UNIVERSIDAD NACIONAL DE COLOMBIA

Control Strategies for Energy Efficiency of Next-generation Cellular Networks with Hybrid Energy Sources

Luis Alejandro Fletscher Bocanegra

Universidad Nacional de Colombia
Facultad de Minas, Departamento de Procesos y Energía
Medellín, Colombia
2018

Control Strategies for Energy Efficiency of Next-generation Cellular Networks with Hybrid Energy Sources

Luis Alejandro Fletscher Bocanegra

Ph.D. dissertation presented as partial requirement to obtain the degree of:
Doctor in Engineering

Advisor:
Catalina Valencia Peroni, Ph.D.

Co-Advisor:
José Maria Maestre Torreblanca, Ph.D.

Universidad Nacional de Colombia
Facultad de Minas, Departamento de Procesos y Energía
Medellín, Colombia
2018

To my wife, for all her support and especially for being my life partner.

To my parents and my grandmother, for being my guides and acting as good examples of how to live life.

Acknowledgements

First, I want to express my gratitude to my thesis advisor, Catalina Valencia Peroni, Ph.D., and to my co-advisor, José María Maestre, Ph.D., for all their orientation and guidance along this lonely path of doctoral research.

I am also extremely grateful to the universities and laboratories where I was a visiting researcher. Thanks to Distinguished Professor Nirwan Ansari of New Jersey Institute of Technology (NJIT) and to Professor Michella Meo from Politecnico di Torino. In particular, I thank Pepe Maestre from Universidad de Sevilla, Carlos Ocampo from Universitat Politècnica de Catalunya, and Julián Barreiro from New York University Abu Dhabi (NYUAD) for teaching me the value of collaborative work.

Finally, I acknowledge to my friends and colleagues of the Universidad de Antioquia for their friendship and support, and, most of all, I am grateful to my family for their support throughout the years.

Abstract

Large-scale systems are characterised by having a large number of components working in coordination. These systems can be composed of geographically distributed elements with resource limitations. In this way, control strategies for large-scale systems have challenges related to information flow, processing time and capacity, controller design, and energy-resource optimisation. One particular large-scale system is the next-generation mobile communications cellular network, which will comprise hundreds of base stations interacting with thousands of users in milliseconds.

One of the main challenges with next-generation cellular networks (NGCNs) is the higher energy consumption caused by the expected number of connected devices. Here, renewable energies are a good option to face the growing demand of energy consumption. However, there are still major challenges related to the appropriate control schemes to minimise on-grid consumption and optimise energy management in cellular networks with hybrid energy sources (grid and renewable energy).

In this thesis, different control strategies for large-scale networks are proposed. These control strategies are assessed over an NGCN powered by hybrid energy sources to reduce grid consumption. The energy-efficiency problem is studied from the viewpoint of the energetic processes – i.e., on-place renewable energy is available, and mechanisms to reduce the grid-energy consumption should be developed.

The proposed mechanisms are based on previous research that shows the relationship between the number of users connected to a cellular network base station (BS) and its energy consumption. For this reason, the study of optimal control mechanisms that balance the load of users over the available BSs according to the renewable energy available is a key element in the field of energy efficiency in cellular networks. These schemes are assessed through simulations and then compared with the scheme actually used to manage the user–BS association in cellular networks. The results show that the proposed control schemes improve grid-electricity consumption compared with the traditional association mechanism while still maintaining adequate quality-of-service (QoS) levels.

The control schemes for the energy-efficiency problem were studied in two timescales. The short timescale (of the order of seconds) was used to analyse the user–BS association problem in a network configuration with hybrid power sources without an energy storage system. The long timescale (of the order of hours) was used to study load balancing of aggregated traffic in each BS with hybrid power sources and an energy storage system. Finally, the proposed controllers are of different types: (i) centralised, (ii) distributed at the base-station level, and (iii) distributed at the user level.

Keywords: Energy efficiency, Renewable energies, Optimal control, Hybrid power sources, Large-scale systems, HetNets.

Resumen

Los sistemas de gran escala se caracterizan por tener un gran número de componentes trabajando de forma coordinada. Estos sistemas están conformados por elementos que pueden estar distribuidos a lo largo de una extensa área geográfica y poseer restricciones en cuanto a la disponibilidad de recursos necesarios para su funcionamiento. Teniendo en cuenta estas características, las estrategias de control para sistemas de gran escala presentan retos relacionados con el flujo de la información, la capacidad y tiempo de procesamiento, el diseño de los controladores y la optimización de los recursos disponibles. Un tipo particular de sistema de gran escala son las redes de comunicación móvil celular de próxima generación, que se encontrarán conformadas por cientos de estaciones base que interactuarán con miles de usuarios en instantes de tiempo del orden de los milisegundos.

Uno de los principales desafíos en las redes celulares de próxima generación (RCPG) es el incremento en el consumo energético causado por el crecimiento esperado de dispositivos conectados. En este contexto, las energías renovables son una buena alternativa para afrontar la creciente demanda de consumo energético. Sin embargo, existen importantes desafíos relacionados con los esquemas de control adecuados para minimizar el consumo de energía proveniente de la red eléctrica convencional (grid) y optimizar la gestión energética en redes celulares con fuentes de alimentación híbrida (grid y renovable).

En esta tesis, se proponen y evalúan diferentes estrategias de control para redes de gran escala, utilizando como caso de estudio las RCPG alimentadas con fuentes híbridas y su objetivo de reducir el consumo grid. El problema de la eficiencia energética es estudiado desde el punto de vista de los procesos energéticos, es decir, de la disponibilidad de energía renovable en el emplazamiento del sistema y los mecanismos para reducir el consumo energético.

Los mecanismos propuestos se basan en investigaciones previas que demostraron la relación existente entre el número de usuarios conectados a las estaciones base (EB) de la red y su consumo energético. Por esta razón, el estudio de mecanismos de control óptimo que balanceen la carga de tráfico sobre las EB de acuerdo con la energía renovable disponible es un elemento clave en el campo de la eficiencia energética en redes celulares. Estos esquemas son evaluados a través de simulaciones y comparados con el mecanismo usado actualmente por las redes celulares para gestionar la asociación de los usuarios a las EB. Los resultados de la tesis muestran que los esquemas de control propuestos mejoran el consumo grid comparado con el mecanismo de asociación tradicional a la vez que mantienen adecuados niveles de calidad del servicio.

Los esquemas de control para el problema de la eficiencia energética fueron estudiados en dos escalas de tiempo. La corta escala de tiempo (del orden de los segundos) fue usada para analizar el problema de la asociación de los usuarios a las EB en una configuración de red con fuentes de potencia híbridas y sin sistema de almacenamiento energético. La larga escala de tiempo (del orden de horas) fue utilizada para estudiar el balanceo de carga de tráfico agregado en cada EB, con fuentes híbridas de potencia y con sistema de almacenamiento

energético. Finalmente, los controladores desarrollados son de diferentes tipos: i) esquema centralizado, ii) esquemas distribuidos a nivel de usuario y iii) esquemas distribuidos a nivel de estaciones base.

Palabras clave: Eficiencia energética, Energías renovables, Control Óptimo, Fuentes híbridas de potencia, Sistemas de Gran Escala, HetNets.

Table of Contents

Table of Figures

Table of Tables

1. Introduction

Large-scale systems are composed of multiple subsystems interacting to reach a common objective. The subsystems are usually distributed over a wide geographical area, and it is necessary to develop control strategies to guarantee optimal system performance. One of the main challenges related to the control of large-scale systems is the collection of information from geographically distributed elements, the coordination of control actions to different types of agents, and the fact that all subsystems are interconnected and the response of one subsystem will affect other subsystems. Many technological systems can be classified as large-scale systems, such as power systems, chemical systems, and telecommunications networks.

Mobile cellular networks are large-scale systems that are expecting an exponential growth of users in next-generation systems caused by the number of subscribers and mobile devices. According to (Cisco, 2017) data traffic has increased about 74 % just from 2014 to 2015 and the number of mobile worldwide devices have reached almost 8 billion devices. The consequences of such an increase on the demand of network capacity are also very well known. For the Telecommunications industry it implies a need to increase infrastructure deployment for the Core and Radio Access Network (RAN), which means higher capital and operational expenditures, i.e. CAPEX and OPEX respectively. Note that, one important item considered inside the OPEX is the energy consumption costs.

Additionally, previous studies have shown that about 0.5 % of the global energy supply is consumed by cellular networks (Lubritto et al., 2011, Hasan et al., 2011). This phenomenon has motivated different projects focused on the study of ways of reducing grid consumption in cellular networks, e.g., ICT-EARTH (ICT-EARTH, 2014), Trend (TREND, 2015), and 5GrEEn (5GrEEn, 2015). One of the conclusions of these projects is that most of grid consumption in cellular networks is caused by base stations (BSs) and it also depends on the traffic load (Auer et al., 2011). Research initiatives in this direction have been called collectively the Green Radio. From the energy efficiency perspective a cellular network is subject to optimization in three different ways: reducing energy consumption, by redesigning the system consuming less energy for achieving the same goal, and changing the energy source to one of lower environmental impact. First two approaches are usually achieved in a network design stage with good engineering practice. The latest approach is the one selected to guide the case study of this thesis, understanding energy efficiency of the network as reducing grid electricity usage by changing the way it operates, resulting in lowing operational costs and CO_2 footprint, by replacing fossil fuel electricity by renewable energies (RE).

In this way, it is necessary to develop control mechanisms focused on the energy efficiency of NGCN that allows incorporating renewable energy sources in the network architecture and to modify the network operation. The utilization of renewable power sources for BS is a proposed alternative to attain the energy efficiency of next generation cellular networks (Dhillon et al., 2014). Renewable energy is also a good option to reduce the use of the grid and to deploy infrastructure in scenarios with connection limitation or without grid connection (off-grid). This approach is particularly interesting for developing and Third World countries. For example, according to the International Energy Agency (IEA), 18 % of the global population (1.3 billion people) lived without electricity in 2012 (International Energy Agency, 2012). This highlights the need for solutions that allow the deployment of telecommunications infrastructure in areas without access to conventional electricity.

Some studies examining the feasibility of using renewable energy sources in NGCN have shown a reduction of network costs (CAPEX/OPEX) (Morea et al., 2007, Marsan et al., 2013, Alsharif et al., 2015) and an improvement of environmental factors (Piro et al., 2013). However, the integration of renewable energy in NGCN presents various challenges related to network architecture and control strategies (Hassan et al., 2013). NGCN will be characterized by the hight number of interacting users and by the need for system control strategies with short response times and lower overhead information exchange.

Regarding the network architecture of NGCN, different alternatives have been proposed, one of them is heterogeneous-cellular networks (HetNets) and it will be used in this thesis. HetNets provide a flexible architecture for next-generation cellular networks composed of two types of base stations (BS), namely, the traditional macro base station (MBS) and small cells base stations (SCBSs) that extend its coverage and capacity. Within HetNets, 2G/3G issues such as frequency interferences have been relegated by energy consumption, load balancing, and deployment cost (Andrews, 2013). Also, an attractive feature of HetNets is the possibility of easily modifying the distribution of SC over the coverage area.

This thesis proposes control strategies for energy efficiency of a large-scale system as NGCN. The proposed control mechanisms focus on traffic load balancing to reduce grid consumption. The studied scenario is a HetNet with hybrid power sources (grid and renewable energies) where SCBSs are powered exclusively by renewable energy. The minimization on the grid consumption is attained through a balance of downlink traffic loads among BSs by appropriated user-BS association mechanisms that take advantage of the renewable energy availability. Additionally, the network planning problem was studied as a way to analyse the impact of network deployment in the energy efficiency of HetNets powered by renewable energy sources.

According to the characteristics of renewable energy sources and the traffic behavior, it is possible to assume that the network operates on two time scales: long-time scale and short time scale (Dhillon et al., 2014). In long-time scale, traffic behavior changes according to the time of the day (temporal variability of traffic) and decisions about network planning are taken. In short-time scale, cell selection decisions are taken over the assumption that

the operational states of the base stations are static in a time instant. In this sense, this thesis presents solutions in both time scales. Initially, the network planning and the users-BS association problems were analysed in the short-time scale considering a hybrid power system without battery support and wind as renewable energy. Later, the problem was analysed in the long-time scale with aggregated BS traffic load per hour and a Photo-voltaic (PV) energy system with storage.
From the control optimisation point of view, and considering the network actors, three different approximations were used:

- Centralised. This approximation was used for the problem of HetNet planning. The proposed solution is based on a coalitional game to determine the optimal location of the SCBSs in the coverage area.
- Distributed at the base-station level. At this level, different user–BS association mechanisms controlled by BSs were proposed to balance traffic loads. Additionally, a model predictive controller (MPC) mechanism was implemented to optimise the renewable energy utilisation in the long timescale.
- Distributed at the user level. This is the lowest optimisation layer and was implemented through a population game to connect the users to BSs.

The proposed schemes were compared with the traditional best-signal-level mechanism actually used by cellular networks and evaluated via simulation and real renewable energy data by using key performance indicators (KPIs) related to energy efficiency and quality-of-service levels.

1.1. Overview of this Thesis

The goal of this thesis is to propose a control scheme that provides energy-efficient management in next-generation cellular networks powered by hybrid energy sources (grid and renewable energy). The proposed scheme should allow self-organising of the traffic load at each BS according to availability of renewable energies (REs) and the state of the network, thus maintaining suitable quality-of-service levels.

1.1.1. Problem Description

The NGCN will be composed by coexisting macrocells and low power nodes (LPNs) such as picocells, femtocells, and relay nodes with the target of establishing a flexible architecture and to respond to the growing traffic demand (Andrews, 2013). The deployment of a large number of LPNs carries on the ever increasing energy consumption in wireless networks, consumption that is today almost exclusively provided by the fossil originated or grid electricity. In this

context, the concept of green power technology appears in the mobile industry, traditionally referring to a renewable energy source used to generate and supply power to a mobile base station site (Hasan et al., 2011). However, the implementation of renewable energy sources in cellular networks has several challenges related to the unavailability of grid connection in many places plus the variability of the sun, wind and other renewable energies.
According to above, it is necessary to develop control mechanisms for reducing the rate of global energy consumption in a large scale system as NGCN, optimizing the use of available green energy and to fulfil requirements for quality of the service (QoS).

1.1.2. Thesis Outline

The outline of the thesis is as follows:

- Chapter 2 states the energy-efficiency problem of next-generation cellular networks as well as the current control strategies for this kind of large-scale system. It also presents a review of the current control techniques used to reduce grid consumption on next-generation cellular networks.

- Chapter 3 presents a planning methodology for large-scale cellular networks, which is based on a coalitional game where small cells are players and the Shapley value determines the contribution of each potential small cell to the global performance of the system. The planning problem is studied with a centralised optimisation approach. The characteristic function of the game is based on three key performance indicators: percentage of users served, reduction of grid consumption, and average transmission rate. The success of the coalitional game-based planning process is considered from an energy-efficiency perspective, which means a reduction of on-grid consumption and an improvement of network performance according to availability of renewable energy. The efficiency of the coalitional design is compared with other heuristic and optimal alternatives in two simulation examples.

- Chapter 4 presents four centralised control mechanisms to reduce on-grid consumption through traffic-load balancing on HetNets. The proposed mechanisms are: a heuristic method to guide users to a BS powered by RE, a heuristic to ease the problem by using traffic flow, and a market approach. Finally, in the long timescale, an MPC based on a traffic-flow perspective is implemented to reduce grid-energy consumption in a HetNet where SCs are powered only by renewable energy (photovoltaic [PV] with storage systems). The MPC uses the system state and weather forecast to optimise users' allocation from the MBS to SCs according to availability of renewable energy. The simplicity of these mechanisms and their good computation times allow for easier implementation in NGCN scenarios.

- Chapter 5 presents a novel distributed control scheme based on population games. The controller is in charge of dealing with the user–BS association process to reduce grid consumption in a HetNet powered by hybrid energy sources without an energy storage system.
- Finally, Chapter 6 gives the conclusions and the suggestions for future work.

1.1.3. Main Contributions

The main contributions of this thesis are the novel control mechanisms for energy efficiency in large-scale cellular networks powered by hybrid energy sources. These contributions can be classified into three categories: a model of HetNets powered by hybrid energy sources, a centralised planning methodology for energy efficiency of HetNets, and different traffic-load balancing mechanisms to reduce grid consumption.
A tractable model to study problems related to energy consumption on an NGCN powered by hybrid energy sources was performed and can be a starting point for future works regarding this type of large-scale network. The model is an integration of previous research but is representative of a real scenario with an appropriate level of complexity to assess different control strategies.
The planning method is based on a coalitional game, which is a novel approach to this type of problem. The advantage of the proposed method is that it can be easily applied to the design or another type of large-scale network. Additionally, the design objectives can be modified by adjusting the KPIs according to the network characteristics desired.
The solutions to traffic-load balancing outperform classic mechanisms and are simple and tractable enough to be implemented in real systems. The controllers were designed at different levels for traffic-load balancing: centralised for the planning problem, distributed at the BS level, and distributed at the user level. It is important to note that this as an advantage since it is possible to choose a controller according to the large-scale cellular network characteristics.

1.1.4. Notation

A summary of the notation used on this thesis can be found in Table **1-1**.

Parameter	Description
$\mathcal{A}$	Geographical area
$\mathcal{B}$	Set of base stations / Set of possible base station locations
b	Number of base stations
j, ℓ	Base station's indexes
$\mathcal{U}$	Set of users

Continued on next page

Parameter	Description
u	Number of users
i	User's index
p	Possible user's location
k	Discrete time step
τ	Time slot duration
N	Simulation horizon
$\mathcal{B}_k$	Set of active base stations in a time instant k
$\mathcal{B}_{i,k}$	Set of base stations available to provide service to user i in a time instant k
$C_{\ell,k}$	Energy consumption of base station ℓ in a time instant k
Δ_ℓ	Slope of load-dependent energy consumption of BS ℓ
$T_{\ell,k}$	Transmission power of BS ℓ at the k^{th} time instant
$\delta_{\ell,k}$	Traffic load of BS ℓ at the k^{th} time instant
E_ℓ^S	Static energy consumption of BS ℓ in each time instant
$E_{\ell,k}^G$	Green energy available for a SCBS ℓ in a time instant k
σ_k	Green energy generation rate in the time instant k
$r_{i\ell,k}^p$	Transmission rate of a user i at location p, associated with a BS ℓ in a time instant k
$\psi_{i\ell}^p$	Signal-to-interference-plus-noise ratio (SINR) perceived by user i at location p from BS ℓ
$\Psi_{i\ell,k}$	Matrix of the SINR received by a user from each BSs in a time instant k. With $i = 1 \ldots u$ and $\ell = 1 \ldots b$
W_ℓ	Operating bandwidth of BS ℓ
φ	Threshold that indicates the minimum signal level required by a user to have service
$y_{i\ell}$	User-BS association indicator for user i with BS ℓ
$Y_{i\ell,k}$	Association matrix for users with BSs in a time instant k. With $i = 1 \ldots u$ and $\ell = 1 \ldots b$
$z_{A,k}$	Active users in a time instant k
$z_{U,k}$	Users not served in a time instant k
$z_{S,k}$	Users served in a time instant k
$z_\ell^{\max}$	Number of users that can be served by a SCBS ℓ simultaneously
KPI_C	KPI Reduction of grid consumption
KPI_U	KPI Percentage of users served
KPI_R	KPI Average Transmission rate
$\mathcal{S}$	Coalition
$\phi_i(\mathcal{B}, u)$	Shapley value (Payoff rule for a player)

Continued on next page

Parameter	Description
$m_i^{\pi}(\mathcal{B}, u)$	Marginal contribution of player i to the players that are ranked before him/her in the order π
$x(\pi)$	Marginal contributions of the players in the order π
$\widetilde{\phi}_i\ (\mathcal{B}, u)$	Approximation of the Shapley value with the sampling method
M	Size of the sample taken to calculate $\widetilde{\phi}_i\ (\mathcal{B}, u)$
$F_{\ell j,k}$	Matrix with the flows that can be exchanged between BSs in a time instant k
$x_{\ell j,k}$	Traffic flow from BS ℓ to BS j in a time instant k
ε	QoS objective (Desired percentage of users served)
$f_{i\ell,k}$	Fitness function perceived for user i from BS ℓ in a time instant k
$\varrho_{i,k}^{h\ell}$	Switching rule from strategy ℓ to strategy h for user i
$R_{ij,k}$	Price of a channel offered by BS j to user i in a time instant k for the market heuristic
$\alpha_1, \ldots, \alpha_5$	Weights of network parameters over the market price
$\Omega_{ij,k}$	Index of modulation scheme offered to user i from BS j in a time instant k
ϑ_k	BS scarcity in the market heuristic
ρ_k	Demand in the market heuristic
ξ^{BS}	Impact of the BS energy source over price in the market heuristic
ξ^{U}	Impact of the BS energy source over utility perceived by users in the market heuristic
$\upsilon_{ij,k}$	Utility perceived by user i for a channel offered by BS j in a time instant k for the market heuristic
$\beta_1, \ldots, \beta_3$	Weights of market characteristics over utility function
$R_{ij,k}^{M}$	Monopoly price in the market heuristic
Θ	Discount factor in the price function for monopoly case in the market heuristic
$\mu_{i,k}$	Money of user i in the time instant k
$\Gamma_{ij,k}$	Buying decisions of user i related to a resource block offered by BS j in a time instant k

Table 1-1.: Notation

2. The Problem of the Energy Efficiency of an NGCN powered by Hybrid Sources

The energy efficiency of next-generation cellular networks has been addressed from different control strategies. The three sections of this chapter present the context and problem statement of this thesis. Initially, a review of the main proposals for the user–BS association problem as an energy-efficiency mechanism for HetNets powered by hybrid energy sources is presented. The second section is the thesis problem statement. Finally, the case study used for assessing the proposed control strategies to solve the problem is defined.

2.1. Control Strategies for Energy Efficiency of NGCN powered by Hybrid Energy Sources

The main energy consumption in a cellular network is produced by base stations (BSs), and it depends on the number of active users in a given time slot (Auer et al., 2011). For this reason, a balance of downlink traffic loads among BSs by an appropriate user - BS association mechanism is needed to minimize on-grid consumption. Besides, renewable energies are a good option to deploy infrastructure in scenarios with connection limits or without grid connection (off-grid), e.g., in developing countries.

In literature, it is possible to find several approximations to solve the load balancing problem in HetNets. Andrews *et al.* present a survey of different technical approaches to HetNet load balancing (Andrews et al., 2014). Here it is possible to observe the need to explore new load balancing mechanism different to traditional optimization techniques because the problem of associating users to base stations is NP-hard and not computable even for small-sized HetNets. From the optimization viewpoint, several load balance approaches to increase energy efficiency in cellular networks have been proposed in recent years. In (Zhou et al., 2010), Zhou *et al.* proposed a heuristic algorithm for target cell selection combined with a power control algorithm for coverage optimization to guide users towards BSs with renewable energy supply. Likewise, Han and Ansari proposed to optimize the utilization of green energy in cellular networks by cell size optimization (Han and Ansari, 2013). To this end, they decomposed the problem into two parts: a multi-stage energy allocation problem and a multi-

BS energy balancing problem. Their algorithm solved both problems to deal with the original one. Liu *et al.* proposed in (Dantong et al., 2014) an offline algorithm to optimize the green energy allocation across different time slots to minimize the on-grid energy consumption of a BS. A general viewpoint can be found in (Kim et al., 2012), where authors presents different distributed user association policies in wireless networks that include cellular networks with spatially inhomogeneous traffic. Silva et al., use the classic optimal transportation approach to study the mobile association problem in cellular networks (Silva et al., 2013).

