.(\mathbf{P^{max}} - \mathbf{P^{min}})$;
Evaluate Fitness Function;
Determine first global best of the swarm;
while $t \leq MaxIteration$ **do**
  Update Position;
  Evaluate Fitness Function;
  Determine best local for each particle;
  Determine best global in the swarm and update the best global;
  Update velocity;
end

model and the benchmark models is that the proposed model performs an analysis of the cluster stability during the clustering process using EGT. Moreover, the mobility of users in a dense femtocell-deployment scenario is added in this paper.

4.7 Simulation results

In this section, we present and analyse results of MATLAB simulations that were performed to evaluate the proposed evolutionary game theoretic approach. In particular, we show the performance of the model in terms of subscribers' satisfaction, network throughput, interference, and running times for the clustering process. Our results were compared with the two benchmark models described in Section 4.6.4.

In the simulations, we consider two scenarios. The first scenario is a non-dense femtocell network and the second scenario considers the increase of the femtocells number to achieve dense-deployment of femtocells in the network. In the first scenario, the number of PUs varies from 10 to 60 with increments of five users. In this case, 10 femtocells are deployed in an area of 500×500 m. In the second scenario, the number of femtocells increases from 10 to 90 while the number of public users remain fixed. For example, for 10 and 90 femtocells the number of public users is 30 and 270, respectively, considering that the maximum number that a femtocell can grant service is 3. In both scenarios, one subscriber is assigned to each FC with variable demand ranging from 128 Kbps to 1 Mbps. Additionally, a dedicated number of macrocell subcarriers is used for the PUs served by femtocells in clusters. This number is defined as $BW_c = b \times Bs \times Ns$, where b is a value between $[0, 1]$ that represents the portion of available subcarriers used by the femto-tier. Besides the case without mobility, a mobility case, with random velocity of $0 - 4$ m/s for the public users is also considered for both scenarios. Table 4.4 presents the system parameters for the network configuration and the PSO parameters.

The clustering process starts with an initial formation of clusters using the K-means algorithm. In order to form the clusters, the K-means algorithm needs to know the number of clusters to form which is set by giving a value to N_c. The following step in the clustering process is to apply the k-EGT model to the already formed clusters. This k-EGT model is also applied every time the number of PUs increases in the case of the first scenario. In Table 4.5, the entries with times different from zero indicate for which PUs increases there was a need to calculate new cluster formations.

4.7.1 Scenario without mobility

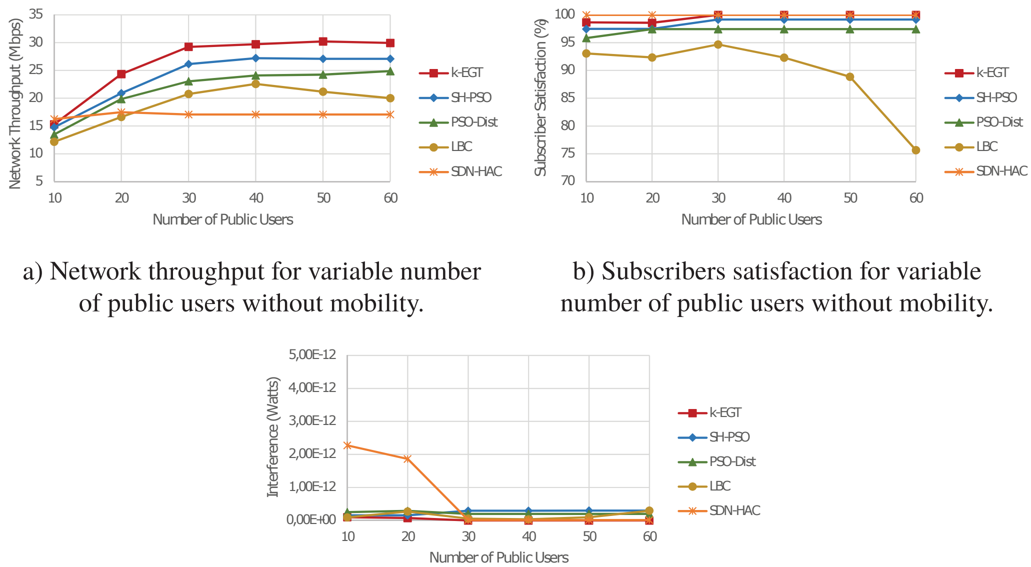
In this section, we analyze the effect of the evolutionary game theory model (k-EGT) on the network throughput, subscribers' satisfaction, and interference for users without mobility. Fig. 4.3a shows the network throughput with the increasing number of public users from 10 to 60 without mobility. As stated before in Section 4.6.2, an initial set of clusters is formed using the K-means algorithm. The number of the initial set of clusters to be formed is defined as $N_c = 5$.

