Univeristat Politecnica De Catalunya

Ph. D. Thesis

Design of Energy Efficient Network Planning Schemes for LTE and LTE-Advanced Wireless Cellular Networks

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"Scientists dream about doing great things. Engineers do them."

James A. Michener

UNIVERSITAT POLITECNICA DE CATALUNYA

Abstract

Department of Signal Theory and Communications

Doctor of Philosophy

Design of Energy Efficient Network Planning Schemes for LTE-based Cellular Networks

by Alexandra Bousia

The rapid expansion of mobile services and the emerging demand for multimedia applications have led to an impressive traffic growth. To this end, Mobile Network Operators (MNOs) seek to extend their infrastructure by installing more Base Stations (BSs), in an effort to increase the network capacity and meet the pressing traffic demands. Furthermore, to fulfill the escalated demands, Heterogeneous Networks (HetNets), which consist of Small Cells (SCs) and the traditional BSs, constitute the new trend of next generation networks.

The deployed infrastructure implies a rise in the Capital Expenditures and has a direct impact on the network energy consumption, thus resulting in higher Operational Expenditures. Hence, the investigation of energy efficient solutions will bring down the energy consumption and the network cost. Since the BS is the most power hungry component, the research community has shifted towards the investigation of BS deactivation schemes. These schemes propose that part of the infrastructure can be temporarily switched off, when the traffic is low, while the active BSs extend their coverage to serve the network.

Based on a comprehensive review of the state-of-the-art, a set of research opportunities were identified. This thesis provides contributions to the field of BS switching off strategies for wireless macro BSs networks and HetNets of single and multiple MNOs by proposing mechanisms that enhance different aspects of the network performance. The BSs deactivation, the innovative trend of infrastructure sharing and the financially driven collaboration among the involved parties of the current and future networks promise significant improvements in terms of energy and cost savings. The main thesis contributions are divided into three parts, described next.

The first part of the thesis introduces innovative BS switching off approaches in single-operator environments, where only macro BSs are deployed. The proposed strategies exploit the inherit characteristics of the traffic load pattern (e.g., distribution of the users, traffic volume, etc.) and the distinctive features of the wireless cellular networks (e.g., BSs position, topology, etc.). Theoretical analysis and computer-based simulations show the performance improvement offered by the switching off strategies with respect to energy efficiency.

The second part of the thesis explores a different challenge in network planning. The coexistence of multiple MNOs in the same geographical area has motivated a new business model, known as infrastructure sharing. A roaming-based deactivation scheme is proposed, by taking into account the rationality and the conflicting interests of the

MNOs. The proposed game theoretic framework enables the MNOs to take individual switching off decisions, thus bypassing potential complicated agreements. The theoretical and simulation results show that our proposal significantly improves the energy efficiency, guaranteeing at the same time the throughput in realistic scenarios. Moreover, the proposed scheme provides higher cost efficiency and fairness compared to the state-of-the-art algorithms, motivating the MNOs to adopt game theoretic strategies.

The third part of the thesis focuses on the exploitation of HetNets and the proposal of energy and cost effective strategies in SC networks with multiple MNOs. We effectively address the cost sharing by proposing accurate cost models for the SCs to share the network cost. Taking into account the impact of the traffic on the cost, we propose novel cost sharing policies that provide a fair outcome. In continuation, innovative auction-based schemes within multiobjective optimization framework are introduced for data offloading from the BSs, owned by the MNOs, to the third-party SC networks. The proposed solution captures the conflicting interests of the MNOs and the third-party companies and the obtained results show that the benefit of proposing switching off approaches for HetNets.

Keywords

[Wireless cellular network, Energy efficiency, Base station switching off, Network planning, Resource allocation, Green networking, Game theory, Shapley value, Auction theory, Multiobjective optimization]

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By writing these lines, I finish an unforgettable journey I started few years ago. This Ph.D dissertation would not have been possible without the help and support of many people. Herein, I would like to express my gratitude to all of them.

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Contents

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Abbreviations

2G	Second Generation
3G	Third Generation
3GPP	Third Generation Partnership Program
4G	Fourth Generation
5G	Fifth Generation
AP	Access Point
BB	Baseband
BS	Base Station
CAGR	Compound Annual Growth Rate
CapEx	Capital Expenditure
CBR	Constant Bit Rate
CoMP	Coordinated Multi-Point transmission or reception
CR	Cognitive Radio
CTMDP	Continuous Time Markov Decision Process
DDSO	Dynamic Distance-aware Switching Off
DSE	Dominant Strategy Equilibrium
DSO	Distance-aware Switching Off
E-bal	Energy-balanced
E-UTRA	Evolved Universal Terrestrial Radio Access
E-UTRAN	Evolved Universal Terrestrial Radio Access Network
FOT	Full Operational Topology
GoS	Grade of Service
GSM	Global System of Mobile Communications
GTIS	Game Theoretic Infrastructure Sharing
HetNet	Heterogeneous Network

HS	Hybrid cost sharing
HSPA	High Speed Packet Access
ICT	Information and Communications Technology
IEEE	Institute of Electrical and Electronics Engineers
ILP	Integer Linear Programming
IMT-Advanced	International Mobile Telecommunications-Advanced
ISO	Income auction-based Switching Off
IT	Information Technology
LTE	Long Term Evolution
MAS	Multiobjective Auction-based Switching off
MDP	Markov Decision Process
MNO	Mobile Network Operator
MSO	Maximization Switching Off
MVNO	Mobile Virtual Network Operator
NE	Nash Equilibrium
NSO	No Switching Off
OP	Operator-peak cost sharing
OpEx	Operational Expenditure
PA	Power Amplifier
PC	Personal Computer
PPP	Poisson Point Process
PRB	Physical Resource Block
QoS	Quality of Service
R-bal	Roaming-balanced
RNC	Radio Network Controller
RSO	Random Switching Off
R-to-1	Roaming-to-One
SAP	Small cell Access Point
SC	Small Cell
SCF	Store-Carry and Forward
SINR	Signal-to-Interference-plus-Noise-Ratio
SNR	Signal-to-Noise-Ratio
SQP	Sequential Quadratic Programming

SV	Shapley value cost sharing
TV	Traffic-volume cost sharing
UMTS	Universal Mobile Telecommunications System
VCG	Vickrey-Clarke-Grooves
WLAN	Wireless Local Access Network

For my parents, Nikos and Mary, and my brother, Vasilis.
To my husband, Kostas.

Chapter 1

Introduction

"Engineers like to solve problems. If there are no problems handily available, they will create their own problems."

Scott Adams

This chapter outlines the context of the problem, the motivation of the proposed solutions and the organization of the thesis. The structure of the chapter is described as follows. Section 1.1 describes the motivation behind the thesis. A description of the structure of the thesis is presented in Section 1.2. Finally, Section 1.3 presents the dissemination of results.

1.1 Context and Motivation

1.1.1 Context

The wireless cellular communications industry witnessed a tremendous growth in the past. Both Global System for Mobile communications (GSM) and Universal Mobile Telecommunications System (UMTS) were a worldwide success, adopted by most countries and Mobile Network Operators (MNOs).

During the last few years, the rapid and radical evolution of mobile telecommunication services along with the emerging demand for multimedia applications due to the widespread use of laptops, tablets and smart-phones have led to a growing demand for data transmission. The traffic load is experiencing a growing increase by the factor of 10 every 5 years approximately [5], [6]. Overall mobile data traffic is expected to reach 24.3 exabytes per month by 2019, a 13-fold increase and at a Compound Annual Growth Rate (CAGR) of 57% from 2014 to 2019. The mobile applications, in particular, are expected to grow in staggering rates, with mobile video showing the higher growth and getting up to 66.5%. Thus, the increasingly expanding market of web-enabled mobile devices opens the path towards a wide range of previously unimagined (data-based) applications and creates the need for ubiquitous availability of Internet (better coverage) and faster broadband connections (higher Quality of Service (QoS)) [7].

To meet these demands, the development of new standards and architectures is more than compulsory. Serious efforts were done in order to improve data transmission capabilities of existing Second and Third Generation (2G and 3G, respectively) technologies. In particular, the Third Generation Partnership Project (3GPP) introduced High Speed Packet Access (HSPA), an enhancement to its 3G technology, named UMTS. In parallel, the Institute of Electrical and Electronics Engineers (IEEE), achieved an important milestone with the introduction of specifications for local and metropolitan wireless area networks, IEEE 802.11 and IEEE 802.16, respectively. Long Term Evolution (LTE) that is the natural upgrade of UMTS, is an evolving wireless standard developed by the 3GPP as a candidate Fourth Generation (4G) system, while LTE-Advanced constitutes the most advanced version of LTE [8], [9]. IEEE 802.16m standard is the 4G system proposed by International Mobile Telecommunications-Advanced (IMT-Advanced). These standards are expected to ensure the competitiveness of the 3GPP for the next 15-20 years and guarantee its presence within the umbrella of the Fifth Generation (5G), which is likely to be deployed around 2020. Fig. 1.1 depicts the evolution of cellular systems, where the different standards, along with the standardization groups, are shown.

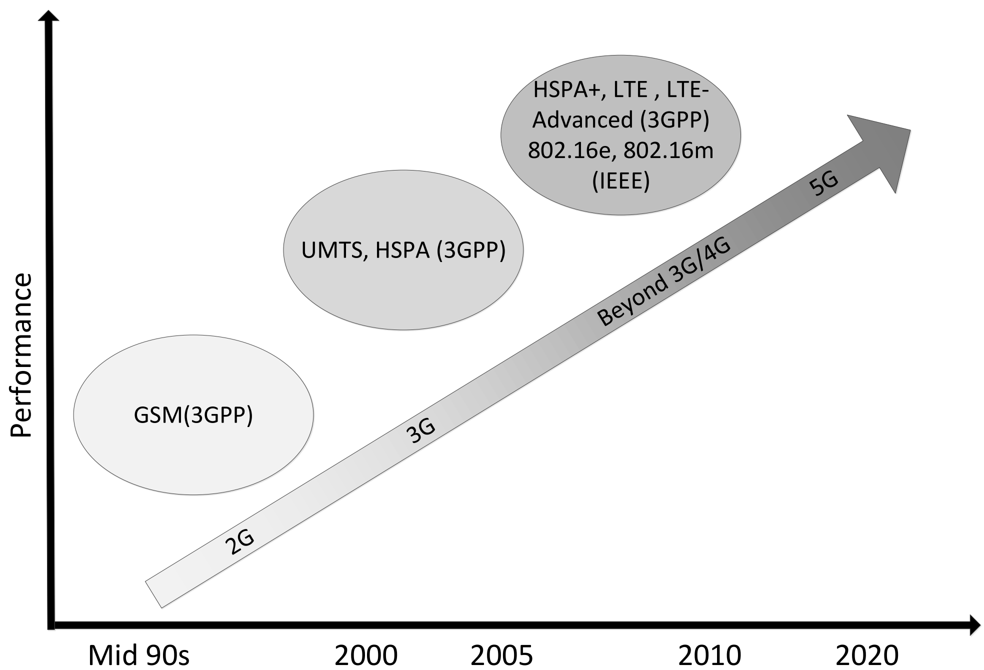


Figure 1.1: Evolution of cellular systems from 2G to 4G and framework for 5G.

4G, and more specifically LTE and LTE-Advanced, have crossed the generational boundary and the limitations of the previously developed standards, offering the next generations of capabilities. With their capacity for high speed data, enhanced data rates for mobile phones and terminals, ubiquitous connectivity, significant spectral efficiency and adoption of advanced radio techniques, their emergence is becoming the basis for all future mobile systems. One of the important LTE and LTE-Advanced benefits is the ability to take advantage of advanced topology networks, such as optimized heterogeneous configurations with a mix of macrocells and low power nodes, such as picocells, femtocells and micro nodes. The 4G standards further improve the capacity and coverage, ensure user fairness and also introduce multicarrier to be able to use ultra wide bandwidth, up to 100 MHz of spectrum supporting very high data rates.

In contrast to 4G that was designed for improving capacity, user data-rates, spectrum usage and latency with respect to the previous standard generations, 5G is not only an evolution of mobile broadband networks [1]. 5G provides significant development in the capabilities of the telecommunications systems. Some insights about what 5G is supposed to be, compared to the requirements of 4G are illustrated in Fig. 1.2 [1]. 5G brings new unique network and service potentials. It ensures user experience continuity in challenging situations such as high mobility (e.g., in trains), very dense or sparsely populated areas, and journeys covered by heterogeneous technologies. Mission critical services requiring very high reliability, global coverage and/or very low latency (e.g., public safety), which are up to now handled by specific networks, are natively supported by the 5G infrastructure. 5G infrastructures are also much more efficient. The enhanced spectral efficiency enables 5G systems to consume a fraction of the energy that a 4G mobile networks consumes today for delivering the same amount of transmitted data, thus, motivating new business models for consumers but also for new industrial stakeholders (e.g., industries, novel forms of service providers or infrastructure owners, third-party companies and providers). At this point, it is highlighted that the solutions of the thesis can be applied in the current 4G systems and can bring further enhancement in future 5G networks, as well.

Along with the development of the new telecommunications standards and in order to tackle with the challenges of future mobile networks and handle the predicted increase in mobile traffic volume, operators face the need to expand their wireless infrastructure. The telecommunications companies work towards the massive deployment of their networks. At this point, it is highlighted that there were more than 8 million Base Stations (BSs) deployed and serving mobile users in 2012 [10]. Let us point out here that the largest mobile telecommunications operators may maintain approximately 238000 BS sites worldwide [11]. Moreover, the number of deployed BSs grows as the users requirements increase every year. Furthermore, Wi-Fi Access Points (APs) and third-party Small Cells (SCs), such as picocells, femtocells and mircocells, are extensively deployed in public and private areas, such as university campuses, business parks, and user homes during the last decade, introducing the trend of Heterogeneous Networks (HetNets). 4G and 5G technologies support these architectural enhancements and infrastructure expansion. More specifically, the future infrastructure shall flexibly and rapidly adapt to a broad range of requirements. The deployment of BSs and SCs is pushed further leading to ultra dense networks. A typical heterogeneous cellular network architecture is presented in Fig. 1.3. In this architecture, multiple stakeholders coexist, since the macro nodes and the smaller cells are owned by different entities, either MNOs or third-party companies. The various telecommunication nodes, along with the several technologies that they support, are also illustrated.

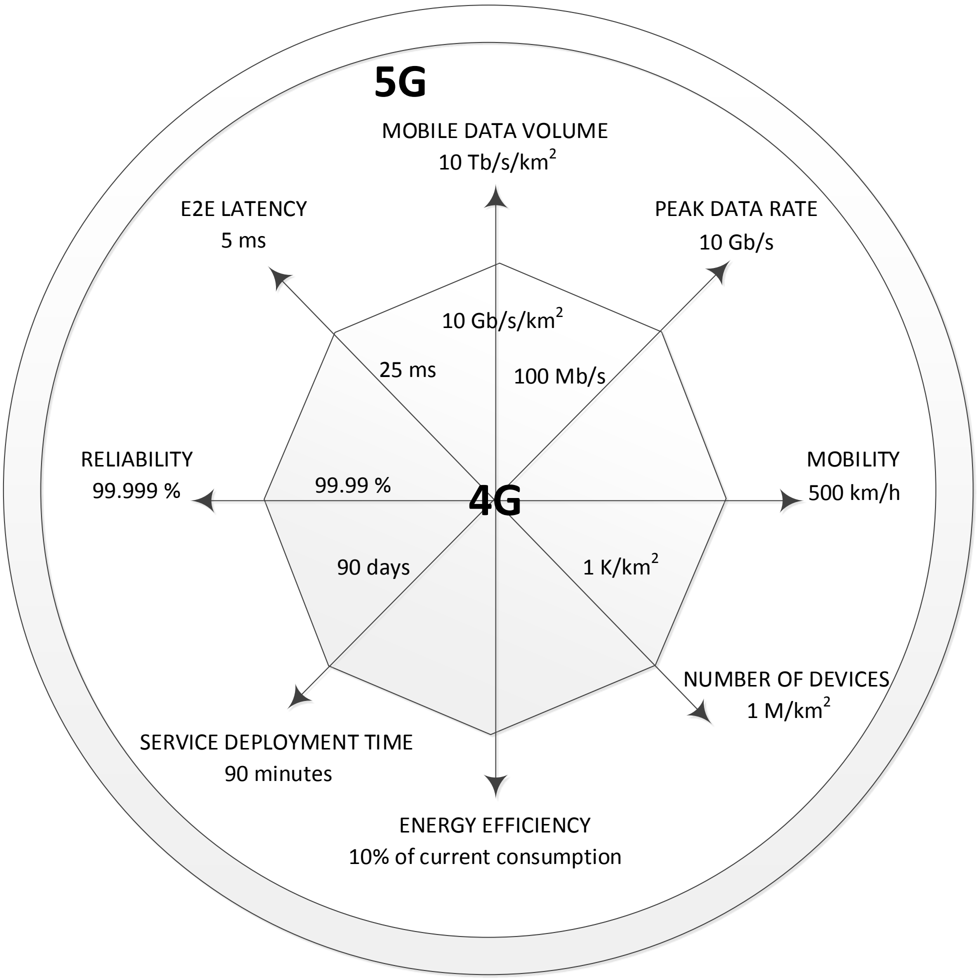


FIGURE 1.2: Diagram of 5G capabilities in comparison to 4G capabilities [1].

1.1.2 Problem Statement

The challenging capabilities that are attained by the 4G and 5G standards and the densification of the wireless cellular networks with the massive deployment of BSs and SCs imply a rise in the Capital Expenditures (CapEx) of the telecommunication companies. In addition, the augmented number of operating HetNets leads to an emerging increase of the total network energy consumption, thus resulting in higher Operational Expenditures (OpEx), as well [12]. In the coming years, it is widely acknowledged that wireless cellular networks will have even greater economic and ecological impact.

The numbers and the reports reveal the gravity of the problem. Overall, the BSs account for 60% of the total energy consumption and carbon emissions caused by the telecommunication companies [11]. In particular, the use of Information and Communication Technology (ICT) across a wide range of applications currently accounts for 5.7% of the world's electricity consumption and 1.8% of global carbon emissions [13], [2], something that translates into electricity bills in the order of $10 billion for the MNOs worldwide [14]. This rather small amount of ICT carbon emissions is, however, comparable to the total carbon emissions caused by

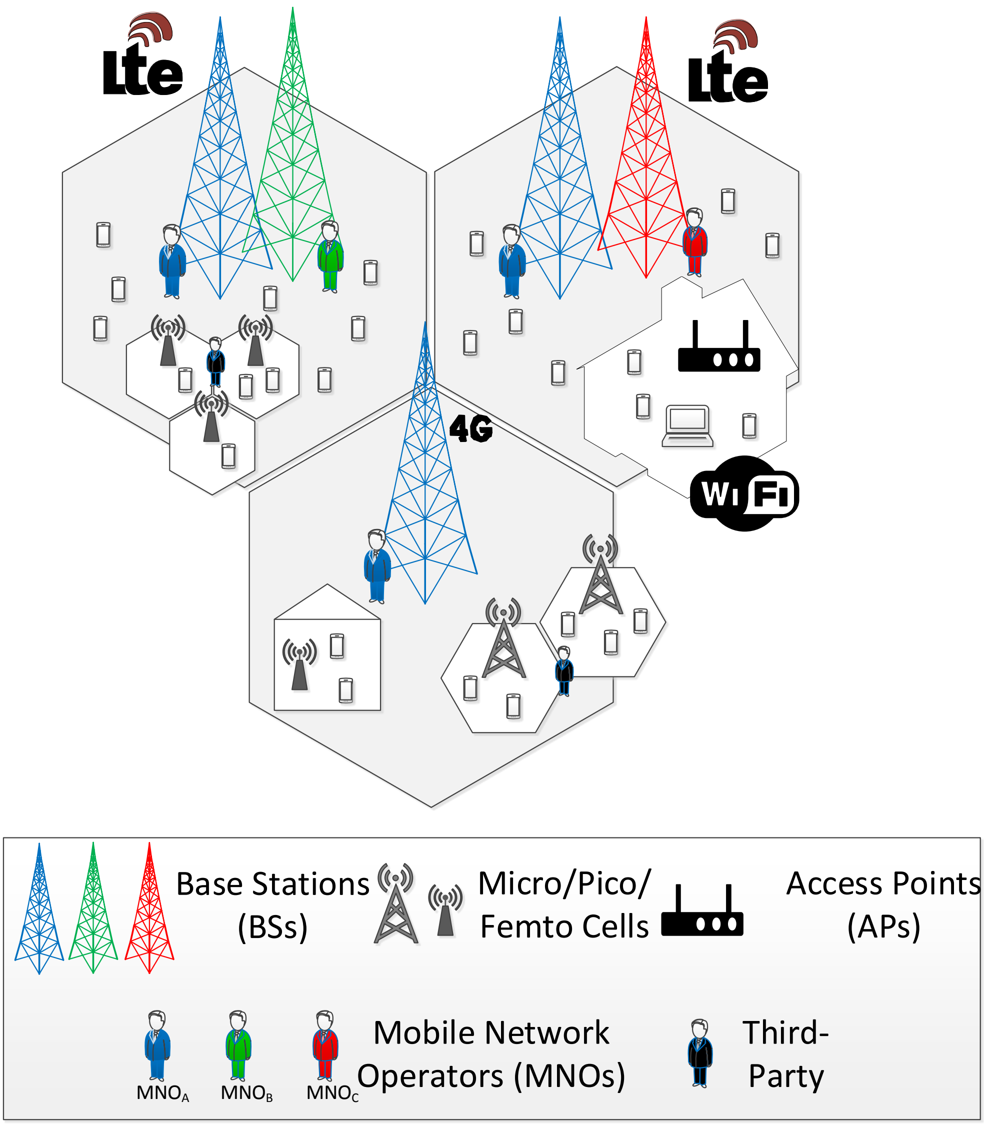


FIGURE 1.3: 5G cellular network architecture.

international air traffic, or one quarter of global carbon emissions by cars [15]. Analyzing the ICT carbon emissions by sector in Fig. 1.4, it can be seen that the carbon footprint of both telecommunications infrastructure and devices has been significantly increasing since 2002, in comparison with those of other ICT sub-sectors like Personal Computers (PCs) and data centers [2]. Peripherals and PCs are not the fastest growing elements of the footprint. Data centers, as well, grow slower than other ICT technologies, since their increase is driven only by the need for storage, computing and other Information Technology (IT) services. Though as the telecommunications footprint continues to grow (from 0.53 GtCO2e to 1.43 GtCO2e by the year 2020), data centers represent a smaller share of the total ICT carbon footprint in 2020, with the telecommunications infrastructure, mobile devices, PCs and peripherals to account for a larger share.

Also, as it is reported in Fig. 1.5, while the share of fixed narrowband networks has remained almost constant through years in real values (64 MtCO2e to 70 MtCO2e), the increasing contribution of wireless networks is expected to dominate the total

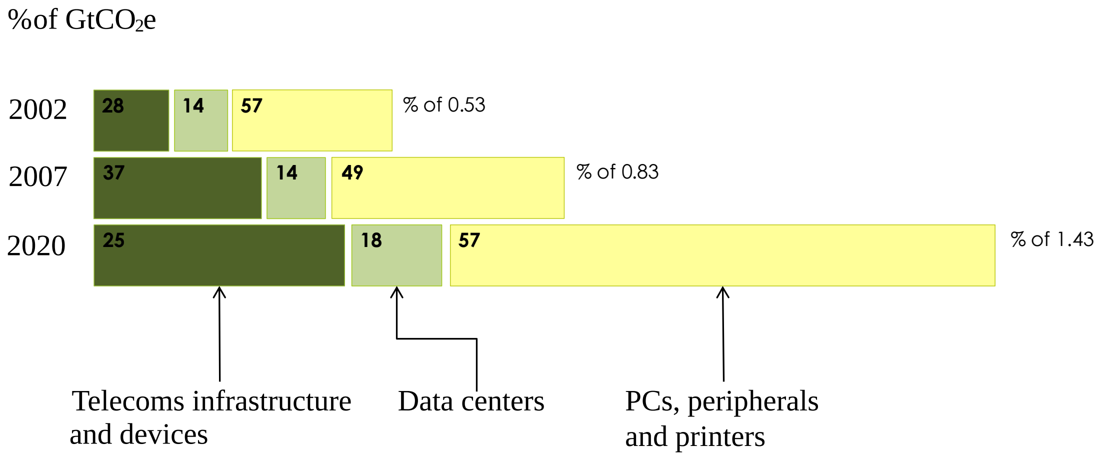


FIGURE 1.4: ICT carbon footprint by sector [2].

telecommunications carbon footprint by 2020. This prediction is mainly based on the rapid growth of mobile network infrastructure (66 MtCO2e to 179 MtCO2e) and the increased emissions caused by the augmented number of wireless devices (18 MtCO2e to 51 MtCO2e). In addition, the global carbon emissions, caused by fixed broadband is expected to grow from 4 MtCO2e to 49 MtCO2e. Therefore and by considering the energy waste in numbers, energy consumption is widely recognized by society as the most important issue for sustainable growth in both developed and developing countries. To enable the low-carbon economy in Europe, the European Commission sets ambitious targets in 2008 to reduce greenhouse gas emissions by 20% and to improve energy efficiency by 20%, both by 2020 [16]. Indeed, the ICT sector can play an important role to meet these challenges by improving energy efficiency and by developing energy-efficient wireless networking solutions to reduce the global ICT carbon footprint by 2020.

Apart from the environmental issues, the financial cost increase attracts great attention among the MNOs and the third-party companies. More specifically, CapEx for site deployment rapidly rises due to the massive network densification. In addition, the radio access equipments, including BSs and SCs, account for the major percentage of the total cost for deploying and operating the network. To attain further insights on the economic aspects, it is pointed out that the price of a macro cellular BS equals 20K – 50K €. The price of a micro and pico cellular SC equals 50% and 15%, respectively, of a macro BS, which is still high [3], [17]. The cost analysis of a BS site is given in Fig. 1.6 and it is clear that the BS equipments dominate the cost expenses. Thus, the need of cost reduction provides strong motivation for the network entities, which can be achieved through the design of cost efficient network planning algorithms.

Summarizing, the great increase in energy consumption, carbon emissions and cost expenses makes the need of the design of cost efficient and energy effective solutions to become more than compulsory. However, the heterogeneous nature of the networks, where multiple MNOs, numerous third-parties and independent users coexist, creates a diversity of conflicting interests and contradictory requirements that pose great complexity in the design of efficient and feasible solutions. The

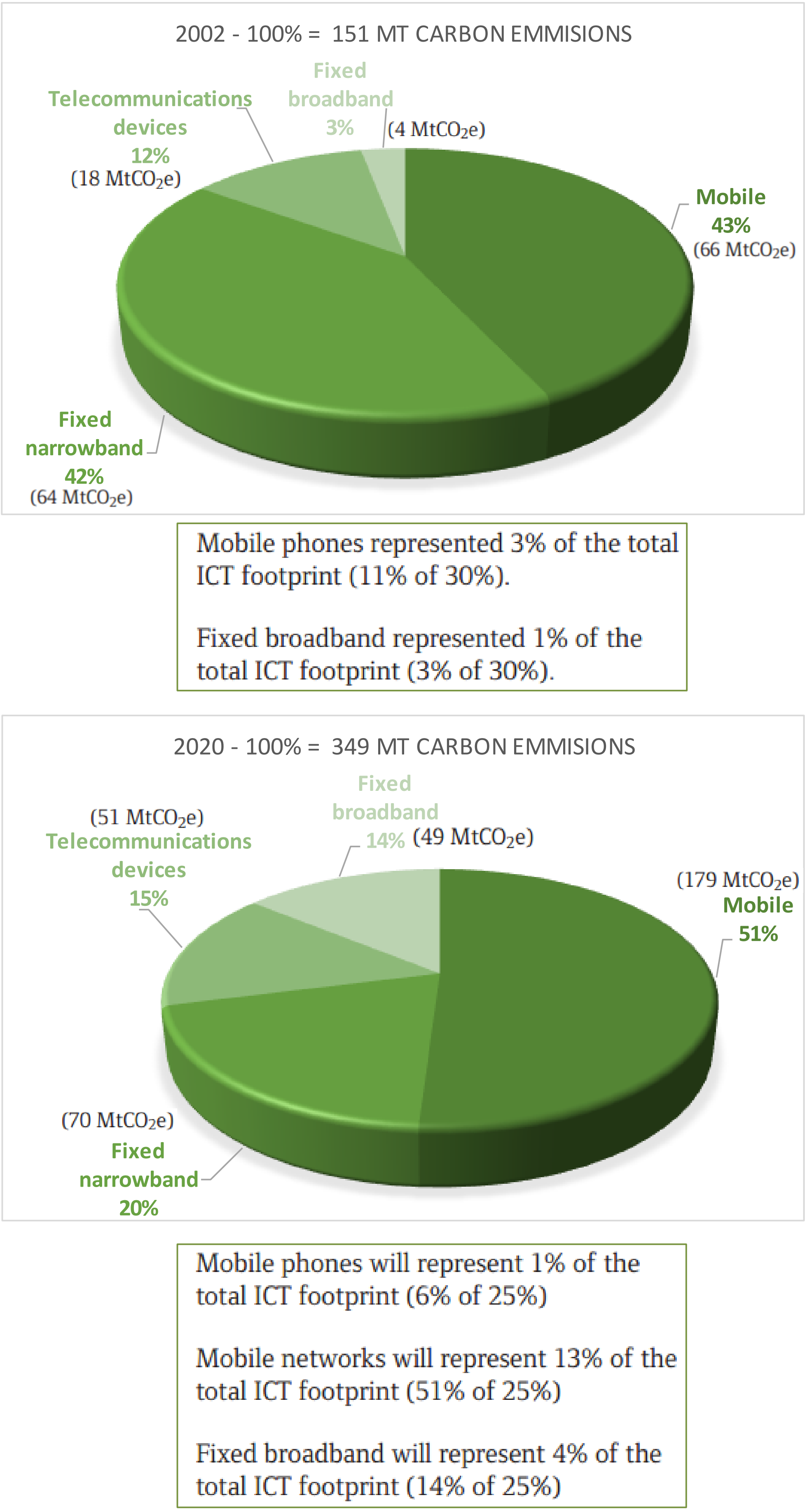


FIGURE 1.5: Global telecommunications carbon footprint by sub-sector [2].

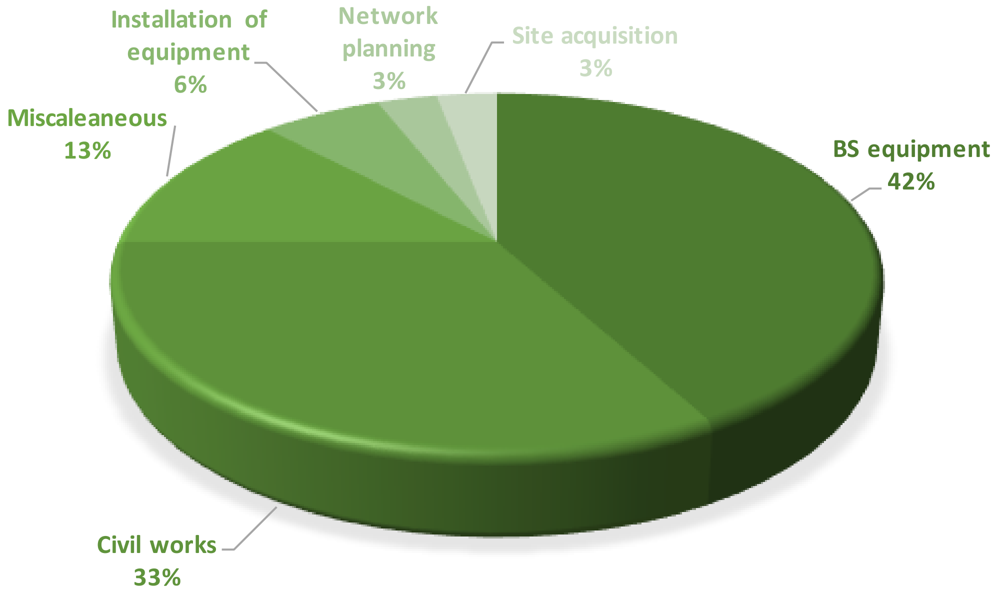


FIGURE 1.6: Breakdown of capital expenditures for a BS site [3].

contribution of the thesis relies on the proposition of novel techniques by accounting the different requirements and needs of the current and future networks.

1.1.3 Motivation

Currently operating wireless networks have been mainly designed and deployed to maximize users performance and QoS related metrics, e.g., throughput, data rates and reliability, while usually paying less attention to energy efficiency. The future designs of wireless networks need to consider energy efficiency, since it is now a priority of the European Commission and the ICT industry to attain energy efficiency gains. Seeing this, a new research discipline called *green cellular networks*, concentrating on environmental influences of cellular networks, has been formed and attracted many researchers. The term *green* is originally a nickname for the dedicated efforts to reduce unnecessary green house gases (e.g., CO_2) emissions from industries. For mobile operators and third-party stakeholders in particular, another motivation and objective of green approaches is to gain extra commercial benefits, mainly by reducing operating expenses related to energy cost. Hence, the identification of the main factors of the energy consumption in wireless cellular networks aims the design of appropriate green solutions.

With currently employed wireless technologies, the main problems of energy consumption can be associated with the two main components operating in wireless networks: central coordinators (wireless network infrastructure) and wireless devices.

- Infrastructure wireless networks are managed by central nodes, referred to as BSs in cellular networks or APs in Wireless Local Access Networks (WLANs) and SCs in HetNets. These central nodes are responsible for coordinating backhaul access to one or several transmission channels among wireless user devices located in their coverage areas. Furthermore, they usually provide access to the Internet for the connected users through a wired network infrastructure.

- Currently, a wide variety of portable devices and user equipments, e.g., laptops, tablets, and smartphones, are equipped with multi-standard radio interfaces, such as UMTS/LTE, Wi-Fi, and Bluetooth, to provide users with a flexible and powerful wireless connection.

Having identified the main components that consume energy in wireless cellular networks, Fig. 1.7 depicts the energy consumption breakdown of both users and network infrastructure. As pointed in Fig. 1.7, the consumed power and the emitted CO_2 by the mobile user devices is significantly lower than the power and carbon emissions, caused by the wireless network components,e.g., BSs and SCs. The numbers are revealing, since 4.8 billion subscribers consume only the 0.0001 of the power consumed by the dense HetNets. Thus, the solutions of this Ph.D. thesis are concentrated towards the energy and cost reduction of infrastructure wireless networks (by greening the BS and SC nodes), instead of working towards the greening of the small mobile devices.

Among the diversity of nodes that coexist in HetNets, such as BSs, micro, femto cells, etc., evidently, due to the size and functionalities of a BS, it is worth-noting that the BS, in contrast to the SCs, is one of the most power hungry component of a cellular network. This fact is also pointed out in Fig. 1.8 [4]. In this figure, the power consumption versus the traffic load is illustrated for both the power-hungry BSs and the low-powered SCs. The research works focus on reducing the number of active nodes, when the traffic load is low. From the figure, it can be concluded that the deactivation of the BSs can lead to greater gains rather than if the SCs are switched off. Thus, since greater power can be saved through reducing the number of active BSs, several research works have focused on this direction.

To gain further insight on the direction that the energy efficient designs should go, the investigation on where the energy is consumed in a BS is necessary. The BSs energy consumption, in turn, consists of different parts including [18]:

- Energy consumption due to BS baseband (BB) processing, mainly at the receiver side. The BB engine (performing digital signal processing) carries out digital up/down conversion, including filtering, modulation/demodulation, digital pre-distortion (only for large BS types), signal detection (synchronization, channel estimation, equalization, compensation of RF non-idealities), and channel coding/decoding. The silicon technology significantly affects the power consumption PBB of the BB interface. However, the increasing leakage, caused by increasing the active power of the BB, puts a limit on the power reduction that can be achieved through technology scaling.

- Energy consumption of the BS RF parts, mainly the transmitter Power Amplifier (PA). The energy that is consumed is really significant due to losses within the PA. For a given PA, such losses are at least partly independent of

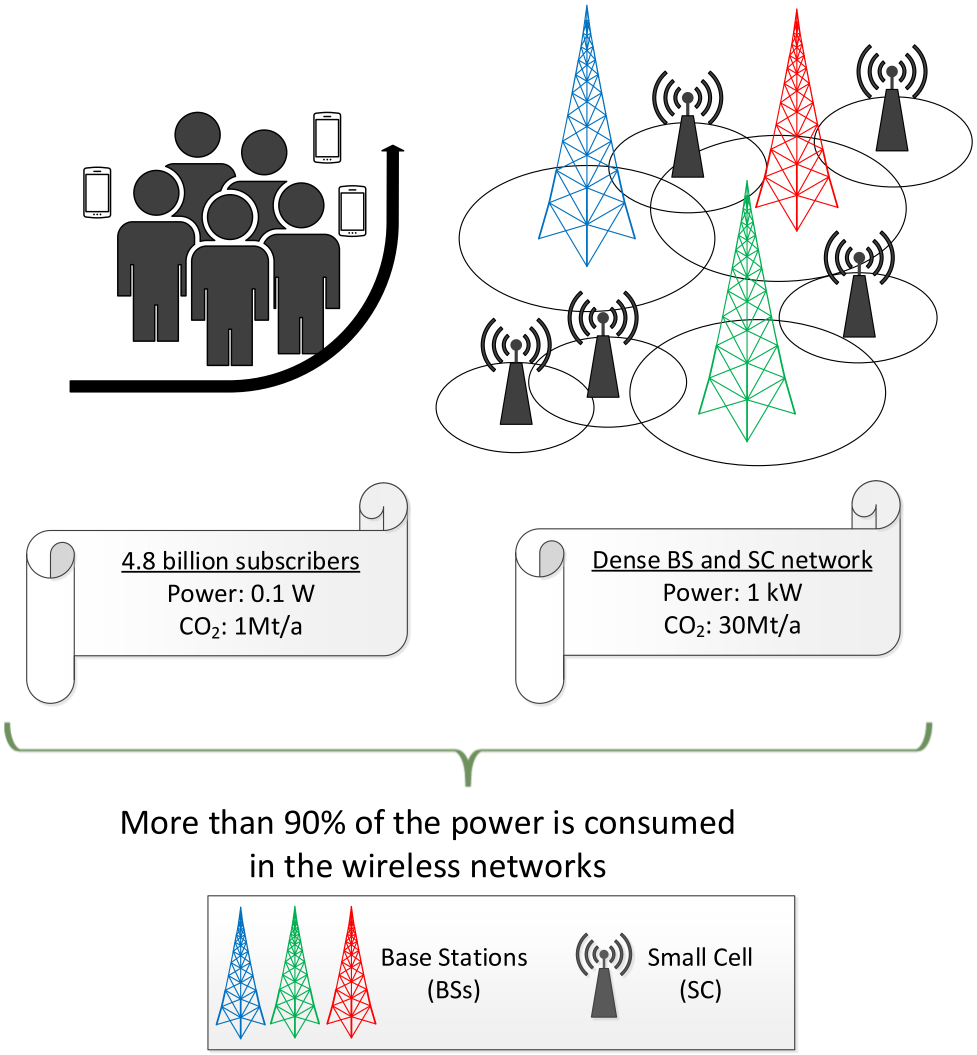


FIGURE 1.7: Mobile communications: where is the power consumed.

the instantaneous output power of the PA and can thus only be avoided by reducing the PA output power to zero, e.g., essentially turning-off the PA.

- Other parts such as energy consumption due to active cooling and power supply. Losses incurred by DC-DC power supply, mains supply, and active cooling scale linearly with the power consumption of the other components. Note that active cooling is only applicable to macro BSs, and is omitted in smaller BS types.

The above can be summarized in Fig. 1.9.

From Fig. 1.8 and Fig. 1.9, it can be concluded that the BSs still consume considerable amount of energy, even when the traffic load is significantly low, due to the power supply and PAs that are always active. More specifically, the fixed part, including air conditioning and power supply, accounts for around one fourth of total energy consumption. This amount of energy is wasted when no traffic is served by the BS, thus its is independent of the traffic load. Hence, the variations of the load and the traffic pattern play an important role on the energy

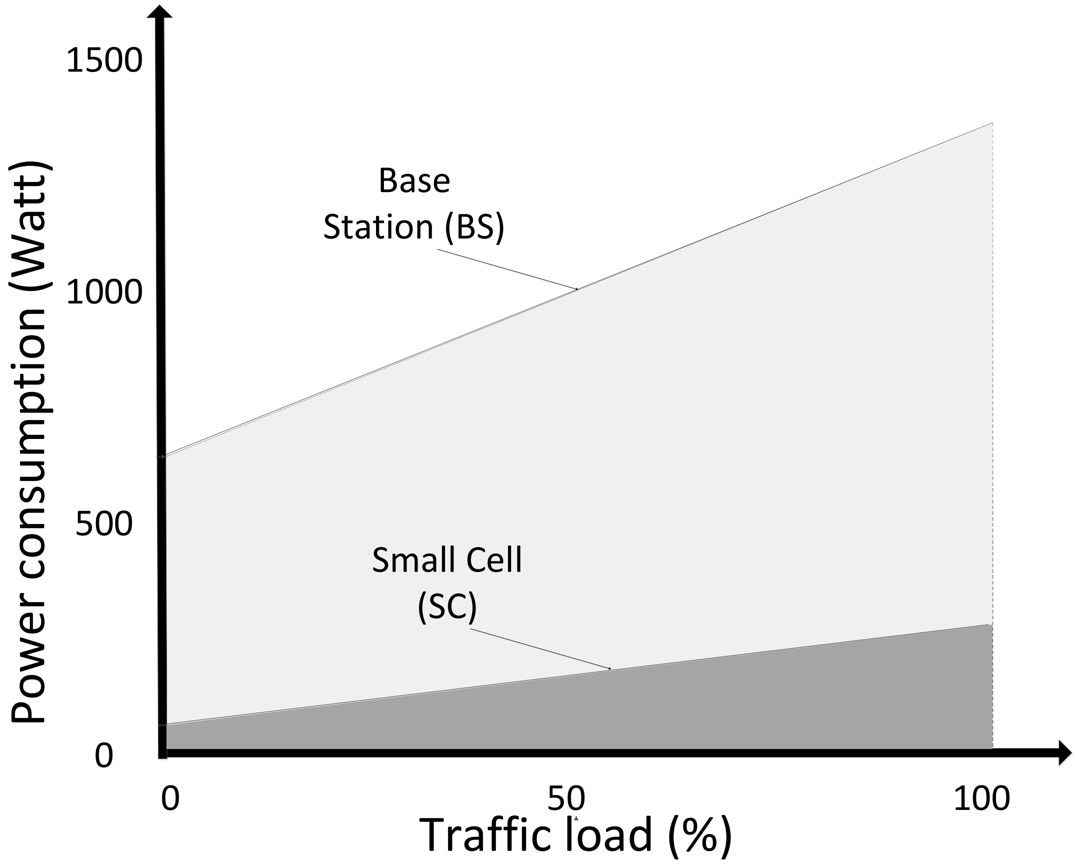


FIGURE 1.8: Power consumption for BS and SC as a function of the load [4].

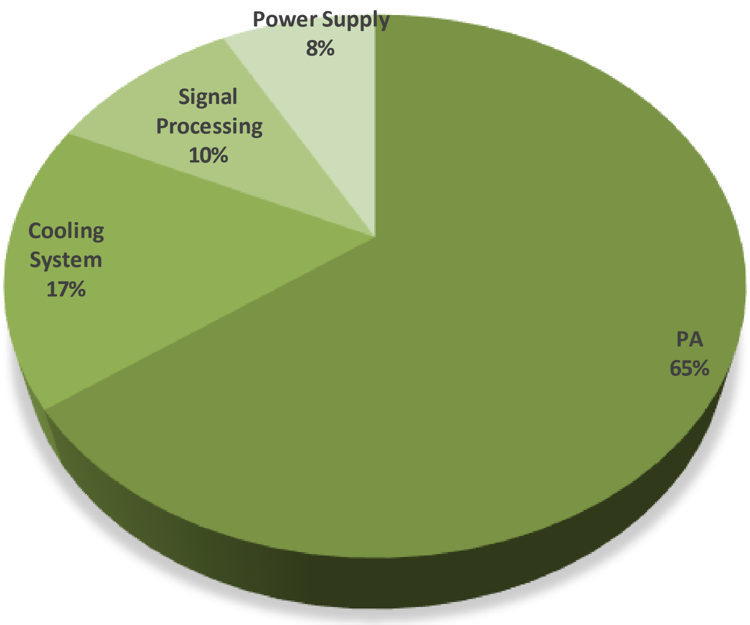


FIGURE 1.9: Energy consumption among the different components of a BS.

consumption, since it is important to know whether or not the traffic is low for long periods during the day. Fig. 1.10 shows the weekly traffic profile of a network operator in Europe in 2012, classified according to different applications including voice calls and mobile data, e-mail, streaming and so on. It is evident that the mobile traffic level throughout a day or a week varies periodically with the living pattern of mobile users. In the daytime on weekdays, people mostly concentrate in business areas in a city and are more likely to make phone calls. At night or on weekends, most people move to residential areas. Phone calls are generally less frequent at night than during the day but larger amount of cellular data is transmitted because more data-intensive applications such as social networking, web browsing, video streaming and video chatting are more likely to run [19], [20].

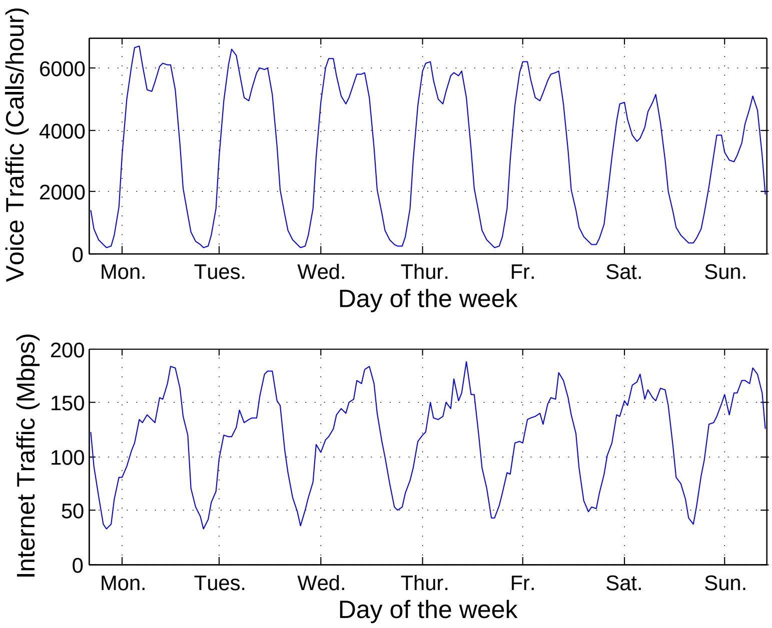


FIGURE 1.10: Measured weekly traffic volumes of a mobile cellular network in a business area.

Thus, the network planning solutions generally try to save energy by monitoring the traffic load in the network and then decide whether to turn off (or switch to sleep mode, also referred as low-power mode or deep idle mode in some literature), or turn on (or switch to active mode, ready mode or awake mode) certain elements of the network. Hence, unnecessary energy consumption, e.g., the power consumed for air conditioning under-loaded nodes, can be avoided by adopting sleep mode mechanisms. These approaches generally involve switching off certain elements including but not limited to power amplifiers, signal processing units, cooling equipments, the entire BSs/SCs, or the whole network, when the traffic load is low. Most often, sleep mode techniques aim to save energy by selectively turning off the corresponding nodes during off-peak hours. As shown in Fig. 1.8, BSs consume significantly higher energy in cellular networks than the low powered SCs. Thus, the BSs deactivation could lead to great energy savings. Given the constraint that some macro sites (e.g., a minimum number of BSs) must always stay on to support the basic operation of the network and avoid any negative impact on the QoS, the remaining active infrastructure components can extend their coverage range in order to serve the whole network area.

