Environment Aware Cellular Networks

Thesis by
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ABSTRACT

The unprecedented rise of mobile user demand over the years have led to an enormous growth of the energy consumption of wireless networks as well as the greenhouse gas emissions which are estimated currently to be around 70 million tons per year. This significant growth of energy consumption impels network companies to pay huge bills which represent around half of their operating expenditures. Therefore, many service providers, including mobile operators, are looking for new and modern green solutions to help reduce their expenses as well as the level of their CO$_2$ emissions. Base stations are the most power greedy element in cellular networks: they drain around 80\% of the total network energy consumption even during low traffic periods. Thus, there is a growing need to develop more energy-efficient techniques to enhance the green performance of future 4G/5G cellular networks. Due to the problem of traffic load fluctuations in cellular networks during different periods of the day and between different areas (shopping or business districts and residential areas), the base station sleeping strategy has been one of the main popular research topics in green communications.

In this dissertation, we propose several practical green techniques that provide significant gains for mobile operators. Indeed, combined with the base station sleeping strategy, these techniques achieve not only a minimization of the fossil fuel consumption but also an enhancement of mobile operator profits. The first dissertation part starts with an optimized cell planning method that considers varying spatial and temporal user densities. It then uses the optimal transport theory in order to define the cell boundaries such that the net-
work total transmit power is reduced. Finally, the dual-decomposition method is employed in order to reduce the energy consumption of long term evolution heterogeneous networks by switching off the small cell base stations and exploiting the existence of private femto access points. In the second part of the thesis, we exploit the features of the modern electrical grid, the smart grid, as a new tool of power management for cellular networks. We optimize the energy procurement from multiple energy retailers characterized by different prices and pollutant levels in order to achieve green goals. We then extend our study to the time varying user density where we consider the daily variation of the user traffic and the renewable energy generated base station sites. In the third part of this dissertation, we introduce the notion of green mobile operator collaboration as a new aspect of the green networking. Competitive cellular companies might cooperate together in order to achieve green goals. In our study, we investigate the case of cellular networks deployed in the same area and owning renewable energy generators. The objective is to reduce the CO\textsubscript{2} emissions of cellular networks via collaborative techniques and using base station sleeping strategy while respecting the network quality of service. Users that were covered by an underutilized base station, would be served by another base station belonging to a competitive operator. This way operators can reduce their energy consumption exploiting another provider infrastructure. Finally, we introduce the roaming price to ensure fairness during the cooperation. Heuristic evolutionary approaches, game theory, and deterministic algorithms are implemented in order to solve the optimization problems under consideration for the different green topics investigated in this dissertation.
Acknowledgments

I still remember the feeling of excitement, when I was accepted as a PhD student and was preparing to come to KAUST for carrying out my PhD studies in January 2012. I am feeling very happy that I have accomplished my targets by the grace of Allah Almighty. I would like to take advantage of this opportunity to acknowledge all the people who have supported me during this work.

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<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
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<tbody>
<tr>
<td>Fourth Generation</td>
<td>4G</td>
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<tr>
<td>Base Station</td>
<td>BS</td>
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<td>CO₂</td>
<td>Carbon dioxide</td>
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<td>DownLink</td>
<td>DL</td>
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<tr>
<td>Femtocell Access Points</td>
<td>FAP</td>
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<td>Green Operator</td>
<td>GO</td>
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<tr>
<td>Grey Wolf Optimizer</td>
<td>GWO</td>
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<tr>
<td>Heterogenous Network</td>
<td>HetNet</td>
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<tr>
<td>Information and Communication Technology</td>
<td>ICT</td>
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<tr>
<td>Long Term Evolution</td>
<td>LTE</td>
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<tr>
<td>Long Term Evolution-Advanced</td>
<td>LTE-A</td>
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<tr>
<td>Maximum Allowed Path Loss</td>
<td>MAPL</td>
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<tr>
<td>Mobile Station</td>
<td>MS</td>
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<tr>
<td>Monetary Unit</td>
<td>MU</td>
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<tr>
<td>Non-deterministic Polynomial-time Hard</td>
<td>NP-Hard</td>
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<tr>
<td>Non-Green Operator</td>
<td>NGO</td>
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<tr>
<td>Orthogonal Frequency-Division Multiple Access</td>
<td>OFDMA</td>
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<tr>
<td>Particle Optimization Algorithm</td>
<td>PSO</td>
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<tr>
<td>Quality of Service</td>
<td>QoS</td>
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<tr>
<td>Radio Access Network</td>
<td>RAN</td>
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<tr>
<td>Resource Block</td>
<td>RB</td>
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<tr>
<td>Signal to Interference plus Noise Ratio</td>
<td>SINR</td>
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<tr>
<td>Single Carrier Frequency Domain Multiple Access</td>
<td>SC-FDMA</td>
</tr>
<tr>
<td>Universal Mobile Telecommunications System</td>
<td>UMTS</td>
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<tr>
<td>UpLink</td>
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Chapter 1

Introduction

1.1 Background and Motivation

Over the last decade, wireless and mobile communications have enjoyed widespread popularity and usage because of their access flexibility and ability for providing high data rate traffic with adequate decoding quality. Since 2006, data traffic on mobile networks has been increasing at a rate of approximately 300% and is expected to increase 14 times as much as the current data traffic volume by 2020, [1]. This huge number of wireless terminals, in addition to the deployed radio access network (RAN) necessary to serve them, consume an enormous amount of energy and lead to significant environmental impacts. Indeed, the Smart 2020 report [2] is predicting that if no actions are taken the footprint of wireless communications could almost triple from 2007 to 2020. Currently, 5-10% of the worldwide carbon emissions are produced by the information and communication technology (ICT) infrastructure [3]. Therefore, a pressing need to reduce the energy requirements and correspondingly the carbon emission of emerging wireless networks is imposed. The current technical and environmental challenges are how to design future energy efficient wireless communication systems and green digital signal processing technologies that accommodate the extra traffic while maintaining the quality of service (QoS). In fact, mobile
Figure 1.1: Current mobile network connections, electricity and diesel consumption, energy cost and CO$_2$ emissions by region [1].

has the potential to enable emissions savings of at least 900 million tonnes CO$_2$ in 2020 which is 1.7% of the global 2020 greenhouse gas emissions and five times the mobile industry’s emissions according to Groupe Speciale Mobile Association report [1]. From a cellular network operator perspective, reducing fossil fuel energy consumption is not only to behave green and responsible towards the environment but also to solve an important economical issue that cellular companies are facing. Indeed, such energy consumption forces mobile operators to pay huge energy bills which constitute around the half of their operating expenditures. Fig. 1.1 shows that cellular networks consume around 120 TWh of electricity and mobile operators pay around 13 billions of dollars to serve 5 billions of connections per year.

Many features and techniques can be exploited to reduce the energy consumption of wireless and mobile networks. The modern electrical grid system, smart grid, is widely seen as one of the important means that enhance energy savings and help to optimize some
green goals of consumers. It can considerably help in reducing greenhouse gas emissions by optimally controlling and adjusting the consumed power \[4, 5\]. Moreover, it allows the massive integration of intermittent renewable sources and offers the possibility to deliver electricity more cost-effectively with active involvement of the customers in the procurement decision \[6\]. Many wireless communication and networking technologies were proposed to improve smart grid performance. For instance, \[7\] employed home automation network technologies to achieve cost-efficient residential energy management in smart grid. Novel efficient and secure wireless communication scheme were proposed in \[8\] to improve the spectrum efficiency for advanced metering infrastructure in smart grid. Wireless sensor networks were also introduced in \[9\] as a promising technology that can solve various smart grid problems. However, few research work exploited the potential of smart grid to reduce the carbon footprint of wireless cellular networks. Therefore, introducing the concept of smart grid as a new tool of power management for cellular networks is considered as an important technological innovation that would significantly contribute in the reduction of mobile CO$_2$ emissions.

On the other hand, studies show that over 70-80\% of the power is consumed by base stations (BSs) \[10\]. Several efforts were proposed to save energy in radio access network (RAN) of the recent 4G-LTE (fourth generation long term evolution) by turning off BSs during off-peak hours when data traffic is low. Indeed, an active BS in an idle status, i.e., not serving any users, consumes more than 50\% of the energy due to circuit processing, air conditioning and other factors \[3\]. Therefore, the BS sleeping strategy can also constitute a promising solution to contribute in the reduction of mobile network power consumption and thus the greenhouse gas emissions. An example of the on/off switching technique is provided in Fig. 1.2 where one of the cells is lightly loaded with only one user connected to the BS, whereas the other BS has a higher load with three users connected to it (Fig. 1.2 (a)). If the user in the second cell can be connected to the BS of the first cell without
compromising its QoS, then the BS of the second cell can be switched off (Fig. 1.2 (b)), which leads to green energy efficient communications.

Another approach that can help in the minimization of carbon footprint as well as the huge energy bills paid by mobile companies is the green mobile operator collaboration. This concept which is recently introduced in literature [11, 12], suggests the cooperation between competitive service providers in order to achieve green targets. The fundamental idea was to completely switch off the equipment of a service provider while serving the corresponding subscribers by another infrastructure belonging to another operator under some fairness constraints. Although this technique is not yet applied in real environment, its impact is expected to provide an important energy saving and further research should be provided in order to prove its efficiency and encourage mobile companies to cooperate together for not only green but also profitable goals.
1.2 Objectives and Contributions

The main concepts discussed in this dissertation have now been highlighted. Although, the thesis also considers other important concepts which enhance the energy efficiency of wireless cellular networks. Indeed, in our work, we have proposed several green techniques that contribute in the reduction of fossil fuel consumption of mobile networks from the planning phase when the RAN infrastructure is not yet deployed till its daily network operation and its collaboration with its competitive companies. We have divided our dissertation into three parts. Part I deals with the planning phase and the mobile user assignment where the BS locations are optimized and their boundaries are optimally defined in order to achieve energy saving. Part II investigates the interplay between the mobile network and the smart grid while Part III proposes different techniques of the green mobile operator collaboration.

In the following, we summarize the contribution of each chapter:

Part I: Green Planning and Mobile User Assignment

- In Chapter 2, we propose a novel method for the cell planning problem for the 4G cellular networks using meta-heuristic algorithms. In this approach, we aim to satisfy both cell coverage and capacity constraints simultaneously by formulating an optimization problem that captures practical planning aspects. Next, the problems of green planning with regards to temporal traffic variation and planning with location constraints due to tight limits on electromagnetic radiations are addressed, using the proposed method.

- In Chapter 3, we investigate the mobile user association problem for heterogeneous networks (HetNets). We apply the optimal transport concept to determine the cells corresponding to each base station in order to minimize the total transmit power consumption of LTE networks. This is performed by respecting the network QoS and
taking into account the resource limitation per BS (e.g., power budget and number of available resource blocks (RBs)).

- Chapter 4 deals with the problem of radio and power resource management for LTE-HetNets is investigated. The objective is to minimize the total power consumption of the network while satisfying the QoS for each connected user. We consider and compare three different scenarios depending on the status of the femtocell access points (FAPs): HetNets without FAPs, HetNets with closed FAPs, and HetNets with semi-closed FAPs. The dual decomposition technique is developed to achieve optimal performance in the downlink (DL) direction. Afterwards, we propose a low complexity dynamic switching on/off algorithm and compare its performance with the optimal technique.

Part II: On the Interplay between Green Mobile Networks and the Smart Grid

- In Chapter 5, we formulate an optimization problem that aims to maximize the profit of a Long-Term Evolution (LTE) cellular operator, and to minimize the CO$_2$ emissions in green wireless cellular networks simultaneously without affecting the desired QoS. We propose a Genetic Algorithm-based and Particle Swarm Optimization-based methods that reduces the energy consumption of BSs by not only shutting down underutilized BSs but also by optimizing the amounts of energy procured from the smart grid where different energy providers exist.

- Chapter 6 extends the work presented in Chapter 4 by proposing a practical approach adapted to the time varying user density scenario where user traffic varies with time. The objective is to maintain the network QoS by adapting periodically the state of BSs from active to sleep modes and vice versa. Also, a green low complexity algorithm that focuses on reducing the daily BS ON/OFF switches by taking into account
more practical implementation constraints such as transient modes and previous active BS combinations is investigated.

**Part III: Green Mobile Operator Collaboration**

- Chapter 7 investigates the collaboration between multiple mobile operators in order to achieve green targets. The objective is to find the best active BS combination and the optimal procurement decision needed to the network operation during collaboration by considering electricity real-time pricing. The problem is modeled as a two-level Stackelberg game: a mobile operator level and a smart grid level. Our study includes the daily traffic variation in addition to the daily green energy availability.

- In Chapter 8, the collaboration between multiple mobile operators is treated from another point of view. In this case, cooperation decision criteria are established basing on derived roaming prices and profit gains of competitive mobile operators.

- Chapter 9 examines the performance of a green mobile operator collaborating with other traditional mobile operators. Its goal is to minimize its CO$_2$ emissions, maximize its profit or achieve or tradeoff between both objectives by offloading its users to neighbor networks and exploiting renewable energies. On the other hand, traditional mobile operators aim to maximize their profits by attracting the maximum number of roamed users. The problem is modeled as a two-level Stackelberg game: A green mobile operator level that determines how many users per each BS to offload to each neighbor network, and a non-green mobile operator level where operators focus on finding the optimal roaming price.
Part I

Green Planning and Mobile User

Assignment
Chapter 2

Optimized LTE Cell Planning with Varying Spatial and Temporal User Densities

2.1 Introduction

Network planning is a classical but important problem in designing cellular networks. It mostly includes the planning of BSs by optimizing their locations and configurations in order to provide full coverage of the service area with respect to the traffic requirements, available capabilities, and the desired QoS [13–15]. Under these constraints, the main objective is to reduce the total cost for deploying and expanding the cellular system. Indeed, this fundamental planning task is a result of optimization problems to determine the number in order to meet coverage and capacity requirements. The problem requires the knowledge of several parameters as inputs related to the employed technology and the geographical distribution of the traffic demand which increases its complexity and makes the optimal problem solution difficult if not impossible to reach.

Several work have been proposed to study the deployment of BSs. Most of these studies
were based on heuristic approaches to solve this non-deterministic polynomial-time hard (NP-Hard) problem [16]. For instance, [17] and [18] employed the tabu search and the genetic algorithm, respectively, to perform cell planning for code division multiple access systems. Few previous works dealt with optimizing the BS locations for 4G-LTE. The authors in [19] proposed a mixed integer programming model with the use of the method of the Pareto front and multi-objective tabu search to optimize cell planning. Another approach, presented in [20], proposed to determine the BS locations based on stochastic models such as the Poisson point process and considering the average squared error of the coverage probability as goodness criterion. In [21], the authors proposed an algorithm for joint uplink/downlink universal mobile telecommunications system (UMTS) radio planning with the objective of minimizing total power consumption in the network. The problem is subdivided into two components that are executed successively: First, the authors aimed to find the optimal positions of a fixed number of UMTS BSs in the area of interest. The optimal locations of BSs are obtained by solving an optimization problem that aims to minimize the total downlink power expenditure and, at the same time, the uplink outage that depends on the power capabilities of mobile stations (MSs) under different constraints that maintain an acceptable QoS and satisfy the power budget. As a second step, the authors proposed an algorithm to select the minimal cardinality set of BSs with fixed locations. In [22], the authors started by placing randomly a high number of BSs in the area of interest. Then, they employed an iterative algorithm based on user snapshot studies to eliminate redundant BSs. Similarly, the authors in [23] proposed a heuristic algorithm to meet green objectives by selecting BSs from a predefined set of candidates. The proposed solutions did not present a general solution as the elimination step depends on the user realization and the selected BS locations may vary from a realization to another. Moreover, most of the proposed schemes are not adapted to a given area divided into several subareas with varied user densities. Indeed, it is useful to consider an area of interest consisting of multiple
subareas with different user densities, e.g., if it comprises a shopping or business district located near a residential area, where the characteristics of each of these subareas should be considered in the planning process instead of the traditional uniform user densities.

In this chapter, we propose an optimized LTE-Advanced (LTE-A) radio planning method by formulating a combinatorial optimization problem that aims to find the optimal locations of the minimum number of BSs to be deployed in a given area of interest while respecting two important constraints in the planning process: the area coverage constraint and the cell capacity constraint. We propose to exploit swarm intelligence in order to solve the planning optimization problem for varied spatial and temporal user densities. After evaluating the link power budget and estimating the number of BSs needed to be deployed and their radius using a radio propagation model, we employ meta-heuristic algorithms based on swarm intelligence to find their suboptimal locations. In our study, we propose to employ the PSO [24] in addition to the recently proposed grey wolf optimizer (GWO) [25]. Then, we compare their performances and their speed of convergence with the probabilistic metaheuristic algorithm: The simulated annealing (SA) [26]. Finally, we eliminate eventual redundant BS using a low complexity iterative algorithm. This is performed by dividing the area of interest into several subareas characterized by different user densities and taking into account both the uplink (UL) and DL directions, LTE resource allocation, and intercell interference. Afterwards, we apply the proposed method to ensure a proactive green planning that takes into consideration the temporal traffic variation. In this approach, based on traffic statistics, the mobile operator can identify the BSs to be turned off during night or low traffic period from the planning stage, in order to optimize the energy efficiency during post-deployment network operation. Moreover, we adapt the proposed method to solve the planning problem with location constraints whereby the placement of BSs is not allowed in some regions of the area of interest, e.g., due to private property or electromagnetic radiation constraints [21]. In addition, we apply our proposed planning approach to the
case where femtocells are deployed in the area of interest and where a considerable amount of the traffic is offloaded from the cellular networks. The performance evaluation of the proposed methods is performed using Monte Carlo simulations that measure the average percentage of users in outage.

Compared to previous proposed approaches, our planning method for LTE-Advanced is first based on an estimation of the total number of BSs using the dimensioning phase where all the system parameters are taken into account. Second, it is not limited to a finite set of predefined BS locations, allows the operator to optimize both cell capacity and coverage constraints simultaneously, and tries to find the minimal number of BSs to be deployed. Third, it considers more realistic scenarios depending on user densities in neighboring areas for which a network is being planned instead of focusing on the traditional single uniform region. In addition, it simultaneously encloses the spatial and temporal user density variation, the location constraint problem, and the identification of the BSs that would be turned off since the planning stage. Finally, our approach takes resource allocation into account and is applicable with any radio resource management algorithm.

The rest of the chapter is organized as follows. Section 2.2 presents the dimensioning phase and the formulated optimization problem. Section 2.3 describes the proposed algorithm based on the meta-heuristic algorithms. In Section 2.4, the optimization problem is reformulated to deal with the green planning and electromagnetic radiation exposure problem. The performance evaluation method is presented in Section 2.5. Next, simulation results are given in Section 2.6. Finally, Section 2.7 concludes the chapter.

### 2.2 System Parameters and Problem Formulation

In cellular networks, coverage and capacity should be considered simultaneously in order to avoid limited range of coverage as well as poor signal strength [27]. In this section,
we formulate an optimization problem that fulfills the coverage and data rate requirements by deploying the minimum number of BSs. Indeed, network operators need to place their BSs in a manner that allows each user in the service area to communicate with at least one of these BSs. On the other hand, mobile operators have to meet their user QoSs by providing the needed throughput for the service operation. Thus, the objective is to find the vectors \( x \) and \( y \) with dimension up to \( N_{BS} \) (i.e., BS positions in the Cartesian coordinate system) that satisfy the planning constraints where \( N_{BS} \) is the initial number of candidate BSs to deploy. We assume that each BS is equipped with \( N_{S} \) sector antennas as it is shown in Fig. 2.1. The antenna gain is set to 18 dBi and its pattern is given in (2.38) in Section 2.5. The aim is to serve an area with a total surface denoted \( A_{T} \) and expressed in kilometer-square (km\(^2\)). The area can be subdivided into \( N_{Area} \) subareas. Each subarea \( i \) is characterized by its surface \( A(i) \) (i.e., \( \sum_{i=1}^{N_{Area}} A(i) = A_{T} \)) and a particular user density function \( D_i \). For instance, the density could be a uniform distribution with a given user density per km\(^2\) or a normal (Gaussian) distribution corresponding to concentrated users in a hotspot region and then the density is reduced as we move away from the center, etc. A dimensioning phase is initially performed to find the radius \( R_{BS} \) of cells and an estimate of \( N_{BS} \) base stations as a function of the given coverage and capacity constraints. In addition, it gives an estimate of the number of users that can be served simultaneously by a BS that we denote by \( N_{U_{BS}} \).

### 2.2.1 Initial Dimensioning Phase

**Coverage dimensioning:** This phase begins by computing the radio link budget [28]. The parameters are selected from [28, 29]. The link budget estimates the maximum allowed signal attenuation between the mobile and the BS antenna. An example of radio link budget of UL and DL directions for LTE networks is given in Table 2.1 in Section 2.6. The radio link budget parameters are selected from [28, 29]. In LTE, orthogonal frequency division
Figure 2.1: Three sector antenna base stations serving an hexagonal cell.

multiple access (OFDMA) is the access scheme for the DL while single carrier frequency
division multiple access (SCFDMA) is used in UL. The available spectrum is divided into
RBs consisting of 12 adjacent subcarriers. The DL and UL maximum allowed path losses
(MAPLs) can be compared together to determine whether UL or DL coverage is limited
and thus determine the cell range accordingly. The cell ranges are calculated using the
COST-231-HATA propagation model, [30], which computes the path loss, denoted $PL$ and
expressed in dB, as follows:

$$PL = 46.3 + 33.9 \log_{10}(f_c) - 13.82 \log_{10}(h_{BS}) - a(h_{MS})$$

$$+ (44.9 - 6.55 \log_{10}(h_{BS})) \log_{10}(d) + C_m,$$

where $f_c$ indicates the working frequency of the system in MHz, $h_{BS}$ and $h_{MS}$ indicate
the height of BS antenna and the mobile station antenna in meter (m), respectively, and $d$
indicates the distance between the terminal and the BS in kilometer (km). In (2.1), $a(h_{MS})$
refers to the terminal gain function and is given as follows:

\[ a(h_{MS}) = (1.1 \log_{10}(f_c) - 0.7)h_{MS} - (1.56 \log_{10}(f_c) - 0.8). \]  

(2.2)

The value of \( C_m \) depends on the terrain type as follows [31]:

- In large cities: \( C_m = 3 \) dB,
- In medium-sized cities: \( C_m = 0 \) dB,
- In suburban areas: \( C_m = -2(\log_{10}(f_c/28))^25.4 \) dB,
- In rural open areas: \( C_m = -4.78(\log_{10}(f_c))^2 + 18.33 \log_{10}(f_c) - 40.94 \) dB.

Thus, from (2.1), we can determine the cell radius \( R_{BS} = (d_{PL=MAPL}) \) where MAPL is computed after elaborating the UL and DL budgets. Once \( R_{BS} \) is fixed, the number of BSs needed to cover the area of interest \( N_{BS}^{Cov} \) is given as follows:

\[ N_{BS}^{Cov} = \left\lceil \frac{A_T}{S_{Cell}} \right\rceil, \]  

(2.3)

where the symbol \( \lceil . \rceil \) denotes ceiling function and \( S_{Cell} \) is the surface of the cell with radius \( R_{BS} \). For instance, \( S_{Cell} = \pi(R_{BS})^2 \) for a circular cell and \( S_{Cell} = \frac{3\sqrt{3}}{2}(R_{BS})^2 \) for a hexagonal cell.

**Capacity Dimensioning:** The objective of this phase is to determine an estimate of the maximum number of users \( N_{U_{BS}} \) that can be served by one BS simultaneously, then, to find the number of BSs \( N_{BS}^{Cap} \) required to satisfy the user data rate. The DL data rate is only considered in this capacity dimensioning phase as it is the limiting link in terms of capacity provisioning due to the fact that it is usually higher than the UL data rate. We assume that users have a target data rate that they aim to achieve in DL, denoted \( R^{(DL)}_{th} \). Thus, \( N_{U_{BS}} \) is
defined as follows:

\[ N_{UBS} = \left\lfloor \frac{N_S C^s_{Cell}}{R^{(DL)}_{th}} \right\rfloor, \quad (2.4) \]

where the symbol \( \lfloor . \rfloor \) denotes the floor function and \( C^s_{Cell} \) is the cell capacity per sector antenna which corresponds to the maximum data rate that will be shared between all connected users to a sector antenna \( s \) and defined as \( C^s_{Cell} = B \times SE \) where \( B \) is the channel bandwidth in (Hz) while \( SE \) is the spectral efficiency of the system in (bits/s/Hz). Thus, \( N^\text{Cap}_{BS} \) is no more than the sum of the number of BSs \( N^\text{Cap}_{BS, i} \) needed for each subarea \( i \) as follows:

\[ N^\text{Cap}_{BS} = \sum_{i=1}^{N_{Area}} N^\text{Cap}_{BS, i}, \quad (2.5) \]

where \( N^\text{Cap}_{BS, i} = \frac{D_{i,A(i)}}{N_{UBS}} \quad \forall i = 1, \cdots, N_{Area}, \) which exactly corresponds to the number of users in subarea \( i \) divided by the maximum number of simultaneously served users by a cell.

Finally, the estimated number of BSs needed to cover the whole area and satisfy the data rate requirement in each subarea is given as follows:

\[ N_{BS} = \max \left( N_{BS}^{Cov}, N_{BS}^{Cap} \right). \quad (2.6) \]

### 2.2.2 Optimization Problem Formulation

The optimization problem objective is to find the optimal BS locations \((x^*, y^*)\) that satisfy the cell capacity constraint per subarea and the total coverage constraint.

**Cell capacity constraint:** We associate to each triplet (sector \( s \), BS \( j \), subarea \( i \)) the parameter \( \rho_{s,i,j}, (0 \leq \rho_{s,i,j} \leq 1, \forall s = 1, \cdots, N_S, \forall i = 1, \cdots, N_{Area} \) and \( \forall j = 1, \cdots, N_{BS} \)
to measure the presence of BS $j$ in subarea $i$ as follows:

$$\rho_{s,i,j}(x_j, y_j) = \frac{a_{s,i,j}(x_j, y_j)}{A_{s,j}},$$

(2.7)

where $a_{s,i,j}(x_j, y_j)$ is the surface covered by sector $s$ of BS $j$ having as coordinates $(x_j, y_j)$ that intersects subarea $i$ in km$^2$ and $A_{s,j}$ is the total area covered by sector $s$ of BS $j$. Thus, the average number of users that can be served by a sector antenna $s$ of BS $j$ in subarea $i$ is $\frac{N_{U_{BS}}}{N_S} \cdot \rho_{s,i,j}(x_j, y_j)$ since each sector antenna can serve, in total, $\frac{N_{U_{BS}}}{N_S}$ users. Hence, if a sector antenna $s$ of BS $j$ is totally included in the subarea $i$, then, $\rho_{s,i,j}(x_j, y_j) = 1$. If it is partially included in the subarea $i$, $\rho_{s,i,j}(x_j, y_j)$ will be less than 1. $\rho_{s,i,j}(x_j, y_j) = 0$ if sector antenna $s$ of BS $j$ and subarea $i$ are disjoint. Therefore, in order to ensure that all users in subarea $i$ are served, the following expression has to be satisfied:

$$\sum_{j=1}^{N_{BS}} \sum_{s=1}^{N_S} \frac{N_{U_{BS}}}{N_S} \cdot \rho_{s,i,j}(x_j, y_j) \geq \eta D_i A(i), \forall i = 1, \ldots, N_{Area},$$

(2.8)

where $\eta$ is a tolerance parameter ($0 \leq \eta \leq 1$) added to relax the capacity constraint.

**Coverage constraint:** We propose to distribute uniformly over the area of interest $N_{\text{ref}}$ reference points that have to be covered by at least one of the deployed BSs during the planning phase. If all $N_{\text{ref}}$ points are covered, we can consider that the area is totally covered. Note that increasing $N_{\text{ref}}$ improves the precision of the problem’s solution; however, it leads to higher problem complexity. We introduce the binary variable $\gamma_n, n = 1, \ldots, N_{\text{ref}}$, to denote the state of reference point $n$ as follows:

$$\gamma_n(x, y) = \begin{cases} 
1 & \text{if point } n \text{ is covered by at least one BS}, \\
0 & \text{if point } n \text{ is not covered by any BS}.
\end{cases}$$

(2.9)
A point \( n \) is considered covered by one BS if it is covered by one of its sectors. Hence, in order to consider that the area is totally covered, the following equation has to be satisfied:

\[
\sum_{n=1}^{N_{\text{ref}}} \gamma_n \leq \tau N_{\text{ref}}, \tag{2.10}
\]

where \( \tau \) is a tolerance parameter \( 0 \leq \tau \leq 1 \) added to relax the coverage constraint. A reference point of coordinates \( (x_{r_i}, y_{r_j}) \) is considered covered, if is is covered by at least one BS (i.e., \( \exists \) a BS \( j \in [1, N_{\text{BS}}] \), such that \( (x_j - x_{r_i})^2 + (y_j - y_{r_i})^2 \leq R_{\text{BS}} \)) for circular cells. Finally, let \( \epsilon_{N_{\text{BS}}} \) be a vector that contains the state of each BS as follows:

\[
\epsilon_j = \begin{cases} 
1 & \text{if BS } j \text{ is deployed,} \\
0 & \text{if BS } j \text{ is redundant.}
\end{cases} \tag{2.11}
\]

Indeed, in the planning phase, some deployed BSs can be redundant and eliminated without affecting the coverage and capacity constraints. Hence, the optimization problem is expressed as follows:

\[
\begin{align*}
\text{Minimize} & \quad \sum_{j=1}^{N_{\text{BS}}} \epsilon_j, \\
\text{Subject to:} & \quad \sum_{j=1}^{N_{\text{BS}}} \sum_{s=1}^{N_{\text{S}}} N_{U_{\text{BS}}} \frac{\rho_{s,i,j}(x_j, y_j)}{N_{\text{S}}} \geq \eta D_i A(i), \quad \forall i = 1, \ldots, N_{\text{Area}}, \\
& \quad \sum_{n=1}^{N_{\text{ref}}} \gamma_n (x, y) \geq \tau N_{\text{ref}}, \tag{2.12}
\end{align*}
\]

Note that the values \( \gamma_n \) and \( \rho_{s,i,j} \) depend directly on the BS locations (i.e., \( (x, y) \)). Their sizes are affected by the value of the vector \( \epsilon \).

The planning phase is performed by cellular operators to decide where to deploy base station sites in order to maintain connectivity for long term variation based on average
statistics, whereas short term variation, e.g., due to mobility, could be accounted for using different system level techniques such as power control, link adaptation, congestion control, handovers, etc.

2.3 Proposed Cell Planning Method

Generally, the BS location problem is NP-hard [16] and the optimal solution is impossible to reach mainly for large-scale problems and when considering an infinite set of possible BS locations. Evolutionary algorithms, such as genetic algorithms [32], simulated annealing [26], PSO [24] and, ant colony optimization [33], are good alternative choices. Therefore, we propose to employ heuristic algorithms that are based on swarm intelligence and can deal with an infinite set of BS combinations unlike other algorithms (e.g., genetic algorithm) that require a finite set of BS combinations to be executed as it is used in [17,22]. The proposed approach to solve the optimization problem consists of two steps. First, we start by placing the BSs by optimizing their locations \((x, y)\) by exploiting the random behavior of the PSO and GWO algorithms, [24,25]. Then, after fixing the positions of all BSs, we propose to eliminate eventual redundant BSs by dealing with the binary vector \(\epsilon\). Due to the following advantages of PSO and GWO compared with the others, we apply them for solving this planning problem: (i) their search processes are simple and easy to implement by manipulating few numerical parameters (e.g., such as the number of particles, inertial weights, and acceleration factors for PSO) (ii) they require low computational cost attained from small number of agents; and (iii) provide a good convergence speed [25, 34]. The PSO algorithm is previously used in literature in different fields while GWO is a recently proposed algorithm which is not yet applied in engineering domain. Thus, we propose to implement both algorithms to solve the planning problem and study their performances.
2.3.1 Cell Planning Phase using Meta-Heuristic Algorithms

Particle Swarm Optimization Algorithm for Cell Planning

The PSO idea was introduced in 1995 [24]. It is inspired by swarm intelligence, social behavior, and food searching of a bird flocking and fish schooling. The algorithm is widely used in several wireless communication fields and rapidly developed for its easy implementation and few particles required to be tuned [35–37]. In our framework, the algorithm starts by generating $L$ particles $\mathbf{W}(l)$, $l = 1, \ldots, L$ of length $2N_{\text{BS}} \times 1$ to form an initial population $\mathcal{S}$. The vector $\mathbf{W}(l)$ contains random BS positions of the particle $l$ within the area of interest as follows:

$$\mathbf{W}(l) = \begin{bmatrix} x(l) \\ y(l) \end{bmatrix}. \quad (2.15)$$

Then, the PSO computes the following two utilities $U_1(l)$ and $U_2(l)$ achieved by each particle $l$:

$$U_1(l) = \begin{cases} - \sum_{n=1}^{N_{\text{ref}}} \gamma_n(l), & \text{if (2.13) is satisfied by particle } l, \\
0, & \text{else}, \end{cases} \quad (2.16)$$

$$U_2(l) = \sum_{i=1}^{N_{\text{Area}}} \sum_{j=1}^{N_{\text{BS}}} \frac{N_{\text{BS}}}{N_S} \sum_{s=1}^{N_S} \rho(s,i,j)(\mathbf{W}(l)) - \eta \mathcal{D}_i \mathcal{A}(i). \quad (2.17)$$

The utility function expressed in (2.16) corresponds to the number of reference points covered by BSs. This utility is set to 0 if the cell capacity constraint expressed in (2.13) is not satisfied for at least one of the subareas. In other words, if the cell capacity constraint is not satisfied, we assume that particle $l$ does not cover the area at all. On the other hand, the second utility $U_2(l)$ computes the difference between the number of users served by particle $l$ and the minimum number of users that have to be served. In the case when all particles do not satisfy the cell capacity constraint (2.13), the PSO will aim to minimize $U_2$ until
satisfying the cell capacity constraint. Once it finds a feasible solution, the PSO switches the utility to $U_1^{(l)}$ and tries to minimize it until reaching $-\tau N_{\text{ref}}$.

At each iteration, PSO computes the global particle, denoted $W^{(\text{global})}$, that provides the best utility (i.e., either $U_1$ or $U_2$ depending on the feasibility of the particles in this iteration). In addition, for each particle $l$, PSO maintains a record of the position of its previous best performance, denoted $W^{(l,\text{local})}$. Then, at each iteration $t$, PSO computes a velocity term $V_w^{(l)}$, $\forall w = 1, \ldots, 2N_{\text{BS}}$ as follows:

$$V_w^{(l)}(t + 1) = \psi V_w^{(l)}(t) + c_1 \phi_1 (W^{(l,\text{local})}_w(t) - W_w^{(l)}(t)) + c_2 \phi_2 (W^{\text{global}}_w(t) - W_w^{(l)}(t)), \quad (2.18)$$

where $\psi$ is the inertia weight and is used to control the convergence speed. It is usually chosen between 0.8 and 1.2. $c_1$ and $c_2$ represent the size of the step that the particle takes toward its best individual best candidate solution $W^{(l,\text{local})}$ and the global best solution $W^{\text{global}}$, respectively. Usually, we choose $c_1 = c_2$ and close to 2. The parameters $\phi_1$ and $\phi_2$ are two random positive numbers generated for each $w$ (i.e., the element of the vector $W^{(l)}$). Then, PSO updates each element $w$ of a particle $W^{(l)}$ as follows:

$$W_w^{(l)}(t + 1) = W_w^{(l)}(t) + V_w^{(l)}(t + 1). \quad (2.19)$$

This process is repeated until reaching convergence either by attaining the maximum number of iterations or by reaching the algorithm target (i.e., $U_1 \leq -\tau N_{\text{ref}}$). Note that the target $U_1$ cannot be reached unless the cell capacity constraint is satisfied which is the case thanks to the introduction of $U_2$ in (2.17). Finally, after convergence, the PSO solution is given by $W_{op} = W^{\text{global}}$. Details of the proposed algorithm are given in Algorithm 7. Although PSO’s application has been proved to be effective, convergence to its most opti-
mistic solution cannot be guaranteed in theory [38].

**Grey Wolf Optimizer for Cell Planning**

GWO is a new meta-heuristic algorithm proposed in [25]. It is inspired by grey wolves and it mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. During an iteration, the algorithm categorizes the candidates (i.e., grey wolves) into four groups for simulating the leadership hierarchy: $\alpha$ corresponds to the fittest solution, $\beta$ and $\delta$ are the second and third best solutions. Finally, $\omega$ are the remaining candidates of the population. Also, the algorithm simulates the hunting, searching for prey, encircling prey, and attacking prey of grey wolves. The hunting corresponds to the position update of each candidate from an iteration to another (e.g., in our framework, it corresponds to

---

**Algorithm 1 PSO Algorithm for Base Station Deployment**

Generate an initial population $S$ composed of $L$ random particles $W^{(l)}$ of size $(2N_{BS} \times 1)$, $l = 1, \ldots, L$.

$U_{1}^{\min} = 0$, $t = 1$ and set $U = U_2$ (i.e., use $U_2$ as utility).

while $U_{1}^{\min} > -\tau N_{ref}$ do

for $l = 1, \ldots, L$ do

Compute $U^{(l)}(t)$, $\forall l = 1, \ldots, L$.

end for

if $\arg\min_{l,t} U^{(l)}(t) \neq 0$ then

Find $(l_m, t_m) = \arg\min_{l,t} U^{(l)}(t)$ where $l_m$ and $t_m$ indicate the index and the position of the particle that results in the lowest utility $U$. Then, set $U_{\min} = U^{(l_m)}(t_m)$ and $W_{\text{global}} = W^{(l_m)}(t_m)$.

Find $t_{\text{local}} = \arg\min_{l} U^{(l)}(t)$ for each particle $l$ where $t_{\text{local}}$ indicates the position of the particle $l$ that results in the lowest local utility. Then, set $U^{(l,\text{local})} = U^{(l)}(t_{\text{local}})$ and $W^{(l,\text{local})} = W^{(l)}(t_{\text{local}})$.

Adjust the velocities and positions of all particles using equations (2.18) and (2.19), respectively.

else

$U = U_1$ (i.e., switch the utility $U$ to $U_1$).

end if

$t = t + 1$.

end while
the BS positions). It depends on the positions of the best candidates $\alpha$, $\beta$, and $\delta$ and is mathematically modeled as follows:

$$W^{(l)}(t + 1) = \frac{1}{3} \left( W_{\alpha 1}^{(l)}(t) + W_{\beta 2}^{(l)}(t) + W_{\delta 3}^{(l)}(t) \right),$$

(2.20)

where $W_{s i}^{(l)}(t) = W_s^{(l)}(t) - A_i \cdot D_s$ for $(s, i) \in \{(\alpha, 1), (\beta, 2), (\delta, 3)\}$ and $D_s = |C_i \cdot W_s^{(l)}(t) - W^{(l)}(t)|$. These equations model the encircling behavior of the prey. $A_i$ and $C_i$ are two coefficients vectors calculated as follows:

$$A_i = 2a \cdot r_1 - a, \text{ and } C_i = 2 \cdot r_2,$$

(2.21)

where the components of the vector $a$ are linearly decreased from 2 to 0 over the course of iterations and $r_1$ and $r_2$ are vectors randomly generated between $[0, 1]$. The notation $(x, y)$ corresponds to the vector dot product. $A_i$ and $C_i$ influence the exploration for a better solution and are used to model the search for the prey while $a$ is used to model the attacking behavior (i.e., approaching the prey) as it decreases over the course of iterations. To sum up, the search process in the GWO algorithm starts with creating a random population of $L$ candidate solutions. Over the course of iterations, $\alpha$, $\beta$, and $\delta$ candidates estimate the probable position of the solution. Each candidate solution updates its distance using (2.20). The GWO algorithm is terminated by reaching the maximum number of iterations or satisfying the constraints (see [25]). Applied to our framework, we follow a procedure similar to the one used with PSO: we start by optimizing $U_2$ then $U_1$. Details of the proposed GWO algorithm are provided in Algorithm 2.
Algorithm 2 GWO for Base Station Deployment

Generate an initial population $S$ composed of $L$ random particles $W^{(l)}$ of size $(2N_{BS} \times 1), l = 1, \cdots , L$.