NGCN will be characterized by the high number of interacting users and the need for control strategies with short response times and lower overhead information exchange, with these being the appropriate scenarios for the application of distributed control solutions (Camponogara and Scherer, 2011, Maestre and Negenborn, 2014, Negenborn and Maestre, 2014). From the distributed perspective, in (Han and Ansari, 2016), Han and Ansari presented a virtually distributed algorithm named vGALA to reach a trade-off between network utilities and green-energy utilization in software-defined radio access networks powered by hybrid energy sources. Likewise, in (Ye et al., 2013), Ye *et al.* proposed a low-complexity distributed algorithm to solve the association problem jointly with resource allocation in an on-grid HetNet. They assume that users can be associated with more than one BS at the same time as a relaxation of the NP-hard problem. Unlike these proposals, in this thesis the user-BS association problem is not relaxed, maintaining constraints as one user being attended by only one BS in a time instant, and responding to the variations of renewable sources using the grid as a backup system.

Game theory has also been used to solve the user-BS association problem. In (Chekroun et al., 2015), authors presented a scheme based on a game of two players moving between a macro-base station and a small cell, with both BSs connected to the grid. To take the association decision, players used a distributed algorithm, trying to maximize their utilities independently. In (Arani et al., 2017), the user-BS association problem in HetNets was modelled as a non-cooperative game and solved with a distributed algorithm inspired by machine learning techniques. In (Khan and Tembine, 2011), Khan and Tembine studied the network-selection problem using coalitional games with an evolutionary perspective. They stated the need for a users-centric paradigm in fully-distributed environments and the multi-objective characteristics of next generation network systems. An introduction to distributed population dynamics applied to optimization and control problems can be found in (Barreiro-Gomez et al., 2017).

The short-time scale proposals presented in this thesis differ from previous works because our target is energy efficiency through grid consumption reduction. Also, our off-grid SCBSs are powered exclusively by wind energy and have no battery support, requiring more demanding control strategies to guarantee QoS levels. Conversely to other works where photovoltaic power generation is assumed (Liu et al., 2015a, Han and Ansari, 2016, Mao et al., 2015), we deal here with real wind data. Finally, we test different alternatives in a complex scenario (37 BS - 750 users).

In long-time scale, MPC appears as a general way to solve control problems with multiple variables and heterogeneous characteristics (Camacho and Bordons, 1999). For this reason, it is not rare to find applications of MPC in communication systems. In (Cea et al., 2012), authors apply MPC to manage the power signal in the BS and reduce the negative impact of disturbance in the transmission process. Likewise, the reduction of co-channel interference through distributed power adaptation using MPC is addressed in (Garcia et al., 2012).

2.2. The Problem of Planning Energy Efficient HetNets

The planning of HetNets powered by RE has significant differences compared to this process in networks powered by traditional energy sources. First, when RE is used, the base stations must be placed according to the features and the behaviour of the energy source being used. In other words, the designer must consider the variations in the renewable source's behaviour and select the best location that guarantees the availability of energy in each time instant. The second element to consider is the quality of service (QoS) and how to maintain the level achieved by traditional networks. Finally, the economic planning in HetNets powered by RE is different because the OPEX reduction must be higher than the CAPEX increment to justify the adoption of alternative energy sources.

According to (Taufique et al., 2017), cell planning objectives include: minimizing total cost of ownership, maximizing capacity, maximizing coverage, minimizing power consumption, and optimizing handover zones. Planning of cellular networks powered by RE has traditionally been studied from two perspectives: the first is economic, and the second is the energy source behaviour and its impact on network performance. From an economic viewpoint, Meo *et al.* analyze the optimal dimensioning of the photovoltaic panel and energy storage of a hybrid base station powering system (Meo et al., 2015). To find it, they propose a minimization problem of the overall system cost over a period of 10 years. The inputs to the problem are the daily traffic profile, sun radiation, energy and supply costs. Likewise, Piro *et al.* present a cost analysis to justify the feasibility of using small cells powered by renewable energies instead of the grid (Piro et al., 2013). Another criterion for network design is the energy source's behaviour. The sun is the most studied and is generally modelled as a stochastic process. For example, in (Wang et al., 2014), the flow of solar energy in a cellular network is modelled by using a stochastic queue model to find an optimal design of the power system that fulfils certain network-performance metrics. In (Leonardi et al., 2016), two discrete-time Markov chain models were proposed. Historical solar irradiation data are used to design the power supply system (battery and photovoltaic panels) of the network. In (Bao et al., 2014), a similar approach is implemented, but it uses artificial neural networks to predict solar energy arrivals in a short period.

Generally, the HetNet planning problem is formulated as an $\mathcal{NP}$-hard problem (Shaowei et al., 2015, Wentao et al., 2017, Taufique et al., 2017). For this reason, the solutions employed to find the optimal number of BSs and the corresponding locations are based on heuristic methods. For example, in (Ghazzai et al., 2016), the authors studied HetNet design with traffic varying spatially and temporally. The optimization objective was to find the BS location that satisfies coverage requirements and user demand. Chalita *et al.* used chance-constrained optimization to select the minimum cardinality set of nodes from a given large set that satisfies target performance requirements (Challita et al., 2016). In (Kaneko et al., 2012), a greedy algorithm is used to find the minimum number of pico BSs needed to fulfil user data traffic requirements. Another interesting approach is proposed in (Wang and Ran, 2016), where authors use a cutting-edge territory division technique to divide a service region into multiple sub-regions with equivalent traffic loads and design a HetNet with specific coverage and capacity characteristics. Other examples of cellular planning methods can be found in (Shaowei et al., 2015, Hassan et al., 2016, Di Francesco et al., 2015, Kashef et al., 2016, Chen et al., 2015, Zeng et al., 2017).

The planning method proposed in this thesis focuses both on energy and technical elements in the base station positioning process. This is the main difference with the other works in the literature, which use only a single criterion for BS placement – see, e.g., (Shaowei et al., 2015, Zhao and Wang, 2013, Wang and Ran, 2016). In particular, we propose a cooperative game in which SCBSs are players and the value of each coalition is characterized as the sum of three key performance indicators (KPIs) received by the aggregation of a new SCBS. The Shapley value (Shapley, 1952) of this game is related to the global performance that the network should expect from the random inclusion of an SCBS into a coalition of BSs. The rationale behind the proposed coalitional planning mechanism is to evaluate the specific contribution of each BS in the global network performance so that the locations providing a reduced contribution can be discarded. This approach is general and could be applied in other planning problems due to the good properties of the Shapley value (e.g., linearity) (Maestre and Hideaki, 2017, Fele et al., 2017). The other parameters can also be taken into account when calculating the placement. The KPI characteristic function of the game includes energy and QoS characteristics in the evaluation of BS contribution. However, the optimal solution to this problem leads to a combinatorial explosion of possibilities, and hence there is a need to develop approximate methods. In particular, an approximation to calculate the Shapley value is used to define the BS locations that contribute to the global performance of the system.

The Shapley value is the most used cooperative game payoff rule, and many works in the extant literature have proposed it as a mathematical tool to measure node centrality in a network. For example, in (Narayanam and Narahari, 2011), the information diffusion process in a network is modelled as a cooperative game, and its Shapley value provides a measure of the node influence. Another related work is (Sharma and Abhyankar, 2017), in which the authors propose a model for loss allocation in an electrical distribution network using the Shapley value to discriminate the contributions of multiple participants. Likewise, it has also been applied to realize mobile traffic offloading in cellular networks with spectrum sharing (Zhang et al., 2016). To this end, they use a Gale-Shapley algorithm to optimize the offloading process and to guarantee privacy for users using a shared spectrum. Game theory has also been used to improve the performance of a working cellular system. For example, the power control problem for two-tier configuration was studied in (Guruacharya et al., 2013) and (Thuc et al., 2015) using a Stackelberg game and a stochastic game, respectively. In (Chekroun et al., 2015), authors present a scheme to solve the user-BS association problem based on a two-player game moving between a macro base station and a small cell. To make the association decision, players use a distributed algorithm to maximize their payoffs independently.

2.3. Problem Statement

As mentioned above, the major sources of energy consumption in a cellular network are base stations (BSs), whose consumption depends on the number of active users in a given time instant (Auer et al., 2011). Hence, a suitable user-BS association mechanism is key to reducing on-grid consumption. Moreover, another challenge in NGCN is the high number of expected nodes and the short decision time, making it essential to have control strategies capable of responding adequately to these requirements.

2.3.1. Network Scenario

HetNets have been designed to respond to NGCN requirements and are used in this thesis. A simplified two-tier downlink HetNet such as that of Figure **2-1** is used, which is composed of one Macro-Base Station (MBS) and multiple Small-Cell-Base Stations (SCBSs). The MBS is always on and is powered by on-grid energy, while the SCBSs are powered exclusively by renewable energy. The MBS provides basic coverage while the SCBSs are deployed to enhance network capacity and to receive a traffic load from MBS.

Let us define a geographical area $\mathcal{A} \subset \mathbb{R}^2$ where base stations and users are located. The set of $b \in \mathbb{Z}_{>0}$ base stations is denoted by $\mathcal{B} = \{1, \ldots, b\}$ and a set of $u \in \mathbb{Z}_{>0}$ users is denoted by $\mathcal{U} = \{1, \ldots, u\}$. Let $p \in \mathcal{A}$ denote a possible location, and $1 \in \mathcal{B}$ represent the MBS. Let $k \in \mathbb{Z}_{\geq 0}$ denote the discrete time with a sampling time given by $\tau \in \mathbb{R}_{>0}$ seconds, and let $N \in \mathbb{Z}_{>0}$ be a simulation horizon. Each SCBS updates its cell size every τ seconds by changing the transmission power according to the amount of renewable energy available at its location. In each time instant k, a set of $\mathcal{B}_{i,k} \subset \mathcal{B}$ base stations are available to provide service to user $i \in \mathcal{U}$.

2.3.2. Energy Consumption Model

The energy consumption model used in this thesis was proposed by project EARTH and has been widely used in works related to energy efficiency in cellular networks (Han and Ansari, 2016, Liu et al., 2015a, Yang et al., 2016). According to EARTH, the energy consumption of a

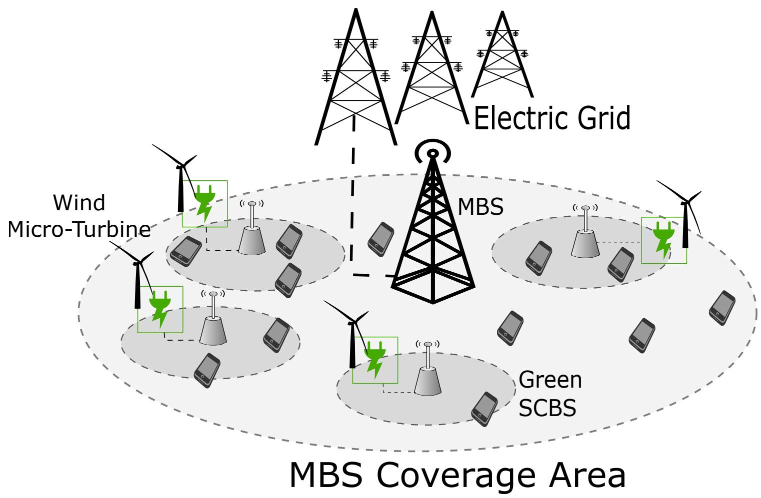

Figure 2-1.: Scenario: A HetNet powered by hybrid energy sources.

BS consists of two parts: the static power consumption and the dynamic power consumption (Auer et al., 2011). The energy consumption can be expressed as

$$C_{\ell,k} = \Delta_\ell \delta_{\ell,k} T_{\ell,k} + E_\ell^S, \ \forall \ell \in \mathcal{B}, \tag{2-1}$$

where Δ_ℓ is the slope of load-dependent energy consumption of BS ℓ, $T_{\ell,k}$ is the transmission power of BS ℓ at the k^{th} time instant, $\delta_{\ell,k}$ is the traffic load of BS ℓ at the k^{th} time instant and E_ℓ^S is the static energy consumption of BS ℓ in each time instant. Static power consumption is related to the energy required for the normal operation of a BS, and the dynamic power consumption is the additional energy demand caused by the traffic load, which is approximated by a linear function of the load.

Here, the total energy consumption of the network scenario in a given time instant is the sum of the grid consumption (due to MBS) and the green consumption (due to SCBSs). Hence, the reduction of consumption in BS $\ell = 1$ (MBS) is the key to increase energy efficiency.

2.3.3. Renewable Energy Model

Introducing renewable energy (RE) power sources in a cellular network requires understanding of RE dynamics and their relationship with energy consumption at a BS. In this thesis, we consider wind as the source of the renewable power in short-time scale. In particular, real data is used to define a Weibull probability distribution that represents the expected wind speed at a specific location and time interval. The Weibull distribution used in an eolic system design is

$$p(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k} \tag{2-2}$$

where v is the wind speed in m/s, c is the scale parameter of the distribution and k is the shape parameter (Villarrubia, 2012). In this case, these parameters are fitted from real data

of Medellín city (Colombia) (SIATA, 2016). This allows a calculation of the amount of energy that can be produced by a micro-turbine in a period.
For the long timescale case a different renewable energy source model is introduced. It is used the solar radiation data of the Medellín city provided by Colombian Institute of Hydrology, Meteorology and Environmental Studies - IDEAM (IDEAM, 2017). Specifically, the IDEAM model provides information about amount of kWh/m^2 in the target area. This information, combined with technical characteristics of solar panels, provide the photovoltaic energy availability in an hour to power green small cells. The IDEAM model is a clear sky model (Bird and Hulstrom, 1981) that estimates the terrestrial solar radiation under a cloudless sky as a function of the solar elevation angle, site altitude, aerosol concentration, water vapour, and various fixed atmospheric conditions. This kind of model is widely used in systems powered by renewable energies. The model computes hourly average solar radiation for every hour of the year, based on different atmospheric parameters such as Aerosol Optical Depth, Ozone, and Water vapour, which are fixed for the entire year.

2.3.4. Traffic Model

Traffic requests are modeled as an inhomogeneous Poisson point process. The traffic size, the arrival rate per area $\lambda^p \in \mathbb{R}_{\geq 0}$, for all $p \in \mathcal{A}$, and the average traffic size $\mu^p \in \mathbb{R}_{\geq 0}$, as well as for all $p \in \mathcal{A}$, are independently distributed. Moreover, these three elements are used in order to capture the spatial traffic variability, as in (Kim et al., 2012).
A mobile user $i \in \mathcal{U}$, at location $p \in \mathcal{A}$, associated with a BS $\ell \in \mathcal{B}_{i,k}$, has a transmission rate denoted by $r^p_{i\ell} \in \mathbb{R}_{\geq 0}$, for all $p \in \mathcal{A}$, which can be generally expressed according to the Shannon-Hartley theorem (Kim et al., 2012) as

$$r^p_{i\ell} = W_\ell \cdot \log_2(1 + \psi^p_{i\ell}), \quad \forall i \in \mathcal{U}, \ell \in \mathcal{B}_{i,k}, \tag{2-3}$$

where $W_\ell \in \mathbb{R}_{\geq 0}$, for all $\ell \in \mathcal{B}$, is the operating bandwidth. The received signal by user $i \in \mathcal{U}$ at location $p \in \mathcal{A}$ from $\ell \in \mathcal{B}_{i,k}$ is given by signal-to-interference-plus-noise ratio (SINR) denoted in this thesis by $\psi^p_{i\ell} \in \mathbb{R}_{\geq 0}$, for all $p \in \mathcal{A}$, and computed as

$$\psi^p_{i\ell} = \frac{T_\ell g^p_\ell}{\sigma^2 + \sum_{i \in \mathcal{B} \setminus \{\ell\}} T_i g^p_i}, \ \forall \ell \in \mathcal{B}, \tag{2-4}$$

where $T_\ell \in \mathbb{R}$ denotes the transmission power, for all $\ell \in \mathcal{B}$, and g^p_ℓ is the channel gain between the ℓ^{th} BS and the user at location p. Additionally, the parameter $\sigma^2 \in \mathbb{R}$ denotes the noise power level. Note that the channel gain here reflects only the slow fading, including the path loss and the shadowing; fast fading is not considered. In (2-4), the denominator represents the interfering BSs transmission toward a user at location p. $\psi^p_{i\ell}$ must be higher than a threshold denoted by $\varphi \in \mathbb{R}$ so that a user $i \in \mathcal{U}$ has useful signal. For simplicity, the location indicator p is omitted when referring to user $i \in \mathcal{U}$.

In this thesis, it is assumed that the network's frequency scheduling is such that each SCBS can only serve a fixed number $z_\ell^{\max}$ of users simultaneously for all $\ell \in \mathcal{B}\backslash\{1\}$. Nevertheless, the MBS has no limit for the number of served users, being able to serve all active users at an instant $z_{A,k}$. Hence, note that the bandwidth assigned to a user $i \in \mathcal{U}$ is affected by the number of users connected to the BS $\ell \in \mathcal{B}_{i,k}$, because the channels availability must be shared between the active users.

Assuming that mobile users are uniformly distributed in the coverage area of all BSs, the traffic load of the ℓ^{th} BS in the k^{th} time instant can be expressed as

$$\delta_{\ell,k} = \frac{\sum_{i\in\mathcal{U}} y_{i\ell,k}}{U_{\ell,k}}, \ \forall \ell \in \mathcal{B}, \tag{2-5}$$

$$U_{\ell,k} = \begin{cases} z_{A,k}, & \text{if } \ell = 1, \\ z_\ell^{\max}, & \text{otherwise,} \end{cases}$$

where $y_{i\ell}$ is the user association indicator, i.e., if user $i \in \mathcal{U}$ is associated to the BS $\ell \in \mathcal{B}$, then $y_{i\ell} = 1$, and $y_{i\ell} = 0$ otherwise. Moreover, note that $0 \leq \delta_\ell \leq 1, \forall \ell \in \mathcal{B}, k$.

The average transmission rate per user in the k^{th} time instant depends on ψ and the number of users connected to the serving BS (Andrews, 2013), which allows us to express (2-3) as

$$r_{i\ell,k}^p = \frac{W_\ell}{\sum_{i\in\mathcal{U}} y_{i\ell,k}} \log_2(1 + \psi_{i\ell}^p), \ \forall\, i \in \mathcal{U}, \ell \in \mathcal{B}_{i,k}. \tag{2-6}$$

It is also assumed that, at each time instant, a user can be associated with the ℓ^{th} BS if the received signal level $\psi_{i\ell}^p$ is greater than a threshold φ that indicates the minimum signal level required by a user to have service.

In traditional cellular networks, mobile users connect to the BS that offers the best SINR. However, this mechanism is not entirely adequate for HetNets, because SCBSs with available resources can be ignored by users when receiving a stronger signal from an MBS (Andrews, 2013). We will refer to this procedure as traditional policy, and it will be the baseline for evaluating the performance of proposed mechanisms. Note that, for simplicity, we used only path loss to determine the user's best received signal.

2.3.5. On-grid Energy Consumption Optimization Problem

As previously mentioned, on-grid consumption reduction is a design requirement in NGCN. Given that the objective is to reduce the overall system grid consumption, it is possible to formulate the following optimization problem::

$$\min_{y_{11,k},\cdots,y_{n1,k}} J(y_{11,k}, \ldots, y_{n1,k}) = \sum_{k=1}^{N} \sum_{i\in\mathcal{U}} y_{i1,k}, \tag{2-7a}$$

s.t.

$$\sum_{i\in\mathcal{U}} y_{i\ell,k} \le z_\ell^{\max}, \quad \forall \ell \in \mathcal{B}\backslash\{1\}, k \in [0,N]\cap\mathbb{Z}_{\ge 0}, \tag{2-7b}$$

$$y_{i\ell,k}\cdot\psi_{i\ell} \ge \varphi, \qquad \forall i \in \mathcal{U}, \ell \in \mathcal{B}_{i,k}, k \in [0,N]\cap\mathbb{Z}_{\ge 0}, \tag{2-7c}$$

$$\sum_{\ell\in\mathcal{B}} y_{i\ell,k} \le 1, \qquad \forall i \in \mathcal{U}, k \in [0,N]\cap\mathbb{Z}_{\ge 0}, \tag{2-7d}$$

$$y_{i\ell,k} \in \{0,1\}, \; \forall i \in \mathcal{U}, \ell \in \mathcal{B}, k \in [0,N]\cap\mathbb{Z}_{\ge 0}, \tag{2-7e}$$

where (2-7a) is the objective function, which focuses on minimizing consumption from the grid with an optimal assignment of active users to available BSs in each time instant. Equations (2-7b)-(2-7e) are the problem constraints: (2-7b) establishes that a small cell ℓ can serve a maximum of $z_\ell^{\max}$ users simultaneously; (2-7c) is the user's received signal level constraint, (2-7d) requires that a user is served only by one BS in a time instant; and (2-7e) establishes that $y_{i,\ell}$ is a binary variable.

The optimization problem (2.7) is a binary integer problem (BIP), a well-known $\mathcal{NP}$-hard problem (Johnson and Garey, 1979), where the search space is composed by a matrix of $|\mathcal{U}| \times |\mathcal{B}|$. For example, the proposed scenario with $|\mathcal{B}| = 2$ and $|\mathcal{U}| = 30$ requires 2^{30} combinations to be evaluated, i.e., a billion value computations, which limits the direct search of a solution.

2.4. Case Study

The case study considered is composed by one MBS and 36 overlapping SCBSs. This is the minimum number of SCBSs needed to cover the MBS area. In this scenario, the MBS is powered by on-grid energy, and it is always on, ensuring constant coverage over the area. Each BS has one sector, and only large-scale loss is considered in the simulation. This case study presents different simplifications but is complex enough to show the potential of the methods proposed in the thesis.

Despite some simplifications made in the case study, it maintains generality and is representative of a real scenario where the complexity of association process is caused in part by the number of base stations and active users.

From a telecommunications viewpoint, technical parameters of the simulation are based on a Long-Term-Evolution system in a coverage area of 3.5 km^2 (3GPP, 2014). The distance between BSs is 500 m and users are uniformly distributed in the coverage area. Also, given the population density of Medellín (2500hab/km^2) and the mobile internet penetration in Colombia at 2015 (10 %), 750 users is the minimum number of users considered in the experiments. Table **2-1** summarizes the parameters used in the simulation.

Table 2-1.: Simulation Parameters

Parameter	**Value**	**Units**
Coverage Area	3.5	km^2
System	LTE	-
BW LTE	20	MHz
RB per BS	100	-
N. Macro Base Station	1	-
N. MBS sectors	1	-
N. SCBS	36	-
Inter-site distance	500	m
Tx power MBS	43	dBm
Tx power SCBS	22	dBm
Static Power Cons. MBS	130	W
Static Power Cons. SCBS	6.8	W
Consumption Slope MBS	4.7	-
Consumption Slope SCBS	4.0	-
Path loss between MBS and user	Cost 231 model	-
Antenna Gain	15	dBi
Max. users simultaneously for an SCBS	100	-
Receiver sensitivity	$-107{,}5$	dBm
Size of request file	500	KB
Time instant length	1	s
Mobility Model	Random walk point	-
Mobility Speed	4	km/h

Table 2-2.: Energy Potential of Micro-Turbine

Wind Speed	Power Potential [watts]
< 2 m/s	0
2 m/s - 3 m/s	26
> 3 m/s	35

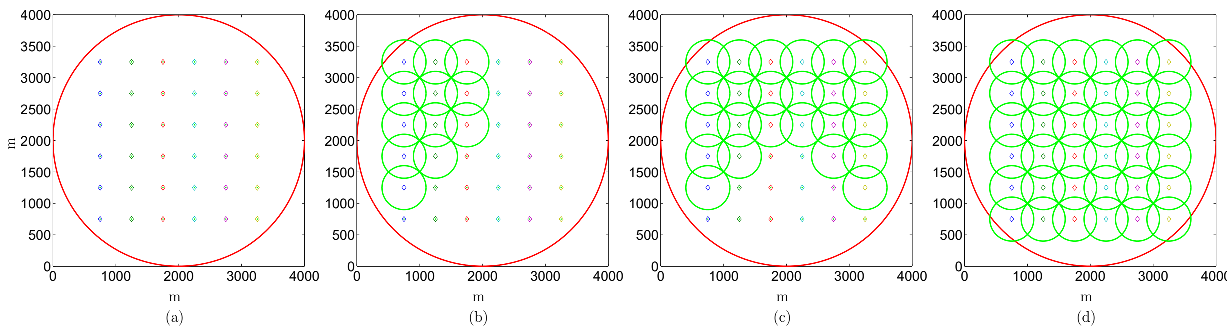

Figure 2-2.: Green-energy availability scenarios for the MBS coverage area.