The BSs deactivation is a really appealing solution to reduce the energy consumption and the network costs. However, there are a lot of issues that should be considered. In a network where only macro nodes exist, the problem of switching off needs to deal only with the switching off decision, the crucial parameters that affect this decision and the constraints that follow the deactivation. Nonetheless, the design of feasible strategies is not that trivial, when the diversity of networks is taken into account.

In the 4G and 5G networks, several MNOs coexist providing service in the same geographical area. The traditional intention of the operators is to deploy and operate their own infrastructure. However, the dense networks with multiple operators challenge the traditional model of single ownership, due to the augmented CapEx and OpEx and motivate the research community towards a new business model, known as infrastructure sharing [21]. More specifically, instead of owning and operating their own network, the MNOs could share their resources. This new paradigm embraces a set of strategies that enable the MNOs to use their resources jointly in order to reach their common goal, which is to guarantee customer service while achieving energy and cost reduction. Infrastructure sharing can be classified into three categories [22]: *i*) passive sharing, limited to the joint use of sites, masts and building premises among MNOs, *ii*) active sharing, where the MNOs share the active network components such as antennas, switches and backhaul equipment, and *iii*) roaming-based sharing, where the MNOs share the cell coverage for a pre-negotiated period of time. Currently, over 65% of European operators are sharing their networks [23]. In addition to the benefits of BSs deactivation, these techniques can be combined and provide even higher energy efficiency. The energy and cost gains can be note-worthy, however, infrastructure sharing requires the MNOs cooperation. Thus, the proposed solutions must take into account the rationality of the MNOs and their conflicting interests.

In continuation, as discussed before, MNOs seek to extend their infrastructure by installing more BSs and in an effort to increase the capacity of their network and meet these pressing traffic demands, they also deploy a large number of SCs or lease capacity and bandwidth resources from third-parties, who deploy low-powered SC networks to provide enhanced services via traffic offloading from macro BSs to SCs during peak hours [24], [25]. Thus, heterogeneous networks were originally designed to improve the spectral efficiency and bandwidth capacity in cellular networks by offloading traffic from classical macro cells during peak hours. In contrast to conventional homogeneous macro cell deployment, such heterogeneous deployment improves the users and the network performance by supporting higher data rates. However, these deployments may lead to increase in energy consumption because of the extra cells that are also underutilized some hours of the day when the traffic load is low. Nevertheless, by introducing sleep mode in BSs, heterogeneous cellular networks can outperform traditional macro-cell-only networks in terms of energy efficiency. The involvement of various entities of corporate nature with different financial goals (e.g., MNOs, third-parties) generates a new ecosystem with interesting dynamics to be studied.

This Ph.D. dissertation provides a contribution to the field of network planning approaches for current and future wireless cellular systems, for both macro BS networks and HetNets, deployed by single or multiple operators and third-party entities. To be precise, various switching off and infrastructure sharing algorithms are investigated and proposed. Several open issues are addressed and new methods, guidelines and strategies are devised accordingly. Throughout the research process, emphasis is placed on achieving not only effective solutions but also feasible innovations and several perspectives of the problem are considered. To summarize, given the aforementioned issues, the main motivation for this work has stemmed from the following factors:

- the importance of addressing the **energy efficiency** problem. The emerging increase in terms of energy consumption is nowadays in the center of attention and there is significant need to provide solutions in order to reduce the energy waste, especially during the night, when the networks are underutilized.
- the significance of tackling the **increased cost** issues. The deployment of dense network infrastructure and the operation of heterogeneous nodes lead to rising cost expenditures. In order to decrease the cost and attain financial gains, novel solutions must be proposed that incorporate the heterogeneous characteristics of the networks and the coexistence of variable network components.
- the importance of addressing the BS **deactivation problem from several perspectives**. The tradeoff cost and energy efficiency-QoS is in the center of attention, but in addition, the increasingly important cost efficiency aspect is also considered in this thesis. The proposed algorithms aim to lower the energy consumption and reduce the network costs without degrading the user services. Switching off strategies and infrastructure sharing techniques are employed in single and multi operators networks. In addition, the third-party SC networks provide further opportunities for the proposal of energy and cost aware solutions, which were not feasible in the networks in past decades.
- the exploitation of deactivation techniques for the BSs in various **network deployments**. Regarding this aspect, the main research objective has been to design effective solutions providing network-specific designs. Real-life networks are all different and hence, these various network characteristics can (and must) be exploited to achieve the maximum benefit. Towards this direction, the examined networks include single and multi-operator cellular networks, with macro BSs and SCs. The coexistence of MNOs and third-party owners and the dense heterogeneous network configuration can be exploited.

1.2 Scope and Structure of the Thesis

The main research objective of this Ph.D. dissertation is the design of new and advanced schemes for the energy efficient network planning in the context of the downlink of realistic 4G (LTE/LTE-Advanced) and 5G deployments. The innovative solutions and the proposed algorithms of this work clearly suggest the different guidelines that can be followed, provided the varying nature of the network configuration characteristics and the different aspects of the traffic demand.

The document is composed of seven chapters and two appendices. Among the next five chapters, one chapter includes the background information of the related works and the rest four chapters correspond to the core of the Ph.D. dissertation, presenting the research contributions. Each chapter focuses on different, but interrelated, strategies to optimize the overall performance of network planning schemes in LTE/LTE-Advanced networks. The last chapter closes the document with final remarks, conclusions and future research lines.

Chapter 2 provides the necessary background information concerning the description of network planning and switching off approaches presented in the literature. It starts with the required background knowledge, including a description of the reference scenarios and architectures. In continuation, a survey of the state-of-the-art and current trends is given. The chapter examines the energy efficient solutions that are applied in three different network configurations *i*) single operator macro BS networks, *ii*) multi-operator macro BS networks, and *iii*) multi-operator Heterogeneous Networks (HetNets).

The innovative contributions of the thesis are organized into three parts. The first part consists of Chapter 3 and is dedicated to the proposal of novel energy efficient solutions in single-operator environments with macro BSs. We incorporate the traffic demand and network configuration characteristics to propose innovative mechanisms for selecting the most suitable BSs to be switched off. Two algorithms, namely Distance-aware Switching Off (DSO) and Dynamic Distance-aware Switching Off (DDSO), are proposed. These policies take into account the varying characteristics of the traffic pattern for the BSs deactivation. The basic idea behind DSO is to use the distance between the users and the BSs as the critical indicator in order to decide the suitable BSs to be deactivated. The BSs deactivation takes place in a predefined period of time, where the traffic load is low and the switching off decision is applied during the whole night zone. This approach is very suitable for scenarios with realistic traffic patterns, where the users are distributed within the coverage area of the BSs. Furthermore, DDSO extends the DSO operation by exploiting the dynamic nature of the traffic load, along with the distance between the users and the BSs, to allow the adequate BSs to be switched off. The switching off decision adapts to the variations of the traffic load and the distance along with the users' requests are examined every hour of the night zone. In continuation, a more general approach, namely Maximization Switching Off (MSO), is also given. This algorithm searches the optimal network configuration of active and switched off BSs. MSO improves the energy efficiency performance of the network by proposing an optimization technique to maximize the energy efficiency. Markov chain models are employed to calculate the performance metrics (e.g., throughput, energy efficiency, etc.) of the three approaches. The three novel approaches are able to significantly improve the energy efficiency without QoS degradation, since the users of the switched off BSs are served by neighboring cells, which extend their coverage. The analytical and simulation results show that the suggested algorithms outperform the baseline configurations and give the incentives for applying the switching off algorithms in current and future scenarios and networks.

The second part of the thesis contributions is formed by Chapter 4 and investigates network planing solutions in networks with multiple operators. The coexistence of multiple MNOs in wireless cellular networks gives the necessary incentives to provide deactivation policies that can be applied in multi-operator environments, by exploiting the inherent characteristics of these configurations (e.g., BSs' and users' positions, dynamic nature of the traffic, heterogeneous configurations, etc.). More specifically, realistic traffic patterns are used and complex Markov chain models are employed to calculate the metrics (e.g., energy efficiency, throughput, network cost, cost gains and cost efficiency) for both the network and the individual MNOs. Game theoretic approaches are investigated and a new energy aware scheme, namely Game Theoretic Infrastructure Sharing (GTIS) is presented to consider the conflicting interests of the existing entities. The performance of the new GTIS scheme is evaluated by means of theoretical analysis and computer-based simulations in various scenarios. Important system parameters, e.g., traffic load, operators' traffic volumes and roaming cost, are considered for the evaluation and comparison of the GTIS with several state-of-the-art approaches. The presented results show that the novel algorithm outperforms the state-of-the-art schemes and provide a wider understanding of intrinsic tradeoffs.

The last part of the thesis, consisting of two chapters (Chapter 5 and Chapter 6), addresses the issue of network cost sharing, telecommunications companies cooperation and deactivation of the BSs in HetNets where numerous MNOs and third-party entities coexist. In Chapter 5, we effectively address the network cost sharing issue by proposing an accurate cost model for the SCs and employing different state-of-the-art techniques, along with our innovative approaches to share the cost. The analytical models investigated in this chapter are significantly important for the examination of network planning solutions in dense cellular networks.

In continuation, in Chapter 6, auction theory and multiobjective optimization tools are employed to provide innovative energy efficient solutions focusing on the area of HetNets where multiple operators and third-party companies coexist. We propose a novel approach, namely Multiobjective Auction-based Switching off (MAS), to foster the opportunistic utilization of unexploited SCs capacity, where the MNOs lease the resources of third-party SCs to serve their customers and deactivate their BSs. Motivated by the conflicting interests of the MNOs and the restricted capacity of the SCs that is not adequate to carry the whole traffic in multi-operator scenarios, we introduce combinatorial auction frameworks, by employing multiobjective formulation to provide an energy efficient solution for the resource allocation problem. Extensive analytical and experimental results to estimate the gains in energy efficiency, throughput, network cost and attainable cost savings are provided. In addition, we investigate the conditions under which the MNOs and the third-party companies should take part in the proposed auction in order to give the necessary incentives to the involved parties to apply the proposed solutions. Relevant system parameters, e.g., traffic load, minimum economic requirements, bidding behavior and number of bidding levels, are used for the evaluation and comparison of the proposed strategy with the state-of-the-art techniques.

In addition, the document is closed with a high level assessment of the achievements accomplished through the research presented herein, conclusions and perspectives for future works in Chapter 7.

Finally, a set of appendices is provided to *i*) facilitate the reading and understanding of the document and, *ii*) complement the thesis with additional, but relevant, background information. More specifically, some background theory and general concepts of optimization theory are presented in Appendix A, whereas in Appendix B, the basic concepts, general guidelines and methodologies concerning the multiobjective optimization techniques are given.

Fig. 1.11 illustrates the structure of the thesis. Some basic ideas and solutions are indicated for better understanding.

1.3 Dissemination of Results

The novel proposals and innovations presented in this thesis have been disseminated through several research contributions. These publications are grouped according to the part of the thesis they correspond to.

The publication list includes:

- [**J**]: 3 journal papers.
- [**B**]: 2 book chapters.
- [**C**]: 6 conference papers.

PART I Chapter 3: 1 book chapter and 3 conference papers.

[**B1**] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis,"Energy Efficient Schemes for Base Station Management in 4G Broadband Systems". *Broadband Wireless Access Networks for 4G: Theory, Application and Experimentation*, IGI Global publication, 2013, pp. 101-121, Chapter 6, ISBN13: 9781466648883; EISBN13: 9781466648890.

[**C1**] **Alexandra Bousia**, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Green Distance-Aware Base Station Sleeping Algorithm in LTE-Advanced," *in Proceedings of IEEE International Communications Conference (ICC)*, Ottawa, Canada, June 2012.

[**C2**] **Alexandra Bousia**, Elli Kartsakli, Luis Alonso, and Christos Verikoukis, "Energy Efficient Base Station Maximization Switch Off Scheme for LTE-Advanced," *in Proceedings of IEEE International Workshop on Computer-Aided Modeling Analysis and Design of Communication Links and Networks (CAMAD)*, Barcelona, Spain, September 2012.

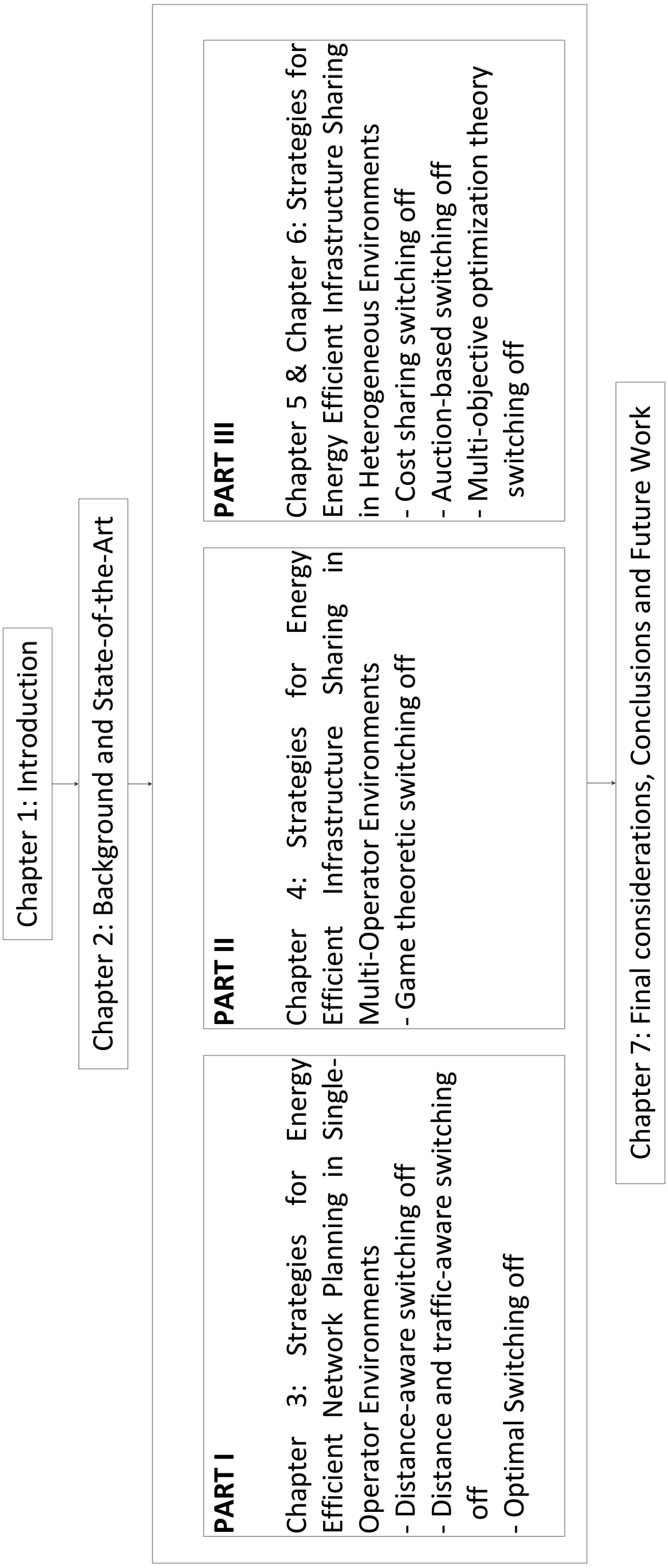


Figure 1.11: Outline of the dissertation.

[C3] **Alexandra Bousia**, Elli Kartsakli, Luis Alonso, and Christos Verikoukis, "Dynamic Energy Efficient Distance-Aware Base Station Switch On/Off Scheme for LTE-Advanced," *in Proceedings of IEEE Global Communications Conference (GLOBECOM)*, California, USA, December 2012.

PART II Chapter 4: 1 book chapter, 2 journal papers and 1 conference paper.

[B2] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Game Theoretic Infrastructure Sharing in Wireless Networks with Two Operators". *Game Theory Framework Applied to Wireless Communication Networks*, IGI Global publication, 2015, pp. TBA, Chapter TBA, ISBN15: TBA; EISBN15: TBA.

[J1] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Game Theoretic Infrastructure Sharing in Multi-Operator Cellular Networks," *IEEE Transactions on Vehicular Technology*, DOI: 10.1109/TVT.2015.2445837 (Accepted for publication).

[J2] Angelos Antonopoulos, Elli Kartsakli, **Alexandra Bousia**, Luis Alonso, and Christos Verikoukis, "Energy Efficient Infrastructure Sharing in Multi-Operator Mobile Networks," *IEEE Communications Magazine, Green Communications and Computing Network Series*, vol.53, no. 5, pp. 242-249, May 2015.

[C4] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Game Theoretic Approach for Switching Off Base Stations in Multi-Operator Environments," *in Proceedings of IEEE International Communications Conference (ICC)*, Budapest, Hungary, June 2013.

PART III Chapter 5 and Chapter 6: 1 journal paper and 2 conference papers.

[J3] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Multiobjective Auction-based Switching Off Scheme in Heterogeneous Networks To Bid or Not To Bid?," *IEEE Transactions on Vehicular Technology*, Minor Revision.

[C5] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Sharing the Small Cells for Energy Efficient Networking: How much does it cost?," *in Proceedings of IEEE Global Communications Conference (GLOBECOM)*, Austin, Texas, USA, December 2014, **Paper granted with Best Paper Award**.

[C6] **Alexandra Bousia**, Elli Kartsakli, Angelos Antonopoulos, Luis Alonso, and Christos Verikoukis, "Auction-based Scheme for Base Stations Switching Off via Offloading in Heterogeneous Networks," *in Proceedings of IEEE International Communications Conference (ICC)*, Submitted.

Chapter 2

Background and State-of-the-art

"Ask Gandhi, and eye for an eye makes us both blind.....ask an engineer, and the numbers don't lie - the first to strike wins."

Steven Ivy, Attorney Entrepreneur

2.1 Introduction

The rapid growth of wireless cellular networks, along with the extensive increase in the data traffic demand in the last few decades, raised the need of strong research and standardization efforts driven by academia and industry. These efforts have been targeted in the design and the optimization of new wireless networking solutions that support more and more enhanced services. For many years, major research efforts have been focused on improving throughput, delay and fairness of wireless networks. However, recently achieving energy efficiency and providing greener networks attracted significant attention. The greening of the wireless network consists of a topic of great importance, due to the increased energy waste, augmented CO_2 emissions and economic losses. This chapter provides a comprehensive review of existing energy efficient network strategies and the relevant state-of-the-art works. The background information is important, since it facilitates the understanding of the contributions of this thesis.

The chapter is structured as follows: Section 2.2 describes the wireless architectures, along with the reference scenarios, used in the Ph.D. dissertation. In Section 2.3, an extensive overview of the state-of-the-art approaches is given. The existing works focus on the deactivation of BSs and the networks sharing in variable network configurations and under different traffic conditions. After presenting the most common methods and widely used solutions found in the literature, a description of the research challenges and open issues is given in Section 2.4. Finally, Section 2.5 concludes the chapter.

2.2 Cellular Network Architectures

The contributions of this Ph.D. dissertation can be applied in various networks architectures, following the visions and the requirements of the current and future wireless cellular networks. The proposed solutions take into account the evolution of the cellular networks and thus, must be adapted to different network configurations. The examined cellular network architectures are depicted in Fig. 2.1 and include the following:

- **Single operator macro BS networks (Fig. 2.1(a)):** Infrastructure wireless networks, owned by a single MNO or third-party owners, are deployed in an area to provide service for the users of the operator. The BSs, located in the center of each macro cell, are interconnected and exchange important information through the X2 interface. At this point, let us clarify that the X2 is a logical interface introduced by the LTE radio access network. It connects neighboring BSs in a peer to peer fashion to assist handover and provide a means for rapid coordination of radio resources. The X2 interface supports exchange of information between BSs to perform the following functions: *i*) Handover: mobility of users between BSs, *ii*) Load Management: sharing of information to help spread loads more evenly, *iii*) Coordinated Multi-Point transmission or reception (CoMP): Neighboring BS coordinate over X2 to reduce interference levels, *iv*) BS configuration update, cell activation, including neighbor list updates, *v*) Mobility Optimization: coordination of handover parameters, *vi*) General Management: initializing and resetting the X2.

  Fig. 2.2 illustrates some existing and future single-operator network architectures, identifying their characteristics and the possible roles of the relevant stakeholders.

  Standalone: A single operator owns the infrastructure in a geographical area and serves its own traffic in the same region (Fig. 2.2(a)). The traditional model of single ownership is widely found in wireless cellular networks, since it is very common for an operator to fully deploy its network or to entirely lease the infrastructure from a telecommunication company (though the second option is rare nowadays). The MNO is responsible for the operation of the network and the increased operational costs. In addition, due to the monopolies and the oligopolies that exist in the telecommunications market, MNOs may prefer to work independently towards the greening of their networks, without any complex agreement among them. The MNO has the full control of its network, but is also responsible for the network deployment and operation expenses. The standalone is the most common case in wireless cellular networks.

  Third-Party: The BSs are deployed and owned by an independent third-party, and the operator, who holds a spectrum license, leases the infrastructure (Fig. 2.2(b)). This architecture implies lower CapEx for the MNO, who is only responsible to provide service to its users. However, the OpEx are increased due to the leasing agreements.

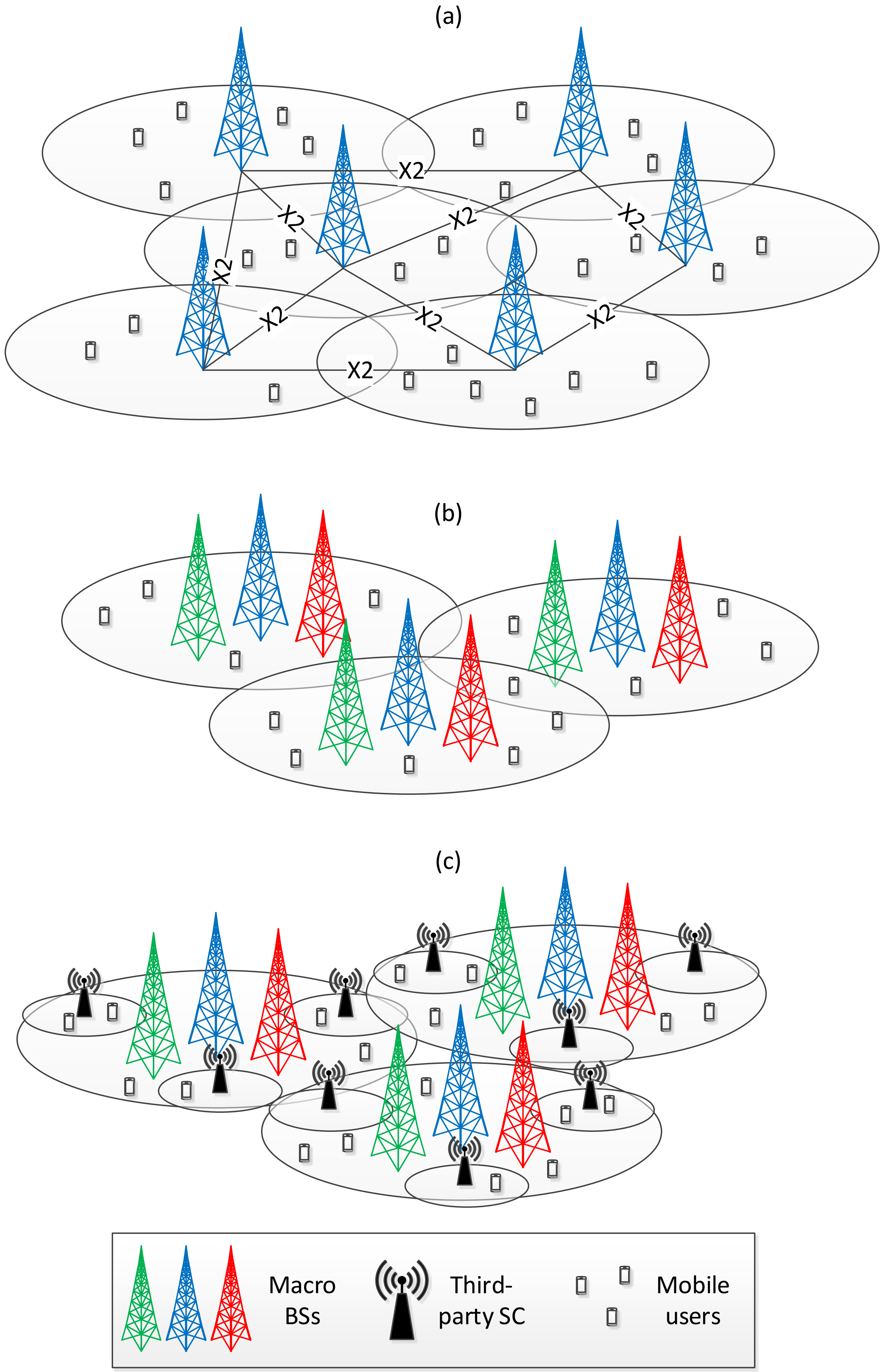


FIGURE 2.1: Cellular network architectures: (a) Single operator macro BSs network, (b) Multi-operator macro BSs network, (c) Multi-operator heterogeneous network.

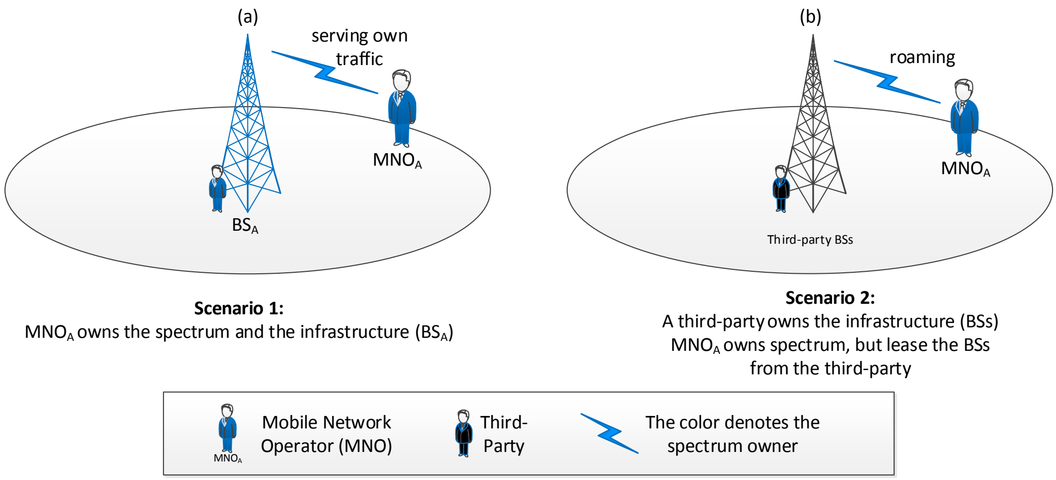


FIGURE 2.2: Single operator cellular network architectures.

- **Multi-operator macro BS networks (Fig. 2.1(b)):** Infrastructure wireless networks, owned by multiple operators or third-party owners, are deployed in an area to provide service for the users of the MNOs. Multiple MNOs coexist. In addition, due to legal regulations [26], telecommunication companies are forced to deploy the BSs on the same building or close to each other, and as a result the multiple BSs cover the same area. In the illustrated scenario, there exist multiple macro BS networks, serving the same area, each one owned by a different operator. The additional deployed infrastructure is responsible for an emerging increase in the CapEx of the MNOs, but also implies a rise on the total network energy consumption, thus resulting in higher OpEx as well. Therefore, energy efficient solutions could reduce the energy consumption and the cost of cellular networks. The increasing competition, rapid commoditization of telecommunication equipments and rising separation of network and service provisioning are pushing the operators to adopt multiple strategies, with network infrastructure sharing in the core and radio access networks, emerging as a more radical mechanism to substantially lower network costs. The new business model, known as infrastructure sharing [21], [27] is motivated by the coexistence of multiple MNOs and third-party companies in the same area.

  In Fig. 2.3, some of the possible scenarios of the multi-operator network architectures are presented, whose challenges and traits are discussed below.

  Mobile Virtual Network Operators (MVNOs): The spectrum and the network infrastructure in a given region are deployed and owned by a single operator (MNO_A in the example of Fig. 2.3(a)). All the other operators in the same area are virtual (MVNOs) and, since they do not own any spectrum or network infrastructure, they must lease resources from MNO_A in order to serve their clients. This model, also known as national roaming, has already been applied successfully in several countries thanks to its simplicity and its inherent advantages. In particular, the existence of MVNOs may be beneficial for the end-user, since it promotes the market competition, while,

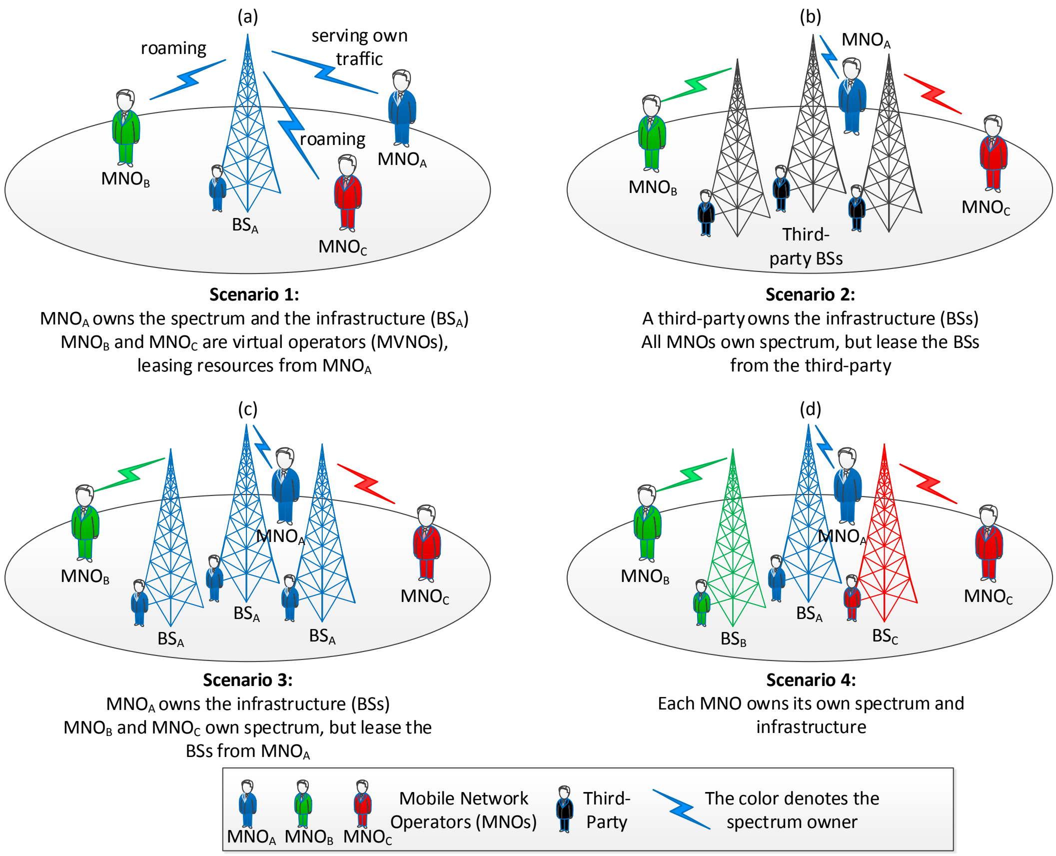


FIGURE 2.3: Multi-operator cellular network architectures.

at the same time, the basic MNO in the area may capitalize the deployed infrastructure. On the other hand, it is uncertain whether this model can be compliant with the foreseen traffic demands in cellular networks, which probably cannot be met using only the existing infrastructure and the limited amount of resources. Moreover, the high spectrum prices make the operators more reluctant to share their resources (and the market) with their competitors [28].

Third-Party: The whole infrastructure in a certain area has been deployed and owned by an independent third-party, and the MNOs, who hold a spectrum license, may enter into agreements for the employment of the access and core network (Fig. 2.3(b)). The main benefit of this model, which is gaining momentum in many countries (e.g., Spain [29]), is the significantly lower CapEx for the MNOs, who are not concerned anymore for the maintenance of the hardware infrastructure, being also able to provide their services dynamically in a given geographic region. However, the lease of the network implies an increased OpEx, which in the long run may be proven unprofitable for the MNOs. In addition, the expected participation of many MNOs in future cellular networks could potentially result in high leasing prices, raising additional barriers and challenges for the effective application of this model.

Unique Infrastructure Provider: There is one operator that has deployed the whole network infrastructure and leases part of it to other interested

MNOs (Fig. 2.3(c)). This scenario is fueled by the fact that the same spots (e.g., rooftops) are usually appropriate for all MNOs and, consequently, an operator that has built out its network is able to capitalize on the potential interest of other MNOs on the specific location. In addition, this architecture can be considered as a hybrid model that combines some basic characteristics of the two aforementioned schemes, having though two main differences: i) the interested MNOs are not virtual, since they have their own spectrum license, and ii) the infrastructure owner is an operator and not an independent entity. In this case, the operator who provides the infrastructure is burdened with considerably high CapEx and OpEx, which, however, can be depreciated through the efficient network leasing. From the perspective of the other MNOs, there is a tradeoff between the expected CapEx (lower) and OpEx (higher), while it should be also taken into account that they rely on a competitive entity rather than a trusted third-party. This architecture includes stakeholders with different levels of risk and profit, thus raising intriguing financial challenges, which require explicit models for the accurate analysis of each entity according to the different profiles.

Standalone: Various MNOs have deployed and run their own network in the same region (Fig. 2.3(d)). This model currently dominates in cellular networks, since it encompasses the lowest possible risk for the operators. Moreover, taking into account the rationality of the operators, along with the competitive nature of the telecommunications market, it is also very possible to appear in future architectures, especially in dense areas with high traffic. In this scenario, the MNOs have full control of their network, thus being able to estimate the expenses both for the network deployment and operation.

- **Heterogeneous networks (Fig. 2.1(c)):** The networks examined so far refer to networks with single or multiple MNOs, where only macro BSs are deployed. Nevertheless, in current and more especially in future deployments the majority of the configurations are HetNets. In HetNets, marco BSs, micro BSs, pico cells and femto sites, which are deployed more often by third-party companies, are used to increase the networks capacity, serve users in cell edges and provide enhanced QoS during high traffic load periods. As a consequence of the massive deployment of BSs and SCs (the term SC is widely used to refer to micro, pico and outdoor femto cells, in general), installation an operational expenses are further augmented and the proposition of cost and energy efficient techniques is more than compulsory in heterogeneous configurations.

  In Fig. 2.4 some of the possible scenarios of the multi-operator heterogeneous network architectures are illustrated, whose challenges and traits are discussed below.

  Standalone: Various MNOs have deployed and run their own network in the same region, consisting of macro BSs and SC nodes (Fig. 2.3(a)). This network architecture is found in dense areas with high traffic, when the need of enhanced capacity is obligatory. In this scenario, the MNOs control their network at the cost of increased deployment and operational expenses. A

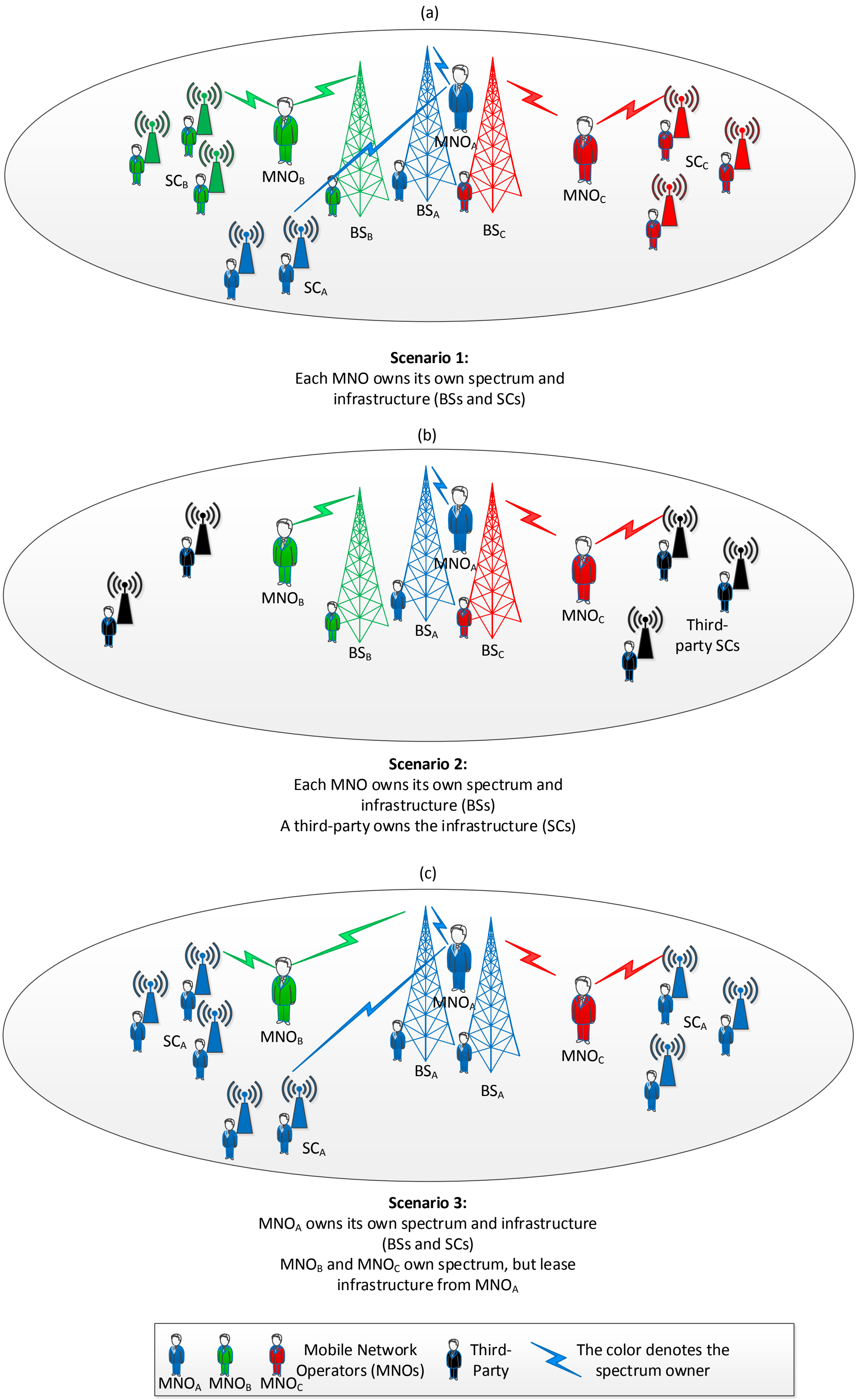


FIGURE 2.4: Multi-operator cellular HetNet architectures.

deactivation policy in each one of the individual networks does not require any agreement or arrangement between the different involved MNOs.

Standalone and Third-Party: Various MNOs have deployed and run their own BS network in the same region, while an independent third-party has deployed its own SC network (Fig. 2.4(b)). Furthermore, the MNOs hold a spectrum license, in contrast to the third-part that only owns the SC infrastructure. In this scenario, the MNOs have full control of their macro BS network, thus being able to estimate the expenses both for the network deployment and operation. The MNOs can also lease the SC infrastructure from the third-party, by proceeding to the corresponding agreements, to increase their bandwidth and provide enhanced services during peak traffic conditions, especially in dense areas.

Unique Infrastructure Provider: One operator has deployed the whole network infrastructure, consisting of both BSs and SCs. In addition, the MNO leases part of its network to other interested MNOs (Fig. 2.4(c)). In this scenario, the operator who owns the infrastructure has to deal with high CapEx and OpEx, which, nonetheless, can be compensated through the income of the network leasing. On the other hand, the other MNOs have only the leasing expenses. The main drawback of this case is that the basic operator (MNO_A in the example) monopolizes the deployed infrastructure and creates unnecessary competition among the other MNOs. In addition, this model may not be feasible in future cellular networks, since the infrastructure owned by one MNO cannot meet the emerging traffic demands.

Depending on the employed architecture, BSs deactivation policies, infrastructure sharing techniques, financial agreements or a combination of these strategies can be applied in an effort to provide energy and cost efficiency. Interesting contributions on the switching off and infrastructure sharing techniques found in the literature are surveyed in the next section.

2.3 State-of-the-art Solutions

This section describes the most relevant energy efficient switching off strategies that are related to our work and are available in the literature. More specifically, Section 2.3.1 describes the state-of-the-art deactivation policies in macro BS networks, owned by a single operator, whereas the infrastructure sharing and deactivation algorithms that can be applied in macro BS networks of multiple MNOs are presented in Section 2.3.2. Finally, Section 2.3.3 includes the cell switching off works of the literature concerning heterogeneous deployments, where multi-operator macro networks and SC infrastructure coexist.

2.3.1 Network Planning Algorithms in Single-Operator Environments

The increasing concern about the energy consumption of telecommunication networks is driving operators to manage their infrastructure (decide whether to keep their BSs active or turn them off) so as to optimize energy utilization without sacrificing the user experience. Since the cellular networks are dimensioned according to peak traffic conditions, part of the BS infrastructure can be switched off, and a smaller number of active BSs can provide service in the region. The critical decision relies on the selection of the appropriate BSs to be switched off.

Fig. 2.5 illustrates an example of a switching off process in a single operator environment, when one MNO controls and operates its own infrastructure (e.g., the architecture presented in Fig. 2.3(a)). When the BS of a cell is switched off (Cell B), the neighboring BS remains active (Cell A), then the active cell can extend its range and serves the users of the switched off BS, along with its own.

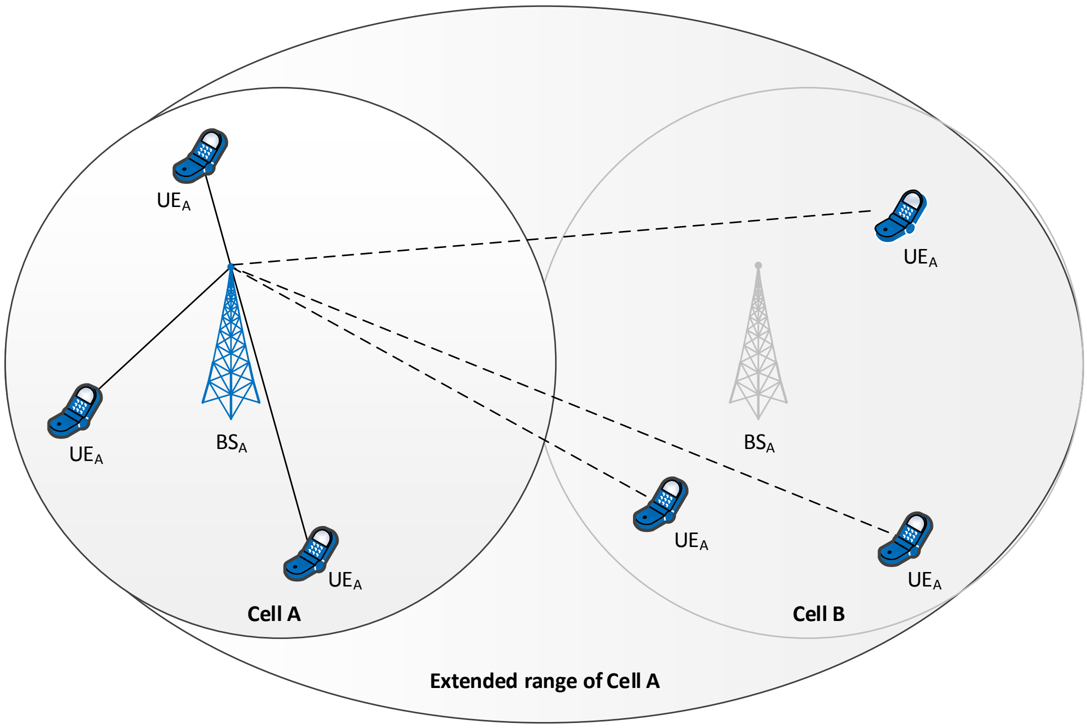


Figure 2.5: Example of BS switching off in single operator network.

In the context of network planning through BS deactivation, several works have been proposed in literature. Initial works concerning the BSs switching off during low traffic periods were proposed in the context of UMTS cellular networks. Particularly, in [30], the authors propose to switch off a random number of BSs and the energy savings are computed by means of simulations for UMTS cellular networks with a simplified traffic model describing three classes of services. The limitation of this work is that the switching off phase is based on a random number of BSs to be switched off. Thus, when the number of switched off cells is small, the QoS is guaranteed in terms of number of missed calls, but the energy savings are not significant. On the other hand, when the number of switched off cells increases, the energy efficiency and the missed calls are increased. The scheme, however, does not work efficiently as number of switched off BSs becomes higher, because in this case the remaining active BSs should increase considerably their transmission power and as a result the energy savings are diminished. In [31], the same authors provide an improvement of their former work. The enhancement of their work is twofold. First, they use a novel traffic model with users generating sessions consisting of a series of elastic file transfers (voice, video, etc) and second, the proposed idea of the previous paper about network planning for switching on/off the BSs considers two scenarios: *i*) a uniform that considers the existence of identical cells with regard to traffic load and transmission power, *ii*) a hierarchical scenario, in which one umbrella cell overlaps with six cells. The umbrella cell guarantees the QoS when the random switch off scheme is applied.

In [32], the authors show how to maximize the energy savings, by assuming that any fraction of cells can be switched off according to a deterministic traffic variation pattern over time. They apply their strategy in different network configurations, including hexagonal, crossroad and Manhattan configurations. The goal of the paper is to identify the best fraction of time that the BSs should be switched off. The limitation stands for the fact that the authors can apply their results to specified cases and the switching off schemes cannot be generalized. In [33], the same authors study the switching off transients for one cell, investigating the amount of time necessary to actually implement the switch off, while allowing terminals to handover to a new BS without overloading the signaling channels. They show that the switch off times do not reduce significantly the energy savings of sleep mode approaches. Even though this latter work does not include the proposal of a novel switching off scheme, its outcome is considered to be fundamental for the proposition of sleeping algorithms.

The random switching off algorithms presented so far do not consider the daily traffic variations, nor the positions of the users as critical parameters for the switching off decision. Towards this direction, another research group proposes several algorithms on BSs switching off. In [34], two approaches that achieve energy savings are proposed: *i*) a greedy centralized algorithm where the traffic load of each BS is examined to determine whether it is going to be switched off or not, and *ii*) a decentralized algorithm where each BS locally estimates its traffic load and decides independently whether it is going to be switched off or not. In both algorithms, the BS with the lowest traffic load concentrates the traffic of the neighboring BSs, which will be then switched off. In [35], an improved dynamic switching on/off algorithm based on blocking probabilities is proposed. The BSs are switched off according to the traffic variation with respect to a blocking probability constraint. The number of BSs in active mode matches the variation of the network traffic in time and space domain, while at the same time, a predefined minimum mode holding time (a BS should be switched on or off for at least a minimum time period) is guaranteed without noticeable performance degradation. A similar idea that exploits the daily traffic load variations is considered in [36] and [37], where the authors deal with the overlapping coverage areas of the BSs. The authors in [36] describe a centralized and a distributed algorithm for BSs switching off. In the centralized algorithm, the BS with the maximum traffic load concentrates the traffic of its neighboring BSs, which allows the BSs with no traffic load to be switched off. The same idea is implemented in the distributed strategy where coordination mechanisms are exploited in order to avoid conflicts. In [37], the authors further analyze the energy saving of self organized networks. The network is reconfigured in a centralized and in a distributed way, but especially, the authors present the switching off algorithms in terms of capacity and delay constraints.

The switching off decision is triggered by the BS with the lowest traffic load. Another interesting approach is presented in [38]. The authors propose algorithms that save energy by switching off BSs based on the traffic demand. In addition, the energy consumption is minimized by assigning frequencies and powers to the active BSs while achieving full coverage and adequate capacity. The idea relies on saving energy through a power control mechanism.