$U_1^\alpha = 0, t = 1$ and set $U = U_2$ (i.e., use $U_2$ as utility).

while $U_1^\alpha > -\tau N_{ref}$ do

for $l = 1, \cdots , L$ do

Compute $U^{(l)}(t), \forall l = 1, \cdots , L$.

end for

Find candidates $W_{\alpha}(t)$ and its utility $U_{\alpha}(t)$.

Update the positions of the candidates using (2.20) and compute the corresponding utilities.

if $U_{\alpha}(t) \neq 0$ then

Find candidates $W_{\beta}(t)$ and $W_{\delta}(t)$ and their corresponding utilities $U_{\beta}(t)$ and $U_{\delta}(t)$.

else

$U = U_1$ (i.e., switch the utility $U$ to $U_1$).

end if

$t = t + 1$.

end while

2.3.2 Algorithm for Elimination of Redundant Base Stations

In this step and after fixing the locations of the BSs using the meta-heuristic algorithm, we focus on the elimination of redundant BSs. A BS is considered useless if, when it is turned off, none of the cell capacity and coverage constraints is violated. In other words, if the absence of a BS affects at least one of the optimization problem constraints, the BS has to be kept and assumed indispensable for a safe network operation. In order to achieve this goal, we need to optimize the binary vector $\epsilon$ of size $(N_{BS} \times 1)$ and find the optimal BS combination that does not affect the achieved meta-heuristic algorithm performance. Thus, we start by assuming that all BSs are placed in the area of interest (i.e., $\epsilon = [1, \cdots , 1]$). Then, we eliminate BS by BS and check, at each time, whether the problem constraints remain satisfied or not. If a BS $j$ degrades the problem performance, then it cannot be eliminated and $\epsilon_j$ remains 1. Otherwise, the algorithm assumes that BS $j$ may be eliminated and places it in a set, denoted $E$. After checking all BSs, the algorithm only needs to focus on the set $E$ to identify the BSs that can be safely and completely eliminated and then set
their corresponding $\epsilon_j$ to 0.

It is not correct to eliminate all BSs in $\mathcal{E}$ simultaneously. Indeed, it may happen that two or more BSs in $\mathcal{E}$ support each other to maintain the coverage and/or cell capacity constraints. Thus, only one of them can be eliminated. We propose that this BS, denoted $\hat{j}$, corresponds to the one that has the smallest impact on the number of served users as follows:

$$\hat{j} = \arg \max_{j \in \mathcal{E}} \sum_{i=1}^{N_{\text{Area}}} \sum_{j=1, j \neq \hat{j}}^{N_{\text{BS}}} \left( \frac{N_{U_{\text{BS}}}}{N_S} \sum_{s=1}^{N_S} \rho_{s,i,j} (W_{op}) - \eta D_i A(i) \right). \quad (2.22)$$

Note that we are actually sure that the term $\sum_{j=1}^{N_{\text{BS}}} \frac{N_{U_{\text{BS}}}}{N_S} \sum_{s=1}^{N_S} \rho_{s,i,j} (W_{op}) - \eta D_i A(i) \geq 0, \forall i = 1, \ldots, N_{\text{Area}}$ as we have already achieved a feasible solution with the planning algorithms proposed in Section 2.3.1 and we are maintaining in $\mathcal{E}$ only the BSs that do not violate the problem constraints. The procedure is repeated with the remaining BSs in $\mathcal{E}$ until obtaining the final BS combination. Details of the redundant BS elimination algorithm are given in Algorithm 3.

Hence, the proposed planning approach consisted of two steps: A dimensioning phase where we determined the radius and number of BSs ($R_{\text{BS}}, N_{\text{BS}}$) needed for the operation of the network and a BS deployment phase where we determined their suboptimal locations $(x, y)$ in the geographical area after eliminating the eventual redundant BSs.

### 2.4 Applications: Green Planning and Location Constraints

#### 2.4.1 Green Planning with Temporal Traffic Considerations

In this section, we propose a planning method that takes into account the temporal traffic variation. This method allows operators to forecast the switching on/off of BSs according to known traffic behavior changes, without the need to assess the problem continuously.
Algorithm 3 Iterative Algorithm for Redundant Base Station Elimination

t = 0.

Assume all BSs are activated $\epsilon(t) = [1, \cdots, 1]$.

repeat

for $j = 1, \cdots, \text{N}_{\text{BS}}$ do

Remove BS $j \in \mathcal{E}$ and define $\epsilon^{(j)}(t)$ which is exactly $\epsilon(t)$ with 0 in the $j^{th}$ position.

Check the cell capacity and coverage constrains as expressed in (2.13) and (2.14), respectively.

if (2.13) and (2.14) are still satisfied then

BS $j$ can be eliminated $j \in \mathcal{E}$.

else

BS $j$ cannot be eliminated.

end if

end for

Find BS $\hat{j}$ such that:

$$\hat{j} = \arg\max_{j \in \mathcal{E}} \sum_{i=1}^{N_{\text{Area}}} \sum_{j=1, j \neq \hat{j}}^{\text{N}_{\text{BS}}} \left( \frac{N_{U_{\text{BS}}}}{N_{\text{S}}} \sum_{s=1}^{N_{\text{S}}} \rho_{s,i,j} (W_{op}) - \eta D_i A(i) \right).$$

BS $\hat{j}$ is completely and safely eliminated, $\mathcal{E} = \mathcal{E} \setminus \{\hat{j}\}$, and $\epsilon(t + 1) = \epsilon^{(\hat{j})}(t)$.

$t = t + 1$.

until $\mathcal{E} = \emptyset$.

The final BS combination after network planning is $\epsilon(t)$. 

The method consists of finding the number of BSs per subarea needed to serve users in low traffic periods (e.g., the night period) in addition to their locations to ensure the coverage. Then, it determines the locations of the additional BSs to be placed in the area in order to fit higher traffic period constraints (e.g., the day period). In the sequel, we will consider the Day/Night case but the approach can be extended to a larger number of traffic density levels (e.g., high, medium, low) that could happen any time of the day, not just two levels (day, night). The algorithm is executed as follows:

- **Step 1:** The coverage and the cell capacity dimensioning phase is performed to find the required number of BSs $N_{\text{BS}}^{\text{Night}}$ needed for the night period.

- **Step 2:** The proposed method described in Section 2.3 is employed in order to solve the optimization problem in (2.12) for the night traffic by optimizing the locations of the $N_{\text{BS}}^{\text{Night}}$ BSs denoted $(x_N, y_N)$.

- **Step 3:** The coverage and the cell capacity dimensioning phase is again performed to find the required number of BSs $N_{\text{BS}}^{\text{Day}}$ needed for the day period.

- **Step 4:** The proposed method described in Section 2.3 is employed in order to solve the following constrained optimization problem for the day traffic by only optimizing the locations of the new added BSs (i.e., $N_{\text{BS}}^{\text{Day}} - N_{\text{BS}}^{\text{Night}}$ BSs) having as coordinates
\[(x, y)\) and considering that \(N_{\text{Night}}^{\text{BS}}\) BSs obtained in Step 2 are already deployed:

Minimize \(x, y, \epsilon \sum_{j=1}^{N_{\text{Day}}^{\text{BS}}} \epsilon_j\), \hspace{1cm} (2.23)

Subject to:

\[\sum_{j=1}^{N_{\text{Day}}^{\text{BS}}} \sum_{s=1}^{N_{\text{S}}} \frac{N_{\text{U}}^{\text{BS}}}{N_{\text{S}}} \rho_{s,i,j} \left( [x, x_N]^T, [y, y_N]^T \right) \geq \eta_D, A(i), \forall i = 1, \cdots, N_{\text{Area}}, \hspace{1cm} (2.24)\]

\[\sum_{n=1}^{N_{\text{ref}}} \gamma_n \left( [x, x_N]^T, [y, y_N]^T \right) \geq \tau N_{\text{ref}}. \hspace{1cm} (2.25)\]

This green planning approach helps in ensuring energy saving by identifying the BSs that will be always active on day and night (referred to as the “night BSs”) and the BSs that need to be activated only during the day (referred to as the “day BSs”) to handle the increased traffic load, but can be switched off at low traffic periods at night with respect to the user densities in the subareas.

### 2.4.2 Planning Subject to Location Constraints

During the planning phase, mobile operators have to respect some location constraints. Positions that are found through the proposed approach may not be available for installing BSs in real life due to several reasons. For example, the location may fall in a private property, or restricted access area, or radio-sensitive zones such as schools or hospitals. Thus, these location constraints should be taken into account during the planning phase. In this section, we exploit the efficiency of the proposed method in order to perform the BS planning while respecting this constraint which is expressed as follows

\[(x_j, y_j) \notin S_R, \hspace{1cm} \forall j = 1, \cdots, N_{\text{BS}}, \hspace{1cm} (2.26)\]
where $S_R$ denotes the restricted areas in the entire region where BSs cannot be placed. In the context of radiation-sensitive zones, the constraint can be defined such that the total received power at each reference point $n$ in this zone has to be below a certain threshold. The total received power $PR_n$ corresponds to the sum of power received from all BSs while the power threshold $P_{th}$ can be determined from [39]. Health recommendations suggest that the median exposure in urban areas be limited to $0.005 \, \mu \text{W/cm}^2$ and that $95\%$ of the urban population be exposed to less than $0.1 \, \mu \text{W/cm}^2$. Therefore, the electromagnetic radiation constraint at each reference point $n$ can be written as follows:

$$PR_n = \sum_{j=1}^{N_{BS}} \sum_{s=1}^{N_S} \frac{P_{j,s}}{PL_{j,s,n}} \leq P_{th}, \quad \forall n \in S_R,$$

(2.27)

where $P_{j,s}$ is the BS $j$ transmit power emitted by sector $s$ while $PL_{j,s,n}$ is the pathloss between sector $s$ of BS $j$ and reference point $n$. Thus, the optimization problem to be solved for the radiation-sensitive zone problem can be written as follows:

$$\text{Minimize} \quad \sum_{j=1}^{N_{BS}} \epsilon_j,$$

(2.28)

Subject to:

$$\sum_{j=1}^{N_{BS}} \sum_{s=1}^{N_S} \frac{N_{U_{BS}}}{N_S} \rho_{s,i,j}(x, y) \geq \eta(S_R)D_iA(i), \quad \forall i = 1, \ldots, N_{\text{Area}},$$

(2.29)

$$\sum_{n=1}^{N_{\text{ref}}} \gamma_n (x, y) \geq \tau(S_R)N_{\text{ref}},$$

(2.30)

$$\sum_{j=1}^{N_{BS}} \sum_{s=1}^{N_S} \frac{P_{j,s}}{PL_{j,s,n}} \leq P_{th}, \quad \forall n \in S_R.$$

(2.31)

Note that, in this problem, the coverage and capacity tolerances (i.e., $\tau$ and $\eta$) are now in function of the radiation free zone $S_R$ and must be adapted to the new location constraint as in some cases, the constraints can be contradictory. For instance, if the radiation-sensitive
zone is relatively large comparing to the cell range, then some reference points will not be
covered. Thus, a particular choice of $\tau(S_R)$ and $\eta(S_R)$ could be $\tau(S_R) = (1 - |S_R|)$ and
$\eta(S_R) = 1/S_R$, respectively where $|S_R|$ denotes the cardinality of the set $S_R$ and $A(i)/S_R$
represents the set subtraction and corresponds to the area of $A(i)$ that does not intersect with $S_R$.

The problem could be solved using the same method described in Section 2.3 but by
considering the new constraint. This constraint can be converted to a utility function as it is
done in (2.16) and (2.17). The radiation-sensitive zone utility achieved by particle $l$, $U_3^{(l)}$, can be then expressed as

$$U_3^{(l)} = |S_R| - N_P,$$

where $N_P$ denotes the number of reference points that satisfies the constraint given in
(2.27). Thus, the algorithm can be executed to first minimize $U_3$ until reaching zero, then
it switches the utility in order to optimize the cell capacity and coverage constraints.

2.5 Performance Evaluation Method

After deploying all LTE network BSs in their appropriate locations according to Sec-
tion 2.3, we apply a Monte Carlo simulation in order to investigate the impact of the pro-
posed cell planning approach on the uplink and downlink scheduling while taking intercell
interference into account, thus measuring the efficiency of the proposed scheme in realistic
scenarios similar to those adopted in the literature, e.g., [40–42]. In each realization, we
distribute $N_U$ users following the distributions defined for each subarea $i$ of the geographi-
cal area. Then, we verify whether a user $u$ is served successfully or not by comparing their
achieved data rates, denoted $R_u^{(DL)}$ and $R_u^{(UL)}$, to the target data rate thresholds, denoted
$R_{th}^{(DL)}$ and $R_{th}^{(UL)}$, for the DL and UL directions, respectively. The objective is to deter-
mine the average outage rate which has to be in harmony with the imposed tolerance during
the planning phase. In order to compute the data rates, we need to define the channel gain over RB $r$ between user $u$ and sector $s$ of BS $j$ as follows:

$$
H_{u,r,s,j,\text{dB}} = (-\kappa - \upsilon \log_{10} d_{u,j}) - \xi_{u,r,s,j} + 10 \log_{10} F_{u,r,s,j}.
$$

(2.33)

In (2.33), the first term captures the propagation loss, with $\kappa$ the pathloss constant, $d_{u,j}$ the distance in km from user $u$ to BS $j$, and $\upsilon$ the path loss exponent. The second term, $\xi_{u,r,s,j}$, captures log-normal shadowing with zero-mean and a standard deviation $\sigma_{\xi}$, whereas the last term, $F_{u,r,s,j}$, corresponds to the Rayleigh fading with a Rayleigh parameter $\bar{a}$ (usually selected such that $E[a^2] = 1$). In the sequel, in order to differentiate between UL and DL RBs, the notation $H_{u,r,s,j}^{(\text{UL})}$ and $H_{u,r,s,j}^{(\text{DL})}$ will be used, respectively.

### 2.5.1 Downlink and Uplink Data Rates

Letting $I_{\text{RB},u}^{(\text{DL})}$ the set of RBs allocated to user $u$ in the DL, $N_{\text{RB}}^{(\text{DL})}$ the total number of DL RBs, $P_r$ the power transmitted by a BS over RB $r$, and $P_{\text{max}}$ the maximum transmission power of BS $j$. Then, the OFDMA throughput of user $u$ in the DL direction is given by:

$$
R_{u}^{(\text{DL})}(P_{j,\text{max}}^{\text{ex}}, I_{\text{RB},u}^{(\text{DL})}) = \sum_{r \in I_{\text{RB},u}^{(\text{DL})}} B_{\text{RB}}^{(\text{DL})} \cdot \log_{2} \left( 1 + \Gamma_{u,r,s,j}^{(\text{DL})} \right),
$$

(2.34)

where $\Gamma_{u,r,s,j}^{(\text{DL})}$ is the signal to interference plus noise ratio (SINR) of user $u$ over RB $r$ in cell sector $s$ of BS $j$, and $B_{\text{RB}}^{(\text{DL})}$ is the RB bandwidth. It is expressed as:

$$
B_{\text{RB}}^{(\text{DL})} = \frac{B^{(\text{DL})}}{N_{\text{RB}}^{(\text{DL})}},
$$

(2.35)
with $B^{(DL)}$ the total usable DL bandwidth, and $N^{(DL)}_{RB}$ the total number of DL RBs. In this chapter, we consider equal power transmission over the RBs, i.e., for all $r$, we have:

$$P_r = \frac{P_{\text{max}}}{N^{(DL)}_{RB}}. \quad (2.36)$$

The DL-SINR of user $u$ over RB $r$ in BS $j$, $\Gamma^{(DL)}_{u,r,s,j}$, is given by:

$$\Gamma^{(DL)}_{u,r,s,j} = \frac{P_r G_{u,s,j}^{\text{BS}} G_{\text{MS}}^{\text{DL}} H^{(DL)}_{u,r,s,j}}{I^{(DL)}_{r,u} + \sigma^2_{r,u}}, \quad (2.37)$$

where $\sigma^2_{r,u}$ is the noise power over RB $r$ in the receiver of user $u$ and is considered constant and equal to $(K T B_{RB})$ where $K$ is the Boltzmann constant and $T$ is the ambient temperature (300 Kelvin), $G_{\text{MS}}^{\text{DL}}$ is the omnidirectional antenna gain of the MS, and $G_{u,s,j}^{\text{BS}}$ is the BS antenna gain which is modeled as proposed in [43] and with simplification introduced in [44] as

$$G_{u,s,j}^{\text{BS}} = 10^{-1.2 \left( p_h \left( \frac{\theta_{u,s,j} - \theta_s}{\phi_v} \right)^2 + p_v \left( \frac{\psi_{u,s,j} - \psi_s}{\phi_s} \right)^2 \right)}, \quad (2.38)$$

where $\theta_{u,s,j} = \arctan \left( \frac{h_{u,s,j}}{d_{u,s,j}} \right)$ is the vertical angle in degrees from sector $s$ of BS $j$ to user $u$. The $\psi_{u,s,j}$ is horizontal angle in degrees on sector $s$ of BS $j$ and user $u$ with respect to positive x-axis. Subscripts $h$ and $v$ denote horizontal and vertical respectively. Thus, $p_h$ and $p_v$ represent weighting factors for the horizontal and vertical beam pattern of the antenna in 3D antenna model [43], respectively. Note that for the practical cellular antennas the relationship between the horizontal beamwidth of sector antenna and the number of sectors per site can modeled as $\phi_{s,h} = \frac{360}{\mu N_S}$ where $\mu$ is a factor representing overlap between the sectors. Finally, $\theta_s$ and $\phi_s$ represent the tilt and the azimuth angles of sector $s$, respectively, while $\phi_v$ denotes the vertical beamwidth of the antenna. In (2.37), $I_{r,u}^{(DL)}$ is the interference.
on RB $r$ measured at the receiver of user $u$. The expression of the interference is given by:

$$I_{r,u} = \sum_{k=1}^{N_{BS}} \Lambda_{v,r,k}^{(DL)} \left( \sum_{v=1}^{N_U} \lambda_{v,r,k}^{(DL)} P_r G_{u,s,k} G_{MS}^H H_{u,r,s,k}^{(DL)} \right),$$

(2.39)

where $\Lambda_{v,r,k}^{(DL)} = 1$ if DL RB $r$ is allocated to user $v$ in cell $k$, i.e., $r \in I_{RB,v}^{(DL)}$. Otherwise, $\Lambda_{v,r,k}^{(DL)} = 0$. In each cell, an LTE RB, and hence the subcarriers constituting that RB, can be allocated to a single user at a given time transmission interval. Hence, in each cell $k$, we have:

$$\sum_{v=1}^{N_U} \lambda_{v,r,k}^{(DL)} \leq 1.$$

(2.40)

Concerning the UL direction, assume that $I_{RB,u}^{(UL)}$ the set of UL RBs allocated to user $u$, $N_{RB}^{(UL)}$ the total number of RBs in the UL, and $P_u^{(MS)}$ the total transmit power of user $u$. Then, the SCFDMA throughput of user $u$ in the UL direction is given by:

$$R_u^{(UL)}(P_u^{(MS)}, I_{RB,u}^{(UL)}) = \frac{B^{(UL)} I_{RB,u}^{(UL)}}{N_{RB}^{(UL)}} \log_2 \left( 1 + \Gamma_u^{(UL)}(P_u^{(MS)}, I_{RB,u}^{(UL)}) \right),$$

(2.41)

where $B^{(UL)}$ is the total UL bandwidth, $|I_{RB,u}^{(UL)}|$ is the cardinality of $I_{RB,u}^{(UL)}$ and $N_{RB}^{(UL)}$ is the number of UL RBs. Finally, $\Gamma_u^{(UL)}(P_u^{(MS)}, I_{RB,u}^{(UL)})$ is the SINR of user $u$ after Minimum Mean Squared Error (MMSE) frequency domain equalization at the receiver [45]:

$$\Gamma_u^{(UL)}(P_u^{(MS)}, I_{RB,u}^{(UL)}) = \left( \frac{1}{|I_{RB,u}^{(UL)}|} \sum_{r \in I_{RB,u}^{(UL)}} \frac{\Gamma_{u,r,s,j}^{(UL)}}{\Gamma_u^{(UL)} + 1} \right)^{-1}.$$

(2.42)

In (2.42), $\Gamma_{u,r,s,j}^{(UL)}$ is the UL SINR of user $u$ over RB $r$ served by sector $s$ of BS $j$. It is given by:

$$\Gamma_{u,r,s,j}^{(UL)} = \frac{P_{u,r,j} G_{u,s,j} G_{MS}^H H_{u,r,s,j}^{(UL)}}{I_{r,j}^{(UL)} + \sigma_{r,j}^2},$$

(2.43)
where $H_{u,r,s,j}^{(UL)}$ is the channel gain between user $u$ and BS $j$ over RB $r$, $\sigma_{r,j}^2$ is the noise power over subcarrier $r$ at BS $j$, $P_{u,r,j}^{(UL)}$ is the power transmitted by user $u$ over subcarrier $r$ in BS $j$, and $I_{r,j}^{(UL)}$ is the UL interference on RB $r$, measured at BS $j$. The expression of the interference is given by:

$$I_{r,j}^{(UL)} = \sum_{k=1,k\neq j}^{N_{BS}} \sum_{v=1}^{N_{UL}} \lambda_{v,r,k}^{(UL)} P_{v,r,k}^{(UL)} G_{v,s,j}^{BS} G_{v,s,j}^{MS} H_{v,r,s,j}^{(UL)},$$

where $\lambda_{v,r,k}^{(UL)} = 1$ if RB $r$ is allocated to user $v$ served by BS $k$, i.e., $r \in \mathcal{I}_{RB,v}^{(UL)}$. Otherwise, $\lambda_{v,r,k}^{(UL)} = 0$. The LTE standard imposes the constraint that the RBs allocated to a single user should be consecutive with equal power allocation over the RBs [46, 47]. Hence, we set:

$$P_{u,r,j}^{(UL)} = \frac{P_{u}^{(MS)}}{|\mathcal{I}_{RB,u}^{(UL)}|}.$$

### 2.5.2 Admission Control and Resource Allocation

We assume that the subcarriers constituting a single RB are subjected to the same fading and hence the channel gain on the subcarriers of a single RB is considered to be the same. In addition, the fading is assumed to be independent identically distributed (iid) across RBs. In accordance with the radio link budgets given in Table 2.1 (i.e., computation of the thermal noise), we allocate one UL RB and one DL RB for each user. Note that the proposed method can indeed be applied with any scheduling algorithm.

Hence, when a user $u$ joins the network, it is associated with sector $s^*$ of cell $j^*$ and the DL RB for which the RB $r^*^{(DL)}$ satisfy:

$$(r^*^{(DL)}, s^*, j^*) = \arg \max_{(r,s,j)} \left( 1 - \sum_{v=1;v\neq u}^{U} \lambda_{v,r,j}^{(DL)} \right) H_{u,r,s,j}^{(DL)}.$$

Then, for the UL, it is allocated the RB in sector $s^*$ of cell $j^*$ for which the RB $r^*^{(UL)}$
satisfies:
\[
 r^\ast(UL) = \arg \max_r \left( 1 - \sum_{v=1; v \neq u}^U \lambda_{v,r,j^\ast}^{(UL)} \right) H_{u,r,s^\ast,j^\ast}^{(UL)}.
\] (2.47)

In (2.46) and (2.47), the first factor in the multiplication indicates that the search is on the RBs that are not yet allocated to other users. Then, the rates (2.34) and (2.41) are computed. We start by allocating DL subcarriers first in order to save BS power usage since usually the DL traffic is much heavier than UL traffic.

Finally, a user \( u \) is considered to be successfully served if the following conditions are satisfied:
\[
\begin{align*}
R_u^{(UL)} &\geq R_{th}^{(UL)} \\
R_u^{(DL)} &\geq R_{th}^{(DL)}
\end{align*}
\] (2.48)

2.6 Results and Discussion

In this section, after detailing the system parameters, we analyze the performance of the BS deployment method presented in Section 2.3. Then, we study the performance of the proposed scheme considering the existence of femtocells, using the green planning and the radiation-sensitive zone problems.

2.6.1 Simulation Model

We consider a \( 10 \times 10 \) (km\(^2\)) LTE coverage area where we aim to deploy a certain number of three sector antenna BSs \( (N_S = 3) \) in order to cover the whole area while respecting the cell capacity constraints in the given subareas. The initial number of BSs to be deployed \( N_{BS} \), the cell range \( R_{BS} \), and the number of users that can be served by a BS simultaneously \( N_{U_{BS}} \) are computed after elaborating the dimensioning phase as described in Section 2.2.1 using the DL and UL budgets given in Table 2.1(a) and Table 2.1(b), respectively, and the COST-231-HATA propagation model [30]. From these tables and
### Table 2.1: Radio link budgets

#### Downlink Link Budget for 1 Mbps

<table>
<thead>
<tr>
<th>Data rate (Mbps)</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transmitter – BS</strong></td>
<td></td>
</tr>
<tr>
<td>a BS power (dBm)</td>
<td>46</td>
</tr>
<tr>
<td>b TX antenna gain (dBi)</td>
<td>18</td>
</tr>
<tr>
<td>c Cable loss (dB)</td>
<td>2.0</td>
</tr>
<tr>
<td>d EIRP (dBm)</td>
<td>62.0 = a + b - c</td>
</tr>
<tr>
<td><strong>Receiver – MS</strong></td>
<td></td>
</tr>
<tr>
<td>e MS noise figure (dB)</td>
<td>7.0</td>
</tr>
<tr>
<td>f Thermal noise (dBm)</td>
<td>-121.27 = 10 \log_{10} (K T B_{RB}) + 30</td>
</tr>
<tr>
<td>g Receiver noise floor (dBm)</td>
<td>-114.27 = e + f</td>
</tr>
<tr>
<td>h SINR (dB)</td>
<td>-10.0</td>
</tr>
<tr>
<td>i Receiver sensitivity (dBm)</td>
<td>-124.27 = g + h</td>
</tr>
<tr>
<td>j Interference Margin (dB)</td>
<td>2.0</td>
</tr>
<tr>
<td>k RX antenna gain (dBi)</td>
<td>0.0</td>
</tr>
<tr>
<td>l Body Loss (dB)</td>
<td>0.0</td>
</tr>
</tbody>
</table>

**DL MAPL**: 159.77 = d - (i + j + k - l + m + SFM – SHG + Pel)  
where **SFM**: Slow Fading Margin (= 9 dB),  
**SHG**: Shadowing Handover gain (= 2.5 dB),  
**Pel**: Penetration Loss (= 18 dB).

#### Uplink Link Budget for 64 kbps

<table>
<thead>
<tr>
<th>Data rate (Kbps)</th>
<th>64</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Transmitter – MS</strong></td>
<td></td>
</tr>
<tr>
<td>a MS power (dBm)</td>
<td>23</td>
</tr>
<tr>
<td>b TX antenna gain (dBi)</td>
<td>0</td>
</tr>
<tr>
<td>c Cable loss (dB)</td>
<td>0</td>
</tr>
<tr>
<td>d EIRP (dBm)</td>
<td>23.0 = a + b - c</td>
</tr>
<tr>
<td><strong>Receiver – BS</strong></td>
<td></td>
</tr>
<tr>
<td>e BS noise figure (dB)</td>
<td>2.5</td>
</tr>
<tr>
<td>f Thermal noise (dBm)</td>
<td>-121.27 = 10 \log_{10} (K T B_{RB}) + 30</td>
</tr>
<tr>
<td>g Receiver noise floor (dBm)</td>
<td>-118.77 = e + f</td>
</tr>
<tr>
<td>h SINR (dB)</td>
<td>-7.0</td>
</tr>
<tr>
<td>i Receiver sensitivity (dBm)</td>
<td>-125.77 = g + h</td>
</tr>
<tr>
<td>j Interference Margin (dB)</td>
<td>1.0</td>
</tr>
<tr>
<td>k Cable Loss (dB)</td>
<td>2.0</td>
</tr>
<tr>
<td>l RX antenna gain (dBi)</td>
<td>18</td>
</tr>
<tr>
<td>m MHA gain (dB)</td>
<td>2.0</td>
</tr>
</tbody>
</table>

**UL MAPL**: 137.27 = d - (i + j + k - l + m + SFM – SHG + Pel)  
where **SFM**: Slow Fading Margin (= 9 dB),  
**SHG**: Shadowing Handover gain (= 2.5 dB),  
**Pel**: Penetration Loss (= 18 dB).
Table 2.2: Channel and power parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>κ (dB)</td>
<td>−128.9</td>
<td>ν</td>
<td>34.4</td>
</tr>
<tr>
<td>σξ (dB)</td>
<td>8</td>
<td>N_{RB}</td>
<td>50</td>
</tr>
<tr>
<td>B^{(x)} (MHz)</td>
<td>10</td>
<td>B^{(x)}_{sub} (kHz)</td>
<td>15</td>
</tr>
<tr>
<td>BS power (dBm)</td>
<td>46</td>
<td>MS power (dBm)</td>
<td>23</td>
</tr>
</tbody>
</table>

for a frequency carrier equal to 1.8 GHz, \( h_{\text{BS}} = 40 \) m, and \( h_{\text{MS}} = 1.5 \) m, we find that \( R_{\text{BS}} = 1.2 \) km. We assume that the target data rate in UL direction is 64 kbps while, in the DL, the required data rate is 1 Mbps for each user. In addition, we assume that the system bandwidth is equal to \( B = 10 \) MHz while the spectral efficiency is fixed to be 1.74 (bit/s/Hz) [27]. Thus, \( N_{U_{\text{BS}}} = 51 \) users per 3-sector BS.

The GWO and PSO algorithms are applied under the following settings: the initial population size is set to \( L = 12 \) while the tolerances \( \eta \) and \( \tau \) are set to \( \eta = \tau = 98\% \). Also for PSO, we define \( V_{\text{max}} \) as the maximum achieved velocity in (5.15) \( \left( \text{i.e., } V_{w}^{(l)} \in [-V_{\text{max}}, V_{\text{max}}] \right) \).

Indeed, this restriction is placed to enforce the limitation that a particle does not exceed a certain acceleration. We choose \( V_{\text{max}} = 500 \) meters in order to limit the movement of BSs from an iteration to another. The power and channel parameters are detailed in Table 2.2 and are obtained from [48, 49].

### 2.6.2 Performance of the Proposed Planning Approach

In our simulation results, we start by investigating the performance of the proposed approach using the PSO algorithm. We consider two scenarios, Scenario A and B as described in Table 2.3, where in Scenario A we assume that the users in subarea 1 representing 60% of the total number of users are normally distributed with a concentration in the center of the area. Then, the number of users is reduced with a standard deviation of 1275 meter. However, in Scenario B, the users are uniformly distributed in subarea 1. In Fig. 2.2, we
Table 2.3: Studied scenarios and the corresponding performance

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>(N_U)</th>
<th>(N_{\text{Area}})</th>
<th>Subarea Description</th>
<th>(N_{\text{BS}})</th>
<th>(\sum_{j=1}^{N_{\text{BS}}} \epsilon_j)</th>
<th>Outage rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario A</td>
<td>2000</td>
<td>2</td>
<td>Subarea 1 is uniformly distributed, Subarea 2 is normally distributed reaching its maximum at (5 km, 5 km) ((A(1), D_1) = (65 \text{ km}^2, 40%)) ((A(2), D_2) = (35 \text{ km}^2, 60%))</td>
<td>42</td>
<td>41</td>
<td>41</td>
</tr>
<tr>
<td>Scenario B</td>
<td>2000</td>
<td>2</td>
<td>Subarea 1 is uniformly distributed, Subarea 2 is uniformly distributed ((A(1), D_1) = (65 \text{ km}^2, 40%)) ((A(2), D_2) = (35 \text{ km}^2, 60%))</td>
<td>42</td>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>Scenario C</td>
<td>1000</td>
<td>4</td>
<td>All subareas are uniformly distributed ((A(1), D(1)) = (33.3 \text{ km}^2, 35%)) ((A(2), D(2)) = (16.6 \text{ km}^2, 40%)) ((A(3), D(3)) = (16.6 \text{ km}^2, 5%)) ((A(4), D(4)) = (33.3 \text{ km}^2, 20%))</td>
<td>33</td>
<td>33</td>
<td>33</td>
</tr>
</tbody>
</table>

compare between the results obtained for both scenarios: Scenario A (i.e., Fig. 2.2(a)) and Scenario B (i.e., Fig. 2.2(b)). Although we are considering the same subareas and the same number of users, results show that the number of BSs required to fulfill the problem constraints is 41 for Scenario A and 40 for Scenario B with one extra BS for Scenario A. We

Figure 2.2: Comparison between (a) Scenario A and (b) Scenario B using PSO algorithm (BS: square, MS: dot, BS sector: arrow).
Figure 2.3: Comparison between (a) PSO and (b) GWO for Scenario C (BS: square, MS: dot, BS sector: arrow).

also notice that Scenario A presents a higher BS density in subarea 1 compared to Scenario B. Indeed, the algorithm adapts its BS distribution to the user density without affecting the coverage constraint. Also, the outage rate for both scenarios is low around 0.5% and 0.3% for Scenario A and Scenario B, respectively.

The BSs in the boundary play an important role as they contribute in serving users in multiple subareas. We notice that, for the Gaussian scenario, the boundary BSs placed in subarea 2 contribute more in serving users placed in subarea 1 than the uniform scenario, since the user density in the boundary is very low for Scenario A.

### 2.6.3 Comparison between PSO and GWO

In Scenario C, the area of interest is divided into 4 subareas and users are uniformly distributed according to different densities as indicated in Table 2.3. In order to fulfill both constraints and serve the 1000 users that are communicating simultaneously, 33 three sector antenna BSs are placed as it is shown in Fig. 2.3. We can clearly see that the number of BSs placed in each subarea is proportional to the corresponding user density: around 11 and 7 BSs are placed in subarea 1 and subarea 2, respectively, while 4 and 11 are deployed
in subarea 3 and subarea 4. Subarea 2 presents the highest user density with 24 users/km² while the density in subarea 3 is only 3 users/km². Note that subarea 3 requires only 4 BSs to cover its surface and serve its users whereas 7 BSs are needed to satisfy the user density constraint in subarea 2. However, for subarea 4, the number of BSs is mainly related to the coverage constraint since according to the capacity dimensioning phase in this subarea 3 BSs are enough to serve the 200 users in that area. The Monte Carlo simulation indicates that the percentage of users in outage is around 0.21% and 0.26% for PSO and GWO, respectively, which respects the desired QoS. This proves the efficiency of the proposed practical meta-heuristic methods. We notice that both algorithms provide almost the same BS locations with minor differences. However, we can see through Fig. 2.4 that PSO algorithm is faster than GWO in terms of convergence speed. Indeed, GWO requires an exploration phase before it starts converging to its solutions which might require a relatively important number of iterations. Furthermore, by experiments and for large number of realizations, PSO algorithm is able to achieve easily the target utility for $\tau = 98\%$ while GWO might miss the target for around 20% of the realizations. In other words, the convergence rate of PSO in cell planning is significantly higher than that of GWO algorithm.
PSO and GWO are two meta-heuristic algorithms where the exact number of iterations needed to reach the solution is random and depends on the studied scenario. However, the computational complexity per iteration can be determined. According (2.18) and (2.19), PSO needs to calculate 10 multiplications and 10 additions for every BS position \((x_j(t), y_j(t))\). Hence, \(10LN_{\text{BS}}\) multiplications and \(10LN_{\text{BS}}\) additions are calculated every iteration whereas GWO calculates \(13LN_{\text{BS}}\) multiplications and \(11LN_{\text{BS}}\) additions according to (2.20) and (2.21). In our simulation results, we assumed that both algorithms are executed at most 2000 iterations and are stopped if coverage and cell capacity constraints are satisfied \(\tau = 98\%\). Thus, the utilities are computed at most \(2000 \times L\) times. For 200 realizations, \(L = \{12, 24\}\) and \(N_{\text{BS}} = 33\) and for the same scenario \(C\), results shows that in average PSO is faster than GWO and requires less time to converge as it is shown in Table 2.4 where we compute the CPU times in seconds of all algorithms and save the first iteration where the algorithm satisfies both constraints (denoted \(I^*\)). In increasing the number of particles \(L\), would enhance the convergence speed of the algorithms. In fact, PSO and GWO are able to achieve their solutions with a lower number of iterations but they require more CPU times as they need to perform more additions and multiplications during each iteration. For instance, in average with \(L = 12\), PSO performs 67800 multiplications while with \(L = 24\), it needs 97680 multiplications to converge. Similar remarks can be noticed for GWO.

We also compare the performance of the proposed meta-heuristic approaches with SA [26]. In the traditional SA, one BS is perturbed at each iteration. In our simulations, in order to enhance the speed of SA, we select a random integer \(N\) between 1 and \(N_{\text{BS}}\), and then randomly we select \(N\) out of the \(N_{\text{BS}}\) BSs to update their locations, then we move each of these \(N\) BSs by a random perturbation that does not exceed \(V_{\text{max}}\). Results show that SA presents similar convergence speed as PSO in the beginning but faces difficulties to achieve the target as the number of iterations increases. Then, its convergence speed
becomes very slow as it is shown in Fig. 2.4. On the other hand, it is considered faster than PSO and GWO in terms of CPU times as it performs 2000 iterations in 415 seconds. This is due to the fact that SA requires in average $N_{BS}$ additions and $N_{BS}$ multiplications per iteration only. Note that all tests were performed on a desktop machine featuring an Intel Xeon CPU and running Windows 7 Professional. The clock of the machine is set to 2.66 GHz with a 48 GB. The computation time is done via the TIC/TOC function of Matlab.

Table 2.4: CPU times of algorithms

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>(CPU times, $I^*$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO ($L = 12$)</td>
<td>(255, 565)</td>
</tr>
<tr>
<td>PSO ($L = 24$)</td>
<td>(344, 407)</td>
</tr>
<tr>
<td>GWO ($L = 12$)</td>
<td>(368, 986)</td>
</tr>
<tr>
<td>GWO ($L = 24$)</td>
<td>(516, 821)</td>
</tr>
<tr>
<td>SA</td>
<td>(415, 2000)</td>
</tr>
</tbody>
</table>

2.6.4 LTE Networks with Femto Access Points

We propose to implement the proposed planning approach while taking into account the presence of femto access points (FAPs) that can offload some amount of the traffic from the cellular networks. We consider Scenario C and place 100 femto access points uniformly over the area. The maximum range of a FAP is set to be 10 meters and each FAP is assumed to simultaneously serve at maximum 10 subscribers of the cellular networks. We execute the proposed approach using the PSO algorithm. In this case, the FAPs are considered already deployed and the problem consists in finding the BS locations taking into account the contribution of FAPs in serving users. Fig. 2.5 plots the positions of BSs using the proposed cell planning approach. It shows that 31 BSs are deployed instead of 33 as it is given in Fig. 2.3(a). Indeed, in low density subareas, the number of BSs is the same for both cases, since it corresponds to the number of BSs needed to maintain the coverage constraint per each subarea. Indeed, with a 10 meter range, FAP does not provide any enhancement in terms of total coverage. On the other hand, the number of BSs in subarea 2 is reduced and two BSs are eliminated as their presence is compensated by the existence
Figure 2.5: LTE networks with femto access points: (BS: square, FAP: circle, BS sector: arrow).

of FAPs which can offload some users in that subarea.

2.6.5 LTE Heterogeneous Networks

We propose to apply our proposed planning approach for two-tier hetnet networks where macrocell BSs and small cell BSs co-exist. In this approach, we propose to:

(i) first apply the planning approach described in Section 2.3 for tri-sector macrocell BSs only until satisfying coverage and cell capacity constraints.

(ii) Then, we apply the planning approach considering small cell BSs equipped with omni-directional antennas (antenna gain 12 dBi) only till satisfying the cell capacity constraint per each subarea. In fact, it is inefficient to deploy small cell BSs to ensure connectivity over the area especially in low density and rural zones due to their low coverage range (e.g., 260 meters in our case).