Table 4.4 System and PSO parameter settings

Network Configuration		
Name	**Description**	**Value**
N_s	Number of subcarriers	256
P_{MC}^{Total}	Transmitted power per MC	60 dBm
P_f^{Total}	Transmitted power per FC f	10 dBm
r_{MC}, r_f	Macrocells and femtocell radius	500 m, 20 m
γ_f	Spectral efficiency for FC f	6
W	Wall loss penetration	-3 dB
f_c	Carrier frequency	2300 MHz
σ	Noise	-174 dBm/Hz
$\|SU\|$	Number of subscribers per FC f	1
$\|PU\|$	Number of public users	5-60
N_f	Number of deployed femtocells	10-90
$v(t)$	Users velocity	0 - 4 m/s
PSO Parameters		
Name	**Description**	**Value**
d_1	Cognitive knowledge parameter	2.0
d_2	Social interactions parameter	1.5
ω	Inertia	0.85

Thus, the k-EGT model analyzes the 5 clusters formed with 10 femtocells based on the replicator dynamic. When the number of femtocells increases to 20, there is a new formation of clusters that takes 0.0156 seconds as can be seen in Table 4.5.

The figure demonstrates that the proposed evolutionary game provides higher throughput than the benchmark models (the centralized LBC model and the distributed SH-PSO, PSO-Dist, and SDN-HAC models). In particular, the throughput gain of the proposed model ranges from 25% to 50% when compared to the LBC model, from 3% to 17% when compared to the SH-PSO model, and from 13% to 27% when compared to the PSO-Dist model. It can also be observed that the lowest throughput is achieved with the SDN-HAC model. This is due to that this model considers femtocells in closed access mode, thus, public users far from the MBS and close to clusters of femtocells can not be served by femtocells. Consequently, the network throughput is reduced since that several public users will not be allocated subcarriers and will be blocked.



a) Network throughput for variable number of public users without mobility.

b) Subscribers satisfaction for variable number of public users without mobility.

c) Average interference by subcarrier for variable number of public users without mobility.

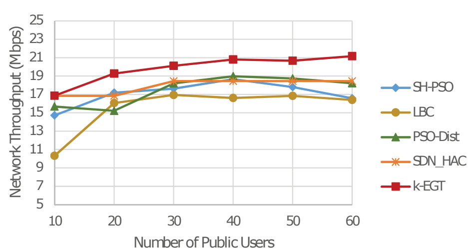
Figure 4.3 Results without mobility incorporated by increasing the number of public users

We define the satisfaction of subscribers as the ratio of the allocated data rate to the demanded data rate of every user. From Fig. 4.3b, it can be seen that our k-EGT model provides the users with higher satisfaction in comparison with the SH-PSO, PSO-Dist and LBC models. Moreover, from 30 PUs, the 100% satisfaction is obtained with the k-EGT model. Furthermore, it is shown that the subscriber satisfaction obtained with the k-EGT model has a gain up to 32% when compared with the LBC model. The subscribers' satisfaction using the SDN-HAC model is 100% from 10 to 60 PUs. This is a consequence of femtocells working in closed access mode and thus the resources allocated to the femtocells are only assigned to their subscribers.

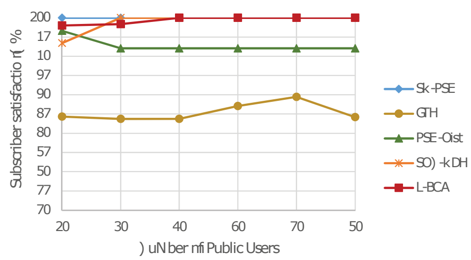
From Fig. 4.3c, we can conclude that the k-EGT model reduces the interference when compared with the interference generated with the SH-PSO, PSO-Dist, SDN-HAC, and LBC models. In particular, starting from 40 PUs, the interference is zero with the k-EGT model.