Apart from the previous studies that propose switching on/off algorithms for UMTS cellular networks, simple analytical models are also introduced for reducing the power consumption in WLANs, with the traffic demand being the one and only factor triggering the switching off decision. In particular, in [39] two energy efficient policies are examined. The first policy is based on the number of users that are associated with each AP (and is, thus, called association-based), the second is based on the number of active users, e.g., users that are generating traffic (and is, thus, called traffic-based). Both policies can be tailored, by defining a value of threshold for the activation of additional APs, and a value of hysteresis to increase the operation stability. In the same context, a switching on/off approach for dense WLANs based on the number of associated users to each AP is presented in [40]. In the aforementioned work, the APs with the lowest traffic load are switched off first. In these works, the traffic load appears to be an appropriate factor to decide the suitable BSs to be switched off. In [41], the authors examine the cell switching off problem with the assumption that each user has a minimum rate requirement, and show that it can be formulated and solved as a binary Integer Linear Programming (ILP) problem when interference is considered to be constant. Their genetic algorithm switches off cells only in increasing order based on traffic load. A traffic-based switching off strategy is given in [42]. The daily and weekly behavior of the traffic is considered for the BSs deactivation and the energy consumption of each BS is the metric, considered for the simulations.

Another fundamental work has been studied in [43]. In this paper, the daily variations of the traffic and the BSs positions are examined in order to decide which is the most energy efficient switching off strategy that achieves the maximum energy saving. The results obtained in the paper show how traffic load and BS density influence the switching off strategy and the energy savings. In areas where the BSs are densely deployed, they are switched off with a higher probability. The results are very promising, even though the maximum number of BSs is not calculated and the network capacity is not exploited to its end. An optimized network management was considered in [44]. The authors propose a centralized network approach based on traffic load and the users location estimations in order to decide the appropriate number of APs that should be sited in a given network configuration. Furthermore, based on the traffic variation the more suitable cell radius is selected. The energy savings are presented in the context of different traffic patterns and a thorough survey on deployment strategies is given, but without considering BSs switching off. The density and the position of the users are considered to be crucial and the importance of this work is to realize how these parameters can be investigated for switching off algorithms. An interesting approach is studied in [45], where the authors propose to divide the network into grids, so that BSs in each local cell can replace each other when serving user clients. The location profile of each BS, along with the traffic load pattern are used to decide the duration of the deactivation.

Working in a different direction, in [46] the authors provide a technique for BSs switching off by using the advantages of Store-Carry and Forward (SCF) relaying. Their algorithm proposes that cooperative relay nodes will route the traffic of low utilization BSs to neighboring BSs. The routing scheme via the SCF relays allows the BSs with the lower traffic load to be switched off and their traffic to be served by the adjacent cells. The switching off decision relies only on the daily traffic load variations and the scheme does not consider other critical factors of the network.

Another field of studies concerns power adaptation through traffic load balancing. In [47], the relationship between the power ratio and overall power consumption/savings to determine the optimized number of BSs from the perspective of energy savings. Eventually, when the power ratio is low, less BSs should be turned on, whereas more BSs remain active as the power ratio goes high.

In a more recent work [48], the authors take traffic dependent energy consumption and penetration loss into consideration in an LTE configuration. The authors integrate sleep/active modes operations with optimization in antenna variables such as tilt, height, vertical beam-width and transmit power, subject to constraints in the Signal-to-Interference-plus-Noise-Ratio (SINR), spectral efficiency and user throughput. An optimized approach based on CoMP is presented in [49] such that the amount of power saving less extra power consumed in backhaul and signal processing is maximized, by selecting an optimized set of points for coordination. CoMP is another feature of LTE standard which can also be utilized for sleep mode applications. It eliminates the need for increasing transmission power of active BSs to maintain the coverage of sleeping BSs.

Analytical models to identify optimal fixed BS switch-off times as a function of the daily traffic pattern are investigated in [50]. The authors compare the cases of only one switch-off per day versus several progressive switch-offs (switching off certain number of BSs at a time in increasing order of load) per day. They also argue that when the number of switch-off configurations per day increases, the complexity in operation will also increase. By analyzing various network configurations, as well as a case study given by a realistic cell deployment, they reach the conclusion that the extra energy saving gained by multiple switch-offs over single switch off is only marginal. Hence, they recommend limited effort on the side of network management would be beneficial enough in terms of energy saving. In [51], the authors propose three strategies for BS sleeping on a queuing model. The three strategies differ in how BSs detect incoming customers while sleeping. The authors point out that a number of parameters including delay constraint, BS setup time and pre-determined time length for sleeping would affect the performances of different strategies. Particularly, if network cost is high enough, more complicated strategies may not necessarily outperform simple strategy even if optimal switching time is achieved.

The authors in [52] discuss energy efficiency planning of BSs in cellular networks that would increase potential energy savings. Notably, an analytical method is presented in the work to approximate real performance in various scenarios. From their work, it is concluded that in order to attain optimal savings, the locations of BSs must be planned carefully. More specifically, parameters including user density, coverage area of single BS, inter-BS distance, number of active BSs and energy consumption are interlinked. For example, too high density of BSs would result in waste of energy while too low density simply would not suffice. A distributed cooperative framework to solve the optimal BS sleeping problem in green cellular networking scenario is proposed in [53]. Within this framework, the neighboring BSs cooperate to optimize the switching strategies in order to maximize the energy saving while guaranteeing users' minimal service requirements. The authors formulate the problem of energy saving as a constrained graphical game, where each BS acts as a game player with the constraint of traffic load.

Given the diversity among existing studies, it is difficult to establish common points for comparison. In order to gain further insight on the traits of the state-of-the-art approaches, a categorization given specific criteria could be considered. Thus, the following criteria are examined:

- *Criterion 1*: It indicates the factor for the **switching off** decision: random, traffic, BSs and users position, power adaptation, etc.
- *Criterion 2*: It indicates the type of **tool** used in the resolution of the problem: analytical tools, heuristics, metaheuristics.
- *Criterion 3*: It indicates the type of **architecture** of each proposal: distributed or centralized.
- *Criterion 4*: It indicates whether coverage/outage or similar **QoS aspects** are considered. Coverage aspects include a minimum SINR or the receiver's sensitivity, e.g., the minimum required power or the transmission power increase.

Table 2.1 shows a comparative assessment based on the previous criteria.

As it can be seen in Table 2.1, the state-of-the-art works examine the BS deactivation in single-operator networks but they show similar behavior concerning these criteria. More specifically, in the majority of approaches the traffic is the critical parameter in the switching off decision and the problem of BS deactivation is solved in a centralize manner. Analytical and heuristic tools are widely used, however, the QoS requirements are neglected in many cases. Hence, there are still many challenges and open issues to be studied. There are many parameters apart from the traffic load that can be used as a crucial factor to decide the appropriate BSs to be switched off, such as the distance between the users and the BSs, the diversity of users individual characteristics (Criterion 1). Note that some of the works propose heuristics to tackle the switching off problem, and sometimes proceed to analytical formulations used as starting point (Criterion 2). This clearly indicates the practical approach followed by many authors, in contrast to the vast majority of resource allocation schemes that rely on optimization formulations. The heuristic approaches consist of trivial solutions, whereas the analytical formulations consider a variety of simplifications that may create dissimilarities with the real networks. In addition, as it can be seen from the table, the majority of

TABLE 2.1: Summary of state-of-the-art proposals for single operator networks

Ref.	Criterion 1 Switching off	Criterion 2 Tool	Criterion 3 Architecture	Criterion 4 QoS aspects
[30]	Random	Analytical	Centralized	No
[31]	Random	Analytical	Centralized	No
[32]	Random	Analytical	Centralized	No
[33]	No switch off	Analytical	Centralized	No
[34]	Traffic-aware	Not specified	Centralized/Distributed	No
[35]	Traffic-aware	Analytic	Centralized	Yes
[36]	Traffic-aware	Analytic	Centralized/Distributed	No
[37]	Traffic-aware	Analytic	Centralized/Distributed	Yes
[38]	Traffic-aware	Analytic	Centralized	No
[39]	Traffic-aware	Analytic	Centralized	No
[40]	Traffic-aware	Not specified	Centralized	No
[41]	Traffic-aware	Heuristic	Centralized	Yes
[42]	Traffic-aware	Heuristic	Centralized	No
[43]	Traffic/Position-aware	Heuristic	Not specified	No
[44]	No switch off	Analytical	Centralized	No
[45]	Traffic/Position-aware	Heuristic	Not specified	No
[46]	SCF relaying	Not specified	Distributed	Yes
[47]	Power adaptation	Analytical	Centralized	Yes
[48]	Traffic-aware	Heuristic	Centralized	Yes
[49]	Traffic-aware	Heuristic	Centralized	No
[50]	Traffic-aware	Analytical	Not specified	No
[51]	Traffic-aware	Not specified	Centralized/Distributed	No
[52]	Traffic/Position-aware	Analytical	Not specified	No
[53]	Traffic/Position-aware	Analytical	Distributed	Yes

schemes require centralized operation (Criterion 3). Regarding this aspect, the preference of centralized solutions among the works of the literature is explained given the nature of the switching off problem, e.g, a certain global knowledge is required in order to determine which BSs can be switched off. Distributed solutions are more complex, however, they offer certain freedom to the networks. From the comparative analysis, it is also clear that coverage analysis is often missed (Criterion 4). It must be ensured that the whole capacity of the network must be exploited in order to find the maximum number of BSs to be switched off while still guaranteeing the QoS. The throughput, energy and energy efficiency analysis still needs a lot of effort and investigation, and it is worth saying that incorporating the coverage feature into the picture makes the problem more realistic. The open issues and the research challenges that need to be explored motivate the contributions of this thesis and through the proposed algorithms, improved solutions are investigated.

2.3.2 Network Planning Algorithms in Multi-Operator Environments

The aforementioned scheme shed some light on the different switching off solutions that can be encountered in single-operator networks. However, a lot of work need to be accomplished in network planning approaches in multi-operator configurations, where sharing agreement between the MNOs can lead to great energy efficiency improvements. Therefore, an efficient joint resource allocation and network planning during low traffic periods (e.g., night zone) would allow the service of the traffic by a smaller number of active BS, thus enabling the deactivation of the remaining unused infrastructure that may belong to different operators. However, the decision of the particular BSs that should be switched off is not trivial, as it engages the end user satisfaction, which is of top priority for the telecommunication operators. In addition, this decision is very complicated in multi-operator environments due to the conflicting interests of the MNOs and the diversity of the involved parameters.

Fig. 2.6 illustrates three possible cases for the cell operation and switching off in multi-operator environments, where each operator controls and operates its own BS (i.e., the architecture presented in Fig. 2.3(d)). In the simple case where all the BSs are active (Cell A), each operator is responsible for serving the traffic of its users. In case that all BSs have been switched off (Cell B), the active BSs of the neighboring cells (Cell A in the example) of each MNO can extend their range in order to prevent the generation of coverage holes. Finally, in case that only a subset of the BSs has been switched off (Cell C), their respective traffic can be roamed to the active BSs of the same cell.

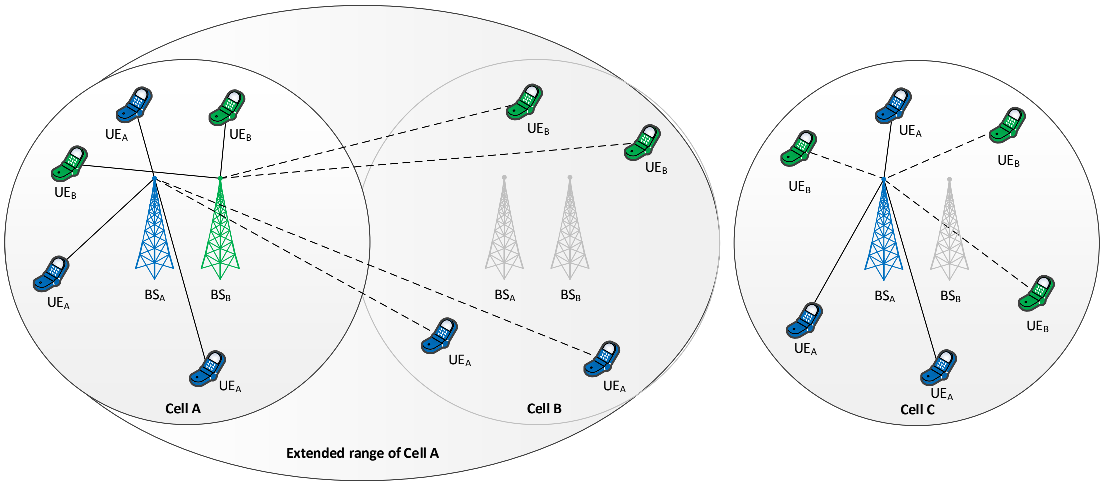


Figure 2.6: Example of BS switching off in multi-operator network.

The concept of network sharing through BS deactivation in multi-operator environments have been investigated in the literature. In particular, significant research attention has been placed on roaming-based infrastructure sharing solutions that consider joint BS switching off among multiple MNOs. In [54], a non-cooperative game for switching off BSs in a two MNOs network is discussed. Preliminary results motivate the use of game theoretic tools in switching off proposals in multi-operator environments. The authors do not propose an exact process for the BS deactivation, neither they investigate the necessary agreements among the MNOs. However, interesting realistic data traffic patterns are provided. The authors in [55] propose four cooperative strategies to switch off BSs in networks with two MNOs, according to the following criteria: *i*) equal switching off time periods, *ii*) equal roaming costs, *iii*) equal energy gains, *iv*) maximum energy savings. In all cases, the traffic of the switched off BS is roamed to the collocated BS of the active MNO. In [56], the authors extend the algorithm that maximizes the energy savings (proposed in [55]) for multi-operator environments with various traffic types and QoS requirements (i.e., throughput, lost calls). It is shown that remarkable savings are possible if operators are willing to cooperate. However, the authors do not examine under which condition the operators could cooperate. In the same context, the authors [57] study the potential energy savings that can be achieved by opportunistically switching off part of the network during low traffic in real-world scenarios. The authors estimate that, by sharing and cooperating traffic between BSs, the energy savings can be translated to 200 to 375 metric tons of annual carbon dioxide emission or about 42000 dollars to 78000 dollars on the bill for the owners of the BSs. They also suggest in the paper that cooperation between operators would be even more profitable, particularly in metropolitan areas where dense deployments are required for every MNO and thus, further investigation is necessary. The authors in [58] consider three network planning strategies: *i*) one minimizes the number of transmitters, namely TX, *ii*) another minimizes the power consumption, namely MP, *iii*) while the last one is the hybrid strategy, namely H, combining the previous two strategies. While the TX strategy effectively lowers the CapEx for the MNOs in the BS planning stage, the MP strategy minimizes the operating expenses by turning under-utilized BSs into sleep mode to reduce energy consumption. The result shows energy savings between 11% and 28% are achievable even for already energy efficiency-optimized BSs deployment. Therefore, by adopting the H strategy, the total expenditure of the mobile operators could be significantly reduced.

Nonetheless, despite their novel insights in the infrastructure sharing concept, the aforementioned works study only particular aspects of the problem. In addition, the consideration of only voice traffic in some works (e.g., [55], [56]) is not realistic, since data traffic forms a significant part of the total traffic load in current cellular networks. Last but not least, the assumption of only two MNOs in the network is a limiting factor for the contribution of the above works, as the most common scenarios in European countries involve three to four MNOs [59]. To conclude, open issues and challenges need to be explored in the field of multi-operator networks.

2.3.3 Network Planning Algorithms in Heterogeneous Networks

The dense HetNets imply a significant increase in the CapEx of the MNOs and the operation of these networks results in even higher OpEx [60] comparing to the networks examined so far. Thus, deactivation policies and network sharing techniques in HetNets have attracted the attention of the research community.

Fig. 2.7 illustrates an example for the cell operation in multi-operator heterogeneous environment, where each operator controls and operates its own BS and a third-party owns a SC network (i.e., the architecture presented in Fig. 2.4(b)). In the simple case where one MNO keeps its BS active (BS_A), whereas the other operator switches off its infrastructure (BS_B). The former operator continues the network operation. On the other hand, the MNO with the switched off BS roams its traffic to the SCs, by leasing the capacity from the third-party.

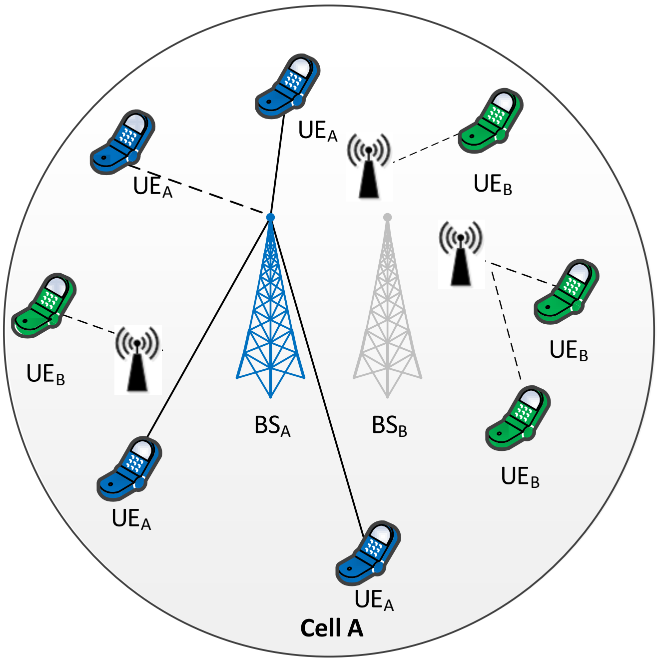


FIGURE 2.7: Example of BS switching off algorithm in multi-operator HetNet.

The greening of HetNets through BS deactivation have been throughly examined by the research community. The use of high temperature electronics, adaptive power management, new network architectures of high density, low transmit power microcells and highly efficient PAs are only few of the solutions that lead to energy consumption reduction. However, higher gains can be achieved by the investigation of network planning and BS switching off schemes in HetNets.

The authors in [61] consider layouts featuring varying numbers of micro BSs per cell in addition to conventional macro sites. They introduce the concept of area power consumption as a system performance metric and employ simulations to evaluate potential improvements of this metric through the use of micro BSs. The presented results show that for the studied propagation scenarios and under the employed power consumption models, the power savings from deployment of micro BSs are moderate in full load scenarios and strongly depend on the offset power consumption of both macro and micro sites. The same authors extend their work in [62], and they provide a framework to evaluate and optimize cellular network deployments with respect to the average number of micro sites per macro cell as well as the macro cell size. The simulation results show that deployment of micro sites allows to significantly decrease the area power consumption in the network while still achieving certain area throughput targets.

In [63], different deployment strategies are investigated and network configurations with micro BSs are compared to conventional pure macro systems by means of area power consumption and system throughput. The conclusion of the paper is that a densification to a certain degree is beneficial, whereas homogeneous micro deployments can be regarded to be superior. In another work [64], the utilization of small, low power BSs is regarded as a promising strategy to enhance a network's throughput and to increase the energy efficiency of homogeneous and heterogeneous networks with regard to traffic load conditions. Different densities have been examined and the power consumption of the different configurations is evaluated. Finally, the authors in [65] develop power models for macro and micro BSs relying on data sheets of several GSM and UMTS BSs with focus on component level, e.g., power amplifier and cooling equipment. The authors investigate the amount of energy consumed in the different states of BS operation. In all these works the deployment of macro and micro BSs in HetNets is thoughtfully examined, but on the other hand switching off macro and micro BSs is not considered.

The SCs can be exploited to allow BSs to be switched off [66], [67], [68]. Telecommunications companies, such as Nokia Networks [69], are building networks of interconnected SCs that help operators to add coverage and capacity to existing macro networks and guarantee the user service when the macro cells are turned off. An overview of existing energy efficient techniques in the literature is presented in [70], highlighting the advantages and the shortcomings of the algorithms and revealing the open issues that should be further studied in the field of HetNets and operators' collaboration.

In [71], the application of dynamic sleep mode in BSs with pico cell deployments is studied. HetNet planning can improve the coverage of the cellular network, but will likely result in even more severe over-provisioning and thus consume more energy if the cells are unable to adapt to traffic load. The solution proposed by the authors is to introduce the dynamic sleep and wake modes in the pico cells. The result shows that the network with both macro cells and pico cells, where dynamic sleep mode algorithm is applied in pico cells, consumes less amount of energy than the network with only macro-cells. The authors in [72] propose an energy model for heterogeneous cellular network and a cross layer optimization method. Several pico cells (lower layer) are in the coverage area of one macro cell. The problem to solve is how to associate users to the group of macro cell and pico cells, so that energy consumption is minimized after lightly-loaded pico cells turned to sleep.

The authors [73] investigate how Small cell Access Points (SAPs) can play a role enhancing energy efficiency of heterogeneous cellular networks. Sleep mode of SAPs actually corresponds to the trade-off between energy consumption and false alarm rate. The authors note that bursty transmissions from macro-cell traffic, due to mobility of users, makes duty cycling of sleep mode in smaller cells more complicated. Poisson Point Process (PPP) is also used to model the locations of SAPs and macro BSs. A similar sleeping strategy is proposed in [74]. This policy suggests that femto cells are switched off when the cell itself is not heavily loaded and the macro cell can serve the overall traffic without deteriorating the QoS. Based mainly on queuing theories, the work utilizes a Continuous Time Markov Decision Process (CTMDP), in which states represent load status of each BS. Every user brings a certain load to its connected BS. Each possible action for the state and transition probabilities is assigned a value of rewards/cost. The cost function is defined as an increasing function of energy consumption and a decreasing function of target throughput, a QoS measure. The switching operation is added to the state space as a new dimension. Apart from the straightforward case that BSs have complete information of its associated traffic, optimal solutions have also been found for partial traffic information (based on Partially Observable

Markov Decision Process (MDP)) and delayed information (by transforming their MDPs into equivalent MDPs without delay).

A stochastic analytical framework for BS sleeping in LTE networks with OFDMA as the physical layer transmission technology is presented in [75]. The authors investigate the theoretical model quantifying the key metrics of the outage probability (e.g., SINR) and the average user capacity to account for the effect of BS sleeping, such that optimal energy saving can be obtained while outage probability is held constant. Furthermore, the authors propose a modified nonsingular path loss model appropriate for small distance between the user equipment and the BS, which is more realistic for micro cells. The authors in [76] consider a scenario where users in macro cells and micro cells have different traffic patterns. They assume that micro cells serve hotspots with higher traffic volume. The authors investigate three energy saving approaches including micro cell BS sleeping and expansion/shrinking coverage of micro cells (similar to cell zooming). The coverage and power consumption of macro cells are held constant. It is shown that each approach is effective under different traffic conditions. The crucial factor affecting the performances of different approaches is traffic rate ratio, namely the ratio of traffic rate per unit area in hotspots to that in non-hotspots.

The previous works propose solutions for single-operator HetNets. However, even though the opportunistic exploitation of the unused SCs capacity and the deactivation of the redundant BSs in multi-operator HetNets can have significant, very few research works exist in the literature. The authors in [77] propose an auction-based offloading scheme for BS switching off, where the operators submit a bidding value for the requested capacity and a third-party's income optimization approach is followed to solve the resource allocation problem. However, only a particular network configuration is considered, where the SC capacity is sufficient to serve the traffic of the whole network, allowing the switching off of all the BSs. Despite the clear benefits of the BSs switching off via offloading, shown by the authors, the proposed scheme could not be applied in real life scenarios, since the SCs may not be able to fully support the network traffic, especially when numerous MNOs are present in the same area [59]. Another limitation of the auction-based state-of-the-art works [77], [78], [79] suggest that the MNOs propose one bidding value for the SCs capacity bandwidth based on the maximum predictions about their traffic that they are willing to offload. However, these predictions do not correspond always to the real values, which can be significantly lower than the maximum values, leading to increased costs for the operators and inefficient use of capacity resources. As an alternative solution, the MNOs could be willing to request lower capacity resources by paying lower bids, since the capacity that is needed to serve the actual traffic may be lower than the maximum capacity for serving the highest traffic predictions, potentially leading to very few unserved users. However, the energy and financial gains could be significant.

Given the promising results of the state-of-the-art works, along with their shortcomings and limitations, it is evident that the application of switching off algorithms in HetNets, where multiple MNOs coexist, could have great advantages in terms of energy and cost reduction. In spite, the presence of multiple involved parties and their individual objectives motivates the use of optimization algorithms and similar methodologies to improve the performance of the HetNets.

2.4 Open Issues and Challenges

As discussed in previous sections, there have been a considerable number of studies aiming at improving the energy efficiency of cellular networks by BS sleep mode techniques. While the contributions and achievements made have been substantial, certain deficiencies cannot be ignored.

One common problem with current research in this area is that the system, traffic or energy models are usually oversimplified and some assumptions are too rigid. Certain conditions that are unrealistic are adopted in the experiments. For example, uniform traffic distribution and arrival pattern in all cells at all times, zero or constant delays in switching operations, energy consumption of BSs only related to the state of the system (sleep/wake), but not by other factors such as traffic load. In fact, the activity levels of both BSs and associated mobile users are limited to only two, e.g., active or sleeping (inactive) in most work. The network configurations examined in some works are trivial and limited scenarios with respect to number of MNOs, sites deployment, are investigated.

The negative impact on QoS when switching some BSs to sleep mode has also been ignored in various publications. However, this must be taken into account as one can always save 100% energy by turning off all BSs without considering the deteriorated QoS. Especially in rural areas where the layouts of BSs are sparse, blocking rate will increase significantly as more BSs go asleep [50].

Another problem is a variety of works implicitly assumes that BSs are able to alternate states between sleeping and active as frequently as possible. Although the most recent BSs have already been designed for frequently entering sleep modes, still most of the existing BSs in use today were designed foreseeing only occasional switch-on and switch-off, otherwise the failure rate of components or BSs would be increased dramatically. In this regard, the use of sleep modes for these devices might be restricted [12], [50].

Another important point which has been ignored, due to uncertainties and difficulties in estimation, is the constant and traffic independent energy consumption (energy consumed in the manufacturing, installation and maintenance process of the equipment), which actually presents around 30% to 40% of total energy consumption for the lifetime of a cellular BS [80], [81]. As discussed previously, a denser BS deployment enlarges the potential saving of sleep mode schemes as more BSs can possibly be switched off under the same amount of traffic, but on the contrary, the constant energy of a newly deployed BS adds to the total energy. This arising tradeoff averts from previous suggestions that more energy savings can be simply achieved with denser BSs deployment with reduced transmission power and enabled sleep mode. Therefore, the optimal strategy for energy saving diverts from the case where embodied energy is ignored [52], [81].

Therefore, green technologies need to catch up with these challenges and open issues. Incorporating different technologies may require significant effort by researchers with a wide range of backgrounds, but the benefit will justify the effort. In summary, the sleep mode technologies as well as the whole green cellular network are promising areas of research. It will probably remain a popular research topic for the coming years, since there are bright prospective as well as issues waiting to be solved.

2.5 Concluding Remarks

This chapter has provided some background information that is relevant to the contributions of this thesis, which will be thoroughly presented in the following chapters. Initially, a set of reference scenarios has been explained. The state-of-the-art works concerning the network planning algorithms have been discussed next. The largest section of this chapter has presented the principles, the contributions, but also the limitations of deactivation designs. In continuation, an overview of the schemes available in the literature by taking into account the solutions that can be applied in single and multi-operator environments and HetNets was given. Finally, the open issues and challenges to achieve energy efficiency and savings, cost reduction and financial gains have been summarized.

The remaining of this thesis is organized in three parts. The first part (Chapter 3) is focused on proposing novel solutions about switching off BSs in single operator networks. The second part of the thesis (Chapter 4) is oriented to switching off techniques in multi-operator environments with macro BSs. Finally, in the third part (Chapter 5 and Chapter 6), switching off solutions are given in HetNets.

Chapter 3

Strategies for Energy Efficient Network Planning in Single-Operator Environments

"The problem in this business isn't to keep people from stealing your ideas; it's making them steal your ideas."

Howard Aiken

3.1 Introduction

Today, nobody can deny the explosive growth of the wireless network industry. The rising cost of energy and the increased environmental awareness have created the urgent need for developing green communications. Thus, this Ph.D. dissertation aims at getting closer to this transversal goal, and consequently to develop energy saving schemes. This is the case of the switching off proposals presented in this chapter. Network planning solutions, through BSs switching off, are without a doubt, among the most promising strategies, and as such, they have captured great attention in the last few years.

The switching off problem consists in determining the largest set of cells that can be switched off without compromising the QoS provided to users, keeping in mind that the power hungry BSs, owned by one operator, can be partly switched off and cover the whole area.

The aim of this chapter is to provide network planning algorithms for single-operator cellular networks by proposing BSs switching off techniques. The system model, the network configuration and the notation used throughout the chapter are described in Section 3.2. Section 3.3 presents three network planning algorithms, applied in single-operator networks with macro BSs. The analyticl models for the calculation of the energy efficiency and the network throughput are given in the same section. Section 3.4 is devoted to the validation of the models and an extensive performance assessment. Finally, Section 3.5 concludes the chapter.

3.2 System Model and Operation

3.2.1 Network Configuration

Our system model, depicted in Fig. 3.1, consists of $M+1$ macro cells distributed with in a geographical area with partially overlapping coverage areas. The network configuration can be viewed as a grid of cells or as a cluster of macro cells. In particular, either we consider each cell individually or each cluster is formed by one central cell, surrounded by M peripheral cells, while each cell is covered by 1 BS. Therefore, the term BS_m is used to denote the BS in the mth macro cell, with $m \in \mathcal{M} = \{0, \dots M\}$. As it will be explained in details in the next section, part of the BS infrastructure in the $M+1$ cells may be switched off during low traffic conditions, while the remaining active BSs can extend their transmission power and range in order to form wider service cells and cover their area and the area of the switched off BSs.

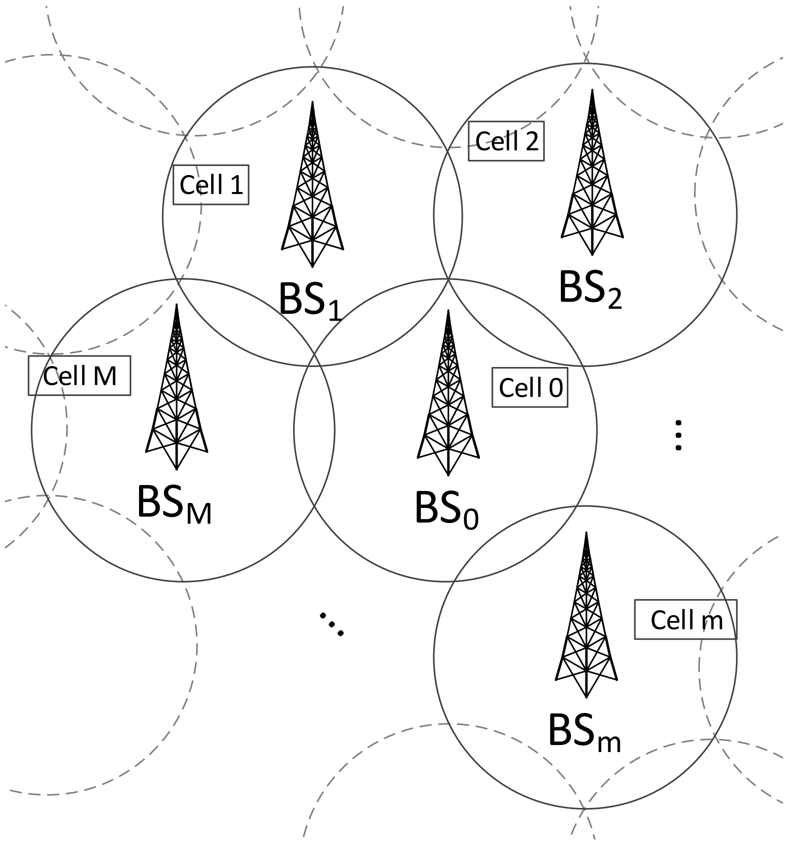


FIGURE 3.1: Network configuration with $M+1$ BSs.

3.2.2 Traffic Load Model

In the network planning policies, described in this chapter, we adopt a realistic traffic pattern (proposed in [82]) that corresponds to the voice traffic per BS in a given cell, during the day. In the traffic pattern, depicted in the Fig. 3.2, the maximum traffic per hour is expressed as a percentage of the total BS capacity resources CR_{BS} that is considered same for all cells. We focus on the time zone during the night, when the traffic demand per BS is relatively low (i.e., less than 10% of the cell's capacity). The peak hours are observed in the morning and during early afternoon, while during night hours the traffic is low. The dissimilarity in traffic load between busy hours and off-peak periods is also reflected on the energy consumption during high and low traffic periods. Since the network is dimensioned according to the peak traffic demand of the users, and the network capacity is adequate for serving the traffic during peak hours, during low traffic periods, the probability of having the system full is low. Thus, a number of network resources are redundant. The underutilization of these resources leads to considerable energy waste.

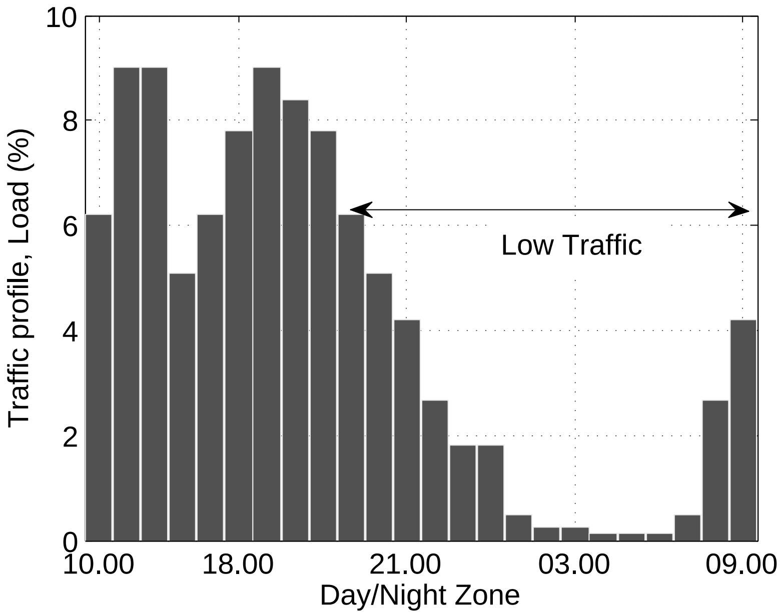


FIGURE 3.2: Voice traffic pattern during the day/night of different BSs for distance-aware switching off algorithms.

The network traffic, depicted in Fig. 3.2, consists of voice traffic with Constant Bit Rate (CBR) R_V. We assume that for each BS_m, voice sessions are Poisson generated processes every hour, h, with rate $\lambda_V^{(m,h)}$ and have exponential service time, denoted by $1/\mu_V^{(m,h)}$. Hence, we model the operation of the node m as an $M/M/c/c$ multi-server Markov chain, depicted in Fig. 3.3.

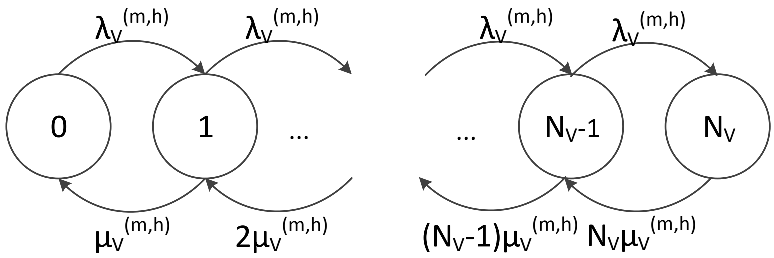


FIGURE 3.3: Markov model's state transition diagram for DSO.

Each state of the system is characterized by the number of active data sessions, denoted by v. The maximum number of simultaneously served sessions is $N_V = CR_{BS}/R_D$ for the BSs, given that CR_{BS} is the total bandwidth of a BS. The balance equation that represents the valid transitions is given by:

$$p_v^{(m,h)} = \begin{cases} \left(\dfrac{\lambda_V^{(m,h)}}{\mu_V^{(m,h)}}\right)^v \cdot \dfrac{1}{v!} \cdot p_0^{(m,h)}, v = 0, 1, ..., N_V, \\ \qquad\qquad 0 \qquad\qquad\qquad , v \geq N_V, \end{cases} \tag{3.1}$$

where $p_0^{(m,h)}$ represents the state probability that the BS_m remains idle, and it is calculated as:

$$p_0^{(m,h)} = \left(\sum_{v=0}^{N_V} \left(\frac{\lambda_V^{(m,h)}}{\mu_V^{(m,h)}}\right)^v \cdot \frac{1}{v!}\right)^{-1}. \tag{3.2}$$

Regarding the concept of the QoS, in our work, the main goal is to ensure a high normalized throughput, defined as the percentage of users that are successfully served by the system, since we consider that it is a key priority for the operators to provide service to all their customers. More specifically, we refer to this requirement for the normalized throughput as QoS in terms of lost calls. Furthermore, the normalized throughput is often employed to represent the Grade of Service (GoS), as explained above.

In addition, we assume that all users in a given cell have the same transmission rate, which corresponds to the required CBR of the voice applications (i.e., 64 kbps). Since the focus of all of our works has been to investigate the potential of BSs deactivation, network planning and infrastructure sharing and motivate operators to employ this paradigm in order to achieve energy and cost efficiency, we adopt a simplified approach with regard to resource allocation. In fact, we have considered the worst case scenario, in which the required resources to guarantee the desired CBR are calculated based on the link quality of users at the cell edge. Specifically, we have calculated the required number of resource blocks that must be assigned to achieve the desired CBR for a given service class, taking into account the SNR of the most distant user from the BS (i.e., in the example of Fig. 3.4, this would correspond to SNR_A at distance d_A). Then, we have considered that no rate adaptation takes place within the cell and all users in the cell require this same amount of resources. Note that P_{BS} is the transmission power to guarantee SNR_A at cell edge, whereas P'_{BS} is the transmission power to guarantee $SNR_B = SNR_A$ at cell edge, after range expansion.

The same principle is adopted in the case of range expansion by the cells that remain active, when some of the BSs are switched off. In the case when some BSs are switched off, the traffic is served by the corresponding BSs of the neighboring cells that must increase their transmission power in order to provide service in an extended area. Hence, the active cells increase their coverage and, as a result, the cell edge user is now located at a longer distance $d_B > d_A$. In order to ensure that the same resources as before are sufficient to guarantee the desired CBR, we increase the transmission power of the active BS so as to provide the same SNR at the cell edge as before (i.e., $SNR_B = SNR_A$ at the new cell edge d_B). Given

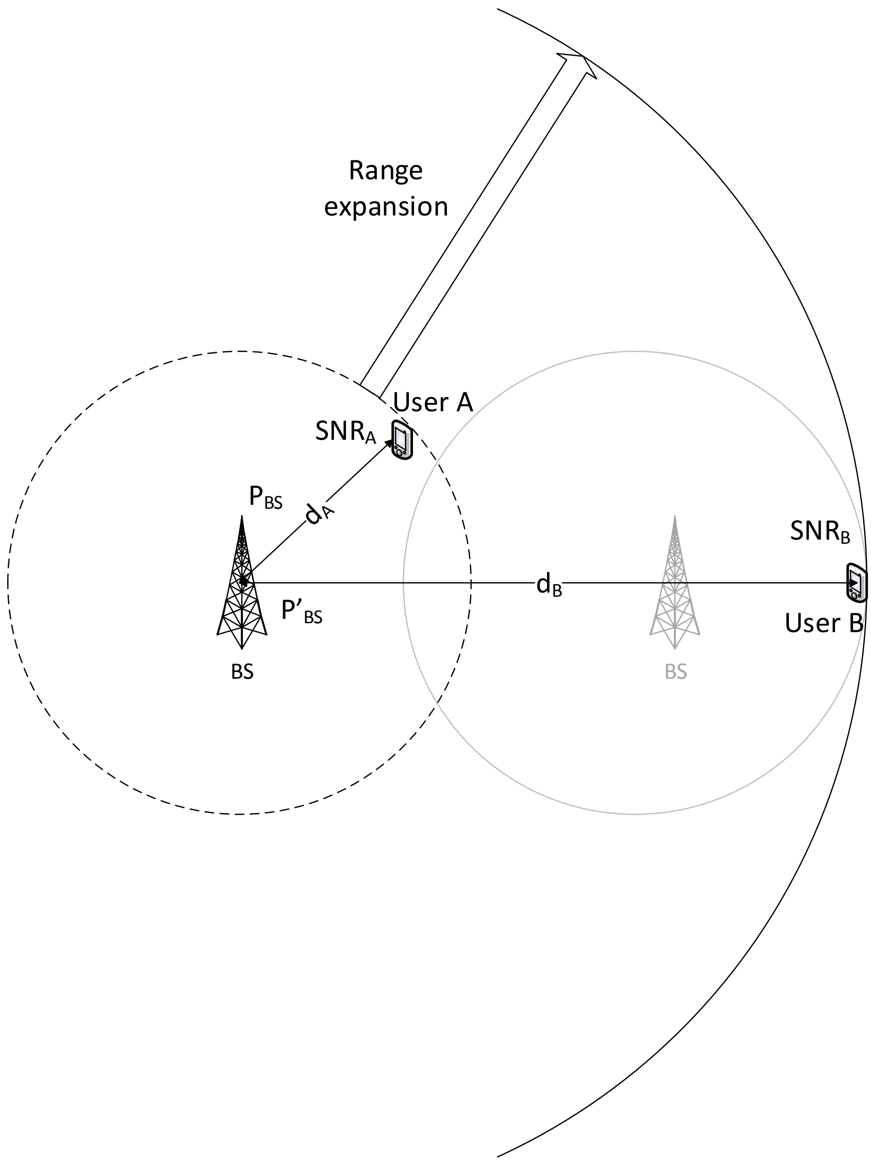


Figure 3.4: Network configuration example with increased transmission power

this power increase, we can assume that the same resource allocation is valid for the extended cell, leading to the same performance as before, with no increase in latency.

Even though this is the worst case scenario, since some users closer to the BS could support higher transmission rates or, equivalently, occupy less resource blocks, we believe that our approach is suitable for our case study. Providing a more realistic rate adaptation scheme would certainly improve the performance of our system but would add complexity without affecting the key findings and conclusions of this work (since it would have the same effect on both our proposal and the state-of-the-art schemes). Furthermore, we should point out that even though spectral efficiency is critical during peak traffic hours, during the night zone when the traffic is low, the allocation of the BS resources is not so crucial to the performance of the system.

Finally, it should be noted that this level of simplification is often employed by works in the literature that are focused on switch off schemes. For instance, a very similar approach is adopted in [31], where the authors employ a link budget calculation to estimate the maximum cell radius that can support the required QoS constraints. In their proposed switched off scheme, the power of a BS must be sufficiently increased to compensate for the increased path loss to serve the area of a switched off neighboring cell. To calculate potential energy savings by switching off schemes, an even higher level abstraction of the resource allocation scheme, where a given transmission rate achieved through a fixed amount of bandwidth is allocated to each use, is adopted in several works such as [30], [32] and [36].

3.2.2.1 Notation

A summary of the main parameters employed in the distance-aware switching off algorithms and the maximization deactivation scheme and their model analysis is given in Table 3.1.

3.3 Network Planning Algorithms for Single-Operator Networks

In this section, the three proposed network planning solutions are described. The first algorithm, where the BSs are deactivated by taking into account the distance between the BSs and their users, is given in Section 3.3.1), along with the analytical models in Section 3.3.1.1. The second scheme considers both the distance and the traffic load variations and the corresponding analytical models are transformed to take into account these corresponding characteristics (Section 3.3.2 and Section 3.3.2.1). Finally, a switching off approach that provides an optimal solution is described in Section 3.3.3 and the analytical models for the this solution are given in Section 3.3.3.1.

3.3.1 Distance-aware Switching Off Algorithm (DSO)

The first proposed switching off mechanism is based on the fact that the transmission power of a BS depends on its distance from the users. The BSs require increased transmission power to cover extended area and serve distant users. Hence, the impact of the distance on the transmission power makes it an appropriate indicator for the decision about the BSs that must be turned off. The Distance-aware Switching Off (DSO) approach proposes to switch off the BS with the maximum average distance value. Our algorithm leads to energy saving, while guaranteeing the QoS in terms of achieved throughput and outage probability of the users. The remaining active BSs extend their coverage to serve the whole network area. In addition, the remaining active BSs are able to serve all the existing traffic at the present time in the network.

Table 3.1: Main Parameters for the DSO, DDSO, MSO model analysis

Symbol	Description
BS_m	BS in mth cell in a the network configuration
CR_{BS}	Capacity resources of a BS
$\mathbb{E}[B]$	Average transmitted bits of a network
$\mathbb{E}[B_{BS_m}]$	Average transmitted bits of BS_m in a network
$\mathbb{E}[E]$	Average energy consumption of a network
$\mathbb{E}[E_{BS_m}]$	Average energy consumption of BS_m in a network
$\mathbb{E}[\eta_\epsilon]$	Expected energy efficiency of a network
$\mathbb{E}[\eta_\epsilon^{(BS_m)}]$	Expected energy efficiency of BS_m in a network
$\mathbb{E}[T]$	Expected throughput of a network
$\mathbb{E}[T_{BS_m}]$	Expected throughput of BS_m in a network
h	Hour of the day
$m \in \mathcal{M}$	Macro cell in a network
$\mathcal{M} = \{0, \dots M\}$	Set of macro cells in a network, with $\lvert\mathcal{M}\rvert = M$
$\mathcal{M}_{OFF} \subseteq \mathcal{M}$	Subset of BSs that are switched off
M_{OFF}	Number of BSs that are switched off
$\mathcal{M}_{ON} \subseteq \mathcal{M}$	Subset of cells that remain active
$\mathcal{M}_{ON,h} \subseteq \mathcal{M}$	Subset of cells that remain active at hour h
$\mathcal{M}_{ON}$	Number of BSs that are active
$\mathcal{M}_{ON,h}$	Number of BSs that are active at hour h
$Load$	Traffic load of a single BS
N_V	Number of voice calls serves simultaneously
$p_b l^{(m,h)}$	Blocking probability of mth cell in a network
P_{const}	Power consumed by a BS for cooling and antenna feeding
P_{idle}	Power consumed by a BS when it is idle
P_{tx}	Power consumed by a BS for data transmission
$p_v^{(m,h)}$	State probability for serving v calls of mth cell in a network
R_V	Transmission rate of voice calls
t_{hour}	Duration of hour h
v	Voice call
x_m	Binary decision variable in MSO
$\lambda_V^{(m,h)}$	Generation rate of voice calls of mth cell in a network at hour h
$\mu_V^{(m,h)}$	Service of voice calls of mth cell in a network at hour h
ρ_m, h	Traffic load percentage of BS_m in a network at hour h

Our research work has two main contributions: *i*) We consider the distance between the BSs and their associated users in the switching off decision in order to minimize the energy consumption of the whole network. *ii*) We apply our algorithm on the LTE-Advanced standard, whereas most works in this field consider older technologies.

The DSO algorithm works as follows:

- **Step 1**: Each BS estimates the distance of its users and obtains the information for the distance of users that are associated with its neighboring BSs through the X2 interface.

- **Step 2**: The BSs calculate the average distance based on the results of the first step and they exchange the outcome among them.
- **Step 3**: The BS with the maximum average distance is switched off first, if there is no QoS degradation, and the neighboring BSs deal with the possible increases in the transmission power. The algorithm is repeated from Step 1, until the maximum number of BSs is switched off and it is guaranteed that there is no QoS degradation.

The steps of the DSO algorithm are shown graphically in the flowchart in the Fig. 3.5.

3.3.1.1 Performance Metrics Analysis for DSO

In this section, we provide the analytical models for the calculation of the network throughput and energy efficiency, when the DSO is applied.

By employing the steady state probabilities of the Markov chain, we define and calculate the key performance metrics both for the individual BSs and the whole network, focusing on the night zone.