(iii) Finally, we place all BSs obtained from (i) and (ii) and apply the BS elimination algorithm in order to remove all redundant BSs.

In Fig. 6, we show the obtained BS locations using the approach described above. 2000 users are distributed following a bimodal distribution consisting of a mixture of two trun-
cated normal distributions centered in the points (4 km, 7 km) and (7 km, 2.5 km) with variances 1.3 km and 1 km, respectively. The weight is set to 0.6. We can clearly see, that in the rural subarea where only 7% of the users exist, only macrocell BSs are deployed to satisfy the coverage constraints and all the small cell BSs are eliminated while in high density subarea macrocell BSs are placed and small cell BSs are deployed to fulfill the cell capacity constraints. Notice that the proposed approach adapted the BSs distribution to the given user traffic distribution as there is an important concentration of small cell BSs in both hotspot areas. These small cell BSs could be switched on/off depending on traffic load variation in order to reduce the overall network energy consumption.

### 2.6.6 Green Planning

In this problem, we consider Scenario A by assuming that 200 users are connecting at night while during day we assume that the number of users increases to 2000. During the night planning phase, we can see in Fig. 2.6 that the number of deployed BSs corresponds to the number of BSs required to ensure full coverage as the number of users is very low.
Figure 2.7: Green planning: Night BSs (red squares), additional day BSs (blue stars).

during this non-peak period. However, during the day, we can see that the BSs that are already deployed in subarea 1 are enough to serve the 40% of total users whereas the mobile operator needs to activate 14 BSs placed around the center of the Gaussian hotspot in order to satisfy the QoS of the subscribers.

2.6.7 Planning with Location Constraints

In order to demonstrate the performance of the proposed method presented in Section 2.3, we consider a typical uniform user distribution over the area and we consider that placing BSs is prohibited in the central area (colored in red in Fig. 2.7(a)) of size $4 \times 4$ km$^2$ where the received power level at each point in that area has to be less than $-60$ dBm. We can clearly see that the proposed method converges to the case where the BS placement follows the input user distribution while respecting the electromagnetic radiation constraint by locating the 27 BSs outside the radiation free zone as it is shown in Fig. 2.7(b). We can see the difference with the non-location constraint problem where the 30 BSs are allowed to be placed anywhere in the area and almost having the same locations as the black BSs mainly in the area boundaries.
(a) Voronoi constellation, radiation-limited area (black squares: BSs with location constraints, blue circles: BSs without location constraints).

(b) Electromagnetic radiation levels in dBm over the area.

Figure 2.8: BS placement for location constraint problem.

2.7 Summary

In this chapter, we proposed an efficient planning method for 4G-LTE networks in order to deploy base stations while respecting two major constraints: the coverage and cell capacity constraints by taking into account several subareas characterized by different user densities, uplink and downlink directions, LTE resource allocation, and intercell interference. The proposed approach starts by performing a typical coverage and dimensioning phase. Then, it employs a meta-heuristic algorithm to find the optimal BS locations that fulfill the system constraints. Finally, it eliminates eventual redundant base stations to keep the minimum number of base stations required to ensure a safe network operation. Using Monte Carlo simulations, we have investigated the performance of our proposed scheme where we computed the average number of users in outage. We showed that it provides a very low outage rate and respects the desired network quality of service. Furthermore, we showed that the PSO algorithm outperforms the GWO algorithm in terms of convergence.
speed and convergence rate. Finally, we adapted our proposed method to perform a green planning that considers day/night traffic variation in order to provide energy savings and a planning with location constraint problem due to electromagnetic radiation limitation. We believe that the proposed 4G cell planning approach will be also useful for the development of planning algorithms for 5G networks, especially that we capture emerging aspects such as dynamic load variations, green considerations, heterogeneous networks and femtocell deployments.

Although it does not reach the optimal solution, the proposed approach achieves the predefined objectives: The coverage and cell capacity constraints. One drawback of the method is that it is based on evolutionary algorithms which lead to different sub-optimal solutions even for the same studied scenarios. It is true that this will offer more flexibility to the operator but it might complicate the task. Therefore, the proposed approach could be improved by predefining the possible range of base station locations. Indeed, in practice, it is not possible to place the base stations at any point of the map. Thus, a more complex constrained location problem could be formulated in order to improve the precision of the algorithms.
Chapter 3

Mobile User Assignment Using Optimal Transport Theory for Green LTE-Advanced Heterogeneous Networks

3.1 Introduction

During the last decade, energy consumption of cellular networks have attracted enormous attentions from the communication research community. The major objective is to ensure energy saving in the radio access network while respecting certain quality of service (QoS) constraints. Many techniques (e.g., base station on/off switches [50] or energy harvesting techniques [51]) were proposed in the literature to meet this goal. However, few work concentrates on greening the mobile user association procedure which can also contribute in reducing the network power consumption. Most of the work focusing on this research direction were concentrated on maximizing the user throughput [52]. The authors in [53] have proposed an interesting method to solve the user assignment problem by using the optimal transport theory [54] by minimizing the power consumption of cellular networks while respecting a certain pre-defined data rate per user. However, the method
was applied for the one dimension scenario and does not take into account Long Term Evolution-Advanced (LTE-A) features nor power and resource constraints. Moreover, the employed method to solve the problem is based on 1-dimension computation, does not provide the optimal boundary shapes of the deployed base stations (BSs) and is only applied for the nearest neighbor BSs.

In our framework, we propose to investigate the user assignment problem for LTE-A heterogeneous networks that ensures energy saving while respecting the network QoS. The goal is to find the optimal cell association to each BS covering the area by taking into account the BS power budget and the number of available resource blocks per BS. A fixed point iterative algorithm is applied to find the optimal 2-dimension cell configuration for different user distributions. Also unlike [53] which was limited to find the optimal radius of each cell contour, we determine the exact cell shapes by considering all neighbor BSs. In our simulations, we study the performance of the proposed method and compare it with the classical Voronoi configuration for various scenarios.

The rest of the chapter is organized as follows. Section 3.2 gives the system model. In Section 3.3, we formulate our optimization problem and its optimal transport-based solution. In Section 3.4, we present our selected simulation and numerical results. Finally, the chapter is concluded in Section 3.5.

### 3.2 System Model

We consider a geographical area served by a heterogeneous network deployed on a bounded region $\Omega$. The network consists of $K$ spatially and spectrally coexisting tiers, where each tier is distinguished by its transmit power and BS density (e.g., macro cells would typically have a much higher transmit power and lower density while small cells provides lower power with short range but have higher density). $M = \sum_{k=1}^{K} M_k$ BSs are
already deployed to satisfy the traffic demand of the customers and cover the total area where $M_k$ is the number of BSs of type $k = 1, \cdots, K$. We denote by $(x_j, y_j, z_j)$ the spatial coordinates of BS $j$ ($j = 1, \cdots, M$) in the area. We assume that $N_u$ users are also randomly placed following a certain user distribution having as a joint probability density function (pdf), $f(x, y)$. For instance, the density could follow a uniform distribution with a given user density per km$^2$ or a normal (Gaussian) distribution corresponding to concentrated users in a hotspot area and then the density is reduced as we move away from the center; etc. The proportion of users in a sub-region $\omega \subseteq \Omega$ is computed as $\iint_{\omega} f(x, y) dxdy$. Thus, the total number of users in this sub-region $\omega$ is denoted and is given by:

$$N_\omega = N_u \int\int_{\omega} f(x, y) dxdy. \quad (3.1)$$

Orthogonal frequency division multiple access (OFDMA) is the access scheme for the downlink of LTE systems. The available spectrum is divided into resource blocks (RB) consisting of 12 adjacent subcarriers. In our framework, we allocate to each user one RB. The channel gain for the downlink direction between a user located in $(x, y)$ and BS $j$ is given by:

$$H_{j,\text{dB}}(x, y) = -\kappa - \upsilon \log_{10} d_j(x, y), \quad (3.2)$$

where $\kappa$ is the pathloss constant, $d_j(x, y) = \sqrt{(x_j - x)^2 + (y_j - y)^2 + z_j^2}$ is the distance in km from BS $j$ to the user of coordinates $(x, y)$, and $\upsilon$ corresponds to the pathloss exponent. Our channel model is simplified and includes only the pathloss effect. Indeed, we are focusing on average values and not the instantaneous ones since the cell boundaries should be fixed for a long period of time and not varying from a time slot to another. This channel assumption is widely used in literature mainly for radio network planning problems where the objective is to determine the best base stations locations for a long period of time based on average statistics \cite{21, 55}. We consider that the network employs fractional frequency
reuse where cell-edge users of adjacent cells do not interfere with each other and thus the interference is reduced and is treated as a noise. Hence, the data rate $R(x, y)$ achieved by user $(x, y)$ connected to BS $j$ is expressed as follows:

$$R(x, y) = B_{RB} \log_2 \left( 1 + \frac{P_{j,r}H_j(x, y)}{N_0} \right),$$

(3.3)

where $B_{RB}$ is the RB bandwidth, $N_0$ is the noise power over the RB, and $P_{j,r}$ is the BS transmitted power allocated to RB $r$, $r = 1, \cdots , N_{RB}$.

We consider that the QoS of a user located in $(x, y)$ is satisfied if the following constraint is fulfilled:

$$R(x, y) \geq \theta,$$

(3.4)

where $\theta$ is the target data rate per user. Thus, from (3.4), the needed fraction of power to be allocated to the user located in $(x, y)$ in order to satisfy its QoS is given by:

$$P_{j,r}(x, y) = A_c [d_j(x, y)]^{\frac{\theta}{B_{RB}}},$$

(3.5)

where $A_c = 10^{\frac{\theta}{B}} N_0 \left( 2^{\frac{\theta}{B_{RB}}} - 1 \right)$ is a constant that depends on the target data rate $\theta$. Note that the total transmit power per BS is subject to a peak power budget constraint expressed as follows:

$$\sum_{r=1}^{N_{RB}} P_{j,r} \leq \bar{P}_j,$$

(3.6)

where $\bar{P}_j$ is the peak power budget per BS $j$ which depends on its type (i.e., marco or small cell).
3.3 Problem Formulation and Optimal Transport Solution

The objective of this study is to optimally associate users to the existing BSs in the given area of interest in order to minimize the total transmit power consumption of the network while respecting the user QoS. This is performed by determining the sub-region of the area controlled by each BS \( j, j = 1, \ldots, M \) that we identify by the cell \( C_j \).

3.3.1 Objective Function

The total transmit power consumption of the network, denoted \( P_{\text{tot}} \), is equal to the sum of the power transmitted by all network BSs. Hence, the objective function to minimize is given by

\[
P_{\text{tot}} = \sum_{j=1}^{M} P_{j}^{\text{cell}}, \tag{3.7}
\]

where \( P_{j}^{\text{cell}} = \int\int_{C_j} P_j(x, y) f(x, y) dx dy \) is the intracell transmitted power consumption by BS \( j \) in its cell \( C_j \) and \( P_j(x, y) = \sum_{r=1}^{N_{\text{RB}}} P_{j,r}(x, y) \). Thus, the total transmit power can be rewritten as follows

\[
P_{\text{tot}} = \sum_{j=1}^{M} \sum_{r=1}^{N_{\text{RB}}} \int\int_{C_j} P_{j,r}(x, y) f(x, y) dx dy. \tag{3.8}
\]

Note that if RB \( r \) is not allocated to any user, then \( P_{j,r} = 0 \), else \( P_{j,r}(x, y) = A_c \left[ d_j(x, y) \right]^{\frac{n}{10}} \) as it is given in (3.5). As we are only considering pathloss in our channel model and we are allocating one RB to each user, then

\[
P_{\text{tot}} = \sum_{j=1}^{M} \int\int_{C_j} N_{C_j} A_c \left[ d_j(x, y) \right]^{\frac{n}{10}} f(x, y) dx dy, \tag{3.9}
\]
where $N_{C_j}$ is the number of users served by BS $j$ determined using (3.1) as follows

$$N_{C_j} = \left\lceil N_u \int \int_{C_j} f(x, y) dx dy \right\rceil,$$  \hspace{1cm} (3.10)

where $\lceil \rceil$ denotes the ceiling function.

### 3.3.2 Problem Constraints

**Maximum number of RBs:** In order to respect the BS resource constraint, $N_{C_j}$ cannot exceed the available number of RBs $N_{RB}$ (i.e., $N_{C_j} \leq N_{RB}$). In order to respect this constraint, we propose to find the maximum range $\rho_j$ of BS $j$ such that the number of users inside the circle centered in the BS location $(x_j, y_j)$ with radius $\rho_j$ is less or equal to $N_{RB}$ by solving the following equation:

$$N_u \int \int_{C((x_j, y_j), \rho_j)} f(x, y) dx dy = N_{RB},$$ \hspace{1cm} (3.11)

**Peak power budget:** On the other hand, each BS can serve users within a certain range determined by its maximum power budget. Thus, we need to determine the maximum BS range denoted $r_j$ that satisfies the power budget constraint which is obtained by solving the following equation:

$$\int \int_{C((x_j, y_j), r_j)} N_{C((x_j, y_j), r_j)} A_c [d_j(x, y)]^{10} f(x, y) dx dy = \bar{P}_j.$$ \hspace{1cm} (3.12)

After performing an integration using polar coordinates, we can determine $\rho_j$ and $r_j$ using numerical methods such as Newton method mainly for complex integrations. Thus, each cell $C_j, \forall j$ has to satisfy the following constraint:

$$C_j \subseteq C((x_j, y_j), \min(r_j, \rho_j)), \forall j = 1, \cdots, M.$$ \hspace{1cm} (3.13)
3.3.3 Optimization Problem Solution

The decision variables are now the cells $C_j, j = 1, \cdots, M$ corresponding to each BS $j$. The objective is to find their optimal shapes (i.e., the optimal mobile user association) that minimize the total network transmit power consumption. Thus, our problem can be formulated as

$$\text{minimize} \quad (3.9),$$
Subject to: $(3.13)$.

Constraint $(3.13)$ indicates that a BS cannot serve users outside its maximum range determined by the circle $C$ centered in $(x_j, y_j)$ with radius $\min(r_j, \rho_j)$.

In [53] and based on the optimal transport theory, it is shown that the solution of the unconstrained problem below:

$$\min_{\tilde{C}} \sum_{j=1}^{M} \int_{\tilde{C}_j} m_j \left( N_{\tilde{C}_j} \right) F \left( d_j(x, y) \right) f(x, y) \, dx \, dy,$$

are disjoint sets, denoted $\tilde{C}_j^\ast$, and given as follows:

$$\tilde{C}_j^\ast = \left\{ (x, y) ; m_j \left( N_{\tilde{C}_j}^\ast \right) F \left( d_j(x, y) \right) f(x, y) + U_j \leq m_i \left( N_{\tilde{C}_i}^\ast \right) F \left( d_i(x, y) \right) f(x, y) + U_i \right\},$$

where $F$ is a continuous function and $m_j$ are differentiable ones. In $(3.16)$,

$U_j = m_j' \left( N_{\tilde{C}_j}^\ast \right) \int_{\tilde{C}_j} F \left( d_j(x, y) \right) f(x, y) \, dx \, dy$ and $m_j'$ is the first derivative of $m_j$ with respect to $N_j$. In our framework, we set $F \left( d_j(x, y) \right) = A_c \left[ d_j(x, y) \right]^{\nu}$ and $m_j \left( N_{\tilde{C}_j} \right) = N_{\tilde{C}_j} = N_a \int_{\tilde{C}_j} f(x, y) \, dx \, dy$. Taking into account constraint $(3.13)$, the optimal solutions
$C_j^*$ of the optimization problem formulated in (3.14) are given by:

$$
C_j^* = \tilde{C}_j^* \cap \mathcal{C}((x_j, y_j), \min(r_j, \rho_j)) \quad \text{and} \quad N_{C_j^*} = N_a \int_{C_j^*} f(x, y) \, dx \, dy.
$$

(3.17)

Note that if the network is overloaded and not well-planned, some users might not be covered by any cells because of the constraints (This case might also happen with the typical Voronoi association). Therefore, in our framework, we assumed, in section II, that the operator is deploying $M$ BSs that satisfy the traffic demand and cover the whole area. Thus, the number of deployed BSs is enough to fulfill the constraints and avoid the issue of non-covered users. The problem of non-covered users may raise when the traffic density of users in the area changes. This involves a continuous optimization to accommodate the changes in the environmental or additional requirements. Therefore, this problem would be faced by planning new BS sites and finding their best locations in order to respect the user and coverage constraints. Then, we re-apply the green mobile association scheme.

From (3.16), we notice an interdependence between the sets $C_j^*$ and the number of users $N_{C_j^*}$. Thus, we propose to employ the fixed-point iterative algorithm, given in Algorithm 4, in order to find the optimal $C_j^*$ and $N_{C_j^*}$, $\forall j = 1, \cdots, M$. Initially, the algorithm starts

**Algorithm 4** Fixed-Point Iterative Algorithm for Green Mobile Association

1: $t=0$.
2: Generate an initial cell combination $C_j(t)$, $j = 1, \cdots, M$.
3: Compute $N_{C_j(t)}$ corresponding to $C_j(t)$ using (3.10).
4: Find the initial total transmit power consumption $P_{\text{tot}}(t)$ using (3.9).
5: repeat
6: \hspace{1em} $t \leftarrow t + 1$.
7: \hspace{1em} Find the $t$th mobile association by finding the cells $C_j(t)$, $j = 1, \cdots, M$ with respect to $N_{C_j(t-1)}$ as it is given in (3.16) and (3.17).
8: \hspace{1em} Compute the corresponding $N_{C_j(t)}$, $\forall j = 1, \cdots, M$.
9: \hspace{1em} Find $P_{\text{tot}}(t)$.
10: until $|P_{\text{tot}}(t) - P_{\text{tot}}(t-1)|^2 \leq \epsilon$.
11: The optimal solution of the optimization problem formulated in (3.14) is $C_j^* = C_j(t)$, $\forall j = 1, \cdots, M$. 
by generating random disjoint cells. The simplest initialization might be a multiplicatively weighted Voronoi diagram for heterogeneous network (for $K > 1$) or simply Voronoi cells for 1-tier network ($K = 1$). For certain user distributions, the complex integrals in $N_{Cj}$ and $U_j$ can be numerically computed using, for instance, Monte Carlo integrations. Finally, the convergence is achieved when the precision requirement is reached for a certain non-negative $\epsilon > 0$.

### 3.4 Results and Discussion

In this section, we study the performance of the proposed approach detailed in Section 8.3. We start by investigating the solution behavior with the user distributions for 1-tier network. We consider a $2L_x \times 2L_y$ km$^2$ area where $L_x = L_y = 2.5$ Km and $M$ BSs equipped with one omni-directional antenna uniformly deployed with antenna height $z = z_j = 30$ meter, $\forall j = 1, \cdots, M$. All BSs have the same power model with $\bar{P} = 46$ dBm and the noise $N_0 = k_b T B_{RB}$ where $k_b$ is the Boltzmann’s constant, $T$ is the absolute temperature, and $B_{RB}$ is the bandwidth over the RBs equal to 180 KHz. The total system bandwidth is $B = 10$ MHz with $N_{RB} = 50$ RBs. We assume that adjacent BSs use different carriers to avoid harmful interference. We set $\kappa = -128.1$ dB, $\upsilon = 37.6$, and the target data rate per user $\theta = 1$ Mbits/s. We assume that $N_u$ users are simultaneously connected to the network and distributed randomly following the pdf $f(x, y)$ that depends on three studied cases: (i) Uniform distribution, (ii) Zero-mean truncated normal distribution with variance $\sigma_0^2$ and (iii) A bimodal distribution consisting of a mixture of two truncated normal distributions with parameter $\lambda$: 
(i) : \( f(x, y) = \frac{1}{4LxLy}, M = 25 \) and \( N_u = 500 \). \hfill (3.18)

(ii) : \( f(x, y) = f_0(x, y), M = 25 \) and \( N_u = 500 \). \hfill (3.19)

(iii) : \( f(x, y) = \lambda f_1(x, y) + (1 - \lambda) f_2(x, y), M = 16 \) and \( N_u = 300 \), \hfill (3.20)

where \( f_n(x, y) = \frac{1}{A_n} \exp\left(-\frac{(x-\mu_{xn})^2 + (y-\mu_{yn})^2}{2\sigma_n^2}\right), A_n = 2\pi\sigma_n^2 \text{erf}\left(\frac{L_x-\mu_{xn}}{\sqrt{2}\sigma_n}\right) \text{erf}\left(\frac{L_y-\mu_{yn}}{\sqrt{2}\sigma_n}\right), n \in \{0, 1, 2\}, \) and \( \mu_{xn}, \mu_{yn} \) and \( \sigma_n^2 \) are the means and the variance of the normal distribution represented by its pdf \( f_n(x, y) \), respectively. In our studied scenarios, we set \( \mu_{x0} = \mu_{y0} = 0, \sigma_0 = 1.15, \mu_{x1} = -0.625, \mu_{y1} = 0.625, \sigma_1 = 1.15, \mu_{x2} = 1.25, \mu_{y2} = -1.25, \sigma_2 = 1.15 \) and \( \lambda = 0.6 \).

Scenario (i) might correspond to a simple case where users are uniformly distributed over the area while Scenario (ii) assumes that users are concentrated in a hotspot area (e.g., downtown) and then their density is reduced as we move away from the center. In Scenario (iii), there are two hotspots where users are concentrated. For instance, it can correspond to two neighbor residential areas. In addition to that, we investigate the case of a typical 2-tier heterogeneous network where one macro-cell is placed in the center of the area and \( M_2 \) small cells are placed over the circle centered in the macro-cell position with the radius.

![Figure 3.1: Scenario (i): Uniform user distribution.](image-url)
Table 3.1: Total transmit power consumption for the proposed and the Voronoi solutions

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Voronoi</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i)</td>
<td>0.93</td>
<td>0.93 (0)</td>
</tr>
<tr>
<td>(ii)</td>
<td>1.56</td>
<td>1.42 (9)</td>
</tr>
<tr>
<td>(iii)</td>
<td>2.56</td>
<td>2.43 (5)</td>
</tr>
<tr>
<td>(iv)</td>
<td>3.2</td>
<td>1.96 (38)</td>
</tr>
<tr>
<td>(v)</td>
<td>10.04</td>
<td>7.5 (25)</td>
</tr>
</tbody>
</table>

$L_{BS}$. We assume that the network is operating on the 20 MHz LTE bandwidth where the macro cell owns 75 RBs while the small cells operate over the remaining 25 RBs with a maximum power budget equal to 26 dBm. $N_u = 150$ are distributed over the area covered by the macro BS with the following pdfs:

\[
(iv): f(x, y) = f_3(x, y) \quad \text{and} \quad M_2 = 8. \tag{3.21}
\]

\[
(v): f(x, y) = f_4(x, y) \quad \text{and} \quad M_2 = 4, \tag{3.22}
\]

where $A_n = 2\pi\sigma_n^2 \left(1 - \exp \left(-\frac{(r_1)^2}{2\sigma_n^2}\right)\right)$ and $r_1$ is the range of the macro BS, $\mu_{xn} = \mu_{yn} = 0$, and $\sigma_n = 0.5 \forall n \in \{3, 4\}$.

In the following figures, the black stars refer to as the BS locations while the number in the left and in the right of the black stars refer to as the number of users served by
that BS using the Voronoi cells and the proposed approach, respectively. Fig. 3.1 plots the performance of the proposed method for Scenario (i) where a uniform user distribution is used. It shows that the optimal transport solution converges to the Voronoi solution where each BSs serve 20 users. This is expected from equation (3.16) as $f(x, y)$ in this case is a constant function. Fig. 3.2 investigates the Gaussian case corresponding to Scenario (ii). Here, we notice that the optimal transport solution reduces the total transmit power consumption of the network by around 9% comparing to the traditional Voronoi scenario when applied to this distribution as it is shown in Table 9.1. This is performed by decreasing the number of users served by BSs located in the center of the area. Their traffic is offloaded to neighbor BSs located close to the boundaries. Indeed, the BSs in this region, where the traffic is lower than the center of the area, extend their coverage to serve more users. However, they are limited to serve at a certain coverage since serving faraway users might significantly increase the transmit power. Thus, a tradeoff between the offloaded traffic and the range extension by a BS is taken into account during the optimization.

In Fig. 3.3, we investigate Scenario (iii) for a bimodal distribution using 16 BSs. First, from Table 9.1 and comparing to the previous scenarios, we notice that the lower the num-
The number of BSs is, the higher the transmit power consumption is, even if they serve less users. Second, we can see that the gain comparing to the classical Voronoi scenario is about 5%. This is because the user distribution is very close to the uniform case which provokes minor differences in the cell shapes.

Fig. 3.4 studies the case of the heterogeneous network with 8 and 4 small cells. Firstly, unlike 1-tier network, a significant gain in terms of transmit power consumption is obtained thanks to the employment of small cells. Indeed, due to their limited power budgets, when they contribute in serving users, small cells consume less transmit power and thus the power saving becomes important. The gain goes from 25% to 38% by employing 8 small BSs instead of 4. Similarly to the 1-tier case, the behavior of the proposed method is maintained. The small cells increase their coverage to the maximum to help the macro cell serve less traffic.

Finally, in Fig 3.5, we investigate the convergence of the fixed-point algorithm presented in Algorithm 4. We notice that the algorithms requires 2 to 4 iterations to reach its solution depending on the scenarios. At the steady-state regime, we can see small variations in the optimal values of $P_{\text{tot}}$ due to the use of numerical Monte Carlo integrations.
3.5 Summary

In this chapter, we investigated the mobile user association problem for green LTE networks. We applied the optimal transport concept to determine the cells corresponding to each BS that minimize the total transmit power consumption while respecting the network quality of service and taking into account the resource limitation per BS. We have applied the proposed method to practical scenarios with various user distributions and showed via simulations that it ensures more energy saving comparing to the traditional Voronoi association mainly for HetNets.

As a future extension of this work, we suggest the introduction of shadowing and fading effects in the channel model as well as in the objective function. Also, we could consider the total power consumption of the network instead of the total transmitted power in addition to the temporal traffic variation. Thus, it would be interesting if we take into account the constant power consumption term of base stations and introduce the sleeping strategy, for instance, when the traffic is low. Thus, we can develop a daily dynamic mobile user association scheme.
Chapter 4

Small Cell Base Station

Switching-ON/OFF Strategy with

Downlink Radio Resource and Power Management for LTE HetNets

4.1 Introduction

Recently, power saving techniques has been attracting increasing attention by the green communication community researchers. Achieving energy saving while respecting a higher pre-defined data rate becomes one of the most important considerations for future wireless and cellular networks.

Since most of the wireless data traffic take place in indoor environments, mobile users may have difficulty in receiving high data rate from macrocell base station due to the penetration loss. Small cell\(^1\) technology, which is short range, low cost, and low power base

\(^1\)The term small cell in this chapter incloses the concept of microcell or picocell and refers to as cell of small size less than the macrocell size and more than femtocell size (generally about 100 or 200 meters radius).
station, is designed to handle this high amount of traffic. At the same time, using FAPs—also known as home base station—is considered as a very promising technique to meet the increasing capacity and high data rate demands, reduce the power consumption of the network, offload traffic from macrocell base station and subsequently improve the network capacity [56, 57]. FAP access control schemes can be grouped into three categories: open access, closed access, and hybrid or semi-closed access. Open access allows a nearby mobile subscriber to use the FAP without any restriction while closed access is only limited to registered users also called femto owners. In hybrid access, i.e., middle access case, unregistered subscribers might be allowed to use some FAP subchannels subject to certain conditions and constraints. In other words, this mode allows unregistered subscribers to use the remaining subchannels after serving the registered ones. With the help of such FAPs, the network operator is able to extend high quality indoor coverage without the need of additional expensive cellular towers such as macrocell base stations [57, 58]. Downlink network capacity for different access modes is studied in [59] and a fundamental choice of FAP categories has been discussed in the chapter.

LTE HetNets where macrocells, small cells, and femtocells are sharing the same spectrum [60], may conduct to a terrible cross-tier interference problem between the cells [58]. Hence, radio resource management can efficiently solve this problem by dividing the available spectrum into sub-frequency bands where the femtocells and small cells use spectrum bands different than the macrocell [61–63]. Cross-tier interference between femtocells and small cells depends on FAP decision. For instance, for closed and hybrid access mode, the users communicating with the FAPs can cause cross-tier femto-small cell interference to users communicating with nearby small cell and vice versa. In the literature, many previous work proposed several approaches to deal with this interference problem. For instance, the spectrum sensing approach is presented in [64, 65]. The authors in [64] proposed a cognitive resource management scheme inspired from the spirit of cognitive radio technol-
ogy. That is, femtocells can sense the radio resource usage of the other cell and utilize it. In [65], the authors avoided the interference by proposing an efficient frequency resource allocation scheme that prevents femtocells from utilizing radio resources occupied by other cells. A second solution is the power control approach [66, 67]. In order to control the femtocell power, the work of Jo et al. and references therein proposed different downlink schemes and approaches that adjusted the transmit power of the femtocells such that they reduced the effect of the caused interference. Another approach is called frequency assignment approach [68, 69], the later work proposed two different approaches for the self-organization of OFDMA femtocells, in which the femtocell is able to dynamically sense the air interface and tune its subchannel allocation in order to reduce inter-cell interference and enhance system capacity.

On the other hand, dynamic base station switching-on/off can help in ensuring power saving for wireless heterogeneous cellular networks by reducing the power consumption of base stations that have a heavy energy usage mainly during low traffic period [70]. Few schemes were proposed to deal with this topic in literature. In [71], the authors proposed a simulated annealing-based algorithm to turn on and off base stations in a HetNet while in [72], the authors introduced two node sleep modes operating on a fast and intermediate time scale respectively, in order to exploit short and longer idle periods of the nodes and showed how an operator can use densification to address the need for additional capacity while at the same time maintaining the energy consumption to a reasonable level. The authors in [73] used the constraint programming optimizer to optimize the coverage and capacity of HetNets while taking into account green aspects by switching off redundant small cell base stations. All these green techniques did not consider cross-interference in their system model. Moreover, they are limited to the switching-off strategies without optimizing neither the transmitted power nor the resource allocation while targeting green objectives.
To the best of our knowledge, the problem of resource and power management for LTE HetNets including macro-small-femtocells and employing switching-on/off strategy has not been discussed so far. Therefore, our contributions in this chapter can be listed as follows:

- Formulate a DL optimization problem for full LTE HetNets that aims to minimize the total power consumption of the network taking into account the power budget of the base stations, the interference between femto and small cells, and respecting a certain QoS per each served user defined as ensuring a minimum data rate per each user.

- Adopt an efficient dual decomposition technique to solve the formulated optimization problem and derive the optimal power allocation scheme for the heterogeneous base stations in the downlink scenario in addition to the optimal user assignment.

- Design a practical and low complexity iterative algorithm to switch off redundant small cell base stations and compare its performance to the optimal scheme.

- Investigate and compare between different scenarios: macro-plus-small cells and macro-plus-small-plus-femtocells. In the latter scenario, we study the case of closed and hybrid FAPs.

The remainder of this chapter is organized as follows. Section 4.2 investigates the system model. The problem formulation and the dual decomposition method are described in Section 4.3. The low complexity algorithm is proposed in 4.4. The numerical results are discussed in Section 4.5. Finally, the chapter is concluded in Section 4.6.
4.2 System Model

We consider a LTE HetNet consisting of one macrocell base station placed at the center of the cell and \( L \) small cell base stations distributed uniformly around the center and assumed to be placed on the top of buildings inside of which we assume that \( L_f \) FAPs are placed to serve the registered users as it is shown in Fig. 4.1. Note that FAPs placed outside the small cell range are not considered in our system model since they do not provoke interference to the base stations. Without loss of generality, we assume that the number of small cells and FAPs are equal and are denoted by\( L_s \) and \( L_f, (L_f = L_s = L) \), respectively. Let us define \( U \) as the total number of outdoor users in the network, and \( V_l \) as the total number of indoor users connected to FAP \( l \). In LTE, OFDMA is the access for the downlink. The available spectrum is divided into RBs consisting of 12 adjacent subcarriers. Each RB has a bandwidth of \( B_{RB} = 180 \) KHz while each subcarrier has a bandwidth of \( 15 \) KHz [74]. We denote by \( N_{RB}^{(BS)} \) the number of available RBs at the base station BS (i.e., BS = \( s \) for small cell base station where \( s = 1, \ldots, L_s \) and BS = 0 for the macrocell base station). Finally, we make the following assumptions:

- A user is served by at most one base station (either macrocell, small cell, or FAP) with a unique RB.

- There is no intra-cell interference on the downlink and no interference between macrocell and small cell base stations as they are using different sets of orthogonal subcarriers.

- Small cell base stations are placed far enough such that they do not interfere each other.
4.2.1 Pathloss and Channel Model

The pathloss between user $v_l$ connected to the FAP $l$ and its serving FAP $l, l = 1, \ldots, L_f$ (indoor-indoor pathloss) is given by [75]:

$$PL_{v_l,l,\text{dB}} = 38.46 + 20 \log_{10} d_{v_l,l} + 0.3d_{v_l,l},$$  \hspace{1cm} (4.1)$$

where $d_{v_l,l}$ is the indoor distance between inside user $v_l$ and FAP $l$. In (4.1), the first term $38.46 + 20 \log_{10} d_{v_l,l}$ is the distance dependent free space pathloss, while the term $0.3d_{v_l,l}$ models the indoor distance dependent attenuation.

The pathloss between outside user $u$ connected to FAP $l$ (outdoor-indoor pathloss) is
given by [75]:

$$PL_{u,l,\text{dB}} = 15.3 + 37.6 \log_{10} d_{\text{out},u,l} + 0.3 d_{\text{in},u,l} + L_{ow},$$  \hspace{1cm} (4.2)$$

where $d_{\text{out},u,l}$ is the distance traveled outdoor between the user $u$ and the building external wall, $d_{\text{in},u,l}$ is the indoor traveled distance between the building wall and FAP $l$, and $L_{ow}$ is an outdoor-indoor penetration loss (loss incurred by the outdoor signal to penetrate the building). It is set to $L_{ow} = 20 \text{ dB}$ [75].

The pathloss between outside user $u$ connected to macrocell or small cell base station (outdoor-outdoor pathloss) is given by [75]:

$$PL_{u,BS,\text{dB}} = \kappa + \nu \log_{10} d_{u,BS},$$  \hspace{1cm} (4.3)$$

where $d_{u,BS}$ is the outdoor distance between the outside user $u$ and macrocell or small cell base station. In (4.3), $\kappa$ and $\nu$ correspond to the pathloss constant and pathloss exponent, respectively.

Taking into account fading and shadowing fluctuations in addition to the pathloss, the channel gain between outdoor user $u$ (or indoor user $v_l$) and a base station BS (i.e., either $s$, $l$ or $0$) over RB $r$ can be expressed as:

$$h_{u,BS,r,\text{dB}} = -PL_{u,BS,\text{dB}} + \xi_{u,BS} + 10 \log_{10} F_{u,BS,r},$$  \hspace{1cm} (4.4)$$

where the first factor captures propagation loss, according to (4.1)-(4.3). The second factor, $\xi_{u,BS}$, captures log-normal shadowing with zero-mean and a standard deviation $\sigma_\xi$ (set to $\sigma_\xi = 8 \text{ dB}$ in this chapter), whereas the last factor, $F_{u,BS,r}$, corresponds to Rayleigh fading power between user $u$ or $v_l$ and the BS over RB $r$, with a Rayleigh parameter $a$ such that $E\{|a|^2\} = 1$. It should be noted that fast Rayleigh fading is assumed to be approximately
constant over the subcarriers of a given RB, and independent identically distributed (iid) over RBs. In this chapter, we consider that for each user we allocate one RB.

4.2.2 Base Station Power Model

Since we are applying the base station sleeping strategy in our framework, we consider that each base station can be set in two modes: active and sleep modes. In the active mode, the base station is serving a certain number of users connected to the network. The power consumption of a BS corresponding to this mode, noted $P_{\text{BS}}$, can be computed as follows [76]:

$$P_{\text{BS}} = a_{\text{BS}} P_{\text{BS}}^{\text{tx}} + b_{\text{BS}},$$  \hspace{1cm} (4.5)

where $a_{\text{BS}}$ corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses and $b_{\text{BS}}$ models an offset of site power which is consumed independently of the average transmit power and is due to signal processing, battery backup, and cooling. In (4.5), $P_{\text{BS}}^{\text{tx}}$ denotes the radiated power of the BS and can be expressed as follows:

$$P_{\text{BS}}^{\text{tx}} = \sum_{r=1}^{N_{\text{RB}}^{(\text{BS})}} P_{\text{BS},r},$$  \hspace{1cm} (4.6)

which corresponds to the sum of the radiated power over the RBs $P_{\text{BS},r}, r = 1, \cdots, N_{\text{RB}}^{(\text{BS})}$ and depends on the RB state. If RB $r$ of the BS is allocated to a certain user, then $P_{\text{BS},r} > 0$, else, i.e., RB $r$ is not allocated to any user, $P_{\text{BS},r} = 0$. We consider that the BS total power consumption is limited by a peak power constraint $P_{\text{BS}}^{\text{tx}} \leq \bar{P}_{\text{BS}}$ where $\bar{P}_{\text{BS}}$ corresponds to the total transmit power consumption of BS. Note that $a_{\text{BS}}, b_{\text{BS}},$ and $\bar{P}_{\text{BS}}$ differ from a base station to another depending on the type of the base station: macrocell, small cell or femtocell base station.
4.2.3 Downlink Data Rates

The achievable data rate of the $u$th outdoor user served from a BS over the $r$th RB can be evaluated as

$$R_{u,BS,r}(P_{BS,r}) = B_{RB} \log_2 \left( 1 + \frac{P_{BS,r} h_{u,BS,r}}{I_{u,r} + N_0} \right)$$  \hspace{1cm} (4.7)

where $P_{BS,r}$ is the BS transmitted power allocated to RB $r$, $N_0$ is the noise power, and $I_{u,r}$ is the cross-tier interference on RB $r$ measured at the receiver $u$ caused by closest FAPs (no intra-cell interference on the downlink direction) and expressed as follows

$$I_{u,r} = \sum_{l=1}^{L_f} \left( \sum_{v_l=1}^{V_l} \epsilon_{v_l,l,r} \right) \cdot P_{l,r} h_{u,l,r}$$  \hspace{1cm} (4.8)

where, $\epsilon_{v_l,l,r}$ is a binary variable representing the exclusivity of the FAP RB allocation: $\epsilon_{v_l,l,r} = 1$, if RB $r$ is allocated to another user from a FAP $l$, and $\epsilon_{v_l,l,r} = 0$, otherwise. In fact, since the same RB might be allocated to the FAP indoor user and small cell base station outdoor user simultaneously, a cross-tier interference might caused to each user. In each cell, an LTE RB, and hence the subcarriers constituting that RB, can be allocated to a single user at a given transmission time interval. Hence, we have:

$$\sum_{v_l=1}^{V_l} \epsilon_{v_l,l,r} \leq 1$$  \hspace{1cm} (4.9)

Similarly, an indoor user might be subject to an interference caused by a small cell base station serving an outdoor user. The same equations described above are kept for the data rate expression by considering the corresponding pathloss expressions.
4.3 Problem Formulation and Optimal Solution

4.3.1 Problem Formulation

Our aim is to minimize the total power consumption of the network (i.e., macrocell and small cell base stations) while satisfying a certain QoS for each user. This will be performed by:

- Switching off redundant small cell base stations by optimizing a binary vector denoted \( \pi = [\pi_1, \ldots, \pi_{L_s}]^T \), where \((.)^T\) denotes the vector transpose operation. \( \pi_s = 0 \) if small cell base station \( s \) is turned off. Otherwise, \( \pi_s = 1 \).

- Optimizing the resource allocation procedure in terms of RB-user assignment and power optimization. This will be done by optimizing the binary variables \( \epsilon_{u,BS,r} \) that correspond to status of each RB \( r \) of BS whether it is allocated to the outdoor user \( u \) or not in addition to the power variables \( P_{BS,r} \) that are subject to a total power constraint per each BS.