4.7.2 Scenario with mobility

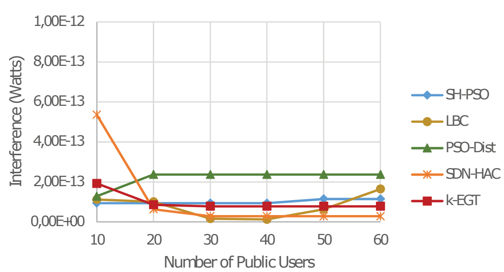
In Fig. 4.4a, we present the network throughput for the scenario with user mobility. As in the case without mobility, the k-EGT model provides higher throughput than the LBC,PSO-Dist, SDN-HAC, and SH-PSO models. Nevertheless, when we compare the network throughput for scenarios with and without mobility, we can observe that higher throughput is obtained when users are static. This is due to the fact that mobile users with higher velocity move out of the nearby femtocell coverage and try to connect to the macrocell.



a) Network throughput using random velocity from 0 m/s to 4 m/s.



b) Subscribers satisfaction using random velocity from 0 m/s to 4 m/s.



c) Average interference per subcarrier using random velocity from 0 m/s to 4 m/s.

Figure 4.4 Results with mobility incorporated by increasing the number of public users

Fig. 4.4b shows that the subscriber satisfaction for the k-EGT and SH-PSO models is similar and is not affected negatively by the users' mobility. For the cases of 10 and 20 PUs, the satisfaction with the SH-PSO model is slightly better than with the k-EGT model due to the fact that in the SH-PSO model subscribers are rewarded with extra-resources. However, the running times for the clustering process of the SH-PSO model are higher than the ones obtained with the k-EGT model, see Section 4.7.5. With regard to the LBC and PSO-Dist models, the k-EGT model provides gain in the range of 35% and 9% of the subscriber satisfaction, respectively. With the SDN-HAC model the subscriber satisfaction is 100% from 20 PUs which is a consequence of femtocells working in closed access mode.

When mobility is added to public users, the interference per subcarrier achieved with our k-EGT model is similar to the interference with the SH-PSO model, see Figure 4.4c. On the other hand, when compared with the LBC model, the interference generated with the k-EGT model is higher. The main reason for this result is that the LBC model applies a power control to mitigate the interference.

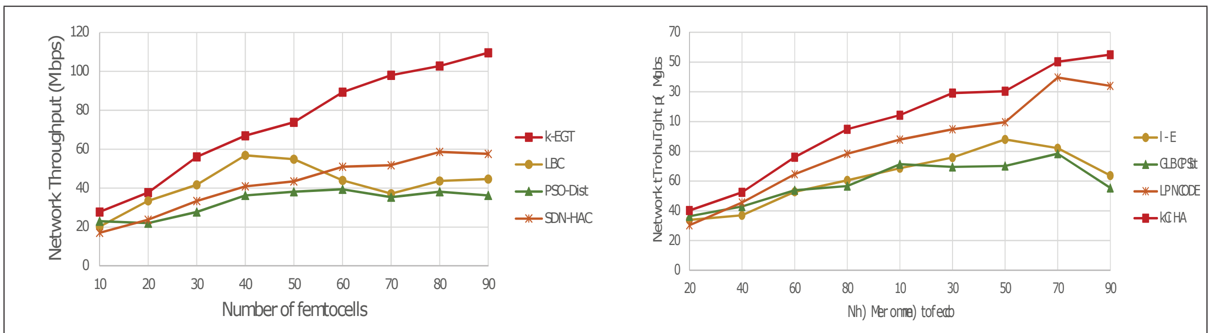
4.7.3 Femtocell dense-deployment

In this section, the network throughput, subscribers' satisfaction, and interference are evaluated for scenarios with and without mobility under a dense-deployment of femtocells. In this case, the k-EGT model is only compared with the centralized LBC model and the PSO-Dist and SDN-HAC models. This is due to the complexity and memory requirements of the SH-PSO model that is prohibitive for Matlab implementation when the number of femtocells is large.

The considered metrics are evaluated by increasing the number of femtocells from 10 to 90. In this scenario, the number of PUs is fixed according to the maximum number of public users that a femtocell can serve, i.e. 3 PUs per femtocell. For example, for 10 and 90 femtocells the fixed number of PUs is 30 and 270, respectively.