Throughput The expected throughput $\mathbb{E}\left[T_{BS_m,h}\right]$ for the BS_m at hour h is defined as the average number (over all possible states of the system) of served sessions in the system multiplied by the transmission rate of the session and calculated as:

$$\mathbb{E}\left[T_{BS_m,h}\right] = \sum_{v=0}^{N_V} v' \cdot R_V \cdot p_v^{'(m,h)}, \tag{3.3}$$

where $p_v^{'(m,h)}$ are the steady state probabilities for the given traffic load rate $\lambda_V^{'(m,h)}$. We define as $\lambda_V^{'(m,h)}$ the new average traffic load of the BS_m, which is equal to the traffic of BS_m and the traffic of the switched off BSs that must be served by BS_m.

Assuming that the DSO is applied from $h = 22.00$ pm until $h = 08.00$ am, for the whole night zone, the expected throughput $\mathbb{E}\left[T_{BS_m}\right]$ for the BS_m is:

$$\mathbb{E}\left[T_{BS_m}\right] = \sum_{h=21.00}^{08.00} \mathbb{E}\left[T_{BS_m,h}\right]. \tag{3.4}$$

In continuation, we calculate the throughput for the network of $\mathcal{M}_{ON}$ cells, after the application of the algorithm. Thus, the total throughput of the network is:

$$\mathbb{E}\left[T\right] = \sum_{m \in \mathcal{M}_{ON}} \mathbb{E}\left[T_{BS_m}\right], \tag{3.5}$$

where $\mathbb{E}\left[T_{BS_m}\right]$ is the average throughput of the mth BS when it serves the traffic $\lambda_V^{'(m)}$.

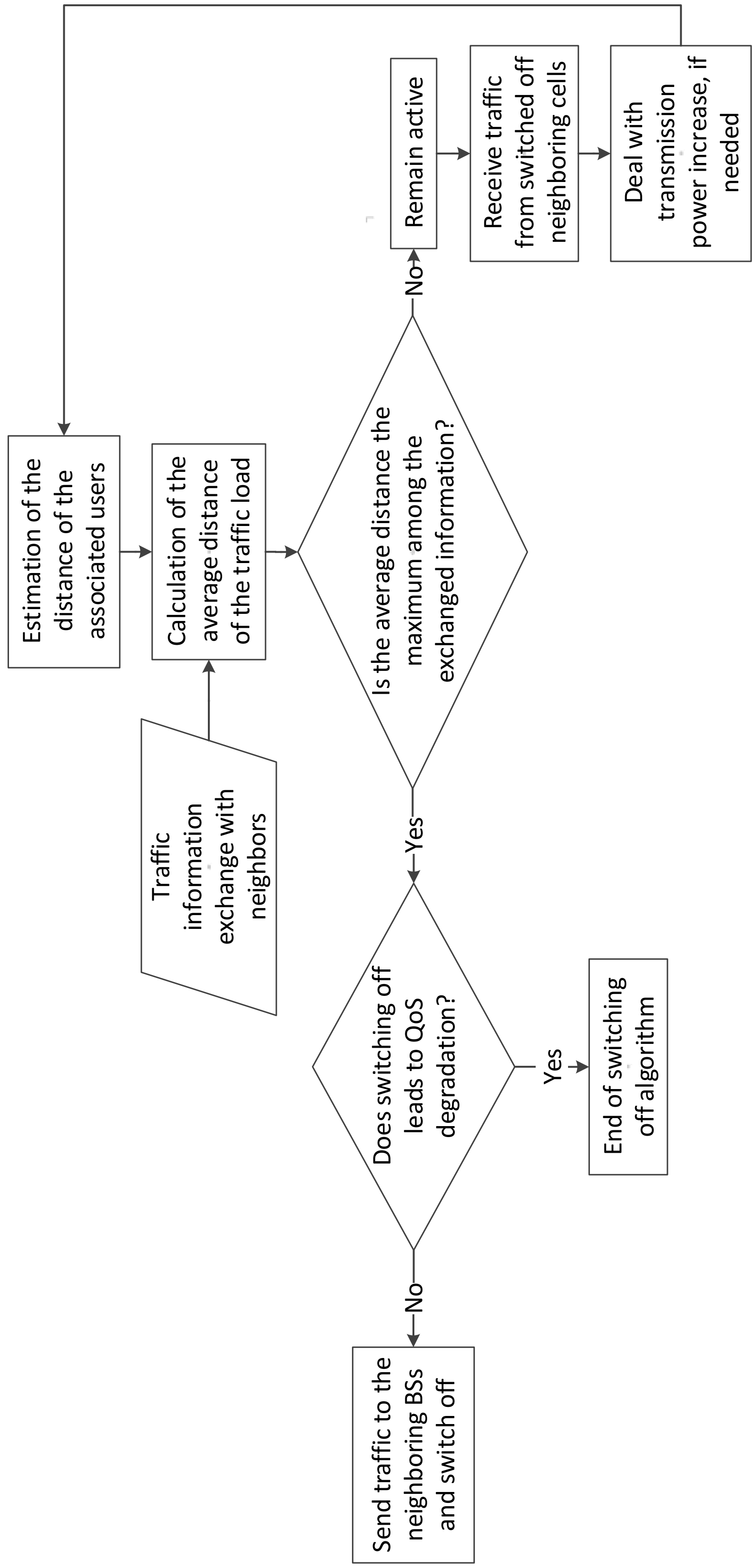


FIGURE 3.5: Flowchart of the distance-aware switching off (DSO) algorithm.

Energy Efficiency The expected energy efficiency $\mathbb{E}[\eta_\epsilon^{(BS_m)}]$ of a BS_m is defined as the ratio of the average transmitted bits $\mathbb{E}\left[B_{BS_m}\right]$ over the average energy consumption $\mathbb{E}\left[E_{BS_m}\right]$:

$$\mathbb{E}[\eta_\epsilon^{(BS_m)}] = \frac{\mathbb{E}\left[B_{BS_m}\right]}{\mathbb{E}\left[E_{BS_m}\right]}. \tag{3.6}$$

The average transmitted bits during the night zone can be calculated by multiplying the average throughput given in Eq. (3.3) with the duration of the hour t_{hour}:

$$\mathbb{E}\left[B_{BS_m}\right] = \sum_{h=21.00}^{08.00} \mathbb{E}\left[T_{BS_m,h}\right] \cdot t_{hour}. \tag{3.7}$$

To calculate the average energy consumption, we should take into account the power consumed by the BS for operation and transmission, consisting of three components: *i*) the constant power P_{const}, consumed by an active BS for operations such as cooling, antenna feeding, etc, *ii*) the idle power P_{idle}, which is the power consumed when the BS remains idle, i.e., when it has no ongoing traffic sessions, *iii*) the transmission power for serving the ongoing traffic sessions corresponding to each state $p_v^{\prime(m)}$, considering that P_{tx} denotes the transmission power for serving a single data session. Hence, the average energy consumption at hour h is given by:

$$\mathbb{E}\left[E_{BS_m,h}\right] = \left(P_{const} + P_{idle} \cdot p_0^{\prime(m,h)} + \sum_{v=0}^{N_V} P_{tx} \cdot v' \cdot p_v^{\prime(m,h)}\right) \cdot t_{hour}. \tag{3.8}$$

For the whole night zone, the average energy consumption of BS_m is given by the following equation:

$$\mathbb{E}\left[E_{BS_m}\right] = \sum_{h=21.00}^{09.00} \mathbb{E}\left[E_{BS_m,h}\right]. \tag{3.9}$$

Finally, the network energy efficiency is defined as:

$$\mathbb{E}[\eta_\epsilon] = \frac{\mathbb{E}\left[B\right]}{\mathbb{E}\left[E\right]}, \tag{3.10}$$

with

$$\mathbb{E}\left[B\right] = \sum_{m \in \mathcal{M}_{ON}} \mathbb{E}\left[B_{BS_m}\right], \tag{3.11}$$

and

$$\mathbb{E}\left[E\right] = \sum_{m \in \mathcal{M}_{ON}} \mathbb{E}\left[E_{BS_m}\right], \tag{3.12}$$

where $\mathbb{E}\left[B_{BS_m}\right]$ and $\mathbb{E}\left[E_{BS_m}\right]$ are the transmitted bits and the energy consumption of the mth BS, when serving traffic equal to $\lambda_V^{\prime(m)}$.

3.3.2 Dynamic Distance-aware Switching Off Algorithm (DDSO)

In the same context, we propose a second switching on/off algorithm that exploits the traffic load variations during night zone, along with the distance between the users and the BSs, as a parameter for the switching off decision. Comparing to the related work presented in Chapter 2, the main contributions of this novel dynamic distance-aware switching on/off strategy are summarized in the following: *i*) This dynamic algorithm is an iterative process and its results vary according to the time changing conditions. The number of BSs that are switched off is not fixed and, in particular, the selection of the deactivated BSs depends on traffic pattern variations and the distance between the BSs and the users. The dynamic nature of the algorithm leads to the extension of the night zone compared to other works in the literature. More specifically, the deactivation of the BSs is progressively occurring as soon as the traffic load decreases and not during a predefined night zone. *ii*) In other works in the literature, the schemes were applied in a static way, with the decision taken at the beginning of the night zone. In contrast, in this work, our adaptive strategy is applied every hour in the low traffic zone, a characteristic that differentiates the Dynamic Distance-aware Switching On/Off (DDSO) scheme from our DSO algorithm, as well. *iii*) Our proposal is not only to switch off the BSs, but the BSs are also switched on gradually, according to the traffic load variations, when the network resources are not sufficient for serving the existing traffic load.

Our algorithm is divided in two phases: the switching off phase that begins when the traffic load decreases and the switching on phase that begins when the traffic demand increases again, early in the morning.

- **Switching off phase**: The switching off phase starts at 19:00 pm (Fig. 3.2) and ends at 07:00 am. During these hours, the traffic load is low, and a reduced number of BSs could be used to serve the existing traffic. In a wireless network that consists of BSs, our algorithm calculates the minimum number of BSs that should remain active based on the traffic variations. Therefore, a maximum number of BSs will be switched off. The algorithm consists of three steps (same steps as the ones presented in the previous algorithm and shown in Fig. 3.5) that are repeated every hour during the switch off phase. The night zone is extended and a greater amount of energy is saved. Based on the total network capacity and the desired data rate, the BSs estimate the maximum number of the users that can be served in the coverage area and they decide if more BSs can be switched off.
- **Switching on phase**: In a typical traffic load scenario, since the cell load increases at 08:00 am, the number of active BSs is not adequate for serving the traffic load. Therefore, the BSs should be switched on gradually in order to have the appropriate number of BSs to serve the existing traffic load. At 08:00 am the existing active BSs calculate the number of BSs that should be turned on in order to serve the traffic of the network based on the traffic requirements and the position of the existing users. The active BSs are responsible for informing the neighboring non-active BSs to be turned on.

At 10:00 am when the traffic load reaches its peak, all the BSs should be turned on.

3.3.2.1 Performance Metrics Analysis for DDSO

In this section, we provide the analytical models for the calculation of the network throughput and energy efficiency, when the DSO is applied.

Throughput The DDSO is applied from $h = 19.00$ pm until $h = 09.00$ am, for the whole night zone. Hence, the expected throughput $\mathbb{E}\left[T_{BS_m}\right]$ for the BS_m is:

$$\mathbb{E}\left[T_{BS_m}\right] = \sum_{h=19.00}^{09.00} \mathbb{E}\left[T_{BS_m,h}\right], \tag{3.13}$$

where $\mathbb{E}\left[T_{BS_m,h}\right]$ is given by Eq. (3.3).

In addition, we assume that $\mathcal{M}_{ON,h}$ are the BSs that remain active at hour h. Hence, after the application of the algorithm, the total throughput of the network during the time that the algorithm is applied is:

$$\mathbb{E}\left[T\right] = \sum_{m \in \mathcal{M}_{ON,h}} \mathbb{E}\left[T_{BS_m}\right]. \tag{3.14}$$

Energy Efficiency The expected energy efficiency $\mathbb{E}[\eta_\epsilon^{(BS_m)}]$ of a BS_m is given by the following equation:

$$\mathbb{E}[\eta_\epsilon^{(BS_m)}] = \frac{\mathbb{E}\left[B_{BS_m}\right]}{\mathbb{E}\left[E_{BS_m}\right]}. \tag{3.15}$$

The average transmitted bits during the night zone can be calculated by multiplying the average throughput given in Eq. (3.3) with the duration of the hour t_{hour}:

$$\mathbb{E}\left[B_{BS_m}\right] = \sum_{h=19.00}^{09.00} \mathbb{E}\left[T_{BS_m,h}\right] \cdot t_{hour}. \tag{3.16}$$

For the whole night zone, the average energy consumption of BS_m is given by the following equation:

$$\mathbb{E}\left[E_{BS_m}\right] = \sum_{h=19.00}^{09.00} \mathbb{E}\left[E_{BS_m,h}\right], \tag{3.17}$$

where $\mathbb{E}\left[E_{BS_m,h}\right]$ is calculated by Eq. (3.8).

The total network energy efficiency is defined as:

$$\mathbb{E}[\eta_\epsilon] = \frac{\mathbb{E}\left[B\right]}{\mathbb{E}\left[E\right]}, \tag{3.18}$$

with

$$\mathbb{E}[B] = \sum_{m \in \mathcal{M}_{ON}} \mathbb{E}[B_{BS_m}], \tag{3.19}$$

and

$$\mathbb{E}[E] = \sum_{m \in \mathcal{M}_{ON}} \mathbb{E}[E_{BS_m}], \tag{3.20}$$

where $\mathbb{E}[B_{BS_m}]$ and $\mathbb{E}[E_{BS_m}]$ are calculated by Eq. (3.16) and Eq. (3.17), respectively.

3.3.3 Maximization Switching Off Algorithm (MSO)

In the previous sections, we proposed two distance-aware algorithms, while in the state-of-the-art, traffic-aware schemes were shown. In this section, the problem of the energy consumption reduction is approached from another perspective. Thus, we propose an algorithm that finds the optimal number of switched off BSs during low traffic conditions.

The two previous algorithms presented strategies for switching off different number of BSs. The objective of the third algorithm is to find the maximum number of BSs that can be switched off for a network configuration of the hexagonal network. In this section, we provide an extension of the previous works in order to achieve this optimization goal. The key point relies on finding the optimal combination of those BSs to be switched off and those that remain active. The optimal solution maximizes the energy savings.

The Maximum Switching Off (MSO) algorithm is applied from 22:00 pm until 08:00 am when traffic load is low. Our algorithm is applied in clusters consisting of $M + 1$ cells (Fig. 3.1) and follows the next steps:

- **Step 1**: Each cluster, having information about the traffic pattern given from Fig. 3.2, computes the average estimated traffic arrival rate for the night zone.
- **Step 2**: For any given cluster of M cells, the energy consumption and the energy efficiency are computed for different combinations of switched off BSs, using the average estimated traffic rate. We assume that the traffic of a BS that is switched off is served by the neighboring BS that has the smallest identification number (the identification numbers appear in Fig. 3.1). The BSs that remain active increase their transmission power accordingly to keep the QoS of the overall area.
- **Step 3**: The combination that gives the maximum energy saving is applied to our network. The BSs that remain active deal with the transmission power increases to serve the existing users.

Let us define x_m as a binary decision variable that indicates whether the corresponding BS (BS_m) will be switched off ($x_m = 1$) or not ($x_m = 0$). The objective that we consider is the minimization of the energy consumption and the maximization of the total energy efficiency. The network energy efficiency is given by the following equation:

$$\mathbb{E}[\eta_\epsilon] = \frac{\mathbb{E}\left[B\right]}{\mathbb{E}\left[E\right]}, \tag{3.21}$$

with,

$$\mathbb{E}[B] = \sum_{m\in\mathcal{M}} \mathbb{E}[B_{BS_m}] \cdot (1 - x_m)\,, \tag{3.22}$$

and,

$$\mathbb{E}[E] = \sum_{m\in\mathcal{M}} \mathbb{E}[E_{BS_m}] \cdot (1 - x_m)\,, \tag{3.23}$$

where $\mathbb{E}\left[B_{BS_m}\right]$ and $\mathbb{E}\left[E_{BS_m}\right]$ are the transmitted bits and the energy consumption of the mth BS, when serving traffic equal to $\lambda_V'^{(m,h)}$. The average transmitted bits and the average energy consumption are calculated by using the Eq. (3.7) and the Eq. (3.8) and the Markov chain analysis.

The ILP problem can be formulated as follows:

$$\max \frac{\sum\limits_{m\in\mathcal{M}} \mathbb{E}[B_{BS_m}] \cdot (1 - x_m)}{\sum\limits_{m\in\mathcal{M}} \mathbb{E}[E_{BS_m}] \cdot (1 - x_m)} \tag{3.24}$$

s.t.

$$p_{bl}^{(m,h)} = 0, \forall m \in \mathcal{M}, \tag{3.25}$$

$$x_m \in \{0,1\}, \forall m \in \mathcal{M}. \tag{3.26}$$

The $p_{bl}^{(m,h)}$ represents the blocking probability of some users to be unserved and is given below:

$$p_{bl}^{(m,h)} = \frac{\dfrac{\left(\frac{\lambda_V'^{(m,h)}}{\mu_V^{(m,h)}}\right)^{N_V}}{N_V!}}{\sum\limits_{v=0}^{N_V} \dfrac{\left(\frac{\lambda_V'^{(m,h)}}{\mu_V^{(m,h)}}\right)^{v}}{v!}} \tag{3.27}$$

The maximization problem is solved trough an exhaustive search algorithm. The flowchart of the MSO algorithm is presented in the Fig. 3.6.

3.3.3.1 Performance Metrics Analysis for MSO

In this section, we provide the analytical models for the calculation of the network throughput and energy efficiency, when the MSO is applied.

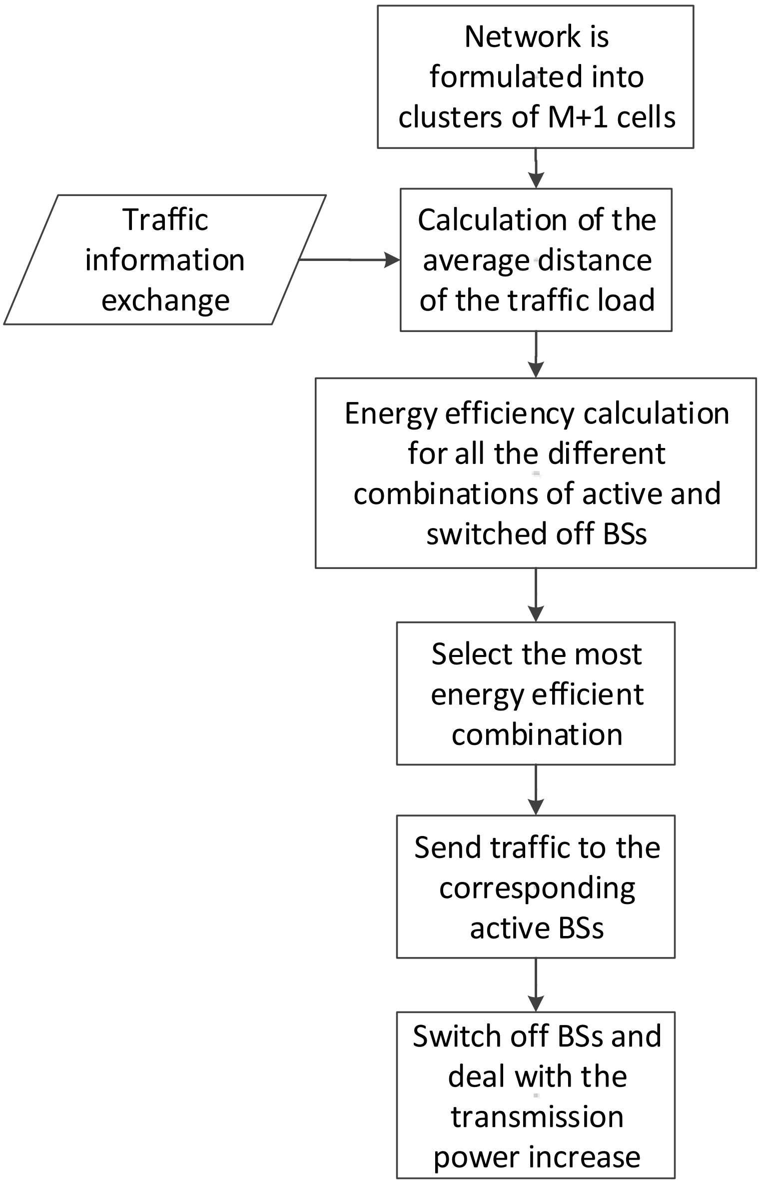


FIGURE 3.6: Flowchart of the maximization switching off (MSO) algorithm.

Throughput The MSO is applied from $h = 22.00$ pm until $h = 08.00$ am, for the whole night zone. Hence, the expected throughput $\mathbb{E}\left[T_{BS_m}\right]$ for the BS_m is:

$$\mathbb{E}\left[T_{BS_m}\right] = \sum_{h=22.00}^{08.00} \mathbb{E}\left[T_{BS_m,h}\right] \cdot (1 - x_m)\,, \tag{3.28}$$

where $\mathbb{E}\left[T_{BS_m,h}\right]$ is given by Eq. (3.3).

Hence, after the application of the MSO scheme, the total throughput of the network during the time that the algorithm is applied is:

$$\mathbb{E}\left[T\right] = \sum_{m\in\mathcal{M}} \mathbb{E}\left[T_{BS_m}\right] \cdot (1 - x_m)\,. \tag{3.29}$$

Energy Efficiency The expected energy efficiency $\mathbb{E}[\eta_\epsilon^{(BS_m)}]$ of a BS_m is given by the following equation:

$$\mathbb{E}[\eta_\epsilon^{(BS_m)}] = \frac{\mathbb{E}\left[B_{BS_m}\right]}{\mathbb{E}\left[E_{BS_m}\right]}. \tag{3.30}$$

The average transmitted bits during the night zone can be calculated by multiplying the average throughput given in Eq. (3.3) with the duration of the hour t_{hour}:

$$\mathbb{E}\left[B_{BS_m}\right] = \sum_{h=22.00}^{08.00} \mathbb{E}\left[T_{BS_m,h}\right] \cdot t_{hour} \cdot (1 - x_m). \tag{3.31}$$

For the whole night zone, the average energy consumption of BS_m is given by the following equation:

$$\mathbb{E}\left[E_{BS_m}\right] = \sum_{h=22.00}^{08.00} \mathbb{E}\left[E_{BS_m,h}\right] \cdot (1 - x_m), \tag{3.32}$$

where $\mathbb{E}\left[E_{BS_m,h}\right]$ is calculated by Eq. (3.8).

The total network energy efficiency is given by Eq. (3.21).

3.4 Performance Evaluation

In order to evaluate the performance of the proposed switching off schemes and verify our analytical formulation, custom-made C/C++ simulation tools that execute the rules of the algorithms have been developed. Monte Carlo methods were employed to compare our approach to state-of-the-art algorithms. In this section, the simulation setup is described, followed by a discussion about the obtained results.

3.4.1 Simulation Scenario

The simulation scenario, where DSO and DDSO schemes are applied, includes 15 cells (i.e., $M = 15$). However, for the MSO algorithm that clusters of cells are formed before the application of the switching off strategy (i.e., $M = 6$), we focus in a simulation scenario with one central cell and six peripheral cells. In our experiments, we assume that the BSs have the same traffic volume equal to $\rho_m \cdot Load$, shown in Fig. 3.2 for the case of $\rho_m = 1.0$.

To assess the performance of our scheme, we compare the proposed energy efficient switching off strategies (DSO, DDSO and MSO) with two state-of-the-art approaches: *i*) a network planning scheme, where a random number of BSs is selected to switched off, referred as Random Switching Off algorithm (RSO) [30], and *ii*) a baseline scenario where all BSs are active and none of the BSs is switched off, referred as No Switching Off approach (NSO). The RSO algorithm considers the selection of a random number of BSs to be switched off and calculates the time that this fraction of BSs should be switched off.

The simulation parameters are summarized in Table 3.2.

TABLE 3.2: Simulation Parameters for DSO and DDSO

Parameter	**Value**
Bandwidth, CR_{BS}	115 Mbps
# of cells, M	15, 6
Traffic load, *Load*	Fig. 3.2
Service rate, $\mu_V^{(m)}$	Mean: 1/50 calls/s
Transmission rate, R_V	64 kbps
Transmission power, P_{tx}	[1.29, 1.5] W
Idle power, P_{idle}	[0.34 0.95] W
Constant power, P_{const}	[591 675] W

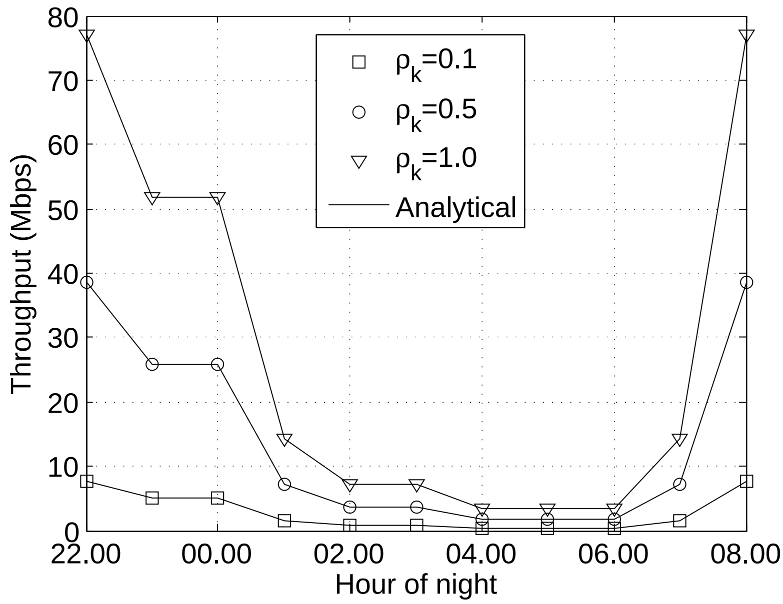
3.4.2 Analytical Models Validation

In this section, we validate via extensive simulations the analytical models for the network throughput and energy efficiency for different traffic profiles.

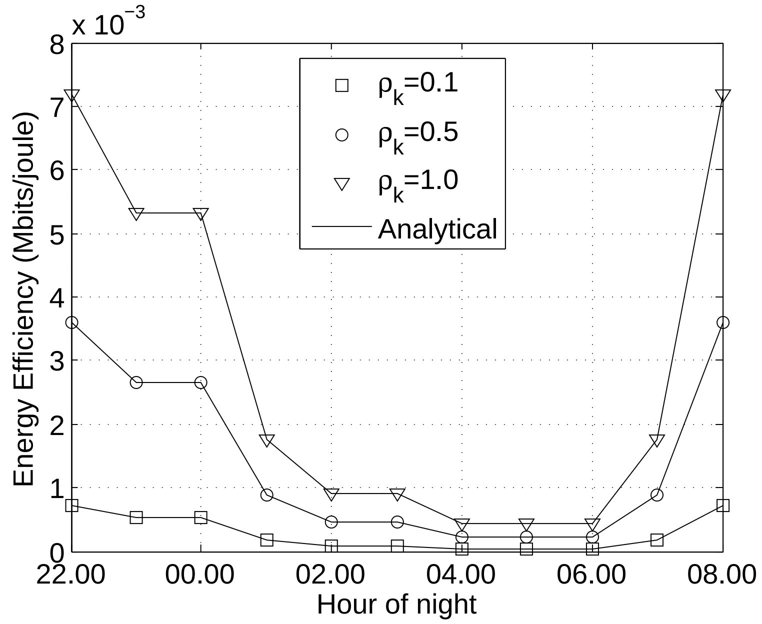
Fig. 3.7(a) and 3.7(b) present the network throughput performance and energy efficiency, respectively, when applying the DSO algorithm. As we can see, the experimental results perfectly match the analysis, thus validating the proposed theoretical expressions. In both figures, we observe that the throughput and the energy efficiency follow similar behavior with the traffic load model, presented in Section 3.2.2. The traffic load variations have direct impact on the throughput. In addition, since the energy efficiency is calculated by the division of the transmitted bits over the consumed energy, the traffic load variations affect also the behavior of the energy efficiency. As expected, the two metrics increase with the traffic load (ρ_m).

Similar observations are concluded from the Fig. 3.8(a) and 3.8(b), where the network throughput and the energy efficiency are plotted, respectively, for the DDSO algorithm. Compared to the DSO, we observe that the night zone is extended in the second approach, due to the dynamic nature of the scheme. More specifically, the night zone of the former algorithm (DSO) starts on 22.00 pm and ends on 08.00 am, whereas for the DDSO approach, the switching off starts on 19.00 pm and at 10.00 am, all the BSs are active.

Fig. 3.9(a) and 3.9(b) present the network throughput performance and energy efficiency, respectively, when applying the MSO algorithm. As we can see, there is a perfect match between the experimental results and the analytical models results, thus validating the proposed theoretical expressions. In both figures, we observe that the throughput and the energy efficiency follow similar behavior with the traffic load model, presented in Section 3.2.2. Furthermore, throughput and energy efficiency increase with the traffic load (ρ_m).



(a) DSO: Throughput validation



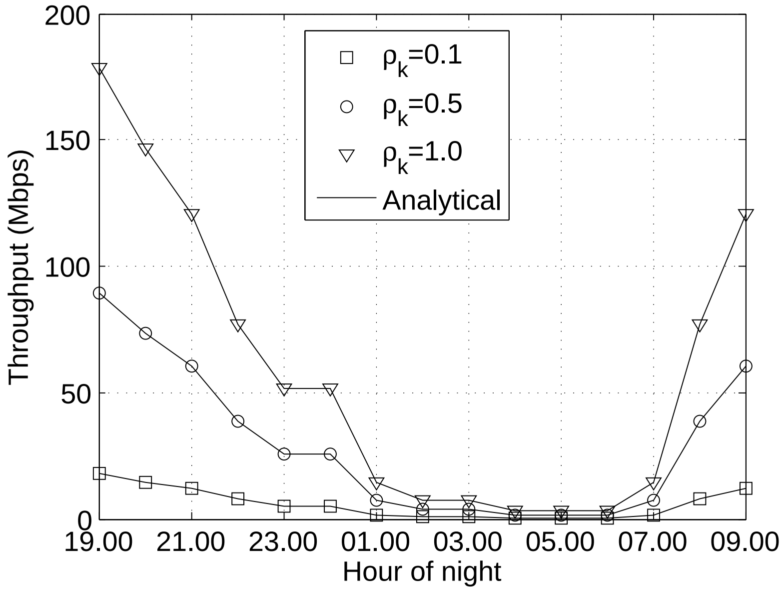
(b) DSO: Energy efficiency validation

FIGURE 3.7: DSO: Analytical models validation under varying traffic load conditions

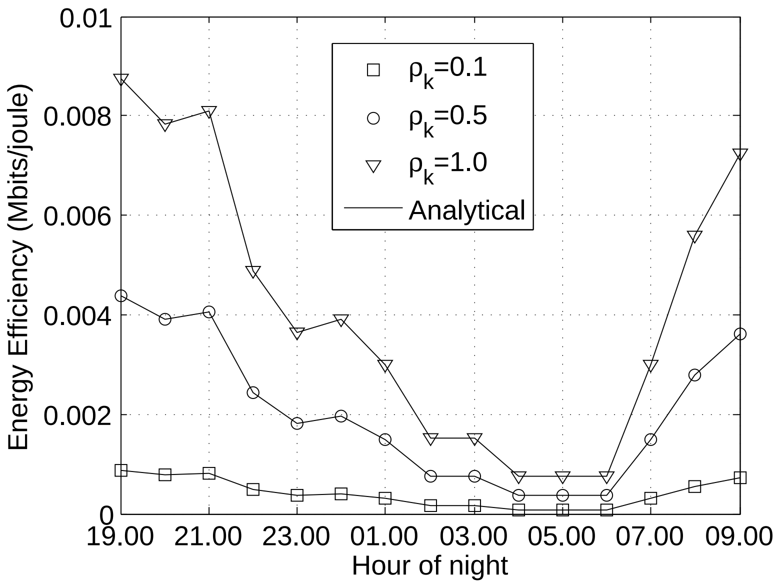
3.4.3 Numerical Results

This section includes the performance results with regard to energy efficiency for the DSO, DDSO and MSO algorithms compared to state-of-the-art approaches.

In Fig. 3.10(a), the DSO proposal is compared to the reference scenarios with respect to energy efficiency. As it was also viewed in the analytical model validation, it is observed that energy efficiency follows the traffic load variations. When



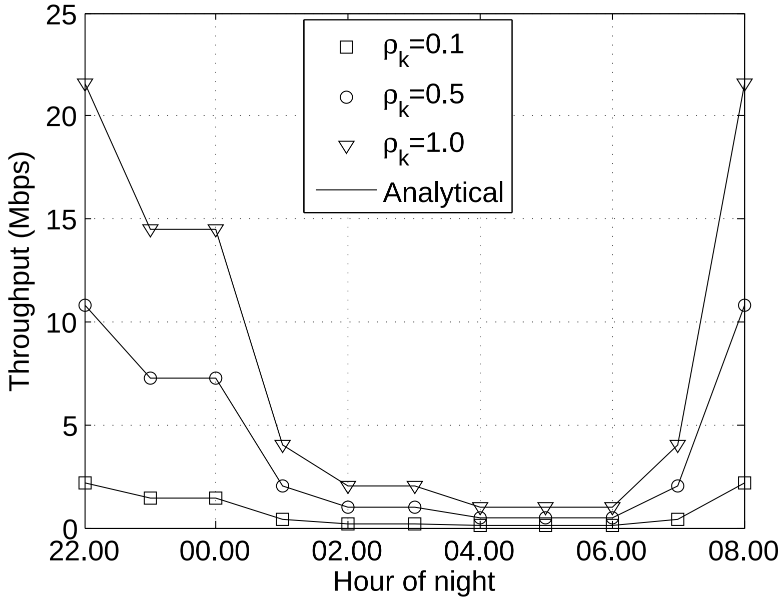
(a) DDSO: Throughput validation



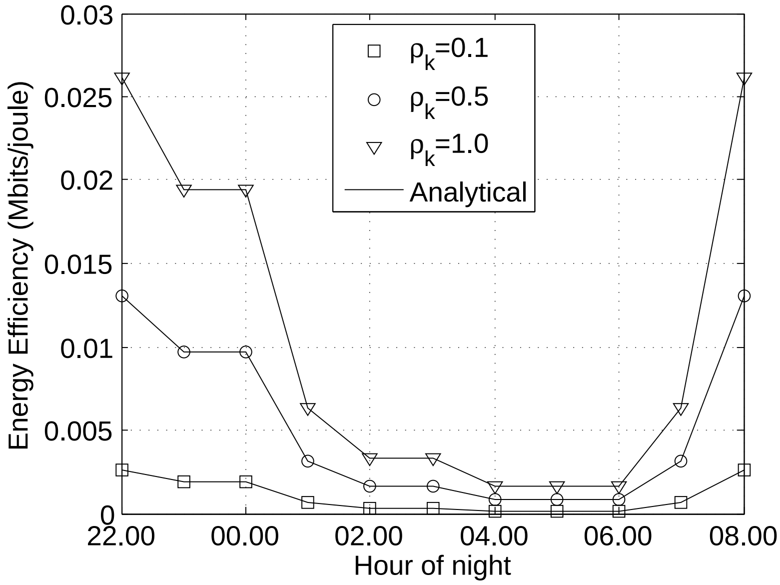
(b) DDSO: Energy efficiency validation

FIGURE 3.8: DDSO: Analytical models validation under varying traffic load conditions

applying the DSO scheme, a fixed number of BSs is switched off, as the switching off decision is taken in the beginning of the night zone. As a consequence, with the traffic decrease, fewer bits are transmitted and less energy is consumed. Nevertheless, since energy consumption includes a constant part that is independent of the traffic, energy decreases at a lower rate with respect to the transmitted bits, thus leading to a reduced energy efficiency. The opposite happens as the traffic increases. Comparing the DSO switching off algorithm to the state-of-the-art schemes during the night zone, we observe that the DSO approach outperforms the RSO scheme in terms of energy efficiency. The throughput of our system is not degraded in comparison to the state-of-the-art approaches, even though it is not



(a) MSO: Throughput validation

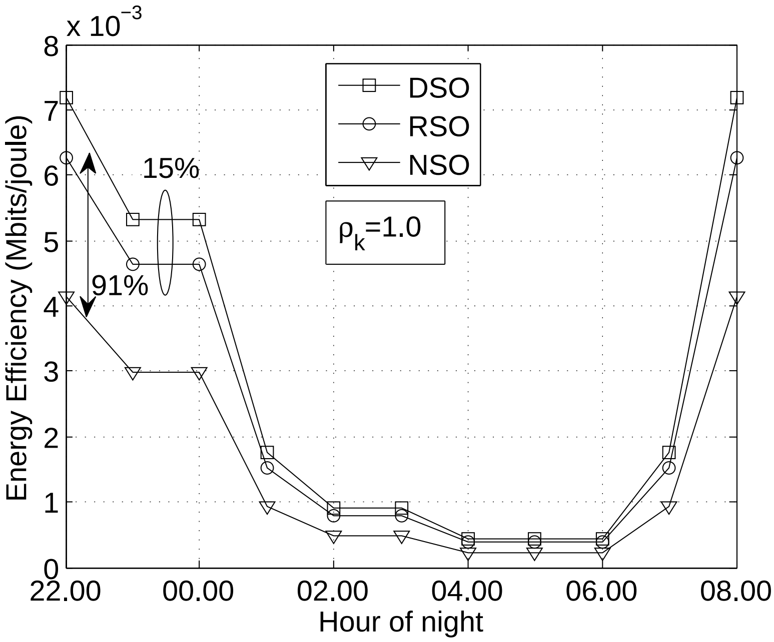


(b) MSO: Energy efficiency validation

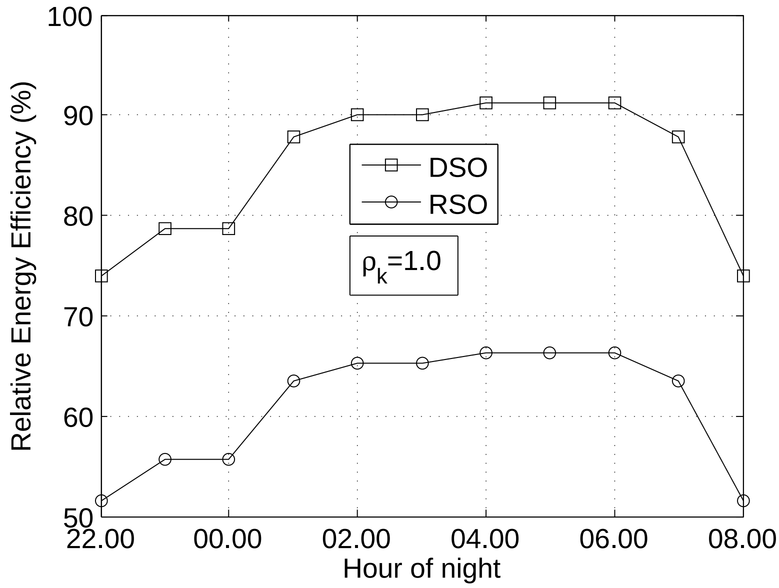
FIGURE 3.9: MSO: Analytical models validation under varying traffic load conditions

graphically presented. Some indicative throughput values are given in Table 3.3. The comparison between the two different strategies, the DSO and RSO, outlines that the DSO algorithm that uses distance for the determination of the switching off BSs gives better performance than the RSO scheme, where a random number of switched off BSs is selected in the switching off process. Therefore, the selection of distance as the critical factor in the deactivation policy is well stated as energy efficient.

Fig. 3.10(b) illustrates the relative energy efficiency gain of DSO and RSO with respect to NSO, where none of the BSs in the network are switched off. It is



(a) DSO: Energy efficiency



(b) DSO: Relative energy efficiency gain

FIGURE 3.10: Energy efficiency of DSO compared to state-of-the-art approaches

TABLE 3.3: DSO: Throughput (Mbps) for $\rho_k = 1.0$

	Hour of night					
Algorithm	22.00	00.00	02.00	04.00	06.00	08.00
DSO	77	52	7	3	3	77
RSO	77	52	7	3	3	77
NSO	77	52	7	3	3	77

observed that, using DSO algorithm, a better system performance is achieved, as there is a significant enhancement in energy efficiency of about 91% when comparing our approach to the NSO scheme, in contrast to the 15% improvement of the RSO scheme.

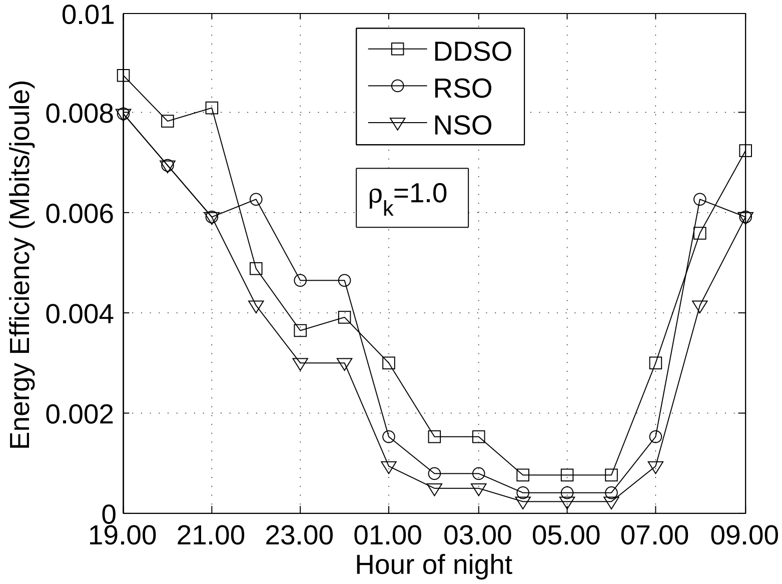
The simulation results of the proposed DDSO algorithm comparing to the state-of-the-art solutions in terms of energy efficiency are presented in Fig. 3.11(a). This algorithm improves the energy efficiency to a greater extend by employing an extended night zone and iteratively applying the switching off policy every hour. The dynamic nature of the algorithm leads to an increased number of BSs that are switched off, and thus to increasing energy savings. The energy efficiency follows the variations of the traffic, while a different number of BSs are turned off each time during the night zone. During the hours 22:00 pm until 00.00 am, we observe that the performance of our algorithm is degraded compared to RSO, since less BSs are switched off through our proposal, in order to carry the traffic, whereas the RSO switches off a constant number of BSs.

The relative comparison of the energy efficiency is presented in Fig. 3.11(b). In this figure the relative energy savings of DDSO and RSO algorithms are presented with respect to the NSO solution. It is worth noting that for low traffic conditions the energy saving of the DDSO scheme can be significant, of the order of 220%. By comparing the results of Fig. 3.10(b) to the relative gain of Fig. 3.11(b), we remark that DDSO algorithm outperforms the distance aware switching off algorithm (DSO) as well as the previous works appearing in the literature (RSO). Thus, the distance, along with the dynamic nature of the traffic load variations should both be taken into consideration in the switching off process.

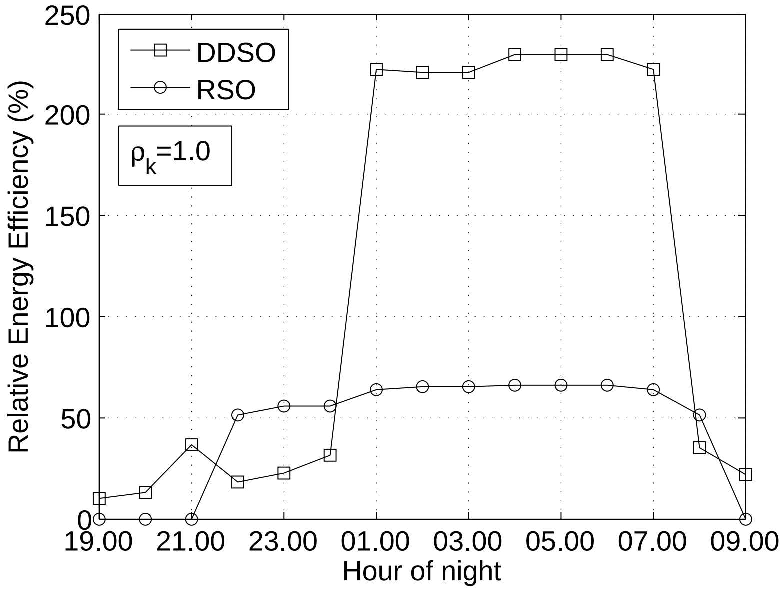
Fig. 3.12 depicts the number of BSs that remain active ($\mathcal{M}_{ON}$). In the dynamic scheme (DDSO), the number of active BSs decreases gradually after 19:00 pm, as the switching off scheme is applied at the beginning of each hour and increases again at 08:00 am, when the switching on strategy is employed. On the other hand, when applying the RSO algorithm and the DSO algorithm, a fixed number of the BSs are switched off.

In Fig. 3.13, we compare the average energy efficiency of the two proposed distance-aware schemes (DSO and DDSO) and the state-of-the-art approaches (RSO and NSO). The calculated values correspond to an average value of the energy efficiency during the whole night zone. It is noted that the proposed schemes outperform the RSO and the NSO. As it is observed, the energy efficiency is increasing for all the schemes as the traffic load increases, however the relative gain is stable, since the number of switched off BSs depends also on the traffic variations. Furthermore, significant higher values in terms of energy efficiency are achieved for the DDSO proposal.

The performance of the proposed MSO algorithm is shown. More specifically, Fig. 3.14(a) depicts the energy efficiency of MSO compared to the state-of-the-art works (RSO and NSO), whereas the relative energy efficiency gains with respect to NSO are illustrated in Fig. 3.14(b). From Fig. 3.14(a), it is evident that the energy efficiency of all the illustrated schemes follows the traffic load variations, an observation that was shown in previous figures (Fig. 3.10(a) and Fig. 3.11(a)).



(a) DDSO: Energy efficiency



(b) DDSO: Relative energy efficiency gain

FIGURE 3.11: Energy efficiency of DDSO compared to state-of-the-art approaches

In addition, MSO outperforms the state-of-the-art schemes, since the application of MSO leads to an optimal number of BSs that are switched off.

Lst but not least, the performance of the MSO scheme is examined. By focusing on Fig. 3.14(b), it is observed that, using our algorithm, a better system performance is achieved, as there is a significant enhancement in energy efficiency. The energy saving is 600% by using our maximization technique. In addition, it is worth noting that the energy savings that we succeed in terms of the percentage of energy efficiency are significant compared to state-of–the-art RSO algorithm. The MSO algorithm outperforms the DSO and DDSO schemes, since it exploits the

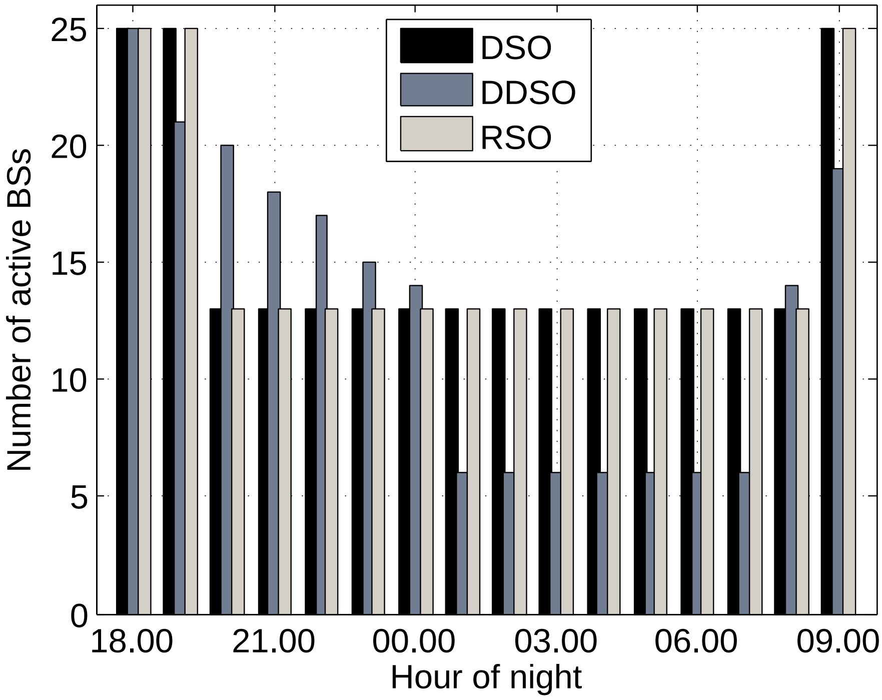


FIGURE 3.12: Number of active BSs.