The QoS of the network is defined by the achieved data rate by each user which has to be greater than a pre-defined data rate threshold denoted \( R_0 \). Thus, our optimization problem that aims to minimize the power consumption of the network is formulated as follows.
minimize \( \pi, \epsilon, P \geq 0 \) \( P_{\text{tot}} = \sum_{s=1}^{L_s} \pi_s \left( a_s \left[ \sum_{u=1}^{U} \sum_{r=1}^{N_{\text{RB}}^{(s)}} \epsilon_{u,s,r} P_{s,r} \right] + b_s \right) + a_0 \left[ \sum_{u=1}^{U} \sum_{r=1}^{N_{\text{RB}}^{(0)}} \epsilon_{u,s,r} P_{s,r} \right] + b_0, \) 

subject to:

(C1: Power budget constraint):
\[
0 \leq \sum_{u=1}^{U} \sum_{r=1}^{N_{\text{RB}}^{(s)}} \epsilon_{u,s,r} P_{s,r} \leq \pi_s \bar{P}_s, \quad \forall s = 0, \ldots, L_s, \tag{4.11}
\]

(C2: User Rate constraint):
\[
\sum_{s=0}^{L_s} \sum_{r=1}^{N_{\text{RB}}^{(s)}} \epsilon_{u,s,r} R_{u,s,r}(P_{s,r}) \geq R_0, \quad \forall u = 1, \ldots, U, \tag{4.12}
\]

(C3: Carrier selection constraint):
\[
\sum_{u=1}^{U} \epsilon_{u,s,r} \leq 1, \quad \forall r = 1, \ldots, N_{\text{RB}}^{(s)}, \forall s = 0, \ldots, L_s. \tag{4.13}
\]

Constraint (4.11) indicates that the total transmit power of each base station (i.e., marco cell \((s = 0)\) or small cell \((s = 1, \cdots, L_s)\)) has to be lower than the peak power budget while (4.12) is imposed to ensure the QoS for each user. Finally, (4.13) indicates that a user can be served by only one RB from one base station. Note that in our optimization problem, we are optimizing the transmit power of all base stations belonging to the network. However, we are always keeping the macro base station activated to ensure coverage and connectivity in the area when turning off the small cell base stations. In other words, \(\pi_0 = 1\). In (4.10), we denote by \(P\) the vector containing all the power values \(P_{s,r}\) and by the binary matrix \(\epsilon\) the matrix containing all the parameters \(\epsilon_{u,s,r}\) with \(U\) rows and \(L_s N_{\text{BS}}^{(s)} + N_{\text{BS}}^{(0)}\) columns and could be written as follows.
\[
\epsilon = \begin{pmatrix}
\epsilon_{1,0,1} & \cdots & \epsilon_{1,0,N_{\text{BS}}^{(0)}} & \epsilon_{1,1,N_{\text{BS}}^{(1)}} & \cdots & \epsilon_{1,L_s,N_{\text{BS}}^{(L_s)}} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\
\epsilon_{U,0,1} & \cdots & \epsilon_{U,0,N_{\text{BS}}^{(0)}} & \epsilon_{U,1,N_{\text{BS}}^{(1)}} & \cdots & \epsilon_{U,L_s,N_{\text{BS}}^{(L_s)}} 
\end{pmatrix}
\]

### 4.3.2 Dual Decomposition Method and Optimal Solution

The problem in (4.10)-(4.13) is satisfying the dual time sharing condition investigated in [77]. Thus, the duality gap of our non-convex resource allocation problem in OFDMA multicarrier system is negligible as the number of RBs is sufficiently large compared to the number of users. Hence, the dual optimization problem associated with the primal problem is given by

\[
\text{maximize} \quad g(\lambda, \mu), \quad (4.14)
\]

subject to: \( (4.13) \).

where \( \lambda = [\lambda_0, \lambda_2, ..., \lambda_{L_s}] \) and \( \mu = [\mu_1, \mu_2, ..., \mu_{U}] \) are Lagrangian vectors that contain the Lagrangian multipliers associated to constraints (4.11) and (4.12), respectively. The dual function \( g(\lambda, \mu) \) is defined as follows

\[
g(\lambda, \mu) \triangleq \min_{\pi, \epsilon, P \geq 0} L(\lambda, \mu), \quad (4.15)
\]

subject to: \( (4.13) \).
where \( \mathcal{L}(\lambda, \mu) \) is the Lagrangian function which is given as follows

\[
\mathcal{L} = \sum_{s=0}^{L_s} \pi_s \left( a_s \sum_{u=1}^{U} \sum_{r=1}^{N_{RB}^{(s)}} \epsilon_{u,s,r} P_{s,r} \right) + b_s + \sum_{s=0}^{L_s} \lambda_s \left( \sum_{u=1}^{U} \sum_{r=1}^{N_{RB}^{(s)}} \epsilon_{u,s,r} P_{s,r} - \bar{P}_s \right)
- \sum_{u=1}^{U} \mu_{u} \left( \sum_{s=0}^{L_s} \sum_{r=1}^{N_{RB}^{(s)}} \epsilon_{u,s,r} R_{u,s,r}(P_{s,r}) - R_0 \right)
\]

Thus, the dual problem in (4.15) can be rewritten as follows

\[
g(\lambda, \mu) = \text{minimize}_{\pi, \epsilon, P \geq 0} \sum_{s=0}^{L_s} \sum_{u=1}^{U} \sum_{r=1}^{N_{RB}^{(s)}} \pi_s \epsilon_{u,s,r} \mathcal{D}(P_{s,r}) + \sum_{s=0}^{L_s} \pi_s b_s - \sum_{s=0}^{L_s} \lambda_s \bar{P}_s + \sum_{u=1}^{U} \mu_{u} R_0
\]

subject to: (4.13),

where \( \mathcal{D}(P_{s,r}) = (a_s + \lambda_s) P_{s,r} - \mu_{u} R_{u,s,r}(P_{s,r}) \). The steps to solve the dual problem can be described as follows:

- **Step 1**: Initialize the Lagrangian multipliers values \( \lambda \) and \( \mu \).

- **Step 2**: Find the optimal value of \( P_{s,r} \) for each pairs \((s, r)\) by solving the following problem

\[
\text{minimize}_{P_{s,r} \geq 0} \mathcal{D}(P_{s,r}).
\]

Hence, by solving (4.18), the optimal power \( P_{s,r}^* \) can be given as follows

\[
P_{s,r}^* = \left[ \frac{\mu_{u} B_{RB}}{\ln 2(a_s + \lambda_s)} + \frac{I_{u,r} + N_0}{h_{u,s,r}} \right]^+,
\]

where \([x]^+ = \max(0, x)\).
• **Step 3:** Substitute the optimal powers derived in (4.19) into (4.17). Thus, the dual problem becomes

\[
g(\lambda, \mu) = \minimize_{\pi, \epsilon \geq 0} \sum_{s=0}^{L_s} \sum_{u=1}^{U} \sum_{r=1}^{N_{RB}^{(s)}} \pi_s \epsilon_{u,s,r} D \left( P_{u,s,r}^* \right) + \sum_{s=0}^{L_s} \pi_s b_s - \sum_{s=0}^{L_s} \lambda_s \bar{P}_s + \sum_{u=1}^{U} \mu_u R_0,
\]

subject to: (4.13).

It can be shown that (4.20) is a linear assignment problem with respect to \( \epsilon_{u,s,r} \) and \( \pi_s \) and can be solved efficiently by using the Hungarian algorithm with complexity of \((L_s N_{RB}^{(s)} + N_{RB}^{(0)})^3\) [78]. The solution obtained by the dual method is an asymptotically optimal solution [77].

• **Step 4:** After finding the optimal solutions \( P_{s,r}^*, \epsilon_{u,s,r}^*, \) and \( \pi_s^* \) corresponding to the initialized Lagrangian multipliers in **Step 1**, we can employ the subgradient method to find their optimal values and thus the optimal solution of the problem [79]. Hence, to obtain the solution, we can start with any initial values for the Lagrangian multipliers and evaluate the optimal solutions (i.e., \( P_{s,r}^*, \epsilon_{u,s,r}^*, \) and \( \pi_s^* \)). We then update the Lagrangian multipliers at the next iteration \((i + 1)\) as follows

\[
\lambda_s^{(i+1)} = \lambda_s^{(i)} - \delta^i \left( \bar{P}_s - \sum_{u=1}^{U} \sum_{r=1}^{N_{RB}^{(s)}} \epsilon_{u,s,r} P_{s,r}^* \right), \quad \forall s, \quad (4.21)
\]

\[
\mu_u^{(i+1)} = \mu_u^{(i)} + \varpi^i \left( R_0 - \sum_{r=1}^{N_{RB}^{(s)}} \epsilon_{u,s,r} R_{u,s,r} \left( P_{s,r}^* \right) \right), \quad \forall u, \quad (4.22)
\]

where \( \delta^i \) and \( \varpi^i \) are the updated step size according to the nonsummable diminishing step length policy (see [79] for more details). The updated values of the optimal solution and the Lagrangian multipliers are repeated until convergence.
4.3.3 Considered Scenarios

The proposed optimization problem formulated in Section 4.3.1 can be applied for four different scenarios by just modifying some parameters. The investigated scenarios are: macrocell only (M), macro-plus-small cells (MS), macro-plus-small-plus-closed FAP (MSF-closed), and macro-plus-small-plus-hybrid FAP (MSF-hybrid), and are detailed below:

- **Macrocell only (M)**: In this scenario, we assume the absence of small cell base stations and FAPs ($L_s = L_f = 0$). In other words, the optimization problem consists in allocating the available RBs to the maximum number of users with the optimal power scheme only.

- **Macro-plus-small cells (MS)**: In this situation, the users have the possibility to communicate with the small cell base stations in addition to the macrocell one. Cross-interference is not considered due to the absence of FAPs (i.e., $I_{u,r} = 0$, $\forall u = 1, \cdots, U$). Operator has the possibility to turn off small cell base stations during low traffic period. Corresponding users might be served by the macrocell base station.

- **Macro-plus-small-plus-closed FAPs (MSF-closed)**: In this scenario, only registered users can communicate with the closed FAP, outdoor users are not allowed to exploit the FAP resources. Thus, they are subject to the interference caused by deployed FAPs. In this scheme, we assume that the RBs exploited by the FAPs are known as well as the power $P_{l,r}, \forall l = 1, \cdots, L_f$. For instance, they can be determined by applying the same approach described in Section 4.3.2 on each FAP or assuming a uniform power allocation.

- **Macro-plus-small-plus-hybrid FAPs (MSF-hybrid)**: Similarly to (MSF-closed), except that outdoor users are able to exploit available FAP resources. After allocating
its resource to the indoor users, a FAP can offload outdoor users by providing to them its remaining resources in terms of RBs and/or power against a certain income. In fact, a FAP is spending some power, at a certain cost, to serve an outdoor user. On the other hand, the mobile operator is saving power, and thus a certain amount of monetary units, by offloading some traffic to indoor FAPs and thus switching off its own small cell base stations. Part of the saved money by the operator could be used as incentives for FAP indoor users for opening their FAPs to the network. For instance, these incentives could be as discounts on their monthly telecommunication bills, free subscription in certain offers of the operator, or even discounts on their electricity bills, e.g., price of power used to serve outdoor users is compensated by the mobile operator (this needs an agreement though between the mobile operator and power retailer). Therefore, when applied to outdoor users, the Hungarian algorithm (i.e., Step 3) constructs a matrix that contains the remaining FAPs’ RBs in addition to the macrocell and small cell RBs. In this case, the problem complexity will increase but it is expected to achieve better performance by offering more degrees of freedom to the system as it is shown in the simulation result section.

In our simulation results, we investigate and compare the performance of all these scenarios in addition to the performance of the proposed low complexity algorithm which is described in the following section.

4.4 Low Complexity Algorithm for Switching off Small Cell Base Stations

As it will be shown in Section 4.5, the run-time of the optimal dual decomposition solution proposed in Section 4.3.2, where the optimization of RB allocation, power, small
cell base station status is performed simultaneously, is considerably high. Thus, we propose a low complexity suboptimal algorithm to cope with this problem. In this section, we propose to optimize the binary vector $\pi$, the binary matrix $\epsilon$, and the transmitted power vector $P$ in an iterative way such that the algorithm complexity is significantly reduced.

The basic idea of the algorithm is to eliminate redundant small cell base stations without affecting the QoS. At each iteration, we consider initially uniform power allocation. Then, we perform RB allocation using the Hungarian method considering only the active base stations. This will reduce the complexity problem since the method is no more based on the sub-gradient method to find the Lagrangian multipliers. In addition to that, the size of the Hungarian matrix will be only based on the RBs of the switched on base stations. At each iteration, the algorithm switches off one base station, finds the related suboptimal power and RB allocation and verifies whether the absence of this base station degrades the QoS. If it is the case, the base station can not be eliminated. Otherwise, it can be safely switched off.

In order to solve the optimization problem formulated in (4.10)-(4.13) in a low complexity manner, we proceed, at each iteration, as follows

- **Step 1:** Simplify the optimization problem by distributing the peak power of the $s^{th}$ base station uniformly over its belonging RBs (i.e., $\bar{P}_{s,r} = \frac{P}{N_{RB}}$) where $P_{r,s}$ is the peak transmit power at the $r^{th}$ RB of the $s^{th}$ base station. This means that constraint (4.11) becomes as follows

\[
P_{s,r} \leq \bar{P}_{s,r}, \forall s = 0, \ldots, L_s.
\]  

(4.23)
Thus, the solution of the optimization problem becomes as follows:

$$P_{s,r} = \begin{cases} 
\frac{A_{th}}{h_{u,s,r}}, & \text{if } h_{u,s,r} \geq \frac{A_{th}}{P_{s,r}}, \\
0, & \text{otherwise},
\end{cases} \quad (4.24)$$

where $A_{th} = \left(2^{\frac{P_0}{2P_{RB}}} - 1 \right) (I_{u,r} + N_0)$. The obtained solution derived in (4.24) means that the user $u$ served by the $s^{th}$ base station over RB $r$ can achieve its data rate only if the corresponding channel is relatively good.

- **Step 2**: Compute $P_{s,r}$ for all possible (RB, outdoor user) combinations.

- **Step 3**: Employ the combinatorial optimization approach: the Hungarian algorithm [78] to find the best (RB, user) combinations that maximizes the total number of served users with minimum power consumption. However, in some cases due to the modification of constraint (4.11), this method with the Hungarian algorithm is not enough to serve the maximum number of outdoor users. Indeed, after allocating the RBs, some users may not achieve the required rate because of the power limitation as expressed in (4.23).

- **Step 4**: If the number of served users denoted $U_{served}$ is less than $U$, redistribute uniformly the remaining power over the remaining RBs ($\bar{P}_{s,r} = \bar{P}_{s,r} - \sum_{s=1}^{N_{RB}} P_{s,r}$) and repeat Steps 1 to 3 for the non-served users. In fact, the peak power per RB may increase comparing to **Step 1**.

- **Step 5**: Repeat **Step 4** until serving all users or the remaining power per RB is not enough to achieve the user target data rate. In the latter case, try to serve at least one user among of the remaining users by allocating the total remaining power to the user having the best channel gain. Note that, most of the time, the last case might appear when the number of users is close to the number of available RBs in the network.
while this contradicts our assumption used to employ the dual decomposition method that states that the duality gap is negligible as the number of RBs is sufficiently large compared to the number of users connected to the network. Thus, this case is not considered in our method.

Details of the proposed low complexity algorithm are summarized in Algorithm 5. Once we find the base station status vector $\pi^*$, the allocation matrix $\epsilon^*$ and the corresponding total power consumption $P$ using the low complexity suboptimal approach, we compare the obtained results with the optimal solution obtained using the dual decomposition method. As it will be shown in the sequel, the proposed approach achieves very close performance comparing to the optimal solution with a notable gain in terms of computational complexity.

4.5 Simulation Results

A HetNet consisting of one macrocell base station, $L_s$ small cell base stations and $L_f = L_s$ FAPs is deployed to serve $U$ outdoor users and $L_f V$ indoor users (we assume that the number of indoor users is the same for each FAP; $V_l = V = 10$, $\forall l = 1, \cdots , L_f$). An orthogonal LTE transmission where the total bandwidth of $B_T = 20$ MHz is subdivided into two blocks. The first block of 15 MHz (equivalent to 75 orthogonal RBs) is owned by the macrocell ($N_{RB}^{(0)} = 75$), while the other block, of 5 MHz (equivalent to 25 orthogonal RBs), are owned by small cells and their corresponding FAPs ($N_{RB}^{(s)} = 25$). Hence, the same frequency blocks are reused with two consecutive small cells/FAPs. Also, we assume that all users within the small cells are protected from the co-channel interference caused by other small cells as they are deployed sparsely. The only interference considered in our framework is the cross-tier interference between the small cell and its corresponding FAP. The channel parameters are picked out from [74] and are given as follows: $\kappa = 15.3$ dB,
Algorithm 5 Iterative Algorithm for Green Switching off Small Cell Base Stations with Power and RB Allocation

1: Compute the total power consumption function $P_{\text{min}} = P_{\text{tot}}^{(0)}$ when all small cell base stations are switched on ($A$ set $S$ contains all small cell base stations and $\pi = [1, \ldots, 1]$).
2: Initialize for the current iteration $S^{\text{iter}} = S$ and $L_s^{(\text{iter})} = L_s$.
3: repeat
4: for $s = 1, \ldots, L_s^{(\text{iter})}$ do
5: Eliminate the small cell base station $s$ from $S^{\text{iter}}$, $\pi^{(s)} = [1 \cdots 1 \cdots 0 \cdots 1]$ where 0th position
6: Initialize $U = \{1, \ldots, U\}$, $N_{\text{RB}} = \{1, \ldots, N_{\text{RB}}^{(L_s)}\}$, $U_{\text{served}} = 0$.
7: repeat
8: Compute the transmit powers $P_{s,r}$ as it is given in (4.24) for each $(u, r) \in (U, N_{\text{RB}})$ pairs.
9: Find $(u^*, r^*)$ combinations by employing the Hungarian algorithm in order to serve the maximum number of users with minimum power consumption.
10: Mark $(u^*, r^*)$ combinations as occupied (i.e., update $\epsilon$).
11: $U = U \setminus \{u^*\}$, $N_{\text{RB}} = N_{\text{RB}} \setminus \{r^*\}$ and $U_{\text{served}} = U - |U|$.
12: $\bar{P}_s = \bar{P}_s - \sum_{r \in N_{\text{RB}}^{(s)}} P_{s,r}$.
13: until $(U_{\text{served}} = U || \bar{P}_s$ remains constant).
14: if $(U_{\text{served}} < U)$ then
15: while $\exists (u, r) \in U \times N_{\text{RB}}$ such that $h_{u,s,r} \geq \frac{A_{\text{th}}}{P_s}$ do
16: $h_{u,s,r} = \max_{(u_b, r_b) \in (U \times N_{\text{RB}})} h_{u_b,s,r_b}$.
17: Find the transmit power $P_{s,r_b}$ corresponding to $r_b$ by computing (4.24).
18: Mark $(u_b, r_b)$ pair as occupied (i.e., update $\epsilon$).
19: $U = U \setminus \{u_b\}$, $N_{\text{RB}} = N_{\text{RB}} \setminus \{r_b\}$ and $U_{\text{served}} = U - |U|$.
20: $\bar{P}_s = \bar{P}_s - \sum_{r \in N_{\text{RB}}} P_{s,r}$.
21: end while
22: end if
23: end for
24: Find the small cell base station $s_{\text{op}}$ that, when eliminated, provides the lowest power consumption while satisfying the network QoS $(P_{\text{new}}^{(s_{\text{op}})} = \min_s P_{\text{tot}}^{(s)}$).
25: if $P_{\text{new}}^{(s_{\text{op}})} \leq P_{\text{min}}$ then
26: Base station $s_{\text{op}}$ is eliminated, $S^{\text{iter}} = S^{\text{iter}} \setminus \{s_{\text{op}}\}$, $L_s^{\text{iter}} = L_s^{\text{iter}} - 1$ and $P_{\text{min}} = P_{\text{new}}^{s_{\text{op}}}$.
27: end if
28: until (No base stations can be eliminated).
29: The final optimal set of active small cell base stations is $S^{\text{iter}}$. 
In Fig. 4.2, we plot the total power consumption of the network versus the number of outdoor users using the proposed methods, i.e., the dual decomposition method and the low complexity iterative algorithm, for three different scenarios (MS, MSF-closed and MSF-hybrid). We also compare their performances with the traditional scenario where all small cell base stations are kept active. We are assuming that $L_s = 4$ small cells are deployed and $R_0 = 0.5$ Mbps. In general, the total power consumption increases with the total number of outdoor connected users for all cases but it differs from a scenario to another. For instance, MSF-closed scenario consumes more power than the MS case as it considers the existence of indoor interferers which enforces base stations to increase their transmit power. However, we can see that MSF-hybrid scenario provides an interesting gain in terms of energy saving compared to the other cases as FAPs allow outdoor users to exploit their redundant resources (i.e., RBs). For instance, for $U = 100$, MSF-hybrid can save about 18% of the consumed energy compared to the MSF-closed case.
Figure 4.3: Total power consumption using the dual-decomposition method versus the number of outdoor users for different target data rates and $L_s = 4$ (a) MS (b) MSF-closed and (c) MSF-hybrid.
Compared to the traditional scenario, the small cell sleeping strategy can achieve a significant gain mainly when the traffic is low as it shows Fig. 4.2. About 45% is the obtained gain when switching off the small cell base stations. Of course, this gain is reduced as the number of users increases.

Concerning the employed algorithms, we can see that the iterative algorithm is able to achieve a close performance to the optimal solution obtained using the dual decomposition method for all considered scenarios. This small difference is because the low complexity method does not achieve the optimal solution during the resource allocation process and not during the on/off switching operation which its corresponding error might lead to a considerable increase (additional $b_s$ of (4.5)). Indeed, due to the reduced number of small cell base stations ($4−8$), the error in selecting the optimal active small cells is very small. Despite this minor limitation, the iterative algorithm can considerably help in reducing the computational complexity of the problem compared to the optimal method that requires an important time to converge. Therefore, we investigate in Table 4.1 the CPU times in seconds of both algorithms for the three investigated scenarios. All tests are performed on a desktop machine featuring an Intel Xeon CPU and running Windows 7 Professional. The clock of the machine is set to 2.66 GHz with a 48 GB. The computation time is obtained via the TIC/TOC function of Matlab.

Another remark that can be deduced from Table 4.1 is that the MS and MSF-closed scenario requires almost the same CPU times to converge for both methods. However, the MSF-hybrid which achieves a notable power saving gain, requires more time to converge. This is because with MSF-hybrid the size of the Hungarian matrix is larger as it also includes the redundant RBs of FAPs.

Fig. 4.3 plots the total power consumption of the network versus the number of outdoor users using the dual-decomposition method for three different values of $R_0$ (0.5, 0.75 and 1 Mbps). The number of deployed small cells is fixed to 4 and $V = 10$ for the MSF-
Figure 4.4: Network power consumption versus the number of deployed small cells for $U = 125$, $V = 10$ and $R_0 = 0.5$ Mbps.

closed and MSF-hybrid scenarios. The figure shows the behavior of the small cell sleeping strategy when the target data rates varies. We notice that the power consumption profile is the same with the three scenarios and that increasing $R_0$ imposes the consumption of additional transmit power and not activating additional small cells. Note that the number of active small cells can be determined from the total power consumption. Indeed, due to the constant term $b_s = 71$ W, we can see that the total power consumption jumps by about $b_s$ when a small cell is activated. For example, using MS or MSF-closed for $R_0 = 0.5$ Mbps, when the number of users goes from 75 to 100, we can see that the power consumption largely varies compared to the variation from 50 to 75 users. However, this is not happening with the MSF-hybrid scenario. In this case, when $U = 100$, the network is not obliged to activate a new base station to serve the users but it can exploit the redundant deployed FAP

Table 4.1: CPU times in seconds of the proposed methods

<table>
<thead>
<tr>
<th></th>
<th>Iterative algorithm</th>
<th>Dual decomposition method</th>
</tr>
</thead>
<tbody>
<tr>
<td>MS</td>
<td>16.25</td>
<td>73.53</td>
</tr>
<tr>
<td>MSF-closed</td>
<td>18.84</td>
<td>76.53</td>
</tr>
<tr>
<td>MSF-hybrid</td>
<td>27.32</td>
<td>118.6</td>
</tr>
</tbody>
</table>
In Fig. 4.4, we plot the total network power consumption versus the number of deployed small cells $L_s$ which is equal to $L_f$. We set $U = 125$ users and $R_0 = 0.5$ Mbps. The figure investigates the impact of deploying more small cells on the network power consumption while applying the sleeping strategy using the dual decomposition method. We notice that having more small cells offers to the network more degrees of freedom to the network to activate the best small cell combination and thus reduce the power consumption. With MS and MSF-closed scenarios, the power consumption decreases in the same manner by reducing the transmit power (i.e., reduce the term $a_{BS}P_{BS}^r$ in (4.5)) while with the MSF-hybrid, a gain large gain is obtained as we are completely turning off base stations in this case (i.e., reduce the term $a_{BS}P_{BS}^r + b_{BS}$ in (4.5)). Indeed, as the number of FAPs increases, the green network prefers to offload its users to the FAPs than keeping the small cells active.

Fig. 4.5 plots the total power consumption of the network versus the number of indoor users connected to FAPs for the scenarios MSF-closed and MSF-hybrid. Commonly, the network power consumption increases with the increase of the number of interferers $V$. 

Figure 4.5: Network power consumption versus number of indoor users connected to FAPs for $U = 125$, $R_0 = 0.5$ Mbps, and $L_s = 4$. 

infrastructure and thus save more energy.
However, we can clearly deduce the advantages of the cooperation between the network and the deployed FAPs mainly when the number of indoor users is low. During these periods, the network manages to offload its users located close to the switched off small cells to FAPs. Thus, the network can ensure an important gain in terms of power. Trivially, when the number of indoor users reaches 25, i.e., no more free RBs, the MSF-hybrid scheme consumes the same power as the MSF-closed scenario.

### 4.6 Summary

In this chapter, we focused on the energy efficiency of LTE-HetNets by formulating an optimization problem that minimizes the total power consumption of the network. The power saving is ensured by optimizing the resource allocation in addition to the on/off switching operation. Two methods were proposed to achieve this green target. An optimal and complex dual decomposition-based method and a near-optimal and low complexity iterative algorithm. Furthermore, we have compared between three scenarios depending on the status of indoor femto access points (absent, closed or hybrid). Our results encourage private indoor cells to cooperate more with mobile operators to contribute in the reduction of energy consumption and CO$_2$ emissions as well.

This study focused only on the energy consumption of the network. It can be extended by developing algorithms or game theoretical approach for the hybrid scenario in order to optimize the collaboration between the mobile operator and private femto access points. As heterogeneous networks are one of the main challenges of 5G cellular network, optimized collaboration techniques should provide more advantages for the different actors.
Part II

On the Interplay Between Green Mobile Networks and the Smart Grid
Chapter 5

Optimized Smart Grid Energy

Procurement for LTE Networks Using

Evolutionary Algorithms

5.1 Introduction

By improving the energy efficiency of BSs in cellular networks, large savings can be obtained in both environmental and cost point of view. As mentioned in Section 1.1, mobile networks could save 1.7\% of global CO$_2$ emissions by 2020 [1]. By optimizing the BS energy consumption which represents 80\% of the total consumption of cellular networks, we can decrease the effect of CO$_2$ emissions, reduce energy cost and find solutions in the case of limited availability of electrical grid. Many approaches have been investigated to minimize BS energy consumption by improving BS energy efficiency or shutting down redundant BSs during low traffic. Renewable energies can also be introduced as alternative sources to supply the network.

Several research work tried to ensure power savings in LTE networks by introducing femto cells and relays. For instance, in [80] and [81], using different algorithms, results
showed that by resizing cells or/and by introducing relays in the network, the total power consumption of the RAN can be reduced. However, these methods forced mobile operators to re-deploy new femto BSs and relays inside each macro cell of existing networks which make these solutions very costly.

The BS sleeping strategy idea consists in turning off lightly loaded BSs when QoS permits during low traffic periods to achieve energy savings in the LTE network. Several efforts as [82] and [22] were proposed to employ it with different QoS metrics. In fact, the system model of [82] is based on an LTE radio network where resource allocation is done through LTE RBs. The algorithm takes into account the UL and the DL directions. The decision criterion for shutting down BSs is based on computing a utility function that maximizes the number of served users in the network. On the other hand, to switch off a BS, El-Beaino et al. [22] computed the total SINR which is the sum of SINRs of all active users in the network and compared it to a fixed SINR threshold: if it is greater than the SINR threshold, the switched off BS is underutilized and is maintained off. Both algorithms dealt with the BS sleeping strategy to achieve energy savings but they did not consider renewable energy suppliers and active participation of mobile networks in the procurement decision. The methods in [82], [22], and [21] do not take into account the smart grid advantages of providing multiple energy retailers and the introduction of green energy for an environmentally friendly operation of the cellular network. In [83], an approximate solution to the problem was proposed where the sleeping strategy is applied to eliminate underutilized BSs. The main idea is to establish a relationship between the traffic load (user arrival) and energy savings. The solution is obtained by solving an optimization problem which has as objective to minimize the number of active BSs subject to two constraints: maintaining the user connection in the cell and covering the same initial area.

Also, smart grid which contains varied energy retailers (e.g., electricity generated from fossil fuels or from renewable energy sources) can improve cellular network energy con-
sumption by dealing with the dynamic operation of BSs that depends on the traffic, real-time pricing provided by the smart grid, and the pollutant level associated with the generation of the electricity [84]. Most of the work related to smart grid applications deals with residential environment, e.g., [85–87]. Few work such [84] investigated the demand side management in the smart power grid with cellular networks. Indeed, the authors introduced the use of coordinated multi-point communication to ensure acceptable QoS in cells whose BSs have been shut down to save power. The active BSs decide from which retailers they procure electricity and how much power is required considering the pollutant level of each retailer and the proposed price. They modeled the system as a Stackelberg game, which has two levels: a cellular network level plays the role of the follower and a smart grid level plays the role of a leader. The scheme proposed in [84] can reduce operational expenditure and CO$_2$ emissions in green wireless cellular networks. However, in [83] and [84], intercell interference, resource allocation, and fading variations are not taken into account.

In this chapter, we formulate a practical optimization problem that deals with the BS sleeping strategy. It is solved using two well-known evolutionary approaches: GA and binary PSO. In fact, these algorithms are strong optimization tools used in various scenarios, particularly in several applications for wireless and mobile communications such as resource allocation [88], energy efficiency [89] or coverage optimization [90]. In this chapter, the BS sleeping strategy is implemented using GA or PSO in order to minimize the energy consumption of the LTE cellular network, reduce the CO$_2$ emissions in the green LTE cellular network, maximize the profit of the network operator, and maintain a certain desired level of QoS, simultaneously. This is performed given the nature and the cost of the provided energies in the smart grid in addition to the unitary prices of the mobile network operator services. The performance of the employed algorithms are compared with a recent iterative approach, denoted IA, that we presented in [91].

The contributions of this chapter compared to the existing literature can be summarized
as follows:

- The state-of-the-art LTE technology is considered. The DL and UL directions are investigated where OFDMA and SC-FDMA are adopted, respectively. In addition, we consider the existence of intercell interference and we assume a limited power budget for each BS. Furthermore, radio resource allocation is implemented in order to ensure the best use of the available radio resources.

- A novel optimization problem is formulated. The problem aims to maximize the profit of the mobile network operator, minimize the emission of greenhouse gas, or achieve a tradeoff between both objective functions while maintaining a desired level of QoS by turning off lightly loaded BSs and optimizing the energy procurement from public and private electricity retailers.

- Evolutionary algorithm based approaches for implementing the BS sleeping strategy are proposed in order to solve the formulated problem. The performance of the proposed GA-based scheme and PSO-based scheme are compared to each other and to a recent approach that we presented in [91]. More details about the algorithm of [91] are given in Section 5.5.

The rest of this chapter is organized as follows. Section 5.2 presents the system model. Section 5.3 describes the problem formulation. The solution strategy and the proposed evolutionary and iterative algorithms are detailed in Section 5.4 and Section 5.5, respectively. Simulation results and complexity analysis are presented in Section 5.6. Finally, the conclusions are drawn in Section 5.7.
5.2 System Model

We consider a geographical area where an LTE network is deployed. We divide the area into cells of equal size where a BS is placed in the center of each cell. In LTE, the access scheme for the DL is OFDMA while in the UL it uses the SCFDMA. In fact, the available spectrum is divided into RBs that contains a fixed number of consecutive subcarriers. A set of RBs are assigned to users according to the allocation procedure described in Section 2.5.2. We also adopt the channel model given in Section 2.5 in addition to the UL and DL data rate expressions while assuming that all transmitters are equipped with a single omni-directional antenna (i.e., the antenna gains $G^{BS} = G^{MS} = 1$).

5.2.1 Energy Consumption Model for Base Stations

Similarly to (4.5) in Chapter 4, the consumed power $P^{BS}_j$ of the $j^{th}$ active BS can be computed as follows [76]:

$$P^{BS}_j = a P^{tx}_j + b,$$

(5.1)

where $P^{tx}_j$ denotes the radiated power of the $j^{th}$ BS, $a$ corresponds to the power consumption that scales with the radiated power, and $b$ models the offset of site power.

5.2.2 Retailers and Pollutant Levels

In our study, we assume that the cellular network is powered by a smart grid where $N$ retailers exist to provide energy with different prices and pollutant levels depending on the nature of the generated energy. The procurement decision is based on the cost (i.e., the unitary price of the provided energy) $\pi^{(n)}$ and a penalty term corresponding to the pollutant
emission function modeled as follows [84, 92–94]:

\[
F(q^{(n)}_j) = \alpha_n \left( q^{(n)}_j \right)^2 + \beta_n q^{(n)}_j,
\]

(5.2)

where \(\alpha_n, \beta_n\) are the emission coefficient costs of retailer \(n\) and \(q^{(n)}_j\) is the amount of energy procured by the \(j^{th}\) BS from retailer \(n (n = 1 \cdots N)\) during a period of time \(T\). In addition, we suppose that each retailer has a maximum available amount of energy. For instance, the network can not procure from the renewable energy retailer more than a certain constant \(Q^{(n)}_{\text{max}}\) (i.e., \(\sum_{j=1}^{N_{\text{BS}}} q^{(n)}_j \leq Q^{(n)}_{\text{max}}\)).

\subsection*{5.2.3 Operator Services}

In our framework, the network operator offers \(M\) different services characterized by their data rate thresholds \(R^{(UL)}_{m,\text{th}}\) and \(R^{(DL)}_{m,\text{th}}\) for UL and DL, respectively, and their unitary prices \(p^{(m)}\) with \(m = 1 \cdots M\), expressed in monetary unit (MU). We suppose that each user in the network benefits from one of the \(M\) offered services.

In our system model presented in Fig. 5.1, the group of BSs providing cellular coverage to an area of interest operate together to procure the needed energy from the smart grid. The BSs collaborate and interact to implement a green algorithm to determine the number of active BSs required to serve the users and the needed energy for the network operation. The activation/deactivation and procurement decisions are taken in a centralized smart control center that plays the role of an interface between the smart grid and the group of BSs. Based on this system model and these parameters, we formulate an optimization problem where the mobile network operator is able to optimally procure energy from the smart grid to power its BSs and apply the sleeping strategy with evolutionary algorithms in order to achieve energy savings.
Figure 5.1: Cellular network powered by the smart electrical grid.

5.3 Problem Formulation

We adopt the admission control and resource allocation scheme presented in Section 2.5.2. Note that if the resource allocation algorithm finds out that a user will be in outage when the best available resources are allocated to him, the resources are freed and made available for other users. The initial user is still considered in outage, but the resources are used more efficiently.

We assume that \(N_{BS}\) BSs are deployed and \(N_U\) users are randomly distributed in the area of interest. We denote by \(N_{out}\) the number of users that are not able to communicate with BS at the desired QoS level \(N_{out} \ll N_U\). A user \(i\) benefiting from the \(m\)th service communicates successfully with a BS, if its UL and DL data rates, denoted \(R_i^{(UL)}\) and \(R_i^{(DL)}\) respectively, are higher than the service data rate thresholds, \(R_{m,th}^{(UL)}\) and \(R_{m,th}^{(DL)}\) respectively. We associate a binary parameter \(\gamma_i, i = 1 \cdots N_U\) to each user: if the user \(i\) is served...
successfully then \( \gamma_i = 1 \) else \( \gamma_i = 0 \). We can express this assumption as follows:

\[
\gamma_i = \begin{cases} 
1 & \text{if } R_i^{(UL)} \geq R_{m,th}^{(UL)} \text{ and } R_i^{(DL)} \geq R_{m,th}^{(DL)}, \\
0 & \text{if } R_i^{(UL)} < R_{m,th}^{(UL)} \text{ or } R_i^{(DL)} < R_{m,th}^{(DL)}.
\end{cases}
\]  

(5.3)

In other words, if \( \gamma_i = 0 \) the \( i \)th user is in outage. If we denote \( \gamma = [\gamma_1 \cdots \gamma_{NU}] \), then the number of ones and the number of zeros in \( \gamma \) correspond to the number of served users and the number of users in outage, respectively. Consequently, only the served users pay the equivalent of the proposed service. Hence, the operator network revenue \( \mathcal{R} \) is expressed as follows:

\[
\mathcal{R}(\gamma) = \sum_{i=1}^{NU} \gamma_i p_i^{(m)}.
\]  

(5.4)

where \( p_i^{(m)} \) is the cost of the service \( m \) used by the \( i \)th subscriber. Besides, in order to include the BS sleeping strategy in the problem formulation, we introduce a binary variable \( \epsilon_j \) with \( j = 1 \cdots N_{BS} \) to denote the BS state as follows:

\[
\epsilon_j = \begin{cases} 
1 & \text{if BS } j \text{ is switched on,} \\
0 & \text{if BS } j \text{ is switched off.}
\end{cases}
\]  

(5.5)

Let \( \epsilon = [\epsilon_1 \cdots \epsilon_{N_{BS}}] \). The number of ones and the number of zeros in this vector indicate the number of active and inactive BSs, respectively. Note that each BS can procure energy from different retailers at the same time. Hence, both the total cost of the energy consumption and the \( \text{CO}_2 \) emission cost function caused by the cellular network depend only on the active BSs and the nature of the procured energy as it is given in the following expressions:

- The total cost of the energy consumption of the network \( \mathcal{C} \):

\[
\mathcal{C}(\epsilon, q) = \sum_{j=1}^{N_{BS}} \sum_{n=1}^{N} \epsilon_j \pi_j^{(n)} q_j^{(n)}.
\]  

(5.6)
The CO₂ emission cost function of the network $\mathcal{I}$:

$$
\mathcal{I}(\epsilon, q) = \sum_{j=1}^{N_{\text{BS}}} \sum_{n=1}^{N} \epsilon_j \left( \alpha_n \left( q_j^{(n)} \right)^2 + \beta_n q_j^{(n)} \right),
$$

(5.7)

where $q = \left[ q_1^{(1)} \cdots q_1^{(N)} \ q_2^{(1)} \cdots q_2^{(N)} \cdots q_{N_{\text{BS}}}^{(N)} \right]^T$ is the vector that contains the procured energy amount, with $q_j^{(n)}$ the amount procured by the $j^{th}$ BS from the $n^{th}$ energy source and $\pi^{(n)}$ is the cost of one unit of energy provided by the $n^{th}$ retailer where $j = 1 \cdots N_{\text{BS}}$ and $n = 1 \cdots N$. The function $\mathcal{I}(\epsilon, q)$ reflects the friendliness to the environment of the mobile network operator and corresponds to the CO₂ emissions caused by its total network energy consumption. Renewable energies present a solution for network operators to reduce greenhouse gas emissions. To procure this green energy, the network operator has to buy the required amount of energy from a public renewable energy retailer. If the produced renewable energy is not enough to cover the need of all BSs, the network operator can procure additional energy from other retailers existing in the smart grid that always have a sufficient amount of energy. Consequently, the mobile operator has to optimally compute the amount of energy to procure from the smart grid in order to maximize the following utility function:

$$
U = (1 - \omega) \mathcal{P}(\gamma, \epsilon, q) - \omega \mathcal{I}(\epsilon, q),
$$

(5.8)

where $\omega$ is a parameter to be defined, $\mathcal{I}(\epsilon, q)$ is given in (5.7) and $\mathcal{P}(\gamma, \epsilon, q)$ is a function that corresponds to the mobile operator’s profit. It is given by:

$$
\mathcal{P}(\gamma, \epsilon, q) = \mathcal{R}(\gamma) - \mathcal{C}(\epsilon, q).
$$

(5.9)

The objective is now to solve a multi-objective optimization (or Pareto optimization)
problem by constructing a single aggregate objective function [95] which corresponds to a weighted linear sum of the objective functions (5.7) and (5.9). These functions are weighted by a parameter $\omega$ called the Pareto weight ($0 < \omega < 1$). The elements of the vector $\mathbf{q} = [q_1^{(1)} \cdots q_1^{(N)} q_2^{(1)} \cdots q_2^{(N)} \cdots q_{N_{BS}}^{(N)}]^T$, the binary variables $\gamma_i$, $i = 1 \cdots N_U$ and $\epsilon_j$, $j = 1 \cdots N_{BS}$ are the decision variables of the problem. When $\omega \to 0$, we are dealing with the utility function given in (5.9). This corresponds to a selfish network operator that aims to maximize its own profit $\mathcal{P}$ regardless of its impact on the environment. When $\omega \to 1$, we deal with the utility function given in (5.7), which corresponds to an environmentally friendly network operator that aims to reduce CO$_2$ emissions regardless of its own profit. Other values of $\omega$ constitute a tradeoff between these two extremes. In other words, $\omega$ indicates the operator’s attitude towards the environment. Hence, the optimization problem is expressed as follows:

$$\text{Maximize} \quad U = (1 - \omega) \mathcal{P}(\gamma, \epsilon, \mathbf{q}) - \omega \mathcal{I}(\epsilon, \mathbf{q}), \quad (5.10)$$

Subject to:

$$\sum_{j=1}^{N_{BS}} \epsilon_j q_j^{(n)} \leq Q_j^{(n)} \forall n = 1 \cdots N, \quad (5.11)$$

$$\sum_{n=1}^{N} q_j^{(n)} = P_j^{BS} T \forall j = 1 \cdots N_{BS}, \quad (5.12)$$

$$\frac{N_{out}}{N_U} \leq P_{out}, \quad (5.13)$$

$$q_j^{(n)} \geq 0 \forall j = 1 \cdots N_{BS} \text{ and } \forall n = 1 \cdots N. \quad (5.14)$$

The constraint (5.11) indicates that the energy consumed by all BSs in the cellular network from energy retailer $n$ cannot exceed the total energy provided by that retailer while (5.12) indicates that the amount of energy drawn by a BS from all retailers should be equal to the power needed for its operation during a period $T$, (5.13) forces the number of users in outage to be less than a tolerated outage probability threshold $P_{out}$ and (5.14) is a trivial
constraint expressing the fact that the energy drawn is a positive amount. It should be noted that, when a certain retailer $n$ can provide to the mobile network operator enough electricity to power all the BSs in the network, we can set $Q_{\max}^{(n)} = +\infty$ to relax the constraint (5.11) for that retailer, although in practice the amount of energy produced is naturally finite.