2.4.1. Renewable Power Potential

As mentioned previously, in the short-time scale the renewable source selected to power SCBSs is wind. The simulation considers the behavior of the wind in Medellín, based on 3-year data provided by weather stations of SIATA (SIATA, 2016). Using @Risk7 (Palisade Corporation, 2015), it was possible to define three sectors with different wind behaviors in the simulation area. It was found that sector one presents a mean wind speed of 1.787 m/s, sector two has a mean wind speed of 1.880 m/s, and sector three has a mean wind speed of 2.238 m/s. According to the average wind speed, a micro-turbine was selected for the SCBSs with a start-up wind speed of 2 m/s and the power potential shown in Table **3-2**.
The case study is configured with different average wind speeds in the sectors under the coverage area of the MBS. Wind dynamics vary every minute. Therefore, according to the data provided by (SIATA, 2016), there are three possible green-energy scenarios (shown in Figure **2-2**): (a) no SCBS has sufficient green-energy, (b) the SCBSs of only one sector have green-energy to operate, and (c) more than one sector has green-energy (this case could be even with all SCBSs having energy in the same period (d)). In this figure, the big red circle represents the MBS coverage area, while green smaller circles are SCBS coverage areas.

3. Coalitional Planning for Energy Efficiency of HetNets Powered by Hybrid Energy Sources

In this chapter, we focus on the problem of planning heterogeneous cellular networks (HetNets) powered by renewable energy sources. The proposed planning mechanism is based on a coalitional game in which small cells are players, with the Shapley value determining the contribution of each potential small cell to the global performance of the system. The results presented in this section were published in (Fletscher et al., 2018).

To evaluate the proposed mechanism, the shot-time scale scenario is used. The coalitional planning method is test in an academic example and a complex scenario (1 MBS, 36 SCBSs, and 750 users), including three geographical areas with different wind profiles. Also, three other planning alternatives are introduced for the sake of comparison. The first is a traditional scheme in which SCBSs are located in an equidistant and uniform way. The second uses two variations of a greedy algorithm to add/remove SCBSs based on their marginal contribution to the system performance. Likewise, an exhaustive search and a genetic algorithm are used to find the best locations for SCBSs in the academic and large-scale examples, respectively. The effect of using the solution found with the coalitional method as a start point of these methods is also assessed.

3.1. Problem Statement

The problem consists of a two-tier downlink HetNet such as presented in Subsection 2.3.1, which is composed of one macro base station (MBS) and multiple feasible locations for small-cell base stations (SCBSs). On-grid energy powers the MBS, which provides basic coverage and service continuity. SCBSs powered exclusively by green energy, without batteries, are to be deployed to enhance network capacity and absorb traffic load. Wind is the only energy source considered to power SCBSs in this work. Also, each BS has one sector, and only large-scale loss is considered. The planning task is to select a subset of candidate sites for deploying small cells to minimize the energy consumption of the HetNet while satisfying practical constraints.

Let us define a geographical area $\mathcal{A} \subset \mathbb{R}^2$ where base stations and users are located. The set of $b \in \mathbb{Z}_{>0}$ possible base stations is denoted by $\mathcal{B} = \{1, \ldots, b\}$, and a set of $u \in \mathbb{Z}_{>0}$

users is denoted by $\mathcal{U} = \{1, \ldots, n\}$, where $u = 1 \in \mathcal{B}$ represents the MBS. Let $k \in \mathbb{Z}_{\geq 0}$ denote the discrete time with a sampling time given by $\tau \in \mathbb{R}_{>0}$ seconds, and let $N \in \mathbb{Z}_{>0}$ be a simulation horizon. Each SCBS updates its cell size every τ seconds by changing the transmission power according to the amount of renewable energy available at its location.

Given the set of BSs in $\mathcal{B}$, we would like to know which ones we should activate according to a certain performance index. Hence, each BS is associated to a binary variable that tells us whether the BS should be activated (e.g., the binary variable is 1 when the BS is used and 0 otherwise). A straight-forward way to find the best topology would be to evaluate the performance index for all the possible combinations. Unfortunately, this approach is valid only for a small number of BSs. In particular, there are b binary variables, which means that it is necessary to explore 2^b combinations. For example, if the cardinality of the set $\mathcal{B}$ is 30, more than one billion options have to be explored. This is not surprising, for integer optimization is a well-known $\mathcal{NP}$-hard problem (Johnson and Garey, 1979). Due to the combinatorial explosion issues, it is necessary to find tractable methods that can be used in real large-scale applications. For this reason, we consider that the BSs in $\mathcal{B}$ are players of a cooperative game that has a Shapley value used to rank them regarding their average marginal contribution, which is used as a criterion for placement. Note that the traditional calculation of the Shapley value also suffers from combinatorial explosion problems, but there are numerical approximations available that can be computed in polynomial time (Castro et al., 2009, Shaheen et al., 2008).

3.1.1. Key Performance Indicators

In this chapter, a KPI is a measurable value that shows how effective the network is in achieving its operating objectives at a specific SCBS location. Hence, in order to quantitatively evaluate the performance of the SCBS in the planning proposals, three KPIs have been defined: (1) reduction of grid consumption, which is directly related to the energy-consumption reduction, (2) percentage of users served, and (3) average transmission rate, which measures technical network variables associated with QoS. KPIs are normalized ($KPI_i \in [0, 1]$) to simplify their comparison and are defined as:

Reduction of grid consumption According to the energy consumption model defined in (2-1), the impact of an SCBS in the network grid consumption is quantified using the next KPI

$$KPI_C = 1 - \left(\frac{\left(\frac{\sum_{k=1}^{N} C_{1,k}}{N} \right)}{\Delta_1 T_1 \tau + E_1^S} \right), \tag{3-1}$$

where the numerator represents the average grid consumption, and the denominator is the maximum possible grid consumption in a time slot.

Percentage of users served The impact of an SCBS on the number of users served is evaluated with the following KPI

$$KPI_U = \left(\frac{\sum_{k=1}^{N} z_{S,k}}{\sum_{k=1}^{N} z_{A,k}} \right), \tag{3-2}$$

where $z_{S,k}$ is the total number of users served, and $z_{A,k}$ is the total number of users active in a time slot.

Average Transmission rate The transmission rate defined of a user i associated with a BS j in the $k-th$ time slot can be expressed as

$$r_{ij,k} = bits_{\text{mod}} 12_{\text{subc}} 7_{\text{symb}} 1_{\text{slot(ms)}}, \tag{3-3}$$

where the first term is the number of bits defined by the modulation scheme (6 for QAM64, 4 for QAM16, and 2 for QPSK), followed by the number of subframe subcarriers in a 20 MHz bandwidth channel, the number of OFDMA symbols, and, finally, the assigned time slots (3GPP, 2017). Hence, it is possible to define the following KPI related to the average transmission rate of the network:

$$KPI_R = \left(\frac{\sum_{k=1}^{N} \sum_i r_{i,k}}{\sum_{k=1}^{N} z_{A,k} R_M} \right) \qquad i = 1, 2, \ldots, z_A \tag{3-4}$$

where $z_{A,k}$ is the number of active users in a time slot and R_M is the maximum user rate, -i.e., when the modulation scheme is QAM64.

3.1.2. Coalitional games approach

The proposed method is based on a coalitional game in which SCBSs are the players. The game is structured by the set of players and a characteristic function. In this work, the characteristic function that assigns a value to each of the possible coalitions of players that can be formed is defined by the set of KPIs.

Here, a cooperative game with transferable utility (TU) is a pair $(\mathcal{B}, f)$, where $\mathcal{B}$ is the set of players and f is a function that assigns a value to each possible coalition $\mathcal{S} \subseteq \mathcal{B}$, with $f(\emptyset) = 0$. In this thesis, the term coalition is understood in the sense of aggregation. A coalition is an aggregation of small cells $\mathcal{S} = \{s_1, s_2 \ldots, s_b\}$ that tries to fulfil the cellular network objectives (with $b \leq B$), without the assistance of the rest of the players. Here, we assume that

$$f = \sum_{w=1}^{W} \frac{KPI_w}{W} \tag{3-5}$$

where W is the number of KPI's used to assess the planning, and $KPI_w \in [0, 1]$ so that $f(s) \in [0, 1], \forall s \in \mathcal{B}$.

A payoff rule is a vector that assigns a certain amount to each player according to its contribution to the game. In this work, we use the Shapley value, which assigns to each player $j \in \mathcal{B}$ the value

$$\phi_j(\mathcal{B}, f) = \sum_{\mathcal{S} \subseteq \mathcal{B} \setminus \{j\}} \frac{|\mathcal{S}|!(|\mathcal{B}| - |\mathcal{S}| - 1)!}{|\mathcal{B}|!}[f(\mathcal{S} \cup \{j\}) - f(\mathcal{S})], \tag{3-6}$$

which can be interpreted as the weighted average of its contributions to the different coalitions. The Shapley value on the class of TU-games satisfies properties such as linearity, efficiency, dummy player and symmetry (Shapley, 1952). However, a well-known problem of the Shapley value is the limitation derived from the combinatorial explosion problem in games with many players (see (Deng and Papadimitriou, 1994, Faigle and Kern, 1992) for more details).

3.2. HetNet Planning Schemes

This section presents the proposed coalitional game planning and other strategies that will be used for comparison: a simple uniform distribution of BSs over the coverage area, a greedy scheme used to rank SCBSs according to their contribution to the network performance and to select the best ones, exhaustive search, and a genetic algorithm to define the best locations of SCBSs according to their contribution to network performance.

3.2.1. Coalitional Planning

In the coalitional planning process, it is assumed that a set of possible locations where BSs can be deployed is available, and them are ranked based on the expected contribution to the overall performance of SCBSs in those positions (the MBS is located at the centre of the geographical area in the three cases). When there are fewer SCBSs than locations available, they are deployed based on the best locations according to the aforementioned ranks. Nevertheless, note that for a total of $\mathcal{B}$ players, $2^{\mathcal{B}}$ different coalitions need to be evaluated. For example, a HetNet with 30 small cells requires that 2^{30} coalitions be evaluated - i.e., a billion value computations - which limits the applicability of this value. The computation problem is solved in this thesis by using the randomized method proposed in (Castro et al., 2009), which allows an approximation of the Shapley value to be obtained in polynomial time.
In the method given in (Castro et al., 2009), an alternative calculation of the Shapley value is used. Indeed, the Shapley value can also be expressed in terms of all possible orders of the set of players $\mathcal{B}$ in the following way

$$\phi_j(\mathcal{B}, f) = \frac{1}{|\mathcal{B}|!} \sum_{\pi \in \prod(\mathcal{B})} m_j^{\pi}(\mathcal{B}, f), \qquad \forall j \in \mathcal{B} \tag{3-7}$$

where $\prod(\mathcal{B})$ is the collection of all permutations $\pi : \mathcal{B} \to \mathcal{B}$ on $\mathcal{B}$, and, for every permutation $\pi \in \prod(\mathcal{B})$,

$$\begin{aligned} m_j^{\pi}(\mathcal{B}, f) = \quad & f(\{\ell \in \mathcal{B} \mid \pi(\ell) \leq \pi(j)\}) \\ & - f(\{\ell \in \mathcal{B} \mid \pi(\ell) < \pi(j)\}) \end{aligned} \tag{3-8}$$

is the marginal contribution of player j to the players that are ranked before him/her in the order π. Therefore, the Shapley value assigns each player the average over its marginal contributions in all the permutations of the player set $\mathcal{B}$.
The solution of the Shapley value by (3-7) and (3-8) can be simplified by using a sampling process to approximate the Shapley value as follows (Castro et al., 2009):

1. Let the population set from which the sample is taken be represented by the set of all possible orders of the set of players $\mathcal{B}$, i.e., $\mathcal{P} = \prod(\mathcal{B})$. It is assumed that a sample M is an element of $\mathcal{P} \times \overset{q}{\cdots} \times \mathcal{P}$, i.e., it is obtained with replacement.

2. The vector to be estimated $\phi = (\phi_1, \ldots, \phi_b)$ is the Shapley value for each $j \in \mathcal{B}$.

3. The characteristics observed for each sampling unit $\pi \in \prod(\mathcal{B})$ correspond to the marginal contributions of the players in the order π, i.e.,

$$x(\pi) = (x_1(\pi), \ldots, x_n(\pi)) \quad \text{with} \quad x_j(\pi) = m_j^{\pi}(\mathcal{B}, f). \tag{3-9}$$

4. The estimate of the Shapley value $\tilde{\phi}_j\,(\mathcal{B}, f)$ will be given by the average of the marginal contributions over the sample M, i.e.,

$$\tilde{\phi}_j\,(\mathcal{B}, f) = \frac{1}{q} \sum_{\pi \in M} x_j(M), \qquad \forall j \in \mathcal{B}. \tag{3-10}$$

5. Any order $\pi \in \prod(\mathcal{B})$ will be taken with equal probability to determine the sample M in the process of selection.

The sampling method described gives an approximation of the Shapley value with desirable properties. For instance, it is possible to calculate the theoretical error in a probabilistic way. In particular,

$$\tilde{\phi}_j\,(\mathcal{B}, f) \sim N(\phi_j(\mathcal{B}, f), \sigma^2/q), \tag{3-11}$$

i.e., the estimator is unbiased and its variance is given by σ^2/q (Castro et al., 2009). Hence, if the sample size satisfies

$$q \geq Z_{\alpha/2}^2 \sigma^2 / e^2, \tag{3-12}$$

then

$$P(\mid \phi_j(\mathcal{B}, f) - \tilde{\phi}_j\,(\mathcal{B}, f) \mid \leq e) \geq 1 - \alpha, \tag{3-13}$$

with e being the approximation error, and $Z \sim N(0,1)$, and $Z^2_{\alpha/2}$ being the value such that $P(Z \geq Z^2_{\alpha/2}) = \alpha/2$. Given that σ^2 is unknown, it is necessary to provide an upper bound, which becomes $\sigma^2 \leq (x^j_{max} - x^j_{min})/4$ for any random variable bounded in a range $[x^j_{min}, x^j_{max}]$ (Castro et al., 2009).

3.2.2. Uniform base station locations

This HetNet planning mechanism is used for comparison: it is a method in which the BSs are uniformly distributed over the geographical area. This is a valid approximation that assigns the same relevance to each SCBS and therefore sets a uniform distance between them. The uniform distribution of BSs is used in cases without information about the spatial distribution of traffic or the contribution of a specific BS, as can be seen in (Carvalho et al., 2016, Liu et al., 2015b).

3.2.3. A greedy planning algorithm

We also implemented a greedy algorithm to evaluate the contribution of each BS to global network performance for the sake of comparison. This algorithm also allows ranking of the BSs.

The greedy mechanism works as follows: In a first round, all BSs are disconnected, and then the algorithm turns on each BS while keeping the rest of them disconnected to evaluate the system response. Once all BSs are assessed individually, the BS with the best marginal contribution with respect to the sum of indicators is selected. This BS remains enabled in the next evaluating round, where a new BS will be enabled based on its marginal contribution. The process continues until a ranking is defined of the working priority of the b locations available.

This method was also implemented in reverse order - i.e., the algorithm starts with all SCBSs enabled and they are disconnected one by one to establish a ranking. Finally, a weighted combination between the results of both methods was also made.

3.2.4. Genetic algorithm planning

Due to the computational complexity of calculating an exact solution in the large-scale scenario, a genetic algorithm (G.A.) was implemented to find an approximate solution. The genetic algorithm was designed to find the best 18 and 24 SCBS locations according to the KPIs defined.

The algorithm begins by creating a random initial population, although seeds can be set as well. The algorithm scores each member of the current population by computing its fitness value according to the KPIs defined. These scores are used to select the best members, called parents. Additionally, some of the individuals in the current population that have better fitness are chosen as being elite. These elite individuals are passed on to the next population. Children are produced either by mutation (making random changes to a single parent) or by crossover (combining the vector entries of a pair of parents). Finally, the current population is replaced with the children to form the next generation. This procedure was performed for 50 generations.

3.2.5. Pattern search

This is a method for solving optimization problems with no information regarding the gradient of the objective function - e.g., the objective function may not be continuous or differentiable. To this end, the method iteratively explores a set of points around the current one to find those with lower value. The sequence of points obtained is expected to approximate the optimal point.

3.2.6. Exhaustive search

This strategy is introduced for the academic example to obtain the optimal solution of the problem, for it is feasible to find it due to the reduced size of this problem. In this case, we consider ℓ possible locations for m SCBSs, requiring assessment $\ell!/(m!(\ell - m)!)$ combinations. The combination with the highest value of $\sum_{w=1}^{W}(KPI_w/W)$ is the optimal location for the SCBSs.

3.3. Case Study

In this section, we provide two different case studies: the first is a reduced-size academic example introduced to evaluate the proposed strategy in a way that it is feasible to obtain the optimal solution; the second is much larger and representative of the complexity of real design problems, and it is only possible to compare the proposed method with other heuristic approaches. Both case studies care based on the network scenario presented in Subsection 2.3.1.

3.3.1. Academic Example

A reduced planning problem was formulated to explicitly calculate the best location of the SCBSs. The goal is to compare the explicit solution with the location provided by coalitional planning. In this case, we consider 12 possible locations for 8 SCBSs, requiring assessment of $12!/(8!(12-8)!) = 495$ combinations. The combination with the highest value of $\sum_{w=1}^{W}(KPI_w/W)$ is the optimal set of locations for the SCBSs. This scenario uses a controlled wind profile to enable different groups of SCBSs during specific time periods. The number

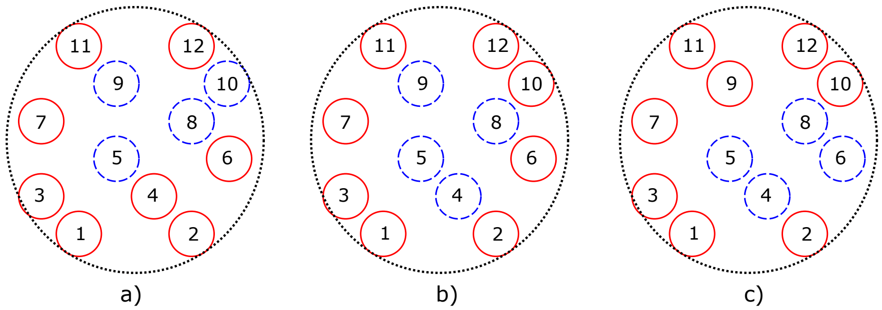

Figure 3-1.: Allocation problem results: (a) Optimal solution, (b) Coalitional planning, and (c) Greedy mechanism.

Table 3-1.: Explicit Solution Comparison

Mechanism	**Best locations**	$\sum_{w=1}^{W} \frac{KPI_w}{W}$	**Order**
Explicit solution	$\{1\ 2\ 3\ 4\ 6\ 7\ 11\ 12\ \}$	1.35	1°
Coalitional planning	$\{1\ 2\ 3\ 6\ 7\ 10\ 11\ 12\ \}$	1.34	2°
Greedy	$\{1\ 2\ 3\ 7\ 9\ 10\ 11\ 12\}$	1.32	10°
Uniform	$\{1\ 2\ 4\ 6\ 8\ 10\ 11\ 12\}$	1.28	56°

of active BSs changes according to a pre-defined sequence, and users move randomly around the simulation area.

Figure **3-1** shows the results obtained in the allocation problem. The numbers indicate possible locations for the SCBSs. The red circles represent the selected locations, while the blue dashed circles are the discarded locations. Additionally, Table **3-1** presents a comparison of the explicit solution with the proposed planning mechanisms. It is possible to observe that coalitional planning is the closest to the optimal solution. The combination provided by the greedy algorithm lies in the tenth position of the combinations found with the explicit solution. Finally, the uniform strategy is the furthermost from the optimal solution.

In Figure **3-2**, we can see how many times each SCBS appears in the top 20 combinations. It is very interesting that the planning generated by our coalitional method contains exactly these SCBSs. But this is not surprising if we take into account that the Shapley value determines which are the best players of the game according to their average marginal contribution.

3.3.2. Large-scale Problem

The simulations to evaluate the BS ranking considers two wind profiles (low average speed and high average speed) with the goal of evaluating the planning mechanisms under different working conditions. The profiles were fitted from real data of Medellín city, based on 3-

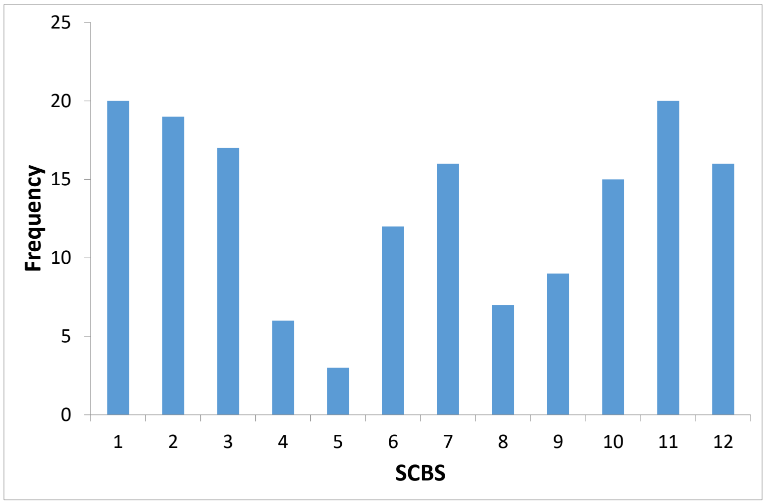

Figure 3-2.: Histogram of the SCBSs in the best 20 combinations in the academic example.

Table 3-2.: Wind profiles

	Low wind speed (m/s)	**High wind speed (m/s)**
Sector 1	1.8 m/s	2.5 m/s
Sector 2	2.0 m/s	3.1 m/s
Sector 3	2.2 m/s	3.7 m/s

year data provided by weather stations of SIATA (SIATA, 2016), to reflect the stochastic behaviour of the wind. Using @Risk7 (Palisade Corporation, 2015), it was possible to define three sectors with different wind behaviors in the geographic area. The average wind speeds are shown in Table **3-2**.

The SCBSs, are equipped with a commercial micro-turbine with a start-up wind speed of 2 m/s and an energy potential of 26 W when wind speed is between 2 m/s and 3 m/s, and 35 W when wind speed is above 3 m/s. The RE-powered HetNet's architecture is presented in Figure **3-3**.