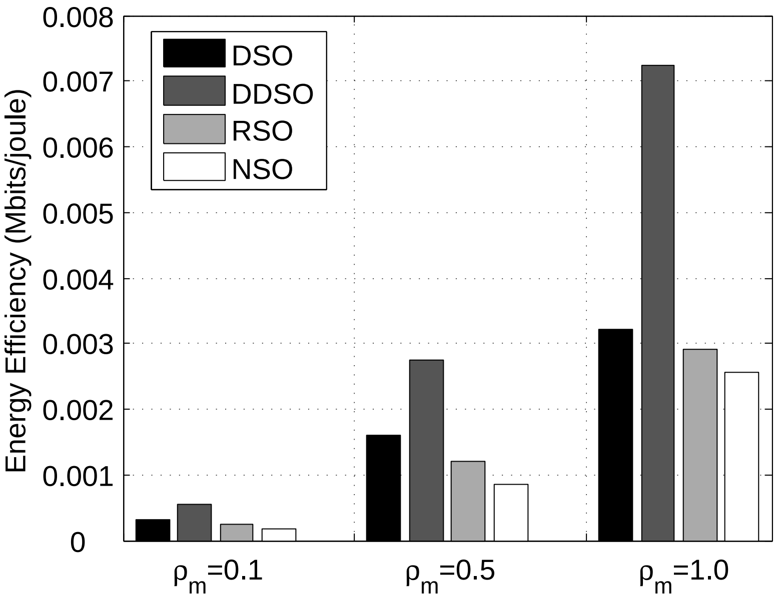
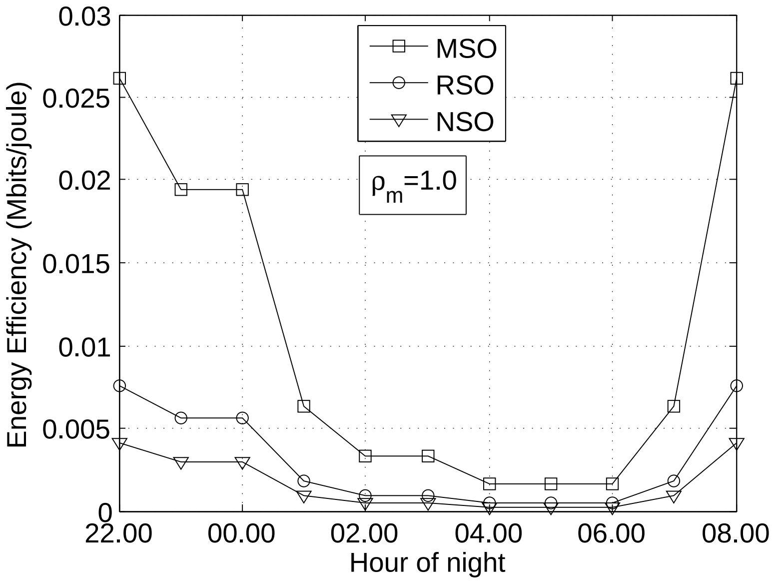
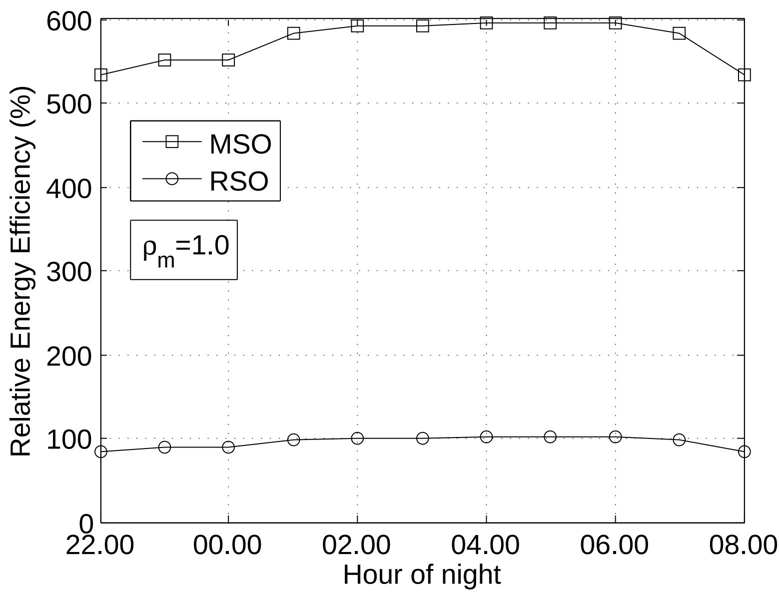


FIGURE 3.13: Energy efficiency comparison.



(a) MSO: Energy efficiency



(b) MSO: Relative energy efficiency gain

Figure 3.14: Energy efficiency of MSO compared to state-of-the-art approaches

capacity of network in a better way and saves the maximum energy, by finding the optimal combination between switched off and active BSs.

3.5 Concluding Remarks

The switching off strategies are a paradigm that has gained popularity is the last few years as it has been shown to be an effective approach to reduce the energy consumption in wireless cellular networks. By exploiting the different aspects of the varying traffic load pattern and the network configurations, novel switching off approaches have been developed and several aspects of this problem have been investigated. Our work proved that not only the volume, but also the position of the BSs and the users plays an important role in the selection of the BSs to be switched off. In addition, our research has revealed that exploiting the tradeoff between aggregate network capacity and the number of active cells is a natural and effective way to reduce the complexity of the energy waste problem. Our approaches achieve the main goal: reduce energy consumption without penalizing QoS. The studies have remarked the need for careful calibration as an important requirement to maximize the profit.

The proposed frameworks have the following desirable features:

- *Robustness:* We propose solutions that can be applied on various network topologies. Indeed, they focus on providing low energy consumption to the areas with high number of BSs. In addition, clusters of cells can be formulated in order to give optimal solutions.
- *Feasibility:* The proposed schemes do not require any new additional functionality. The operation could be done in a time scale of tens of minutes or hours. In addition, integration in existing (operative) networks is transparent. Information exchange is required, but this can be easily be done through the X2 interface.
- *Real time complexity and scalability:* The real time complexity is minimum, since only some information about the traffic load is required.

The conclusions can be summarized as follows:

- The proposed frameworks define new approaches to analyze the energy consumption problem through switching off the redundant BSs and by 1) explicitly considering the spatial traffic distribution, 2) taking into account the time-varying nature of the traffic load, and 3) searching the optimal solution for the BSs switching off.
- All the proposed algorithms are based on the inherent tradeoff between energy consumption and aggregate capacity. In this manner, the proposed methods lead to a reduced number of active BSs, serving the whole network. The results indicate that the proposed strategies offer a convenient tradeoff in terms of complexity, performance, and feasibility.
- System level experiments confirm that the performance obtained is excellent. In addition, it clearly outperforms reference schemes both in terms of achievable gains and feasibility/complexity. Although achievable energy savings are, in general, network dependent, the proposed frameworks provide a suitable way to observe the impact of variable parameters such as users' position and network configuration on the performance of the switching off strategies.

Chapter 4

Strategies for Energy Efficient Infrastructure Sharing in Multi-Operator Environments

"I was originally supposed to become an engineer but the thought of having to expend my creative energy on things that make practical everyday life even more refined, with a loathsome capital gain as the goal, was unbearable to me."

Albert Einstein, The Ultimate Quotable Einstein

4.1 Introduction

The contributions of this chapter are motivated by the emerging demand for multimedia applications and mobile services, along with the rise in the CapEx and OpEx of the multiple coexisting MNOs and the underutilized infrastructure during off-peak hours. A roaming-based infrastructure sharing scheme is proposed, applicable in multi-operator environments during low traffic periods. Taking into account the rationality of the MNOs and their conflicting interests, we introduce a game theoretic framework that enables the MNOs to make individual switching off decisions for their own BSs, thus bypassing potential complicated service level agreements among them. Besides the expected energy efficiency benefits, the proposed scheme allows the MNOs to significantly reduce their financial costs independently of the strategies of the coexisting MNOs, providing them with the incentives to participate in the game. Our contributions are summarized as follows:

1. As a part of an integrated roaming-based infrastructure sharing scheme for multi-operator environments, we introduce a game theoretic switching off algorithm that aims at minimizing the individual MNO cost in a distributed manner. We define a realistic cost function that explicitly considers actual roaming and operational costs for the MNOs. We show that, in the proposed game, a Dominant Strategy Equilibrium (DSE) can be reached, defined as

the strategy yielding the minimum cost for each MNO, regardless of the other MNOs' actions.

2. To address the heterogeneous nature of voice and data traffic in current and future cellular networks, we design an analytical model, based on a two-dimensional Markov chain that theoretically estimates the throughput, the energy efficiency and the cost expenses both for the individual MNOs and the whole network.

3. We validate the theoretical analysis and assess the effectiveness of the proposed infrastructure sharing scheme with the aid of extensive simulation experiments. We introduce a new performance metric, namely cost efficiency that connects the network performance with the financial benefits of the MNOs. The results indicate the potential total energy efficiency gains in the network and highlight the individual cost and energy gains for the MNOs.

The remainder of the chapter is organized as follows. The system model, the network configuration and the notation used throughout the chapter are described in Section 4.2. In Section 4.3, we introduce the infrastructure sharing scheme, along with the game formulation of the switching off decision. In Section 4.4, we present the analytical models for the energy efficiency, the network throughput and the cost metrics. The validation of the model and an extensive performance assessment are provided in Section 4.5. Finally, Section 4.6 concludes this chapter.

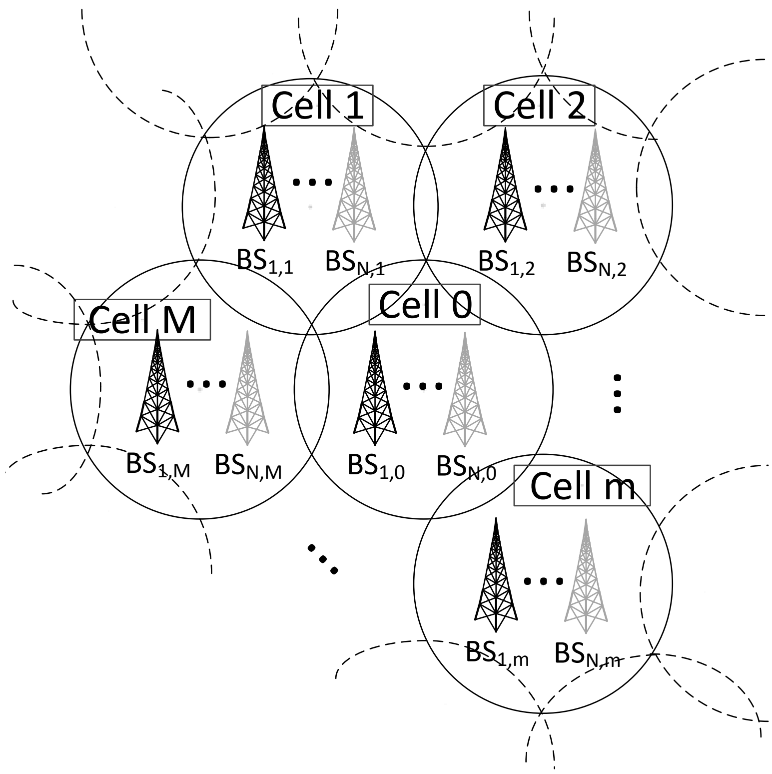
4.2 System Model and Operation

4.2.1 Network Configuration

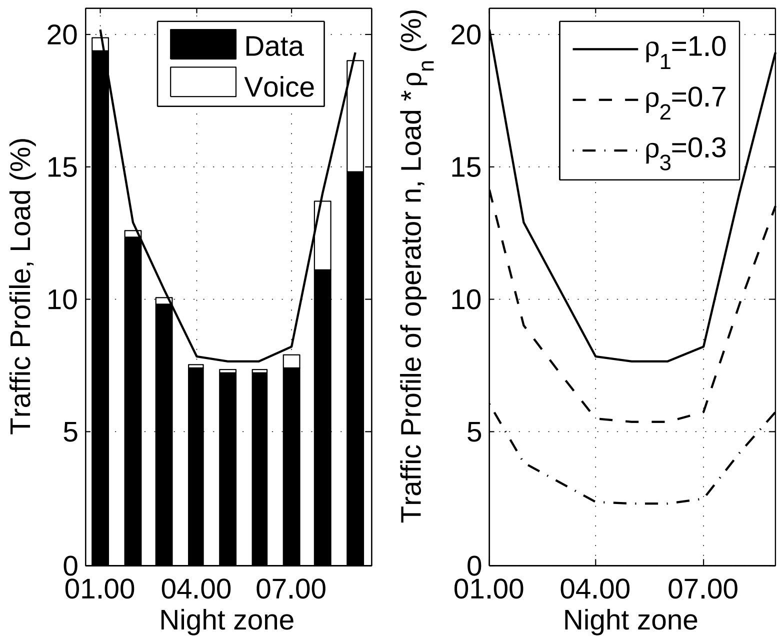
Our system model, depicted in Fig. 4.1(a), considers clusters of multi-operator cells. In particular, each cluster is formed by one central cell surrounded by M peripheral cells, while each cell includes N BSs of different MNOs. Therefore, the term $BS_{n,m}$ is used to denote the BS of the nth operator in the mth macro cell, with $n \in [1, N]$ and $m \in [0, M]$. As it will be explained in detail in the next section, part of the BS infrastructure in the M surrounding cells may be switched off during low traffic conditions, motivating the operators to reach roaming agreements and share the resources of the remaining active BSs in the same cell. In contrast, the BSs of the central cell always remain active and increase their transmission power and range to form an umbrella cell, in the extreme case where all the BSs of a peripheral cell are switched off.

4.2.2 Traffic Load Model

Since the proposed infrastructure sharing scheme is applied during periods of low network traffic, the selection of an accurate traffic model is quite critical. In this work, we adopt a realistic traffic pattern [82], [83], [84] that corresponds to the aggregated voice and data traffic per operator in a given cell, during the night zone.



(a) Cluster of one central and M peripheral macro cells, covered by N telecommunication operators



(b) Voice and data traffic patterns during the night zone for different operators

FIGURE 4.1: Scenario and traffic model

In the traffic pattern, depicted in the leftmost part of Fig. 4.1(b), the maximum traffic per hour is expressed as a percentage of the total BS capacity CR_{BS} that is considered same for all cells. We focus on the time zone between 01.00 am and 09.00 am[1], when the aggregated traffic per BS is relatively low (i.e., less than 20% of the cell's capacity).

In addition, for the sake of generality, we assume that the traffic volumes of different operators may be different, although they follow the same pattern. Hence, we define $\rho_n \in [0,1]$ the percentage of each operator's traffic load with respect to the maximum traffic for the respective hour. An example is given in the rightmost part of Fig. 4.1(b), where the traffic of three operators is depicted. In this particular example, the first operator has the maximum traffic volume (i.e., $\rho_1 = 1$), whereas the second and the third operator have 70% and 30% (i.e., $\rho_2 = 0.7$ and $\rho_3 = 0.3$) of the maximum traffic, respectively. Finally, the voice and data connections are served at a Constant Bit Rate (CBR) of R_V and R_D, respectively. We consider that no rate adaptation takes place within the cell and all users of a given service class are allocated the same amount of resources, calculated for cell edge users. Even though this is the worst case scenario, since some users closer to the BS could support higher transmission rates or, equivalently, occupy less resource blocks, we believe that our approach is suitable for our high-level case. Furthermore, we point out that even though spectral efficiency is critical during peak traffic hours, during the night zone when the traffic is low, the allocation of the BS resources is not so crucial to the system performance.

4.2.3 Notation

A summary of the main parameters employed in the gamet theoretic switching off algorithm and their model analysis is given in Table 4.1.

TABLE 4.1: Main Parameters for the GTIS model analysis

Symbol	Description
$\mathcal{A}$	State space of Markov model
$BS_{n,m}$	BS of nth MNO in mth cell
c_1	Electricity charge per energy unit
C_{const}	Fixed operational cost
$C_{inc}^{(n,m)}$	Transmission increase cost of nth MNO in the mth cell
$C_{n,m}$	Cost of nth MNO in the mth cell
$C_{roam}^{(n,m)} \approx C_{roam}^{(m)}$	Roaming cost of nth MNO in the mth cell
$C_{tr}^{(n,m)} \approx C_{tr}^{(m)}$	Traffic dependent cost of $BS_{n,m}$
CR_{BS}	Capacity resources of a BS
d	Data session
$\mathbb{E}[B]$	Average transmitted bits of network
$\mathbb{E}[B_{n,m}]$	Average transmitted bits of $BS_{n,m}$
$\mathbb{E}[C]$	Expected cost of a network
$\mathbb{E}[C_{n,m}]$	Expected cost of MNO_n

Continued on next page

[1]Nonetheless, our algorithm can be adapted to different traffic conditions and the selection of the hours of the night zone may vary according to the variations of the actual traffic.

Table 4.1 – continued from previous page

Symbol	Description
$\mathbb{E}[C_{i,m}^{ON,ON}]$	Expected cost for the case (ON,ON)
$\mathbb{E}[C_{i,m}^{ON,OFF}]$	Expected cost for the case (ON,OFF)
$\mathbb{E}[C_{i,m}^{OFF,ON}]$	Expected cost for the case (OFF,ON)
$\mathbb{E}[C_{i,m}^{OFF,OFF}]$	Expected cost for the case (OFF,OFF)
$\mathbb{E}\left[E\right]$	Average energy consumption of a network
$\mathbb{E}\left[E_{n,m}\right]$	Average energy consumption of $BS_{n,m}$
$\mathbb{E}\left[\eta_c^{n,m}\right]$	Cost efficiency of $BS_{n,m}$
$\mathbb{E}[\eta_\epsilon]$	Expected energy efficiency of a network
$\mathbb{E}[\eta_\epsilon^{(n,m)}]$	Expected energy efficiency of $BS_{n,m}$
$\mathbb{E}\left[T\right]$	Expected throughput of a network
$\mathbb{E}\left[T_{n,m}\right]$	Expected throughput of $BS_{n,m}$
$m \in \mathcal{M}$	Macro cell in hexagonal cells
MNO_n	Identification of the nth MNO
$\mathcal{M} = \{0, \dots M\}$	Set of cells in hexagonal grid, with $\lvert\mathcal{M}\rvert = M$
$\mathcal{M}_{OFF} \subseteq \mathcal{M}$	Subset of BSs that are switched off
M_{OFF}	Number of BSs that are switched off
$\mathcal{M}_{ON} \subseteq \mathcal{M}$	Subset of cells that remain active
$\mathcal{M}_{\mathcal{ON}}$	Number of BSs that are active
$n \in \mathcal{N}$	Identification of MNO
$\mathcal{N} = \{1, \dots N\}$	Set of MNOs, with $\lvert\mathcal{N}\rvert = N$
$\mathcal{N}_{OFF}^{(m)} \subseteq \mathcal{N}$	Subset of MNOs with switched off BSs in mth cell
$N_{OFF}^{(m)}$	Number of MNOs with switched off BSs in mth cell
$\mathcal{N}_{ON}^{(m)} \subseteq \mathcal{N}$	Subset of MNOs with active BSs in mth cell
$\mathcal{N}_{\mathcal{ON}}{}^{(m)}$	Number of MNOs with active BSs in mth cell
$\mathcal{N}_{roam}^{(n,m)} \subseteq \mathcal{N}_{OFF}^{(m)}$	Subset of MNOs who roam their traffic to MNO_n
$Load$	Traffic load of a single BS
N_V	Number of voice calls serves simultaneously
P_{const}	Power consumed by a BS for cooling and antenna feeding
P_{idle}	Power consumed by a BS when it is idle
P_{tx}	Power consumed by a BS for data transmission
$p_v^{(k)}$	State probability for serving v calls of kth cell in a grid
$p_{(\nu,d)}$	State probability for serving v calls and ν data sessions
R_D	Transmission rate of data sessions
R_V	Transmission rate of voice calls
$\mathcal{S}_{n,m}$	Set of actions of $BS_{n,m}$
$s_{n,m}$	Switching off probability of $BS_{n,m}$
t_{night}	Night zone duration
ν	Voice call
α	Roaming cost parameter
Γ	Non-cooperative game
$\vartheta_{\nu,d}$	Characteristic function
$\lambda_D^{(n,m)}$	Generation rate of data sessions of $BS_{n,m}$
$\lambda_V^{(n,m)}$	Generation rate of voice calls of $BS_{n,m}$
$\mu_D^{(n,m)}$	Service of data sessions of $BS_{n,m}$

Continued on next page

Table 4.1 – continued from previous page

Symbol	Description
$\mu_V^{(n,m)}$	Service of voice calls of $BS_{n,m}$
ρ_n	Percentage of nth MNO with respect to maximum traffic
$\varphi_{\nu,d}$	Characteristic function

4.3 Infrastructure Sharing Scheme with Game Theoretic Switching Off Decision (GTIS)

In this section, we introduce the infrastructure sharing framework for multi-operator environments. The proposed solution consists of two parts: *i*) an infrastructure sharing algorithm and *ii*) a game theoretic switching off decision strategy. To that end, in Section 4.3.1, we propose the infrastructure sharing algorithm that defines the rules for the collaboration among the MNOs, given that part of the BS infrastructure is switched off during the night zone. Then, in Section 4.3.2, we formulate the BS switching off decision as a game theoretic strategy that enables each operator to determine the best course of action in each cell, in order to significantly reduce its own cost and energy consumption.

4.3.1 Infrastructure Sharing Scheme

Let us recall that the considered system model (Section 4.2) includes N MNOs that provide coverage to a cluster of cells formed by one central and M peripheral cells. For the low-traffic night zone, a subset of each operator's BSs in the peripheral cells is switched off. Once this BS subset is determined (through the game theoretic algorithm that will be described in the next section), the proposed infrastructure sharing scheme is applied to determine how the traffic will be served by the remaining active infrastructure, taking into account the corresponding operation and roaming costs.

The proposed infrastructure sharing algorithm is applied in the network, after the execution of the independent switching off decisions. According to the outcome of the decision process, there are three possible outcomes in a given peripheral cell m:

1. If all the BSs remain active (i.e., $\mathcal{N}_{ON}^{(m)} = \mathcal{N}$), no infrastructure sharing takes place in the cell. Hence, each BS consumes energy for operation and service of its own traffic.
2. If a subset $\mathcal{N}_{ON}^{(m)} \subset \mathcal{N}$ of the BSs remains active, then they undertake the service of the traffic of the switched off BSs in the same cell (i.e., $\mathcal{N}_{OFF}^{(m)}$). In particular, the traffic of each switched off BS is roamed to an active BS of the same cell, selected randomly with equal probability p_s from the subset $\mathcal{N}_{ON}^{(m)}$.

The MNOs of the deactivated BSs should pay the corresponding roaming cost to the active operators. However, the increased energy consumption (due to the higher traffic) of the active BSs implies a higher cost that should also be considered.

3. If no BSs remain active, (i.e., $\mathcal{N}_{ON}^{(m)} = \emptyset$), the BSs of the central cell ($BS_{n,0}$) increase their transmission power to cover the area of the peripheral cell. In this case, there is no collaboration between operators, since the traffic of each switched off BS is served by the central BS of the same operator. Hence, no roaming costs are involved, while the operators take into account the extra cost for the increased power consumption in the central cell.

Having defined the general network operation, each MNO_n is able to make an individual switching off decision without the need of exchanging any information with the other MNOs and, subsequently, to execute the infrastructure sharing algorithm (Algorithm 1), illustrated in Fig. 4.2, that determines the traffic flow in the network. Given the aforementioned three possible outcomes, we have four different cases that can be distinguished for the MNO_n in a given cell m depending on the state of the MNO_n and the state of the rest MNOs in the same cell. More specifically, the case where a subset $\mathcal{N}_{ON}^{(m)} \subset \mathcal{N}$ of the BSs remains active is subdivided in two separate cases depending on the state of the MNO under study. Thus, we have:

- *Case 1 - Operator n is ON and $N_{ON}^{(m)} = N - 1$ operators are ON*: The total cost for the MNO_n is $C_{n,m} = C_{const} + C_{tr}^{(n,m)}$, where C_{const} represents the fixed operational cost for the BS and $C_{tr}^{(n,m)}$ corresponds to the cost for serving the BS's traffic.
- *Case 2 - Operator n is ON and $N_{OFF}^{(m)} > 0$ operators are OFF*: In this case, MNO_n may have to pay a higher cost due to the increased served traffic (i.e., its own traffic along with the roamed traffic of other BSs), while receiving the corresponding roaming income from each operator $MNO_i \in \mathcal{N}_{roam}^{(n,m)}$. More specifically:
  - The total operation cost can be expressed as $C'_{n,m} = C_{const} + C_{tr}^{(n,m)} + \sum_{i \in \mathcal{N}_{roam}^{(n,m)}} C_{tr}^{(i,m)}$
  - The received roaming income by MNO_n can be expressed as $C'^{(n,m)}_{roam} = \sum_{i \in \mathcal{N}_{roam}^{(n,m)}} C_{roam}^{(i,m)}$, where $C_{roam}^{(i,m)}$ is the roaming cost paid by MNO_i and can be considered as a portion of the total operational cost, i.e., $C_{roam}^{(n,m)} = \alpha \cdot \left(C_{const} + C_{tr}^{(n,m)}\right)$, with $\alpha \in [0, 1]$.

  Consequently, in this case, the total cost for operator MNO_n can be written as:
  $C_{n,m} = C_{const} + C_{tr}^{(n,m)} + \sum_{i \in \mathcal{N}_{roam}^{(n,m)}} C_{tr}^{(i,m)} - \alpha \cdot \left(C_{const} \cdot \sum_{i \in \mathcal{N}_{roam}^{(n,m)}} C_{tr}^{(i,m)}\right)$.
- *Case 3 - Operator n is OFF and $N_{ON}^{(m)} > 0$ operators are ON*: In this case, operator n should pay the roaming cost to one operator from the active set

$\mathcal{N}_{ON}^{(m)}$ randomly selected with equal probability $p_s = 1/N_{ON}^{(m)}$. Hence, in this case, $C_{n,m} = C_{roam}^{(m,m)}$.

- *Case 4 - Operator n is OFF and $N_{OFF}^{(m)} = N-1$ operators are OFF*: In this case, the cost paid by the MNO_n corresponds to the extra energy consumption for the power increase of the central BS ($BS_{n,0}$), in order to cover the area of a switched off BS in a peripheral cell. Hence, $C_{n,m} = C_{inc}^{(n,0)}$.

Algorithm 1 Infrastructure sharing algorithm of $BS_{n,m}$ in peripheral cell m

Require: Switching off decision of all MNOs in cell m

for all $m \in \mathcal{M}$ **do**
    for all $n \in \mathcal{N}$ **do**
        if $\Big((n \in \mathcal{N}_{ON}^{(m)})\ \&\ (\mathcal{N}_{OFF}^{(m)} = \emptyset)\Big)$ **then** ▷ Case 1
            $C_{n,m} = C_{const} + C_{tr}^{(m)}$
        else if $\Big((n \in \mathcal{N}_{ON}^{(m)})\ \&\ (\mathcal{N}_{OFF}^{(m)} \neq \emptyset)\Big)$ **then** ▷ Case 2
            $C_{n,m} = C_{const} + C_{tr}^{(m)}$
            for all $(r \in \mathcal{N}_{roam}^{(n,m)})$ **do**
                $BS_{n,m} \xleftarrow{roam} BS_{r,m}$
                $C_{n,m} = C_{n,m} + C_{tr}^{(m)} - C_{roam}^{(m)}$
            end for
        else if $\Big((n \in \mathcal{N}_{OFF}^{(m)})\ \&\ (\mathcal{N}_{ON}^{(m)} \neq \emptyset)\Big)$ **then** ▷ Case 3
            Select operator $r \in \mathcal{N}_{ON}^{(m)}$ with probability $p_s = 1/N_{ON}^{(m)}$
            $BS_{n,m} \xrightarrow{roam} BS_{r,m}$
            $C_{n,m} = C_{roam}^{(m)}$
        else if $\Big((n \in \mathcal{N}_{OFF}^{(m)})\ \&\ (\mathcal{N}_{ON}^{(m)} = \emptyset)\Big)$ **then** ▷ Case 4
            $BS_{n,m} \xrightarrow{roam} BS_{n,0}$
            $C_{n,m} = C_{inc}^{(n,0)}$
        end if
    end for
end for

4.3.2 Game Theoretic Switching Off Strategy

The proposed infrastructure sharing algorithm defines the rules of agreements among the operators, taking as an input the subset of switched off BSs in the peripheral cells. Hence, the individual decisions with regard to the BSs switching off constitute the core of the proposed scheme and main contribution of our work. Taking into account the conflicting interests and the interaction among the different MNOs, as well as the different available courses of action, we propose a feasible game theoretic switching off strategy for the BSs in the network. In particular, we model the switching off decision process as a static non-cooperative game with complete information [85], [86], played by the N operators in each of the M peripheral cells of a given cluster.

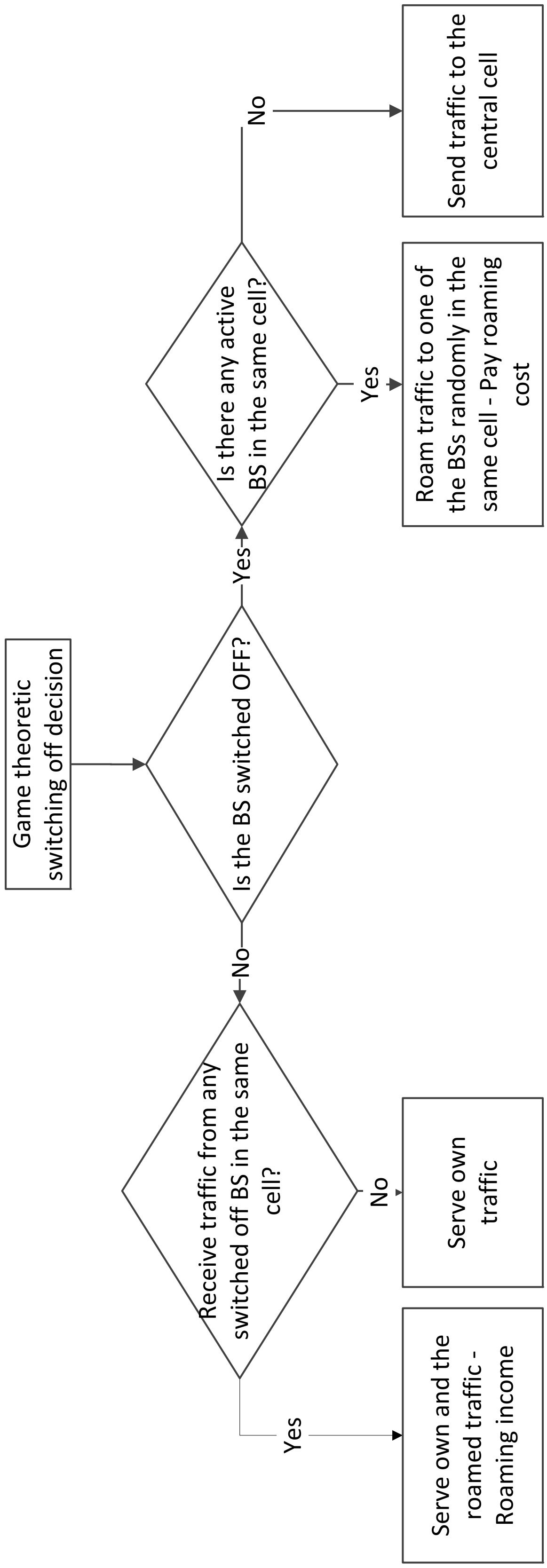


Figure 4.2: Flowchart of the infrastructure sharing algorithm

Non-cooperative game theory is a very powerful analytical tool that provides multifold advantages, as it enables us:

- to model the aforementioned conflicting situations between the MNOs with high accuracy;
- to minimize the exchange of information among the different MNOs. This is very important, since, in competitive environments, the MNOs may not be willing to disclose extensive network information to their competitors. Furthermore, minimizing interactions can reduce the risk of misbehavior, since selfish operators could choose to modify their statistics in order to increase their personal benefits;
- to reach distributed close-to-optimal solutions for realistic scenarios. In the proposed non-cooperative game, a DSE can be achieved, which can be easily calculated with limited required information. The calculated DSE represents the solution where each player's assigned strategy minimizes its cost, regardless of the other players' strategy and, in our formulation, it is very close to the Pareto optimal solution.

The remaining of this section is divided into three parts. First, the game formulation and the cost matrix are given, followed by the individual cost minimization analysis in the second part. Finally, the DSE of the game is discussed, along with some numerical results on the switching off probabilities.

4.3.2.1 Game Formulation

Definition 1. *The non-cooperative game* Γ *can be represented in strategic form by the triplet:* $\Gamma = (\mathcal{N}, \mathcal{S}_{n,m}, C_{n,m})$*, with* $n \in \mathcal{N}, m \in \mathcal{M}$*, where:*

- $\mathcal{N} = \{1, \ldots, N\}$ *is the finite set of players corresponding to the* N *operators.*
- $\mathcal{S}_{n,m} = \{ON, OFF\}$ *is the set of the two possible actions for each* MNO_n *with respect to the* $BS_{n,m}$*, i.e.,* $BS_{n,m}$ *can be active (state ON) or switched off (state OFF).*
- $C_{n,m} : \mathcal{S} \to \mathbb{R}^+$ *is the cost function for player* n *in the peripheral cell* m*, where* $\mathcal{S} = \mathcal{S}_{1,m} \times \cdots \times \mathcal{S}_{n,m} \times \cdots \times \mathcal{S}_{N,m}$ *represents the Cartesian product of the strategy sets.*

The cost function of the game $C_{n,m}$ has been selected to match the cost paid by each operator in every peripheral cell, as described in Section 4.3.1. However, at this point, we can exploit an observation that holds true for the low traffic conditions that characterize the night zone. In particular, the traffic load variations during the night have a very small impact on the operational cost of the BS. Hence, it can be realistically assumed that all operators have approximately the same cost for serving the traffic in a given cell m, i.e., $C_{tr}^{(n,m)} \approx C_{tr}^{(m)}$. Similarly, the roaming cost, which is expressed as a function of the operational cost, is also simplified to $C_{roam}^{(n,m)} \approx C_{roam}^{(m)}$.

This realistic simplification has two direct implications on the game formulation. First, the operators can calculate their cost function with considerable accuracy by using average traffic statistics for a given cell. As a result, there is no need for information exchange among MNOs (to obtain the actual traffic values) prior to the application of the game, thus facilitating its implementation and eliminating any concerns about truthfulness. Second, by simplifying the cost functions, the MNOs obtain the same payoffs for a given action and, as a result, the outcome of the game is independent of the identity of the players. Hence, by definition, the proposed game is symmetric, allowing its formulation as an N-player game with 2 macro-players: *i*) player A is a given MNO_i, with $i \in \mathcal{N}$ *ii*) player B is the set $\mathcal{N} \setminus \{i\}$, formed by the remaining $N-1$ operators, excluding MNO_i. The matrix representation of the game is given in Table 4.2, showing the costs of player A with respect to the different contingencies of player B.

TABLE 4.2: Cost matrix of the proposed game

		Player B: $N-1$ operators in $\mathcal{N} \setminus \{i\}$	
		ON	**OFF**
Player A: Operator i	**ON**	$C_{const} + C_{tr}^{(m)}$	$C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot N_{roam}^{(i,m)}$
	OFF	$C_{roam}^{(m)}$	$C_{inc}^{(i,0)}$

The costs in Table 4.2 correspond to the different cases of the infrastructure sharing algorithm described in Section 4.3.1, after applying the simplification mentioned above. The formulation of our problem in a strategic form reveals one pure strategy, corresponding to the case where the MNOs switch off in all peripheral cells, thus minimizing the number of active BSs. However, this strategy would require major transmission power increase of the central BSs and could lead to lost sessions, since the central cells may not have sufficient capacity to support all the traffic of the cluster. This limitation of the pure strategy, along with the motivation of the MNOs to achieve energy efficiency without sacrificing ubiquitous service in the network, have motivated us to study the problem in the mixed strategies domain, in order to provide feasible and applicable solutions for distributed systems. Therefore, we proceed to a mixed strategy approach, where the MNOs randomize over the possible actions with a certain probability distribution. In the next section, we calculate the strategy that minimizes the cost of each player, and, then, by exploiting the symmetry of the game, we prove that a DSE is achieved.

4.3.2.2 Individual Cost Minimization Analysis

In this section, we estimate the strategy that attains the minimum individual cost of each player according to the adopted cost-based functions. The aim of the game is to calculate the set of the switching off probabilities that minimizes the expected cost of MNO_i, $\forall i \in N$, given by:

$$\mathbb{E}[C_{i,m}] = \mathbb{E}[C_{i,m}^{ON,ON}] + \mathbb{E}[C_{i,m}^{OFF,OFF}] + \mathbb{E}[C_{i,m}^{OFF,ON}] + \mathbb{E}[C_{i,m}^{ON,OFF}]. \tag{4.1}$$

To that end, we define as $s_{i,m}$ the probability of player A (i.e., MNO_i) switching off the $BS_{i,m}$. Furthermore, due to the symmetry of the game, the remaining

$N-1$ operators are grouped together into player B, having a common switching off probability $s_{j,m}$. Subsequently, the expected costs of player A in each state of the game are estimated as follows:

1. *Case 1 (ON,ON)*: The expected cost for operator i (player A) is:
$$\mathbb{E}[C_{i,m}^{ON,ON}] = (1-s_{i,m}) \cdot (1-s_{j,m})^{N-1} \cdot \left(C_{const} + C_{tr}^{(m)}\right). \tag{4.2}$$

2. *Case 2 (ON,OFF)*: Each of the $N_{OFF}^{(m)}$ switched off BSs randomly selects one of the $N_{ON}^{(m)}$ active BSs of the same cell m with equal probability $p_s = 1/N_{ON}^{(m)}$. The random decision does not affect the outcome of our approach, since the roaming cost is indifferent to the BS selection. Hence, the number of switched off BSs that will select operator i to serve their traffic ($N_{roam}^{(i,m)}$) will determine its actual cost. To calculate the expected cost, all the possible roaming combinations that involve the ith operator must be taken into account. Therefore:
$$\begin{aligned}\mathbb{E}[C_{i,m}^{ON,OFF}] = &\sum_{N_{ON}^{(m)}=1}^{N-1} (1-s_{i,m}) \cdot \binom{N-1}{N_{ON}^{(m)}-1} \cdot (1-s_{j,m})^{N_{ON}^{(m)}-1} \cdot s_{j,m}^{N-N_{ON}^{(m)}} \\ &\cdot \left[\sum_{N_{roam}^{(i,m)}=0}^{N-N_{ON}^{(m)}} \binom{N-N_{ON}^{(m)}}{N_{roam}^{(i,m)}} \cdot p_s^{N_{roam}^{(i,m)}} \cdot (1-p_s)^{(N-N_{ON}^{(m)}-N_{roam}^{(i,m)})} \right. \\ &\left. \cdot \left(C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot N_{roam}^{(i,m)}\right) \right] \Rightarrow \\ \mathbb{E}[C_{i,m}^{ON,OFF}] = &\sum_{N_{ON}^{(m)}=1}^{N-1} (1-s_{i,m}) \cdot \binom{N-1}{N_{ON}^{(m)}-1} \cdot (1-s_{j,m})^{N_{ON}^{(m)}-1} \cdot s_{j,m}^{N-N_{ON}^{(m)}} \\ &\cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot \frac{N-N_{ON}^{(m)}}{N_{ON}^{(m)}}\right].\end{aligned} \tag{4.3}$$

3. *Case 3 (OFF,ON)*: In this case, the traffic of the switched off $BS_{i,m}$ is roamed to one active BS, with an expected cost:
$$\mathbb{E}[C_{i,m}^{OFF,ON}] = s_{i,m} \cdot \left(1-(1-s_{j,m})^{N-1}\right) \cdot C_{roam}^{(m)}. \tag{4.4}$$

4. *Case 4 (OFF,OFF)*: The BSs of all operators are switched off and the traffic is served by the corresponding BSs of the central cell, which increase their transmission power to cover the peripheral cell, with an expected cost:
$$\mathbb{E}[C_{i,m}^{OFF,OFF}] = s_{i,m} \cdot s_{j,m}^{N-1} \cdot C_{inc}^{(i,0)}. \tag{4.5}$$

Substituting Eq. (4.2)-(4.5) to Eq. (4.1), we derive:

$$
\begin{aligned}
\mathbb{E}[C_{i,m}] = {} & s_{i,m} \cdot s_{j,m}^{N-1} \cdot C_{inc}^{(i,0)} + s_{i,m} \cdot \left(1 - (1 - s_{j,m})^{N-1}\right) \cdot C_{roam}^{(m)} \\
& + \sum_{N_{ON}^{(m)}=1}^{N} (1 - s_{i,m}) \cdot \binom{N-1}{N_{ON}^{(m)} - 1} \cdot (1 - s_{j,m})^{N_{ON}^{(m)}-1} \cdot s_{j,m}^{N-N_{ON}^{(m)}} \\
& \cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot \frac{N - N_{ON}^{(m)}}{N_{ON}^{(m)}}\right].
\end{aligned}
\tag{4.6}
$$

Let us recall that the goal of each operator to estimate its individual switching off probability that minimizes its cost. To that end, the best response of $s_{i,m}$ to the strategy $s_{j,m}$ is given by calculating the roots of the partial derivative of the expected cost function with respect to $s_{i,m}$:

$$
\begin{aligned}
\frac{\partial \mathbb{E}[C_{i,m}]}{\partial s_{i,m}} = 0 \Rightarrow {} & s_{j,m}^{N-1} \cdot C_{inc}^{(i,0)} + \left(1 - (1 - s_{j,m})^{N-1}\right) \cdot C_{roam}^{(m)} \\
& - \sum_{N_{ON}^{(m)}=1}^{N} \binom{N-1}{N_{ON}^{(m)} - 1} \cdot (1 - s_{j,m})^{N_{ON}^{(m)}-1} \cdot s_{j,m}^{N-N_{ON}^{(m)}} \\
& \cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot \frac{N - N_{ON}^{(m)}}{N_{ON}^{(m)}}\right] = 0.
\end{aligned}
\tag{4.7}
$$

Having provided the analysis for the best response strategy, in the following section, we exploit the symmetry of the game to prove that the estimated value for the $s_{j,m}$ corresponds to the DSE.

4.3.2.3 DSE Characterization and Numerical Results

According to [87][Definition 3.4]:

Definition 2. *A strategy profile $\boldsymbol{s}^* = \{s_1^* \dots s_n^*\} \in \mathcal{S}$ is the DSE if every element s_i^* of $\boldsymbol{s}^*$ is a dominant strategy of player i.*

Proposition 1. *The equilibrium of the game Γ is a DSE and is calculated as:*

$$
\begin{aligned}
& {s^*}^{N-1} \cdot C_{inc}^{(i,0)} + \left(1 - (1 - s^*)^{N-1}\right) \cdot C_{roam}^{(m)} - \sum_{N_{ON}^{(m)}=1}^{N} \binom{N-1}{N_{ON}^{(m)} - 1} \\
& \quad \cdot (1 - s^*)^{N_{ON}^{(m)}-1} \cdot s^{*N-N_{ON}^{(m)}} \cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot \frac{N - N_{ON}^{(m)}}{N_{ON}^{(m)}}\right] = 0.
\end{aligned}
\tag{4.8}
$$

Proof. Going back to Definition 2, we want to calculate the strategy s_i^* that minimizes the expected cost of player i in the system. Furthermore, the symmetry of the game suggests that all MNOs have identical switching off probabilities, i.e., $s_{i,m} = s_{j,m}$. By substituting these probabilities in Eq. (4.7), we can obtain the strategy s^*, thus deriving Eq. (4.8). The roots of Eq. (4.8) correspond to the strategy of all players that minimizes the individual cost of each player.

According to [87][Definition 3.4]:

A strategy profile $\mathbf{s}^* = \{s_1^* \dots s_n^*\} \in \mathcal{S}$ is the DSE if every element s_i^* of $\mathbf{s}^*$ is a dominant strategy of player i.

In our particular case, we estimate the solution s_i^* of the game, such as:

$$\mathbf{E}[C_i](s_i^*, s_{-i}^*) \leq \mathbf{E}[C_i](s_i, s_{-i}^*) \forall i \in \mathcal{N}. \tag{4.9}$$

Following this approach, we derive a strategy profile that is common for all operators, i.e., $s_i^* = s^*$. Each element s^* is the dominant strategy for a given player, as it minimizes her expected cost, irrespectively of the strategies of the other players. Consequently, the solution, calculated in Eq. (4.8), is proven to be a DSE in our game. □

Proposition 2. *The DSE of the game* Γ *is unique.*

Proof. Having highlighted the symmetry of the game in Section 4.3.2.3 and by using the equality $s_{i,m} = s_{j,m} = s^*$, we will show that, under specific conditions and reasonable assumptions, the proposed game has a unique mixed strategy DSE. To begin with, Eq. (4.6) is rewritten as follows:

$$\mathbb{E}[C_{i,m}] = {s^*}^N \cdot C_{inc}^{(i,0)} + s^* \cdot \left(1 - (1-s^*)^{N-1}\right) \cdot C_{roam}^{(m)} \cdot \sum_{N_{ON}^{(m)}=1}^{N} (1-s^*) \cdot \binom{N-1}{N_{ON}^{(m)}-1} \cdot (1-s^*)^{N_{ON}^{(m)}-1} \cdot {s^*}^{N-N_{ON}^{(m)}} \cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)}\right) \cdot \frac{N-N_{ON}^{(m)}}{N_{ON}^{(m)}}\right]. \tag{4.10}$$

Each operator has as an upper goal to estimate its individual switching off probability that minimizes its cost. To that end, we calculate the roots of the partial derivative of the expected cost function with respect to s^*. Thus, we have:

$$\begin{aligned}
&\frac{\partial \mathbb{E}[C_{i,m}]}{\partial s^*} = 0 \Rightarrow N \cdot {s^*}^{N-1} \cdot C_{inc}^{(i,0)} \\
&+ \left(\left(s^* + s^* \cdot (N-1) \cdot (1-s^*)^{N-2} \right) + \left(1 - (1-s^*)^{N-1} \right) \right) \cdot C_{roam}^{(m)} \\
&+ \Bigg[\sum_{N_{ON}^{(m)}=1}^{N} \binom{N-1}{N_{ON}^{(m)}-1} \left(N - N_{ON}^{(m)} \right) (1-s^*)^{N_{ON}^{(m)}} {s^*}^{N-N_{ON}^{(m)}-1} \\
&- \sum_{N_{ON}^{(m)}=1}^{N} \binom{N-1}{N_{ON}^{(m)}-1} N_{ON}^{(m)} (1-s^*) {s^*}^{N-N_{ON}^{(m)}} \Bigg] \\
&\cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)} \right) \cdot \frac{N - N_{ON}^{(m)}}{N_{ON}^{(m)}} \right].
\end{aligned} \tag{4.11}$$

According to Heine-Borel Theorem [88], there exists a unique solution to our problem if the cost function is concave, by showing that the second derivative of Eq. (4.10) is always positive and the first derivative has opposite sign in the limits of the interval $[0, 1]$. The second derivative of the expected cost function with respect to s^* is derived as follows:

$$\begin{aligned}
&\frac{\partial \mathbb{E}[C_{i,m}]}{\partial s^* \cdot \partial s^*} = 0 \Rightarrow \\
&N \cdot (N-1) \cdot {s^*}^{N-2} \cdot C_{inc}^{(i,0)} \\
&+ (1-s^*)^{N-3} \cdot (N-1) \cdot (N-2) \cdot (1 + (N-3) \cdot s^*) \cdot C_{roam}^{(m)} \\
&+ \sum_{N_{ON}^{(m)}=1}^{N} \binom{N-1}{N_{ON}^{(m)}-1} \cdot (1-s^*)^{N_{ON}^{(m)}-2} \cdot {s^*}^{N-N_{ON}^{(m)}-1} \cdot \left[s^* \cdot N_{ON}^{(m)} \cdot \left(N_{ON}^{(m)} + 1 \right) \right. \\
&+ \left. \left(N - N_{ON}^{(m)} \right) \cdot \left(N - N_{ON}^{(m)} - 1 \right) \cdot (1-s^*) \right. \\
&\cdot \left[C_{const} + C_{tr}^{(m)} + \left(C_{tr}^{(m)} - C_{roam}^{(m)} \right) \cdot \frac{N - N_{ON}^{(m)}}{N_{ON}^{(m)}} \right].
\end{aligned} \tag{4.12}$$

We examined the estimated derivative of Eq. (4.12) and we found out that it is positive for the following realistic values of variables: *i)* $N = \{2, 3, \ldots, 6\}$, *ii)* $C_{const} \in [465.1, 598.3]$€, *iii)* $C_{tr}^{(m)} \in [4.8, 591.6]$€, *iv)* $C_{inc}^{(i,0)} \in [5.4, 613.1]$€, and *v)* $C_{roam}^{(m)} = \alpha \cdot \left(C_{const} + C_{tr}^{(m)} \right)$, with $\alpha \in [0, 1]$. Provided that the second derivative is always positive, the first derivative is an increasing function with a unique solution for s^* in the interval $s^* \in [0, 1]$. □

Unlike other widely-employed game theoretic concepts (e.g., Nash Equilibrium (NE)) that require a number of iterations before converging to an acceptable solution [89], [90], [91], DSE can be always achieved in one-shot, something that is particularly important in our case. More specifically, such solutions cannot be adopted due to the particular nature of the problem in our study. The continuous interchangeable switching on and off of the macro BSs is not considered as an option by the mobile operators [4], [87] and, as a result, even a small number of iterations would not be a viable solution. However, our practical and realistic formulation of the game enables the operators to reach the DSE by estimating one-shot switching off probabilities, which is particularly important in our problem. Hence, instead of applying an iterative algorithm that follows the best response dynamics to converge to an equilibrium point, we demonstrate that one operator can estimate the DSE switching off strategies by knowing only the total number of operators (N) in the network.