For the considered dense-deployment of femtocells, with and without mobility, we conclude that our k-EGT model outperforms the LBC, SDN-HAC, and PSO-Dist models according to the following results. Fig. 4.5a shows that the network throughput of the k-EGT model without mobility is three times higher and four times higher than the throughput obtained with the LBC model and the PSO-Dist model, respectively, while for the case with mobility the k-EGT model gives the network throughput three times higher compared with the LBC and PSO-Dist model, as can be seen in Fig. 4.5b. When compared the k-EGT model with the SDN-HAC model, our model obtains a throughput gain in the range from 8% to 32% and from 63% to 90%, for the scenarios with and without mbility, respectively.

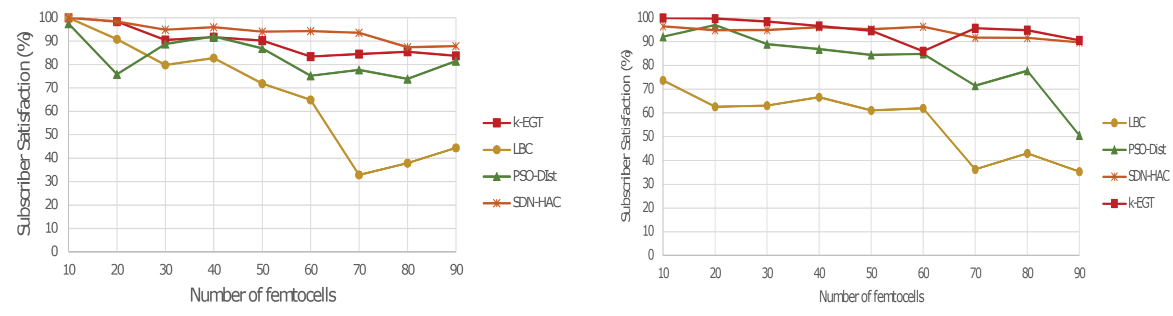
Regarding the subscribers' satisfaction, Fig. 4.6a and Fig. 4.6b show that users achieve higher satisfaction with the k-EGT model than with the LBC and PSO-Dist models. However, it can be observed that the SDN-HAC model achieves higher subscribers satisfaction than our model k-EGT. The reason is that femtocells work in closed access mode in the SDN-HAC model, and thus the resources for the subscribers are guaranteed since they do not have to share them with public users. In addition, it can be observed that satisfaction decreases with an increasing number of femtocells. This is because the throughput is affected by the interference which gets severe when the density of femtocells grows. However, from Figs. 4.7a and 4.7b, we conclude that our k-EGT model reduces the interference level below the values obtained with the LBC and the PSO-Dist models, for the mobility and no mobility scenarios.



a) Without mobility　　b) With mobility

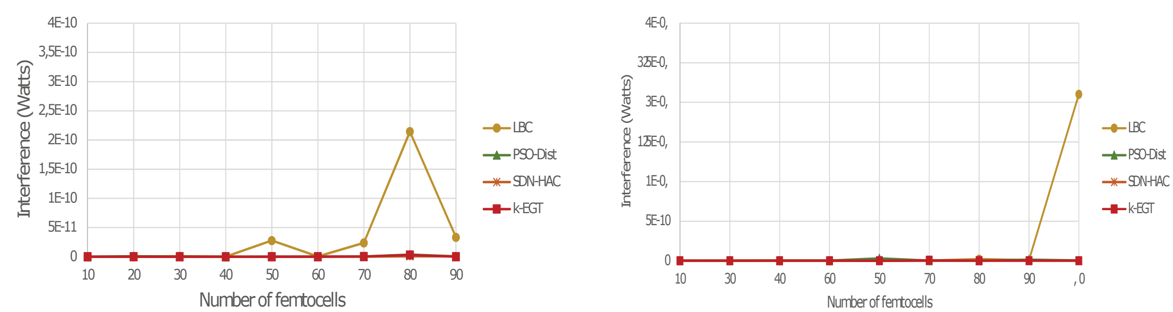
Figure 4.5　Network throughput for dense-deployment of femtocells

The main reasons for the better performance of our model against the centralized model are that the k-EGT model uses the replicator dynamic to guarantee the stability of the clusters and that the resources allocated to each member of the cluster are fairly allocated since their payoff is similar to the average payoff of all clusters. On the other hand, the LBC model forms balanced clusters that tend to have the same size and that does not guarantee fairness. Furthermore, the



a) Without mobility b) With mobility

Figure 4.6 Subscriber satisfaction for dense-deployment of femtocells



a) Without mobility b) With mobility

Figure 4.7 Average interference per subcarrier for dense-deployment of femtocells

LBC and the PSO-Dist models does not consider any criteria to evaluate the stability of the clusters. Regarding the SDN-HAC model, the co-tier interference is highly reduced since that this model allows more femtocells to join into clusters, thus forming larger clusters.