Using MATLAB®(The MathWorks, 2015), it was possible to evaluate the proposed schemes and their impact on network performance. The confidence interval (±16 W) for grid consumption was calculated with data obtained from 6 simulations with 900 samples by simulation. A ranking of the contribution of each BS to the performance of the system was calculated. In the coalitional case, the marginal increase caused by one SCBS to a particular coalition was evaluated. The method proposed in (Castro et al., 2009) was implemented with a maximum error of 0.01 with 90 % probability. These parameters required the calculation of 1691 random orderings of players to evaluate the corresponding marginal contributions of

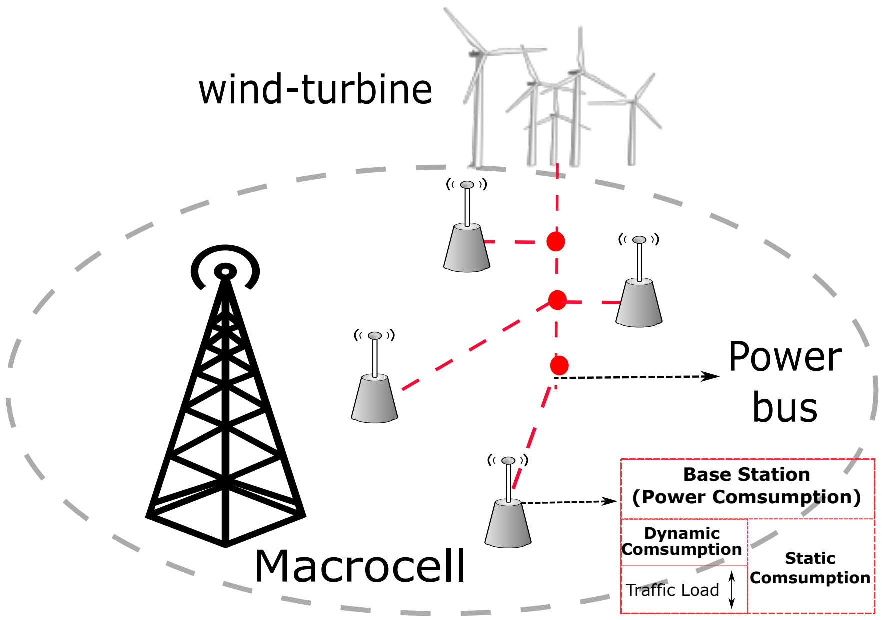

Figure 3-3.: Green HetNet's power architecture.

the 37 players of the game. Figure **3-4** shows the results.

As can be seen, the MBS has the primary role in the network performance. In second place, there is a group of SCBSs located on the edges of the coverage area. Figure **3-5** shows the distribution of the contributions over the network layout. There, we observe lower contributions of SCBSs near to the MBS, while contributions are increased with distance.

Figure **3-6** shows the ranking given by the greedy algorithm. The red circles represent the BSs with greater contributions to system performance, and hight priority to be included in HetNet deployment. The big red circle represents the macro base station, which is located at the centre of the geographical area. The blue dotted circles are the small cells with the

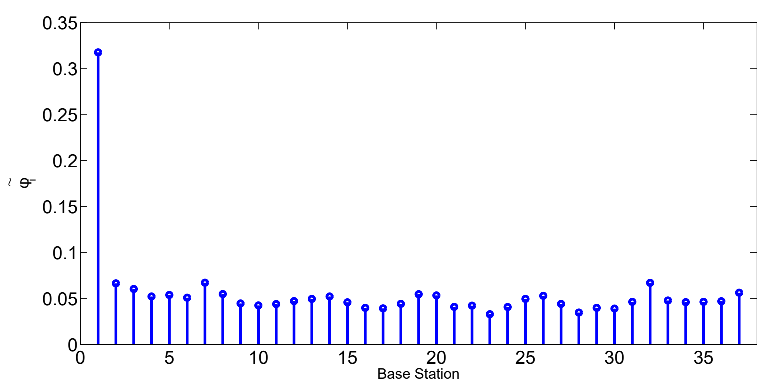

Figure 3-4.: Total contribution of each BS.

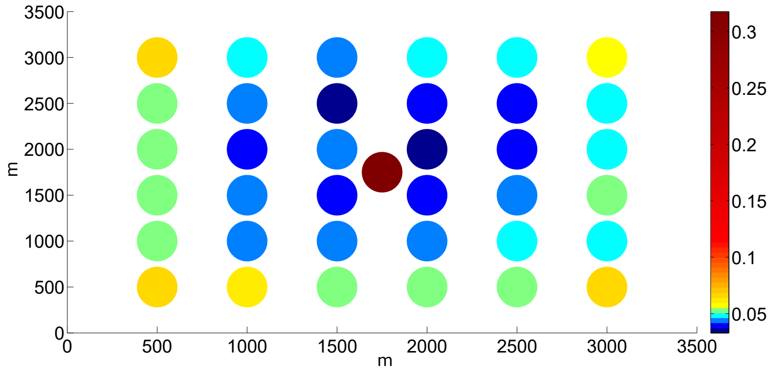

Figure 3-5.: Behaviour of contributions over coverage area.

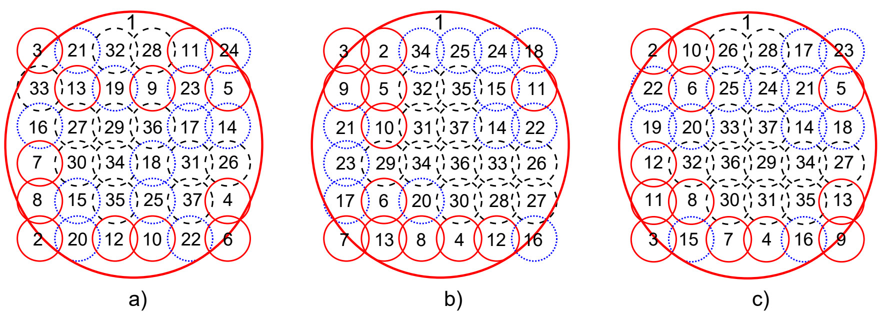

Figure 3-6.: Greedy planning results (a) Scheme with all off to turn on, (b) Scheme with all on to turn off, and (c) weighing results.

second priority in planning, and, finally, the black dashed circles are the base stations with the lowest contribution to network performance. As in the coalitional case, we can observe that the main contribution lies at the edges of the geographical area. This can be explained by the MBS being located at the centre of the coverage area. The SCBSs at the border are useful for receiving traffic because the signal received from the MBS is smaller in that zone. In Figure **3-7**, we can observe the locations selected by the genetic algorithm. The red circles represent the selected SCBS locations. The big red circle represents the macro base station, which is located at the centre of the geographical area. As in the other cases, we can observe that the most relevant SCBSs lie at the edges of the geographical area.

After ranking the SCBSs, we evaluated the network performance with different numbers enabled (18, 24, and 36). The scenario described in Subsection 2.3.1 was simulated with two wind profiles and 750 users. The temporal variability of traffic on the cellular network was not considered. For this reason, a simulation time of 15 minutes (900 time slots) was used to observe the behaviour of the proposed planning solutions. The indicators used to evaluate the network performance in the different configurations were grid consumption, percentage of users served, average user transmission rate, and the average time spent by a user to finish the request (delay). Table **3-3** shows the average results of six experiments

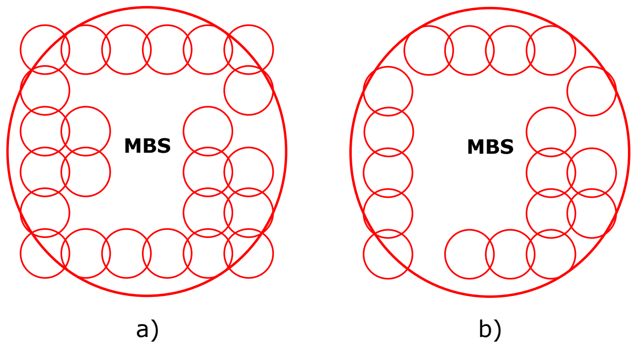

Figure 3-7.: Genetic Algorithm results: (a) 24 best SCBS locations, (b) 18 best SCBS locations.

with similar conditions for each scenario.

As can be seen, the optimization-based proposals are better than uniform distributions in all scenarios. For the low wind-speed profile, the coalitional scheme has better performance in grid consumption and percentage of users served. However, the average user transmission rate is slightly lower than with the greedy scheme. The smaller average transmission rate and higher percentage of users served in coalitional planning is evidence that the network is attending to users with a low received signal at the edges of the coverage area. These users would probably be without service in other schemes. In the high wind-speed profile, the difference between the two proposals is smaller, but the coalition approach continues to predominate in all KPIs.

An interesting result produced by the increase of average wind speed is the increased percentage of users served, but with a smaller transmission rate (given that the network is serving more users, including some at the border with a low received signal from base stations). Nevertheless, with more channels available, the delay is lower compared to the low-wind profile.

Another analysis assessed how decreasing the number of SCBSs affected network performance. In Table **3-4**, we can observe that coalitional planning has the lowest negative impact. For example, when the number of SCBSs is reduced by 50 % in a scenario with a low wind profile, the grid consumption increases by 3.16 % with coalitional planning, 3.25 % with greedy planning, 3.63 % with the genetic algorithm, and 4.7 % with uniform distribution. In the same way, the percentage of users served decreases by 7.79 %, 8.73 %, 7.95 % and 11.51 %, respectively, for each method. In the high wind-speed profile, the results maintain this tendency. Based on the simulation results, it is possible to state that a cooperative game perspective is a good option for planning of HetNets according to specific QoS requirements.

Another simulation with 2000 users (an increase of around 250 %) was made to evaluate the response of the planning mechanism in more demanding conditions. The results obtained can be found in Tables **3-3** and **3-4**. It is important to note that the grid-consumption reduction under coalitional planning continues to be lower than the equidistant mechanism

Table 3-3.: Network Performance

	750 Users				2000 Users			
	Low wind profile		High wind profile		Low wind profile		High wind profile	
	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off
	Average Grid Consumption (watts/min)							
All SCBSs Available	4624.74		4520.51		4338.03		4181.68	
Coalitional	4701.51	4770.88	4594.72	4654.71	4338.17	4378.71	4214.12	4253.91
G.A.	4716.01	4792.78	4607.82	4693.53	4343.19	4396.7	4225.08	4272.95
Greedy	4707.23	4774.92	4620.31	4663.12	4350.38	4385.69	4216.95	4258.00
Uniform	4740.89	4842.30	4622.96	4696.56	4355.27	4396.24	4233.89	4284.15
	Users Served (%)							
All SCBSs Available	90.34		95.38		81.5		89.0	
Coalitional	86.62	82.55	92.32	89.09	76.6	72.1	83.78	78.77
G.A.	85.88	81.61	91.65	86.74	75.8	69.8	82.50	76.60
Greedy	86.21	82.39	90.92	88.57	74.7	71.1	83.54	78.46
Uniform	84.85	79.94	90.81	86.16	73.6	70.8	79.32	70.71
	Average Transmission Rate (Mbps)							
All SCBSs Available	1.04		0.99		0.72		0.3652	
Coalitional	1.12	1.18	1.19	1.10	0.86	0.82	0.43	0.47
G.A.	1.10	1.15	1.00	0.98	0.92	0.85	0.43	0.47
Greedy	1.10	1.15	1.00	0.98	0.92	0.85	0.44	0.48
Uniform	1.07	1.13	0.88	1.03	0.86	0.83	0.43	0.48
	Delay (seconds)							
All SCBSs Available	9.39		7.37		6.4		3.9	
Coalitional	9.91	12.53	7.48	9.26	6.30	6.81	4.57	5.20
G.A.	10.51	11.63	7.68	9.38	6.41	7.45	4.61	5.59
Greedy	10.35	12.27	8.58	9.78	6.20	7.29	4.35	5.32
Uniform	11.38	13.08	9.08	10.23	6.32	7.41	4.98	5.96

in both scenarios. Additionally, the impact of reducing the number of SCBSs increases the grid consumption by 0.94 % in the worst case (low wind speed and 18 SCBSs off) and 0.80 % in the best case (high wind speed and 12 SCBSs off). In the same way, it is possible to observe that coalitional planning has the lowest degradation of the indicators in the high wind-speed scenario compared with the other schemes.

Finally, the results of the proposed planning method were used as a seed of the heuristic approaches to find the best 18 SCBSs. In particular, we tested the genetic algorithm and the pattern search (P.S.) method. Regarding the latter, several searches were made, as well using the best response of other planning methods proposed in this work as starting point (seeds) (coalitional, greedy, and equidistant).

The comparison of the cost function values evaluated with the result of each method is presented in Table **3-5**. Note that in this case the goal is to minimize the cost function by combining the key performance indicators defined. Since the cost function is evaluated in a scenario with controlled wind but moving users generating traffic requests randomly, 20 simulations for each method were used to average the results. As can be seen, the solutions of coalitional-based methods have the minimum values. This result is aligned with that of Figure **3-2** and shows the potential of the proposed coalitional method not only as a planning tool but also as a generator of seeds for other heuristic methods. This idea is illustrated in Table **3-6**, where the performance of these methods is compared in detail in a simulation

Table 3-4.: Network Performance Comparison

	750 Users				2000 Users			
	Low wind profile		High wind profile		Low wind profile		High wind profile	
	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off	12 SCBSs Off	18 SCBSs Off
	Increase of Grid Consumption (%)							
Coalitional	1.65	3.16	1.64	2.97	0.0	0.94	0.80	1.73
G.A.	1.97	3.63	1.93	3.83	0.12	1.35	1.04	2.16
Greedy	1.78	3.25	2.21	3.15	0.28	1.1	0.84	1.83
Uniform	2.51	4.70	3.0	3.89	0.40	1.34	1.00	2.45
	Reduction of % Users Served (%)							
Coalitional	3.72	7.79	3.06	6.29	3.12	7.41	5.19	10.20
G.A.	4.46	8.73	3.73	8.64	3.66	9.69	6.47	12.37
Greedy	4.13	7.95	4.46	6.80	4.82	8.37	5.43	10.51
Uniform	6.07	11.51	4.79	9.67	9.69	13.13	10.87	20.55
	Increase of Average Transmission Rate (%)							
Coalitional	8.48	14.00	19.57	10.55	10.31	5.28	18.42	30.47
G.A.	6.35	11.08	0.57	-0.78	17.54	9.22	18.47	30.55
Greedy	6.26	11.00	0.38	-0.99	17.49	9.18	20.17	33.01
Uniform	2.87	8.65	-11.11	4.04	19.44	13.52	17.74	31.43
	Increase of Delay (%)							
Coalitional	5.49	33.46	1.48	25.72	-1.57	6.38	15.28	31.14
G.A.	11.91	23.79	4.32	27.23	0.16	16.58	16.22	41.18
Greedy	10.19	30.15	16.57	32.76	-3.23	13.71	9.74	34.21
Uniform	21.19	39.30	23.20	38.8	1.25	15.78	27.69	52.82

Table 3-5.: Comparison of Cost Function Values

Mechanism	**Mean Cost Function**
Coalitional planning	1.1323
P. S. based on Coalitional	1.1338
G. A. - Coalitional	1.1509
Greedy	1.1524
P. S. based on Uniform	1.1653
P. S. based on Greedy	1.1881
Uniform	1.2570

of the large-scale scenario. It is possible to observe that the genetic algorithm improves its performance using the initial population provided by the coalitional method. Regarding the pattern search, the best performance is obtained with the coalitional initial point. Also, there is no significant improvement compared with the proposed planning method, a fact that highlights the quality of this solution when used as a seed in this experiment.

Table 3-6.: Network Performance Comparison of Heuristic Methods

	Low wind profile				High wind profile			
	750 Users		2000 Users		750 Users		2000 Users	
	Grid Consumption							
	Average (W/min)	Increase (%)	Average (W/min)	Increase (%)	Average (W/min)	Increase (%)	Average (W/min)	Increase (%)
All SCBS Available	4529.64	-	4291.85	-	4496.06	-	4205.57	-
Coalitional	4695.01	3.65	4377.61	2.00	4670.78	3.89	4301.11	2.27
G.A. - Coalitional	4689.02	3.52	4359.76	1.58	4672.50	3.92	4272.8	1.60
Greedy	4698.62	3.73	4385.58	2.18	4676.61	4.02	4301.13	2.27
Uniform	4781.32	5.56	4421.63	3.02	4785.02	6.43	4329.18	2.94
P.S. Coalitional	4707.30	3.92	4379.46	2.04	4675. 02	3.98	4303.84	2.34
P.S. Greedy	4737.29	4.58	4419.79	2.98	4700.99	4.56	4326.41	2.87
P.S. Uniform	4790.93	5.77	4430.08	3.22	4768.70	6.06	4337.83	3.14
	Users Served							
	%	Reduction (%)	%	Reduction (%)	%	Reduction (%)	%	Reduction (%)
All SCBS Available	94.28	-	84.28	-	95.02	-	86.96	-
Coalitional	86.06	8.22	72.94	11.34	88.28	6.74	75.62	11.34
G.A. - Coalitional	86.37	7.91	72.28	12.00	88.37	6.65	77.22	9.74
Greedy	85.86	8.42	71.46	12.82	87.81	7.21	75.53	11.43
Uniform	81.25	13.03	64.48	19.80	82.52	12.5	70.45	16.51
P.S. Coalitional	85.33	8.95	72.20	12.08	88.05	6.97	75.25	11.71
P.S. Greedy	83.93	10.35	67.81	16.47	86.45	8.57	72.84	14.12
P.S. Uniform	80.91	13.37	65.20	19.08	82.91	12.11	70.38	16.58

4. Centralized Control Mechanisms for Energy Efficiency of HetNets

In this chapter are presented different control mechanisms to energy efficiency through traffic load balancing on HetNets. To reduce the consumption from the grid in the HetNet, different user-BS connection policies are proposed. In short-time scale five different methodologies are presented and compared here. The first is based on traditional discrete optimization techniques. The second is the standard better-signal-level mechanism, which is introduced for the sake of comparison. The third is a greener version of this policy. The fourth uses a flow relaxation of the discrete problem. The fifth is a new green market model. Finally, in the long-time scale, a MPC based on a traffic flow perspective is implemented. The results presented in this section were published in (Fletscher et al., 3227) and (Fletscher et al., 2017).

4.1. Mechanisms for energy efficiency in short-time scale

4.1.1. Direct Optimization

The optimal connection policy is attained solving (2-7a) by means of an integer linear optimization problem. To find a solution, a branch-and-bound method is used. Information preprocessing and the previous knowledge of the problem are also helpful to reduce the computational burden. In particular, the following preprocessing was applied to the data given to the optimizer:

1 *Reduction of space search.* The matrix $\Psi_{ib,k}$, with $i = 1 \dots u$ and $\ell = 1 \dots b$, was simplified according to the number of active BSs ($\mathcal{B}_{i,k}$) to reduce the search space.

2 *Time instant adjustment.* Since the optimization is performed in each time instant, it is important that its length is sufficient to perform the calculations, but not too much, thus avoiding changes in the system being ignored.

4.1.2. Green Policy Algorithm

The second approach is a heuristic method proposed to reduce consumption from the grid by first checking the possibility of attaching the user's request to SCBSs (green BSs), even

if the received signal level of an MBS is better. The association process is managed jointly between the user and the network in a hybrid scheme. The main difference between this scheme and a proposal such as that presented in (Zhou et al., 2010), where the priority of green base stations is established only during the handover process, is that we give priority to green BSs at any moment of the communication, not only during the handover.
To overcome the perceived negative environmental and economic impacts of on-grid energy with respect to renewable energy, a user association policy incentives users to connect to renewable energy cells. This is can be operate with many types of renewable energy source or network configuration. The objective of the algorithm is to check first the possibility to attach one user request to a SCBS (green BS) according to a fitness function, even if the received signal level of the MBS is stronger. The output of the algorithm is the association matrix $Y_{i\ell,k}$, with $i = 1 \ldots u$ and $\ell = 1 \ldots b$. Therefore, if user $i \in \mathcal{U}$ is associated to the BS $\ell \in \mathcal{B}$ in the time instant k, then $y_{i\ell,k} = 1$, and $y_{i\ell,k} = 0$ otherwise.
The proposed user association algorithm can be condensed in the next steps:

1. *Definition of initial system parameters.* The system defines users positions $\mathcal{U}_k^p$, green energy available for each SCBS according to the wind potential $E_{\ell,k}^G$, and BS transmission power $T_{\ell,k}$.

2. *Definition of initial signal level available for each user.* All users are associated with a virtual BS zero at the beginning of the process, to enable comparison. The theoretical received signal level from BS zero $\psi_{i,0}^p$, is a very small number equivalent to a base station without transmission power. Next, the system calculates signal level matrix $\psi_{i\ell,k}^p$ with $i = 1...u$ and $\ell = 1...b$. Where $\psi_{i\ell,k}^p$ is the received signal level for the user i in location p from the BS ℓ in the time instant k.

3. *Inspection of the signal levels from green base stations.* The system executes a loop verification of the user's received signal, starting with the SCBS (green base stations), $\psi_{i\ell,k}^p$ with $\ell = 2, ..., b$. The system selects the SCBS that provides the best signal level. If the signal level is higher than the threshold, φ, the user is connected with the green base station, otherwise, the system checks the MBS level. If none of the received signals is enough to provide service, the user is associated with the BS zero and accounted as an unserved user.

4. *Association of users to SCBSs.* If the user i is connected with a green BS ℓ and this BS has available resources, a number of resource blocks is assigned to the user until the transmission is finished, and $y_{i\ell,k} = 1$. If the BS has not available resources, the centralized manager check if another green BS can be used to serve the user. If some neighbor BS has resources, the user is connected to a new green BS. If no green BS has resources or renewable energy in the time instant of interest, the user is assigned to the MBS and $y_{i1,k} = 1$.

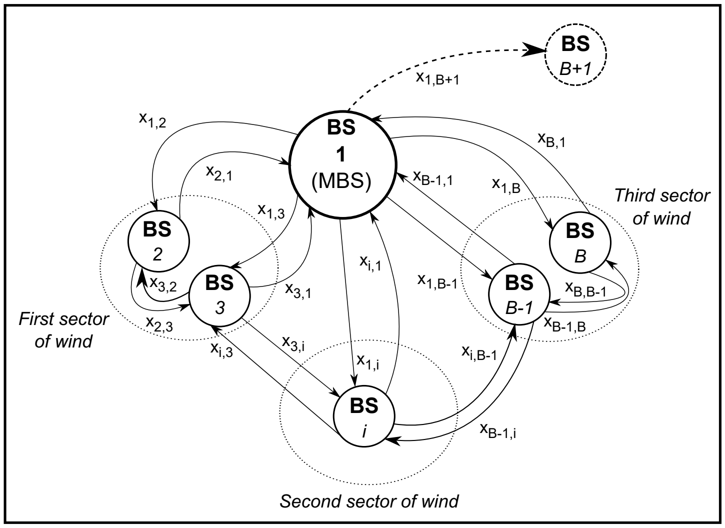

Figure 4-1.: Traffic flow approximation.

5. *Computation of Grid consumption and number of served users.* Finally, the amount of grid consumption and the average of users served are calculated for the time instant.

The purpose of this heuristic algorithm is that at each time instant, the network utilizes the available renewable energy, with on grid energy left as a last resource. This mechanism guarantees that at each time instant the system consumes as much green energy as possible and uses grid energy only as a last resort.