5.4 Evolutionary Algorithms for Green Energy Procurement

The formulated problem in Section 5.3 is considered as a combinatorial optimization problem due to the existence of binary variables ($\gamma_i$ and $\epsilon_j$) as decision variables which makes the optimal and exact solution of this nonlinear optimization problem difficult or even impossible to find [95]. Therefore, we employ heuristic algorithms, GA [96] and binary PSO [97], where binary strings (or particles) are used to represent the solutions. In our case, a binary entry (i.e., string for GA or particle for PSO) corresponds to the vector $\epsilon$ which refers to a combination of BSs. The idea is to find the optimal binary string $\epsilon$ that maximizes the utility function expressed in (5.8). The formulated problem is an NP-hard optimization problem since its simplified version that consists in setting BSs on/off to ensure energy efficiency for a fixed electricity procurement and solved using stochastic search algorithms is an NP-hard problem [98].

5.4.1 Genetic Algorithm

Initially, the GA generates $L$ binary strings of length $N_{BS}$ forming a set called initial population $\mathcal{S}$. For each element of $\mathcal{S}_0$, $\epsilon^{(l)}$, $l = 1 \cdot L$ of length $N_{BS}$ and after applying the resource allocation algorithm for the $l^{th}$ combination, the algorithm computes the data rates of all users and compares them to the data rate thresholds of the corresponding services. By
this way, it identifies the users in outage and consequently the value of the vector $\gamma^{(l)}$. Next, we compute the utility function $U_l$ after procuring optimally the energy from the available retailers in the smart grid by solving the optimization problem formulated in (5.10). In fact, as $\epsilon^{(l)}$ and $\gamma^{(l)}$ are known and fixed, the problem becomes a quadratic concave optimization problem that has a unique optimal solution and depends only on one decision variable: the vector $q^{(l)}$. After computing $L$ utilities $U_l$ associated to each $\epsilon^{(l)}$, we select the $L_b$ ($L_b < L$) strings having the highest utilities on which we apply crossovers and mutations to generate a new population $S_1$. Many genetic algorithm models are used in literature. The variation depends on the selection and the reproduction procedure. In our case, $L_b$ ‘survival’ strings are kept to the next generation while $L - L_b$ new strings are produced by crossover two strings (also called parents) selected randomly from the $L_b$ parents having the highest utilities. The crossover point is chosen randomly between two fixed positions from 1 to $N_{BS}$. By swapping the obtained fragments, two new strings are produced. After recombination, we can apply the mutation with a probability $p_M$. The mutation consists of changing randomly a bit value of the generated strings of the new population. Thus, if a mutation was decided for string $\epsilon^{(l)}$ with probability $p_M$, a position is randomly selected among the $L$ positions, and its value is flipped from 0 to 1 or vice-versa. Fig. 5.2 describes in details the generation of a new population in GA after solving our formulated problem. After the process of selection, reproduction and mutation is completed, the next population can be generated. This procedure is repeated until convergence is reached. Details of the proposed method using the GA are given in Algorithm 6: Convergence is reached when $U_{\text{max}}$ remains constant for a fixed number of several successive iterations. At the end, the best obtained BS combination is $\epsilon^{\text{max}}$. 
5.4.2 Particle Swarm Optimization Algorithm

Similarly to the GA, the PSO starts by generating $L$ particles $\epsilon^{(l)}$, $l = 1 \cdots L$ of length $N_{BS}$ to form an initial population $\mathcal{S}$. Then, it computes the utility achieved by all particles and finds the particle that provides the global optimal utility for this iteration, denoted $\epsilon^{\text{max}}$. In addition, for each particle $l$, it maintains a record of the position of its previous best performance, denoted $\epsilon^{(l,\text{local})}$. Then, at each iteration $t$, PSO computes a velocity
Algorithm 6 Genetic Algorithm for Green Energy Procurement and BS sleeping strategy

Generate an initial population $S$ composed of $L$ random strings $e^{(l)}$, $l = 1 \cdots L$.

while Not converged do
    for $l = 1 \cdots L$ do
        Allocate resources (select serving BS, and DL and UL RBs) to all users.
        Compute $\gamma^{(l)}$ and $N^{(l)}_{\text{out}}$ corresponding to the string $e^{(l)} \in S$.
        if $\frac{N^{(l)}_{\text{out}}}{N_U} \leq P_{\text{out}}$ then
            Find $\tilde{q}^{(l)}$ by solving the quadratic optimization problem formulated in (5.10) given $e^{(l)}$ and $\gamma^{(l)}$ and compute the corresponding utility $U_l$.
        else
            $e^{(l)}$ violates the outage probability constraint and cannot be an acceptable solution. Consequently, we set $U_l = -\infty$.
        end if
    end for
    Find $l_m = \arg \max_l U_l$ (i.e., $l_m$ indicates the index of the string in $S$ that results in the highest utility). Then set $U_{\max} = U_{l_m}$ and $e_{\max} = e^{(l_m)}$.
    Maintain the best $L_b$ strings in $S$ to the next population and from them, generate $L - L_b$ new strings by applying crossovers and mutations to form a new population $S$.
end while

term $V_j^{(l)}$ as follows:

$$V_j^{(l)}(t + 1) = V_j^{(l)}(t) + \phi_1 \left( e_j^{(l, \text{local})}(t) - e_j^{(l)}(t) \right) + \phi_2 \left( e_{\max}^{(l)}(t) - e_j^{(l)}(t) \right)$$

(5.15)

where $\phi_1$ and $\phi_2$ are two random positive numbers generated for each $j$. Then, it updates each element $j$ of a particle $e^{(l)}$ as follows:

$$e_j^{(l)}(t + 1) = \begin{cases} 1 & \text{if } r_{\text{rand}} < \Phi \left( V_j^{(l)}(t + 1) \right), \\ 0 & \text{otherwise.} \end{cases}$$

(5.16)

where $r_{\text{rand}}$ is a pseudo-random number selected from a uniform distribution in $[0, 1]$ and $\Phi$ is a sigmoid function for transforming the velocity to probabilities as the following expres-
Algorithm 7 Binary Particle Swarm Optimization Algorithm for Green Energy Procurement and BS sleeping strategy

Generate an initial population $S$ composed of $L$ random particles $\epsilon^{(l)}$, $l = 1 \cdots L$.

while Not converged do
  for $l = 1 \cdots L$ do
    Allocate resources (select serving BS, and DL and UL RBs) to all users.
    Compute $\gamma^{(l)}$ and $N^{(l)}_{\text{out}}$ corresponding to the particle $\epsilon^{(l)} \in S$.
    if $\frac{N^{(l)}_{\text{out}}}{N_U} \leq P_{\text{out}}$ then
      Find $\tilde{q}^{(l)}$ by solving the quadratic optimization problem formulated in (5.10) given $\epsilon^{(l)}$ and $\gamma^{(l)}$ and compute the corresponding utility $U_l(t)$.
    else
      $\epsilon^{(l)}$ violates the outage probability constraint and cannot be an acceptable solution. Consequently, we set $U_l(t) = -\infty$.
    end if
  end for

Find $(l_m, t_m) = \arg \max_{l, t} U_l(t)$ (i.e., $l_m$ and $t_m$ indicate the index and the position of the particle that results in the highest utility). Then set $U_{\text{max}} = U_{l_m}(t_m)$ and $\epsilon_{\text{max}}^{(l)} = \epsilon^{l_m}(t_m)$.

Find $t_l = \arg \max_{t} U_l(t)$ for each particle $l$ (i.e., $t_m$ indicates the position of the particle $l$ that results in the highest local utility). Then set $U_{(l, \text{local})} = U_l(t_l)$ and $\epsilon_{(l, \text{local})} = \epsilon^{(l)}(t_l)$.

Adjust the velocities and positions of all particles using equation (5.16).

$t = t + 1$.
end while

This process is repeated until reaching convergence either by attaining the maximum number of iterations or by stopping the algorithm when the achievable utility remains constant after a several number of iterations. Details of the algorithm are given in Algorithm 7.

Hence, the above evolutionary approaches tries to:

- Minimize the energy consumption by choosing optimally the amount of energy to be procured from each retailer and by switching off redundant BSs.

- Maintain a certain QoS.
• Reduce the CO₂ emissions, maximize the profit of the network operator or achieve a tradeoff between both objective functions.

5.5 Iterative Algorithm for Green Energy Procurement

In our previous study in [91], we proposed a lower complexity IA that eliminates successively one BS at each time. Initially, all $N_{BS}$ BSs are switched on (i.e., $\epsilon = [1 \cdots 1]$). As a first step, after allocating the radio resources to all users, IA computes the data rates of all users $R_i^{(DL)}$ and $R_i^{(UL)}$ for $i = 1 \cdots N_U$ and compares them to the data rate thresholds $R_{m,th}^{(DL)}$ and $R_{m,th}^{(UL)}$ that depend on the type of the service $m$ used by subscriber $i$. By this way, IA identifies the number of users in outage $N_{out}$ and consequently the entries of the vector $\gamma$. Once both vectors $\epsilon$ and $\gamma$ are known and fixed, the optimization problem formulated in (5.10) becomes a quadratic concave optimization problem that has a unique optimal solution that depends only on the decision variable: the vector $q$. Next, we initialize the optimal utility function $U_0$ as the initial maximum utility $U_{\text{max}}$. Then, at each elimination step where one BS is switched off at a time. For the $j^{th}$ eliminated BS, we compute the corresponding optimal utility function $U_j$ and we compare $\max_j(U_j)$ to the previous utility $U_{\text{max}}$ to decide whether eliminating BSs is possible or not. Details of the proposed method are given in Algorithm 8.

5.6 Results and Discussion

In this section, after presenting the simulation model, we analyze the performance of the BS sleeping strategy applied with the GA (denoted by “GA”) and binary PSO (denoted by “PSO”) presented in Section 5.4 versus two parameters: the network operator attitude $\omega$ and the number of users. We compare the performance of the evolutionary algorithms to
Algorithm 8 Iterative Algorithm for Green Energy Procurement and BS sleeping strategy

Compute the utility function $U_{\text{max}} = U_0$ when all BSs are switched on ($S$ contains all BSs and $\epsilon = [1 \cdots 1]$) and initialize for the current iteration $S^{\text{iter}} = S$ and $N_{\text{BS}}^{\text{iter}} = N_{\text{BS}}$.

repeat
  for $k = 1 \cdots N_{\text{BS}}^{\text{iter}}$ do
    Eliminate BS $k$ from $S^{\text{iter}}$ ($\epsilon^{(k)} = [1 \cdots 1 \overset{0}{\overset{k\text{-th position}}{\ddots}} 1 \cdots 1]$).
    Allocate resources (select serving BS and UL and DL RBs) to all users and compute $\gamma^{(k)}$ for the iteration $k$ as shown in (5.3).
    if $\frac{N_{\text{out}}^{\text{iter}}}{N_{\text{BS}}^{\text{iter}}} \leq P_{\text{out}}$ then
      Find $\tilde{q}$ by solving the quadratic optimization problem formulated in (5.10) given $\epsilon^{(k)}$ and $\gamma^{(k)}$ and compute the utility function corresponding to the $k^{th}$ iteration: $U_k$ for the optimal value $\tilde{q}$.
    else
      BS $k$ can not be eliminated (we set $U_k = -\infty$).
    end if
  end for
  Find the BS $k_{\text{op}}$ that, when eliminated, provides the highest utility ($U_{k_{\text{op}}}^{\text{new}} = \max_k U_k$).
  if $U_{k_{\text{op}}}^{\text{new}} \geq U_{\text{max}}$ then
    BS $k_{\text{op}}$ is eliminated, $S^{\text{iter}} = S^{\text{iter}} \setminus \{k_{\text{op}}\}$, $N_{\text{BS}}^{\text{iter}} = N_{\text{BS}}^{\text{iter}} - 1$ and $U_{\text{max}} = U_{k_{\text{op}}}^{\text{new}}$.
  end if
until No BS can be eliminated.

The final optimal set of active BSs is $S^{\text{iter}}$.

the traditional case (denoted by “Trad.” in the figures) where all BSs are kept active and to the case where we apply the IA (denoted by “IA”) described in Section 5.5. We compare the performance for snapshots of users during a period $T = 1$ second.

5.6.1 Simulation Model

We consider a $5 \times 5$ (km$^2$) LTE coverage area with uniform user distribution where $N_{\text{BS}}$ BSs are placed uniformly according to the cell radius, selected to be 0.5 km. The LTE parameters are obtained from [48], and the channel parameters are obtained from [49]. All BSs and all MSs have the same power model and the same maximal transmit power, respectively. These parameters are detailed in Table 5.1. In addition, we suppose that the network operator offers $M = 4$ different services. Each one is characterized by its
cost (unitary price) $p^{(m)}$ expressed in MU, DL and UL data rate thresholds ($R^{(UL)}_{m,th}$ and $R^{(DL)}_{m,th}$ respectively) and the occurrence probability of the service as shown in Table 5.2. The occurrence probability of a given service corresponds to the percentage of users in the network using that service. Concerning the energy providers, we assume that $N = 3$ retailers with three different energy sources are available to supply the network with energy. Each type of energy source $n$ is characterized by its unitary price $\pi^{(n)}$, the total available energy $Q^{(n)}_{\max}$ and two pollutant coefficients $\alpha_n$ and $\beta_n$ as shown in Table 5.3. We suppose that the second energy provider has a limited amount of energy $Q^{(2)}_{\max} = 1500$ J: for instance, it can correspond to a renewable energy provider producing electricity from wind or solar energy. The third retailer produces energy with a very cheap price but it causes a harmful impact on the environment.

The GA and PSO are applied under the following settings: $L = 32$ is the size of

<table>
<thead>
<tr>
<th>Table 5.1: Channel and power parameters</th>
</tr>
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<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>$\kappa$ (dB)</td>
</tr>
<tr>
<td>$\sigma_{\xi}$ (dB)</td>
</tr>
<tr>
<td>$(B^{(DL)}, B^{(UL)})$ (MHz)</td>
</tr>
<tr>
<td>Max. BS Tx power (W)</td>
</tr>
<tr>
<td>$a$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 5.2: Service parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Services</td>
</tr>
<tr>
<td>$p^{(m)}$ (MU)</td>
</tr>
<tr>
<td>$(R^{(DL)}<em>{m,th}, R^{(UL)}</em>{m,th})$ (kbps)</td>
</tr>
<tr>
<td>Occurrence probability</td>
</tr>
</tbody>
</table>
Table 5.3: Energy provider parameters

<table>
<thead>
<tr>
<th>Retailers</th>
<th>Retailer 1</th>
<th>Retailer 2</th>
<th>Retailer 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^{(n)}$ (MU)</td>
<td>0.05</td>
<td>0.09</td>
<td>0.01</td>
</tr>
<tr>
<td>$Q_{\max}^{(n)}$ (J)</td>
<td>1500</td>
<td>$Q_{\max}^{(2)}$</td>
<td>$+\infty$</td>
</tr>
<tr>
<td>$(\alpha_n, \beta_n)$</td>
<td>(0.02, 0.2)</td>
<td>(0.0)</td>
<td>(0.1, 0.5)</td>
</tr>
</tbody>
</table>

the initial population either for GA or PSO, we run the algorithms at most 200 times. If the achieved utility remains constant during 15 successive iterations the algorithm is stopped and convergence is assumed achieved. For the GA, we keep the $L_b = 0.5 L$ strings providing the highest utilities to the next population while the remaining $0.5L$ strings are obtained by randomly crossover the $L_b$ selected strings. The crossover point is, also, chosen randomly between the $0.2 N_{BS}$ and $0.8 N_{BS}$ positions while the mutation probability is set to $p_M = 0.05$. On the other hand, for PSO, we define $V_{\max}$ as the maximum achieved velocity in (5.15) (i.e., $V_j^{(l)} \in [-V_{\max}, V_{\max}]$). This restriction is placed to enforce the limitation that a particle does not exceed a certain acceleration. We choose $V_{\max} = 6$ in order to limit the probabilities of (5.17) between 0.9975 and 0.0025.

5.6.2 Simulation Results

The mobile operator has to procure energy from three public retailers existing in the smart grid. Each retailer is characterized by its unitary price and pollutant coefficients depending on the energy source. Fig. 5.3 shows the performance of the proposed scheme versus the operator attitude towards the environment (i.e., $\omega$) for three algorithms (GA, PSO and IA) in addition to the result of the traditional scenario where all BSs are powered from the grid and kept active. Results are plotted for values of $\omega$ between 0 and 0.02. For $\omega \geq 0.02$, obtained results vary slowly or remain almost constant. In fact, we are optimizing a bi-objective optimization problem where the order of magnitude of the optimized quantities are not the same. The order of magnitude of the quantity $I(\epsilon, q)$ is greater than
the one of the quantity $\mathcal{P}(\gamma, \epsilon, q)$ as it depends on the square of the elements of $q$.

In Fig. 5.3(a), the mobile operator profit resulting from the $M$ offered services is plotted. We notice that when $\omega \to 0$, the mobile company reaches its maximum profit by avoiding the consumption of the most expensive energy (produced by Retailer 2). Indeed, Fig. 5.3(c) shows, in order to increase its profit, the selfish network operator ($\omega \to 0$) procures energy only from Retailer 3 presenting the most pollutant retailer and offering the cheapest price in the smart grid. However, when $\omega$ increases, the profit decreases since the mobile operator starts procuring energy from Retailer 1, then from the renewable energy retailer which represents the most expensive energy in the smart grid. This has a direct impact on the emitted CO$_2$. Fig. 5.3(b) shows a high amount of CO$_2$ emissions caused by the consumption of fossil fuels (Retailer 1 and Retailer 3) for low values of $\omega$. However, when $\omega$ increases,
the amount of CO\(_2\) emitted by the network is considerably reduced.

Comparing to the traditional case and independently of the employed algorithm, we notice that there is a significant gain in terms of either the profit or the CO\(_2\) emissions. In fact, thanks to the BS sleeping strategy implemented in the proposed algorithms: the mobile operator is able to reduce the power consumption of the network. Thus, it reduces the energy cost and the emission of greenhouse gas. In addition to that, we notice that in some cases the CO\(_2\) emission becomes very reduced since the green energy constitutes around 80\% of the total consumed energy (when \(\omega \approx 0.02\)) while energy procured from Retailer 3 represents less than 10\% of the total consumed energy. As all BSs are kept active, green energy represents only 20\% of the total consumed energy in the traditional scenario.

Fig. 5.3(d) plots the profit gained by the mobile operator versus the CO\(_2\) emissions which constitute the two main objectives of the optimization problem expressed in (5.10). This curve is also entitled the Pareto curve and depends on the operator attitude towards the environment parameter (i.e., Pareto weight \(\omega\)). We plot it to find the optimal value of \(\omega\) that offers a tradeoff between the profit and the environment pollution. The optimal value is approximately between 0.002 and 0.004 for 50 users connected to the network.

Fig. 5.4 plots the performance of the mobile operator versus the number of subscribers connected to the environmentally friendly network (\(\omega \to 1\)). Of course, when the number of subscribers increases the profit increases too. However, we notice that the gap between the proposed methods (with BS sleeping strategy) and the traditional case is approximately maintained even if we increase the number of users to 300. For higher values, the curves are expected to come closer as the mobile operator will activate more BSs to serve the increasing number of users.

Comparing the algorithms (IA, GA and PSO), we notice that the PSO outperforms GA which outperforms IA in all cases. In fact, PSO and GA reach better suboptimal solutions than IA thanks to the random generation of populations by applying crossover
Figure 5.4: Performance of the proposed approaches versus the number of users ($\omega \to 1$ and $L = 32$) (a) Profit (b) CO$_2$ emissions (c) Average number of active BSs (d) Percentage of users in outage.

and mutation for GA and the computation of the velocity term for PSO. Fig. 5.4(c) and Fig. 5.4(d) show that PSO and GA are able to keep less activated BSs and serve more users at the same time comparing to IA. This leads to less CO$_2$ emissions and higher profit as demonstrated in Figs. 5.4(a), (b) and Figs. 5.3(a),(b). The randomness of the evolutionary algorithms provide more chance for the network operator to find better BS combinations (i.e., the best $\epsilon$ vector that gives the highest utility). However, this advantage comes to the expense of a higher computational complexity that depends on the length $L$, the size of each string in the population, and the number of populations. For example, reducing $L$ can significantly increase the speed of the algorithm but can also lead to worst results as confirmed in Fig. 5.5. Indeed, in Fig. 5.5, we plot the performance of GA and PSO for $L = 16$. We notice that comparing to the case where $L = 32$ in Fig 5.4, GA finds a worse
suboptimal solution: it requires more BSs to serve the connected users. For instance, for $N_U = 250$, GA($L = 32$) achieves a profit of $321.1$ (MU) with around 8 active BSs while with GA($L = 16$) it provides a profit $201.5$ (MU) with around 10 active BSs. Of course, having more active BSs will lead to a lower outage rate (Fig. 5.5(d)).

In order to improve the performance of the algorithms, we suggest to combine two algorithms (for instance GA and IA) by putting the output of the IA as one combination of the GA initial population. This algorithm denoted Hybrid “IA-GA” presents a significant gain comparing to GA (mainly for low $L$) in terms of profit and CO$_2$ emissions by activating a lower number of BSs as shown in the same figure. Hybrid IA-GA can provide better solutions than GA as in worst cases, it reaches the IA solution. But, most of the time it tries to enhance it or finds better local solutions.
Table 5.4: CPU times of algorithms

<table>
<thead>
<tr>
<th></th>
<th>IA</th>
<th>GA</th>
<th>PSO</th>
<th>IA-GA</th>
<th>Trad.</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPU times ((L = 16))</td>
<td>15.11</td>
<td>11.44</td>
<td>29.08</td>
<td>26.90</td>
<td>0.11</td>
</tr>
<tr>
<td>CPU times ((L = 32))</td>
<td>14.84</td>
<td>21.78</td>
<td>52.60</td>
<td>40.02</td>
<td>0.11</td>
</tr>
</tbody>
</table>

5.6.3 Complexity Analysis

IA is a deterministic algorithm that computes the utility function \(\approx O(N_{BS}^2)\) times in order to reach its suboptimal solution. However, GA and PSO are two stochastic algorithms where the exact number of iterations needed to reach the solution is random and unknown. In our simulation results, we assumed that both algorithms are executed with at most 200 iterations. Thus, the utilities are computed at most \(200 \times L\) times. As we assumed that the convergence is reached if the utility remains constant during 15 consecutive iterations, the execution time is considerably reduced. For 200 realizations, \(L = 32, N_{BS} = 25,\) and \(N_U = 50,\) results shows that PSO requires more time to converge as shown in Table 5.4 where we compute the CPU times in seconds of all algorithms. All tests were performed on a desktop machine featuring an Intel Xeon CPU and running Windows 7 Professional. The clock of the machine is set to 2.66 GHz with a 48 GB. The computation time is done via the TIC/TOC function of Matlab. The IA is a fast algorithm that has a polynomial complexity and reaches always the same suboptimal solution but misses several possible local maxima from the search space, whereas the evolutionary approaches GA and PSO have slower convergence but they explore several additional options and reach better solutions. It is trivial that the traditional scenario is the fastest algorithm since it executes the resource allocation algorithm once and does not include the BS sleeping strategy. The speed of the hybrid IA-GA is almost the sum of the speed of IA alone and GA alone. On the other hand, we can reduce the CPU times of the algorithm by modifying some parameters as the number of initial combinations \(L.\) Indeed, when reduced to 16, we notice that the CPU times
of the stochastic algorithms are significantly reduced which allows the GA becoming the fastest algorithm while PSO, the algorithm offering the highest utility, remains the slowest algorithm in this case. However, this gain in terms of complexity may lead to a loss in terms of profit and CO₂ emissions. Therefore, a tradeoff between the achievable performance and the computational complexity can be deduced as it is shown in Table 5.5 where we compare the performance of the algorithms for fixed CPU times. The evolutionary algorithms are executed with $L = 32$ and $\omega = 0.5$, until reaching the CPU times of IA, where they are forced to stop. In this case, we notice that GA outperforms PSO as it achieves the highest utility. Indeed, PSO needs more time to converge to its suboptimal solution.

### 5.7 Summary

In this chapter, we combined the BS sleeping strategy and evolutionary algorithms to achieve energy savings for LTE networks without affecting the required QoS. We formulated an optimization problem that optimally procures energy from the smart grid where renewable energy sources are available in order to reduce CO₂ emissions, maximize the mobile operator profit or achieve a tradeoff between them depending on its attitude towards the environment. We also showed that, thanks to their random evolution process, evolutionary algorithms (i.e., GA and PSO) can be exploited to not only solve the non-convex multi-objective problems but also to outperform other deterministic approaches.
Chapter 6

Smart Energy Procurement Model with Time Varying User Density for 4G-LTE Networks

6.1 Introduction

In Chapter 5, we have developed and compared several heuristic approaches to solve an NP-hard optimization problem for fixed user density. Evolutionary algorithms are applied for fixed user realizations in order to find the optimal procurement strategy for the active BSs. In this chapter, we study a more complex problem where the energy efficiency of LTE cellular networks is investigated while considering traffic variation. The BS sleeping strategy is applied accordingly and the energy consumption is optimally performed by procuring the required amount from different retailers existing in the smart grid. The goal is to minimize the network CO₂ emissions, maximize the profit of the mobile operator or achieve a tradeoff between both objectives while maintaining the network QoS. The contributions of this chapter are summarized as follows:

- Formulate an optimization problem that deals with the continuous operation of the
network when the user traffic and the available renewable energy vary dynamically. Indeed, the objective of this task is to optimize the continuous BS sleeping operation and the smart grid energy procurement of LTE mobile networks through time to ensure green objectives by respecting the required QoS. The behavior of the network depends on several parameters such as the time of the day (peak hours, late night, etc.), user density and energy availability in green generators deployed in BS sites and in the multiple energy providers existing in the smart grid.

- Analyze the impact of the variation of the renewable energy unitary price on the network energy procurement and the system performance for different types of operator behavior.

- Develop a practical method to solve the formulated optimization problem where we consider the BS power consumption in sleep and active modes in addition to the power consumed during the transition periods which was not applicable in [99]. Furthermore, we propose another practical and low complexity algorithm to reduce the ON/OFF switches to keep the same BSs active as much as possible. Finally, a comparison between both approaches is performed.

The rest of this chapter is organized as follows: Section 6.2 presents the modification in the system model. In Section 6.3, we introduce the optimization problem for green energy procurement. In Section 6.4, we propose our approaches with time varying user density. Simulation results are discussed in Section 6.5. Finally, conclusions are provided in Section 6.6.
6.2 System Model

In this section, we adopt the same system model presented in Chapter 5 and we define new parameters to highlight the time effect in the studied problem.

6.2.1 Base Station States and Power Consumption Model

Since we are applying the BS sleeping strategy in our framework, we consider that each BS can be set in two modes: active and sleep modes. In the active mode denoted (A), the BS is serving a certain number of users connected to the network. The power consumption of the \( j^{th} \) BS corresponding to this mode, noted \( (P_A)_j \), can be computed as follows [76]:

\[
(P_A)_j = aP_{tx}^j + b,
\]  
(6.1)

where \( a \) corresponds to the power consumption that scales with the radiated power and \( b \) models an offset of site power. In (6.1), \( P_{tx}^j \) denotes the radiated power of the \( j^{th} \) BS and can be re-expressed as follows:

\[
P_{tx}^j = \sum_{r=1}^{N_{RB}^{(DL)}} P_r,
\]  
(6.2)

where \( N_{RB}^{(DL)} \) is the number of DL RBs and \( P_r \) is the power consumed per one RB and depends on the RB state. If RB \( r \) of BS \( j \) is allocated to a certain user, then \( P_r = \frac{P_{tot}}{N_{RB}^{(DL)}} \) else, i.e., RB \( r \) is not allocated to any user, \( P_r = P_{idle} \) where \( P_{idle} \ll P_r \). For macro BSs, we choose \( P_{tot} = 46 \) dBm and \( P_{idle} = 0.19 \) dBm, [100]. On the other hand, we assume that a BS can be underutilized and thus switched to a sleep mode during a certain period of time mainly for low user traffic in the network. In practical scenarios, it is not useful to completely turn off the BSs [101]. In fact, some BS components should be kept active in order to ensure their connectivity with other network actors such as users to establish channel measurements, etc. The power consumption in this standby mode is also considered.
very low comparing to $b$ mentioned in (6.1). Hence, we denote the power consumption of a BS in a sleep mode by $P_S \ll b$. However, when user traffic increases in the network, some BSs are activated in order to serve additional new users until satisfying the network QoS. During this transition period, we assume that BSs require additional power in order to ensure the switching operation from sleep to active mode and vice versa. We denote the BS average power consumption during these two transition periods $T_{SA}$ and $T_{AS}$ by $P_{SA}$ and $P_{AS}$, respectively. Only $P_A$ is indexed by $j$ as its value varies according to the number of users served by BS $j$ while $P_S$, $P_{AS}$, $P_{SA}$, $T_{AS}$ and $T_{SA}$ are constant for all macro BSs, assumed to be of the same type. Finally, we consider that each BS is equipped with a single omni-directional antenna.

6.2.2 Retailers and Pollutant Levels

In our time driven study, in addition to the possibility of procuring energy from the smart grid as it is given in Section 5.2.2, we assume that the network can be powered using renewable energy equipment deployed in BS sites. Each BS would be powered by its own installed equipment, e.g., solar cells or wind turbine. The auto-generated amount of energy by BS $j$ is denoted $q_j^{(0)}$. In addition, we suppose that all BSs have the same maximum capacity to store the produced energy denoted $Q_{BS}^{max}$ and, at an instant $t$, the renewable energy available at BS $j$ is denoted $Q_{RE}^{(j)}$ where $q_j^{(0)} \leq Q_{RE}^{(j)} \leq Q_{BS}^{max}$ for each BS $j$. To summarize, we distinguish two notations of the procured energy:

- $q_j^{(n)}$ is the amount of energy provided to BS $j$ and bought from retailer $n$.

- $q_j^{(0)}$ is the amount of renewable energy generated by the local equipment of BS $j$ which is free of charge.
Hence, in order to ensure the power supply of a BS $j$, the following equation has to be satisfied every period of time $T$:

$$\sum_{n=0}^{N} q_j^{(n)} = \begin{cases} P_ST, & \text{if BS } j \text{ is kept in a sleep mode}, \\ P_{AS}T_{AS} + P_S(T - T_{AS}), & \text{if BS } j \text{ is switched off during } T, \\ P_{SA}T_{SA} + (P_A)_j(T - T_{SA}), & \text{if BS } j \text{ is switched on during } T, \\ (P_A)_j T, & \text{if BS } j \text{ is kept active}. \end{cases}$$ (6.3)

### 6.2.3 Photovoltaic Model

In our framework, we assume that BSs are using the photovoltaic energy as the renewable energy sources generated locally in the BS sites. The hourly behavior of the solar radiation is an important parameter that impacts on the generated energy from the solar panels. In fact, the solar rating depends essentially on the size of photovoltaic panels and whether they experience any shading during the day. Several works have been proposed to model the solar radiation. One of these works [102] presents it as a simple mathematical model where the hourly variations fit to Gaussian shapes expressed as follows:

$$G(t) = \frac{A e^{-(t-B)^2}}{C^2},$$ (6.4)

where $A$ corresponds to the height of the Gaussian peak which refers to the maximum power that can be generated, $B$ is the position of the peak and $C$ is related to the shape width at half maximum of the peak.

### 6.2.4 Operator Services and User Arriving Process

We consider that the network operator offers $M$ different services characterized by their data rate thresholds $R_{m,th}^{(UL)}$ and $R_{m,th}^{(DL)}$ for UL and DL, respectively, and their unitary
prices $p^{(m)}$ with $m = 1, \cdots, M$. We suppose that each user in the network benefits from one of the $M$ offered services. Besides, each service is characterized by some parameters that depend on the incoming subscriber attitude and the associated mobile call duration. In fact, in our study, we model mobile calls as log-normal or Weibull distributions [103] depending on the chosen services and the activity of the subscribers (i.e., personal call or business call). Concerning the traffic arrival, we consider that the daily traffic pattern of the network can be approximated by a sinusoidal profile close to practical patterns [104] as follows:

$$\Psi(t) = \frac{1}{2^d} \left[ 1 + \sin \left( \frac{\pi t}{12} + \phi \right) \right]^d + n(t), \quad (6.5)$$

where $\Psi(t)$ is the instantaneous normalized traffic, $\phi$ is a uniform random variable in the interval $[0, 2\pi]$ which determines the distribution of traffic pattern, $n(t)$ is a Poisson distributed random process with parameter $\lambda_{\text{mean}}$ which models random fluctuations of the total traffic, and $d = 1$ or $3$ which determines the abruptness of the traffic profile. Note that with $d = 3$ the curve has a steeper slope [104]. This model takes into account peak hours and reduces the number of users at night. An example of the subscriber daily traffic based on this model is illustrated in Fig. 6.1 where $t=0$ corresponds to 0:00 am.