4.7.4 Stability Analysis

In the proposed model, stability is obtained by keeping femtocells in their clusters as long as their payoffs are higher or equal than the average payoff of all clusters. This stability criteria is based on the replicator dynamic of the evolutionary game theory. In particular, the replicator dynamic states that a cluster is stable if all the clusters have an equal or similar payoff to the average payoff, i.e. $\pi_c = \bar{\pi}$ for all $c \in C$. In Figure 4.8 we illustrate the stability of the formed clusters by showing the payoffs obtained by clusters with the k-EGT and LBC models for the case of ten femtocells. The figure shows that the set of clusters formed with the k-EGT model achieved its stability from iteration three. On the other hand, the clusters of the LBC model do not achieve stability, e.g. the payoff of the fourth cluster is below the average payoff. The results presented in Figure 4.9 illustrate that the stability convergence depends on the number of femtocells. In this particular cases with 15 and 20 femtocells, the stability is achieved at iterations four and five, respectively.

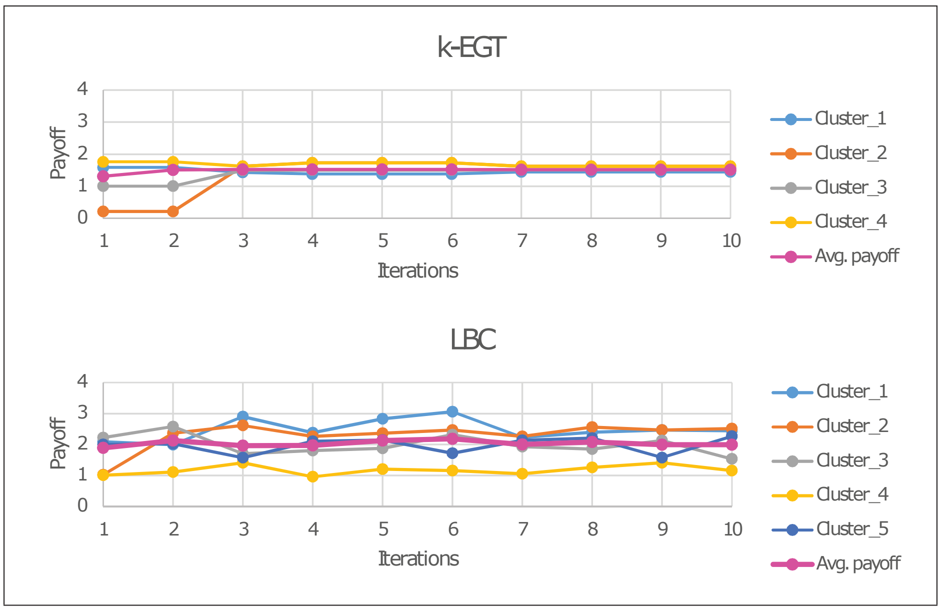


Figure 4.8 Average payoff per cluster for 10 femtocells using the k-EGT ($N_c = 5$) and LBC models

4.7.5 Running time

In this section, we present the running times of the clustering process for scenarios with and without mobility. Table 4.5 reports the computation time associated with the clustering process of the k-EGT, SH-PSO, SDN-HAC, and PSO-Dist models for different public users density with and without mobility. The first column represents the number of PUs, the second and sixth columns correspond to the clustering time using the SH-PSO model with and without mobility,