4.1.3. Traffic Flow Approximation

Approximation based on traffic flows was also considered to solve the computation burden issues of integer optimization. This perspective uses a relaxation of the discrete problem and generates a solution with the optimal flows exchanged between BSs. This approach has been successfully applied to problems such as traffic management (Smulders, 1990) and supply chains (Sarimveis et al., 2008).
Figure **4-1** presents an illustration of this perspective. The incorporation of a new virtual BS ($B+1$) can be observed, which is used to discard traffic according to the defined QoS level. In this sense, $\mathcal{B}^f = \mathcal{B} \cup \{B+1\}$. The mechanism uses input information from a matrix with the flows that can be exchanged between BSs ($F_{\ell j,k}$) in each time instant. This matrix is built from the received signal level of each user from each BS, the active BSs according to the wind speed, the BS adjacency matrix, and the number of users connected to each BS.
This matrix, the number of RBs available in each BS, and the QoS level are used as constraints of a linear optimization problem that minimizes the sum of flows from any base station to the MBS (BS 1). Equations (4-1a)-(4-1f) present the formal description of the

optimization problem.

$$\min_{x} \sum_{k=1}^{N} \sum_{\ell \in \mathcal{B}^f} x_{\ell 1,k}, \tag{4-1a}$$

s.t.

$$\sum_{\ell \in \mathcal{B}^f} x_{\ell j,k} \leq F_{\ell j,k}, \qquad \forall j \in \mathcal{B}^f, k \in [0,N] \cap \mathbb{Z}_{\geq 0}, \tag{4-1b}$$

$$\frac{\sum_{j \in \mathcal{B}} \sum_{\ell \in \mathcal{B}} x_{\ell j,k}}{\sum_{k=1}^{T} z_{A,k}} \geq \varepsilon, \tag{4-1c}$$

$$\sum_{\ell \in \mathcal{B}^f} x_{\ell j,k} \leq z_{\ell}^{max}, \qquad \forall j \in \mathcal{B}^f, k \in [0,N] \cap \mathbb{Z}_{\geq 0}, \tag{4-1d}$$

$$\sum_{j \in \mathcal{B}} x_{\ell j,k} = x_{\ell,k}, \qquad \forall \ell \in \mathcal{B}, k \in [0,N] \cap \mathbb{Z}_{\geq 0}, \tag{4-1e}$$

$$0 \leq x_{\ell j,k}, \qquad \forall \ell, j \in \mathcal{B}^f, k \in [0,N] \cap \mathbb{Z}_{\geq 0}, \tag{4-1f}$$

where $x_{\ell j,k}$ is the traffic flow from BS ℓ to BS j in a time instant k. Equation (4-1a) is the objective function, which seeks to minimize the flows to the MBS and hence reduce the overall consumption from the grid of the cellular network. The constraint (4-1b) specifies that the flow between two BSs cannot exceed the limits established by the potential flows matrix. Equation (4-1c) defines the QoS level and guarantees that the sum of all flows is higher than the desired percentage of users served ε. Constraint (4-1d) establishes the limit in the number of users to be served by a BS. This limit is defined by the number of RBs available in the destination BS in each time instant. Constraint (4-1e) imposes flow conservation. This means that all users will be served, even by the $B+1$ BS or the same BS that originated the flow. Finally, (4-1f) defines that flows must be positive.

Once the solution to this problem is found, a rounding process is executed to obtain integer values and assign users to BSs according to these values.

Finally, a remarkable feature of this approach is that it can be implemented easily in a distributed fashion (Camponogara and Scherer, 2011, Maestre and Negenborn, 2014).

4.1.4. Green Market Approach

This approximation is another contribution of this thesis to the user-BS association schemes in HetNets powered by hybrid sources. Pindyck and Rubinfeld defined a market as "a collection of buyers and sellers that, through their actual or potential interactions, determine the price of a product" (Pindyck and Rubinfeld, 2013). The BSs are sellers, and the users are buyers, with both interacting through of a market price by the resource blocks. When green BSs are active, the system works like a competitive market; but when only the MBS is working, the market is a monopoly. In the competitive market, the price is defined depending on the technical characteristics of the offer and the demand. In the monopoly, it is necessary to include additional constraints to avoid abuses by the exclusive seller (MBS). This approach has been employed in other areas such as the electricity sector (Pinto et al., 2015, Maaz et al., 2015) and hydro storage systems (Gu et al., 2014), where it is common to analyze the interaction between its actors using models that include the market behavior.

Market definition

The market is composed of $\mathcal{B}$ base stations, acting like vendors, and $\mathcal{U}$ users, in the role of buyers. In each time instant, four key processes are implemented:

1. Resource block's price definition by sellers.

2. Utility function definition by customers.

3. Money assignment to active users.

4. Buying decision.

BSs establish the price of resource blocks according to the technical aspects of the network as follows

$$R_{ij,k} = \alpha_1 * \Omega_{ij,k} + \alpha_2 * \delta_{j,k} + \alpha_3 * \vartheta_k + \alpha_4 * \rho_k + \alpha_5 * \xi_j^{BS}, \tag{4-2}$$

where $R_{i,j}$ is the price of a channel offered by BS j to user i, and $\alpha_1, \ldots, \alpha_5$ are the weights of network parameters over the market price; Ω is the index of modulation scheme offered to user i from BS j; δ is the traffic load of BS j; $\vartheta_k = 1 - \frac{|\mathcal{B}_k|}{|\mathcal{B}|}$ stands for BS scarcity; $\rho_k = \frac{z_{A,k}}{|\mathcal{U}_k|}$ is the demand, where $z_{A,k}$ is the number of active users in the time instant; and ξ^{BS} is the BS energy source. From (4-2), it is possible to observe that if a channel of a BS powered by the grid is more expensive than a green channel, it is possible to establish an incentive to boost the use of green energy.
On the customer's side, we define a utility function for users according to the market characteristics

$$\upsilon_{ij,k} = \beta_1 * \Omega_{ij,k} + \beta_2 * \xi_j^U + \beta_3 * \vartheta_k, \tag{4-3}$$

where $\upsilon_{ij,k}$ is the utility perceived by user i for a channel offered by BS j, and $\beta_1, \ldots, \beta_3$ are the weights of market characteristics over utility function. From (4-3), it is possible to observe that ξ^U can be an incentive for a user to buy a channel from a green BS. This utility function will be the key factor in making a buying decision.

The monopoly case

When the renewable energy source is insufficient to power any base station, only the MBS will be working. In this case, it is common to regulate prices. In our proposal, we implemented two control policies: a discount factor in the price function (Θ), and a subsidy for users. The role of the discount factor is to reduce the price when the number of unserved users grows

$$R^M_{ij,k} = R_{ij,k} * (1 - \Theta * \left(1 - \frac{z_{U,k}}{z_{A,k}}\right)), \tag{4-4}$$

where $R^M_{ij,k}$ is the monopoly price, $R_{ij,k}$ is the competitive market price, $z_{U,k}$ is the number of unserved users, and $z_{A,k}$ is the number of active users in the time instant k. The discount factor is an incentive for users to buy at a lower price. The subsidy is an increase in the money assigned to active users.

Money and buying decision

At each time instant, the system assigns to active users an amount of money, which allows them to buy channels and is sufficient to afford the price plus an extra percentage to cover variations. With the information about the costs of different channels, the utility function, and the money available, users take buying decisions. The selected option will maximize the consumer's surplus

$$\Gamma_{ij,k} = \max(\upsilon_{ij,k} - R_{ij,k} \mid \mu_{i,k} \geq R_{ij,k}) \tag{4-5}$$

where $\mu_{i,k}$ is the money of user i in the time instant k. After buying, the user utilizes the channel along the time instant and returns it to the BS once the time is over. If in the next time instant the user still needs a channel, he or she can buy the same or select another that is cheaper.

4.1.5. Market Characteristics

Table **4-1** shows the market parameters used in the simulation. The weights α and β were chosen by trial and error but with the objective of fostering the green market. For this reason, the energy source factor has the higher value in function price and utility. The second most important element is the number of active base stations, reflecting how the scarcity of resources affects the price.

4.1.6. Performance Comparison

Using MATLAB®(The MathWorks, 2015) and IBM Cplex Optimizer (IBM, 2015), it was possible to evaluate the different connection schemes and their impact on grid power consumption. The temporal variability of traffic on the cellular network was not considered. For

Table 4-1.: Market Parameters

Parameter	**Value**
$[\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5]$	$[15, 20, 20, 15, 25]$
$[\beta_1, \beta_2, \beta_3]$	$[40, 20, 40]$
Ω	1 for QAM64 0.5 for QAM16 0.2 for QPSK
ξ^{BS}	1 for the grid (MBS) 0.2 for RE (SCBS)
ξ^{U}	0.2 for the grid (MBS) 1 for RE (SCBS)
Θ	20 %
subsidy	10 %
money increase	market price + 10 %

Table 4-2.: Association Schemes Comparison

User Association Scheme	**Average Grid Consumption (watts/min)**	**Users Served (%)**	**Average Transmission Rate (Mbps)**	**% of reduction**	**bits/watts**
Signal Level Policy	6055 ±24	85.8 ±0.1	265.76 ±5.1 %	-	791.1
Green Policy	5922 ±35	86 ±0.1	256.98 ±2.7 %	2.2	801.6
Optimizer 80 %	5542 ±18	80.8 ±0.7	166.76 ±2.5 %	8.5	520.1
Optimizer 85 %	5733 ±17	85.5 ±0.3	183.54 ±3.1 %	5.3	578.1
Optimizer 90 %	5903 ±16	90.2 ±0.1	207.46 ±1.8 %	2.5	609.1
Traffic Flows 85 %	5765 ±11	86.1 ±0.2	194.37 ±2.2 %	4.8	578.4
Green Market	5724 ±51	85.4 ±2.1	168.23 ±3.2 %	5.4	493.3

this reason, a simulation time of 15 minutes was used to assess the behavior of the proposed solutions. The active BSs along the corresponding 450 time instants define the $\Psi_{i\ell}$ matrix and the search space in each optimization.

To compare the performance of the mechanisms with the traditional best-signal-level scheme, six key performance indicators (KPI) are proposed: average grid consumption (watts/min), percentage of users served, average transmission rate (Mbps), percentage of consumption reduction compared to the traditional scheme, transmitted bits per grid-consumed watts, and simulation time. Table **4-2** shows the KPI results for each scheme. As can be seen, the green policy reduces the consumption by 2.2 % compared to the traditional scheme and maintains similar levels of users served and average transmission rates, thus demonstrating itself as a good option to reduce consumption in the presence of renewable energy sources. In addition, the green policy has a best bits/watts performance, followed by signal-level policy and traffic flows.

The optimizer policy was implemented for three different QoS objectives, being equivalent to

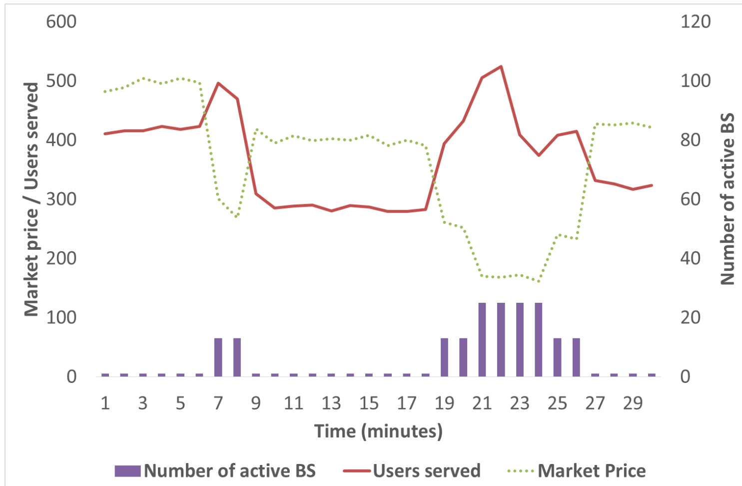

Figure 4-2.: Green market behavior.

85 % of the baseline defined by the traditional scheme. We found a reduction in consumption with respect to the traditional connection scheme. In particular, the optimizer of 85 % has good grid energy savings of 5.3 % compared to the signal-level policy. Only when $z_{S,k} = 90\,\%$ do we observe that the optimizer grid consumption is close to the traditional scheme. However, the average transmission rate is lower. This is caused by the relation between the signal level and the modulation scheme. Therefore, if the best signal level is not the main criteria for selecting a base station, a reduction in the average rate can be achieved. It is important to remember that the optimizer does not have constraints or incentives related to the transmission rate.

Regarding traffic flows, it is possible to observe a reduction of the consumption from the grid to levels comparable to those of the discrete optimizer (4.8 %). This result is very important because the discrete optimizer delivers the optimum consumption of the system according to a QoS level. The other key element is the quality of service ($z_{S,k}$) in the system, which presents a small improvement if the traditional scheme is compared to the traffic flow. However, being a mechanism based only on grid consumption optimization, the average transmission rate is lower than signal level-based policies.

The green market scheme has a 5.4 % energy saving and a percentage of users served closer to 85 %, but with high variation caused by market dependence on the number of active BSs. Its transmission rate is the lowest. This phenomenon, similar to the variation in served users, is caused by the high influence of the competition (number of active SCBSs) on the market price and buying decisions. Figure **4-2** shows the green market behavior. We observe a market price that is significantly influenced by the offer (number of active green base stations), and users sensitive to price variations. Also, it is possible to see the control mechanism in the case of a monopoly and its function to avoid abuses in price and maintain buying tendencies. Regarding the computational time required for the simulations, Table

Table 4-3.: Computation Time for the Simulations[s]

User Association Scheme	500 Users	750 Users	1000 Users
Signal Level Policy	210.99 ±15	287.28 ±12	261.13 ±11
Green Policy	211.19 ±12	287.39 ±13	261.62 ±9
Optimizer 85 %	506.46 ±9	1157.4 ±22	2077 ±32
Traffic Flows 85 %	391.53 ±10	553.64 ±25	507.28 ±28
Green Market	195.28 ±15	215.69 ±15	217.5 ±18

4-3 shows a comparison of the results of implementing the different policies when different amounts of users are present in the network. It can be observed that the optimizer increases its computational time markedly when the number of users grows. Another interesting result about the computational time is the similarity between the traditional policy and the green algorithm proposed (Figure **4-3**). The processing time of the traffic flows and green market approaches are lower than the discrete optimizer's and remain practically constant despite the growth of users, thus representing a good option for improving consumption and maintaining QoS levels in scenarios with a large number of users.

4.2. Energy efficiency in long-time scale

For long-time scale the traffic behaviour is treated in an aggregated form. This means that the average load of BS ℓ (δ_ℓ) per hour is considered instead of individual user-BS associations considered for the short time scale scenario. In this section, a Model Prediction Controller (MPC) alternative based on a traffic flow is evaluated to reduce grid energy consumption on a HetNet where SCBSs are powered by Photovoltaic (PV) energy with energy storage system. The MPC is implemented to incorporate a weather forecast in the flow allocation decision process. This approach makes it possible to analyze the impact of load balancing with MPC on the grid consumption reduction in a scenario with renewable sources. This model is also quite suitable when a storage system is affordable or absolutely necessary to be included into the system.

The network scenario includes an energy storage system for the SCBSs and PV is used instead of using wind energy. The goal is to minimize on-grid consumption by balancing

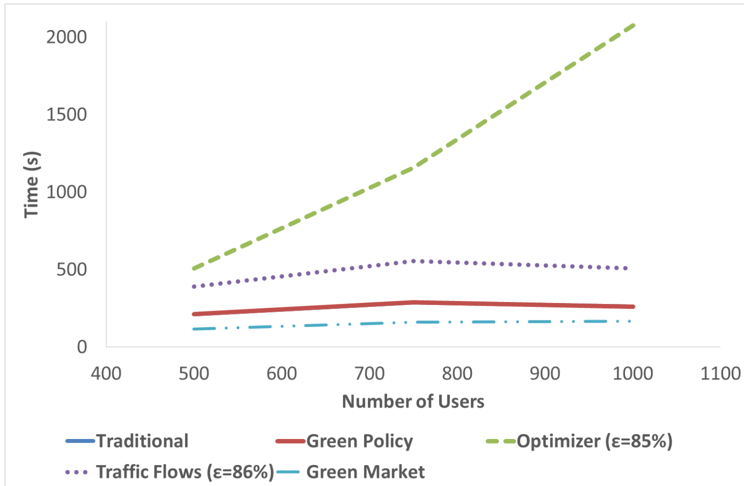

Figure 4-3.: Comparison of computational time required to carry out the policies.

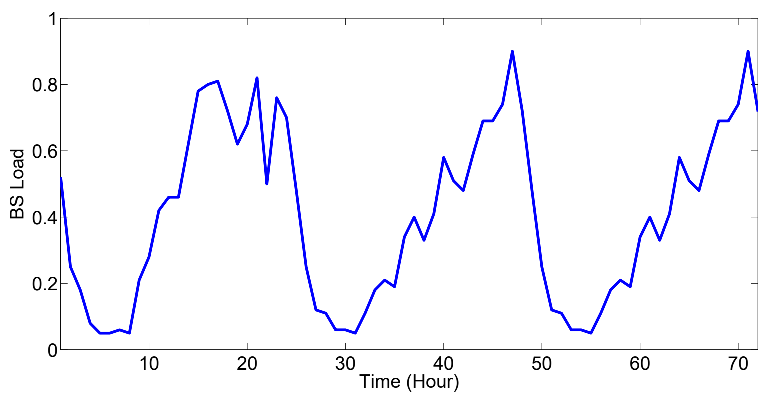

Figure 4-4.: Network Traffic Profile.

downlink traffic loads among BSs. The SCBSs update their state (on/off) every hour by changing the transmission power according to the amount of renewable energy available at its location. If the energy provided by a PV panel is more than the amount required by each SCBS, it is stored in the battery. The stored energy is used when the energy produced by the PV panel is insufficient to power the SCBS. This is a particular relevant for the solar energy in comparison to the wind scenarios, which is more likely to be continuously available. The traffic profiles presented in (Meo et al., 2015) are used to model the load traffic of the MBS, which were measured at 30-minute intervals on cells of a mobile network operator. In this way, it is possible to establish a normalized profile to weekdays and another to weekends. The network traffic profile for a 72 hours window is presented in Figure **4-4**. The first 24 hours show the traffic profile on a weekend and the rest on weekdays.
The average solar radiation data from Medellín provided by (IDEAM, 2017) are presented in figure **4-5**. Each small cell can only receive a maximum of 10 % of the MBS overall load. The amount of load received by a SC is directly related to the amount of renewable energy

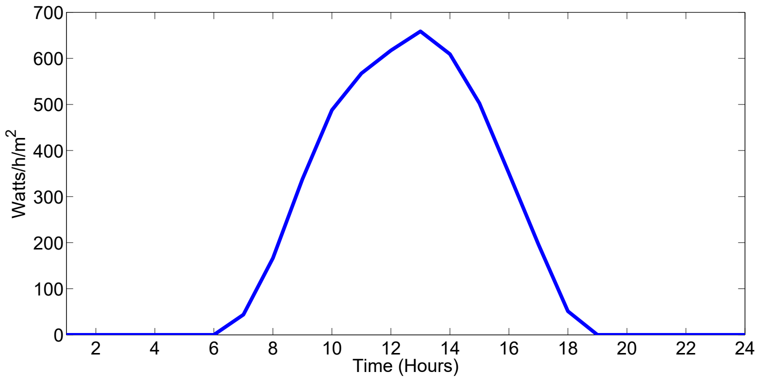

Figure 4-5.: Green Energy Source Behaviour for 24 hours.

available.
At the $k-th$ time instant, the green energy available at SCs j ($E^G_{j,k}$) depends on the green energy generation rate σ_k in the time instant k plus the stored energy ($E^G_{j,k-1,j}$), and green consumption in the previous time instant ($C_{j,k-1}$) as follows:

$$E^G_{j,k} = E^G_{j,k-1} - C_{j,k-1} + \sigma_k \tag{4-6}$$

The renewable energy system is composed of a commercial monocrystalline photovoltaic panel with a maximum power of 183.3 Wp and open circuit voltage 34.6 V. The storage system is a 12 V - 1C battery for renewable energy solutions. Note that, for simplicity, the behaviour of other electronic components is not considered.

4.2.1. MPC Mechanism

A mechanism based on traffic flows as presented in 4.1.3 is considered to solve a linear optimization problem of load assignation over BS. In this case, a flow is an integer value representing an aggregation of users, in other words, the traffic load density of a BS in a time instant.
The MPC is based on the traffic flow scheme but incorporates a prediction horizon that allows it to take into account the forecast of the renewable energy source and the traffic load network behaviour in the decision-making process. In this way, the controller considers the following N time steps to decide the best control actions, where N is the prediction horizon. The general scheme of controller appears in Figure **4-6**. The MPC optimization problem is described in equations (4-7a) - (4-7d):

$$\min_{\forall x_{\ell j,k}} \sum_{k=0}^{N-1} \sum_{j \in \mathcal{B}} x_{j1}(k+1) \tag{4-7a}$$

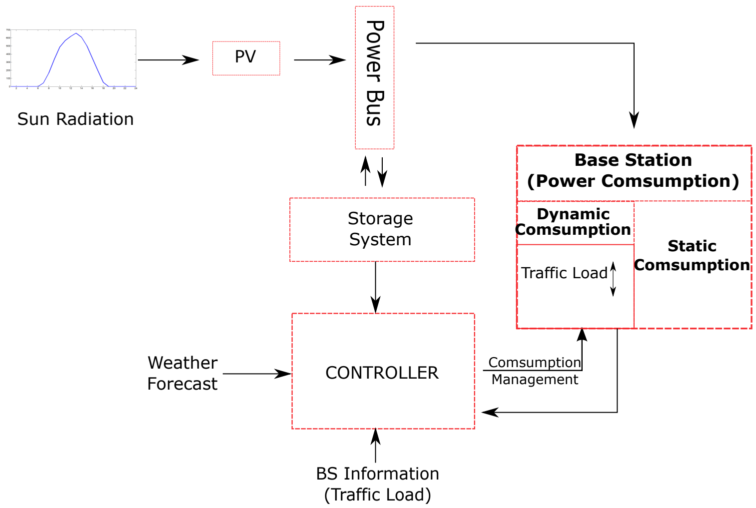

Figure 4-6.: MPC Scheme.

s.t.

$$\sum_{\ell \in \mathcal{B}} x_{\ell j}(k) \leq F_{\ell j}(k) \quad j = 1, \dots, B, \quad k = 0, \dots, N-1, \tag{4-7b}$$

$$\sum_{j \in \mathcal{B}} x_{\ell j}(k) = x_{\ell}(k) \quad \ell = 1, \dots, B, \quad k = 0, \dots, N-1, \tag{4-7c}$$

$$0 \leq x_{\ell j}(k) \quad \ell, j = 1, \dots, B, \quad k = 0, \dots, N-1, \tag{4-7d}$$

where $x_{\ell j}(k+1)$ is the traffic flow from BS ℓ to BS j a time instant of the prediction horizon. Note that (4-7a) - (4-7d) are extensions along the prediction horizon of (4-1a) - (4-1f).
The solution of the optimization problem is a sequence of matrices $X(k)$ that define the flows exchanged between BSs and minimize grid consumption along prediction horizon

$$X(k) = \begin{pmatrix} x_{1,1}(k) & x_{1,2}(k) & \dots & x_{1,B}(k) \\ \vdots & \vdots & \vdots & \vdots \\ x_{B,1}(k) & x_{B,2}(k) & \dots & x_{B,B}(k) \end{pmatrix} \tag{4-8}$$

for $k = 0, \dots, N-1$. Only the components of the optimal matrix flows $X(0)$ are actually applied. The rest of the sequence is discarded. It is important to notice that the choice of the size N for the prediction horizon is fundamental. N should be large enough to provide enough visibility to the predictor for making a decision, however not too large as N could increase unnecessarily the computation process.
The case study considered is composed of one MBS and 8 overlapping SCBSs. In this case, each SCBS has a renewable energy storage system. In contrast to the short-time scale, the temporal variability of traffic on the cellular network is considered in this case. A time slot of 1 hour is used to observe the behavior of the proposed solutions along 10 days. This number

Table 4-4.: MPC Performance Comparison

Mechanism	Average Grid Consumption (W/h)
Without controller	167.9173
Traffic Flow	151.9807
MPC (N=2)	150.516
MPC (N=3)	149.0318
MPC (N=5)	145.9032
MPC (N=6)	146.6847
MPC (N=9)	149,0291

of days allows seeing the full behavior of the MPC including the traffic patterns in weekdays and the weekend. For displaying the results we concentrate in a window of 72 hours, one day in the weekend and two weekdays, as the traffic patterns only differ significantly during this transition. The MPC target is to manage the renewable energy available and optimize its use according to the storage capacity and the weather and consumption forecasts.