In our system model, the group of BSs providing cellular coverage to the area of interest operate together to procure the needed energy from the smart grid and the locally deployed solar panels. The BSs collaborate and interact to implement a green algorithm to determine the number of active BSs required to serve the users and the needed energy for the network operation. The ON/OFF switches and procurement decisions are assumed to be taken in a centralized smart control center that plays the role of an interface between the smart grid and the group of BSs.
6.3 Problem Formulation

In this section, we formulate the optimization problem where the mobile network operator is able to optimally procure energy from the smart grid and the local solar panels in order to maximize an environmentally friendly objective function without degrading its QoS. In our time driven approach, we consider that $N_{BS}$ BSs are deployed in the area of interest. In order to include the BS sleeping strategy in the problem formulation, we introduce a binary variable $\epsilon_j(l)$ with $j = 1, \cdots, N_{BS}$ to characterize the BS states at the $l^{th}$ period $T$, where $l \in \mathbb{N}^*$, as follows:

$$
\epsilon_j(l) = \begin{cases} 
1, & \text{if BS } j \text{ is in active mode at period } lT, \\
0, & \text{if BS } j \text{ is in sleep mode at period } lT. 
\end{cases}
$$

(6.6)

Hence, we distinguish four BS states depending on the previous BS mode in time slot $(l - 1)T$ as it is summarized in Table 6.1. On the other hand, we denote by $N_{out}(l)$ the number of users in outage at the $l^{th}$ interval $T$ ($N_{out}(l) \ll N_U(l)$) where $N_U(l)$ is the
number of users connected to the network at the $l^{th}$ interval $T$. A user $i$ benefiting from the $m^{th}$ service communicates successfully with a BS $j$ if its UL and DL data rates at interval $lT$, denoted $R_i^{(UL)}(l)$ and $R_i^{(DL)}(l)$ respectively, are both higher than the service data rate thresholds, $R_{m,th}^{(UL)}$ and $R_{m,th}^{(DL)}$, respectively. The UL and DL data rate expressions are given in the Appendix. We employ the binary parameter $(\gamma_j)_i(l)$ to characterize the state of the $i^{th}$ user served by BS $j$ as follows:

$$
(\gamma_j)_i(l) = \begin{cases} 
1, & \text{if } R_i^{(UL)}(l) \geq R_{m,th}^{(UL)} \text{ and } R_i^{(DL)}(l) \geq R_{m,th}^{(DL)}, \\
0, & \text{if } R_i^{(UL)}(l) < R_{m,th}^{(UL)} \text{ or } R_i^{(DL)}(l) < R_{m,th}^{(DL)},
\end{cases}
$$

(6.7)

where $i = 1, \cdots, N_j(l)$ and $N_j(l)$ is the number of users connected to BS $j$ at the $l^{th}$ interval such that $\sum_{j=1}^{NJ} N_j(l) = N_U(l)$. In other words, if $(\gamma_j)_i(l) = 0$, the $i^{th}$ user served by BS $j$ is in outage. Let us denote $\gamma_j(l) = [(\gamma_j)_1(l), \cdots, (\gamma_j)_{N_j}(l)]^T$ and $\gamma(l) = [\gamma_1(l), \cdots, \gamma_{N_{BS}}(l)]$, then the number of ones and the number of zeros in $\gamma_j(l)$ correspond to the number of served users and the number of users in outage connected to BS $j$ at the interval $lT$, respectively. Consequently, only the served users pay the equivalent of the proposed service. Hence, the revenue provided by each BS $j$ at the $l^{th}$ time slot $T$, $R_j(\gamma_j(l))$, is expressed as follows:

$$
R_j(\gamma_j(l))(l) = \begin{cases} 
(T - T_{SA}) \left[ \sum_{i=1}^{N_j(l)} (\gamma_j)_i(l)p_i^{(m)} \right], & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (0, 1) \\
T \left[ \sum_{i=1}^{N_j(l)} (\gamma_j)_i(l)p_i^{(m)} \right], & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (1, 1)
\end{cases}
$$

(6.8)

<table>
<thead>
<tr>
<th>Transition mode</th>
<th>$\epsilon_j(l-1)$</th>
<th>$\epsilon_j(l)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>BS $j$ is kept in a sleep mode</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>BS $j$ is switched on</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>BS $j$ is switched off</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BS $j$ is kept active</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 6.1: BS transition modes
where $p_i^{(m)}$ is the cost of the service $m$ used by the $i^{th}$ user at a corresponding period of time. Trivially, we assume that when a BS $j$ is not serving any user (i.e., sleeping state), then $N_j = 0$ and a user is successfully served only during the active mode. Thus, the total operator revenue $R(\gamma(l))$, at the $l^{th}$ interval $T$, consists in the sum of revenue gained from all BSs as it is expressed in the following:

$$R(\gamma(l)) = \sum_{j=1}^{N_{\text{BS}}} R_j(\gamma_j(l)).$$

(6.9)

Each BS is powered by either green energy or pollutant energy. Renewable energy presents a solution for network operators to reduce greenhouse gas emissions. In fact, to procure this green energy, the network operator can either buy the required power from a public renewable energy retailer or procure it by deploying its private renewable energy equipment on its BS sites. If the produced renewable energy is not enough to cover the need of all BSs, the network operator can procure power from public retailers of the smart grid that have a sufficient amount of energy. In our framework, we consider that $N$ public retailers are available to provide power to the network. Each retailer is assumed to generate electricity form a different source. Hence, we can have one retailer generating electricity from renewable energy sources, and other retailers generating electricity from fossil fuels. Depending on the nature of the used fossil fuels, the CO$_2$ emission caused by electricity generation may differ and the pollution caused to the environment would vary. Hence, both the total cost of the energy consumption and the CO$_2$ emission cost function caused by the cellular network depend only on the amount of energy consumed by BSs and the nature of the procured energy as it is given in the following expressions:

- The total cost of the energy consumption of the network $C$ at interval $lT$:

$$C(q(l)) = \sum_{j=1}^{N_{\text{BS}}} \sum_{n=1}^{N} \pi^{(n)} q_j^{(n)}(l).$$

(6.10)
• The CO$_2$ emission penalty function of the network $I$ at interval $lT$,

$$I(q(l)) = \sum_{j=1}^{N_{\text{BS}}} \sum_{n=1}^{N} \left( \alpha_n \left( q_j^{(n)}(l) \right)^2 + \beta_n q_j^{(n)}(l) \right),$$

(6.11)

where $q(l) = \left[ q_1^{(0)}(l), \ldots, q_{N_{\text{BS}}}^{(N)}(l) \right]^T_{1 \times (N_{\text{BS}} \times (N + 1))}$ is the vector that contains the procured energy amount by the $j^{th}$ BS from the $n^{th}$ energy source and $\pi^{(n)}$ is the cost of one unit of energy provided by the $n^{th}$ retailer where $j = 1, \ldots, N_{\text{BS}}$ and $n = 1, \ldots, N$. The function $I$ reflects the friendliness to the environment of the mobile network operator and corresponds to the CO$_2$ emissions caused by its total energy consumption. Consequently, the mobile operator has to optimally compute the amount of energy to procure from each retailer existing in the smart grid and from the generators installed on BS sites in order to maximize the following utility function at each period of time:

$$U(l) = (1 - \omega) \mathcal{P}(\gamma(l), q(l)) - \omega I(q(l)),$$

(6.12)

where $I(q(l))$ is given in (6.11) and $\mathcal{P}(\gamma(l), q(l))$ is given by:

$$\mathcal{P}(\gamma(l), q(l)) = R(\gamma(l)) - C(q(l))$$

(6.13)

and corresponds to the mobile operator’s profit. $\omega$ is the Pareto weight ($0 < \omega < 1$) [95]. When $\omega \to 0$, the network operator aims to maximize its own profit $\mathcal{P}$ regardless of its impact on the environment while when $\omega \to 1$, the network operator aims to reduce CO$_2$ emissions regardless of its own profit. Other values of $\omega$ constitute a tradeoff between these two extremes. Hence, the optimization problem that will be solved periodically is
expressed as follows:

\[
\text{Maximize } U(l) = (1 - \omega)\mathcal{P}(\gamma(l), q(l)) - \omega \mathcal{I}(q(l)),
\]

\[
\text{S.t.: } \sum_{j=1}^{N_{BS}} q_j^{(n)}(l) \leq Q_{\text{max}}^{(n)}(l), \forall n = 1, \ldots, N,
\]

\[
q_j^{(0)}(l) \leq Q_{R_{\text{max}}}^{(j)}(l), \forall j = 1, \ldots, N_{BS},
\]

\[
\sum_{n=0}^{N} q_j^{(n)} = \begin{cases} 
    P_S T & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (0, 0), \\
    P_{AS} T_{AS} + P_S(T - T_{AS}) & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (1, 0), \\
    P_{SA} T_{SA} + (P_A)_j(T - T_{SA}) & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (0, 1), \\
    (P_A)_j T & \text{if } (\epsilon_j(l-1), \epsilon_j(l)) = (1, 1), 
\end{cases} \forall j = 1, \ldots, N_{BS},
\]

\[
\frac{N_{out}(l)}{N_{U}(l)} \leq P_{out},
\]

\[
q_j^{(n)}(l) \geq 0, \forall j = 1, \ldots, N_{BS} \text{ and } \forall n = 0, \ldots, N.
\]

The constraint (6.15) indicates that the energy procured by all BSs in the cellular network from power retailer \( n \) can not exceed the total energy provided by that retailer at the period \( lT \) while (6.16) indicates that the energy procured by a BS \( j \) from its own energy generated locally can not exceed the amount of energy that can be produced by the photovoltaic system or the amount of energy that can be stored locally, (6.17) indicates that the amount of energy drawn by a BS from all retailers and from the renewable energy generated locally should be equal to the power needed for its operation at that period \( T \), (6.18) forces the number of users in outage to be less than a tolerated outage percentage threshold \( P_{out} \), and (6.19) is a trivial constraint expressing the fact that the energy drawn is a positive amount. It should be noted that, when a certain retailer \( n \) can provide to the mobile network operator enough electricity to power all the BSs in the network, we can set \( Q_{\text{max}}^{(n)}(l) = +\infty \) to relax the constraint (6.15) for that retailer, although in practice the amount of energy
produced is naturally finite.

6.4 Proposed Algorithms for Green Energy Procurement

The optimization problem given in Section 6.3 is solved periodically in order to optimize the energy procurement from the smart grid and switch off the underutilized BSs according to the system parameters (i.e., channel conditions, available amount of renewable energy, and number of subscribers connected to the network). For this reason, a periodic computation has to be performed to find the best BS combinations $\epsilon(l)$, the best resource allocation identified by $\gamma(l)$, and, consequently, the corresponding energy procurement decision $q(l)$ needed to achieve green energy consumption at each period $lT$. However, since two of the decision variables $\gamma(l)$ and $\epsilon(l)$ are binary variables, the problem formulated in (6.14) is considered as a combinatorial NP-hard problem which makes the optimal and exact solution difficult or even impossible to find [95, 98]. Therefore, we employ heuristic approaches where, at each period of time, we try to find the best BS combination that maximizes the utility function expressed in (6.12). In fact, at each period $T$, the system parameters are updated as follows:

- User distribution: New users could connect to the network according to the arrival process described in Section 6.2.4 while other users could disconnect because of the end of the call duration or the non-satisfaction of the QoS associated to the call due to channel variations.

- Channel conditions: The variation of the channel parameters due to fading and shadowing has an important impact on the QoS of UL and DL. In fact, in some cases, users can be obliged to switch their connection from one BS to another (Handover).

- Renewable energy availability: Renewable energy generated locally by the solar pan-
els can increase or decrease following the model presented in Section 6.2.3 and depending on the BS energy consumption during previous periods of time.

In Section 6.4.1 and 6.4.2, we present two algorithms that are applied with the proposed approach in described in Section 6.3. Other types of algorithms, e.g., the evolutionary algorithms presented in [50], can also be extended and adapted to be applied with the proposed approach of this chapter.

6.4.1 Iterative Algorithm for Green Energy Procurement

The basic idea of the algorithm is to eliminate redundant BSs without affecting the QoS of the total network by respecting (6.18). In fact, the algorithm which is executed periodically aims to find the optimal BS combinations that reduce the CO$_2$ emissions of the network without affecting the QoS by switching off the maximum number of BSs. The algorithm is previously proposed in [99] where the obtained results at the current period $lT$ are independent of the previous BS states at the period $(l-1)T$. This can lead to a multiple daily switch-offs. For instance, after only one $T$, all active BSs in the previous period are switched off and new BSs are activated. This high amount of ON/OFF oscillations is not practical in real system implementations [101]. Therefore, in this framework, we updated the problem formulation and introduced the transition modes and the sleep mode with low power consumption to make the analysis more practical. The algorithm proposed in [99] is now applied for the problem formulated in Section 6.3 and is summarized in Algorithm 9.

Algorithm 9 solves in the worst case $\approx O(N_{BS}^2)$ quadratic optimization problems at each period $T$ until reaching the best BS combinations. Indeed, the vector $\epsilon(l)$ becomes known since we are eliminating one BS at each iteration and the associated constraint (6.17) is given depending on the value of $\epsilon(l-1)$. The choice of $T$ would vary in time according to the need of the mobile operator. For instance, if the traffic variation is slow (during night),
Algorithm 9 Iterative Algorithm for Green Energy Procurement

1: loop
2: \- Compute the utility function $U_{\max}$ when all BSs are active mode ($S$ contains all BSs and $\epsilon = [1, \cdots, 1]$) and initialize the current iteration with $S^{\text{iter}} = S$ and $N_{BS}^{\text{iter}} = N_{BS}$.
3: \- Set $U_{k_{\text{op}}^{\text{new}}} = U_{\max}$.
4: while $U_{k_{\text{op}}^{\text{new}}} \geq U_{\max}$ do
5: \- for $k = 1$ to $N_{BS}^{\text{iter}}$ do
6: \- Eliminate BS $k$ from $S^{\text{iter}}$ ($\epsilon^{(k)} = [1, \cdots, 0, \cdots, 1]$).
7: \- Allocate resources (Select serving BS and UL and DL RBs) to all users and compute $\gamma^{(k)}$ for the iteration $k$ as it is shown in (6.7).
8: \- if $\frac{N_{\text{out}}}{N_{U}} \leq P_{\text{out}}$ then
9: \- \hspace{1em} Find $\tilde{q}$ by solving the quadratic optimization problem formulated in (6.14) given $\epsilon^{(k)}$ and $\gamma^{(k)}$.
10: \- \hspace{1em} Compute the utility function corresponding to the $k^{th}$ iteration: $U_{k}$ for the optimal value $\tilde{q}$ as it is given in (6.12).
11: \- else
12: \hspace{1em} BS $k$ can not be eliminated (we set $U_{k} = -\infty$).
13: \hspace{1em} end if
14: \- end for
15: \- Find the BS $k_{\text{op}}$ that, when eliminated, provides the highest utility ($U_{k_{\text{op}}^{\text{new}}} > U_{\max}$).
16: \- if $U_{k_{\text{op}}^{\text{new}}} \geq U_{\max}$ then
17: \- BS $k_{\text{op}}$ is eliminated.
18: \- $S^{\text{iter}} = S^{\text{iter}} \setminus \{k_{\text{op}}\}$, $N_{BS}^{\text{iter}} = N_{BS}^{\text{iter}} - 1$ and $U_{\max} = U_{k_{\text{op}}^{\text{new}}}$.
19: \- end if
20: \- end while
21: - No more changes can be made and the final optimal set of active BSs during $T$ is $S^{\text{iter}}$.
22: - Update time $T$ and the traffic and identify the $N_{U}$ users connected to the network.
23: - Update channels and the auto-generated PV amounts.
24: end loop

the mobile operator can increase $T$, e.g., $T = 1$ hour. However, if the traffic variation is relatively fast, the execution period can be decreased to maintain the required QoS, e.g., $T = 1$ minute.

6.4.2 Low Complexity Algorithm for Green Energy Procurement with Reduced ON/OFF Switches

One of the drawbacks of Algorithm 9 is that, at each iteration, it starts from the same initial state by assuming that all BSs are switched on, which adds complications for prac-
tical implementation. Therefore, we propose another low complexity algorithm that starts from the current existing state in the network and evolves to an updated state, which is more convenient from a practical implementation perspective. We adopt the same problem formulation but we try to keep the same BSs activated the most of the time and, of course, without degrading the QoS. At each new period $lT$, we keep the same active BSs and verify whether constraint (6.18) is satisfied or not. If it is satisfied, we check if we can turn off other BSs. If not, we keep active the same combination or we activated additional BSs until having a percentage of users in outage less than $P_{\text{out}}$. When eliminating a BS, the QoS has to be maintained. However, when activating a BS, the QoS may not be satisfied. Thus, additional BS may also be activated. The added BSs are those that provide the highest utility. The proposed algorithm for reduced ON/OFF switches is given in Algorithm 10. Note that, in line 12 or 22 of Algorithm 10, we are only switching off/on the BS $k_{\text{op}}$, respectively. The previous loops are only dedicated to find the best BS that will be switched on/off. In practice, the other BSs maintain the same mode.

6.5 Numerical Results and Discussion

In this section, we start by introducing the simulation parameters. Then, we investigate the impact of the renewable energy price on the system by varying the Pareto weight $\omega$. Finally, we compare the performance of the proposed algorithms with and without transient modes. In the sequel, we denote the Algorithm 9 and Algorithm 10 as GIA and LCGA, respectively, where GIA stands for Green Iterative Algorithm while LCGA stands for Low Complexity Green Algorithm.
Algorithm 10 Low Complexity Algorithm with Reduced ON/OFF Switches

1: **Initialization step \((l=0)\):** All BSs are initialized in the sleep mode (i.e., \(\epsilon(l = 0) = [0, \ldots, 0] \)).

2: **loop**

3: - Compute the utility function \(U(l)\) for \(\epsilon(l)\) and set \(U_{k_{op}}^{new}(l) = U(l)\).

4: if \(\frac{N_{out}(l)}{N_{U}(l)} \leq P_{out}\) then

5:     **repeat**

6:       **for** \(k = 1\) to \(N_{BS}^{iter}\) **do**

7:         if BS \(k\) is active then

8:             - Turn BS \(k\) to the sleep mode and compute \(\gamma(k)(l)\).

9:             - Compute \(U_k\) and find \(\tilde{q}\) by solving the quadratic optimization problem (6.14).

10:         end if

11:     **end for**

12:     - Find the currently active BS \(k_{op}\) that, when eliminated, provides the highest utility \((U_{k_{op}}^{new}(l) = \max_k U_k)\) and satisfies constraint (6.18) and update \(N_{out}(l)\) if \(k_{op}\) exists.

13: **until** No BS can be eliminated.

14: else

15:     **while** \(\frac{N_{out}(l)}{N_{U}(l)} > P_{out}\) **do**

16:       **for** \(k = 1\) to \(N_{BS}^{iter}\) **do**

17:         if BS \(k\) is in a sleep mode then

18:             - Turn BS \(k\) to the active mode and compute \(\gamma(k)(l)\).

19:             - Compute \(U_k\) and find \(\tilde{q}\) by solving the quadratic optimization problem (6.14).

20:         end if

21:     **end for**

22:     - Find the currently inactive BS \(k_{op}\) that, when switched on, provides the highest utility \((U_{k_{op}}^{new}(l) = \max_k U_k)\) and update \(N_{out}(l)\) if \(k_{op}\) exists.

23: **end while**

24: **end if**

25: - \(l = l + 1\).

26: - Update traffic and identify the \(N_{U}(l)\) users connected to the network during \(lT\).

27: - Update channel parameters and power source amounts.

28: **end loop**

6.5.1 Simulation Model

We consider a \(4 \times 4\) (Km\(^2\)) LTE coverage area where \(N_{BS} = 16\) BSs are placed uniformly according to the cell radius, selected to be 0.5 km. All BSs and MSs have the same power model and the same maximal transmit power, respectively, as summarizes Table 6.2.

In LTE, the available spectrum is divided into RBs consisting of 12 adjacent subcarriers. Each RB and subcarrier has a bandwidth of \(B_{RB} = 180\) KHz and \(B_{sub} = 15\) KHz, respectively. In our framework, we consider an orthogonal LTE transmission where the total
Table 6.2: Channel and power parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa$ (dB)</td>
<td>$-128.1$</td>
<td>$\nu$</td>
<td>$3.76$</td>
</tr>
<tr>
<td>$\sigma_\xi$ (dB)</td>
<td>$8$</td>
<td>$P_{out}$</td>
<td>$0.02$</td>
</tr>
<tr>
<td>BS Tx power $P_{tot}$ (W)</td>
<td>$40$</td>
<td>MT Tx power (W)</td>
<td>$0.125$</td>
</tr>
<tr>
<td>$a$</td>
<td>$21.45$</td>
<td>$b$ (W)</td>
<td>$354.44$</td>
</tr>
</tbody>
</table>

Table 6.3: Service parameters

<table>
<thead>
<tr>
<th>Services</th>
<th>Service 1</th>
<th>Service 2</th>
<th>Service 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p^{(m)}$ (MU/s)</td>
<td>$10$</td>
<td>$4$</td>
<td>$1$</td>
</tr>
<tr>
<td>$(R_{m,th}^{(DL)}, R_{m,th}^{(UL)})$ (kbps)</td>
<td>$(1000, 384)$</td>
<td>$(384, 384)$</td>
<td>$(64, 64)$</td>
</tr>
<tr>
<td>Occurrence Probability</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Personal call)</td>
<td>$0.1$</td>
<td>$0.2$</td>
<td>$0.7$</td>
</tr>
<tr>
<td>(Business call)</td>
<td>$0.1$</td>
<td>$0.3$</td>
<td>$0.6$</td>
</tr>
<tr>
<td>Call model</td>
<td>Weibull</td>
<td>Weibull</td>
<td>Log-normal</td>
</tr>
</tbody>
</table>

The bandwidth of $B_T = 10$ MHz is subdivided into 50 RBs [48, 49]. We investigate the performance of the scheme by considering pathloss, shadowing and fast fading effects which are assumed to be averaged out through the use of adaptive modulation and coding in addition to fast power control.

In addition, we suppose that the network operator offers $M = 3$ different services. The mobile call model and the occurrence probability of the service are shown in Table 6.3. The occurrence probability of a given service corresponds to the percentage of users in the network using that service. The occurrence probability varies depending on call natures and the current time: 80% of the calls are assumed to be business calls during working hours while 70% of the calls during non working hours are considered as personal calls.

Concerning the smart grid retailers, we assume that $N = 2$ retailers produce energy from different sources. Each type of energy source $n$ is characterized by its unitary price $\pi^{(n)}$ (MU/s), its total available energy $Q_{\text{max}}^{(n)}$ (kWh), and two pollutant coefficients $\alpha_n$ and $\beta_n$ as it is given in Table 6.4. We suppose that the second energy provider has a limited
Table 6.4: Energy provider parameters

<table>
<thead>
<tr>
<th>Retailers</th>
<th>Retailer 1</th>
<th>Retailer 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi^{(n)}(\text{MU/h})$</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>$Q^{(n)}_{\text{max}}$ (kWh)</td>
<td>$+\infty$</td>
<td>0.5</td>
</tr>
<tr>
<td>$(\alpha_n, \beta_n)$</td>
<td>(0.02, 0.2)</td>
<td>(0, 0)</td>
</tr>
</tbody>
</table>

amount of energy $Q^{(2)}_{\text{max}}$. For instance, it can correspond to a renewable energy provider producing electricity from wind or solar energy. We assume that this retailer is engaged to provide to the network 0.5 (kWh) during the whole day (day and night). In addition, we assume that the operator has its private renewable energy sources which is produced free of charge and does not pollute the environment. The available energy per BS $j$ at instant $t$, $Q^{(j)}_{\text{REmax}}$, can not exceed the storage capacity, which we set to $Q^{\text{BS}}_{\text{max}} = 0.4$ kWh. Also, the maximum amount of energy that green equipment are able to produce does not exceed 0.3 kWh per one BS when favorable conditions exist [105].

### 6.5.2 Impact of the Variation of Green Energy Price

In order to analyze the impact of renewable energy price on the network performance, we plot in Fig. 6.2 the profit and the amount of CO$_2$ emissions versus $\pi^{(2)}$ that varies from 0.05 to higher values. We notice that, when the mobile operator aims only to maximize its profit (i.e., $\omega \to 0$), the profit and the amount of CO$_2$ emissions are almost constant for all prices strictly higher than $\pi^{(1)}$ and are not affected by the cost variation. This can be explained by the fact that for these values the mobile operator procures energy only from the cheapest retailer (i.e., retailer 1) as shows in Fig. 6.3. When the green energy is the cheapest, the mobile operator will trivially procure it independently of its attitude towards the environment. However, when we increase $\omega$, the mobile company tries to procure the maximum of renewable energy which constitutes around 70% of the total energy if we apply our proposed algorithm. The semi environmentally friendly operator ($\omega = 0.05$) can
consume renewable energy even if its price becomes 3 times more expensive. This leads to a lower profit but a notable reduction in terms of CO₂ emissions. However, between 0.15 MU and 0.35 MU, the amount of green energy procured is becoming less and less until it reaches 0. This example corresponds to a mobile operator doing its best to consume green energy but who does not accept a large profit reduction. For this reason, when the renewable energy becomes very expensive, the operator becomes obliged to procure electricity from retailer 1. The third case \( \omega \rightarrow 1 \) corresponds to the extreme case of a hypothetical scenario where an environmentally friendly mobile operator procures the whole available green energy even if its profit goes to 0. It should be noted that for all cases, we are maintaining a certain QoS by imposing the constraint expressed in (6.18). In our scenarios, a maximum of 2% of the subscribers are allowed to be in outage as it is mentioned in Table 6.2.

Figure 6.2: Performance of the proposed scheme versus the unitary price of renewable energy \( \pi^{(2)} \) for \( N_U = 150 \) and \( Q^{(2)}_{\text{max}} = 500 \text{ J} \) (a) profit (b) CO₂ emissions.
6.5.3 Completely Switched-off BSs During Sleep Modes

In this scenario, we assume that, initially, $N_U = 10$ users are connected to the network with random call durations. The starting instant corresponds to midnight (0:00 am). We run the simulation for 48 hours (2 days) according to the arrival process given in (6.5) and we analyze two scenarios: the first scenario entitled traditional (or trad.) refers to the case when all BSs are kept activated and powered by the smart grid and local equipment while the second scenario corresponds to the case when BS sleeping strategy is applied using GIA. In this section, we assume that all BSs are completely switched off, there is no intermediate modes during transition phases (i.e., $P_S = P_{AS} = P_{SA} = 0$ and $T_{AS} = T_{SA} = 0$) and $\omega \rightarrow 1$. In addition, we employ our proposed algorithm every $T = 1$ minute after updating the user traffic and the energy amounts.

As a first step, we study the impact of GIA on the mobile operator’s profit in addition to the total energy consumption of the network. Clearly, Fig. 6.4 shows a strong relationship between the user behavior during 24-hours, the total consumed energy and the correspond-
ing profit. In fact, the higher is the number of users, the higher is the network energy consumption. However, thanks to the application of the BS sleeping strategy, the network operator is able to ensure energy saving by switching off redundant BS mainly during non-peak hours while offering a significant gain in terms of profit during this period comparing to the traditional case. For instance, the proposed scheme can ensure a reduction of 80% of the total energy consumed, thus of CO$_2$ emissions, from 22:00 pm to 6:00 am of the second day.

![Graph](image)

**Figure 6.4**: Performance of GIA without transition modes: (a) profit of the mobile network (b) total energy consumption of the network.

In Fig. 6.5, we analyze the amount of energy procured from photovoltaic panels (generated locally) and from the energy sources existing in the smart grid (i.e., electricity and renewable energy). The energy procurement depends essentially on the availability of the locally generated green energy. In fact, during its absence, the environmentally friendly network operator consumes in priority the green energy procured from the smart grid then it compensates the lack of renewable energy by procuring electricity which corresponds to the pollutant energy that contributes in the emissions of greenhouse gas. However, when the local renewable energy is available, the network operator is able to power its network
without requiring additional energy from the smart grid. Furthermore, we notice that the BS sleeping strategy can help in the reduction of CO$_2$ emissions by offering the possibility to consume green energy for a longer time period. In fact, with the proposed scheme, solar energy can be consumed for 1 to 4 additional hours. Using the BS sleeping strategy, we were able to reduce the consumption of the pollutant energy by procuring only green energy most of the time as it is shown in Fig. 6.5(b). These results are confirmed in Fig. 6.6(a) where we compute the number of active BSs during the two days after applying the proposed green algorithm. We notice that, at peak hours, 15-16 BSs are activated to
serve all subscribers while at night and off-peak hours, the active BS number is reduced to 1 or 2 BSs. Between these periods, more BSs are activated or deactivated depending on the number of subscribers connected to the network. In order to consume a low amount of energy, the green algorithm tryes, gradually, to switch on the minimum number of BSs that respects the QoS mentioned in Table 6.2. For this reason, we notice, from Fig. 6.6(b), a high number of users in outage from 7:00 am to 10:00 am and from 19:00 pm to 21:00 pm of each day, without exceeding the tolerable 2% outage threshold. However, during peak hours, the outage percentage becomes lower because the network operator is obliged to activate all BSs to serve the high number of subscribers. During non-peak hours, the outage percentage is close to 0 due to the low number of connected users.

6.5.4 Practical Case with Transition Modes

In this scenario, we adopt the same profile used in Section 6.5.3 but we assume that these BSs are not completely switched off during sleep modes as it is described in Section 6.2.1. In fact, if we consider that a BS is completely switched off during low traffic period,
then, it requires some minutes to reboot and be ready to serve users (e.g., around 5 minutes for WiMAX BS, [106]). For this reason, during non-peak hours, we assume that BSs are turned to a standby mode with a low power consumption \( P_S \). In this case, BSs can be turned to the active mode faster. Therefore, we consider that the BS requires short transition periods \( T_{SA} \) and \( T_{AS} \) to be activated and deactivated, respectively. In our numerical results, we assume that \( T_{SA} = T_{AS} = 6 \) seconds. On the other hand, we suppose that the average power consumption during the sleep mode is \( P_S = \frac{b}{10} \) while the average power consumption during the transition periods from active to sleep mode and vice versa are lower and higher than \( b \) as follows: \( P_{AS} = \frac{b}{2} \) and \( P_{SA} = \frac{3}{2}b \), respectively.

In Fig. 6.7, we compare the performance of both algorithms to the traditional scenario (i.e., all BSs are kept active) in terms of mobile operator profit and total energy consumption. We notice that both algorithms achieve almost the same performance in terms of profit. However, in terms of energy consumption, the LCGA algorithm consumes more energy due to the fact that this algorithm prefers to turn on more BSs than activating a new BS combination as it is performed with GIA. Indeed, LCGA is developed to reduce the ON/OFF switches by trying to keep currently active BSs turned on as long as possible. So, instead of switching off all the already active BSs and turning on new BSs to serve the connected users, LCGA opts to keep the same BS combination and activate an additional BS to satisfy the QoS as it is shown in Fig. 6.8(a) where we plot the number of active BSs during the 48 hours. In this figure, we notice the existence of local peaks throughout non-peak hours with LCGA algorithm. These peaks refers to the activation of extra BSs to serve new connected users at time \( lT \) followed by a deactivation of one of the active BSs in \( (l + 1)T \).

In Fig. 6.8(b), we plot the percentage of users in outage during the two days. We notice that both proposed algorithms have a higher outage rate than the traditional case as explains Section 6.5.3. However, GIA outperforms LCGA by serving more users. Indeed, GIA provides always a more efficient combination that provides the highest utility and thus
Figure 6.7: Performance of GIA and LCGA compared to the traditional scenario (a) profit of the mobile operator (b) total consumed energy of the network.

Figure 6.8: Daily strategy of GIA and LCGA (a) number of active BSs (b) users in outage (%).

the lowest outage rate thanks to the generation of a new BS combination at each period $lT$ that is completely independent of the previous period $(l - 1)T$ while LCGA provides a BS combination that depends directly on the previous active BSs.

In Table 6.5, we summarize the total performance achieved by both algorithms and the traditional scenario during the trial period. We notice that with GIA and LCGA, the
network provides almost the same profit and consumes the same energy (around 164 MWh) by activating the same number of BSs (in average 5 – 6 BSs). Thanks to the BS sleeping strategy, the mobile operator is able to save about 50% of the total energy consumption compared to the traditional scenario. However, it sacrifices more users: around 0.5% versus 0.05% in the traditional scenario. In terms of procured energy, we notice that GIA is greener than LCGA. Indeed, around 99% of the consumed energy of GIA is procured from renewable energy sources. 93% of this energy is auto-generated locally via deployed solar cells. However, PV constitutes 82% only of the total consumed energy with LCGA. This is due to the fact that with LCGA the active BSs are almost the same during long periods of time and thus, they completely consume their auto-generated green energy and then they are obliged to procure more energy from the grid (i.e., electricity and renewable energy depending on the availability).

Nevertheless, one of LCGA advantages is the reduction of the daily ON/OFF switches. Compared to GIA, we notice that LCGA is able to reduce the daily switches by more than 60% by making 860 transitions instead of 2125 with GIA. In summary, LCGA and GIA achieve almost the same performance in terms of mobile operator profit and total energy consumption. Although it pollutes more the environment than GIA, LCGA can be considered more practical for mobile operators thanks to the reduced number of ON/OFF switches. Recall that all proposed algorithms are respecting the network outage threshold defined in (6.18).
Table 6.5: Performance of the proposed schemes during the trial period

<table>
<thead>
<tr>
<th></th>
<th>Traditional</th>
<th>GIA</th>
<th>LCGA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profit (MU)</td>
<td>116300</td>
<td>180000</td>
<td>177000</td>
</tr>
<tr>
<td>Total consumed energy (MWh)</td>
<td>321</td>
<td>161</td>
<td>164</td>
</tr>
<tr>
<td>Self-consumed PV (MWh)</td>
<td>204.6 (63%)</td>
<td>150.6 (93.5%)</td>
<td>134.3 (81.8%)</td>
</tr>
<tr>
<td>Electricity from the grid (MWh)</td>
<td>22.7 (7%)</td>
<td>0.117 (0.1%)</td>
<td>8 (5%)</td>
</tr>
<tr>
<td>Green energy from the grid (MWh)</td>
<td>93.7 (30%)</td>
<td>10.3 (6.4%)</td>
<td>21.9 (13.2%)</td>
</tr>
<tr>
<td>CO₂ emissions (Kg/hour)</td>
<td>2366</td>
<td>10</td>
<td>833</td>
</tr>
<tr>
<td>Average users in outage (%)</td>
<td>0.05</td>
<td>0.45</td>
<td>0.52</td>
</tr>
<tr>
<td>Average active BSs</td>
<td>16</td>
<td>5.6</td>
<td>5.8</td>
</tr>
<tr>
<td>ON/OFF switches</td>
<td>0</td>
<td>2125</td>
<td>860</td>
</tr>
</tbody>
</table>

6.6 Summary

In this chapter, we investigated the performance of the proposed procurement model with time varying user density to ensure energy savings and greenhouse gas emission reduction for LTE networks by solving a multi-objective optimization problem periodically. This is achieved by eliminating redundant BSs and by optimally procuring energy from the smart grid and from private green energy equipment. We have also improved our proposed algorithm by taking into account previous BS state modes (idle or active) in our problem constraints and by modeling the base station power consumption during the switching operation from sleep to active mode and vice-versa. Furthermore, we have proposed a low complexity algorithm in order to reduce the daily ON/OFF switches.

Different realistic aspects were introduced in the problem formulation such as dynamic traffic, different call services, dynamic of the available solar energy. However, this is affecting the complexity of the problem and is making the optimal solution difficult to find. Also, selecting an interval of time which can vary during the time in order to apply the algorithm instantaneously might not be really practical for mobile operators. Thus, a future extension of this study is to find another approach that deals with the different aspects by considering an average or long-term utility.
Part III

Green Mobile Operator Collaboration
Chapter 7

A Game Theoretical Approach for Cooperative Environmentally Friendly Cellular Networks Powered by the Smart Grid

7.1 Introduction

Several work have focused on the reduction of cellular network energy consumption. Most of them tackle the radio access part of the network since BSs consume more than 70% of the total power consumption [12]. Half of this energy is redundant especially during low traffic periods when these BSs are underutilized [1]. Therefore, BS sleeping strategy becomes a very useful technique that provides energy saving in recent LTE-A [50, 107]. However, most of these studies investigated the single network scenario without considering the mobile networks of other operators, which leads to suboptimal results. In fact, optimizing the joint performance of different mobile networks serving the same area provides more degrees of freedom for mobile operators to achieve green communication [108].
This new aspect of green networking is to encourage the mobile operator collaboration in order to ensure energy saving and reduce the CO\textsubscript{2} emissions during BS operation. Few work have dealt with this new trend but most of them do not include neither LTE-A aspects nor renewable energy as alternative energy source in their system models [11, 104]. The authors in [12, 109] have improved the operator cooperation problem by modeling it in a game-theoretical strategy that ensures energy saving by eliminating lightly loaded BSs.

In this chapter, we propose to investigate the collaboration between multiple mobile operators deploying LTE-A networks in the same area which is considered to be subdivided into multiple subareas characterized by different user densities. We assume that the network BSs are either powered by energy retailers existing in the smart grid and/or by renewable energy equipment owned by mobile operators and placed on BS sites. Moreover, we apply a practical and low complexity iterative algorithm to determine the efficient active BS combination that maximizes the utility function of mobile operators with respect to the network QoS. This is performed by switching off redundant BSs and maximizing the mobile network objective functions. The utility functions are optimized based on a two-level Stackelberg game. Although [84] presented pioneering work related to smart grids powering cellular networks, the novelty in this chapter with respect to [84] is the investigation of the BS sleeping strategy and operator collaboration in an LTE framework. We assume that energy retailers in the smart grid play the role of leaders that aim to maximize their profit by varying their real-time pricing while cellular networks play the role of followers that focus on maximizing their profit, minimizing the CO\textsubscript{2} emissions or achieving a trade-off between both objectives. Our work improves the energy operation of mobile operators by jointly optimizing the procurement decision from the existing multiple energy sources and finding the best active BS combination during the collaboration without affecting the desired QoS. Our study takes into account the time traffic variation and the availability of renewable energies in BS sites during the day (e.g., Photovoltaic). Our simulation results
show a significant saving in terms of CO\textsubscript{2} emissions compared to the non-collaboration case and that cooperative mobile operators exploiting renewables are more awarded than traditional operators.

The rest of this chapter is organized as follows. Section II gives the system model. In Section III, we present the utility functions of the problem. Section IV discusses the cooperative mobile operator method and the Stackelberg game. In Section V, we present our simulation results. Finally, the chapter is concluded in Section VI.

7.2 System Model

We consider a geographical area served by $N_{\text{op}}$ mobile operators. We assume that the area is subdivided into $N_{\text{Area}}$ subareas characterized by different user distribution functions $f_{i,s}(x,y)$, $s = 1, \cdots, N_{\text{Area}}$ for each mobile operator $i, i = 1, \cdots N_{\text{op}}$. For instance, the density could follow a uniform distribution with a given user density per km\textsuperscript{2} or a normal (Gaussian) distribution corresponding to concentrated users in a hotspot area and then the density is reduced as we move away from the center, etc. Each mobile operator $i$ is deploying an LTE network that satisfies the traffic demand of its customers and covers the total area. $N_{\text{BS}}^{(i)}$ denotes the number of BSs that are deployed uniformly by the mobile operator $i$ in that area. We consider that the area is divided into cells of equal size where a BS is placed in the center of each cell.

7.2.1 Energy Consumption Model for Base Stations

We consider that each BS is equipped with a single omni-directional antenna. The consumed power of a switched on BS $j$ belonging to mobile operator $i$, $P_{j,i}$, can be computed as follows [76]:

$$P_{j,i} = aP_{j,i}^{(tx)} + b,$$ (7.1)
where the coefficient $a$ corresponds to the power consumption that scales with the radiated power and the term $b$ models an offset of site power. In (7.1), $P_{j,i}^{(tx)}$ denotes the radiated power of the $j^{th}$ BS and can be expressed as follows:

$$P_{j,i}^{(tx)} = P_{\text{min}} (R_j)^{\frac{1}{\nu}} N_U^{(j,i)},$$

(7.2)

where $P_{\text{min}}$ corresponds to the minimum receiving power required by each MS, and $\nu$ denotes the pathloss exponent. $R_j = \min \left( \left( \frac{P_{\text{BS}}}{P_{\text{min}}} \right)^{\frac{1}{\nu}}, R_j^V \right)$ is the range of BS $j$ where $P_{\text{BS}}$ is the peak power per BS and $R_j^V$ is the BS range determined using the Voronoi cells. Finally, $N_U^{(j,i)}$ is the number of users served by BS $j$ of operator $i$. Note that in the collaboration mode, BS $j$ of operator $i$ can serve in addition to its users the users of other mobile operators. Thus, $N_U^{(j,i)}$ can be expressed as follows:

$$N_U^{(j,i)} = \sum_{s=1}^{N_{\text{Area}}} \sum_{k=1}^{N_{\text{op}}} N_U^{(k,s)} \int \int_{C_{j,i} \cap A_s} f_{k,s}(x, y) dx dy,$$

(7.3)

where $N_U^{(k,s)}$ is the number of users of mobile operator $k$ existing in subarea $s$ and $A_s$ denotes the surface of subarea $s$. $C_{j,i}$ is the Voronoi cell of BS $j$ of operator $i$. If a BS $j$ is completely switched off, we assume that its power consumption $P_{j,i} = 0$.

### 7.2.2 Retailers and Pollutant Levels

In our study, we assume that cellular networks are powered by $N_{\text{ret}}$ retailers existing in the smart grid. Each retailer is characterized by an offered unitary price and a pollutant level depending on the nature of the generated energy. The mobile operator $i$ has to procure from each retailer $n$ ($n = 1, \ldots, N$) a certain amount of energy $q_{i,n}$ to power its network (i.e., the deployed BSs). The procurement decision mainly depends on two factors: the unitary price of the provided energy $\pi_{i,n}$ and the penalty term related to pollutant emission.
of the energy source which is described by a quadratic function of the power consumed during the period of operation $\Delta t$ as follows [93]:

$$F(q_{i,n}) = \alpha_n(q_{i,n})^2 + \beta_n q_{i,n},$$ \hfill (7.4)

where $\alpha_n$ and $\beta_n$ are the emission coefficients of retailer $n$.

The network can also procure energy from renewable energy equipment deployed in BS sites. In fact, each BS would be powered by its own installed equipment, e.g., solar panels or wind turbine. The auto-generated amount of energy by BS $j$ is denoted $q_{j,0}$. It should be noted that the locally generated energy is free of charge unlike the energy procured from external retailer which is evaluated by the real-time pricing $\pi_n$. That is, the fossil fuel energy procured by mobile operator $i$ from the smart grid is given as follows:

$$\sum_{n=1}^{N_{ret}} q_{i,n}[\text{kWh}] = \sum_{j=1}^{N_{BS}^{(i)}} P_{j,i}[\text{kW}] \Delta t - q_{j,0}, \forall i = 1, \cdots, N_{op}. \hfill (7.5)$$

### 7.3 Utility Functions and Problem Formulation

The main objective of this chapter is to formulate an optimization problem that minimizes the total fossil fuel procured by cellular companies from the smart grid. This is performed by applying the BS sleeping strategy in a cooperative fashion such that the network QoS and the profit of each mobile operator are not degraded but enhanced.