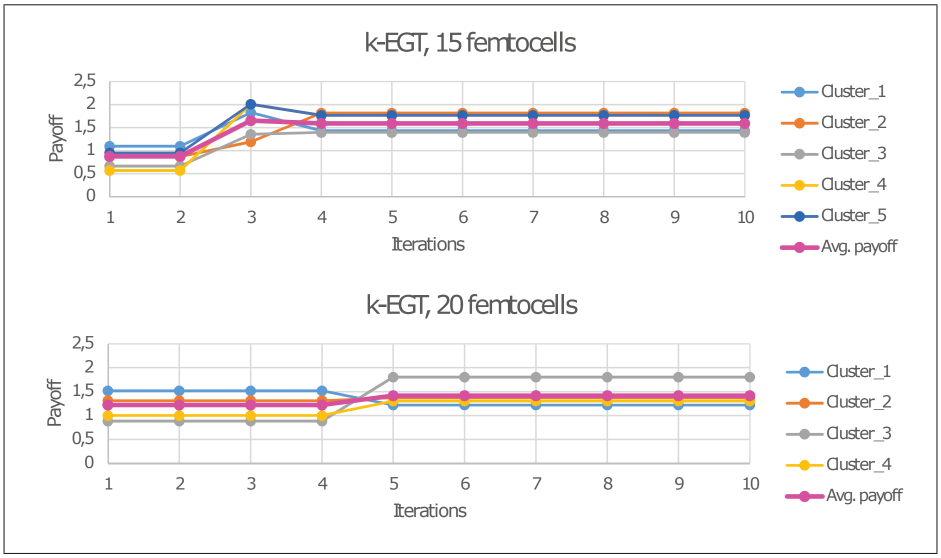


Figure 4.9 Average payoff per cluster for 15 and 20 femtocells using the k-EGT model

the third and seventh columns show the clustering time of the k-EGT model with and without mobility, the fourth and eighth columns represent the clustering time of the PSO-Dist model with and without mobility, and the fifth and nineth columns show the clustering times of the SDN-HAC model, respectively. Note that in the scenario without mobility the running times are

Table 4.5 Running times for the clustering component in a scenario with and without mobility varying the number of PUs from 10 to 60.

Number of PUs	Clustering time with mobility (sec)				Clustering time without mobility (sec)			
	SH-PSO	k-EGT	PSO-Dist	SDN-HAC	SH-PSO	k-EGT	PSO-Dist	SDN-HAC
10	1.2031	0.1094	1.1970	0.1399	0.241	0.0625	1.81	0.0999
20	0	0.0156	1.7580	0.0799	0	0.0156	2.22	0.0200
30	0	0	2.0430	0	0.075	0	1.62	0.0399
40	0	0	0	0	0	0	0	0
50	0.375	0	0	0	0	0	0	0
60	0	0	0	0	0	0	0	0

significant only for the cases with 10 and 30 PUs for the SH-PSO model. This is owing to the fact that only in these cases there is formation of new clusters. On the other hand, the evolutionary solution stops forming clusters from 30 PUs since stability was found at that moment. This means, that all the clusters are stable and the achieved payoff is equal to the average payoff.

Table 4.6 Clustering times using K-means and EGT algorithms

No. FCs	Nc	K-means	k-EGT
10	5	0.02	0.09375
20	5	0.02	0.09375
30	5	0.02	0.07813
40	5	0.03	0.07813
50	5	0.03	0.07813
60	10	0.03	0.07813
70	10	0.03	0.17188
80	10	0.03	0.14063
90	10	0.03	0.14063

For the mobility scenario and the k-EGT model, the formation of clusters stops from 30 PUs similarly to the no mobility scenario this means that stability was achieved. On the other hand, the SH-PSO model stops forming clusters for 20, 30, 40 and 60 PUs when stability is found. In this scenario, it can be observed that for the initial set of clusters with 10 PUs, the clustering process takes 1.2031 seconds for the SH-PSO model while the k-EGT model takes a much lower time of 0.1094 seconds.

It can be observed that the higher clustering times are obtained with the PSO-Dist model for both scenarios with and without mobility. In particular, after 30 PUs the running time of the clustering process becomes 0 meaning that neither the clusters can increase their utility by admitting new femtocells nor the femtocells can get extra resources to increase their subscribers' satisfaction. On the other hand, the clustering times achieved with the SDN-HAC model are slightly larger when compared with the k-EGT model. In particular, the clustering process ends from 30 PUs and from 40 PUs, for the mobility and no mobility scenarios, respectively. This means, that from 30 and 40 PUs the suitability function used to form the clusters is negative or that the grand cluster was formed.

In Table 4.6, the running times for the clustering process for different FC numbers are presented. It can be observed that the clustering times achieved by the k-EGT model are low. It is worth noting that the initial set of clusters is formed by using the K-means algorithm, e.g. we set the number of clusters to 5 (Nc=5) for a number of 10 to 50 FCs and to 10 (Nc=10) from 60 to 90 femtocells, as can be seen in the second column of Table 4.6. Consequently, the cluster size is not large, thus the resource allocation solved by the cluster head within each cluster converges within a short time.