To evaluate the performance of the MPC, several prediction horizons (N) were used. Table **4-4** shows a performance comparison between a reactive flow optimizer strategy (N=1) and the best MPC horizon. It can be observed that both mechanisms reduce the average grid consumption, but MPC provides greater reductions. The best response of the MPC corresponds to N=5, where the lowest on-grid consumption is obtained. This horizon size makes it possible to make the most accurate decisions based on the forecasts. Higher N could incur in an error due to including estimations of far remote future instants. The power grid consumption saved with MPC is 22 kW/h compared to the baseline scenario (On-grid energy only) which represents 13 % savings. Figure **4-7** shows the average grid energy consumption for each mechanism over the simulation time in a window of 72 hours. In this analysis, the prediction horizon of MPC is set to 5 hours. It can be observed that for both schemes, reactive flow optimizer and MPC, it is possible to reduce grid consumption in the network and take advantage of the renewable energy available. However, it is remarkable that in some periods the MPC uses grid energy even when renewable energy is available. It means that the predictive strategy because of the fact of having this far-sighted way of solution, allows storing renewable energy for periods where such energy is not available. This is particularly important for the solar powered models as during night periods this is a relevant issue. Figure **4-8** shows the stored energy behavior for both optimization mechanisms. It can be seen that as well the levels of renewable energy availability through the time. As it can be observed, the reactive flow optimizer (N=1) spends the energy stored once the renewable energy is no longer available. In constrast, with MPC (N=5), which has a strategy to anticipate future behaviour, stored is kept for when there is no availability of renewable sources. This is particularly important where the MBS is overwhelmed during high traffic load periods, and therefore, this is the best moment to efficiently use this harvested energy. An important decision of

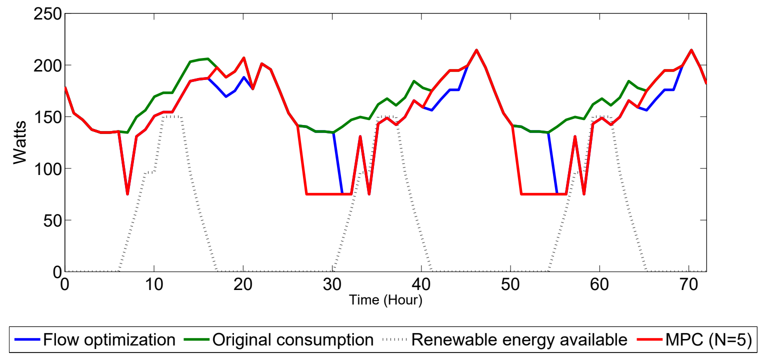

Figure 4-7.: MPC Average Grid Consumption.

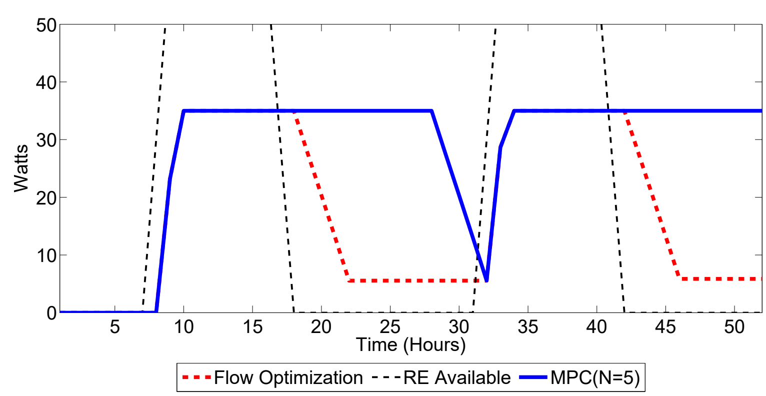

Figure 4-8.: Stored Energy Behaviour.

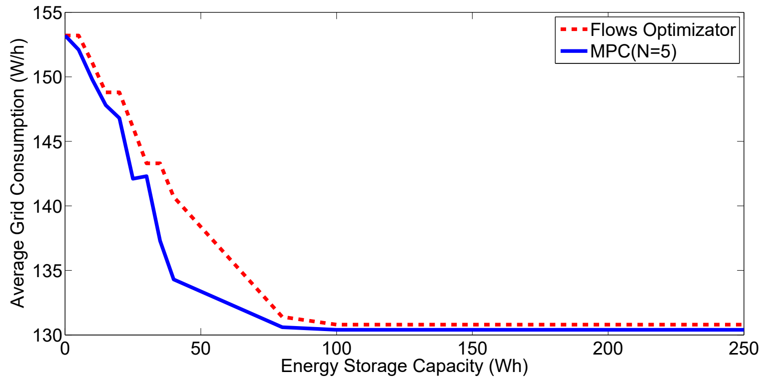

Figure 4-9.: Impact of Storage Capacity.

designing during the planning process is to determine the energy storage capacity of the batteries. Figure **4-9** shows the grid consumption behavior with different storage capacity. It is possible to observe that by increasing storage capacity up to 70W-h at each SCBS, it reduces grid consumption up to 22 %. However, higher storage increases do not improve grid consumption saving, since the static power consumption of MBS (130W) must kept active in order to avoid compromising the coverage and network availability. In this second part of the analysis for long time scale, it is observed how the MPC approach provides an interesting way of managing energy over long timescales, in contrast with the short timescale association algorithm that is intended to address rapid decisions in order to respond to the continuous fluctuations of a renewable energy source like the wind. MPC in combination with a storage system is a robust and energy efficient solution for cases where the environmental conditions slowly change and planning based on forecast through the time is possible. This approach matches perfectly with the behavior of solar radiation in the daytime period. The solar case is a scenario that particularly requires storage during night time and MPC strategy has shown how the harvested energy can be efficiently utilized. In the case of using MPC with wind, the short timescale fluctuations are neglected and the forecast is done over the long timescale.

5. Distributed Control Mechanism for Energy Efficiency of HetNets

In this chapter, a novel distributed user-BS association scheme based on population games is designed to reduce grid consumption in HetNets powered by hybrid sources. This mechanism is designed to operate in the short-time scale, hence small cells are powered by wind and without storage systems.

In particular, characteristics of atomicity and non-anonymity are considered to take into account that one user decision affects the global performance of the system. The controller is in charge of dealing with the energy consumption problem in HetNets powered by hybrid energy sources (grid and renewable energy) while guaranteeing an appropriate quality of service (QoS) levels at the same time. It is important to note that atomicity and non-anonymity are novel features of the population games approach proposed. In addition, the revision protocol implemented maintains the optimization problem constraints and attains grid consumption reduction and energy efficiency in a tractable way. The potential of the proposed distributed mechanism based on game theory is to maximize the system utility with the users decisions being taken using partial information of the network status.

5.1. On-grid Energy Consumption and Average Transmission Rate Optimization Problem

As previously mentioned, on-grid consumption reduction and adequate transmission rates are design requirements in NGCN. Hence, in this chapter, the optimization problem has two objectives: *i)* to reduce the overall system grid consumption and, *ii)* to maximize the average transmission rate per user. According to this, it is possible to formulate the following optimization problem:

$$\min_{y_{11,k},\cdots,y_{n1,k}} J(y_{11,k},\ldots,y_{n1,k}) = \tag{5-1a}$$
$$\sum_{k=1}^{N}\left\{\gamma_1\sum_{i\in\mathcal{U}} y_{i1,k} - \gamma_2\frac{W_\ell}{\sum_{i\in\mathcal{U}} y_{i\ell,k}}\log_2(1+\psi_{i\ell}^{p})\right\},$$

s.t.

$$\sum_{i\in\mathcal{U}} y_{i\ell,k} \leq z_\ell^{\max}, \ \forall \ell \in \mathcal{B}\backslash\{1\}, k \in [0,N]\cap\mathbb{Z}_{\geq 0}, \tag{5-1b}$$

$$y_{i\ell,k}\cdot\psi_{i\ell} \geq \varphi, \qquad \forall i \in \mathcal{U}, \ell \in \mathcal{B}_{i,k}, k \in [0,N]\cap\mathbb{Z}_{\geq 0}, \tag{5-1c}$$

$$\sum_{\ell\in\mathcal{B}} y_{i\ell,k} \leq 1, \qquad \forall i \in \mathcal{U}, k \in [0,N]\cap\mathbb{Z}_{\geq 0}, \tag{5-1d}$$

$$y_{i\ell,k} \in \{0,1\}, \ \forall i \in \mathcal{U}, \ell \in \mathcal{B}, k \in [0,N]\cap\mathbb{Z}_{\geq 0}, \tag{5-1e}$$

where (5-1a) is the objective function, which focuses on minimizing consumption from the grid and maximizing user's transmission rate with an optimal assignment of active users to available BSs in each time instant. Moreover $\gamma_1, \gamma_2 \in \mathbb{R}$ are weights assigned to each objective. Equations (5-1b)-(5-1e) are the problem constraints: (5-1b) establishes that a small cell ℓ can serve a maximum of $z_\ell^{\max}$ users simultaneously; (5-1c) is the user's received signal level constraint, (5-1d) requires that a user is served only by one BS in a time instant; and (5-1e) establishes that $y_{i,\ell}$ is a binary variable.

The optimization problem (5-1a) is a multi-objective mixed integer problem (MIP), a well-known $\mathcal{NP}$-hard problem (Johnson and Garey, 1979). However, the distributed control strategy based on population games proposed in this thesis is a suitable alternative in reducing the computational burden. Improving computational burden is possible since each user solves a limited maximization problem based only on the comparison of its current fitness function with the offered by the subset of BSs ($\mathcal{B}_{i,k}$).

Another key element in the proposed game-theory-based-mechanism is the possibility of designing a fitness function according to the cost function in the optimization problem. In this case, the fitness function maintains the weight for each objective and includes an incentive to choose a BS powered by renewable energy. These features are here expressed as

$$f_{i\ell,k} = \gamma_1 P_{i\ell} + \gamma_2 \tilde{r}^p_{i\ell,k}, \ \forall \ell \in \mathcal{B}_{i,k}, \tag{5-2}$$

where the condition $\gamma_1+\gamma_2 = 1$ must hold, $P_{i\ell}$ is the incentive received for user $i \in \mathcal{U}$ to choose a cell $\ell \in \mathcal{B}_i$ according to the energy source, and $\tilde{r}^p_{i\ell,k}$ is the normalized transmission rate that can receive user $i \in \mathcal{U}$ from BS $\ell \in \mathcal{B}_i$ at time instant $k \in [0,N]\cap\mathbb{Z}_{\geq 0}$. As previously mentioned, on-grid energy has a higher economic and environmental impact compared to green-energy, being suitable to consider a network-operator policy focused on encouraging users to use cells powered by renewable energies. For this reason, in this thesis we propose a green incentive G for users such that

$$P_{i\ell} = \begin{cases} G, & \text{if } \ell = 1, \\ 2G, & \text{if } \ell \in \mathcal{B}\backslash\{1\}. \end{cases} \tag{5-3}$$

Table 5-1.: Equivalence between population dynamics and the optimization problem

Variable	Population dynamics	Optimization problem
$\mathcal{B}$	Set of possible strategies	Set of base stations
b	Number of strategies	Number of base stations
ℓ	Strategy's index	Base station's index
$\mathcal{U}$	Set of rational decision makers	Set of users
u	Number of decision makers	Number of users
i	Decision maker's index	User's index
$\mathcal{B}_{i,k}^{p}$	Set of possible strategies for decision maker i at time instant k depending of its geographical position p	Set of base stations available to provide service to user i at location p in a time instant k
$\mathcal{U}_{k}^{\ell}$	Set of decision makers selecting the strategy ℓ at time instant k	Number of users connected to BS ℓ at time instant k
$y_{i\ell}$	Agent-strategy choice indicator for decision maker i with strategy ℓ	User-BS association indicator for user i with BS ℓ
$z_{\ell}^{\max}$	Maximum number of possible decision makers selecting strategy ℓ simultaneously	Number of users that can be served by a SCBS ℓ simultaneously

5.2. Atomicity and Non-anonymity in Population Games

Some of the main characteristics of population dynamics, which can be seen as restrictive features for applying this game theoretical approach in engineering applications, are the anonymity and non-atomicity (Djehiche et al., 2016).

Definition 1. *(Anonymity (Djehiche et al., 2016)) The anonymity describes the situation in which the index of decision makers does not affect the utility function. This concept can also be associated with the homogeneousness of decision makers selecting strategies, i.e., decision makers are assumed to be indistinguishable within the same strategy.* $\diamondsuit$

Definition 2. *(Atomicity (Djehiche et al., 2016)) The atomicity describes the situation in which a single decision maker affects the global utility.* $\diamondsuit$

This chapter presents an alternative population approach that allows dealing with atomicity and non-anonymity. In fact, it is assumed that each decision maker within the population is different, and consequently each decision maker has a different utility. Therefore, each individual decision maker affects the global utility. In addition, all the decision makers selecting the same strategy are considered to be different even though they belong to the same strategy. Also, given that the population games approach looks at the optimization problem (5-1a) from a different perspective, we show the equivalence between elements in the population dynamics approach with elements in the optimization problem in Table **5-1**. Let $\mathcal{U}$ be the set of rational decision makers in a population located throughout a bi-dimensional

geographical area denoted by $\mathcal{A} \subset \mathbb{R}^2$. These agents are rational in the sense that they make decisions pursuing the improvement of their individual benefits. Moreover, let $\mathcal{B} = \{1, \ldots, b\}$ denote the set of choices that the set of decision makers have. More precisely, let $\mathcal{B}^p_{i,k} \subset \mathcal{B}$ denote the possible choices that the i^{th} decision maker has at time instant k depending on its geographical position $p \in \mathcal{A}$, where $\mathcal{B}^p_{i,k} \neq \emptyset$, for all $i \in \mathcal{U}$, $k \in \mathbb{Z}_{>0}$, $p \in \mathcal{A}$. In other words, the sets $\mathcal{B}_i$, for all $i \in \mathcal{U}$ define possible interaction sets. For simplicity, it is omitted the superscript p, indicating that the set of available strategies for each decision maker depends on its position, i.e., $\mathcal{B}_{i,k} = \mathcal{B}^p_{i,k}$.
The set of decision makers selecting the strategy $\ell \in \mathcal{B}$ at time instant k is given by $\mathcal{U}^\ell_k \subseteq \mathcal{U}$. Note that the cardinality $|\mathcal{U}^\ell_k| = \sum_{i\in\mathcal{U}} y_{i\ell,k}$ for all k and $|\mathcal{U}| = \sum_{\ell\in\mathcal{B}} \sum_{i\in\mathcal{U}} y_{i\ell,k}$. Moreover, consider a strategic profile given by a distribution of decision makers $\mathcal{U}$ throughout the set of choices $\mathcal{B}$, i.e., $\left(\mathcal{U}^1_k, \ldots, \mathcal{U}^b_k\right)$, which represents the population state, where $\bigcap_{\ell\in\mathcal{B}} \mathcal{U}^\ell_k = \emptyset$, and $\bigcup_{\ell\in\mathcal{B}} \mathcal{U}^\ell_k = \mathcal{U}$. Also, let $g_i = \{\ell \in \mathcal{B} : i \in \mathcal{U}^\ell\}$ return the strategy that a decision maker $i \in \mathcal{U}$ is choosing. In addition, let the amount of decision makers be constrained at each possible choice, i.e., $|\mathcal{U}^\ell_k| \leq z^{\max}_\ell$, being $z^{\max}_\ell \in \mathbb{Z}_{>0}$, for all $\ell \in \mathcal{B}$.

Assumption 1. *The initial distribution of decision makers* $\left(\mathcal{U}^1_0, \ldots, \mathcal{U}^b_0\right)$ *in the population is feasible, i.e.,* $|\mathcal{U}^\ell_0| \leq z^{\max}_\ell$*, for all* $\ell \in \mathcal{B}$*. It implies that* $n = |\mathcal{U}| \leq \sum_{\ell\in\mathcal{B}} z^{\max}_\ell$*. Moreover,* $\bigcap_{\ell\in\mathcal{B}} \mathcal{U}^\ell_0 = \emptyset$*, and* $\bigcup_{\ell\in\mathcal{B}} \mathcal{U}^\ell_0 = \mathcal{U}$*.* ♢

Let $f_{i\ell,k} \in \mathbb{R}$ be the fitness function for the decision maker $i \in \mathcal{U}$ selecting the strategy $\ell \in \mathcal{B}$ at time instant $k \in \mathbb{Z}_{>0}$. If two decision makers $i, j \in \mathcal{U}$ are selecting the same strategy $\ell \in \mathcal{B}$, then $f_{i\ell,k} \neq f_{j\ell,k}$ since the population considers non-anonymity. Furthermore, since the decision maker $i \in \mathcal{U}$ cannot select the strategies $\mathcal{B}\backslash\mathcal{B}_{i,k}$, then for simplicity it is considered that the decision maker has no incentives to move to such a strategy, i.e., $f_{i\ell,k} = 0$, for all $\mathcal{B}\backslash\mathcal{B}_{i,k}$. The objective within the population is to achieve a Local ε-Equilibrium (Obando et al., 2016) as presented in Definition 3, which also provides notions about Local Nash Equilibrium (Marden, 2014), (Marden, 2016).

Definition 3. *(Local* ε*-Equilibrium). Let* $\varepsilon \in \mathbb{R}_{\geq 0}$*. A population distribution* $\left(\mathcal{U}^{1*}, \ldots, \mathcal{U}^{b*}\right)$ *is a Local* ε*-Equilibrium with respect to the interaction sets* $\mathcal{B}_i$ *if all decision makers* $i \in \mathcal{U}^{\ell*}$*, for all* $\ell \in \mathcal{B}$*, satisfy the following condition:*

$$f_{i\ell} \geq f_{i\ell'} - \varepsilon, \quad \forall\, \ell, \ell' \in \left\{h \in \mathcal{B}_i : |\mathcal{U}^h| < z^{\max}_h\right\}. \tag{5-4}$$

On the other hand, if condition (5-4) holds with $\varepsilon = 0$*, then* $\left(\mathcal{U}^{1*}, \ldots, \mathcal{U}^{b*}\right)$ *is a Local Nash Equilibrium with respect to the interaction sets* $\mathcal{B}_i$*.* ♢

The population evolves according to switching rules, which determine the timing and the result of decision makers' choices. Let $\varrho^{h\ell}_{i,k} \in \mathbb{R}_{\geq 0}$ represent the switching rule for the i^{th} decision maker. Therefore, if $\varrho^{h\ell}_{i,k} > 0$, then the decision maker $i \in \mathcal{U}$ has incentives to move from the h^{th} strategy to the ℓ^{th} at time instant k. The evolution of the population is made by assigning a revision opportunity as described in (Sandholm, 2010): a decision maker is chosen randomly from the population, and it receives an opportunity to decide whether or not it should *move* to another strategy by comparing its utility with those it would obtain by selecting the strategy with a higher fitness function from the set $\mathcal{B}_{i,k}$.

Assumption 2. *Suppose that a decision maker $i \in \mathcal{U}$ receives a revision opportunity. Then, before its next revision opportunity, all decision makers $j \in \mathcal{U}\backslash\{i\}$ receive a revision opportunity.* ♢

Being $i \in \mathcal{U}$ the decision maker with a revision opportunity, then the procedure is as follows:

$$\mathcal{U}_{k+1}^{g_i} = \mathcal{U}_k^{g_i} \backslash \left\{ i \text{ sgn}\left(\varrho_{i,k}^{g_i\ell}\right)\right\}, \text{ for any } i \in \mathcal{U}, \tag{5-5a}$$

$$\mathcal{U}_{k+1}^{\ell} = \mathcal{U}_k^{\ell} \cup \left\{ i \text{ sgn}\left(\varrho_{i,k}^{g_i\ell}\right)\right\} \backslash \{0\}, \text{ for any } \ell \in \mathcal{B}_{i,k}. \tag{5-5b}$$

Notice that the equilibrium in (5-5) is achieved when $\varrho_i^{g_i\ell} = 0$, for all $i \in \mathcal{U}$, $\ell \in \mathcal{B}_i$, i.e., when the decision maker $i \in \mathcal{U}$ has not incentives to move to any strategy $\ell \in \mathcal{B}_{i,k}$. In such case, $\mathcal{U}_{k+1}^{\ell *} = \mathcal{U}_k^{\ell *}$, for all $\ell \in \mathcal{B}$.

Remark 1. *Notice that in (5-5) each decision maker $i \in \mathcal{U}$ does not require full information from the population, but only local information from $\mathcal{B}_i$.* ♢

Now, it is necessary to define an appropriate switching rule for the population. Consider the following switching rule similar to the one considered in (Obando et al., 2016):

$$\varrho_{i,k}^{h\ell} = \left(z_\ell^{\max} - |\mathcal{U}_k^\ell|\right) \max\left(0, f_{i\ell,k} - f_{ih,k} - \varepsilon\right), \forall h, \ell \in \mathcal{B}_i, \tag{5-6}$$

where $\varepsilon \in \mathbb{R}_{\geq 0}$. Notice that the switching rule in (5-6) indicates that the i^{th} decision maker has incentives to *move* from the h^{th} to the ℓ^{th} strategy only if it represents an improvement over its utilities greater than ε and there is available capacity at the ℓ^{th} strategy. Proposition 1 shows that an equilibrium in dynamics (5-5) with the aforementioned switching rule implies a Local ε-Equilibrium with respect to the allowed interactions within the population.

Proposition 1. *(ε-Equilibrium Point) The equilibrium point of the dynamics in (5-5) with the switching rule in (5-6) implies a Local ε-Equilibrium with respect to the interaction sets $\mathcal{B}_i$, for all $i \in \mathcal{U}$.*

Demostración. It immediately follows from the fact that the equilibrium in (5-5) implies that $\varrho_i^{g_i\ell} = 0$, with $i \in \mathcal{U}^{g_i *}$, for all $i \in \mathcal{U}$, $\ell \in \mathcal{B}_i$. Therefore, $f_{i\ell,k} \leq f_{ig_i,k} + \varepsilon$, with $i \in \mathcal{U}^{g_i *}$, for all $i \in \mathcal{U}$, $\ell \in \mathcal{B}_i$ such that $z_\ell^{\max} < |\mathcal{U}_k^\ell|$, which is the required conclusion according to Definition 3. □

In addition to obtaining a local equilibrium (Definition 3), Proposition 2 shows the satisfaction of constraints stated involving the initial condition in Assumption 1, for all the time instants $k \in \mathbb{Z}_{>0}$.

Proposition 2. *(Satisfaction of constraints) If Assumption 1 holds, then,* $|\mathcal{U}_k^\ell| \leq z_\ell^{\max}$, $\bigcap_{\ell\in\mathcal{B}} \mathcal{U}_k^\ell = \emptyset$, *and* $\bigcup_{\ell\in\mathcal{B}} \mathcal{U}_k^\ell = \mathcal{U}$ *under dynamics in (5-5) for all time instants* $k \in \mathbb{Z}_{>0}$.