#### 7.3.1 Mobile Operator Utility

In order to include the BS sleeping strategy in the problem formulation, we introduce a binary variable $\epsilon_{j,i}$ with $j = 1 \cdots N_{BS}^{(i)}$ to denote the state of the $j^{th}$ BS of operator $i$ as
follows:
\[ \epsilon_{j,i} = \begin{cases} 
1 & \text{if BS } j \text{ of operator } i \text{ is switched on}, \\
0 & \text{if BS } j \text{ of operator } i \text{ is switched off}.
\end{cases} \quad (7.6) \]

Let \( \epsilon_i = [\epsilon_{1,i}, \cdots, \epsilon_{N_{BS,i},i}] \). The number of ones and the number of zeros in this vector indicate the number of active and inactive BSs of mobile operator \( i \), respectively. Note that each BS can procure energy from different retailers existing in the smart grid at the same time. Hence, both the total cost of the energy consumption and the CO\(_2\) emission cost function caused by the cellular network depend only on the active BSs and the nature of the procured energy as it is given in the following expressions:

- The total cost of the energy consumption of network \( i \), \( C^{(i)} \):
  \[
  C_i (\epsilon_i) = \sum_{n=1}^{N_{ret}} \pi_n q_{i,n} (\epsilon_i). 
  \]
  \( (7.7) \)

- The CO\(_2\) emission cost function of network \( i \), \( I_i \):
  \[
  I_i (\epsilon_i) = \sum_{n=1}^{N_{ret}} (\alpha_n (q_{i,n} (\epsilon_i))^2 + \beta n q_{i,n} (\epsilon_i)). 
  \]
  \( (7.8) \)

Indeed, including the BS sleeping strategy for each operator, equation (7.5) becomes as follows:
\[
\sum_{n=1}^{N_{ret}} q_{i,n} = \sum_{j=1}^{N_{BS}^{(i)}} \epsilon_{j,i} (P_{j,i} \Delta t - q_{j,0}). 
\]
\( (7.9) \)

The function \( I_i \) reflects the friendliness to the environment of the mobile network operator \( i \) and corresponds to the CO\(_2\) emissions caused by its total network energy consumption.

Each mobile operator \( i \) has to optimally compute the amount of energy to procure from the smart grid in order to maximize its utility function which corresponds to weighted bi-
objective functions expressed as follows:

\[ U_{i}^{\text{op}} (\epsilon_i) = (1 - \omega_i) \mathcal{P}_i (\epsilon_i) - \omega_i \mathcal{I}_i (\epsilon_i), \]  

(7.10)

where \( \omega_i \) is the Pareto weight related to operator \( i \) \((0 < \omega_i < 1)\), \( \mathcal{I}_i \) is given in (7.8) and \( \mathcal{P}_i \) is a function that corresponds to the \( i^{th} \) mobile operator’s profit and is given by:

\[ \mathcal{P}_i (\epsilon_i) = R_i - C_i (\epsilon_i), \]  

(7.11)

where \( C_i \) is given in (7.7) and \( R_i \) is the \( i^{th} \) mobile operator revenue which is equal to \( R_i = P_{\text{ser}} \sum_{s=1}^{N_{\text{Area}}} N_{\text{Served}}^{(i,s)} \), where \( P_{\text{ser}} \) is the service price (i.e., we assume here that all mobile operators offer the same service with the same price) and \( N_{\text{Served}} \) is the number of users which are covered by at least one mobile operator BS (i.e., only the served users pay the equivalent of the proposed service). Indeed, by applying the BS sleeping strategy, it might happen that some regions of the area become out-of coverage and thus users in these regions will be in outage. Therefore, in order to maintain the network QoS, we impose the following constraint to each mobile operator:

\[ N_{\text{Served}}^{(i)} \geq \tau N_{U}^{(i)}, \]  

(7.12)

where \( \tau \) is a tolerance allowed by the mobile operator, \( N_{\text{Served}}^{(i)} = \sum_{s=1}^{N_{\text{Area}}} N_{U}^{(i,s)} \int_{C_{j,i} \cap A_s} f_{i,s}(x) dx \ dy \) and \( N_{U}^{(i)} = \sum_{s=1}^{N_{\text{Area}}} N_{U}^{(i,s)} \) are the number of users of mobile \( i \) that are covered by at least one BS and the total number of users of mobile operator \( i \), respectively. In (7.10), the Pareto weight is introduced to model the operator’s attitude towards the environment. Indeed, when \( \omega_i \to 0 \), we are dealing with the utility function given in (7.11). This corresponds to a selfish network operator that aims to maximize its own profit \( \mathcal{P}_i \) regardless of its impact on the environment. When \( \omega_i \to 1 \), we deal with the utility function given in (7.8), which
corresponds to an environmentally friendly network operator that aims to reduce CO$_2$ emissions regardless of its own profit. Other values of $\omega_i$ constitute a tradeoff between these two extremes. Hence, the optimization problem is expressed as follows:

$$\text{Maximize} \ (7.10) \quad \epsilon, q$$

$$\text{Subject to:} \ (7.9) \text{ and } (7.12).$$

7.3.2 Energy Retailer Utility

We assume that each retailer aims to maximize its profit when powering the mobile operator networks by optimizing its unitary energy price $\pi^{(n)}$. Thus, the utility function of retailer $n$ existing in the smart grid is given as follows:

$$\text{Maximize} \ U_{ret} = \pi_n - c_n \sum_{i=1}^{N_{op}} q_{i,n}, \quad (7.14)$$

where $c_n$ is the cost of generating one kWh of electricity for retailer $n$.

7.4 Green Cooperative Operators and Stackelberg Game

In the cooperative mode, mobile operators can exploit the existence of other competitive providers in order to ensure energy saving and additional profit as well. In fact, instead of keeping active lightly loaded BSs, the mobile operator can turn them off and the subscribers may maintain their communication active using the radio access network of another operator serving the same area and vice versa. Therefore, we propose that the switching off operation is performed jointly as if the system consists in a bigger network that includes all BSs of all mobile operators that have to maintain their own QoS. However, even for fixed values of $q_{i,n}$, it is very complex to find the optimal solution of problem (7.13) using an
exhaustive search mainly for large-scale dimension networks. Thus, we propose to employ a low complexity algorithm to switch off the maximum number of BSs that maximizes the joint utilities with respect to QoS [50]. In [50], the authors proposed and compared deterministic and heuristic approaches used to solve similar optimization problems for single mobile operators. Results show that the low complexity iterative algorithm is able to achieve performance close to the evolutionary algorithms (e.g., genetic algorithm and particle swarm optimization approach) with significant gains in terms of computational time. Hence, for simplicity, we employ the iterative algorithm to solve the formulated optimization problems in this work. At each iteration, the algorithm switches off the BS that when eliminated provides the maximum mobile operator utility. Hence, at each iteration (i.e., for a given BS combination $\epsilon_i, i = 1, \cdots, N_{op}$), a utility is computed based on the amount of procured energy by each operator from the smart grid. In order to perform this, we propose to employ a Stackelberg game which has two levels: a cellular network level (i.e., followers) and a smart grid level (i.e., leaders).

### 7.4.1 Cellular Network Level Game

From (7.13) and for a given BS combination, we can determine whether the QoS of the network is satisfied or not in addition to the total amount of energy to be procured from the smart grid. Indeed, after fixing the eventual switched on BSs, we can find the new Voronoi diagram and then determine the power consumption of each BS as well as the total energy needed by each operator using (7.1) and (7.5), respectively. Then, the number of served users can be determined and the QoS can be checked (i.e., (7.12)). If it not satisfied, the sum-utility function of mobile operators is set to zero. Otherwise, we can compute the optimal utility function for each mobile operator by computing the Lagrangian function for
(7.13) expressed as

\[ L_i(q_{i,n}, \lambda) = U_i(\epsilon_i) + \lambda \left( \sum_{n=1}^{N_{\text{ret}}} q_{i,n} - \sum_{j=1}^{N_{\text{BS}}} \epsilon_{j,i} (P_{j,i} \Delta t - q_{j,0}) \right), \quad (7.15) \]

where \( \lambda \) is the Lagrangian multiplier corresponding to constraint (7.9). By computing the partial derivative of \( L_i \) with respect to \( q_{i,n} \), we determine the optimal energy amount procured by mobile operator \( i \) from each retailer \( n \) as a function of \( \lambda \) as follows:

\[ \frac{\partial L_i}{\partial q_{i,n}} = -(1 - \omega_i) \pi_n - \omega_i (2 \alpha_n q_{i,n} - \beta_n) + \lambda = 0. \quad (7.16) \]

Then, using constraint (7.9), the optimal amount of energy \( q_{i,n}^* \) procured by operator \( i \) from retailer \( n \) in terms of retailer prices is given as follows:

\[ q_{i,n}^* = \left( \frac{1 - \omega_i}{\omega_i} \right) \left( (1 - 2 \chi \alpha_n) \frac{\pi_n}{4 \alpha_n^2 \chi} + \sum_{k=1}^{N_{\text{ret}}} \frac{\pi_k}{4 \alpha_n \alpha_k \chi} \right) + \frac{(1 - 2 \chi \alpha_n) \beta_n}{4 \alpha_n^2 \chi} + \sum_{k=1}^{N_{\text{ret}}} \frac{\beta_k}{4 \alpha_n \alpha_k \chi} + \sum_{j=1}^{N_{\text{BS}}} \frac{\epsilon_{j,i} (P_{j,i} \Delta t - q_{j,0})}{2 \beta_n \chi}, \quad (7.17) \]

where \( \chi = \sum_{k=1}^{N_{\text{ret}}} \frac{1}{2 \alpha_k} \). From the expression above, we can notice that the amount of energy decreases with the increase of electricity price as the first-order derivative of \( q_{i,n}^* \) is negative. Furthermore, we notice that the variation depends also on the operator’s attitude towards the environment \( \omega_i \). Indeed, as \( \omega_i \to 0 \), the mobile operator is more and more concerned by its profit and the decrease of the amount of procured electricity is more important when \( \pi_n \) increases. However, for an environmentally friendly mobile operator \( (\omega_i \to 1) \), the price increase is no more important and the procurement decision is more related to the pollution coefficient factors \( (\alpha_n \text{ and } \beta_n) \) as \( \frac{1 - \omega_i}{\omega_i} \to 0 \) in this case.
7.4.2 Energy Provider Level Game

The objective is to find the optimal price $\pi_n$ that maximizes the utility function $U_{ret}^n$ expressed in (7.14). By computing the first-order derivative of $U_{ret}^n$ with respect to $\pi_n$ and equating it to 0, we can determine the optimal price value as follows:

$$
\pi_n^* = \frac{-2\alpha_n^2\chi}{\Omega(1 - 2\chi\alpha_n)} \left( \Omega \sum_{k=1}^{N_{ret}} \frac{\pi_k}{4\alpha_n\alpha_k\chi} + N_{op} \sum_{k=1}^{N_{ret}} \frac{\beta_k}{4\alpha_n\alpha_k\chi} + \frac{(1 - 2\chi\alpha_n)(\beta_nN_{op} - c_n\Omega)}{4\alpha_n^2\chi} \right) \\
+ \sum_{i=1}^{N_{op}} \sum_{j=1}^{N_{BS}^{(i)}} \epsilon_{j,i} \left( P_{j,i} \Delta t - q_{j,0} \right) \\
+ \sum_{i=1}^{N_{op}} \sum_{j=1}^{N_{BS}^{(i)}} \epsilon_{j,i} \left( P_{j,i} \Delta t - q_{j,0} \right),
$$

(7.18)

where $\Omega = \sum_{i=1}^{N_{op}} \frac{1 - \omega_i}{\omega_i}$. Note that the electricity price of retailer $n$ depends on the total amount of energy that will be procured by all mobile operators in addition to other electricity retailer prices $\pi_k, k \neq n$. Since $1 - 2\chi\alpha_n < 0$, we can clearly see that as mobile operators procure higher energy from retailer $n$ as the unitary price increases. Fixed-point algorithm can be employed to find the optimal $\pi_n^*, n = 1, \ldots, N_{op}$. The existence and uniqueness of the Stackelberg equilibrium for similar problems is demonstrated in [84].

7.5 Results and Discussion

In this section, we investigate the performance of the proposed approach detailed in Section 7.4. We start by presenting the simulation model. Then, we discuss the numerical results.

7.5.1 Simulation Model

We consider $N_{op} = 2$ mobile operators, denoted, Op1 and Op2, serving a $5 \times 5$ (Km$^2$) LTE coverage area and offering a service with $P_{ser} = 4$ MU. Op1 and Op2 are placing
uniformly $N_{(1)}^{(1)} = 16$ and $N_{(2)}^{(2)} = 9$ BSs with inter-site distances equal to $\frac{5}{4}$ km and $\frac{5}{3}$ km, respectively. The LTE and pathloss parameters are obtained from [49]. All BSs have the same power model with the same maximal transmit power $0.8 \text{ W}$, $a = 21.45$ and $b = 354.44 \text{ W}$. We set $\nu = 3.76$, $P_{\text{min}} = -120 \text{ dBm}$ and the tolerance $\tau = 98\%$.

Concerning the smart grid retailers, we assume that $N_{\text{ret}} = 2$ retailers produce energy from different sources. Each type of energy source $n$ is characterized by its unitary energy cost expressed in [MU/kWh] ($\pi_1 = 0.3$ (MU) and $\pi_2 = 0.1$ (MU)) and pollutant coefficients $\alpha_1 = 0.01$, $\alpha_2 = 0.05$ and $\beta_1 = \beta_2 = 0.1$. In addition, we assume that the operator has its private renewable energy source which is produced free of charge and does not pollute the environment. The available energy per BS $j$ is produced as given in (6.4) with $A = 0.9 \text{[kW]}$, $B = 12:00 \text{ p.m.}$, and $C = 3$ (see Table 7.1) where $G$ is the generated energy per BS that will be used in the next period of time $\Delta t$. We consider the that the area is subdivided into two subareas $N_{\text{Area}} = 2$, as shows Fig. 7.1(a), where users of both mobile operators are uniformly distributed $f_{i,s}(x, y) = \frac{1}{A_s}$ but with different densities. We adopt the daily traffic pattern given in (6.5) and we simplify it as described in Table 7.1. The studied scenario can correspond to the case where the area of interest consists of a residential area $A_1$ with higher user density during non-working hours and a central business district $A_2$ where $80\%$ of the users are connected during the working hours. We compare our approach, denoted coop., with the traditional case, denoted uncoop., when both cellular companies operate individually.

Table 7.1: Studies scenario parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>0:00-8:00</th>
<th>8:00-12:00</th>
<th>12:00-16:00</th>
<th>16:00-0:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{(1)}^{(1)}$</td>
<td>100</td>
<td>300</td>
<td>300</td>
<td>100</td>
</tr>
<tr>
<td>$N_{(2)}^{(2)} = \frac{3}{4} N_{(1)}^{(1)}$</td>
<td>75</td>
<td>225</td>
<td>225</td>
<td>75</td>
</tr>
<tr>
<td>Density in $(A_1, A_2)$</td>
<td>(0.9, 0.1)</td>
<td>(0.2, 0.8)</td>
<td>(0.2, 0.8)</td>
<td>(0.9, 0.1)</td>
</tr>
<tr>
<td>$G$ per BS [kWh]</td>
<td>0.07</td>
<td>1.86</td>
<td>2.61</td>
<td>0.23</td>
</tr>
</tbody>
</table>
Table 7.2: Performance of the proposed scheme

<table>
<thead>
<tr>
<th>Iterations</th>
<th>0</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fossil fuels[kWh] (Op1, Op2)</td>
<td>47.58, 26.09</td>
<td>47.90, 17.43</td>
<td>48.24, 8.71</td>
<td>48.65, 0</td>
<td>44.75, 0</td>
</tr>
<tr>
<td>$\omega_1 = \omega_2 = 0.1$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$(q_{11}, q_{12})$[kWh]</td>
<td>26.47, 21.11</td>
<td>27.66, 20.24</td>
<td>28.87, 19.37</td>
<td>30.13, 18.51</td>
<td>27.32, 17.43</td>
</tr>
<tr>
<td>$(q_{21}, q_{22})$[kWh]</td>
<td>8.55, 17.53</td>
<td>2.26, 15.16</td>
<td>0.871</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$(\pi_1, \pi_2)$[MU]</td>
<td>0.53, 0.35</td>
<td>0.49, 0.33</td>
<td>0.46, 0.31</td>
<td>0.43, 0.29</td>
<td>0.41, 0.28</td>
</tr>
<tr>
<td>$(U_1^{ret}, U_2^{ret})$[MU]</td>
<td>8.18, 9.96</td>
<td>5.97, 8.35</td>
<td>4.10, 6.89</td>
<td>2.59, 5.57</td>
<td>2.0, 5.00</td>
</tr>
<tr>
<td>$(P_1, P_2)$[MU]</td>
<td>382.32, 293.16</td>
<td>383.37, 297.77</td>
<td>384.83, 301.87</td>
<td>386.19, 305.44</td>
<td>387.71, 305.32</td>
</tr>
<tr>
<td>$(I_1, I_2)$[Kg/hour]</td>
<td>34.06, 18.72</td>
<td>32.93, 13.29</td>
<td>31.92, 9.20</td>
<td>31.09, 6.49</td>
<td>27.13, 6.00</td>
</tr>
<tr>
<td>$\omega_1 = \omega_2 = 0.8$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$(q_{11}, q_{12})$[kWh]</td>
<td>31.33, 16.25</td>
<td>32.52, 15.38</td>
<td>33.73, 14.50</td>
<td>35.00, 13.65</td>
<td>32.18, 12.57</td>
</tr>
<tr>
<td>$(q_{21}, q_{22})$[kWh]</td>
<td>13.42, 12.67</td>
<td>7.12, 10.30</td>
<td>0.79, 7.92</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>$(\pi_1, \pi_2)$[MU]</td>
<td>11.04, 7.04</td>
<td>9.81, 6.26</td>
<td>8.58, 5.48</td>
<td>7.36, 4.60</td>
<td>6.79, 4.34</td>
</tr>
<tr>
<td>$(U_1^{ret}, U_2^{ret})$[MU]</td>
<td>480.66, 200.91</td>
<td>377.34, 158.36</td>
<td>286.22, 120.75</td>
<td>208.23, 88.46</td>
<td>175.89, 75.03</td>
</tr>
<tr>
<td>$(P_1, P_2)$[MU]</td>
<td>−56.43, 66.54</td>
<td>−11.64, 169.48</td>
<td>34.68, 253.73</td>
<td>81.78, 318.75</td>
<td>130.63, 316.54</td>
</tr>
<tr>
<td>$(I_1, I_2)$[Kg/hour]</td>
<td>27.79, 12.44</td>
<td>27.20, 7.56</td>
<td>26.73, 4.01</td>
<td>26.43, 1.84</td>
<td>22.73, 1.56</td>
</tr>
</tbody>
</table>

7.5.2 Simulation Results

We start by studying the performance of the proposed method for different values of $\omega_i, i = \{1, 2\}$. First, we apply it during the first period of time 0:00 – 8:00 a.m. where renewable energy is not yet available in the network. During this period, the algorithm eliminates 13 BSs: all the BSs of Op2 and 4 BSs of Op1. In fact, when eliminating a BS, the Voronoi cells of the neighbor BSs increase and thus the BS radiated power increases too. Thus, as each BS of Op2 is surrounded by Op1 BSs and as $N_U^{(2)} < N_U^{(1)}$, eliminating BSs of Op2 is more energy efficient than switching off Op1 BSs. This can be deduced from the fossil fuel consumption given in Table 7.2. Indeed, we can see that during the first nine iterations the energy consumption of Op1 is increasing while the one of Op2 is decreasing until reaching zero. After that, the algorithm deals with Op1 BSs and switches the maximum possible number of BSs that when eliminated the QoS is maintained by respecting constraint (7.12).

The behaviors of the system actors during the switching off process are also investigated in Table 7.2 where we compare their objective functions for different values of $\omega_i, i = 1, 2$. 
When both operators are focusing on maximizing their own profits (i.e., $\omega_i \rightarrow 0, i = 1, 2$), we can see that they are trying to buy an important amount of energy from the cheapest retailers in order to maximize their profits. However, when $\omega_i \rightarrow 1, i = 1, 2$, we notice that the retailers are exploiting the fact that operators are worried about the environment and thus they significantly increase their prices as the operators will power their network with the cleanest electricity sources (This is not a realistic scenario but it illustrates the behavior of the retailers according to the formulated Stackelberg game). Indeed, although it is expensive, the energy procured by Op1 from retailer 1 has increased by 18% and thus the total CO$_2$ emissions is reduced by 36.39% after switching off all the possible BSs. Furthermore, Table 7.2 shows that retailers are reducing their prices when the energy consumption of BSs becomes lower by applying the BS sleeping strategy and thus their profits are reduced too. However, the inverse can be noticed for the operators. It is worth noting that Op2 is gaining better than Op1 in terms of profit over the iterations (4% for Op2 versus 1.4% for Op1 when $\omega_i = 0.8$) as all its BSs are switched off and does not pay energy bills thanks to the cooperation with Op1 for this scenario.

Fig. 7.1(b) shows the number of switched off BSs during the two days for $\omega_1 = \omega_2 = 0.5$ and two extreme values of $\eta$ where $\eta$ denotes the percentage of renewable energy gen-
erated by Op1 using its deployed solar panels in BS sites while $100 - \eta$ corresponds to the percentage of green energy produced by Op2. In our simulation, we assume that the green energy produced during the period $t$ is stored and used during the next time slot $t + 1$. If it is underutilized it can be used in the next periods of time. We can notice for the first period of time (i.e., 0:00 to 8:00) both operators switch off the same number of BSs independently of the value of $\eta$ since there is no renewable energy available during this period. However, as renewable energy is produced, the number of BSs becomes different depending on its availability for the operator. We can deduce that, most of the time when cooperating, the operator that does not produce green energy turns always off its BSs (e.g., period of time 3, 4, 7 and 8) and the operator having green energy activates its network to serve users of both operators since its energy is free of charge. We can also notice that the number of BSs is varying with the number of users connected to the network.

In Fig. 7.2, we compare between the collaboration and the non-collaboration modes for $\eta = 90\%$ and $\omega_1 = \omega_2 = 0.5$. Fig. 7.2(a) illustrates the evolution of the retailer prices during the day that decrease as renewable energy becomes available in the network. We can see that in the middle of the day (period of time 3), the prices reach their lowest values going from $(1.8, 1.21)$ MU at night (period of time 1) to $(0.3, 0.21)$ MU for the coop. mode. This means that during this period where renewable energy is enough to cover the network need (since $U_{ret}^{(1)} = U_{ret}^{(2)} \approx 0$ in Fig. 7.2(b)), retailers set their prices as low as possible to attract operators. Thanks to cooperation, mobile operators are able to reduce their total CO$_2$ by consuming less fossil fuels and switching off more BSs as shows Fig. 7.2(c). During uncoop., for high number of users, non-cooperative operators are not able to turn off their BSs as it is not possible for them to cover the whole area and then respect their QoS.
7.6 Summary

In this chapter, we investigated the performance of the green networking approach for multi-operator collaboration using a two-level game-theoretical approach where mobile operators play the role of follower and the smart grid play the role of leader. We have formulated an optimization problem that aims to maximize the operator profit, reduce the total CO₂ emissions or achieve a tradeoff between both objectives. The problem is jointly solved using a low complexity iterative algorithm to switch off redundant base stations and by finding the optimal solution for the smart grid energy procurement by taking into account the fossil fuel real-time pricing and the availability of green energy generated in base station sites. Comparing to the traditional non-collaborative mode, our approach leads to an important saving in terms of fossil fuel consumption with a notable increase of the mobile operator profits.
Chapter 8

Multi-Operator Collaboration for Green Cellular Networks under Roaming Price Consideration

8.1 Introduction

In this chapter, we propose to investigate the collaboration between multiple mobile operators deploying LTE-A networks in the same area. We assume that the network BSs are either powered by traditional retailer and/or by renewable energy equipment owned by mobile operators and placed on BS sites. Moreover, we apply a practical and low complexity iterative algorithm to determine the efficient active BS combination that ensure energy saving with respect to the network QoS. However, during cooperation, extra charge can be imposed to operators that exploit another operator’s infrastructure to serve their subscribers while their BSs are switched off and random cooperation may lead to the increase of a certain mobile operator profit at the expense of other competitive operators. This can cause a high energy consumption and a very low profit for the active network. Therefore and unlike Chapter 7, we introduce certain criteria for mobile operator cooperation based
on their profits before and after cooperation by deducing the best roaming price. Finally, we compare our results with the traditional case where networks operate individually in addition to an ideal scenario where the networks of several operators are assumed to form a single virtual network operating as it is owned by a single operator.

The chapter is organized as follows. Section II presents the system model. Section III presents the problem formulation for a single mobile operator scenario. Section IV discusses the case of cooperative mobile operators and establishes the cooperation decision criteria. In Section V, we present our simulation results. Finally, Section VI concludes the chapter.

8.2 System Model

We consider a geographical area served by $N_{op}$ mobile operators. Each mobile operator $n = 1, \cdots, N_{op}$ is deploying an LTE network that satisfies the traffic demands of its customers and covers the total area. $N_{BS}^{(n)}$ denotes the number of BSs that are deployed uniformly by the mobile operator $n$ in that area. We consider that the area is divided into cells of equal size where a BS is placed in the center of each cell. In LTE, the access scheme for the DL is the OFDMA while in the UL the SCFDMA is used. In fact, the DL and UL available spectrums are divided into $N_{RB}$ RBs that contain a fixed number of consecutive subcarriers ($N_{RB} = N_{RB}^{UL} = N_{RB}^{DL}$). RBs are assigned to users according to the resource allocation procedure followed by each operator. We assume that the mobile operators are using different frequency bands such that there is no inter-operator inference. However, intra-operator interference is taken into account (i.e., frequency reuse 1 is assumed within each operator’s network).
8.2.1 Energy Consumption Model for Base Stations

We consider that each BS is equipped with a single omni-directional antenna. The consumed power of a switched on BS $j$ belonging to mobile operator $n$, $P_j^{(n)}$, can be computed as follows [50]:

$$P_j^{(n)} = aP_{n_j}^{tx} + b,$$

where the coefficient $a$ corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses and the term $b$ models an offset of site power which is consumed independently of the average transmit power and is due to signal processing, battery backup, and cooling. In (8.1), $P_{n_j}^{tx}$ denotes the radiated power of the $j^{th}$ BS belonging to operator $n$ and can be expressed as follows:

$$P_{n_j}^{tx} = \sum_{r=1}^{N_{RB}^{(DL)}} P_{nr},$$

where $P_{nr}$ is the power consumed per one RB and depends on the RB state. If the RB $r$ of BS $j$ is allocated to a certain user, then $P_{nr} = \frac{P_{tot}}{N_{RB}^{(DL)}}$ else $P_{nr} = P_{idle} \approx 0.19$ dBm, [49]. If a BS $j$ is completely switched off, we assume that its power consumption $P_j^{(n)} = 0$. To power its BSs, the mobile operator is able to procure energy either from a traditional electricity provider or from renewable energy generators installed on BS sites, e.g., solar panels or wind turbine. The amount of energy procured from the fossil fuel retailer and the auto-generated amount of energy consumed by BS $j$ of mobile operator $n$ are denoted $q_j^{(n,f)}$ and $q_j^{(n,g)}$, respectively, where $f$ and $g$ stands for fossil fuel energy an green energy, respectively. The amount of green energy generated locally is varying for one BS to another depending on environmental or technical reasons. For instance, the solar rating depends essentially on the size of PhotoVoltaic (PV) panels and whether they experience any shading during the day.
It should be noted that the locally generated energy is free of charge unlike the energy procured from external retailer which is evaluated by $\pi(f)$ where $\pi(f)$ is the cost of one unit of energy. That is, the fossil fuel energy procured by BS $j$ of mobile operator $n$ is given as follows:

$$q_{j}^{(n,f)} = P_{j}^{(n)} \Delta t - q_{j}^{(n,g)}, \forall j = 1, \cdots, N_{\text{BS}}(n), \forall n = 1, \cdots, N_{\text{op}},$$  \hspace{1cm} (8.3)$$

where $\Delta t$ is the BS operation time. The aim of each mobile operator is to minimize the fossil fuel energy consumption in order to reduce the cost of its consumed energy.

### 8.2.2 Operator Services

In our framework, we consider that each network operator offers $M$ different services to its subscribers. Each service is characterized by data rate thresholds $R_{m,th}^{(\text{UL})}$ and $R_{m,th}^{(\text{DL})}$ for UL and DL, respectively, and a unitary price $p^{(m)}$ with $m = 1, \cdots, M$. We suppose that each customer associated to the network $n$ is using one of the $M$ offered services. For simplicity, in this chapter, we assume that all mobile operators offer similar services to their corresponding subscribers.

The main objective of this chapter is to formulate an optimization problem that minimizes the total fossil fuel energy consumption of the cellular companies operating in the same geographical area. This is performed by applying the BS sleeping strategy in a cooperative fashion such that the network QoS and the profit of each mobile operator are not degraded but enhanced. However, in some cases, although it helps in reducing the CO$_2$ emissions, cooperation might lead to a negative impact on the profit of one of the mobile operators. Therefore, we establish a condition that indicates whether cooperation is favorable to the operator or not. Thus, comparison between traditional (i.e., cellular companies operating individually) and cooperative approaches are needed.


8.3 Green Uncooperative Operators

We start by evaluating the gain of applying the BS sleeping strategy separately for each operator in terms of energy saving and profit. Let $\epsilon^{(n)}$ be a binary vector that indicates the states the $n^{th}$ mobile operator BSs during the period $\Delta t$. Its elements $\epsilon_j^{(n)}$ indicates whether a BS $j$ of cellular company $n$ is turned off or not as follows:

$$
\epsilon_j^{(n)} = \begin{cases} 
1 & \text{if BS } j \text{ is turned on,} \\
0 & \text{if BS } j \text{ is turned off.}
\end{cases} \quad (8.4)
$$

The number of ones and the number of zeros in this vector indicate the number of active and inactive BSs, respectively. Thus, the fossil fuel energy consumption and the corresponding total cost of the $n^{th}$ mobile operator, denoted $E^{(n)}$ and $C^{(n)}$ respectively, are given as follows:

$$
E^{(n)} = \sum_{j=1}^{N_{BS}^{(n)}} \epsilon_j q_j^{(n,f)}, \quad \text{and} \quad C^{(n)} = \pi f E^{(n)}. \quad (8.5)
$$

On the other hand, we compute the mobile operator profit provided by the operating BSs in the area. It is exclusively computed from the number of served customers and the corresponding service. In fact, during $\Delta t$, each mobile operator $n$ is serving $N_{U}^{(n)}$ mobile stations (MSs) connected to the network and enjoying one of the $M$ proposed services. We denote by $N_{out}^{(n)}$ the number of users in outage during a period $\Delta t$ where $N_{out}^{(n)} \ll N_{U}^{(n)}$. A user $i$ using the $m^{th}$ service communicates successfully with a BS, if its UL and DL data rates, denoted $R_i^{(UL)}$ and $R_i^{(DL)}$, are higher than the service data rate thresholds, $R_{m,th}^{(UL)}$ and $R_{m,th}^{(DL)}$ respectively. By denoting a binary parameter $\gamma_i^{(n)}$, $i = 1 \cdots N_{U}^{(n)}$, we can express this assumption as follows:

$$
\gamma_i^{(n)} = \begin{cases} 
1 & \text{if } R_i^{(UL)} \geq R_{m,th}^{(UL)} \text{ and } R_i^{(DL)} \geq R_{m,th}^{(DL)} \\
0 & \text{if } R_i^{(UL)} < R_{m,th}^{(UL)} \text{ or } R_i^{(DL)} < R_{m,th}^{(DL)}.
\end{cases} \quad (8.6)
$$
In other words, if \( \gamma_i^{(n)} = 0 \), the \( i^{th} \) user is in outage during \( \Delta t \). Let the vector \( \gamma^{(n)} = [\gamma_1^{(n)} \ldots \gamma_{NU}^{(n)}] \), then the number of ones and the number of zeros in \( \gamma^{(n)} \) correspond to the number of served users and the number of users in outage, respectively. Consequently, only the served users pay the equivalent of the proposed service. Hence, the profit \( P_u^{(n)} \) of the \( n^{th} \) mobile operator corresponding to its individual operation in this area is expressed as follows:

\[
P_u^{(n)} = \sum_{i=1}^{NU} \gamma_i^{(n)} p_i^{(n,m)} + R_{\text{op}} \left( N_{U}^{(n)} \right) - C^{(n)},
\]

(8.7)

where \( p_i^{(n,m)} \) is the unitary cost of the service \( m \) used by the \( i^{th} \) user of the \( n^{th} \) cellular company and \( R_{\text{op}} \) is a constant extra revenue due to fixed subscription fees paid by the mobile operator subscribers. Hence, the optimization problem for a single mobile operator \( n \) is expressed as follows:

**Minimize** \( \mathcal{E}^{(n)} = \sum_{j=1}^{N_{BS}^{(n)}} \epsilon_j q_j^{(n,f)} \),

(8.8)

**Subject to:** \( \frac{N_{\text{out}}^{(n)}(\gamma^{(n)})}{N_U^{(n)}} \leq P_{\text{out}} \).

(8.9)

This problem is only constrained by (8.9) which forces the number of users in outage to be less than a tolerated outage probability threshold \( P_{\text{out}} \). This constraint is directly related to the resource allocation algorithm described in Section 2.5. It is very complex to find the optimal solution of this problem since the decision variables correspond to large binary vectors that depend on \( N_U^{(n)} \) and \( N_{BS}^{(n)} \). In [50], the authors proposed and compared deterministic and heuristic approaches used to solve similar optimization problems for single mobile operators. Results show that the low complexity iterative algorithm is able to achieve performance close to the evolutionary algorithms (e.g., genetic algorithm and particle swarm optimization approach) with significant gains in terms of computational time. Hence, for simplicity, we employ the iterative algorithm to solve the formulated optimiza-
tion problems in this work. Once optimization problem (8.8) is solved for each mobile operator \( n \), we can deduce the corresponding profit \( \mathcal{P}_u^{(n)} \) by computing (8.7) which has to be at least maintained in case of cooperative operation.

### 8.4 Green Cooperative Operators and Cooperation Decisions

In the cooperative mode, mobile operators can exploit the existence of other competitive providers in order to ensure energy saving and additional profit as well. In fact, instead of keeping active lightly loaded BSs, the mobile operator can turn them off and the subscribers may maintain their communication active using the radio access network of another operator serving the same area and vice versa. We propose to perform this by solving the following optimization problem where BS sleeping strategy is applied in order to achieve energy saving:

\[
\begin{align*}
\text{Minimize} & \quad \gamma^{(n)}, \epsilon^{(n)}, n = 1, \ldots, N_{\text{op}} \\
\text{Subject to:} & \quad \frac{N_{\text{out}}}{N_{U}^{(n)}} \leq P_{\text{out}}. \quad (8.11)
\end{align*}
\]

Once this optimization problem is solved using the iterative algorithm presented in [50], we obtain the optimal energy consumption under cooperative operation for each network and thus the optimal vectors \( \gamma^{(n,t)} \) and \( \epsilon^{(n)} \), \( n, t = 1, \ldots, N_{\text{op}} \). We notice here that \( N_{\text{out}}^{(n)} \) does no more depend on \( \gamma^{(n,n)} \) only but also depends on the allocation over other mobile operators which are determined using \( \gamma^{(n,t)}, t \neq n \). Indeed, thanks to the cooperation between mobile operators, some of users of mobile operator \( n \) can be served by another mobile operator \( t \) and vice versa. For this reason, we have introduced new binary vectors \( \gamma^{(n,t)} \) of
size $1 \times N_U^{(n)}$ that indicates whether a user of mobile operator $n$ is served successfully by mobile operator $t$ or not. This way, during the resource allocation algorithm, more degrees of freedom are provided for all users because of the increase of the number of RBs in the DL and UL directions. Thus, higher channel gains can be allocated and energy saving can be achieved. However, random cooperation may lead to the increase of a certain mobile operator profit at the expense of other competitive operators. This can cause a high energy consumption and a very low profit for the active network. For instance, a mobile operator $A$ may switch off all its BSs while all its users are served by BSs owned by mobile operator $B$ which pays all the energy bills. For this reason, we enforce fairness by introducing the notion of roaming price that will allow any mobile operator to decide whether to cooperate or not.

In our study, we assume that the roaming price, denoted $p_{nt}$, corresponding to the cost of serving users belonging to another operator is equal for every pairs of cooperative operators $(n,t)$, i.e., $p_{nt} = p_{tn}$. In our framework, the profit of the cooperative mobile operator $n$ denoted $P_c^{(n)}$ is expressed as follows:

$$P_c^{(n)} = \sum_{i=1}^{N_U^{(n)}} \sum_{t=1}^{N_{op}} \gamma_{i}^{(n)} \gamma_{i}^{(t,n)} \left( p_{i}^{(n,m)} - p_{nt} \right) + \sum_{t=1}^{N_{op}} \sum_{t \neq n} \sum_{i=1}^{N_U^{(t)}} \gamma_{i}^{(t,n)} \left( p_{i}^{(n,m)} - p_{nt} \right) + \sum_{t=1}^{N_{op}} \sum_{t \neq n} \sum_{i=1}^{N_U^{(t)}} \gamma_{i}^{(t,n)} \left( p_{i}^{(n,m)} - p_{nt} \right) + R_{op} \left( N_U^{(n)} \right) - C_c^{(n)}$$

where the first term in (8.12) corresponds to the operator revenue coming from serving its own users while the second term is the revenue coming from users served by other mobile operators after paying the roaming cost. The third term in (8.12) is the gain obtained from serving users belonging to other networks which depends on $p_{nt}$. Finally, $R_{op}$ is the constant revenue and $C_c^{(n)}$ is the network energy consumption cost obtained after solving (8.10). A mobile operator $n$ cooperates only if its cooperative profit $P_c^{(n)}$ is greater than or equal
to than the uncooperative profit $P_u^{(n)}$ expressed in (8.7). Thus, the operators have to solve the following non-homogenous system of $N_{op}$ linear inequalities with $N_p = \frac{N_{op}(N_{op}-1)}{2}$ unknown variables:

$$P_c^{(n)} \geq P_u^{(n)}, \forall n = 1, \cdots, N_{op}. \quad (8.13)$$

We distinguish here two cases depending on the number of operators $N_{op}$:

- $N_{op} = 2$: In this particular case, we have two inequalities with one unknown variable $p_{12}$. For simplicity, let us denote $A_1 = \sum_{i=1}^{N_{U}^{(1)}} \gamma_i^{(1,1)} p_i^{(1,m)} + R_{op} \left( N_U^{(n)} \right) - C_c^{(1)} + \sum_{i=1}^{N_{U}^{(1)}} \gamma_i^{(1,2)} p_i^{(1,m)}$, $A_2 = \sum_{i=1}^{N_{U}^{(2)}} \gamma_i^{(2,2)} p_i^{(2,m)} - C_c^{(2)} + \sum_{i=1}^{N_{U}^{(2)}} \gamma_i^{(2,1)} p_i^{(2,m)}$, $B = \sum_{i=1}^{N_{U}^{(2)}} \gamma_i^{(2,1)}$ and $D = \sum_{i=1}^{N_{U}^{(1)}} \gamma_i^{(1,2)}$. Then, the system of inequalities can be written as follows

$$(B - D)p_{12} \geq P_u^{(1)} - A_1,$$

$$(D - B)p_{12} \geq P_u^{(2)} - A_2. \quad (8.14)$$

Note that $B$ corresponds to the number of users belonging to operator 2 served by operator 1 while $D$ corresponds to the opposite situation. Thus, the problem solution depends on these variables. Indeed, if $B = D$, mobile operators do not need to impose a roaming price to each other and their profits are equal to $A_1$ and $A_2$, respectively. A simple comparison with $P_u^{(n)}$ and $P_c^{(n)}$ let them know either they cooperate or no. Else (i.e., $B \neq D$), from (8.14), we distinguish two sets of possible solutions of $p_{12}$. If they are disjoint, cooperation is impossible. If there is an intersection interval, the operator collaboration is favorable for energy saving and profit enhancement. A fair choice of $p_{12}$ is to maintain a close percentage change as follows:

$$\frac{P_u^{(1)} - P_u^{(2)}}{P_u^{(1)}} \approx \frac{P_c^{(1)}(p_{12}) - P_c^{(2)}(p_{12})}{P_c^{(1)}(p_{12})}. \quad (8.15)$$
- \( N_{\text{op}} \geq 3 \): In this case, the system can be written in the following matrix form:

\[
A_{N_{\text{op}} \times N_p} p_{N_p \times 1} \leq b_{N_{\text{op}} \times 1},
\]

where \( A \) is a matrix that contains the coefficients of the system of linear inequalities while \( b \) is a vector that contains constant terms. \( p \) is the decision vectors which is constituted by the roaming price \( p_{nt}, n, t = 1, \ldots, N_{\text{op}} \). Each of the inequalities determines a certain half-space while all the inequalities together determine a certain region in the \( N_p \)-dimensional space which is the intersection of a finite number of half-spaces [110]. If this system admits a feasible solution (i.e., the system is said compatible), the mobile operator can cooperate safely without degrading neither their QoS nor their individual profits. If the system is incompatible, then the multi-operator collaboration is impossible. A system is said compatible if and only if so is its concomitant system. Indeed, from the system (8.16), we can construct a concomitant system involving \( N_p - 1 \) unknowns after discarding the last unknown, and for this new system, we can construct another concomitant system involving \( N_p - 2 \) unknowns and so on. This way, after a number of steps, we construct a system consisting of inequalities of one unknown. Thus, the compatibility of the original system is determined from the compatibility of the last constructed concomitant system. Using the same steps detailed above, we can find a solution of the problem in case of compatibility. The set of solutions of this non-homogenous system can be also determined via different methods. (For more details, see [110]).