4.8 Conclusion

In this paper, we addressed the problem of resource allocation for dense femtocell networks by proposing a model that forms stable clusters using an evolutionary game where femtocells learn from the environment and make their decisions considering the achieved payoff related to the throughput. In order to guarantee the cluster stability, we use the replicator dynamics that find the evolutionary equilibrium of the evolutionary game. In particular, we show that the stability is achieved when the payoff of each cluster is equal to the average payoff of all clusters. In addition, Particle Swarm Optimization is used for the local resource allocation within each cluster since this approach provides near-optimal solution while speeding up the optimization process. Two scenarios were analyzed by means of simulations, the first one having a variable number of public users and the second one with increasing number of femtocells. For the non-dense femtocell deployment (10 femtocells in the considered scenario) the results show that the network throughput improves significantly (up to 50%) when compared with the centralized LBC model and up to 27% when compared with the PSO-Dist model. The improvement is smaller (up to 17%) when compared with the SH-PSO model, which is due to the fact that the SH-PSO model has a fair allocation of resources by means of the Shapley value and this is not present in the LBC model. While the SH-PSO model provides better throughput than the LBC model, its complexity is significant and even prohibitive for the considered dense femtocell deployment (90 femtocells in the considered scenario). In high-density scenario, the comparison between the k-EGT and LBC models indicated that the throughput of our model can be increased by factor of three for the static mobiles case and by factor of three for the case with user mobility, respectively. When compared with the PSO-Dist model, the k-EGT model increases the throughput by factor of four for the static mobiles case while for the case with user mobility the throughput is increased by factor of three.

CONCLUSION AND RECOMMENDATIONS

In this thesis, we proposed solutions for resource allocation algorithms for macro-femtocell networks that consider clustering techniques, coalitional and evolutionary games, users mobility and dense-femtocell networks.

In Chapter 2, we proposed a distributed clustering model based on a coalitional game that incentives cooperation between macrocell and femtocells. We developed a game-theoretical framework that determines a top-coalition that is able to define the bandwidth that should be allocated for the macro-tier and the femto-tier. Once the bandwidth of the femto-tier is determined, other coalitions are formed using a fair portion of that allocated bandwidth where resources unused in the macrocell are allocated to the public users served by femtocells in coalitions. The WWF and PSO algorithms were used for the resource allocation. The former was applied in the base station selection for the public users while the latter was carried out for the final resource allocation. For comparison purposes, two benchmark models were used. The first benchmark model (BC-WWF) is a centralized clustering approach that uses WWF for the resource allocation. This model balances the traffic load of the public users among the clusters without causing the bandwidth starvation at the macro-tier. The second model (WWF-Dist) is a modified version of the solution presented in Chapter 2, it uses only the WWF algorithm for the resource allocation instead of using the PSO algorithm. Simulation results showed that our proposal (PSO-Dist) achieved similar values of network throughput when compared with the centralized approach (BC-WWF) without reducing the subscribers satisfaction. With our proposal, the subscriber satisfaction is at least 85% for the femtocells within coalitions while for the stand-alone femtocells it is 60%.

In Chapter 3 we presented a solution that focuses on the fairness of the resource distribution among all femtocells by using the Shapley value of game theory. The main contribution of this model (SH-PSO) lies in the formation of stable clusters of femtocells while enhancing the subscriber's satisfaction using the ε-core concept. In our approach, femtocell subscribers are rewarded with extra-subcarriers and resources are fairly allocated by means of the Shapley value, as a result, all femtocells are within coalitions. In consequence, the users served by femtocells suffer less interference which results in higher data rates. The SH-PSO model was compared with the centralized approach LBC and with the distributed approach ED-WWF. The LBC model uses the WWF algorithm for resource allocation and proposes a femtocell power control to mitigate interference. On the other hand, the ED-WWF model allocates resources in an equal distribution manner using as well the WWF algorithm. The results obtained showed that our model achieves gain up to 26% for the network throughput and a gain in the range from 60% to 90% for the public users' throughput when compared with the no coalition model.