Demostración. Regarding the first constraint, it is assumed that $|\mathcal{U}_0^\ell| \leq z_\ell^{\max}$, for all $\ell \in \mathcal{B}$. Moreover, notice that the cardinality $|\mathcal{U}_k^\ell|$ can only growth one by one, for all $\ell \in \mathcal{B}$, due to the fact $z_\ell^{\max} \in \mathbb{Z}_{>0}$ and that $\varrho_{i,k}^{g_i\ell} = 0$ in (5-5) if constraint $|\mathcal{U}_k^\ell| \leq z_\ell^{\max}$ is active. Then $|\mathcal{U}_k^\ell| \leq z_\ell^{\max}$, for all $\ell \in \mathcal{B}$ and all $k \in \mathbb{Z}_{>0}$. Regarding the second constraint, notice that $0 \notin \mathcal{U}_k^\ell$, for all $\ell \in \mathcal{B}$. It follows that if $\bigcap_{\ell\in\mathcal{B}} \mathcal{U}_k^\ell = \emptyset$, then for any $i \in \mathcal{U}$, $\mathcal{U}_k^{g_i} \cap \mathcal{U}_k^\ell = \emptyset$, and $\{\mathcal{U}_k^{g_i} \backslash \mathcal{T}\} \cap \{\mathcal{U}_k^\ell \cup \mathcal{T}\} = \emptyset$, for any set $\mathcal{T}$.
Regarding the third constraint:
$\mathcal{U}_{k+1}^{g_i} \cup \mathcal{U}_{k+1}^\ell = \left\{\mathcal{U}_k^{g_i} \backslash \left\{i \text{ sgn}\left(\varrho_{i,k}^{g_i\ell}\right)\right\}\right\} \cup \left\{\mathcal{U}_k^\ell \cup \left\{i \text{ sgn}\left(\varrho_{i,k}^{g_i\ell}\right)\right\} \setminus \{0\}\right\} = \mathcal{U}_k^{g_i} \cup \mathcal{U}_k^\ell$, completing the proof. □

5.3. Distributed Population Dynamic Approach

The energy efficiency problem is studied using a distributed population dynamic approach with atomicity and non-anonymity characteristics. Hence, in each time instant $k \in [0, N]$ a user $i \in \mathcal{U}$ with revision opportunity evaluates its fitness function $f_{i\ell,k}$ among available choices $\mathcal{B}_{i,k}^p \subset \mathcal{B}$ and selects the destination BS according to the switching rule $\varrho_{i,k}^{h\ell}$. The distributed user-BS association mechanism is implemented according to Algorithm 1 and Algorithm 2.

5.4. Case Study

To evaluate the performance of the proposed game-theory-based-mechanism, three scenarios were used:

1 Static scenario. In this scenario, users are not moving and it is assumed constant wind to have all BSs active during the simulation horizon.

2 Dynamic scenario with controlled wind. This scenario uses a controlled wind profile to enable different groups of SCBS during specific time periods. The number of active BSs changes according to a pre-defined sequence and users are moving.

3 Fully-dynamic scenario. In this scenario, the number of active BSs are defined by the stochastic wind behaviour. Also, users are moving and data transmission requests are variable. This configuration uses the variable wind profile fitted from real data of SIATA (SIATA, 2016).

Scenario 1 is used to evaluate the stability of the game. In scenarios 2 and 3, the game-theory-based scheme is compared to the traditional best-signal-level mechanism and evaluated by

Algorithm 1 Distributed population dynamic for user-BS association

```
/*Initial association of decision makers to strategy 1 (MBS)*/
for i = 1 to u do
    y_i1 = 1
    for h = 2 to b do
        y_ih = 0
    end for
end for
/*Evaluation of switching rule from strategy h to strategy ℓ for user i according to the
best fitness function in his neighbourhood (B_{i,k})*/
k = 0
while 1 do
    k = k + 1
    Obtain U_k from the current total users in the network
    while U_k ≠ ∅ do
        i=rand (U_k)
        U_k = U_k \ {i}
        (f_iℓ, ℓ)=bestneighbour(i)
        Compute ϱ_{i,k}^{g_i ℓ} according to (5-6)
        if ϱ_{i,k}^{g_i ℓ} > 0 then
            y_{i g_i, k} = 0
            y_{iℓ, k} = 1
        end if
    end while
end while
```

Algorithm 2 Function: bestneighbour

```
/*Calculation of the highest utility function in the neighbourhood of user i (B_{i,k})*/
Require: i
    fitness = 0, bestneighbour = 0
    for ℓ = 1 to b do
        if ψ_iℓ ≥ φ and bestneighbour < f_iℓ then
            bestneighbour = ℓ
            fitness = f_iℓ
        end if
    end for
    return bestneighbour, fitness
```

using key performance indicators (KPI) related to grid consumption, average transmission rate per user, and average utility per user. A simulation horizon of nine minutes (540 time instants) was defined to assess the behaviour of the proposed approach.

5.4.1. Static Scenario

Figure **5-1** presents the behaviour of proposed mechanism in the static scenario with 1000 users. This scenario is configured with all BSs active during the simulation horizon (Figure **5-3**(a)) and has a limit of 100 active users connected simultaneously at each BS. The initial condition ($k = 0$) to start the process is that users are associated to the BS with better signal level.

In Figure **5-1**(a), it is possible to observe that users perceive greater utility from SCBS, represented by gray lines, compared to MBS, which is the black line. This result is coherent with the utility function proposed, where green-energy has an incentive in the decision process. Another element to note is the stability of average utility per BS after 300 time instants, the time in which the equilibrium between energy source of BS, the number of users connected, and the transmission rate that BS can offer reach the steady state in each cell and users have no incentive to deviate their decision.

In Figure **5-1**(b), it is possible to observe the tendency of the number of users connected to each BS. The solid black line represents the MBS, the pointed line is the number of users not served and gray lines are users connected to small cells. The first element to note is the accomplishment of the base station capacity constraint, where all values are less than 100. Also, it is possible to observe an initial concentration of users in the MBS according to the initial condition of select BS with the best signal level. Once the process begins, the users distribution is modified to reach an equilibrium as can be seen after 300 time instants. In the same way, the number of not served users is high in initial time instants caused by the limit on the BSs capacity, but the game balances the users' distribution until a null value.

Regarding the performance of the proposed mechanism, in Figure **5-3**(d) it is possible to observe a gradual reduction of grid consumption along the simulation time. This behavior is in line with the first element of the objective function presented in (5-1a), and it is explained because, over time, users find more utility in SCBS compared to MBS changing their associated decision to a cell powered by renewable energy that offers a similar transmission rate to the current BS. In the same way, in Figure **5-3**(g) we can see a gradual maximization of average user rate until a stable point.

The average utility per user behaviour can be observed in Figure **5-3**(j), where we can observe a continuous increase in the first 100 time instants followed by a stabilization period until 300 instants. Once a steady state is reached, utility remains constant because the users have no incentive to deviate from their BS selection. This behaviour is explained because in first time instants users easily find base stations with better utility and deviate their initial cell selection, but over time a smaller number of users have incentives to change their current

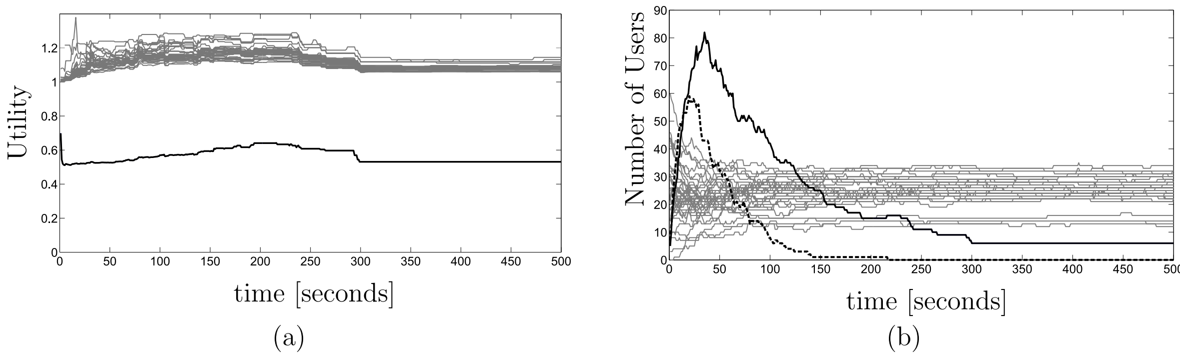

Figure 5-1.: Average utility by BS and Number of users connected to BS.

decision until reaching the point where no user has the incentive to select a different base station than the one that is already connected.
The obtained results in the static scenario allow us to observe the function utility maximization and the steady state of the game, as well as key elements in game theory, making it possible to extend its application to scenarios with dynamic features.

5.4.2. Game Behaviour in Dynamic Scenario with Controlled Wind

To analyse the impact and behaviour of the proposed approach in an environment with changing characteristics of renewable sources, Figure **5-2** shows the user-BS association process in the scenario with the controlled wind and 1000 users, which changes the network topology each 60 time instants according to Figure **5-3**(b).
Initially, users are connected to the MBS because it is the only one active. In time instant 61 (Figure **5-2**(a)) a sector of small cells is activated and some users change their BS according to the revision protocol. It is important to note that the revision opportunity is a probabilistic process, hence not all users make a decision at the same time. In Figure **5-2**(b), it is possible to observe the game evolution at the end of this wind behavior ($k = 120$), in which the largest number of users in the area with active SCBS are distributed over green cells. It is important to note that some users continue to connect to the MBS despite being in a location with coverage of green cells. This result is the consequence of finding a better utility in the MBS due to the cells overloading, or because these users are located on the edges of small cells where the transmission rate is better from MBS. In this case, the second element of the objective function presented in (5-1a) has a dominant role in the utility function.
Figure **5-2**(c) presents the game evolution in $k = 360$. Here, it is observed that the largest number of users with the possibility of accessing a green cell is associated with one of these. Finally, Figure **5-2**(d) shows the last time instant in the period with all SCBS active. There, it is possible to observe a uniform distribution of users over green cells and the accomplishment of the objective of discharging traffic load from MBS to cells powered by renewable energies. Regarding the users connected to the MBS, besides the evaluation of utility fun-

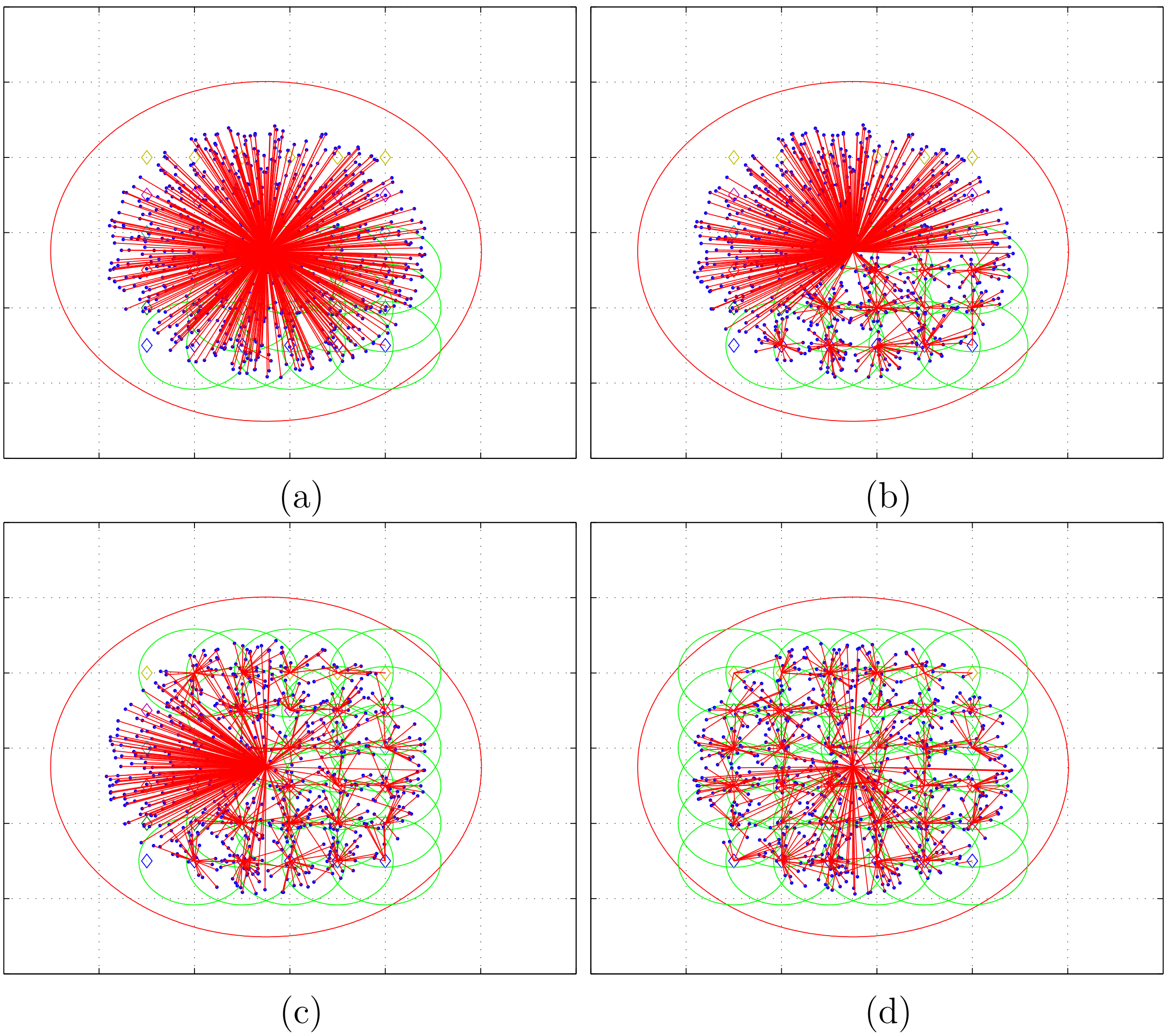

Figure 5-2.: User-BS association process with the proposed game-theory-based scheme.

ction mentioned previously, it is important to remember that the process of user generation is dynamic and, for this reason, at each time interval there will be users who have not started the game. These new active users are connected to the base station with the best signal level, in this case the MBS.

5.4.3. Dynamic Scenarios

The dynamic scenarios are configured with 5000 users, different wind profiles, and MBS without limit to serve users simultaneously. In the scenario with the controlled wind, the number of active base stations changes in defined time intervals, as can be seen in Figure **5-3**(b). The fully-dynamic scenario uses a wind profile fitted from real data of Medellín city to reflect the stochastic behaviour of the wind (Figure **5-3**(c)).

Regarding grid consumption, in the scenario with the controlled wind it is possible to observe the proper response of the proposed mechanism in the presence of renewable energy, minimizing grid consumption to levels near to static consumption (130 watts) when all SCBS are active (Figure **5-3**(e)). This result maintains coherence with the behavior observed in the user-BS association process presented in the previous sections. Here, it is possible to observe that reducing the number of users connected to MBS has a positive impact on the energy efficiency of the network. The reduction of grid utilization is maintained in the fully dynamic scenario as can be seen in Figure **5-3**(f). There, it is possible to observe during all simulation horizon a lower grid consumption with the game-theory-based scheme compared to the traditional mechanism. The consumption difference between both schemes is more notorious in the presence of green cells.

Regarding the average transmission rate, Figures **5-3**(h)-(i) show that it is lower with game theory based mechanism compared to the traditional scheme. This is caused by the relation between $r^p_{i\ell}$ and ψ^p_ℓ (2-4). Therefore, if the best signal level is not the main criteria for selecting a base station, a reduction in the average rate can be achieved. However, despite the reduction in the average transmission rate, Figures **5-3**(h)-(i) allow observing that degradation is not sufficient to consider it a critical problem. It is important to remember that the transmission power of SCBS is lower than the MBS, and this has an important impact on the perceived rate by users. This situation can be countered with accurate scheduling methods to assign more bandwidth to users connected to small cells, but this problem is beyond the scope of this thesis.

As was expected, it is possible to observe that the average utility received by users has a high sensitivity with wind variations, especially in the fully-dynamic scenario (Figure **5-3**(l)) compared to the wind-controlled scenario (Figure **5-3**(k)), where changes in wind speed are less drastic and values between both schemes are closer. Here, it is important to note the suitable utilization of renewable energies by the designed mechanism compared to the traditional scheme. In this way, it is notorious the system utility increasing when the number of active green base stations grows.

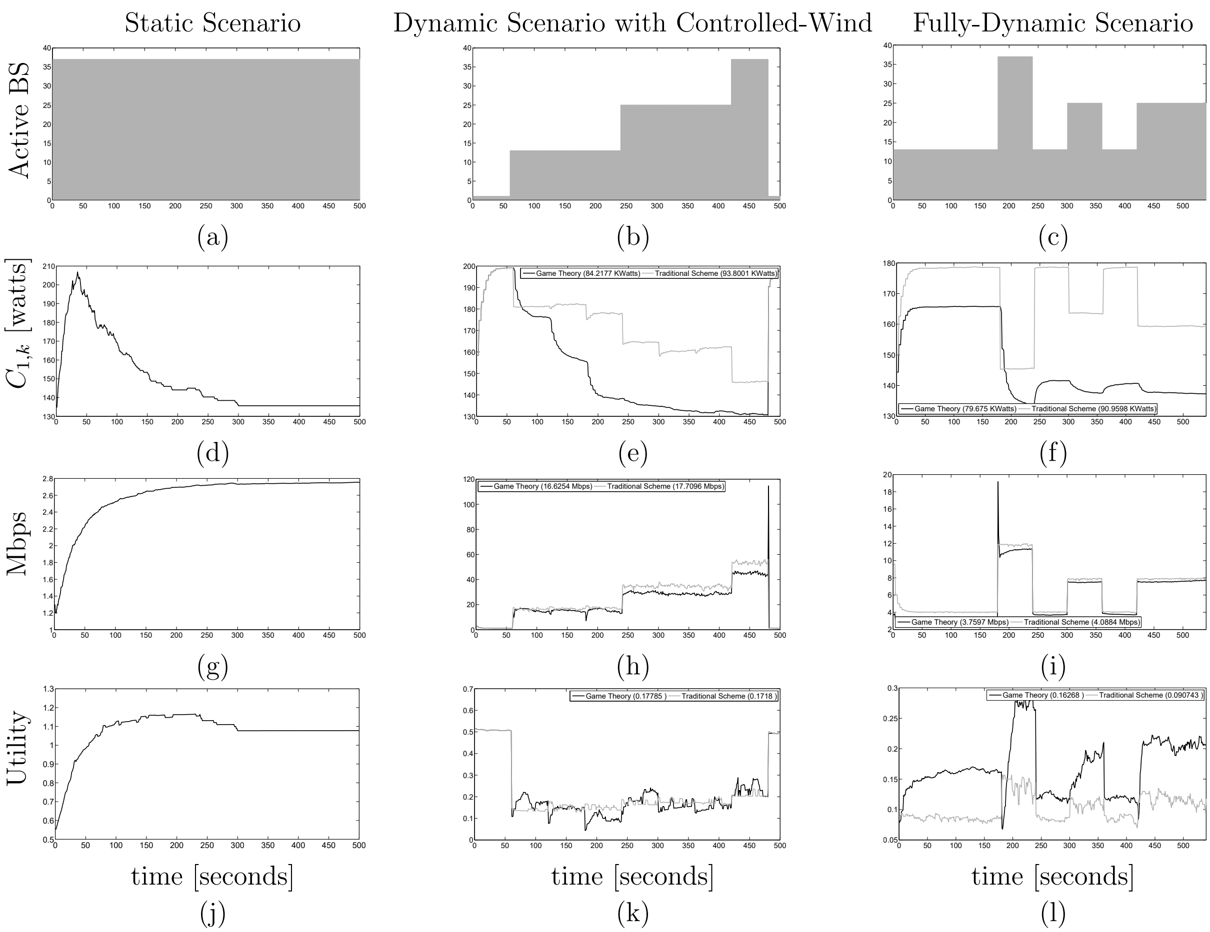

Figure 5-3.: Behaviour comparison of proposed scheme in different scenarios.

Table 5-2.: Schemes Comparison Distributed Population Games

Association Scheme	Grid Consumption (kwatts)	% of reduction	Average Transmission Rate (Mbps)	% of increase	Transmitted bits per grid-consumed (Kbits/watts)	% of increase
Signal Level Policy (C. S.)	93.8	-	17.71	-	12.8	-
G.T Scheme (C. S.)	84.21	10.22	16.63	- 5.9	13.1	2.35
Signal Level Policy (D. S.)	90.96	-	4.09	-	2.69	-
G.T Scheme (D. S.)	79.67	12.4	3.76	- 8.1	3.14	16.7

5.4.4. Comparison with Traditional Best-Signal Level Mechanism

To compare the performance of the proposed game-theory-based mechanism with the traditional best-signal-level scheme, six KPI are proposed: grid consumption (watts), percentage of consumption reduction compared to the traditional scheme, average transmission rate per user (Mbps), percentage of variation in the transmission rate, transmitted bits per grid-consumed (bits/watts), and average utility per user. Table **5-2** shows the KPI values for each scenario.

As can be seen, the game-theory-based mechanism reduces the grid consumption about 10.12 % in the dynamic-wind controlled scenario and about 12.4 % in the fully-dynamic scenario compared to the traditional scheme. However, the average transmission rate is lower in both cases. The user rate behavior is caused by the relation between the signal level and the user rate presented in (2-3) being an expected result.

Considering the proper response of the population-game approach in grid consumption but the decrement in average transmission rate, the KPI transmitted bits per grid-consumed was defined to find the amount of grid energy required to transmit a bit of information. Table **5-2** shows that the proposed game-theory-based mechanism has a better performance in both scenarios, being possible to improve the bit/watts relation up to 16.7 % compared to the traditional best signal level mechanism using a hybrid power infrastructure in a fully-dynamic environment.

It is important to emphasize the suitable response of the transmitted bits per grid-consumed KPI since this is a measure of the energy efficiency of the system and an objective indicator to compare both mechanisms according to the components of the objective function. In this sense, it is possible to conclude that the proposed game-theory-based mechanism improves the energy efficiency of HetNets powered by hybrid energy sources in scenarios with similar characteristics to those presented in this thesis.

6. Conclusions and Future Work

6.1. Conclusions

The aim of this thesis was to propose different control strategies to reduce grid consumption in next-generation cellular networks powered by hybrid energy sources. Particularly, the selected cellular network architecture was a two-tier HetNet where the MBS was powered by on-grid energy and the SCBSs were powered by renewable energies. The case study had simplifications but is representative of a real scenario with an appropriate level of complexity due to the energy-source data and the number of users and BSs considered in the simulations. The control strategies were designed from three perspectives: centralised, distributed at the base-station level, and distributed at the user level. Additionally, from a time perspective, two scales were considered: short timescale (in the order of seconds) to study the planning and user–BS association problems, and long timescale (in the order of hours) to analyse the efficient storage-energy problem.

An important element for the energy efficiency of HetNets powered by hybrid sources is the planning process. In this thesis, a new planning mechanism based on coalitional games was proposed and compared with other mechanisms widely used. The simulations allowed us to observe that optimisation-based schemes result in better network performance with respect to uniform small-cell location. The greedy mechanism also had a good response, but the coalitional approach is more accurate in adverse conditions – e.g., low wind speed and a high number of users.

Note that the problem formulation incorporates the impact of renewable-energy sources indirectly, because the evaluation of the characteristic function, which is based on the KPI considered, depends on the RE that powers the infrastructure. Hence, wind scenarios should be carefully selected to represent the real conditions in which the HetNet is going to be used. It is remarkable that the optimisation-based methods, which evaluate the contribution of each small cell into the overall system performance under different conditions, can also be used in other planning problems as long as the sum of different KPIs can be used as a selection criterion for SCBSs. In particular, the coalitional approach can be used with other definitions of the characteristic function of the game that include other factors – e.g., costs of deployment, bandwidth, or transmission power. Hence, it provides a general way of dealing with planning problems with a feasible computation burden. In addition, it was possible to observe that the proposed coalitional planning mechanism can boost other methods such as genetic algorithms and pattern search, for it detects the most relevant elements in the solution space of the optimisation problem.

After studying the planning issue, three different centralised user–BS association schemes were proposed for the user–BS association problem. In particular, the traffic flow and green market policies deserve special attention in view of the obtained results and their novelty. The simplicity of the green policy is also a good characteristic in complex scenarios. Our simulations show that optimisation-based schemes result in lower power-grid consumption, but the average transmission rate is also lower because optimiser schemes prioritise grid consumption over the signal level.

Regarding the performance of the green policy algorithm, lower consumption was observed compared with the traditional scheme, but the classical optimiser performance at the same US level (85 %) is better. However, the green algorithm can be a good option in scenarios with a large number of users and active BSs, because its simplicity demands fewer computational resources than the optimiser. The green market scheme is a good option in situations with many users and high wind speeds, since this increases the number of active small cells and encourages users to use green energy.