Having derived the theoretical expression for the mixed strategies DSE, we study the impact of the number of MNOs N and the roaming cost parameter α on the switching off probabilities through some numerical results, presented in Table 4.3. The cost values are calculated based on the average traffic volume, given the Fig. 4.1(b). We consider values from $N = 2$ up to $N = 6$ operators, while we assume five different values for α ($\alpha = 0.1$, $\alpha = 0.3$, $\alpha = 0.5$, $\alpha = 0.7$ and $\alpha = 0.9$) with respect to the definition of roaming cost in Section 4.3.1.

TABLE 4.3: DSE Switching Off Probabilities

N	$a = 0.1$	$a = 0.3$	$a = 0.5$	$a = 0.7$	$a = 0.9$
2	0.459	0.377	0.296	0.215	0.133
3	0.679	0.629	0.568	0.486	0.357
4	0.799	0.749	0.675	0.584	0.466
5	0.854	0.826	0.795	0.758	0.713
6	0.880	0.861	0.843	0.819	0.798

Two main conclusions can be derived from Table 4.3. First, the DSE switching off probabilities increase with the number of MNOs in each cell. In particular, the coexistence of many operators in one cell motivates a given MNO to switch off its BS, as it implies a higher probability of having its traffic roamed to a different MNO. Regarding the second basic observation, as expected, the switching off probability decreases for higher roaming cost, which is a prohibitive factor for the BS deactivation. However, it is worth noting that the DSE probability is severely reduced for higher roaming in networks with few MNOs, due to the risk of switching off all BSs in the cell. On the other hand, in a network with many MNOs, where the aforementioned risk is not so evident, the switching off probability for high a is still significant.

In addition, we compare the DSE to the global optimal solution to provide further insights for our game formulation. We further analyze how our non-cooperative solution that obtains the DSE, is compared to a global and centralized solution. In Fig. 4.3, we illustrate the DSE for different number of MNOs, along with the global optimal solution (Pareto optimal), that represents the solution with the minimum expected cost. The DSE switching off probabilities result in low cost values that are very close to the optimal ones. In addition, it is worth noticing the difference between DSE and Pareto optimal points varies with the number of MNOs. In particular, the presence of numerous participants in the network leads to higher differences, thus requiring the precise calculation of the DSE in order to avoid undesirable higher cost. However, in most typical scenarios in European countries where $N = 4$ operators are involved [59], our proposed game theoretic formulation estimates accurate, close to optimal switching off probabilities.

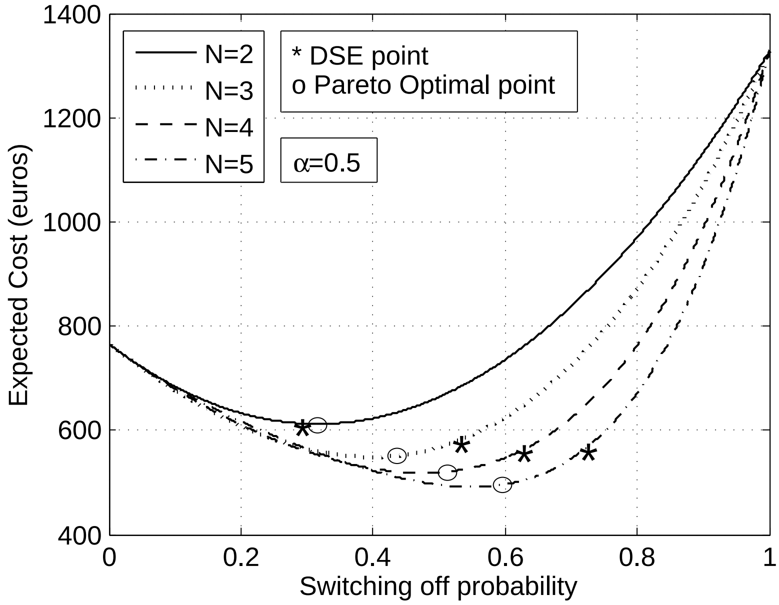


FIGURE 4.3: The DSE point and the global optimal solution for different number of users

4.4 Performance Metrics Analysis

In this section, we provide the analytical expressions and definitions for the calculation of the network throughput, energy efficiency and financial cost, when the infrastructure sharing algorithm is applied.

As mentioned in Section 4.2, the network traffic consists of voice and data, with constant bit rates R_V and R_D, respectively. We assume that for each $BS_{n,m}$, voice calls and data sessions are Poisson generated processes with rates $\lambda_V^{(n,m)}$ and $\lambda_D^{(n,m)}$ and have exponential service times, denoted by $1/\mu_V^{(n,m)}$ and $1/\mu_D^{(n,m)}$, respectively. Hence, we model the operation of $BS_{n,m}$ as a multi-server $M_1, M_2/G_1, G_2/N/N_1, N_2$ queue, resulting in a two-dimensional Markov chain, illustrated in Fig. 4.4. Each state of the system (ν, d) is characterized by the number of active voice and data sessions, denoted by ν and d, respectively. The state space of this Markov model, along with the bandwidth restrictions, is:

$$\mathcal{A} = \{(\nu, d)\,|0 \leq \nu \leq N_V, 0 \leq d \leq N_D, \nu \cdot R_V + d \cdot R_D \leq CR_{BS}\}, \tag{4.13}$$

given that CR_{BS} is the total bandwidth of the BS, $N_V = CR_{BS}/R_V$ and $N_D = CR_{BS}/R_D$ represent the maximum number of simultaneous voice calls and data sessions, respectively.

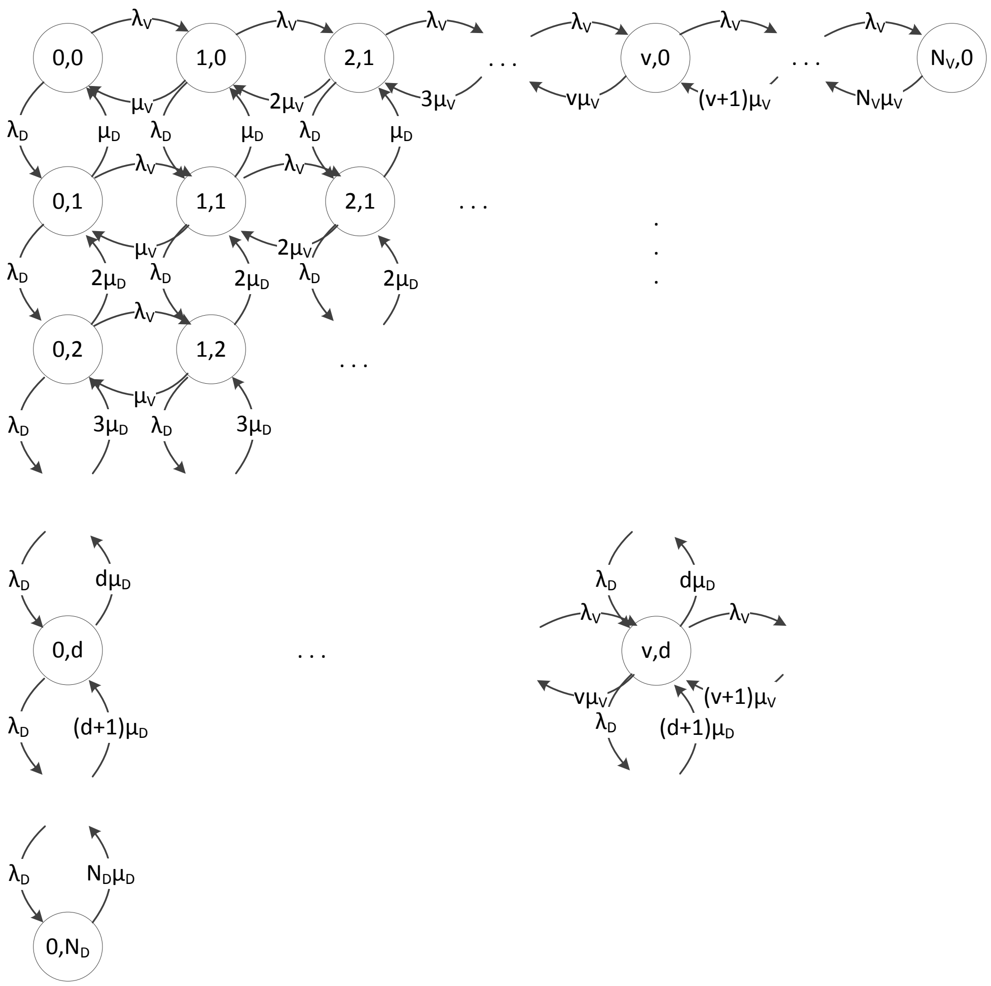


FIGURE 4.4: Two-dimensional Markov state transition diagram for the voice and data traffic served in a BS

By analyzing the state transition diagram (Fig. 4.4), we can obtain the system of linear equations for steady state probabilities, $p_{(\nu,d)}$. The balance equation that represents the valid transitions is:

$$
\begin{aligned}
p_{(\nu,d)} \cdot \Big(\lambda_V^{(n,m)} \cdot \varphi_{\nu+1,d} + \lambda_D^{(n,m)} \cdot \varphi_{\nu,d+1} \cdot \vartheta_{\nu,d+1} + \nu \cdot \mu_V^{(n,m)} \cdot \varphi_{\nu-1,d} + d \cdot \mu_D^{(n,m)} \cdot \varphi_{\nu,d-1}\Big) \\
= \lambda_V^{(n,m)} \cdot p_{(\nu-1,d)} \cdot \varphi_{\nu-1,d} + \lambda_D^{(n,m)} \cdot p_{(\nu,d-1)} \cdot \varphi_{\nu,d-1} \cdot \vartheta_{\nu,d} \\
+ (\nu+1) \cdot \mu_V^{(n,m)} \cdot p_{(\nu+1,d)} \cdot \varphi_{\nu+1,d} + (d+1) \cdot \mu_D^{(n,m)} \cdot p_{(\nu,d+1)} \cdot \varphi_{\nu,d+1},
\end{aligned}
\tag{4.14}
$$

where $\varphi_{\nu,d}$, $\vartheta_{\nu,d}$ denote the characteristic functions:

$$
\varphi_{\nu,d} = \begin{cases} 1, (\nu,d) \in \mathcal{A} \\ 0,\text{otherwise} \end{cases} \tag{4.15}
$$

and

$$\vartheta_{\nu,d} = \begin{cases} 1, \nu \cdot R_V + d \cdot R_D \leq CR_{BS} \\ 0, \text{otherwise} \end{cases} \tag{4.16}$$

The steady state probabilities are calculated given the condition that the sum of the state probabilities is equal to 1, which must be satisfied:

$$\sum_{\nu=0}^{N_V} \sum_{d=0}^{\lfloor \frac{BW - \nu \cdot R_V}{R_D} \rfloor} p_{(\nu,d)} = 1. \tag{4.17}$$

In continuation, employing the steady state probabilities of the Markov chain, we define and calculate some key performance metrics both for the individual BSs and the whole network.

4.4.1 Operator-wide performance metrics

In this section, we analyze the performance of a $BS_{n,m}$ with total bandwidth of BW, belonging to operator n in a given cell m. We focus on the night zone, with duration t_{night}, when voice and data sessions have an average generation rate of $\lambda_V^{(n,m)}$ and $\lambda_D^{(n,m)}$, respectively.

4.4.1.1 Cell Throughput

Definition 3. *Cell Throughput: The expected throughput* $\mathbb{E}[T_{n,m}]$ *for the* $BS_{n,m}$ *is defined as the average number (over all possible states of the system) of served sessions in the system multiplied by the transmission rate of each session (i.e.,* R_V *and* R_D *for voice and data, respectively) and calculated as:*

$$\mathbb{E}[T_{n,m}] = \sum_{\nu=0}^{N_V} \sum_{d=0}^{\lfloor \frac{CR_{BS} - \nu \cdot R_V}{R_D} \rfloor} (\nu \cdot R_V + d \cdot R_D) \cdot p_{(\nu,d)}, \tag{4.18}$$

where $p_{(\nu,d)}$ *are the steady state probabilities for the given traffic load rates* $\lambda_V^{(n,m)}$ *and* $\lambda_D^{(n,m)}$*.*

In addition, a very important metric in our work is the normalized throughput, defined as the ratio of the served connections to the total existing connections in the network. This metric is often employed to represent the GoS in telecommunication systems, showing the level of user satisfaction in the system. Achieving a normalized throughput of 100% signifies that all users are served, which is a key requirement for MNOs.

4.4.1.2 Cell Energy Efficiency

Definition 4. *Cell Energy Efficiency: The expected energy efficiency $\mathbb{E}[\eta_{\epsilon}^{(n,m)}]$ for $BS_{n,m}$ is defined as the ratio of the average transmitted bits $\mathbb{E}\left[B_{n,m}\right]$ over the average energy consumption $\mathbb{E}\left[E_{n,m}\right]$:*

$$\mathbb{E}[\eta_{\epsilon}^{(n,m)}] = \frac{\mathbb{E}\left[B_{n,m}\right]}{\mathbb{E}\left[E_{n,m}\right]}. \tag{4.19}$$

The average transmitted bits during the night zone can be calculated by multiplying the average throughput given in Eq. (4.18) with the duration of the night zone t_{night}:

$$\mathbb{E}\left[B_{n,m}\right] = \mathbb{E}\left[T_{n,m}\right] \cdot t_{night}. \tag{4.20}$$

To calculate the average energy consumption, we should take into account the power consumed by the BS for operation and transmission, consisting of three components: *i*) the constant power P_{const}, consumed by an active BS for operations such as cooling, antenna feeding, etc, *ii*) the idle power P_{idle}, which is the power consumed when the BS remains idle, i.e., when it has no ongoing traffic sessions[2], and *iii*) the transmission power for serving the ongoing traffic sessions corresponding to each state $p_{(\nu,d)}$, considering that P_{tx} denotes the transmission power for serving a single voice or data session. Hence, the average energy consumption during the night zone t_{night} is given by:

$$\mathbb{E}\left[E_{n,m}\right] = \left(P_{const} + P_{idle} \cdot p_{(0,0)} + \sum_{\nu=0}^{N_V} \sum_{d=0}^{\lfloor \frac{CR_{BS} - \nu \cdot R_V}{R_D} \rfloor} (\nu + d) \cdot P_{tx} \cdot p_{(\nu,d)} \right) \cdot t_{night}. \tag{4.21}$$

4.4.1.3 Cost

In this section, we provide analytical expressions for the different terms (i.e., C_{const}, $C_{tr}^{(n,m)}$, $C_{inc}^{(n,0)}$, $C_{roam}^{(n,m)}$) that compose Eq. (4.6), which provides the expected cost for an operator.

First, C_{const}, $C_{tr}^{(n,m)}$ and $C_{inc}^{(n,0)}$ refer to the costs related to the operation of an active BS and the service of the existing traffic. These costs depend directly on the energy that is consumed for the different functionalities of the BSs. Therefore, provided that c_1 is the electricity charge per energy unit, in [€$/kWh$], the operational costs of a BS can be expressed as a function of the average energy consumption [92]. Thus, we have:

$$C_{const} = c_1 \cdot P_{const} \cdot t_{night}, \tag{4.22}$$

[2] The fraction of time that the BS remains idle is expressed by the probability $p_{(0,0)}$ in the Markov chain (Fig. 4.4).

$$C_{tr}^{(n,m)} = c_1 \cdot \left(P_{idle} \cdot p_{(0,0)} + \sum_{\nu=0}^{N_V} \sum_{d=0}^{\lfloor \frac{BW-\nu \cdot R_V}{R_D} \rfloor} (\nu + d) \cdot P_{tx} \cdot p_{(\nu,d)} \right) \cdot t_{night}, \tag{4.23}$$

$$C_{inc}^{(n,0)} = c_1 \cdot \left(P'_{idle} \cdot p_{(0,0)} + \sum_{\nu=0}^{N_V} \sum_{d=0}^{\lfloor \frac{BW-\nu \cdot R_V}{R_D} \rfloor} (\nu + d) \cdot P'_{tx} \cdot p_{(\nu,d)} \right) \cdot t_{night}, \tag{4.24}$$

where P'_{idle} and P'_{tx} denote the power consumed when the BS remains idle and the transmission power for serving a single voice or data session, when the central BS increases its power.

With regard to the roaming cost, $C_{roam}^{(n,m)}$ corresponds to the amount paid when an operator roams its traffic to the BSs of another operator. In Section 4.3.1, we have already given the definition of the roaming cost with respect to C_{const} and $C_{tr}^{(n,m)}$. In this subsection, we extend this definition considering the electricity charges for the operation and the traffic service. Based on the energy consumption of a BS, $\mathbb{E}[E_{n,m}]$, the roaming cost is given by:

$$C_{roam}^{(n,m)} = \alpha \cdot c_1 \cdot \mathbb{E}[E_{n,m}]. \tag{4.25}$$

4.4.1.4 Cost efficiency

Having defined theoretical expressions for the network performance and cost, we introduce a novel metric, namely cost efficiency, that connects the performance with the total cost for each operator.

Definition 5. *Cell Cost Efficiency, measured in $[Mbits/€]$, is defined as the ratio of the average transmitted bits over the operator's total expenses. Accordingly, the cost efficiency of an operator n in a peripheral cell m is expresses as:*

$$\mathbb{E}[\eta_c^{n,m}] = \frac{\mathbb{E}[B_{n,m}]}{\mathbb{E}[C_{n,m}]}. \tag{4.26}$$

4.4.2 Network-wide performance metrics

In continuation, we calculate the above metrics for the network of N operators in a cluster of one central and M peripheral cells, for the proposed infrastructure sharing algorithm. Based on the game theoretic analysis presented in Section 4.3.2, each operator n may choose to switch off the BS of a peripheral cell m with a switching off probability s^*. As explained before, depending on the case, the traffic of each switched off BS is served either by the central BS of the same operator, or by a different operator of the same cell.

To calculate the global performance metrics of the network, we calculate the average traffic load that is served by each BS after the application of the infrastructure sharing algorithm. We define as $\lambda_J^{'(n,m)}, J = \{V, D\}$ the new average traffic load of the $BS_{n,m}$ for voice and data traffic, which is equal to the traffic $\lambda_J^{(n,m)}$ of the nth operator plus any additional traffic of a switched off BS that must be served by $BS_{n,m}$. We distinguish the cases for the central and the peripheral cells in the network:

- For each $BS_{n,0}$ of the central cell:

$$\lambda_J^{'(n,0)} = \lambda_J^{(n,0)} + \sum_{i \in \mathcal{M}_{OFF}} \lambda_J^{(n,i)}. \tag{4.27}$$

- For each $BS_{n,m}$ of the peripheral cells ($m \in [1, M]$) that remains active:

$$\lambda_J^{'(n,m)} = \lambda_J^{(n,m)} + \sum_{i \in \mathcal{N}_{roam}^{(n,m)}} \lambda_J^{(i,m)}, \tag{4.28}$$

  where $\mathcal{N}_{roam}^{(n,m)}$ is the subset of operators that roam their traffic to $BS_{n,m}$.

Using these values for the traffic load, the steady state probabilities $p'_{(\nu,d)}$ for each BS are recalculated and employed for the estimation of the key network metrics, as explained below.

4.4.2.1 Total Network Throughput

Definition 6. *Total Network Throughput: The total throughput of the cluster network, $\mathbb{E}[T]$, is the sum of the average throughput of the active BS in the M peripheral cells plus the average throughput of the central cell that always remains active:*

$$\begin{aligned}\mathbb{E}[T] = &\sum_{M_{OFF}=0}^{M} \binom{M}{M_{OFF}} \cdot {s^*}^{N \cdot M_{OFF}} \cdot \left(1 - {s^*}^{N}\right)^{(M-M_{OFF})} \\ &\cdot \sum_{N_{OFF}^{(m)}=0}^{N-1} \binom{N}{N_{OFF}^{(m)}} \cdot {s^*}^{N_{OFF}^{(m)}} \cdot (1-s^*)^{N-N_{OFF}^{(m)}} \\ &\cdot \left(\sum_{m \in \mathcal{M}_{ON}} \sum_{n \in \mathcal{N}_{ON}^{(m)}} \left(\mathbb{E}\left[T'_{n,m}\right]\right) + \sum_{n \in \mathcal{N}} \cdot \mathbb{E}\left[T'_{n,0}\right] \right),\end{aligned} \tag{4.29}$$

where $\mathbb{E}[T'_{n,m}]$ is the average throughput of an active $BS_{n,m}$ of a peripheral cell and can be calculated by Eq. (4.18) by taking into account the average traffic load given by Eq. (4.28). Similarly, $\mathbb{E}[T'_{n,0}]$ is the average throughput of the central BSs, with average traffic load given by Eq. (4.27).

4.4.2.2 Total Network Energy Efficiency

Definition 7. *Total Network Energy Efficiency: The total energy efficiency* $\mathbb{E}[\eta_\epsilon]$ *in the cell cluster is calculated as the total number of transmitted bits* $\mathbb{E}[B]$ *divided by the total energy consumption* $\mathbb{E}[E]$*:*

$$\mathbb{E}[\eta_\epsilon] = \sum_{M_{OFF}=0}^{M} \binom{M}{M_{OFF}} \cdot {s^*}^{N \cdot M_{OFF}} \cdot \left(1 - {s^*}^{N}\right)^{(M-M_{OFF})} \cdot \frac{\mathbb{E}[B]}{\mathbb{E}[E]}. \tag{4.30}$$

Similarly to Eq. (4.29), the total number of transmitted bits is calculated as:

$$\begin{aligned} \mathbb{E}[B] = \sum_{N_{OFF}^{(m)}=0}^{N-1} \binom{N}{N_{OFF}^{(m)}} \cdot {s^*}^{N_{OFF}^{(m)}} \cdot (1 - s^*)^{N-N_{OFF}^{(m)}} \cdot \\ \left(\sum_{m \in \mathcal{M}_{ON}} \sum_{n \in \mathcal{N}_{ON}^{(m)}} \left(\mathbb{E}\left[B'_{n,m}\right]\right) + \sum_{n \in \mathcal{N}} \cdot \mathbb{E}\left[B'_{n,0}\right] \right), \end{aligned} \tag{4.31}$$

where $\mathbb{E}[B'_{n,m}]$ and $\mathbb{E}[B'_{n,0}]$ the average transmitted bits for the BSs of the peripheral and the central cells, respectively, calculated by Eq. (4.20) for the corresponding traffic (Eq. (4.28) and (4.27)).

Accordingly, the total energy consumption is derived as:

$$\begin{aligned} \mathbb{E}[E] = \sum_{N_{OFF}^{(m)}=0}^{N-1} \binom{N}{N_{OFF}^{(m)}} \cdot {s^*}^{N_{OFF}^{(m)}} \cdot (1 - s^*)^{N-N_{OFF}^{(m)}} \cdot \\ \left(\sum_{m \in \mathcal{M}_{ON}} \sum_{n \in \mathcal{N}_{ON}^{(m)}} \left(\mathbb{E}\left[E'_{n,m}\right]\right) + \sum_{n \in \mathcal{N}} \cdot \mathbb{E}\left[E'_{n,0}\right] \right). \end{aligned} \tag{4.32}$$

4.4.2.3 Total Network Cost

Definition 8. *Total Network Cost: The total cost of the network,* $\mathbb{E}[C]$*, is the sum of the average cost of all operators for the operation of their active BSs and for the service of the existing traffic load, estimated as:*

$$\mathbb{E}[C] = \mathbb{E}[E] \cdot c_1, \tag{4.33}$$

where $\mathbb{E}[E]$ *is calculated by Eq. (4.32) for the average traffic served over a year. Apparently, the total network cost is not affected by the roaming cost, which only specifies the amount of money that is going to be exchanged among the operators.*

4.5 Performance Evaluation

We have developed a custom-made C/C++ simulator for the network operation to validate the analytical expressions and assess the performance of the proposed infrastructure sharing scheme. In this section, we present the simulation setup along with the analytical and experimental results.

4.5.1 Simulation scenario

The simulation scenario includes a 7-cell cluster with one central and six peripheral cells (i.e., $M = 6$), where each cell is served by N BSs of different MNOs, as described in Section 4.2. In our experiments, we consider $N = \{2, 4, 6\}$ in order to address the impact of the number of MNOs in our proposed framework.

To assess the performance of our scheme, we compare the proposed Game Theoretic Infrastructure Sharing strategy (referred as GTIS in the rest of the paper) with three state-of-the-art approaches [55], [56]: *i)* a Roaming-to-One scheme (R-to-1), where the MNO with the highest traffic serves the total traffic in the network, while the rest MNOs switch off their BSs during the entire night zone, *ii)* a Roaming-to-All approach, namely Energy-balanced (E-bal), where the MNOs switch off their BSs for different portions of time in order to balance their energy saving, and *iii)* a Roaming-to-All approach, namely Roaming-balanced (R-bal), where the MNOs switch off their BSs for different portions of time in order to balance their roaming costs. In the Roaming-to-All strategies, the MNOs roam their traffic to all the active networks with a probability proportional to their network size. Moreover, we consider a baseline approach (No Switch Off), where all BSs are active. The simulation parameters are summarized in Table 4.4.

TABLE 4.4: Simulation Parameters for GTIS

Parameter	**Value**
Bandwidth, BW	115 Mbps
# of peripheral cells, M	6
# of operators, N	{2,4,5,6}
Traffic load, $Load$	Fig. 4.1(b)
Traffic load ratio, ρ_n	[0.1, 1.0]
Service rates, $\mu_V^{(n,m)}, \mu_D^{(n,m)}$	Mean: 1/50 calls/s
Transmission rates, R_V, R_D	64, 256 kbps
Idle power, P_{idle}	[0.34, 1.39] W
Transmission power, P_{tx}, P'_{tx}	[1.29, 1.5] W
Constant power, P_{const}	[591, 675] W
Cell radius	[500, 1500] m
Night zone duration, t_{night}	9· 3600 s
Roaming cost variable, α	[0.1, 1.0]
Electricity charge, c_1	0.1 €/kWh

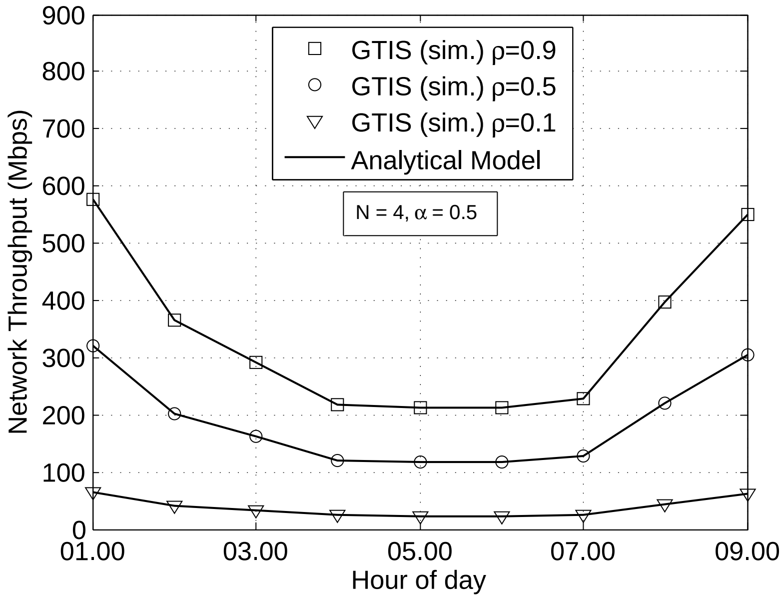
4.5.2 Model Validation

In this section, we validate via extensive simulations the analytical models for the network throughput, energy efficiency and network cost for different traffic profiles, roaming cost values and number of MNOs in each cell. In this set of experiments, we assume that all operators have the same traffic volume, i.e., $\rho_n = \rho$.

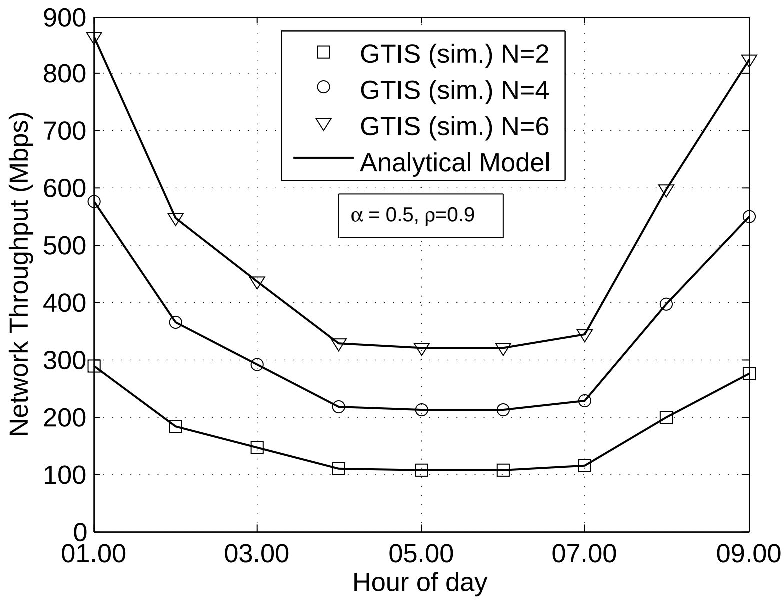
Fig. 4.5(a) and 4.5(b) present the network throughput performance for different traffic profiles and number of operators, respectively. As we can see, the experimental results perfectly match the analysis, thus validating the proposed theoretical expressions. In both figures, we observe that the throughput presents similar behavior with the traffic load model, presented in Section 4.2. As expected, the network throughput also increases with the traffic load of each operator (ρ), as well as with the number of MNOs in each cell (N). It is worth mentioning that the roaming cost does not affect the throughput performance in the case of $N = 4$ MNOs, since there are no lost calls in the network. For higher number of operators, there are missed calls and this impact will be also studied in Section 4.5.4.

Fig. 4.6 illustrates the network energy efficiency achieved by the proposed infrastructure sharing policy for different traffic profiles (Fig. 4.6(a)), number of operators (Fig. 4.6(b)) and roaming cost values (Fig. 4.6(c)), which affect the switching off probabilities and, consequently, the total energy efficiency. First, the analytical expressions given in Section 4.4 are again validated, while we observe a very similar behavior with the throughput case. More specifically, we observe that the network energy efficiency increases as the network becomes more loaded (i.e., for heavier traffic loads or higher number of operators). Hence, the proposed algorithm provides an effective energy efficient solution that encourages the operators to share their infrastructure in order to reduce the energy consumption. Furthermore, energy efficiency increases as the roaming cost drops, since lower roaming costs lead to increased switching off probabilities, as seen in Table 4.3, thus reducing the energy consumption of the network.

In order to gain more insight on the network performance, we have plotted in Fig. 4.7 the average energy efficiency during the night zone versus different traffic volumes (Fig. 4.7(a)) and roaming cost values (Fig. 4.7(b)). In Fig. 4.7(a), we observe that although the absolute value of the network energy efficiency increases with the number of operators, the relative difference ratio is independent of the traffic load. More specifically, in all cases (i.e., $\rho = 0.1, \rho = 0.5, \rho = 0.9$), a network of $N = 6$ operators is approximately 80% and 280% more energy efficient compared to networks of $N = 4$ and $N = 2$ operators, respectively. This interesting fact can be explained by taking into account that the outcome of the game theoretic algorithm (i.e., switching off probabilities) is not affected by the traffic load variations. However, the switching off probabilities are higher as the number of MNOs increases. This is explained by the fact that the number of BSs is higher when $N = 6$ operators exists and thus, there are more than enogh BSs that can be switched off when comparing to a network with $N = 2$ operators. Referring to Table 4.4, we observe that the difference between the constant power and the transmission power is significant. Thus, small variations on the traffic do not affect the probabilities calculation. On the other hand, as shown in Section 4.3.2.3,



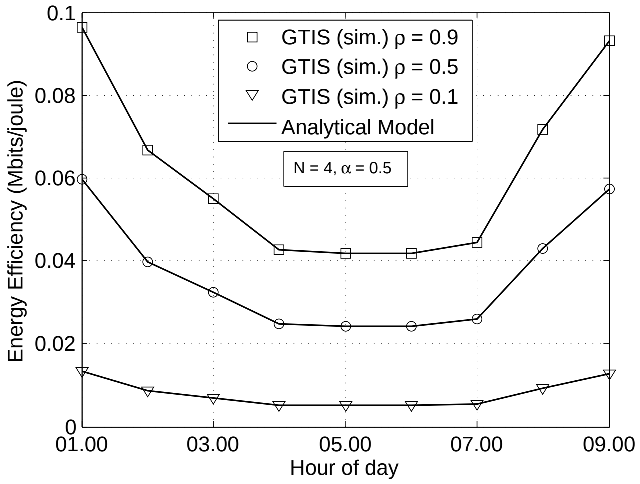
(a)



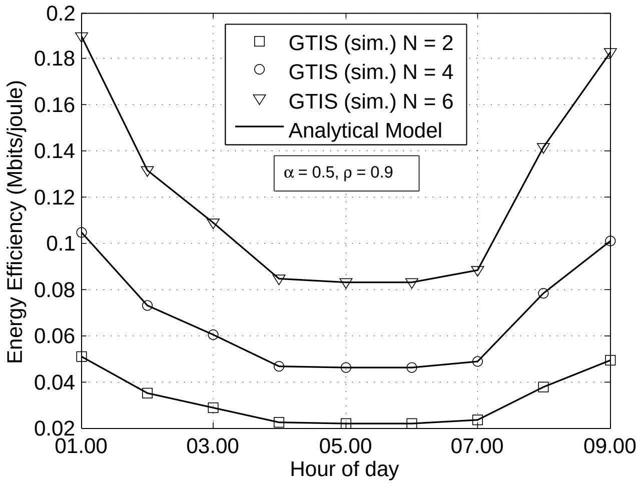
(b)

FIGURE 4.5: Throughput validation for different (a) traffic profiles, (b) number of operators

the switching off probabilities strongly depend on the roaming cost value, thus affecting the network energy efficiency (Fig. 4.7(b)). As also shown in Fig. 4.6(c), the energy efficiency is reduced as the roaming cost increases, while this impact is stronger for smaller number (N) of operators. However, the relative difference of the energy efficiency gain with respect to N increases for higher roaming costs. For instance, for low traffic loads ($\alpha = 0.1$), a network of $N = 6$ operators achieves 36% higher energy efficiency than a network of $N = 4$ operators, while this difference is considerably increased to 174% in case of $\alpha = 1.0$. This occurs because, even



(a)



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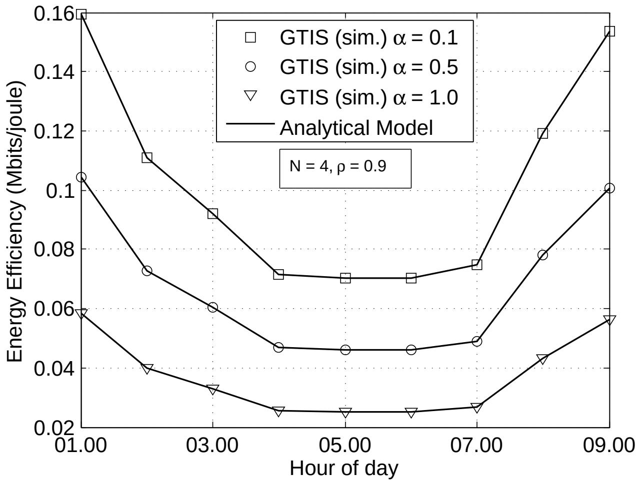
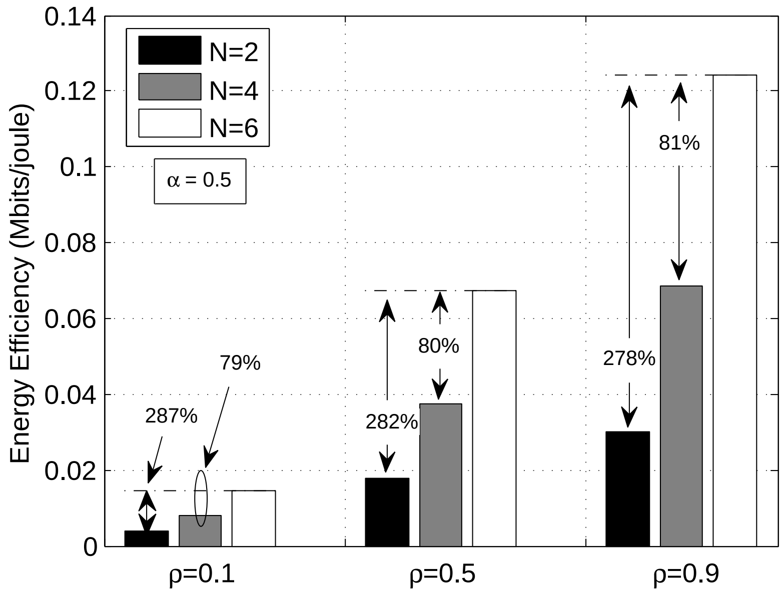


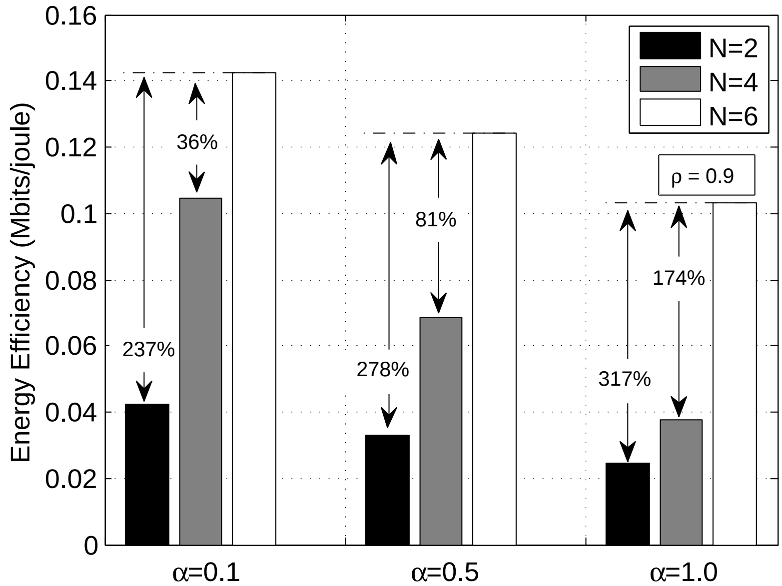
(c)

FIGURE 4.6: Energy efficiency validation for different (a) traffic profiles, (b) number of operators, and (c) roaming cost

though the switching off probabilities are low for high roaming costs, the presence of more operators leads to a higher probability of sharing the infrastructure.



(a)



(b)

FIGURE 4.7: Energy efficiency validation for different number of operators and different (a) traffic profiles, (b) roaming costs

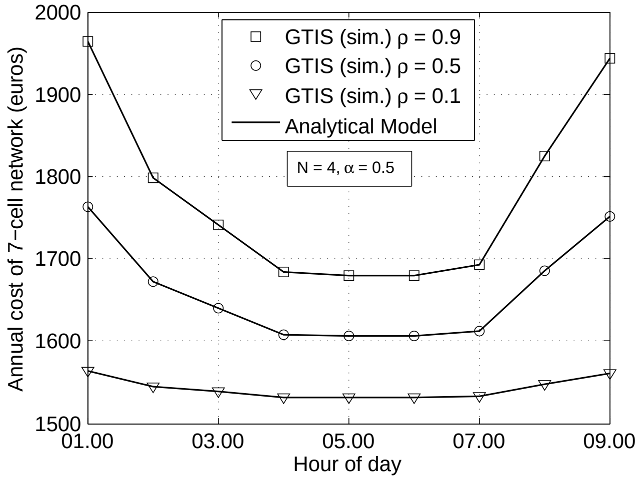
Fig. 4.8 illustrates the aggregated annual cost for different traffic profiles (Fig. 4.8(a)), number of operators (Fig. 4.8(b)) and roaming cost (Fig. 4.8(c)). The analytical expressions given in Section 4.4 are again validated, while the results follow a very similar behavior with the throughput and energy efficiency only in the case of varying traffic profiles. On the other hand, the annual cost decreases with higher number of MNOs and decreasing roaming cost values. Given the switching off probabilities, depicted in Table 4.3, in networks with high number of MNOs, the switching off probability increases, leading to smaller number of active BSs, which contribute to the total network cost according to Eq. (4.33). At this point, it is reminded that the coexistence of many MNOs in a network gives the incentive to the operators to switch off their BS, since there exists a higher number of BSs to roam the traffic of the switched off BSs. On the other hand, with increasing roaming cost, the MNOs are unwilling to switch off their BSs, resulting in higher aggregate cost.

4.5.3 Roaming Cost Analysis

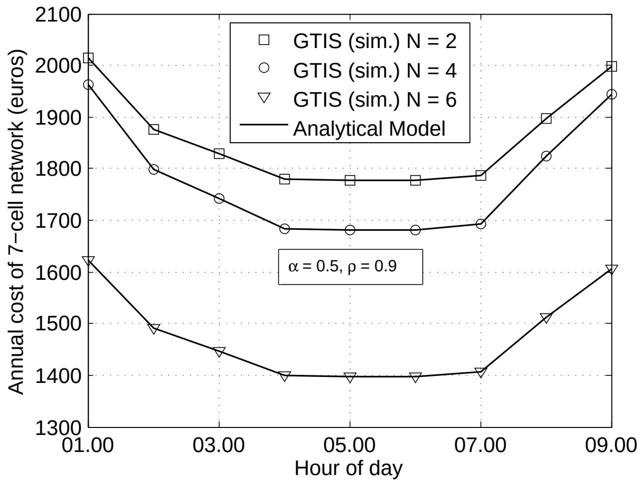
The analysis and the experiments have revealed the criticality of the roaming cost parameter in roaming-based infrastructure sharing schemes. Therefore, the selection of an appropriate range of α for the performance evaluation of our proposal becomes of paramount importance. To that end, Fig. 4.9 presents the network energy efficiency achieved by the proposal compared to four schemes for the whole range of roaming cost values. We compare GTIS with the baseline scenario (i.e., No Switch Off) and three state-of-the-art approaches (i.e., R-to-1, E-bal and R-bal), which do not depend on the roaming cost. As we already mentioned, by employing the R-to-1, the MNO with heavier traffic load concentrates the traffic of the whole network, giving the opportunity to the rest of the MNOs to switch off their BSs. In E-bal and R-bal, the MNOs switch off their BSs for different portions of time in order to achieve equal energy gains and roaming costs, respectively. As a result, the switching off time of each MNO depends on their traffic load but is independent of the specific value of the roaming cost. In Fig. 4.9, we observe that the proposed scheme outperforms the R-bal approach independently of α, while there is an interesting trade off with regard to the R-to-1 and E-bal schemes. Our proposed solution achieves higher energy efficiency for low values of α (i.e., $\alpha < 0.5$ comparing to R-to-1 and $\alpha < 0.78$ comparing to E-bal). However, performance drops as the roaming cost increases and, consequently, R-to-1 and E-bal achieve higher energy efficiency compared to our scheme for high values of alpha (i.e., $\alpha > 0.5$, $\alpha > 0.78$, respectively). When employing GTIS, for high roaming values, the operators do not have a strong incentive to switch off their BSs and roam their traffic. Since energy efficiency is one of the key goals of the proposed GTIS algorithm, we focus on the values of α that ensure enhanced energy efficiency performance with respect to the state-of-the-art schemes (i.e., $\alpha \in [0, 0.5]$). Consequently, we have selected two indicative values of α within this range (i.e., $\alpha = 0.1$ and $\alpha = 0.5$) for the performance assessment of our proposed infrastructure sharing solution.