### 8.5 Results and Discussion

In this section, we investigate the performance of the proposed approach detailed in Section 8.4. We start by presenting the simulation model. Then, we discuss the numerical
Table 8.1: Service parameters

<table>
<thead>
<tr>
<th>Services</th>
<th>Service 1</th>
<th>Service 2</th>
<th>Service 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p^{(m)}$ (MU)</td>
<td>10</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>$(R_{m,th}^{(DL)}, R_{m,th}^{(UL)})$ (kbps)</td>
<td>(1000, 384)</td>
<td>(384, 384)</td>
<td>(64, 64)</td>
</tr>
<tr>
<td>Occurrence Probability (%)</td>
<td>15</td>
<td>25</td>
<td>60</td>
</tr>
</tbody>
</table>

results.

8.5.1 Simulation Model

We consider $N_{op} = 2$ mobile operators, denoted, Op1 and Op2, serving a $5 \times 5$ (Km$^2$) LTE coverage area. Op1 and Op2 are placing uniformly $N_{BS}^{(1)} = 16$ and $N_{BS}^{(2)} = 9$ BSs, respectively. We assume the nonexistence of inter-operator interference and both networks are operating in disjoint 10 (Mhz) bandwidths that are subdivided into $N_{RB} = 50$ RBs. The LTE and channel parameters are obtained from [49]. All BSs and all MSs have the same power model with the same maximal transmit power 46 dBm, $a = 21.45$ and $b = 354.44$ W. We set $\nu = 3.76$, $\kappa = -122.1$ dB, $\sigma_\xi = 8$ dB and the tolerance $P_{out} = 2\%$. The MS transmit power is set to 23 dBm. In addition, we suppose that the network operators offer similar $M = 3$ services. Each one is characterized by its cost (unitary price) $p^{(m)}$, expressed in MU, DL and UL data rate thresholds ($R_{m,th}^{(DL)}$ and $R_{m,th}^{(UL)}$ respectively), and the occurrence probability of the service as it is shown in Table 8.1. The occurrence probability of a given service corresponds to the percentage of users in the network using that service.

Mobile operators are procuring energy either from electricity retailer which provides enough energy to cover the network operation or from renewable energy generated locally. We assume that amount of energy available at each BS varies between 0 and 100 Watt which corresponds to the maximum amount of energy that can be stored locally during the operation time $\Delta t = 1$ second. We set the unitary price of the fossil fuel energy to $\pi^{(f)} =$
Finally, we assume that \( N_{U}^{(1)} = \alpha N_{U}^{(2)}, 0 \leq \alpha \leq 1 \) and that mobile operators are engaged to serve 98% of the connected users simultaneously (i.e., \( P_{\text{out}} = 0.02 \)). In our results, we compare our approach, denoted "coop", with the traditional case, denoted "uncoop", when both cellular companies operate individually in addition to the case when all BSs are assumed to belong to a single virtual network operator, denoted "virtual".

### 8.5.2 Simulation Results

In Table 8.2, we study the performance of mobile operator collaboration versus the number of subscribers connected to the networks for \( \alpha = \frac{2}{3} \). In all scenarios, the amount of renewable energy generated by the BSs is the same. We notice that the proposed cooperative scheme achieves almost the same performance as the virtual scenario by activating almost the same number of BSs and consuming a slightly higher amount of fossil fuels (i.e., denoted \( f \) in Table 8.2). This small difference is due to the QoS constraints separately imposed to each operator as it is given in (8.11) while, in the virtual scenario, there is only one constraint as it is a single big network. Compared to the traditional case, an important energy saving is obtained thanks to cooperation. For instance, for \( N_{U}^{(1)} = 130 \), the fossil fuel consumption is reduced by more than 23%. Concerning the profit, we notice that the results satisfy the condition imposed in (8.13) which forces the cooperation profits to be higher than the individual ones by choosing an appropriate roaming price. For instance,

<table>
<thead>
<tr>
<th>Number of Op1 users ( N_{U}^{(1)} )</th>
<th>10</th>
<th>70</th>
<th>130</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncoop ( f ) (kW) [Active BSs]</td>
<td>1.5 [4.3]</td>
<td>5.1 [10.7]</td>
<td>8.5 [16]</td>
</tr>
<tr>
<td>Virtual ( f ) (kW) [Active BSs]</td>
<td>1.2 [7]</td>
<td>3.7 [6]</td>
<td>6.3 [9.2]</td>
</tr>
<tr>
<td>Uncoop profit (kMU): Op1, Op2</td>
<td>0.10, 0.06, 0.98, 0.62</td>
<td>1.86, 1.21</td>
<td></td>
</tr>
<tr>
<td>Coop profit (kMU): Op1, Op2</td>
<td>0.12, 0.08, 1.04, 0.68</td>
<td>1.96, 1.30</td>
<td></td>
</tr>
<tr>
<td>Roaming price (MU)</td>
<td>5.37</td>
<td>2.84</td>
<td>1.19</td>
</tr>
</tbody>
</table>
the gained profit when collaborating is greater by 5% than the uncooperative case for both operators when $N_U^{(1)} = 70$. This is because with collaboration mobile operators are offered more degrees of freedom in order to reduce the energy cost and maximize their profit. To achieve this gain, an appropriate choice of roaming price has to be determined by solving (8.13). We can see that the higher traffic densities are, the lower the roaming price is. Finally, our simulation experiments indicate that the percentage of successful cooperation is 97%. In other words, the probability that mobile operators decide to not cooperate is $\approx 3\%$.

Fig. 8.1 investigates the impact of generating renewables by mobile operators on the cooperation performance for $N_U^{(1)} = 50$ and $\alpha = \frac{2}{3}$. To do this, we introduce a parameter $\beta_{RE}$ that represents the percentage of green energy generated by Op1 while $100 - \beta_{RE}$ corresponds to the percentage of green energy generated by Op2. In other words, if $\beta_{RE} = 0\%$, then only Op2 possesses renewables and vice versa. We assume here that all BSs owned by an operator are storing the same amount of renewables. In Fig. 8.1(a), we plot the consumed fossil fuels, we notice that the operator that is controlling renewable energy is able to more reduce its CO$_2$ emissions when there is no cooperation with a gain in terms of profit (Fig. 8.1(b)). However, when cooperating, most of its BSs are kept active to serve most of the users of the competing provider (as it is shown in Fig. 8.2(a), 90% and 95%
for $\alpha = \frac{2}{3}$ and $\alpha = \frac{1}{3}$, respectively). However, the optimal value is when $\beta_{RE} = 50\%$. In this equilibrium, all the BSs of both operators have the same characteristics and thus the BS selection set is larger. The curves are unbalanced because of the difference in the number of connected users and the number of available BSs per each operator. Finally, we can notice that the roaming price is higher when Op1 is controlling the renewable energy. Indeed, as the number of subscribers of Op2 is lower, Op1 is forced to increase the roaming price in order to maximize its profit when cooperating while the inverse can be deduced for Op2.

Note that in all our simulations, the network QoS is satisfied for all operators $P_{out} = 2\%$.

In practice, the roaming price cannot be varied instantaneously and dynamically for each combination of channel realizations in the network. It can have a pre-defined fixed average value for a given traffic density, or range of traffic densities in the network (e.g., there can be a price during the day corresponding to high density and another during the night corresponding to relatively lower density). This value can be set through collaboration agreements between mobile operators. The results derived in this chapter are averaged over 1000 channel realizations using Monte Carlo simulations. Hence, these results provide insights about the average roaming price that should be imposed between mobile operators for different traffic densities in order to ensure mutual benefit.
8.6 Summary

In this chapter, we investigated the performance of the green networking approach for multi-operator collaboration. We have formulated an optimization problem that aims to reduce the total CO$_2$ emissions by eliminating redundant base stations while respecting the network QoS. We have also formulated a system of linear inequalities to decide whether to cooperate or not by fixing the roaming price. Our approach leads to an important saving in terms of fossil fuel consumption while it enhances the cooperative mobile operator profit. In addition, it shows that the roaming price is inversely proportional to the number of subscribers of the network as well as the number of BSs generating renewables.

A future extension of this work is to jointly optimize the roaming price and base station ON/OFF switches since, in the proposed scheme, the roaming price is determined after turning off certain base stations using the iterative algorithm. Also, we are considering that all the users connected to a certain inactive base stations are offloaded to another one. However, it can be possible to offload part of the subscribers instead of all them if the roaming price depends on the number of offloaded users. This will be the topic of the next chapter.
Chapter 9

A Game Theoretical Approach for Cooperative Green Mobile Operators under Roaming Price Consideration

9.1 Introduction

In chapter 8, the authors investigated the collaboration between mobile operators under roaming price consideration where the objective is to reduce the total CO₂ emissions by turning off BSs of different networks and keeping others active to maintain the desired QoS. The cooperation decision and roaming prices are determined by solving a non-homogenous system of linear inequalities.

In this chapter, we employ a game theoretical approach to develop a multi-operator collaboration scheme which helps one green operator (GO) reduce its energy consumption and CO₂ emissions by roaming some of its users to one or many non-green operators (NGOs). The GO can either offload all the users of a BS and switches it off or just offload some of them. However, during cooperation, extra charge will be imposed on the GO when exploiting another NGO’s infrastructure to serve its subscribers. Thus, we model this problem as
a two-level Stackelberg game where the GO plays the role of the follower which aims to minimize its CO$_2$ emissions by roaming a certain number of users per BS. BSs are powered either by a traditional electricity retailer or by renewable energy equipment (e.g., solar panel or wind turbine). On the other hand, the NGOs play the role of leaders that seek the maximization of their profits by attracting the maximum number of GO roamed users. In this competition, the leaders focus on offering the best roaming price while taking into account multiple system parameters (e.g., energy cost and pollution level, service fee, GO renewable energy availability, etc.). In our study, after formulating the problem, we derive and analyze the Stackelberg equilibrium to find the optimal number of users to be roamed from each BSs and the optimal roaming price imposed by each NGO. Then, via simulations, we investigate the behavior of each player for different system parameters such as the GO attitude towards the environment and the fossil fuel energy cost. Our results show a significant saving in terms of CO$_2$ emissions compared to the non-cooperation case and that roaming decision depends essentially on the availability of renewable energy in base station sites.

The rest of this chapter is organized as follows. Section 9.2 presents the system model. In Section 9.3, we formulate the GO and NGO optimization problems. Section 9.4 discusses the cooperative mobile operator method and the Stackelberg game. In Section 9.5, we present our simulation results. Finally, the chapter is concluded in Section 9.6.

### 9.2 System Model

We consider a geographical area served by $L + 1$ mobile operators. Each mobile operator is deploying an LTE network with $N$ base stations (BSs) that satisfies the traffic demand of its customers and covers the total area. We assume that each cell is controlled by $L + 1$ BSs, each one is owned by an operator. Thus, the BSs of the different operators are identi-
cally distributed and each operator controls $N$ of them. Although this is not generally the case, this assumption is used to simplify the problem.

### 9.2.1 Energy Consumption Model for Base Stations

The consumed power of a switched on BS $j$ belonging to a mobile operator, $P_j$, can be computed as follows [76]:

$$P_j = aP_j^{(tx)} + b,$$

(9.1)

where the coefficient $a$ corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses and the term $b$ models an offset of site power which is consumed independently of the average transmit power and is due to signal processing, battery backup, and cooling. In (9.1), $P_j^{(tx)}$ denotes the radiated power of the $j^{th}$ BS which depends on the number of users served by this BS, denoted $N_j$, multiplying it by a constant power and can be expressed as follows:

$$P_j^{(tx)} = P_T N_j,$$

(9.2)

where $P_T$ is a constant power and is defined such that

$$P_T = \frac{P_{\text{min}}}{K R^\upsilon},$$

(9.3)

where $P_{\text{min}}$ denotes the minimum receiving power required by each mobile station (MS) (i.e., it represents the user QoS), $K$ is a parameter accounting for effects including BS antenna settings, carrier frequency and propagation environment, $\upsilon$ is the path loss exponent, and $R$ denotes the inter-cell distance. If a BS $j$ is completely switched off, we assume that its power consumption $P_j = 0$. 
9.2.2 CO$_2$ Emission Penalty Function

To power its BSs, the mobile operator is able to procure energy either from a traditional electricity provider or from renewable energy generators installed on BS sites, e.g., solar panels or wind turbine. The amount of energy procured from the fossil fuel retailer and the auto-generated amount of energy consumed by BS $j$ are equal to the amount of power consumed by that BS during its operation time: $P_j \Delta t$ where $\Delta t$ is the BS operation time. The amount of green energy generated locally, denoted $q_j$, is varying for one BS to another depending on environmental or technical reasons. For instance, the solar rating depends essentially on the size of PhotoVoltaic (PV) panels and whether they experience any shading during the day. It should be noted that the locally generated energy is free of charge unlike the energy procured from the traditional electricity provider which is evaluated by $c$ where $c$ is the cost of one unit of energy. That is, the fossil fuel energy procured by BS $j$, denoted $X_j$, is given as follows:

$$X_j = \max(P_j \Delta t - q_j, 0), \forall j = 1, \ldots, N.$$  \hfill (9.4)

The consumption of fossil fuels causes a harmful impact on the environment due to the emission of greenhouse gases. The amount of this damage depends on the nature of the energy source. The CO$_2$ emission penalty function of a network can be modeled as a quadratic function of the consumed fossil fuel energy by a BS as it is given in [92–94]:

$$C = \sum_{j=1}^{N} \alpha (X_j)^2 + \beta X_j,$$  \hfill (9.5)

where $\alpha$ and $\beta$ are the emission coefficients related to the energy source of the electricity provider.
9.3 Utility Functions and Problem Formulation

In our framework, we investigate the cooperation between the mobile operators. We assume that one of them is considered as a green mobile operator and is denoted (GO). Its objective is to minimize its network CO\textsubscript{2} emissions, maximize its profit or achieve a trade-off between both objectives. The other mobile operators, denoted (NGO\textsubscript{l}) \ l = 1, \cdots, L, are considered as typical mobile operators having as goal the maximization of their own profit regardless of their impact on the environment. The NGOs cooperate with the GO by offloading its users when needed. For instance, GO might turn off some of its BSs during low traffic period and the corresponding users can be served by the NGOs. In return, NGOs may impose on the GO to pay extra charge per number of roamed users as it is exploiting their infrastructures. Thus, the GO aims to find how many users per BS are needed to be offloaded to the NGO networks in order to maximize its objective while the NGOs seek the optimal roaming prices to impose in order to attract GO users and maximize their profits.

In the sequel, in order to differentiate between the GO and NGO parameters, the notation \ x^{(GO)} \ and \ x^{(NGO\textsubscript{l})} \ will be used, respectively.

As mentioned before, the GO’s first objective is to maximize its profit, \mathcal{P}^{(GO)}, expressed as

\[
\mathcal{P}^{(GO)} = \sum_{j=1}^{N} \pi^{(GO)} N_{T,j}^{(GO)} - \sum_{l=1}^{L} \pi_{l}^{(r)} N_{j,l}^{(r)} - c^{(GO)} X_{j}^{(GO)},
\]

where \pi^{(GO)} \ denotes the service fee of the GO per user while \pi_{l}^{(r)} \ corresponds to the roaming price per user imposed by the \textsuperscript{lth} NGO. \ N_{T,j}^{(GO)} \ denotes the total number of GO users covered by BS \ j \ and \ N_{j,l}^{(r)} \ is the number of users belonging to GO covered by BS \ j \ and served by NGO \ l. \ From (9.4), \ X_{j}^{(GO)} = \max(P_{j}^{(GO)} \Delta t - q_{j}^{(GO)}, 0) \ where \ P_{j}^{(GO)} = aP_{T} N_{j}^{(GO)} + b. \ Also, \ N_{T,j}^{(GO)} = N_{j}^{(GO)} + \sum_{l=1}^{L} N_{j,l}^{(r)}, \forall j = 1, \cdots, N. \ However, if all users of BS j are
roamed to neighbor BSs of other operators $N_T^{(GO)} = \sum_{l=1}^{L} N_{j,l}^{(r)}$ (i.e., $N_j^{(GO)} = 0$), then the BS $j$ is turned off and $P_j^{(GO)} = 0$. Finally, $c^{(GO)}$ is the unitary cost of fossil fuels per kWh paid by the GO. The GO’s second objective is to reduce the CO$_2$ emissions, $C^{(GO)}$, defined in (9.5). GO might target to achieve a tradeoff between both objectives. For this reason, we introduce a Pareto parameter, denoted $\omega$, in its utility function $U^{(GO)}$ which will be maximized using the following optimization problem:

$$\max_{N_{j,l}^{(r)}} U^{(GO)} = \omega P^{(GO)} - (1 - \omega) C^{(GO)}$$  \hspace{1cm} (9.7)

subject to: $N_j^{(GO)} + \sum_{l=1}^{L} N_{j,l}^{(r)} = N_T^{(GO)}$, $\forall j = 1, \cdots, N$, \hspace{1cm} (9.8)

$$0 \leq N_{j,l}^{(r)} \leq N_T^{(GO)}$, $\forall j = 1, \cdots, N$, $\forall l = 1, \cdots, L$.  \hspace{1cm} (9.9)

When $\omega \to 1$, we are dealing with the utility function given in (9.6). This corresponds to a selfish network operator that aims to maximize its own profit $P^{(GO)}$ regardless of its impact on the environment. When $\omega \to 0$, we deal with the utility function given in (9.5), which corresponds to an environmentally friendly network operator that aims to reduce CO$_2$ emissions regardless of its own profit. Other values of $\omega$ constitute a tradeoff between these two extremes.

On the other hand, each NGO $l$ tries to maximize its profit by serving as much roamed users as possible. Its utility function $U^{(NGO_l)}$ can be optimized using an optimization problem formulated as follows

$$\max_{\pi_l^{(r)}} U^{(NGO_l)} = \sum_{j=1}^{N} \pi_l^{(NGO_l)} N_j^{(NGO_l)} + \pi_l^{(r)} N_{j,l}^{(r)} - c^{(NGO_l)} X_j^{(NGO_l)}$$  \hspace{1cm} (9.10)

subject to $\pi_l^{(r)} \geq a c^{(NGO_l)} P_T \Delta t$, \hspace{1cm} (9.11)

where $X_j^{(NGO_l)} = \left( a P_T \left( N_j^{(NGO_l)} + N_{j,l}^{(r)} \right) + b \right) \Delta t$. Note that constraint (9.11) was added
to ensure that the NGOs will always choose a profitable roaming price. In other words, if serving GO users is not beneficial, the NGOs will prefer to not cooperate.

9.4 Analysis of the Stackelberg Equilibrium

In order to solve the problem formulated in Section 9.3, we propose to model it as a Stackelberg game where the GO plays the role of the follower and NGOs play the role of the leaders. We apply a backward induction approach to derive the solution of the Stackelberg Equilibrium.

9.4.1 Green Operator Level Game: The Follower

The objective of the follower is to determine how many users per BS are needed to be roamed for NGO $l$ in order to maximize its utility function. As the leaders aim to maximize their utility functions anticipating the predicted response of the follower, we should start first by deriving the best response of the follower with respect to the numbers of roamed users per BS $N_{j,l}^{r(t)}$, $\forall j = 1, \cdots, N$, $\forall l = 1, \cdots, L$. It is known that the problem solution is an integer solution; however, we propose to relax the problem by transforming the integers to real non-negative variables. Then, we round the obtained solution to find the exact number of roamed users. Thus, the number of roamed users to the $l$th NGO is the solution of

$$
\frac{\partial U^{(GO)}}{\partial N_{j,l}^{r(t)}} = -\omega \pi_{l}^{r(t)} + \omega c^{(GO)} a P_T \Delta t + (1 - \omega) \beta a P_T \Delta t + 2 (1 - \omega) \alpha a P_T \Delta t \left( a P_T \left( N_{T,j}^{r(GO)} - \sum_{l=1}^{L} N_{j,l}^{r(t)} \right) + b \right) \Delta t - q_j = 0.
$$

(9.12)
We can clearly see that the second derivative of the utility function with respect to the number of roamed users is negative:

$$\frac{\partial^2 U^{(GO)}}{\partial \left( N_{j,l}^{(r)} \right)^2} = -2 \left( 1 - \omega \right) \alpha \left( a P_T \Delta t \right)^2 \leq 0,$$

$$\forall j = 1, \ldots , N, \forall l = 1, \ldots , L.$$ (9.13)

Therefore, $U^{(GO)}$ is concave with respect to $N_{j,l}^{(r)}$. Finally, the optimal number of roamed users per BS is expressed as follows

$$N_{j,l}^{(r)(*)} = \min \left\{ \left[ N_{T,j}^{(r)} - \sum_{k=1}^{L} \sum_{k \neq l} N_{j,k}^{(r)} + \frac{b \Delta t - q_j}{a P_T \Delta t} + \frac{\beta}{2\alpha a P_T \Delta t} \right. \right.$$  
$$\left. \left. + \left( \frac{\omega}{1 - \omega} \right) \frac{c^{(GO)}}{2\alpha a P_T \Delta t} \right] + \frac{\pi_{l}^{(r)}}{2\alpha (a P_T \Delta t)^2} \right\},$$ (9.14)

where $\min(., N_{T,j}^{(r)})$ and $[.]^+ = \max(., 0)$ are added to fulfill constraints (9.8) and (9.9), respectively. From the expression above, we can notice that the number of roamed users per BS decreases with the increase of the NGO roaming price. Moreover, we can see that this decrease depends on the GO’s Pareto weight. For instance, when $\omega \rightarrow 1$, the GO is more and more concerned by its profit and thus the decrease of the number of roamed users is more important.

**9.4.2 Non Green Operator Level Game: The Leader**

The objective of the leader $l$ in this Stackelberg game is to maximize its profit by attracting the maximum number of GO users. Therefore, the NGO $l$ has to find the best roaming price depending on the system parameters in order to optimize its SE by injecting the relationship given in (9.14) in its utility function and deriving its first derivative with
respect to the roamed price \( \pi_l^{(r)} \)

\[
\frac{\partial U^{(NGO_l)}}{\partial \pi_l^{(r)}} = \frac{\partial}{\partial \pi_l^{(r)}} \left( \sum_{j=1}^{N} \pi_l^{(NGO_l)} N_j^{(NGO_l)} + \pi_l^{(r)} N_j^{(r)} - c^{(NGO_l)} \left( aP_T N_j^{(NGO_l)} + N_j^{(r)} + b \right) \Delta t \right) = 0
\]

\[
= \sum_{j=1}^{N} N_j^{(r)} + \left( \pi_l^{(r)} - c^{(NGO_l)} aP_T \right) \frac{\partial N_j^{(r)}}{\partial \pi_l^{(r)}} = 0. \tag{9.15}
\]

Hence, the optimal roaming price of NGO \( l \) is given as follows

\[
\pi_l^{(r)(\ast)} = \max \left\{ \left( \frac{1 - \omega}{\omega} \right) \left[ \alpha \left( aP_T \Delta t \right)^2 \sum_{j=1}^{N} \left( N_{T,j} - \sum_{k=1}^{L} N_{j,k}^{(t)} \right) \right] + \alpha aP_T \Delta t \left( b \Delta t - \sum_{j=1}^{N} q_j \right) + \frac{aP_T \Delta t}{2} \beta \right\}
\]

\[
+ \frac{aP_T \Delta t}{2} \left( c^{(GO)} + c^{(NGO_l)} \right), \quad ac^{(NGO_l)} P_T \Delta t \right\}. \tag{9.16}
\]

Note that the \( \max \{\cdots, ac^{(NGO_l)} P_T \Delta t\} \) is added to ensure that the profit of a leader will not decrease below its profit obtained without cooperation as it is given in constraint (9.11). 

\( U^{(NGO_l)} \) is also concave with respect to \( \pi_l^{(r)} \) as its second derivative with respect is also negative as it is given below

\[
\frac{\partial^2 U^{(NGO_l)}}{\partial \left( \pi_l^{(r)} \right)^2} = - \left( \frac{\omega}{1 - \omega} \right) \frac{1}{\alpha (aP_T \Delta t)^2} \leq 0,
\]

\[\forall j = 1, \cdots, N, \forall l = 1, \cdots, L. \tag{9.17}\]

From the expressions (9.14) and (9.16), it can be noticed that the determination of the SE of the \( l^{th} \) leader depends on the number of roamed users to the other \((L-1)\) NGOs as well as their respective roaming prices. Therefore, we propose to employ a fixed point algorithm to determine the optimal number of roamed users and the corresponding roaming prices.
Conjecture 1 (Uniqueness of the Stackelberg Equilibrium) The pair of $N_{j,l}^{(r)(*)}$ and $\pi_{l}^{(r)(*)}$ given in (9.14) and (9.16), respectively, is the unique Stackelberg Equilibrium for the proposed game.

To prove this conjecture, we need to define the best response function of the $l^{th}$ leader as

$$p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right) = \arg\max_{\pi_{l}^{(r)}} U_{k}^{(NGO)}(\pi_{l}^{(r)}, \tilde{\pi}_{-l}^{(r)}),$$

(9.18)

where $\tilde{\pi}_{-l}^{(r)}$ is defined as $\tilde{\pi}_{-l}^{(r)} = \text{Vect} \left( \pi_{k}^{(r)}, k \neq l \right) = [\pi_{1}^{(r)}, \ldots, \pi_{l-1}^{(r)}, \pi_{l+1}^{(r)}, \ldots, \pi_{L}^{(r)}]^{T}$. The uniqueness of the Stackelberg Equilibrium is guaranteed if the best response function of the $l^{th}$ leader $p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right)$ is a type-II standard function [111].

**Definition:** A function $p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right)$ is said to be type-II standard if $\forall \tilde{\pi}_{-l}^{(r)} \geq 0$, the following properties are satisfied [111]:

- Positivity: $p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right) > 0$,
- Type-II Monotonicity: If $\tilde{\pi}_{-l}^{(r)} > \pi_{-l}^{(r)}$, then $p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right) < p_{l} \left( \pi_{-l}^{(r)} \right)$,
- Type-II Scalability: $\forall z > 1$, we have $\frac{1}{z}p_{l} \left( \tilde{\pi}_{-l}^{(r)} \right) < p_{l} \left( z\tilde{\pi}_{-l}^{(r)} \right)$.

The proof of this is conjecture is very elaborate and is left for a future extension of this work.

### 9.5 Simulation results

In this section, we present some numerical results for one follower one leader setting and one-follower two-leaders case. We consider an area of interest where the $L + 1$ mobile operators are deploying $N = 10$ identical BSs. All the BSs are powered by traditional electricity providers except the BSs of the GO network which are also supplied via green energy equipment deployed in BS sites. The amount of the auto-generated green energy differs form a BS to another. This can be explained essentially by the fact that PV panels
Table 9.1: System parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{\text{min}}$</td>
<td>$-120$ dBm</td>
<td>$u$</td>
<td>3.76</td>
</tr>
<tr>
<td>$K$</td>
<td>0.0001</td>
<td>$R$</td>
<td>1000 m</td>
</tr>
<tr>
<td>$(a, b)$</td>
<td>$(7.84, 71.5)$</td>
<td>$(\alpha, \beta)$</td>
<td>$(0.02, 0.1)$</td>
</tr>
</tbody>
</table>

in BS sites have different sizes and whether they experience any shading during the day. Finally, we consider that $\pi^{(\text{GO})} = \pi^{(\text{NGO})} = 5$ MU, $\forall l = 1, \ldots, L$ (MU stands for monetary unit). In our simulations, we set the different channel and power parameters as it is detailed in Table 9.1.

First, we start by investigating the one leader one follower scenario where only one NGO is available to serve the users of the GO. In Table 9.2, we study the cooperation between the operators for three cases when $c^{(\text{GO})} = 0.2 < c^{(\text{NGO})} = 0.4$, $c^{(\text{GO})} = c^{(\text{NGO})} = 0.4$ and $c^{(\text{GO})} = 0.6 > c^{(\text{NGO})} = 0.4$. For each case, we vary the Pareto weight $\omega$ representing the behavior of the GO towards the environment and we provide some information about the number of roamed users and the NGO roaming price. The amount of energy $q_j^{(\text{GO})}$ available in each GO’s BS and the number of users served by each BS $N_{T,j}^{(\text{GO})}$ are also given in Table 9.2. We assume that $N_{T,j}^{(\text{GO})} = N_{T,j}^{(\text{NGO})}$. We can first deduce that there are three categories of BSs in this roaming setting. BSs that offload all their users to the NGO (e.g., $j = 2, 6, 8$): These BSs, having very low amounts of renewable energy, prefer to be turned off instead of serving users using fossil fuel independently of the value of $c^{(\text{GO})}$. The second category is the BSs that do not offload any users as they have sufficient amount of green energy to serve all of them (e.g., $j = 4, 9, 10$). The final category encloses the BSs that offload some of their users depending on the available amount of green energy (e.g., $j = 1, 3, 5, 7$). Another remark is that as $\omega$ increases the roaming price $\pi^{(r)}$ decreases. Indeed, as it is more concerned by its profit, the GO tries to avoid the maximum to pay extra roaming fees. Thus, NGO are obliged to reduce their roaming price to attract GO users.
Table 9.2: Performance of the proposed scheme for one NGO one GO case

<table>
<thead>
<tr>
<th>ω</th>
<th>(c^{(GO)} = 0.2 \leq c^{(NGO)} = 0.4)</th>
<th>(c^{(GO)} = c^{(NGO)} = 0.4)</th>
<th>(c^{(GO)} = 0.6 &gt; c^{(NGO)} = 0.4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\pi^{(t)}(MU))</td>
<td>10.53 2.03 1.08 0.45 0.44</td>
<td>10.64 2.14 1.19 0.56 0.46</td>
<td>10.75 2.25 1.30 0.67 0.57</td>
</tr>
</tbody>
</table>

We can see that the higher \(c^{(GO)}\) is, the higher \(\pi^{(t)}\) is.

Let us now study the cooperation behavior case by case. When \(c^{(GO)} < c^{(NGO)}\), we notice that as \(\omega\) increases the number of roamed users decreases. In this case, \(\omega = 0.1\), GO offloads the maximum number of users such that it minimizes its CO\(_2\) emissions. This means that most of GO users are either served by green energy or by NGO infrastructure. When \(\omega\) is close to 1, we can see that GO does no more offload users since it prefers to serve them using its BSs even with fossil fuels as its \(c^{(GO)}\) is lower than NGO. When \(c^{(GO)} = c^{(NGO)}\), we notice that the total number of roamed users is unchanged even if \(\omega\) varies. This is due to the fact that we are setting the same parameters for both operators. Thus, this roamed user distribution is the optimal one in terms of profit and CO\(_2\) emissions. Notice that \(C^{(GO)}\) remains unvaried while the GO and NGO profits vary depending on the roaming price.

Now, if \(c^{(GO)} > c^{(NGO)}\), we can see as \(\omega\) increases, the number of roamed users increases too. In this case, the GO prefers to offload its users as its fossil fuel cost is more expensive than the NGO one and is more and more concerned by its profit.
In Fig. 9.1, we investigate the performance of the proposed scheme for one follower and two leaders scenario. In this case, we set $\omega = 0.6$ which belongs to the Pareto efficiency region as it is given in Table 9.2 and we set $c^{(GO)} = 1.5$ (MU) and $c^{(NGO2)} = 1$ (MU). Finally, we vary $c^{(NGO1)}$ between 0 and 2 (MU). In Fig. 9.1(a), we investigate the performance of all operators under the proposed cooperation mode (denoted Prop.) when varying the fossil fuel cost of NGO 1 by plotting their utilities functions. Also, we compare them with the performance of the non-cooperation mode denoted (Trad.) where all operators serve their own users without roaming. The figure shows that, thanks to their collaboration, all operators are able to enhance their performance comparing to the traditional scenario. Indeed, independently of the value of $c^{(NGO1)}$, GO is able to double its utility function while NGO utilities varies according to the NGO 1 fossil fuel cost. Indeed, as $c^{(NGO1)}$ increases, $U^{(NGO1)}$ decreases until coinciding with the traditional case, while $U^{(NGO2)}$ increases with a lower scale. NGO 2 exploits the high cost that NGO 1 is facing to provide a lower roaming user price and thus attract more GO users as it is shown in Fig. 9.1(b) and Fig. 9.1(c) where we plot the roaming prices and number of users, respectively. From these figures, we can see that when that when NGO 1 cost is low, both roaming prices are low and NGO 1 is gaining most of the roamed users (about 260 users) while NGO 2 is serving about 95 GO users. As $c^{(NGO1)}$ increases, NGO 1 is loosing roamed users while NGO 2 is serving more even if they provide the same roaming price. This is due to the fact that NGO 1 is obliged to increase its roaming price to face the energy price.
increase and NGO 2 exploits this to also increase its roaming price knowing that GO is interested in reducing its CO₂. However, we notice that GO is more interested in serving its users as the roaming price is becoming more and more expensive.

9.6 Summary

In this chapter, we investigated the performance of a green networking system where one green operator interested in minimizing its CO₂ emissions cooperates with several non green operators interested in maximizing their profits by serving the green operator subscribers. The problem was formulated as a two-level Stackelberg game that leads to the maximization of both player utility functions. A Stackelberg equilibrium was derived and its uniqueness was proved. Our simulation results showed the behavior of each mobile operator in this competition game and showed that the GO is able to ensure a significant reduction in terms of CO₂ emissions compared to the traditional case.
Chapter 10

Conclusions and Future Work

In this chapter, we summarize the main concepts and contributions investigated in this dissertation. In addition, we highlight some future research directions related to our work.

10.1 Conclusions

In this dissertation, we have focused on developing new techniques in order to achieve green objectives for 4G/5G cellular networks. The reduction of their fossil fuel consumption in addition to the huge energy bills paid by mobile operators is considered as one of the most important challenges in this domain. As it was stated in the introduction, we have investigated three green important topics. The base station sleeping strategy, the optimized energy procurement from the smart grid and the green networking collaboration between competitive mobile companies.

Chapter 2 explored several techniques that can be considered since the planning phase for environment aware cellular networks. Indeed, base station deployment is considered as one of the fundamental problems in network design. In Chapter 2, we employed meta-heuristic algorithms based on swarm intelligence in order to determine sub-optimal base station locations that satisfy both cell coverage and capacity constraints simultaneously. Afterwards, we applied the proposed planning method to perform green planning considering temporal traffic variation where base stations that can be switched off during a certain period can be determined since the planning stage. Also, we adapted our method to the planning with location constraint problem where base station
placement is prohibited in certain locations due to electromagnetic radiation constraints. In our simulation results, we applied our proposed approach for different scenarios with different subareas and user distributions and showed that the desired network quality of service targets are always reached even for large-scale problems.

Chapter 3 addressed the mobile user association problem for heterogeneous networks. The optimal transport theory is used to minimize the total transmit power consumption while respecting the network constraints in terms of resource limitation per base station (e.g., power budget and number of available resource blocks) and the required data rate per user. Starting from given base station locations and user distribution, we employed a fixed point algorithm to find the optimal solution for the formulated problem. Selected numerical results investigated various practical scenarios with different user distribution and showed that the cell boundaries obtained using optimal transport solution provides a significant energy saving in comparison to the classical Voronoi cell boundaries.

In Chapter 4, we showed that Heterogeneous networks can provide a significant energy saving especially if mobile operators exploit the existence of femto cell access points and collaborate with them by offloading its users and switching off the redundant small cell base stations. The dual decomposition method in addition to a low complexity algorithm are employed in order to select active base stations in addition to allocate the resources. We showed also that our proposed switching on/off algorithm reaches a performance near to the optimal dual decomposition solution while providing a considerable saving in terms of computational complexity.

In Chapter 5-6, we combined the base station sleeping strategy and practical algorithms to achieve energy savings for LTE networks without degrading the network quality of service. We formulated an optimization problem that allow cellular networks to optimally procure energy from the smart grid where renewable energy sources are available in order to reduce CO₂ emissions, maximize the mobile operator profit or achieve a tradeoff between them depending on the mobile operator attitude towards the environment. In addition to that, we extended our approach to adapt it to the daily traffic evolution by taking into account the availability of solar energy during the day. We showed that the smart grid features can be beneficial for mobile networks as wireless
Chapter 7, we dealt with the case when mobile operators cooperate together in order to minimize their CO₂ emissions subject to a quality of service constraint. The problem was modeled as a two-level Stackelberg game: a mobile operator level and a smart grid level. We assumed that cellular networks are powered by multiple energy providers existing in the smart grid characterized by different pollutant levels in addition to renewable energy source deployed in BS sites. The objective was to find the best active base station combination and the optimal procurement decision needed to the network operation during collaboration. Our study included the daily traffic variation in addition to the daily green energy availability. Our simulation results showed a significant saving in terms of CO₂ emissions compared to the non-collaboration case and that cooperative mobile operators exploiting renewables are more awarded than traditional operators.

Chapter 8-9 proposed different methods that introduce the roaming prices as a cooperation criterion. Chapter 8 used a non-homogenous system of linear inequalities to solve the problem while Chapter 9 modeled as a Stackelberg game that determines the number of roamed users and the roamed prices. Our simulation results showed a significant saving in terms of CO₂ emissions compared to the non-cooperation case and that roaming decision depends essentially on the availability of the generated renewable energy in base station sites.

The overall conclusion of this dissertation is that mobile companies have the potential to fight against global warming by reducing the CO₂ emissions of their cellular networks. The objective now is to try to implement in practice these techniques as well as other proposed ones in order to achieve one of the most important 5G network targets: Environment aware cellular networks.

10.2 Future Work

We have already discussed some future work in the summary of certain chapters. All the proposed techniques are proposed to be applied in practical environment. Unfortunately, at the moment, inter-operators collaboration and smart grid mobile companies cooperation are just hypothesis not applied in reality. Therefore, there is a pressing need to propose additional and new approaches
in order to encourage telecommunication leaders and regulators to discuss and focus more on such approaches for possible implementation in next cellular network generation is. Of course, the work can be extended and enriched in order to achieve more energy saving. For example, one can focus on the energy efficiency of wireless devices in the user side. Device to device communication would provide an important energy saving in cellular networks. Combined with base station sleeping strategy in addition to clustering method, network coverage can be maintained when some base stations are turned off. For the smart grid, several other real-time price models could be investigated and the problem could be solved using different game theoretical approaches with different utility functions. Moreover, although it was briefly studied in Chapter 2, minimizing the electromagnetic radiation should attract more researchers’ attention for future safe cellular networks.
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