It is important to emphasise the good response of the traffic-flow approximation, despite being a relaxation of the original optimisation problem. It reaches KPI values closer to those of the discrete optimisation. The possibility of implementing the traffic-flow mechanism in a distributed scenario is another advantage, with it being difficult in discrete optimisation-based schemes.

Finally, in the short timescale, a distributed game-theory-based mechanism to control the user–BS association process was proposed. This mechanism is based on a population game with characteristics of atomicity and non-anonymity, elements not previously considered in proposals based on this methodology. Three scenarios with different wind behaviours were considered to test the performance of the proposed mechanism and to compare it with the traditional best-signal-level policy.

The distributed population dynamics mechanism has been shown to be a suitable option for balancing traffic in dense HetNets and reducing grid consumption through traffic discharge from the MBS to green SCBSs. Another important characteristic observed is the possibility to reduce the users' search-space to a subset of strategies, which facilitates solving the integer association problem, being a proper option for controlling systems with a large amount of users, as expected in next-generation cellular networks. Also, it is important to emphasise that the proposed distributed game-theory-based mechanism can be used to achieve other goals related to the performance of the network through the modification of the utility function.

Regarding atomicity and non-anonymity, it was possible to demonstrate under a population dynamic approach that one agent's decision can influence the global utility of the system, as can be observed in the reduction of grid consumption when users are transferred from a macro base to small cells.

In the long timescale, an MPC energy management scheme based on traffic flows was desig-

ned. The simulations show that the MPC scheme results in lower grid-energy consumption, with variations in the energy savings that depend on the prediction horizon, but showing better results than a reactive flow optimiser.
Regarding the performance of the MPC, the best response corresponds to a prediction horizon of 5 hours. Nevertheless, the reactive flow optimisation also provides good results and reaches values closer to those of the MPC. The possibility of implementing the mechanisms in a distributed scenario is another advantage of both methods. Future work in this line will explore a detailed prediction model with spatial traffic variability and alternatives to energy management in HetNets by using a distributed MPC.
Finally, it was demonstrated that efficient energy management in systems powered with hybrid sources can be implemented by using mechanisms that incorporate predictions of the renewable sources' behaviour.

6.2. Future Work

The next stage in the study of alternatives for improving the energy consumption of these kinds of networks should include analysis of delays in the user–BS association process and their impact on the QoS of the system. Also, it is important to analyse the scheduling in resource-block assignation from SCBSs to users to improve the transmission rate.
In the same way, it is important to note that, to reach minimum grid-energy consumption levels, it is necessary to guarantee a continuous provisioning of green energy, which can be achieved by means of storage systems or by using more stable renewable sources.
Regarding the planning problem, future work should deal with the incorporation of additional KPIs related to traffic characteristics and the assessment of the sub-optimality of the final design.

A. List of Publications

The publications produced by this thesis are presented below.

A.1. Journals - Published

Title: Coalitional Planning for Energy Efficiency of HetNets Powered by Hybrid Energy Sources.
Authors: Luis A. Fletscher, José M. Maestre, and Catalina Valencia Peroni.
*Journal:*IEEE Transactions on Vehicular Technology.
Year: 2018.
DOI: 10.1109/TVT.2018.2809639.
Ranking: Q1.
Index: WoS-JCR.

Title: An assessment of different user–BS association policies for green HetNets in off-grid environments.
Authors: Luis A. Fletscher, José M. Maestre, and Catalina Valencia Peroni.
Journal: Transactions on Emerging Telecommunications Technologies.
Year: 2017.
DOI: 10.1002/ett.3227.
Ranking: Q2.
Index: SJR.

Title: SON Mechanism for Green Heterogeneous Cellular Networks.
Authors: Luis A. Fletscher, Catalina Valencia Peroni, and Juan Felipe Botero.
Journal: Lecture Notes in Computer Science.
Year: 2015.
DOI: 10.1007/978-3-319-20034-7_4.
Ranking: Q2.
Index: SJR.

A.2. Journals - In process

Title: Atomicity and Non-anonymity in Population-like Games for the Energy Efficiency of Hybrid-Power HetNets.
Authors: Luis A. Fletscher, J. Barreiro-Gomez, C. Ocampo-Martinez, José M. Maestre, and Catalina Valencia Peroni.
Journal: IEEE Transactions on Network and Service Management.
Status: Major revision.
Year: 2018.
Ranking: Q1.
*Index:*WoS-JCR.

Title: Energy-Aware Resource Management in Heterogeneous Cellular Networks with Hybrid Energy Sources.
Authors: Luis A. Fletscher, Luis A. Suárez, David Grace, José M. Maestre, and Catalina Valencia Peroni.
Journal: IEEE Transactions on Network and Service Management.
Status: Major revision.
Year: 2018.
Ranking: Q1.
Index: WoS-JCR.

A.3. Conferences - Presented

Title: Model Predictive Controller with Traffic Offloading for Energy Efficiency in Hetnets Powered by Renewable Energies.
Authors: Luis A. Fletscher, José M. Maestre, and Catalina Valencia Peroni.
Conference: IEEE 3rd Colombian Conference on Automatic Control (CCAC).
Year: 2017.
Location: Cartagena.

A.4. Conferences - Accepted

Title: Energy Efficiency of Hybrid-Power HetNets: A Population-like Games Approach.
Authors: Luis A. Fletscher, J. Barreiro-Gomez, C. Ocampo-Martinez, José M. Maestre, and Catalina Valencia Peroni.

Conference: IEEE American Conference Control (ACC).
Year: 2018.
Location: Milwaukee.

Bibliography

3GPP (2014). Lte evolved universal terrestrial radio access network (e-utran); self-configuring and self-optimizing network (son) use cases and solutions. `http://www.3gpp.org/dynareport/36902.htm`.

3GPP (2017). 3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Evolved Universal Terrestrial Radio Access (E-UTRA); Further advancements for E-UTRA physical layer aspects (Release 9).

5GrEEn (2015). Towards Green 5G Mobile Networks. `https://wireless.kth.se/5green/`.

Alsharif, M., Nordin, R., and Ismail, M. (2015). Energy optimisation of hybrid off-grid system for remote telecommunication base station deployment in Malaysia. *EURASIP Journal on Wireless Communications and Networking*, 2015(1):64–79.

Andrews, J. (2013). Seven ways that hetnets are a cellular paradigm shift. *IEEE Communications Magazine*, 51(3):136–144.

Andrews, J., Singh, S., Ye, Q., Lin, X., and Dhillon, H. (2014). An overview of load balancing in hetnets: old myths and open problems. *IEEE Wireless Communications*, 21(2):18–25.

Arani, A., Omidi, M., Mehbodniya, A., and Adachi, F. (2017). A distributed learning based user association for heterogeneous networks. *Transactions on Emerging Telecommunications Technologies*, 28(5):1–13.

Auer, G., Giannini, V., Desset, C., G'odor, I., Skillermark, P., Olsson, M., Imran, M., Sabella, D., Gonzalez, M., Blume, O., and Fehske, A. (2011). How much energy is needed to run a wireless network? *IEEE Wireless Communications*, 18(5):40–49.

Bao, Y., Wang, X., Liu, X., Zhou, S., and Niu, Z. (2014). Solar Radiation Prediction and Energy Allocation for Energy Harvesting Base Stations. In *2014 IEEE International Conference on Communications (ICC)*, pages 3487–3492.

Barreiro-Gomez, J., Obando, G., and Quijano, N. (2017). Distributed Population Dynamics: Optimization and Control Applications. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(2):304–314.

Bird, R. E. and Hulstrom, R. L. (1981). Simplified Clear Sky Model for Direct and Diffuse Insolation on Horizontal Surfaces. Technical report, Solar Energy Research Institute.

Camacho, E. and Bordons, C. (1999). *Model Predictive Control*. Springer, New York, 1 edition.

Camponogara, E. and Scherer, H. (2011). Distributed Optimization for Model Predictive Control of Linear Dynamic Networks With Control-Input and Output Constraints. *IEEE Transactions on Automation Science and Engineering*, 8(1):233–242.

Carvalho, G., Woungang, I., Anpalagan, A., and Hossain, E. (2016). QoS-Aware Energy-Efficient Joint Radio Resource Management in Multi-RAT Heterogeneous Networks. *IEEE Transactions on Vehicular Technology*, 65(8):6343–6365.

Castro, J., Gómez, D., and Tejada, J. (2009). Polynomial calculation of the Shapley value based on sampling. *Computers & Operations Research*, 36(5):1726–1730.

Cea, M., Goodwin, G., and Wigren, T. (2012). Model Predictive Zooming Power Control in Future Cellular Systems under Coarse Quantization. In *2012 IEEE Vehicular Technology Conference (VTC Fall))*, Quebec, Canada.

Challita, U., Dawy, Z., Turkiyyah, G., and Naoum-Sawayac, J. (2016). A chance constrained approach for LTE cellular network planning under uncertainty. *Computer Communications*, 73(10):34–45.

Chekroun, S., Sabir, E., Kobbane, A., Tembine, H., Bouyakhf, E., and Ibrahimi, K. (2015). A distributed open-close access for Small-Cell networks: A random matrix game analysis. In *Wireless Communications and Mobile Computing Conference (IWCMC)*, pages 321–325, Dubrovnik, Croatia.

Chen, R., Shaowei, W., and Chonggang, W. (2015). Cellular networks planning: A workload balancing perspective. *Computer Networks*, 84(19):64–75.

Cisco (2017). Cisco visual networking index: Global mobile data traffic forecast update, 2016–2021. Technical report, Cisco Systems, Inc.

Dantong, L., Yue, C., Kok, C., Tiankui, Z., and Chengkang, P. (2014). Adaptive user association in HetNets with renewable energy powered base stations. In *21st International Conference on Telecommunications (ICT)*, pages 93–97, Lisbon, Portugal.

Deng, X. and Papadimitriou, C. (1994). On the complexity of cooperative solution concepts. *Mathematics of Operations Research*, 19(2):257–66.

Dhillon, H., Ying, L., Nuggehalli, P., Zhouyue, P., and Andrews, J. (2014). Fundamentals of Heterogeneous Cellular Networks with Energy Harvesting. *IEEE Transactions on Wireless Communications*, 13(5):2782–2797.

Di Francesco, P., Malandrino, F., Forde, T., and DaSilva, L. (2015). A Sharing- and Competition-Aware Framework for Cellular Network Evolution Planning. *IEEE Transactions on Cognitive Communications and Networking*, 1(2):230–243.

Djehiche, B., Siwe, A., and Tembine, H. (2016). Mean-Field-Type Games in Engineering. *ArXiv Preprint*, pages 1–22.

Faigle, U. and Kern, W. (1992). The Shapley value for cooperative games under precedence constraints. *International Journal of Game Theory*, 21(3):249–266.

Fele, F., Maestre, J. M., and Camacho, E. F. (2017). Coalitional Control: Cooperative Game Theory and Control. *IEEE Control Systems*, 37(1):53–69.

Fletscher, L., Maestre, J., and Valencia, C. (2017). Model predictive controller with traffic offloading for energy efficiency in hetnets powered by renewable energies. In *IEEE 3rd Colombian Conference on Automatic Control (CCAC)*, pages 1–5.

Fletscher, L., Maestre, J., and Valencia, C. (2018). Coalitional Planning for Energy Efficiency of HetNets Powered by Hybrid Energy Sources. *IEEE Transactions on Vehicular Technology*, pages 1–13.

Fletscher, L., Valencia, C., and Maestre, J. (2017. e3227. https://doi.org/10.1002/ett.3227). An assessment of different user–BS association policies for green HetNets in off-grid environments. *Transactions on Emerging Telecommunications Technologies*, pages 1–15.

Garcia, V., Lebedev, N., and Gorce, J.-M. (2012). Model predictive control for smooth distributed power adaptation. In *2012 IEEE Wireless Communications and Networking Conference (WCNC)*, Paris, France.

Ghazzai, H., Yaacoub, E., Alouini, M.-S., Dawy, Z., and Abu-Dayya, A. (2016). Optimized LTE cell planning with varying spatial and temporal user densities. *IEEE Transactions on Vehicular Technology*, 65(3):1575–1589.

Gu, Y., Bakke, J., Zhou, Z., Osborn, D., Guo, T., and Bo, R. (2014). A Novel Market Simulation Methodology on Hydro Storage. *IEEE Transactions on Smart Grid*, 5(2):1119–1128.

Guruacharya, S., Niyato, D., Kim, D., and Hossain, E. (2013). Hierarchical Competition for Downlink Power Allocation in OFDMA Femtocell Networks. *IEEE Transactions on Wireless Communications*, 12(4):1543–1553.

Han, T. and Ansari, N. (2013). On Optimizing Green Energy Utilization for Cellular Networks with Hybrid Energy Supplies. *IEEE Transactions on Wireless Communications*, 12(8):3872–3882.

Han, T. and Ansari, N. (2016). A Traffic Load Balancing Framework for Software-Defined Radio Access Networks Powered by Hybrid Energy Sources. *IEEE/ACM Transactions on Networking*, 24(2):1038–1051.

Hasan, Z., Boostanimehr, H., and BhargavaGhazzai, V. (2011). Green Cellular Networks: A Survey, Some Research Issues and Challenges. *IEEE Communications Surveys and Tutorials*, 13(4):524–540.

Hassan, H., Singh, K., and Nuaymi, L. (2016). Grid energy consumption of mixed-traffic cellular networks with renewable energy sources. In *2016 IEEE Online Conference on Green Communications (OnlineGreenComm)*, pages 1–6.

Hassan, H. A. H., Nuaymi, L., and Pelov, A. (2013). Classification of renewable energy scenarios and objectives for cellular networks. In *IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC*, pages 2967–2972, London.

IBM (2015). IBM ILOG CPLEX Optimization Studio.

ICT-EARTH (2014). ICT-EARTH web page. `https://www.ict-earth.eu`.

IDEAM (2017). Instituto de Hidrología, Meteorología y Estudios Ambientales - IDEAM. `http://atlas.ideam.gov.co/visorAtlasRadiacion.html`.

International Energy Agency (2012). Conference Mondiale De L'Energie. In *World Energy Outlook*, pages 43–46, Paris. International Energy Agency.

Johnson, D. and Garey, M. (1979). *Computers and Intractability: A Guide to the Theory of NP-Completeness*. Bell Telephone Laboratories, Incorporated, New Jersey, NJ, USA, 1 edition.

Kaneko, S., Matsunaka, T., and Kishi, Y. (2012). A Cell-Planning Model for HetNet with CRE and TDM-ICIC in LTE-Advanced. In *2012 IEEE 75th Vehicular Technology Conference (VTC Spring)*, pages 1–5.

Kashef, M., Ismail, M., Serpedin, E., and Qaraqe, K. (2016). Balanced Dynamic Planning in Green Heterogeneous Cellular Networks. *IEEE Journal on Selected Areas in Communications*, 34(12):3299–3312.

Khan, M. and Tembine, H. (2011). Evolutionary Coalitional Games in Network Selection. In *Wireless Advanced (WiAd)*, pages 185–194, London, UK.

Kim, H., de Veciana, G., Yang, X., and Venkatachalam, M. (2012). Distributed α-Optimal User Association and Cell Load Balancing in Wireless Networks. *IEEE/ACM Transactions on Networking*, 20(1):177–190.

Leonardi, G., Meo, M., and Ajmone, M. (2016). Markovian models of solar power supply for a LTE macro BS. In *2016 IEEE International Conference on Communications (ICC)*, pages 1–7.

Liu, D., Chen, Y., Chai, K., Zhang, T., and Elkashlan, M. (2015a). Two Dimensional Optimization on User Association and Green Energy Allocation for HetNets with Hybrid Energy Sources. *IEEE Transactions on Communications*, 63(11):4111–4124.

Liu, D., Chen, Y., Chai, K., Zhang, T., and Elkashlan, M. (2015b). Two-Dimensional Optimization on User Association and Green Energy Allocation for HetNets With Hybrid Energy Sources. *IEEE Transactions on Communications*, 63(11):4111–4124.

Lubritto, C., Petraglia, A., Vetromile, C., Curcuruto, S., Logorelli, M., Marsico, G., and D'Onofrio, A. (2011). Energy and environmental aspects of mobile communication systems. *Energy*, 36:1109–1114.

Maaz, A., Grote, F., and Moser, C. (2015). Agent-based price simulation of the German wholesale power market. In *12th International Conference on the European Energy Market (EEM)*, pages 1–5, Lisbon, Portugal.

Maestre, J. and Hideaki, I. (2017). A PageRank Based Coalitional Control Scheme. *International Journal of Control, Automation and Systems*, pages 1–8.

Maestre, J. M. and Negenborn, R. R. (2014). *Distributed Model Predictive Control Made Easy*. Springer Science & Business Media, New Jersey, 1 edition.

Mao, Y., Zhang, J., and Letaief, K. (2015). A Lyapunov Optimization Approach for Green Cellular Networks With Hybrid Energy Supplies. *IEEE Journal on Selected Areas in Communications*, 33(12):2463–2477.

Marden, J. (2014). The role of information in multiagent coordination. In *53rd IEEE Conference on Decision and Control (CDC)*, pages 445–450, Los Angeles, CA, USA.

Marden, J. (2016). The Role of Information in Distributed Resource Allocation. *IEEE Transactions on Control of Network Systems*, PP(99):1–12.

Marsan, M., Bucalo, G., Di Caro, A., Meo, M., and Yi, Z. (2013). Towards zero grid electricity networking: Powering BSs with renewable energy sources. In *2013 IEEE International Conference on Communications (ICC)*, pages 596–601, Budapest.

Meo, M., Zhang, Y., Gerboni, R., and Ajmone, M. (2015). Dimensioning the Power Supply of a LTE Macro BS Connected to a PV Panel and the Power Grid. In *2015 IEEE International Conference on Communications (ICC)*, pages 178–184.

Morea, F., Viciguerra, G., Cucchi, D., and Valencia, C. (2007). Life cycle cost evaluation of off-grid PV-wind hybrid power systems. In *INTELEC 07 - 29th International Telecommunications Energy Conference*, pages 439–441, Rome. IEEE.

Narayanam, R. and Narahari, Y. (2011). A shapley value-based approach to discover influential nodes in social networks. *IEEE Transactions on Automation Science and Engineering*, 8(1):130–147.

Negenborn, R. and Maestre, J. (2014). Distributed Model Predictive Control: An Overview and Roadmap of Future Research Opportunities. *IEEE Control Systems Magazine*, 34(4):87–97.

Obando, G., Barreiro-Gomez, J., and Quijano, N. (2016). A class of population dynamics for reaching epsilon-equilibria: Engineering applications. In *American Control Conference (ACC), 2016*, pages 4713–4718, Boston, MA, USA.

Palisade Corporation (2015). @Risk 7.

Pindyck, R. and Rubinfeld, D. (2013). *Microeconomics*. Pearson, Boston, 8 edition.

Pinto, T., Silva, H., Vale, Z., Santos, G., and Praca, I. (2015). Pan-European Electricity Market Simulation Considering the European Power Network Capacities. In *26th International Workshop on Database and Expert Systems Applications (DEXA)*, pages 91–95, Valencia, Spain.

Piro, G., Miozzo, M., Forte, G., Baldo, N., Grieco, L., Boggia, G., and Dini, P. (2013). HetNets Powered by Renewable Energy Sources: Sustainable Next-Generation Cellular Networks. *IEEE Internet Computing*, 17(1):32–39.

Sandholm, W. (2010). *Population Games and Evolutionary Dynamics*. MIT Press., Cambridge, MA, USA, 1 edition.

Sarimveis, H., Patrinos, P., Tarantilis, C., and Kiranoudis, C. (2008). Dynamic modeling and control of supply chain systems: A review. *Computers & Operations Research*, 35(11):3530–3561.

Shaheen, F., Wooldridge, M., and Jenningsc, N. (2008). A linear approximation method for the Shapley value. *Artificial Intelligence*, 172(14):1673–1699.

Shaowei, W., Wentao, Z., and Chonggang, W. (2015). Budgeted Cell Planning for Cellular Networks With Small Cells. *IEEE Transactions on Vehicular Technology*, 64(10):4797–4806.

Shapley, L. (1952). A value for n-person games. *Contributions to the Theory of Games II - Annals of Mathematics Studies*, 28:307–317.

Sharma, S. and Abhyankar, A. R. (2017). Loss Allocation for Weakly Meshed Distribution System Using Analytical Formulation of Shapley Value. *IEEE Transactions on Power Systems*, 32(2):1369–1377.

SIATA (2016). Medellín and Aburrá Valley Early Warning System, A project of the Aburrá Valley Metropolitan Area and the City of Medellín. SIATA - Sistema de Alertas Tempranas. `http://www.siata.gov.co/`.

Silva, A., Tembine, H., Altman, E., and Debbah, M. (2013). Optimum and Equilibrium in Assignment Problems With Congestion: Mobile Terminals Association to Base Stations. *IEEE Transactions on Automatic Control*, 58(8):2018 – 2031.

Smulders, S. (1990). Control of freeway traffic flow by variable speed signs. *Transportation Research Part B: Methodological*, 24(2):111–132.

Taufique, A., Jaber, M., Imran, A., Dawy, Z., and Yacoub, E. (2017). Planning Wireless Cellular Networks of Future: Outlook, Challenges and Opportunities. *IEEE Access*, 5:4821–4845.

The MathWorks (2015). Matlab® R2012a. `https://www.mathworks.com`.

Thuc, T., Hossain, E., and Tabassum, H. (2015). Downlink Power Control in Two-Tier Cellular Networks With Energy-Harvesting Small Cells as Stochastic Games. *IEEE Transactions on Communications*, 63(12):2637–2642.

TREND (2015). Towards Real Energy-efficient Network Design. `http://www.fp7-trend.eu/`.

Villarrubia, M. (2012). *Ingeniería de la Energía Eólica*. Marcombo, Barcelona, 1 edition.

Wang, H., Li, H., Wang, Z., Chen, X., and Ci, S. (2014). Stochastic Queue Modeling and Key Design Metrics Analysis for Solar Energy Powered Cellular Networks. In *2014 International Conference on Computing, Networking and Communications (ICNC)*, pages 472–477.

Wang, S. and Ran, C. (2016). Rethinking cellular network planning and optimization. *IEEE Wireless Communications*, 23(2):118–125.

Wentao, Z., Shaowei, W., and Chonggang, W. (2017). Approximation Algorithms for Cell Planning in Heterogeneous Networks. *IEEE Transactions on Vehicular Technology*, 66(2):1561–1572.

Yang, H., Geraci, G., and Quek, T. (2016). Energy-Efficient Design of MIMO Heterogeneous Networks With Wireless Backhaul. *IEEE Transactions on Wireless Communications*, 15(7):4914–4927.

Ye, Q., Rong, B., Chen, Y., Al-Shalash, M., Caramanis, C., and Andrews, J. (2013). User Association for Load Balancing in Heterogeneous Cellular Networks. *IEEE Transactions on Wireless Communications*, 12(6):2706–2716.

Zeng, X., Sun, M., Jian, X., Du, D., and Miao, L. (2017). Optimal base stations planning for Coordinated Multi-Point system. *AEU - International Journal of Electronics and Communications*, 73:193–201.

Zhang, Y., Mao, Y., and Zhong, S. (2016). Joint Differentially Private Gale-Shapley Mechanisms for Location Privacy Protection in Mobile Traffic Offloading Systems. *IEEE Journal on Selected Areas in Communications*, 34(10):2738–2749.

Zhao, W. and Wang, S. (2013). Cell Planning for Heterogeneous Cellular Networks. In *IEEE Wireless Communications and Networking Conference (WCNC)*, pages 1032–1037.

Zhou, J., Li, M., Liu, L., She, X., and Chen, L. (2010). Energy Source Aware Target Cell Selection and Coverage Optimization for Power Saving in Cellular Networks. In *2010 IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Physical and Social Computing*, pages 1–8, Hangzhou, China.