4.5.4 Numerical Results

This section includes the performance results with regard to various metrics, either telecommunication - oriented (network throughput and energy efficiency) or cost - oriented (annual cost and cost efficiency). In order to generalize the assessment of our proposal, we consider different traffic volumes for the network operators. In particular, we assume that MNO_1 has the maximum possible traffic load (i.e.,



(a)



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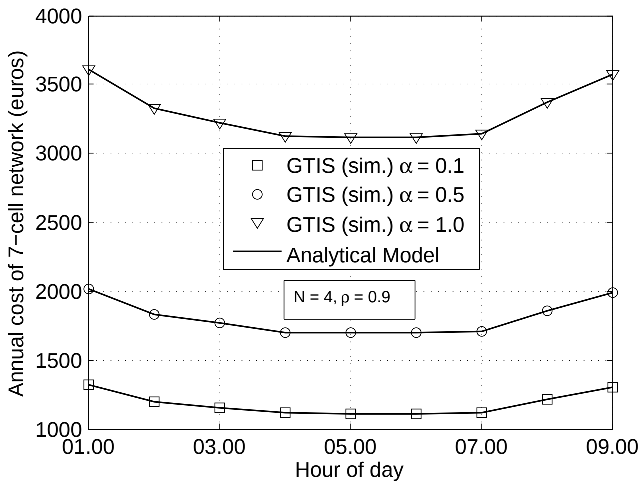


(c)

FIGURE 4.8: Annual cost of 7-cell network validation for different (a) traffic profiles, (b) number of operators, and (c) roaming cost

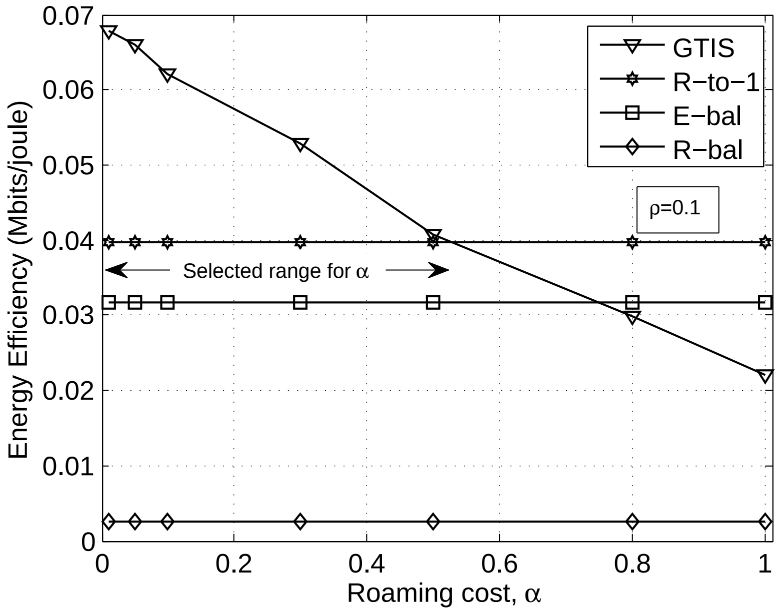


FIGURE 4.9: Energy efficiency versus roaming cost values to select the appropriate α

$\rho_1 = 1$), while the rest MNOs have a common traffic volume ρ, which is a portion of the maximum load (i.e., $\rho_2 = ... = \rho_N = \rho \in [0, 1]$).

4.5.4.1 Telecommunication Metrics

Despite the importance of estimating the absolute values of throughput in the system, the deactivation of BSs in the cells potentially implies loss of connections. To that end, we consider the normalized thoughput which is an important GoS indicator that represents the percentage of served connections in the system. Fig. 4.10 presents the normalized throughput of the three infrastructure sharing schemes for different number of operators in the network. In Fig. 4.10(a) ($N = 4$), we can see that all schemes guarantee the user service for variable traffic load conditions (i.e., $\rho < 0.8$). However, as the traffic volume grows, the R-bal, E-bal and R-to-1 approaches experience small losses (around 2% 3% and 5%, respectively), which still can be prohibitive for wireless cellular networks, while the proposed GTIS approach is able to guarantee the service of all the connections in the network. Hence, our scheme can guarantee the service of all connections for the case of $N = 4$ operators, which is highlighted as the most typical scenario in recent studies [59]. For higher number of operators, our proposal still outperforms the other three solutions and it guarantees the proper service in the network for traffic volume values up to $\rho = 0.8$ (case $N = 5$) and $\rho = 0.7$ (case $N = 6$). The degraded performance of the R-to-1 scheme is explained by the high number of deactivated BSs and the traffic service by one MNO only, whereas our approach proposes a distributed traffic roaming among the coexisting MNOs. In addition, we observe that GTIS achieves different performance with respect to the varying values of roaming cost, thus justifying once again the importance of this variable. For relatively small values of α (i.e., $\alpha = 0.1$), there are less active BSs and as a result the number of lost calls increases. However, compared to the state-of-the-art schemes, the GTIS supports higher traffic without losing any calls. For instance, in the case of $N = 6$ MNOs and $\alpha = 0.5$, the GTIS provides full traffic service, while R-bal supports up to $\rho = 0.6$, E-bal up to $\rho = 0.5$ and R-to-1 only up to $\rho = 0.2$.

Fig. 4.11 presents the network energy efficiency versus ρ for two different values of α and $N = 4$ operators. We observe that all schemes have the same behavior, since the energy efficiency increases with the traffic load. An important remark is that, for low roaming cost ($\alpha = 0.1$), GTIS significantly outperforms the baseline scenario (where no BS is switched off), as well as the three state-of-the art algorithms. However, for higher values of α, the energy efficiency gain of GTIS compared to the R-to-1 scheme gradually decreases and, eventually, the two schemes achieve similar performance for $\alpha = 0.5$. The increase of α discourages the operators to apply a switching off stratgy, due to the increased expenses. Even though the total network energy efficiency performance is the same, it is interesting to study the individual energy efficiency gains of the different MNOs. To that end, the individual gains for the specific (but representative) case of $\rho = 0.1$ and $N = 4$ are quantified in Table 4.5, where interesting conclusions can be extracted. In particular, independently of α, the R-to-1 scheme is beneficial only for the group of operators that switch off their BSs, while the operator with the active BSs faces important energy efficiency degradation. More specifically, the active operator is subject to higher energy consumption to serve the traffic of the whole network, while the rest operators theoretically achieve infinite energy efficiency, as they have their traffic served at zero energy cost. The proposed GTIS eliminates this unfairness, by guaranteeing energy efficiency gains to all operators, providing them with extra incentives to switch off their BSs by participating in the game. Comparing to the also fair E-bal and R-bal that allow all MNOs to switch off their BSs for different time periods, the respective energy efficiency gains of the GTIS approach are clearly higher due to the lower number of active BSs.

Table 4.5: Energy Efficiency Gain/Loss with Respect to the No Switch Off Scheme for $\rho = 0.1$

	$\alpha = 0.1$				$\alpha = 0.5$			
Scheme	MNO_1	MNO_2	MNO_3	MNO_4	MNO_1	MNO_2	MNO_3	MNO_4
GTIS	93.2	27.1	27.1	27.1	94.2	45.3	45.3	45.3
R-to-1	-82.3	∞	∞	∞	-82.3	∞	∞	∞
E-bal	12.3	15.6	15.6	15.6	12.3	15.6	15.6	15.6
R-bal	11.9	13.2	13.2	13.3	11.9	13.2	13.2	13.2

4.5.4.2 Cost Metrics

The aggregated annual cost of the network and the individual annual gains for the operators, having as a benchmark the No Switch Off scheme, are presented in Fig. 4.12(a) and 4.12(b), respectively. With regard to the former, the first observation is that the total annual cost is not significantly affected by the traffic load variations, since the fixed cost for the network operation is much higher than the cost due to the energy consumption in the radio part of the network and the

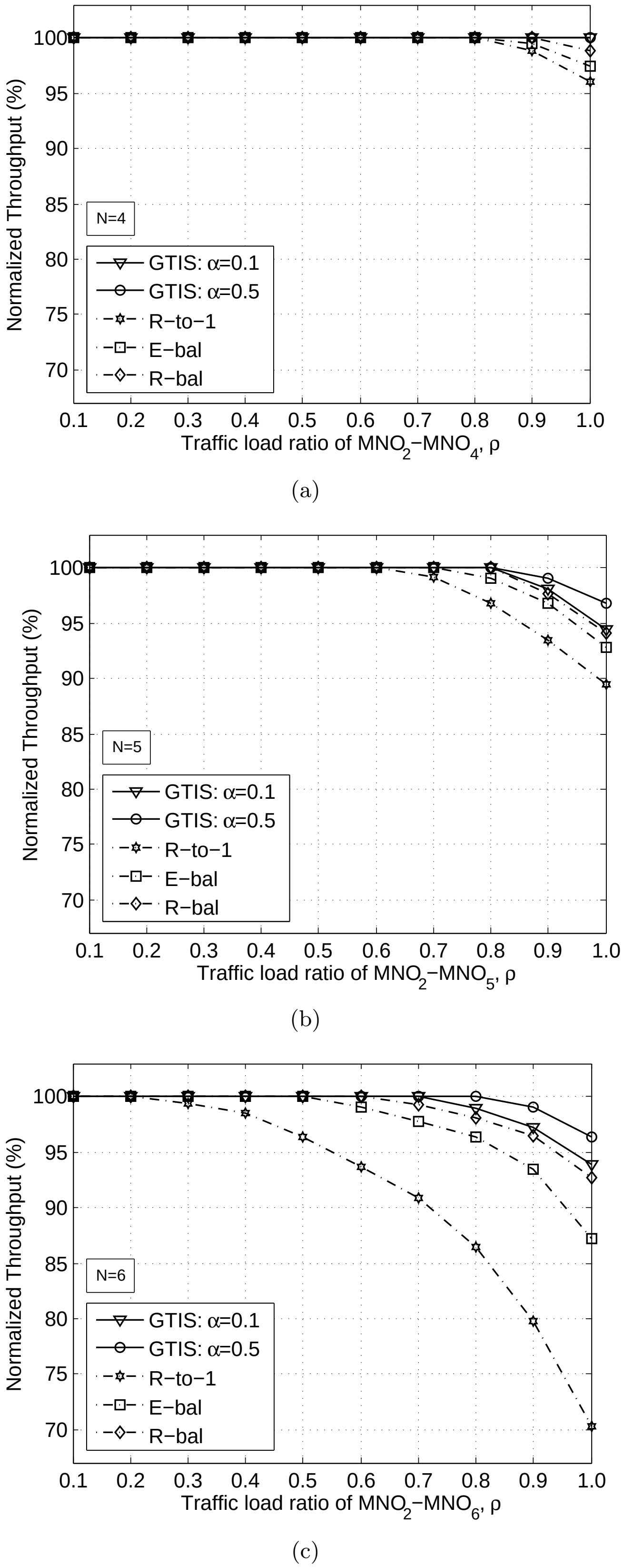


FIGURE 4.10: Normalized throughput for (a) N=4, (b) N=5 and (c) N=6

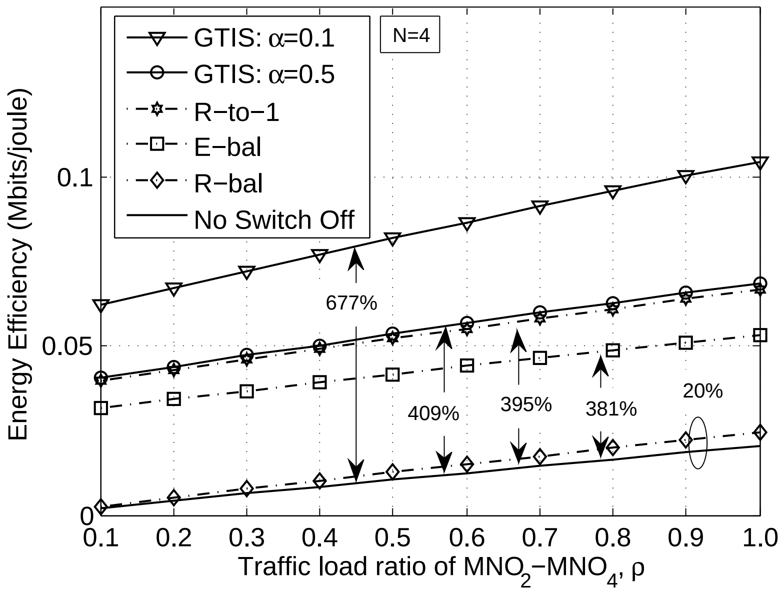
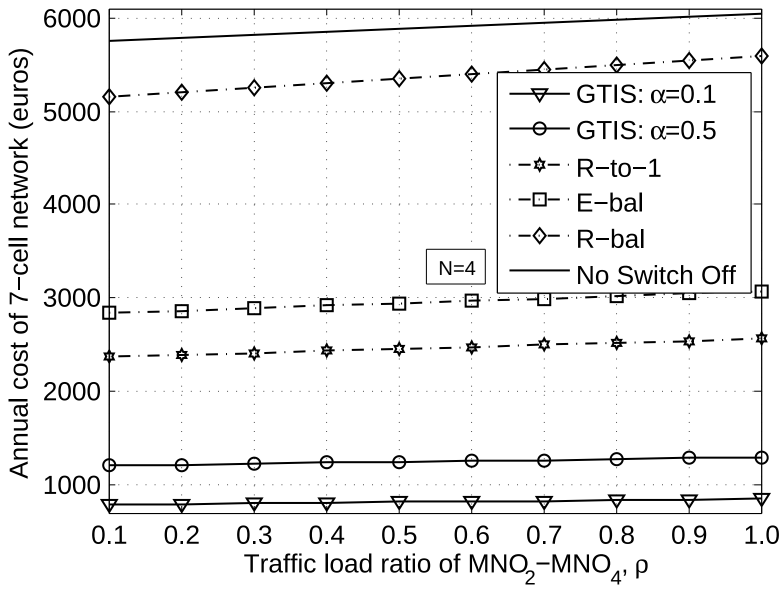


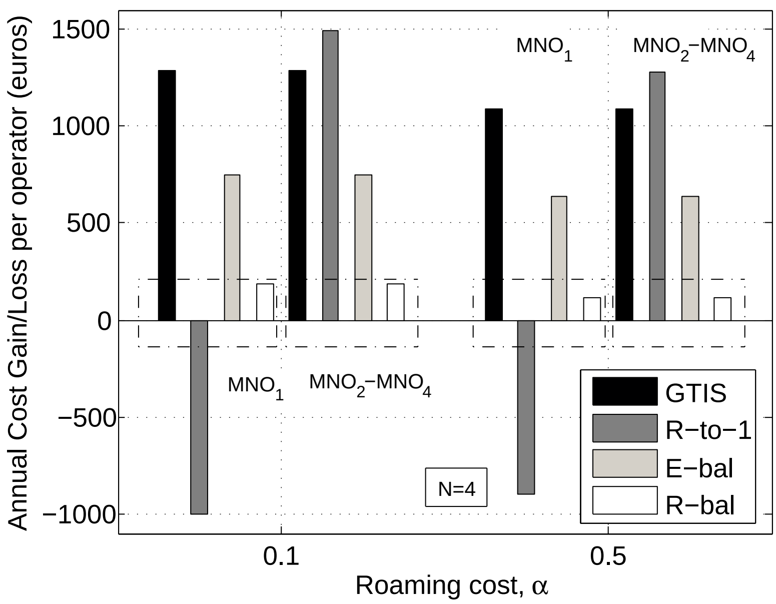
FIGURE 4.11: Energy efficiency for different traffic profiles and variable roaming costs and comparison to the state-of-the-art schemes

corresponding values are also shown in Table 4.4. In addition, for low roaming cost values ($\alpha = 0.1$), GTIS achieves a considerable reduction (around 86%) of the annual network cost, mainly due to the deactivation of many underutilized BSs in the network. Regarding the individual revenue of each operator, plotted in Fig. 4.12(b), we may observe that, similar to the energy efficiency gains, the R-to-1 scheme provides financial gains only to particular operators, and more particularly for the MNOs that switch off their networks, whereas the economic expenses of the MNO_1 are higher than the expenses of the No Switch Off scheme. On the other hand, for the proposed GTIS approach, all operators in the network are able to have higher economic benefits compared to the E-bal and R-bal schemes, since all MNOs switch off a higher number of BSs. Furthermore, as α increases, the GTIS algorithm achieves higher financial gains for the operators due to the increased roaming cost values.

Finally, Fig. 4.13 depicts the cost efficiency of the operators, which is a metric that provides an indication for the relation between the served traffic with regard to the financial cost. In Fig. 4.13(a), we illustrate the individual cost efficiency with respect to different values of roaming cost. The cost efficiency increases with the lower roaming cost due to the reduced energy consumption. In addition, Fig. 4.13(b) presents the cost efficiency gains of the infrastructure sharing schemes, having as benchmark the No Switch Off scheme. The plot in Fig. 4.13(b) verifies our results so far, as it highlights the great difference in the R-to-1 approach between the active operator and the rest operators in the system. The proposal of switching off the whole network that belongs to the MNO with the lower traffic (R-to-1) results to great cost efficiency for $MNO_2 - MNO_4$, who do not consume any energy and are encumbered only with the compensation of the roaming cost to the active operator. Contrariwise, MNO_1 serves the whole traffic of the network and consumes significant energy, leading to an increased cost that is not compensated



(a)



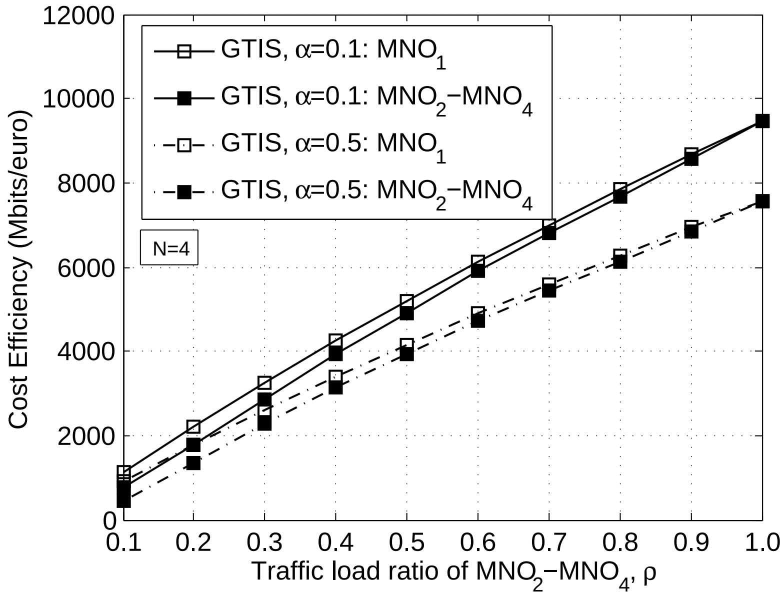
(b)

FIGURE 4.12: (a) Annual cost of 7-cell network for different traffic profiles and variable roaming costs and (b) Gain for each operator under variable values of roaming cost

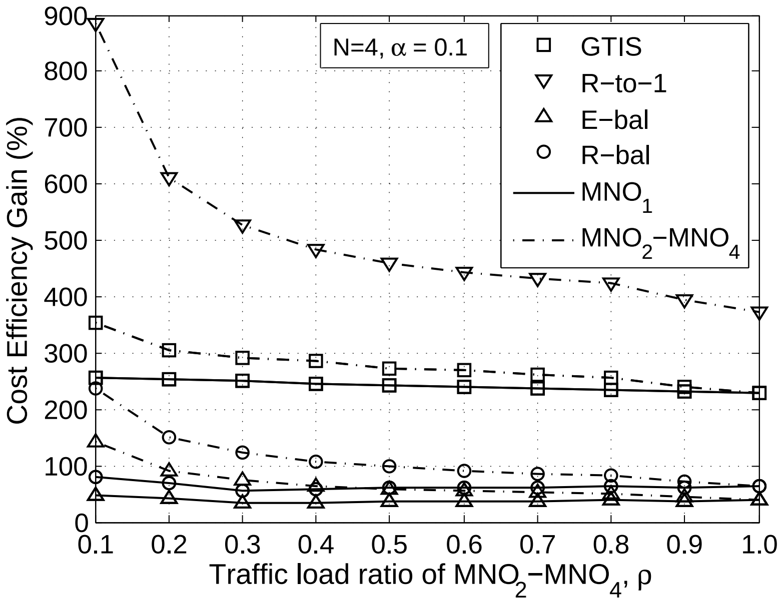
by the received roaming. The proposed GTIS strategy overcomes this issue by providing cost efficiency gains to all operators, outperforming, at the same time, the E-bal and R-bal schemes.

4.5.5 Discussion

Based on the analysis in Section 4.5.4 and the analytical results, we have shown that the proposed GTIS outperforms the state-of-the-art approaches in terms of



(a)



(b)

FIGURE 4.13: (a) Cost efficiency under different traffic profiles (b) Cost efficiency gain versus No Switch Off

throughput, energy efficiency and annual network cost. In addition, it achieves balanced results for all the MNOs with respect to the individual energy efficiency, cost gains and cost efficiency. Furthermore, through an extensive assessment, we have identified the significance of the roaming cost parameter, α. In particular, higher values of α achieve higher throughput. On the other hand, better performance results are attained in terms of energy efficiency, aggregate network cost, individual cost gains and cost efficiency, when lower values of α are chosen. Hence, the MNOs should choose the suitable value of α depending on their priorities. Thus, the motivation is stimulated by the performance results that they want to attain. For example, if energy efficiency is not priority, each MNO could achieve better individual performance by setting higher α. On the other hand, lower α leads to great energy efficiency gains for the network, whereas the individual performance of each operator is enhanced.

4.6 Concluding Remarks

In this chapter, motivated by the low BSs utilization during the night and the coexistence of multiple operators in the same area, we proposed a novel infrastructure sharing algorithm that achieves energy savings and cost reduction by encouraging MNOs to share their resources and switch off redundant BSs. We investigated a game theoretic framework to improve the performance of a multi-operator environment. Moreover, by employing game theoretic tools and realistic cost functions, we introduced a novel switching off scheme that allows the MNOs to reduce their expenditures in multi-operator cellular environments. The energy efficiency of the wireless network was enhanced by reducing the number of active BSs, guaranteeing at the same time the network throughput in realistic scenarios (i.e., up to four MNOs). The proposed scheme has been evaluated in terms of throughput, energy and cost efficiency for various traffic conditions and roaming cost values. The results have shown that our proposal can significantly improve the network energy efficiency. Regarding the financial costs/gains, the proposed scheme provides higher cost efficiency and fairness compared to the state-of-the-art algorithms, motivating the operators to adopt game theoretic strategies for their decisions. After evaluating the merit of the novel strategy, the main conclusions can be summarized as follows:

- Both network and operator-wise improvements are achievable by switching off the redundant BSs and by sharing the existing infrastructure.
- A cooperative approach is not feasible to be applied in a competitive environment. However, the formulation presented in this chapter captures the essence of the problem and it takes an operator-oriented approach by focusing on improving the performance of the individual MNO networks, along with the whole network.
- The use of game theoretic tools in the context of BSs switching off was investigated. The results and experience obtained during the research indicate that appropriate calibration results both in effective optimization and good performance. As it was mentioned earlier, in problems such as the one studied herein, the use of exact or deterministic optimization techniques is not possible without relaxing the problem due to the competitive nature of the involved parties. Thus, in order to keep expressions that capture accurately the behavior of the MNOs, non-cooperative games has been successfully employed. The main advantage of the method resides on the fact that fair solutions are provided and the different tradeoffs on the coexisting MNOs are considered.

Finally, it is important to remark that the implementation and use of the solutions obtained through the novel strategy are transparent in current system such as LTE and LTE-Advanced. Indeed it does not require either any change with respect to the current specifications or assume any particular interworking with other network functionalities. The game theoretic models capture the network geometry and focus on the optimization of long term traffic conditions, thus, they feature an attractive tradeoff between performance and feasibility.

Chapter 5

Strategies for Cost Sharing in Heterogeneous Networks

"A good scientist is a person with original ideas. A good engineer is a person who makes a design that works with as few original ideas as possible."

Freeman Dyson

5.1 Introduction

The dense HetNets, which consist of one tier of SCs underlaid in traditional macro BSs, constitute the new trend of next generation networks for traffic offloading [93]. However, the deployment of additional infrastructure implies higher CapEx and OpEx for the telecommunication operators, raising at the same time the energy consumption in the whole network. To that end, there is an entity, known as third-party, that provides the SCs to the operators [94]. Therefore, leasing the infrastructure by the third-party, the operators can potentially reduce their financial costs, whereas the third-party increases its income, resulting in a win-win situation.

Even though the potential gains from infrastructure sharing can be easily envisioned, as they were also shown in the previous chapter, there are still many challenges to overcome in order to achieve a viable business model appealing to the operators [95]. The problem becomes more intense in HetNets, where the existence of different tiers along with additional stakeholders (e.g., third-party) further complicates the sharing conditions. Thus, it is very important to comprehend the cost models and the conditions that should be taken into account, when conflicting entities interact.

In this chapter, we focus on a scenario where two operators, instead of deploying their own SC infrastructure, lease the capacity of a SC network owned by a third-party. We show that there are different strategies to share the SC cost among the operators, depending on the volume and the daily patterns of their traffic. The contribution of this work lies on the following points:

1. We provide an explicit model for the expenditures of the SC network, taking into account both the CapEx and the OpEx.

2. We study the outcome that different cost sharing policies provide with regard to the estimated SC cost. We identify the discrepancies of these policies, highlighting their particular traits.

3. We propose a novel cost sharing policy, called Hybrid-Sharing (HS), that combines different characteristics of already existing policies. Our proposed policy considers various aspects of the traffic patterns (i.e., traffic volume and peak times) for the cost sharing estimation, being less complex compared to state-of-the-art approaches.

The remainder of the chapter is organized as follows. The system model, the network configuration and the notation used throughout the chapter are described in Section 5.2. In Section 5.3, we introduce the model to estimate the total cost of a SC deployment, along with the model for the SC energy consumption calculation. Section 5.4 presents cost sharing techniques for the SC networks, when the network is shared among different MNOs. The validation of the model and an extensive performance assessment are provided in Section 5.5. Finally, Section 5.6 is devoted to conclusions.

5.2 System Model

5.2.1 Network Configuration

In this section, we present the network model of our work, along with the different traffic patterns that will be studied. We consider a set of two operators, denoted by $I = \{A, B\}$, that lease the available resources of a SC owned by a third-party[1]. The users of each operator are uniformly distributed within the coverage area of the SC, as shown in Fig. 5.1.

5.2.2 Traffic Load Model

To quantify the cost of the SC and assess the proposed cost sharing policies, we consider different cases for the traffic patterns of the operators during the day, as it is illustrated in Fig. 5.2. In particular, different pricing schemes can move the traffic peaks in different time periods during the day, while the traffic distribution is affected by the specific location of the SC. For example, in urban areas, the traffic follows the typical pseudo-sinusoidal teletraffic pattern, while in places such as malls or university campuses, the traffic can be extremely bursty during specific hours within a day. Accordingly, we can distinguish the following cases for the two operators:

[1]Even though we only consider two operators in this work, the proposed cost sharing models can also be applied in large scale networks where more than two operators are present.

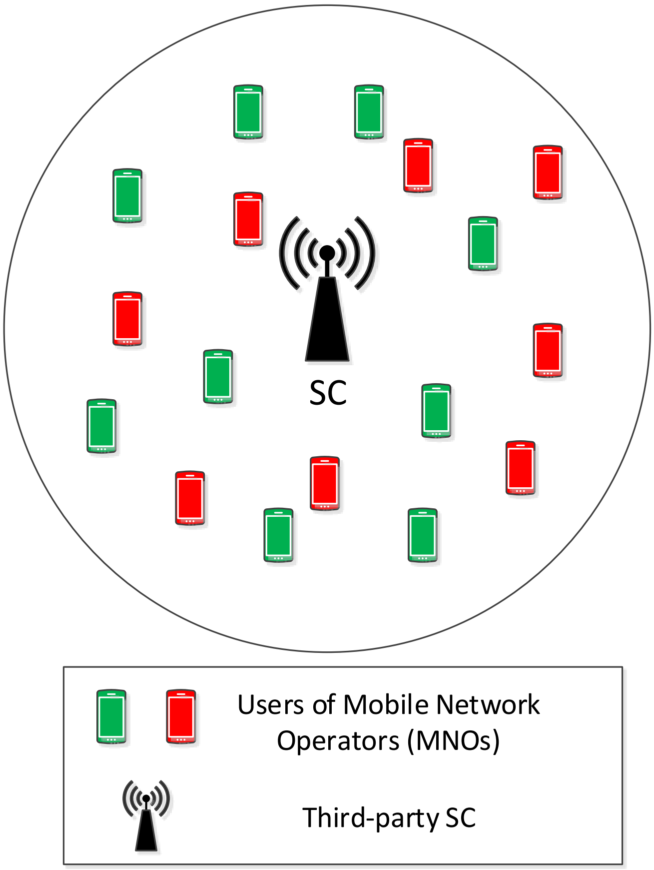


FIGURE 5.1: Example of network layout

- **Case I (Fig. 5.2(a)):** Typical traffic - Peaks at the same time
- **Case II (Fig. 5.2(b)):** Typical traffic - Peaks at different time
- **Case III (Fig. 5.2(c)):** Bursty traffic - Peaks at the same time
- **Case IV (Fig. 5.2(d)):** Bursty traffic - Peaks at different time

From the traffic patters of Fig. 5.2 we can derive the total traffic $\Lambda_i(T)$ of operator $i \in \{A, B\}$ over a specific time interval $t \in [0, T]$ as:

$$\Lambda_i(T) = \int_0^T \lambda_i(t)\,\mathrm{d}t, \tag{5.1}$$

where $\lambda_i(t)$ is the operator's traffic load at time t.

We also define the parameter a to express the relationship between the total traffic loads of the two operators A and B:

$$\Lambda_B(T) = \mathrm{a} \cdot \Lambda_A(T), \mathrm{a} \in \mathbb{R}^+. \tag{5.2}$$

When the two operators share the SC, their aggregated traffic must not exceed the total available bandwidth of the SC, denoted by CR_{SC}, in order to guarantee

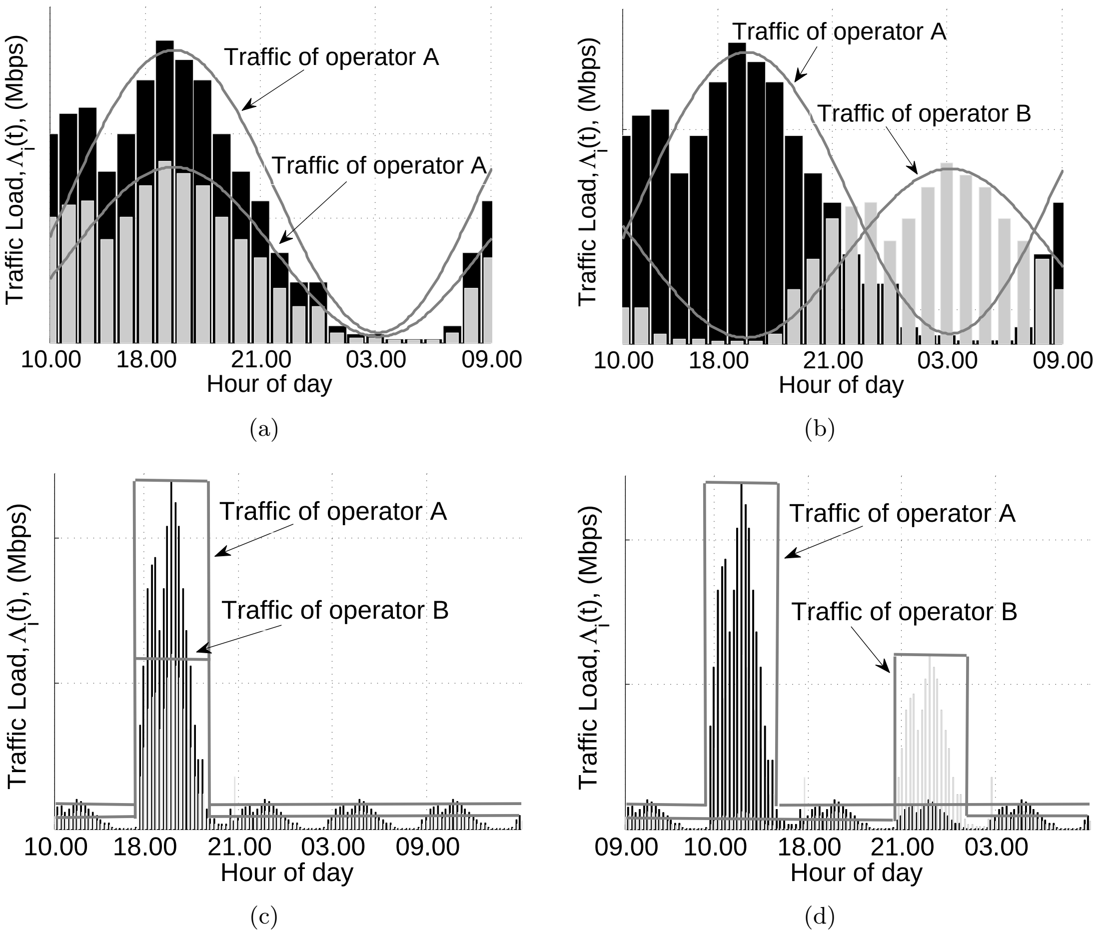


FIGURE 5.2: Daily traffic variations for two operators: (a) Typical traffic - Peaks at the same time, (b) Typical traffic - Peaks at different time, (c) Bursty traffic - Peaks at the same time, (d) Bursty traffic - Peaks at different time

service to all users. This condition is expressed as:

$$\sum_{i \in I} \Lambda_i(T) = \Lambda_A(T) + \Lambda_B(T) = b \cdot CR_{SC}, b \in [0, 1] \,. \tag{5.3}$$

5.2.3 Notation

A summary of the main parameters employed in the cost sharing techniques and their model analysis is given in Table 5.1.

In the following sections, we introduce a model for the calculation of the total cost of the SC, taking into account the energy consumption due to the traffic load, and we study different techniques that share this cost among the operators according to their traffic patters.

TABLE 5.1: Main Parameters for the HS model analysis

Symbol	Description
$I = \{A, B\}$	Set of MNOs
$i \in I$	Identification number of MNOs
T	Time interval
$t \in [0, T]$	Time
$\Lambda_i(T)$	Total traffic of ith operator over time T
$\lambda_i(t)$	Traffic of ith operator at time t
$\lambda(t)$	Traffic of SC
a	Parameter showing the relationship between operators' traffic
b	Parameter showing the relationship between operators' traffic and the CR_{SC}
CR_{SC}	Capacity resources of a SC
C_{Ca}	CapEx
C_{Op}	OpEx
C^C_{BS}	Cost of BS equipment
C^C_{SC}	Cost of SC equipment
C^C_{Site}	Cost of site installation and buildout
C^C_{RNC}	Cost of RNC equipment
C^C_{BT}	Cost of backhaul transmission equipment
C^O_{BT}	Cost of backhaul and transmission lease
C^O_{OM}	Cost of operation and maintenance
C^O_{Pw}	Cost of electric power
$C_{SC}(\lambda(t))$	Cost of a SC
c_1	Electricty charge per energy unit
c_0	Cost of BS equipment
$E_{SC}(\lambda(t))$	Energy consumption of a SC
$P_{SC}(\lambda(t))$	Power consumption of a SC
$P_{out}(\lambda(t))$	Transmission power of a SC
P_{max}	Maximum transmission power of SC
P_0	Minimum power consumption of a SC
Δ_p	Slope of load-dependent power consumption of a SC
C_i	Cost of ith operator
t_m	Time with maximum aggregated SC traffic
$S \subset I$	Coalitions of operators' set
$C(S)$	Cost of a coalition
$\phi_i(C)$	Shapley value of ith operator
$d(C_i^1, C_i^2)$	Discrepancy between two operators' costs

5.3 Cost and Energy Consumption Models

In this section, we, first, introduce a model to estimate the total cost of a SC deployment and, then, we describe a model for the SC energy consumption.

5.3.1 Cost Analysis Breakdown

The cost of a SC consists of the CapEx, for deployment and installation, and the OpEx for its operation. Chen et al. presented a detailed breakdown of the

CapEx and OpEx for macrocells in [96]. Following a similar approach and taking into account the typical cost of SC equipment [97], we have adapted the model in order to estimate the different costs in the case of a SC.

Table 5.2 shows the CapEx and OpEx breakdown for SCs, whereas the respective values for the BS case ([96]) are also given for reference. In particular, the CapEx consists of four factors: i) the cost C^C_{SC} for the small cell equipment ii) the cost for deployment and installation of the SC, denoted by C^C_{Site}, iii) the cost C^C_{RNC} of the Radio Network Controller (RNC), and iv) the cost for backhaul transmission equipment (C^C_{BT}) that is almost negligible in the case of SCs. The OpEx, on the other hand, can be broken down to four terms: i) the cost of backhaul transmission (C^O_{BT}), corresponding to the bandwidth needed to serve the traffic and calculated according to a simple leased line pricing, ii) the cost C^O_{Site} for site leasing, iii) the cost C^O_{OM} for operation and maintenance, and iv) the electric power cost C^O_{Pw} that depends on the power consumption to serve the traffic $\lambda(t)$ of the SC.

TABLE 5.2: CapEx and OpEx breakdown for BSs and SCs

CapEx	C_{Ca}	BS	SC
BS/SC equipment	C^C_{BS},C^C_{SC}	c_0	$c_0/70$
Site installation and buildout	C^C_{Site}	$c_0/4$	$c_0/20$
RNC equipment	C^C_{RNC}	$3c_0/2$	$c_0/210$
Backhaul transmission equipment	C^C_{BT}	$c_0/4$	0
OpEx	C_{Op}		
Backhaul and transmission lease	C^O_{BT}	$c_0/4$	$c_0/20$
Site lease	C^O_{Site}	$c_0/4$	0
Operation & Maintenance	C^O_{OM}	$c_0/16$	$9c_0/700$
Electric power	C^O_{Pw}	$c_1 E_{BS}$	$c_1 E_{SC}$

In order to calculate a realistic annual SC cost, we assume that the CapEx estimated from Table 5.2 is equally distributed within 5 years. Therefore, the annual cost of a SC, $C_{SC}(\lambda(t))$ is the sum of the CapEx that corresponds to one year and the traffic-dependent OpEx[2]:

$$C_{SC}(\lambda(t)) = C_{Ca}/5 + C_{Op}(\lambda(t)). \tag{5.4}$$

As shown in Table 5.2, the first seven cost values have been expressed with respect to the equipment cost of a macro BS c_0 measured in € [96]. The last term, i.e., the electric power, depends on the electricity charge per energy unit c_1, measured in €/kWh, and the energy consumption of a SC $E_{SC}(\lambda(t))$, which will be calculated in the next section. With these relations in mind, Eq. (5.4) is expressed as:

$$C_{SC}(\lambda(t)) = 0.0768 \cdot c_0 + c_1 \cdot E_{SC}(\lambda(t)). \tag{5.5}$$

[2]To calculate the annual cost, the SC traffic $\lambda(t)$) must be averaged over a year.

5.3.2 Energy Consumption Analysis Breakdown

Unlike macro BSs, the SC power consumption is load-dependent. The consumed energy $E_{SC}(\lambda(t))$ over a specific time interval $t \in [0, T]$ can be calculated as:

$$E_{SC}(\lambda(t)) = \int_0^T P_{SC}(\lambda(t))\,\mathrm{d}t. \tag{5.6}$$

The relationship between the power consumption $P_{SC}(\lambda(t))$ of the SC and the relative transmission power $(P_{out}(\lambda(t)))$ can be formulated as a linear function. To that end, a linear approximation of the power model is adopted, given by [4]:

$$P_{SC}(\lambda(t)) = P_0 + \Delta_p \cdot P_{out}(\lambda(t)), \quad 0 < P_{out} \leq P_{max}, \tag{5.7}$$

where P_0 is the minimum power consumption in case of no traffic in the system and Δ_p is the slope of the load-dependent power consumption.

5.4 Cost Sharing Policies and Discrepancies

In this section, we present four different policies for sharing the cost of a SC owned by a third-party between two operators [98], [99] and we try to quantify the discrepancies between these methods. In addition, we propose a novel cost sharing policy, called Hybrid-Sharing, that combines two different strategies in order to provide a fairer cost distribution according to the particular traits of the SCs.

5.4.1 Cost Sharing Policies

Traffic-Volume (TV): According to TV, the cost of the SC is shared proportionally to the traffic volumes of the operators. Hence, the cost of operator i is:

$$C_i = \frac{\Lambda_i}{\sum\limits_{j \in I} \Lambda_j} \cdot C_{SC}\left(\sum_{j \in I} \Lambda_j\right), \tag{5.8}$$

where Λ_i is the total traffic of operator $i \in \{A, B\}$ (Eq.(5.1)) and $C_{SC}\left(\sum\limits_{j \in I} \Lambda_j\right)$ the total cost of the SC (Eq. (5.5)) when serving the aggregate traffic of all operators in I[3].

Operator-Peak (OP): According to OP, the SC cost is shared based on the traffic peak of the ith operator within a time period $t \in T$, with respect to the sum of the individual traffic peaks of all operators sharing the SC. Thus, the cost

[3]Note that for convenience, all time notations have been dropped, when not necessary.

of operator i is:

$$C_i = \frac{\max_{t \in T} \lambda_i(t)}{\sum_{j \in I} \max_{t \in T} \lambda_j(t)} \cdot C_{SC}\left(\sum_{j \in I} \Lambda_j\right). \tag{5.9}$$

Aggregate-Peak (AP): In AP, the cost is shared according to the traffic of the ith operator with respect to the traffic peak of the aggregated SC traffic, which occurs at a particular time period t_m. Consequently, the cost of operator i is:

$$C_i = \frac{\lambda_i(t_m)}{\sum_{j \in I} \lambda_j(t_m)} \cdot C_{SC}\left(\sum_{j \in I} \Lambda_j\right). \tag{5.10}$$

Shapley-Value (SV). Shapley-value is a solution concept in cooperative game theory employed to predict a unique expected payoff allocation when different coalitions may be formed among the players. To understand the concept behind the SV calculation, consider the following example. If a SC is leased by operator A alone, then A must assume the total CapEx of the SC, as well as the OpEx that corresponds to its traffic. If B decides to join the SC after A, then B must only pay the OpEx corresponding to its traffic (i.e., its marginal contribution), given that A has already covered the remaining SC expenses. Accordingly, the marginal contribution of operator A would be different if the arrival order of the two operators in the coalition was changed.

In our specific case, we have $S \subset I$ possible coalitions of the two operators. The set of coalitions is $S = \{\{A\}, \{B\}, \{A, B\}\}$, where $\{A\}$ and $\{B\}$ are the cases when each operator owns its own SC and $\{A, B\}$ is the grand coalition where the two operators share an SC. The cost of each coalition $C(S)$ is given by Eq. (5.5), by considering the traffic of operator A, B and the aggregate traffic of both, respectively. The SV shares the total cost of the SC to the operators in a way proportional to each operator's average marginal contribution, after considering all the possible permutations Π of the operators' arrival order to the grand coalition. If $\pi \in \Pi$ any permutation of operators, we define $S(\pi, i)$ as the set of operators that arrived to the coalition before operator i. Then, the Shapley value of the ith operator, denoted by $\phi_i(C)$, is given by:

$$\phi_i(C) = \frac{1}{|I|!} \cdot \sum_{\pi \in \Pi} \Big(C\left(S\left(\pi, i\right)\right) - C\left(S\left(\pi, i\right) \setminus i\right) \Big), \tag{5.11}$$

and the cost of operator i is:

$$C_i = \frac{\phi_i(C)}{\sum_{j \in I} \phi_j(C)} \cdot C_{SC}\left(\sum_{j \in I} \Lambda_j\right). \tag{5.12}$$

The SV is considered the most fair solution for cost sharing but requires high complexity in terms of computational power (to calculate the marginal costs in all possible coalitions). To achieve a compromise between complexity and fairness, we propose a hybrid cost sharing solution, described next.

Hybrid-Sharing (HS): Let us emphasize that telecommunication operators design their networks based on the peak traffic utilization, even though the network remains underutilized during a large part of the day. As a result, the peak traffic also determines the backhaul equipment that should be employed. Therefore, the AP policy seems to be the most appropriate technique to share the operational cost of the backhaul (C^O_{BT}). On the other hand, the TV method is a simple and fair way to share the costs that directly depend on the traffic load. Hence, we propose a hybrid policy (HS) that combines these two methods and calculates the cost of operator i as:

$$C_i = \frac{\lambda_i(t_m)}{\sum\limits_{j\in I} \lambda_j(t_m)} \cdot C^O_{BT} + \frac{\Lambda_i}{\sum\limits_{j\in I} \Lambda_j} \cdot (C_{Ca} + C^O_{Site} + C^O_{OM} + C^O_{Pw}). \tag{5.13}$$

5.4.2 Cost Sharing Policies Discrepancies

Interesting discrepancies are observed among the aforementioned cost sharing policies, since each of them results in different pricing schemes for the operators. Hence, we introduce the discrepancy metric, which quantifies the difference in the operator's costs when two distinct cost sharing policies are employed. To that end, the discrepancy of the two policies is defined as:

$$d(C^1_i, C^2_i) = \frac{C^1_i - C^2_i}{C^1_i} \cdot 100\%, \tag{5.14}$$

where C^1_i and C^2_i denote the costs of operator $i \in I$ according to the policy 1 and 2, respectively.

5.5 Performance Evaluation

In this section, we present the scenarios under study along with the analytical results of the different cost sharing policies.

5.5.1 Simulation Scenario

We consider the scenario depicted in Fig. 5.1, where two operators (A and B) lease the capacity of a third-party SC. To assess the performance of the cost sharing algorithms (TV, OP, AP, SV and HS), we consider the four traffic patterns shown in Fig. 5.2 with varying values of the traffic load volume (i.e., various values for the parameter a). Table 5.3 summarizes the key parameters employed in the cost and energy breakdown analysis explained in Section 5.4. Regarding the discrepancies, SV is used as the reference policy and the most extreme percentage differences of the other policies with regard to the SV are highlighted in each case. Note that despite its complexity, SV is assumed as the most fair solution for cost sharing.

5.5.2 Numerical Results

We begin the performance evaluation by emphasizing the energy efficiency gains that can be achieved through infrastructure sharing. Even though these gains are independent of the adopted cost sharing scheme, they can strongly motivate the operators to cooperate, thus creating the need to select effective cost policies. Fig. 5.3 depicts the energy efficiency gains achieved through infrastructure sharing versus the parameter b that determines the SC occupation. More specifically, we examine two scenarios: i) a scenario where the SC is shared among two operators (Sharing), and ii) a baseline scenario where each operator owns its own SC (NoS) and, hence, no cooperation takes place. As we can see, for low SC utilization (i.e., $b = 0.1$), the energy efficiency in shared networks is significantly higher, as we avoid the deployment of numerous SCs. As the traffic load increases, the percentage of the gain decreases, but there is no cross point, since sharing is more energy efficient in all cases. Motivated by these results, in the remainder of the paper, we study various ways and policies to share the SC cost among operators, focusing on the applicability, the complexity and the fairness of the different solutions.

Fig. 5.4 illustrates the costs of the operators A and B considering the traffic patterns of Fig. 5.2(a) (Case I), where the traffic patterns follow a typical distribution and their peaks coincide in time. In this figure, we observe that the discrepancies of the different policies are more intense when the the difference in the traffic load of the two operators is high (i.e., a = 0.1). As the difference in their traffic load decreases, the discrepancies fade and, eventually, all policies provide the same outcome for equal traffic volume (i.e., a = 1). It is also worth noticing that, in this scenario, OP and AP cannot be distinguished, as the operator and the aggregated peak traffic takes place at the same time. Regarding our proposed policy, we can see that HS provides costs between TV and OP (or AP), as it combines the properties of both techniques.