So far, the two previous contributions have not tackled a dense-deployment of femtocell due to the computational complexity that increases exponentially with the number of femtocells. Thus, in Chapter 4, we addressed this problem by using an evolutionary game for the clustering process since that in EGT it is assumed that players have bounded rationality, which reduces the complexity and makes it suitable for densely-deployed femtocell networks. The proposed model (k-EGT) provides stable clusters by means of the replicator dynamic. According to the replicator dynamic, the stability is achieved when all formed clusters tend to have payoffs equal to the average payoff of all clusters. The solution includes the random walk mobility model to evaluate the system performance under mobile conditions of pedestrians or cyclists. The benchmark models used are the centralized approach (LBC), the PSO-Dist model presented in Chapter 2, the SH-PSO model presented in Chapter 3, and the SDN-HAC model. Simulation results showed an improvement of the network throughput up to 50% when compared with the LBC model, and up to 17% and 27% when compared with the SH-PSO model and PSO-Dist model, respectively, for a non-dense femtocell deployment. For a dense-femtocell deployment, our model increases the throughput by a factor of three for the case of the static mobiles and by a factor of two for the case with user mobility when compared with the LBC model.

Recommendations for future work

In the presented work, we have addressed the resource allocation for macro-femtocell networks considering non-dense and dense deployment of femtocells, game theory models for the clustering of femtocells and for the demonstration of the network stability, and users' mobility. However, there are some other research issues that need to be considered based on the current research work. The following specifies the future work related to this thesis:

1. New games can be investigated for the clustering of femtocells in order to reduce the resource allocation problem in dense-femtocell networks such as repeated games and Stackelberg games.
2. The work proposed in Chapter 2 can be extended by investigating other evolutionary computational techniques for the resource allocation to reduce further the computational time, evaluating other cluster head selection techniques, and incorporating new inter-cluster interference models.
3. The approach presented in Chapter 3 does not consider a dense-femtocell deployment due to the complexity of calculating the Shapley value when the number of femtocell increases. New studies could analyze optimization tools for the fair resource allocation problem based on the Shapley value.
4. In Chapters 3 and 4, the network stability was demonstrated by using the ε-core concept of game theory and the replicator dynamic of the evolutionary game theory. New stability criteria can be applied in order to demonstrate the clusters' stability.
5. In Chapter 4, the random walk mobility model considers users with pedestrian/cyclist velocities to analyze the system performance. Future work can extend this analysis for medium and high velocities. In addition, other mobility models can be applied under dense-femtocell deployment scenarios.

6. An evolutionary game to group femtocells into clusters was proposed in Chapter 4. New strategies can be investigated in order to fully analyze the femtocells behavior.

APPENDIX I

RESOURCE ALLOCATION MODEL CONSTRAINTS

The objective function of our research work is the maximization of the throughput of the femtocells' cluster and is defined as:

$$\max_{\boldsymbol{\epsilon},\boldsymbol{\alpha},\boldsymbol{\beta},\mathbf{P}} \sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} \gamma_f^s \tag{A I-1}$$

The objective function is subject to the following constraints:

1. In order to avoid the cross-tier interference, where a subcarrier being used in the macro-tier is not used by any cluster in the femto-tier, the following constraint is defined

$$\sum_{k\in\{m,F^c\}} \sum_{s\in\{SC\}} \beta_i^{s,k} \leq 1 \quad ; i \in MS \tag{A I-2}$$

2. The constraint A I-3 sets the upper bound for the allocated subcarriers to the clusters in the femto-tier. This constraints avoids the starvation of resources in the macro-tier.

$$\sum_{f\in\{F^c\}} \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \epsilon_f^c \alpha_i^f \beta_i^{s,f} \leq N_s - \sum_{i\in\{MS\}} \sum_{s\in\{SC\}} \alpha_i^m \beta_i^{s,m} \tag{A I-3}$$

3. In order to guarantee that the spectral efficiency achieved by a mobile user within a cluster is higher or equal to a target spectral efficiency, the following constraint is declared.

$$log_2\left(1 + SINR_i^{s,f}\right) \geq \alpha_i^f \beta_i^{s,f} \gamma_f \quad ; i \in MS, f \in \{F^c\}, s \in \{SC\}, \tag{A I-4}$$

4. A constraint related to the lower bound for minimum data rate achieved by a public user is given by

$$\sum_{k \in \{F^c\}} \alpha_i^k \leq 1 \quad ; i \in MS \tag{A I-5}$$

5. The following constraint states that one mobile user can only be assigned to one base station, e.g. to the macro base station or to a femtocelll.

$$B_s \times \sum_{s \in \{SC\}} \beta_i^{s,k} \gamma_k^s \geq \alpha_i^k \times D_i \quad ; i \in MS \tag{A I-6}$$

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