Fig. 5.5 presents the costs for the two operators according to the different policies, considering a scenario where the traffic follows again a typical distribution, but the peaks take place at different times during the day (Fig. 5.2(b)). Unlike the previous case, in this figure, OP and AP sharing policies have distinct performance,

TABLE 5.3: System Parameters for Cost Sharing Techniques

Parameter	**Value**
SC capacity resources, CR_{SC}	30 Mb/s
Maximum transmission power, P_{max}	24 dBm
Minimum power consumption, P_0	4.76 W
a, b	[0,1]
Cost of BS equipment, c_0	20000 €
Electricity charge, c_1	0.1 €
Slope of load-dependent power, Δ_p	16.15

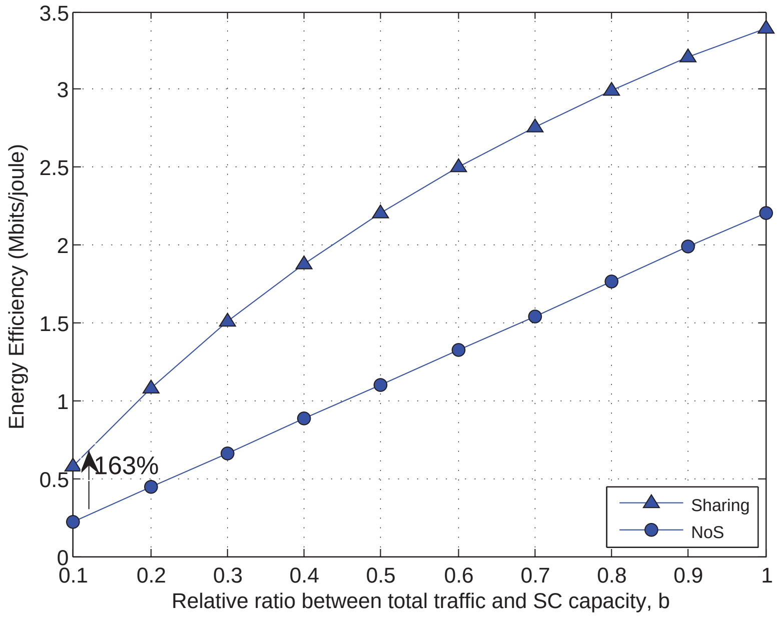


FIGURE 5.3: Total Network Energy Efficiency

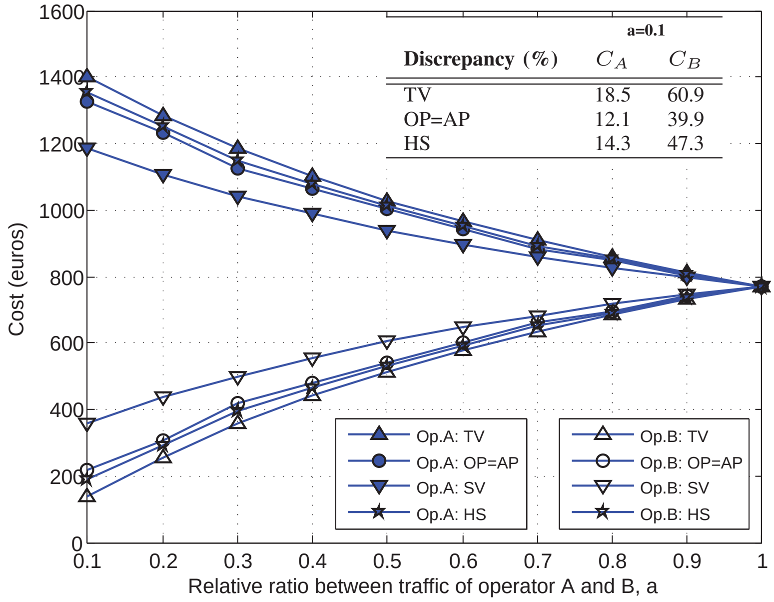


FIGURE 5.4: Costs of operators given the traffic pattern of Case I (Fig. 5.2(a)) and cost sharing policies discrepancies in [%]

since the aggregated peak utilization time does not coincide with the maximum traffic value of each individual operator. In particular, although OP still provides similar outcome with the TV policy, the discrepancy between AP and SV is extremely higher. However, similar to the previous case, the proposed HS provides an intermediate solution by considering different parts of the cost using different techniques.

In Fig. 5.6 and 5.7, we study the operators cost in case of bursty traffic models (Fig. 5.2(c) and 5.2(d), respectively). Unlike the previous cases, here we consider

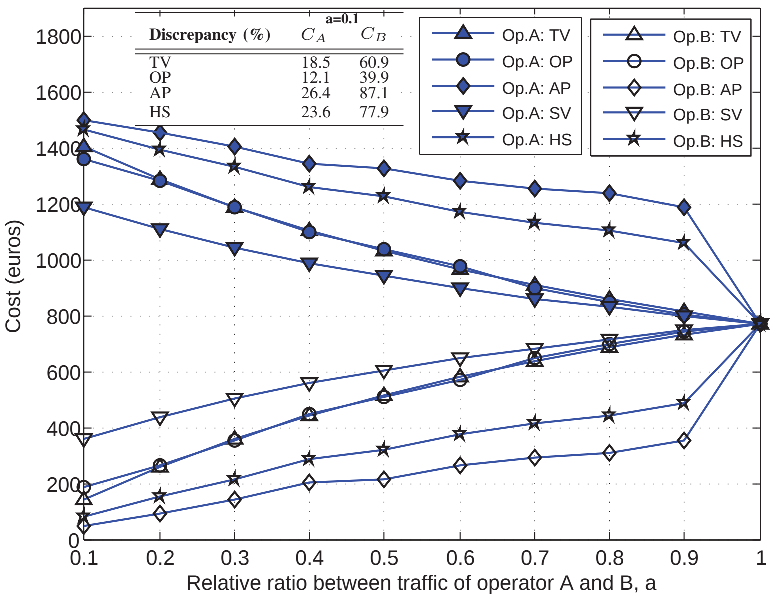


FIGURE 5.5: Costs of operators given the traffic pattern of Case II (Fig. 5.2(b)) and cost sharing policies discrepancies in [%]

that the parameter a affects only the high traffic period. For example, when a = 1, the peak traffic of operator B would be higher than operator's A peak traffic, since i) both operators are expected to have the same traffic volume and ii) during the rest of the day, operator A has slightly higher traffic compared to operator B.

In particular, in Fig. 5.6, we notice again that the OP and the AP policy have the same outcome, as the peak values coincide in time, despite their different values. On the other hand, TV and SV exhibit similar performance, converging to the same point when the traffic volume of the operators is the same (i.e., a = 1). Our proposed solution (HS) manages to reduce the great discrepancy of OP and AP, without neglecting the impact of the peak traffic in the system. In Fig. 5.7, we can see that OP and AP have similar behavior, although the peak times take place in different time periods during the day. However, HS achieves again lower discrepancies from both strategies, with regard to the reference policy (SV).

5.5.3 Discussion

Based on the analysis in Section 5.4.1 and the analytical results, we have shown that the proposed HS policy considers different characteristics of the traffic pattern, unlike TV, OP and AP, which examine only one aspect (either volume or peak times). In addition, through an extensive assessment, we have identified significant discrepancies between the sharing policies and the SV policy, which was used as a reference strategy. In particular, the TV method shows a steady performance regardless of the variations in the traffic profile (i.e., its discrepancy remains stable in all cases). Hence, despite its simplicity, the TV does not seem effective for future networks, where the different traffic patterns are expected to play a crucial role. On the other hand, the OP and the AP policies are greatly affected by the adopted

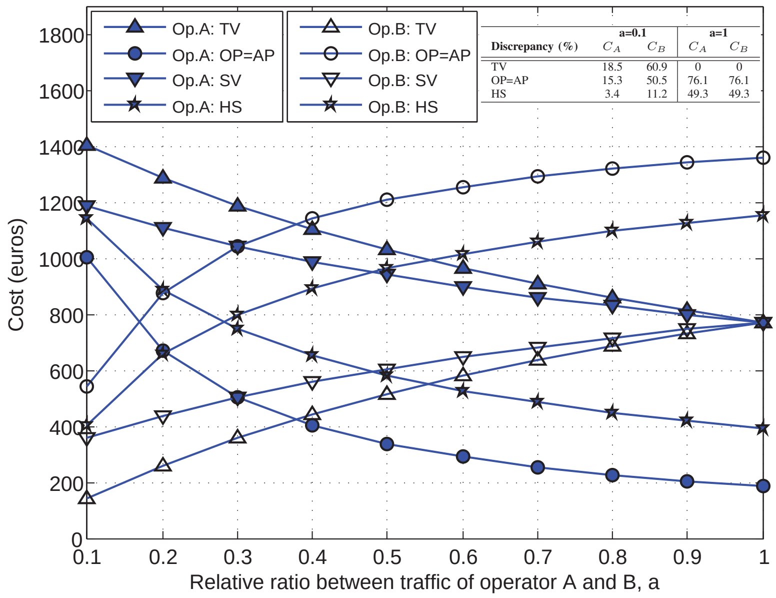


FIGURE 5.6: Costs of operators given the traffic pattern of Case III (Fig. 5.2(c)) and cost sharing policies discrepancies in [%]

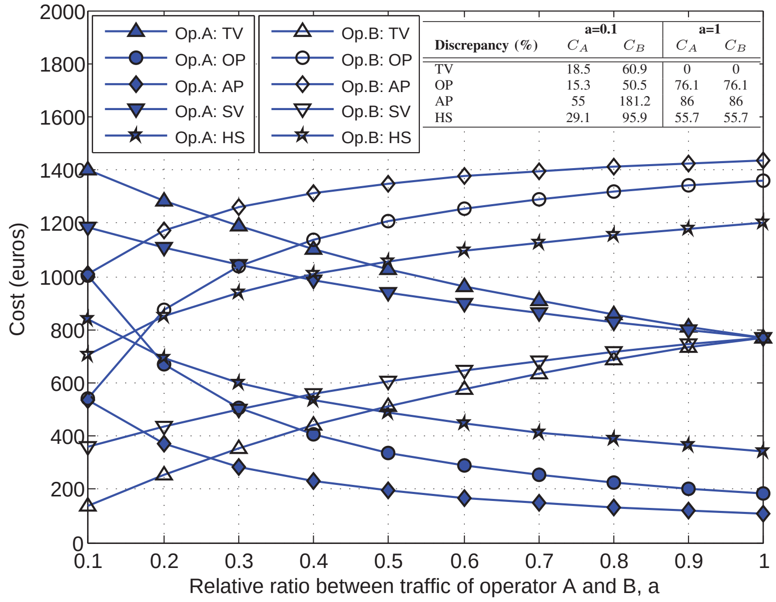


FIGURE 5.7: Costs of operators given the traffic pattern of Case IV (Fig. 5.2(d)) and cost sharing policies discrepancies in [%]

traffic pattern, especially in bursty traffic conditions, due to the misalignment of the operators' peak values.

However, in future wireless networks, where third-parties are expected to offer services through SCs, a cost sharing policy that considers the individual and specific needs of the operators is more than necessary. In particular, different traffic patterns affect the shared costs and, as a result, different factors of traffic, such as volume, peak times and burstiness, should be taken into account. To that end, our proposed approach (HS) estimates a cost according to both the traffic volume and the peak time traffic, offering a fairer solution to the operators. Therefore, the discrepancies of the proposed HS policy fluctuate between the discrepancies of the other policies, independently of the particular scenario. It is worth noting that HS policy is less complex than SV, as it does not require extra overhead information, thus being a useful tool for sharing the network cost among the operators in the near future.

5.6 Concluding Remarks

This chapter was motivated by the traits of the heterogeneous network configuration and the low utilization of the BSs and the SCs during the night. The possibility of a third-party that provides a tier of SCs in HetNets can provide significant gains in energy efficiency, but at the same time raises important issues with regard to the SC cost sharing among different operators. In this chapter, we introduced an accurate cost model for the SCs that takes into account the traffic load for a precise estimation of the energy consumption. In order to effectively share this cost, we investigated four different state-of-the-art cost sharing techniques and we introduced a new hybrid policy that achieves a traffic aware sharing of the total expenses. Our results highlighted the potential energy efficiency gains in the network, along with the fair sharing of the SC cost that can be achieved through our proposed policy. In our future work, we are planning to exploit these results by providing the operators with the necessary incentives to share the SC infrastructure during low traffic periods in order to be able to switch off the macro BSs, thus reducing further the energy consumption inside the network.

Chapter 6

Strategies for Energy Efficient Infrastructure Sharing in Heterogeneous Networks

"Anything which is physically possible can always be made financially possible; money is a bugaboo of small minds."

Robert A. Heinlein, The Moon Is a Harsh Mistress

6.1 Introduction

In this chapter, motivated by the involvement of various entities (i.e., MNOs, third-party owners) in the dense HetNets, the rising operating costs and the opportunities of traffic offloading to the SC networks, we propose a novel energy efficient solution for dense HetNets, which considers the interests of the involved parties (MNOs and third-party) and the time-varying traffic characteristics. More specifically, we introduce an offloading mechanism, where the operators lease the capacity of an SC network owned by a third-party, in order to be able to switch off their BSs and maximize their energy efficiency, when the traffic demand is low. The MNOs request capacity from several SCs and can only switch off their BS if all their requests are satisfied, enabling them to offload all their traffic to the SC network.

To that end, the allocation of the SC resources among a set of competing MNOs is mathematically formulated as an auction. Since the exact resource requirements of the network are unknown beforehand, the MNOs employ past reports to predict the maximum expected traffic load. Then, exploiting the fact that, with a high probability, the actual traffic will be lower than the predicted maximum (especially during low traffic periods), the MNOs submit a set of bids to the SCs, requesting for lower capacity resources (with respect to the maximum estimated capacity requirements). With this approach, the SC resources can be more efficiently utilized and the MNOs are likely to pay a lower price for the leased capacity, taking a small risk of not being able to serve all users under some circumstances (i.e., when the traffic approaches the maximum predictions and the leased capacity is not sufficient). Our key contribution is to study this very interesting tradeoff between the potential energy and financial gains of this solution and the risk of not fully satisfying all the network users, thus providing the MNOs with the necessary insights to decide whether it is profitable to participate in the auction, depending on their tolerance to the potential loss of some users.

In addition, the conflicting interests of the involved parties are also taken into consideration. On the one hand, the MNOs aim to reduce their energy consumption and expenditures by offloading their traffic and switching off their BS infrastructure. However, to deactivate a BS, all its traffic should be offloaded to the SC network (i.e., the MNO should win in all the auctions involving the particular BS). On the other hand, the third-party wants to maximize its income by leasing the maximum possible amount for resources to the MNOs. However, the resource allocation policy that maximizes the third-party income may not enable the operators to switch off their BSs. Our proposed auction-based strategy takes into account these conflicting interests to achieve a feasible, efficient and energy saving resource allocation scheme.

Summarizing, the contribution of this chapter is described next:

1. *Bidding Strategy.* We propose a novel bidding strategy, where operators submit a set of bids (and not only one bid) to the third-party, requesting different capacity resources, based on the predictions about their maximum traffic load. The diversity of bids allows different offloading opportunities, which is profitable for both the MNOs and the third-party.
2. *Auction Design and Switching Off Decision.* We design an auction scheme that enables the efficient usage of SCs resources under low traffic conditions. Our framework motivates the MNOs to quantify their tolerance about requesting less resources and form the different levels of bids. We show that the proposed auction-based scheme has three desirable properties: *i*) truthfulness, *ii*) individual rationality, and *iii*) low computational complexity. The mechanism is designed based on a multiobjective framework, where the conflicting interests of the involved parties are considered, so as to provide the optimal solution that maximizes the economic profit of both the third-party and the MNOs and minimizes the network energy consumption at the same time.
3. *Performance Evaluation.* We validate the theoretical analysis of the multi-objective problem by computing the Pareto Front (i.e., the set of optimal) solutions and assess the effectiveness of the proposed auction-based switching off algorithm. The analytical and simulation results indicate the potential energy efficiency and economic gains in the network and give the necessary insights to the MNOs to decide whether is beneficial to enter in a resource allocation negotiation with the third-party.

The remainder of the chapter is organized as follows. The system model, the network configuration, the capacity demand model and the notation used throughout the chapter are described in Section 6.2. Section 6.3 introduces the auction-based optimization approach that is used for the switching off decision of the BSs. In Section 6.4, we present the analytical models for the energy efficiency, the network throughput and the cost metrics. The performance evaluation is provided in Section 6.5 and, finally, Section 6.6 concludes the paper.

6.2 System Model

6.2.1 Network Configuration

We consider an urban scenario, focusing on an area covered by a macro cell and a number of uniformly deployed SCs, owned by a third-party. In the macro cell, we assume that N MNOs provide coverage and services through their BSs, denoted by BS_n, where $n \in \mathcal{N} = \{1, \ldots, N\}$ characterizes the MNO_n. Each SC is represented as SC_f, where $f \in \mathcal{F} = \{1, \ldots, F\}$. We assume that the number of SCs is adequate to cover the area of the macro cell [97]. As it will be explained in detail in the next section, the operators are motivated to offload their traffic to the third-party SCs by paying the corresponding price, thus enabling part of the BS infrastructure to be switched off during low traffic conditions. The network configuration adopted in this work is illustrated in Fig. 6.1.

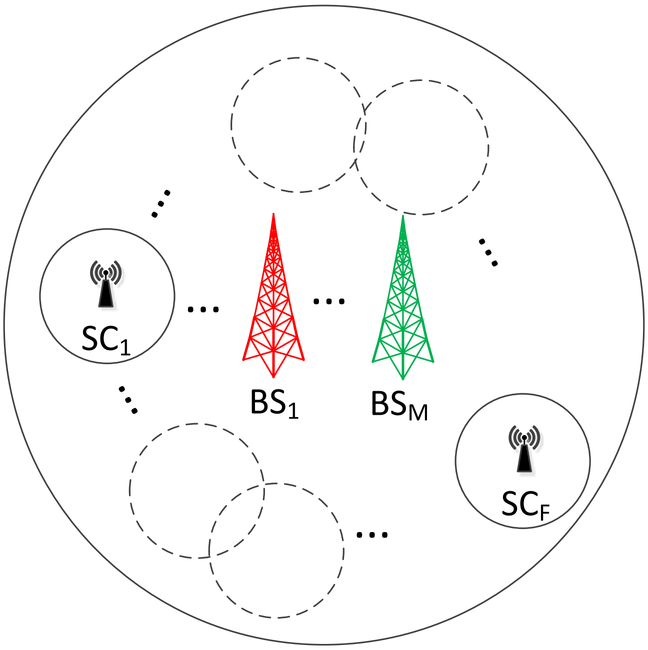


FIGURE 6.1: Network configuration, where 1 macro cell is served by N MNOs and covered by F SCs.

In order to calculate the adequate number of SCs that are needed to cover the area of the macro cell, we consider the following analysis. We consider a network configuration involving N_{BS} macro cells, owned by one operator and F_{SC} SCs, located uniformly on a coverage area. In the general case, where multiple operators serve the same area, we assume that the BSs of the different MNOs are collocated in the each one of the macro cells. Assuming that the cell radius of the BSs is r_{BS}, the cell radius of the SCs is $r_{SC} = \alpha \cdot r_{BS}$, with $\alpha \in (0, 1)$. Respectively, the number of BSs and SCs are associated with the following equation:

$$F_{SC} = \beta \cdot N_{BS} \text{ with } \beta > 1. \tag{6.1}$$

According to connectivity theory [100] (Eq. (28) from [100]), the probability that all nodes, N_{BS}, are connected is given by:

$$P_{fc,BS} = 1 - N_{BS} \cdot e^{-4\cdot\pi\cdot r_{BS}^2\cdot\rho_{BS}} \cdot \left(1 + \mathcal{O}\left(\rho_{BS}^{-1}\right)\right), \tag{6.2}$$

where ρ_{BS} is the BSs density and $\mathcal{O}(\cdot)$ represent the complexity of the $P_{fc,BS}$ calculation. Equivalently, the probability that the SC network, consisting of F_{SC} SCs, is connected, is denoted by:

$$P_{fc,SC} = 1 - F_{SC} \cdot e^{-4\cdot\pi\cdot r_{SC}^2\cdot\rho_{SC}} \cdot \left(1 + \mathcal{O}\left(\rho_{SC}^{-1}\right)\right), \tag{6.3}$$

where ρ_{SC} is the SCs density.

Our objective is that the two networks should be equivalent and cover the same area. Thus, we have:

$$\begin{aligned}
P_{fc,BS} &= P_{fc,SC} \Rightarrow \\
1 - N_{BS} \cdot e^{-4\cdot\pi\cdot r_{BS}^2\cdot\rho_{BS}} &= 1 - F_{SC} \cdot e^{-4\cdot\pi\cdot r_{SC}^2\cdot\rho_{SC}} \Rightarrow \\
\alpha &= \sqrt{\frac{1}{\beta} \cdot \left(1 + \frac{\ln\beta}{4\cdot\pi\cdot r_{BS}^2\cdot\rho_{BS}}\right)} \Rightarrow \\
\beta &= -\frac{W\left(-4\cdot\alpha^2\cdot e^{-4\cdot\pi\cdot r_{BS}^2\cdot\rho_{BS}}\cdot\pi\cdot\rho_{BS}^2\cdot\rho_{BS}\right)}{4\cdot\pi\cdot\alpha^2\cdot r_{BS}^2\cdot\rho_{BS}},
\end{aligned} \tag{6.4}$$

where $W(\cdot)$ is the Lambert-W function, defined as:

$$W(x) = \sum_{n=1}^{\infty} \frac{(-1)^{n-1}\cdot n^{n-2}}{(n-1)!} \cdot x^n. \tag{6.5}$$

6.2.2 Traffic Load Model

In this work, we adopt a realistic traffic pattern [82], [84] that corresponds to the maximum traffic per operator in a given cell, during the night zone. Fig. 6.2(a) plots the maximum traffic per hour, denoted by $Load^{max}(h)$, throughout the day[1]. Without loss of generality, we focus on the time zone between 01.00 and 09.00 am, when the traffic per BS is relatively low (i.e., less than 40 Mbps, which corresponds to 35% of the cell's capacity). In addition, we assume that the traffic volumes of different operators may be different, although they follow the same pattern. Hence, we define $\rho_n \in [0, 1]$ as the percentage of each operator's traffic load with

[1]The parameter h can be dropped for the sake of simplicity.

respect to the maximum traffic for the respective hour. However, apart from the maximum traffic volume values, the monthly and annual past reports, available to the MNOs, can provide further estimations about the minimum and average traffic load values and the fluctuations of the traffic through time. In this work, based on real data concerning the traffic load information, we have obtained some necessary insights about the minimum, maximum and average values of the traffic load, and we have plotted some indicative numbers in Fig. 6.2(b). Each one of the six values corresponds to the average traffic load that was observed in different days during the year. In addition, we express the BS utilization as a percentage of the total BS's capacity resources for the extreme cases of minimum and maximum traffic loads. The two values, $Load^{min}$ and $Load^{max}$, are very critical and it is very important for the MNOs to be able to predict them.

Unlike the existing works in the literature, where each MNO places only one bid corresponding to the maximum capacity requirements, in our work, we propose that the MNOs place multiple bids corresponding to different levels of the predicted traffic load, depicted in Fig. 6.2(b). Thus, given the estimated minimum and maximum levels of traffic load and assuming that the actual traffic load values will, most probably, lie between these two extreme values, we are able to calculate different levels of traffic load. In this work, we consider $L+1$ different traffic load levels. The number of levels depends on the MNOs' strategy that will be further explained in detail in the next sections. Each level $l \in \mathcal{L} = \{0, \dots, L\}$ corresponds to traffic that is equal to:

$$Load^{l} = Load^{min} + \frac{Load^{max} - Load^{min}}{L} \cdot l = \left(1 - \frac{l}{L}\right) \cdot Load^{min} + \frac{l}{L} \cdot Load^{max}. \tag{6.6}$$

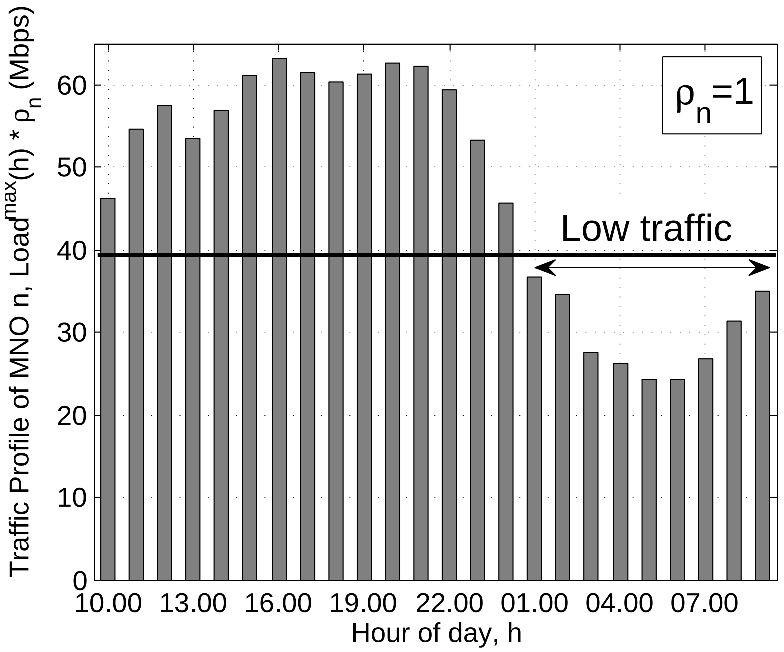
Evidently, the two extreme values are $Load^{0} = Load^{min}$ and $Load^{L} = Load^{max}$. Fig. 6.3 illustrates an example, depicting various traffic levels for a specific hour (h = 02.00 am). Let us recall that information about the two extreme values are shown in Fig. 6.2(b).

Based on the aforementioned issues, in the following subsection, we calculate the capacity that each MNO requests from the third-party network, taking into account the traffic load variations.

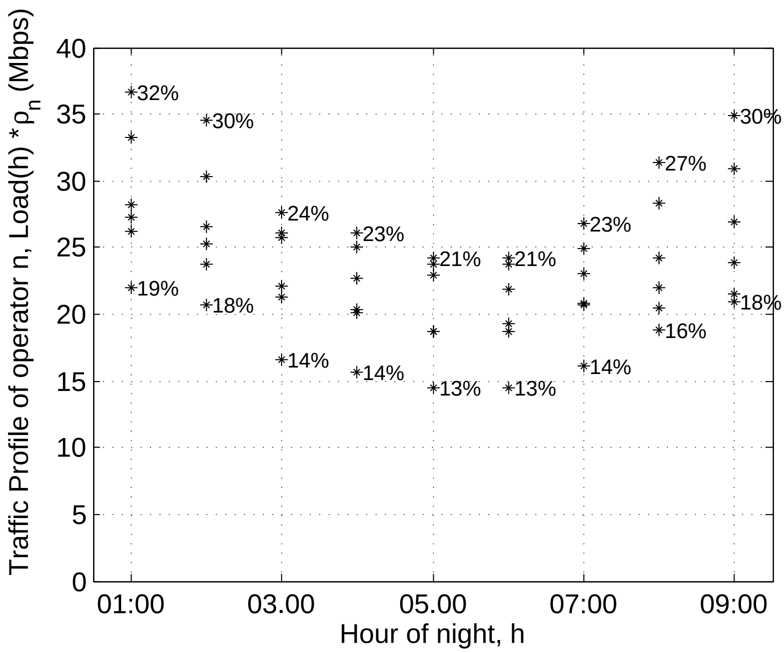
6.2.3 Capacity Demand Calculation

In the proposed auction-based switching off algorithm, a subset of MNOs offloads all their traffic by leasing bandwidth resources from the SCs, thus being able to switch off their BSs. In order to calculate the capacity resources that a BS requests from each SC, it is necessary to determine the traffic demands of the users and to which SC they will be associated. Thus, we study the downlink transmission (from SC to the user) with the following assumptions:

- Only one MNO provides service to a particular user.



(a) Traffic load during the 24-hour day



(b) Real data for traffic load patterns

FIGURE 6.2: Traffic pattern scenario and real data traffic values

- Each user can be associated with only one SC. In case that the corresponding MNO switches off the BS, the user will transmit its data through the SC, otherwise the user will remain associated with the BS of the MNO.
- We assume that the total transmit power of the BSs and SCs is equally distributed among its subcarriers.

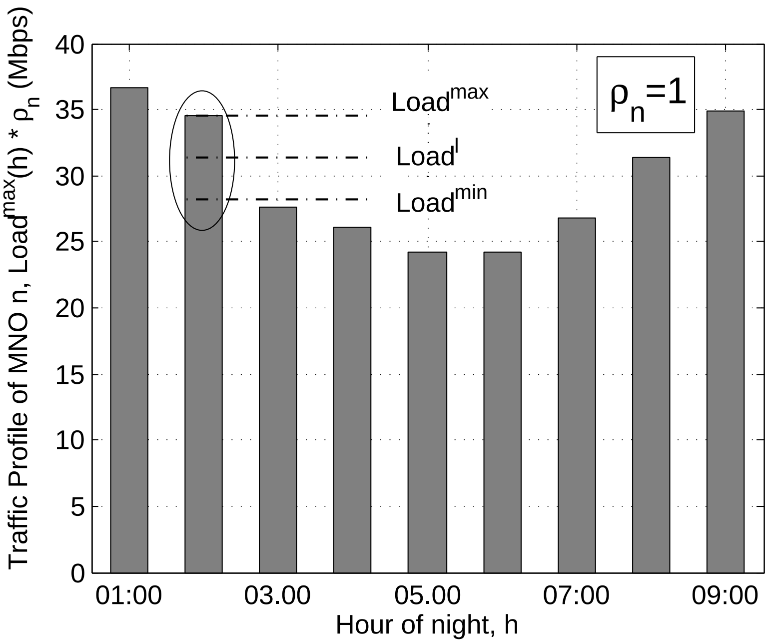


FIGURE 6.3: Traffic pattern during the night zone and different levels of traffic load estimation

Let us define as $\mathcal{U}_n = \{1, \ldots, U_n\}$ the set of users of each MNO n. We use the notation $u_{i,n} \in \mathcal{U}_n$ (with $i \in U_n$) to represent user i that is being served by the BS of the nth MNO. Similarly, we denote as $u_{i,n:f}$ the ith user of the nth MNO that is being served by the fth SC (i.e., after the corresponding BS is switched off). We assume that user $u_{i,n:f}$ is associated to the SC with the strongest signal, denoted by the following equation:

$$\arg\max_{f \in \mathcal{F}} \left(G_{SC} \cdot g_u \cdot L_{u_{i,n:f}} \cdot P^{max}_{tx,SC} \right), \tag{6.7}$$

where G_{SC} is the SC antenna gain, g_u is the user antenna gain, $L_{u_{i,n:f}}$ denotes the pathloss between the SC f and the user $u_{i,n:f}$, and $P^{max}_{tx,SC}$ is the maximum transmission power of the SCs. We assume that the pathloss is distance-dependent, and is defined as $L_{u_{i,n:f}} = d^{-\gamma}_{u_{i,n:f}}$, where $d_{u_{i,n:f}}$ is the distance between the users $u_{i,n:f}$ and the SC m, and γ is the pathloss exponent.

Therefore, the SNR received by a user $u_{i,n:f}$ from SC f is given by:

$$SNR_{u_{i,n:f}} = \frac{G_{SC} \cdot g_u \cdot L_{u_{i,n:f}} \cdot P_{s,SC}}{P_{noise}}, \tag{6.8}$$

where P_{noise} represents the thermal noise and $P_{s,SC}$ represents the power that is allocated by the SC to each subcarrier, and is calculated by the following equation [101], [102]:

$$P_{s,SC} = 10 \cdot \log \left(\frac{P^{max}_{tx,SC}}{12 \cdot N^{max}_{PRB}} \right), \tag{6.9}$$

where N_{PRB}^{max} is the maximum number of Physical Resource Blocks (PRBs)[2] allocated to the user $u_{i,n:f}$. Thus, given that the throughput demand of the user $u_{i,n:f}$ is $R_{u_{i,n:f}}$, and CR_{SC} is the bandwidth of the SCs, the number of PRBs needed for the association of the user $u_{i,n:f}$ with the SC m is given by [103]:

$$N_{PRB_{u_{i,n:f}}} = \frac{R_{u_{i,n:f}}}{CR_{SC} \cdot \log_2 \left(1 + SNR_{u_{i,n:f}}\right)}. \tag{6.10}$$

Consequently, from each SC f, the nth MNO requests a number of PRBs that is equal to the summation of the PRBs allocated for each one of the users that are in the coverage area of the fth SC, denoted by:

$$N_{PRB_{n,f}} = \sum_{u_{i,n:f} \in U_n} N_{PRB_{u_{i,n:f}}}. \tag{6.11}$$

Based on this analysis, the number of PRBs that are requested by the nth MNO for all the different levels of traffic load, defined as $N^l_{PRB_{n,f}}$, can be calculated by employing the aforementioned equations and by using the corresponding parameters for each user.

6.2.4 Notation

A summary of the main parameters employed in the gamet theoretic switching off algorithm and their model analysis is given in Table 6.1.

Table 6.1: Main Parameters for the MAS model analysis

Symbol	Description
BS_n	BS of nth MNO
$B^l_{n,f}$	Bid pair of nth MNO for fth SC at lth bidding level
$b^l_{n,f}$	Bid of nth MNO for fth SC at lth bidding level
$b^l_{res,n,f}$	Reservation price of nth MNO for fth SC at lth level
CG_n	Financial profit of nth MNO
CG_n^{min}	Minimum profit of nth MNO
CG_{SC}	Financial gain of SC network
CG_{SC}^{min}	Minimum profit of SC network
CR_{BS}	Capacity resources of a BS
CR_{SC}	Capacity resources of a SC
C_{BS}	BS cost
C_{SC}	SC cost
d	Data session
D	Maximum number of simultaneous sessions for a node
D^{BS}	Maximum number of simultaneous sessions for BS

Continued on next page

[2]It should be mentioned that each PRB consists of 12 subcarriers, with a bandwidth of 180 kHz and a duration of 0.5 ms.

Table 6.1 – continued from previous page

Symbol	Description
D^{SC}	Maximum number of simultaneous sessions for SC
$d_{u_{i,n:f}}$	Distance between user $u_{i,n:f}$ and fth SC
$\mathbb{E}[B]$	Average transmitted bits of network
$\mathbb{E}[B_{BS_n}]$	Average transmitted bits of BS_n
$\mathbb{E}\left[B_{SC_f}\right]$	Average transmitted bits of SC_f
$\mathbb{E}[E]$	Average energy consumption of a network
$\mathbb{E}[E_{BS_n}]$	Average energy consumption of BS_n
$\mathbb{E}\left[E_{SC_f}\right]$	Average energy consumption of SC_F
$\mathbb{E}[\eta_\epsilon]$	Expected energy efficiency of a network
$\mathbb{E}[\eta_\epsilon^{(BS_n)}]$	Expected energy efficiency of BS_n
$\mathbb{E}[\eta_\epsilon^{\left(SC_f\right)}]$	Expected energy efficiency of SC_f
$\mathbb{E}[T]$	Expected throughput of a network
$\mathbb{E}[T_{BS_n}]$	Expected throughput of BS_n
$\mathbb{E}\left[T_{SC_f}\right]$	Expected throughput of SC_f
$f \in \mathcal{F}$	Identification of SC
$\mathcal{F} = \{0, \dots F\}$	Set of SCs, with $\lvert\mathcal{F}\rvert = F$
F_{SC}	Number of SCs for connectivity analysis
$f_1(\mathbf{x})$	Third-party's objective
$f_2(\mathbf{x})$	MNO's objective
$f_3(\mathbf{x})$	Overall objective
g_u	User antenna gain
G_{SC}	SC antenna gain
h	Hour of the day
k	Identification of a node
$l \in \mathcal{L}$	Identification of bidding level
$\mathcal{L} = \{0, \dots L\}$	Set of bidding levels, with $\lvert\mathcal{L}\rvert = L$
$Load(h)$	Traffic load of a single BS at hour h
$Load^l(h)$	Traffic load of a single BS for level l at hour h
$Load^{max}(h)$	Maximum traffic load of a single BS at hour h
$Load^{min}(h)$	Minimum traffic load of a single BS at hour h
$L_{u_{i,n:f}}$	Pathloss between mth SC and user $u_{i,n:f}$
MNO_n	Identification of the nth MNO
$n \in \mathcal{N}$	Identification of MNO
$\mathcal{N} = \{1, \dots N\}$	Set of MNOs, with $\lvert\mathcal{N}\rvert = N$
N_{BS}	Number of BSs for connectivity analysis
N_{PRB}^{max}	Maximum number of PRBs
$N_{PRB_{n,f}}$	Number of PRBs allocated to nth MNO
$N_{PRB_{n,f},lack}$	Number of lacking PRBs of nth MNO
$N_{PRB_{i,n:f}}$	Number of PRBs allocated to user $u_{i,n:f}$
$\mathcal{N}_{OFF} \subseteq \mathcal{N}$	Subset of MNOs with switched off BSs
N_{OFF}	Number of MNOs with switched off BSs
$\mathcal{N}_{ON} \subseteq \mathcal{N}$	Subset of MNOs with active BSs
$\mathcal{N}_{\mathcal{ON}}$	Number of MNOs with active BSs
P_{const}	Power consumed by a BS for cooling and antenna feeding
P_{idle}	Power consumed by a BS when it is idle

Continued on next page

Table 6.1 – continued from previous page

Symbol	Description
P_{tx}	Power consumed by a BS for data transmission
$p_d^{(k)}$	State probability for serving d sessions of kth node
$p_d^{(BS_n)}$	State probability for serving d sessions of BS_n
$p_d^{\left(SC_f\right)}$	State probability for serving d sessions of SC_f
$P_{fc,BS}$	Connectivity probability
P_{noise}	Thermal noise power
$p_{n,f}^l$	Price of nth MNO for fth SC at lth level
P_s^{SC}	Power of SC allocated to a subcarrier
$P_{tx,SC}^{max}$	Maximum transmission power of a SC
r_{BS}	BS cell radius
r_{SC}	SC cell radius
R	Bit rate
$R_{u_{i,n:f}}$	Throughput demand of user $u_{i,n:f}$
SC_f	Identification of the fth SC
$SNR_{u_{i,n:f}}$	SNR received by user $u_{i,n:f}$
t_{night}	Night zone duration
$u_{i,n} \in \mathcal{U}_n$	User i of MNO_n
$u_{i,n:f} \in \mathcal{U}_n$	User i of MNO_n associated with fth SC
$u_{n,f}^l$	Valuation of nth MNO for fth SC at lth bidding level
$\mathcal{U}_{n,f}^l$	Payoff function
U_n	Number of users of MNO_n
$\mathcal{U}_n = \{1, \ldots, U_n\}$	Set of users of MNO_n
x_n	Binary decision variable of nth MNO
$x_{n,f}^l$	Binary decision variable of nth MNO for fth SC at lth level
$\left(x_{n,f}^l\right)^{\{-i\}}$	Binary decision variable when ith does not participate
y	Parameter for SC minimum profit
z	Parameter for BS minimum profit
α	Parameter for the relationship between BSs and SCs radius
β	Parameter for the relationship between BSs and SCs number
γ	Pathloss exponent
δ	Parameter of satisfaction function
$\lambda^{(BS_n)}$	Generation rate of sessions of BS_n
$\lambda^{\left(SC_f\right)}$	Generation rate of sessions of SC_f
$\lambda^{(k)}$	Generation rate of sessions of kth node
$\mu^{(BS_n)}$	Service of sessions of BS_n
$\mu^{\left(SC_f\right)}$	Service of sessions of SC_f
$\mu^{(k)}$	Service of sessions of kth node
ρ_{BS}	BSs density
ρ_{SC}	SCs density
ρ_n	Percentage of nth MNO with respect to maximum traffic

6.3 Multiobjective Auction-based Switching Off Algorithm (MAS)

In this section, we present the combinatorial auction employed to select the MNOs that can offload their traffic to the SCs, thus being able to switch off their BSs. We provide the bidding strategy and we formulate the ILP model which ensures the optimal allocation and the switching off strategy for the auction. In addition, to ensure truthful bidding, the Vickrey - Clarke - Grooves (VCG) payment mechanism [104] is employed.

6.3.1 The Big Picture

By considering the limited capacity of the SCs and the MNOs' incentive to switch off their BSs, we use an auction-based mechanism to motivate the operators to offload the traffic to the third-party SC network. Fig. 6.4 illustrates the main idea of the scheme. In our proposal, both the MNOs and the third party take part in the decision process, each one having a separate role in the framework. On one hand, the MNOs act as buyers, who are willing to lease the SCs resources and opportunistically offload their traffic. On the other hand, the third party, acting as seller, collects the bids and, through an auction, the subset of MNOs that can offload their traffic, is selected. The proposed auction-based switching off scheme consists of three main steps: bidding, allocation and pricing, whose process and the respective decision makers (in parenthesis) are presented below: *i*) In the *bidding phase* (MNOs), the MNOs place their bids to the third party according to the different values of the requested bandwidth. Each bid includes the information of the requested capacity and the corresponding price that the MNO is willing to offer. *ii*) In the *allocation step* (third party, MNOs), the third party collects the MNOs' bids. The selection of the optimal resource allocation can be derived through the solution of the resource allocation problem. *iii*) In the *pricing step* (third party), the third party decides each winner's payment price, based on the resource allocation of the previous step. The winning MNOs offload their whole traffic to the SCs and switch off their BSs, while the losing bidders keep their BSs active.

6.3.2 Bidding Strategy

Each SC_f of the third-party (seller) has unexploited capacity resources that is willing to lease to the MNOs. The MNOs (buyers) are willing to offload their traffic to the SCs by requesting specific capacity resources to lease, based on the predictions of the traffic load and the number of the PRBs calculated through Eq. (6.11). The MNOs valuate the requested resources, $N^l_{PRB_{n,f}}$ at a given price $u^l_{n,f}$, unknown to the third-party and the other bidders, where l is the level of resources, $n \in \mathcal{N}$ refers to the corresponding operator and $f \in \mathcal{F}$ corresponds to the specific SC that the MNO is interested in leasing the resources from. In the proposed auction-based scheme, each operator submits a set of bid pairs $B^l_{n,f} =$

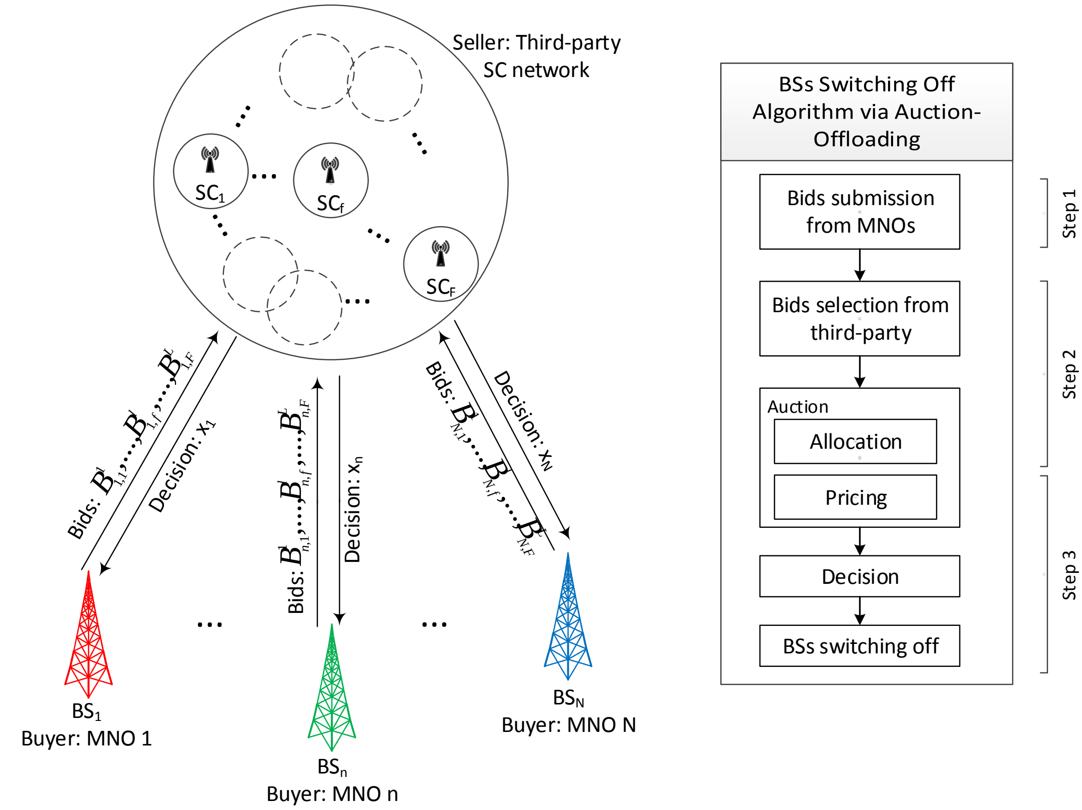


FIGURE 6.4: Auction illustration and proposed algorithm flowchart

$\left(b^l_{n,f}, N^l_{PRB_{n,f}}\right)$, representing the price, $b^l_{n,f} \leq u^l_{n,f}$, that the nth MNO pays for leasing the capacity $N^l_{PRB_{n,f}}$ from the fth SC. In general, these two values (i.e, $b^l_{n,m}$, $u^l_{n,m}$) may not necessarily be the same. However, in a truthful auction as the the one that we have (the truthfulness property of the auction will be explained in Section 6.3.4, it is proved that the private valuation and the bidding price are equal, and thus, $b^l_{n,f} = u^l_{n,f}$ [78], [79]. After receiving the bid pairs, the third-party proceeds to the selection of the subset of the MNOs, whose traffic can be offloaded to the corresponding SCs.

To gain further insights on the proposed bidding strategy, let us consider the following example. We assume that, given the predicted expectations about the traffic load, each MNO f submits multiple bids, $b^0_{n,f}, b^1_{n,f}, \ldots, b^l_{n,f}, \ldots, b^L_{n,f}$, indicating the offered price for the requested number of PRBs. Through the different bid pairs, the MNOs actually reveal their outage probability tolerance. In particular, by leasing the maximum calculated number of PRBs ($N^L_{PRB_{n,f}}$) for the highest bid $b^L_{n,f}$, the MNOs guarantee service to all their users. On the other hand, by obtaining a smaller number of PRBs (e.g., $N^l_{PRB_{n,f}}$ with $l < L$), the operator will pay a smaller price at a risk of leaving some users in outage. The minimum number of requested PRBs $N^0_{PRB_{n,f}}$ constitutes an upper bound of the operator's outage tolerance. Another parameter determined by each MNO is the number of levels. A higher number of levels results in more bid pairs, thus increasing the performance of the auction (since more offloading options become available) while inducing more communication overhead and higher computational complexity.

To flexibly model the MNOs' outage tolerance, we introduce a satisfaction function which represents the bidding value that the MNO is willing to pay for leasing specific bandwidth. To that end, we define the number of lacking PRBs as the difference between the maximum number of required PRBs minus the actually obtained PRBs allocated the MNO, given by:

$$N^l_{PRB_{n,f},lack} = N^L_{PRB_{n,f}} - N^l_{PRB_{n,f}}. \tag{6.12}$$

The satisfaction function is determined by the requested capacity of each MNO and is monotonically decreasing with the number of lacking PRBs. We also consider that for each MNO there is a lower bound for the minimum number of requested PRBs, which minimizes the MNO's satisfaction. This bound indicates that for less PRBs the MNO will not participate in the auction. Fig. 6.5 shows three examples of the outage tolerance function. Three bidding values are emphasized in the plot: the highest bid $b^L_{n,f}$, corresponding to the maximum requested capacity, $N^L_{PRB_{n,f}}$ (with $N^l_{PRB_{n,f},lack} = 0$), the lowest bid $b^0_{n,m}$, and an intermediate value $b^l_{n,f}$. As the number of lacking PRBs increases (depicted by the arrow direction in Fig. 6.5), the bid values decrease and, as a consequence, losses in terms of the served users may be observed. If the number of lacking PRBs exceeds $N^0_{PRB_{n,f},lack}$, the MNO will not participate in the auction and, thus, no bid lower than $b^0_{n,f}$ will be submitted. The three points (A, B and C) marked in Fig. 6.5, correspond to the different tolerance functions of three operators. An outage-tolerant MNO (point C) requests for less bandwidth for the same bidding value, $b^l_{n,f}$, compared to a non-tolerant MNO (point A) that still requests high capacity from the third-party. Hence, the non-tolerant MNO places higher priority on guaranteeing user service, whereas the outage-tolerant MNO is willing to sacrifice some resources in order to increase its probability of winning the auction and switching off its BS, thus enhancing energy efficiency. Finally, point B corresponds to an intermediate bidding strategy defined by a linear function between the two examined parameters.

The user outage tolerance function is modeled as:

$$b^l_{n,f} = b^L_{n,f} - \frac{b^L_{n,f} - b^0_{n,f}}{N^L_{PRB_{n,f}} - N^0_{PRB_{n,f}}} \cdot \left(N^l_{PRB_{n,f}}\right)^{\delta}. \tag{6.13}$$

The values of $b^0_{n,f}$ and $b^L_{n,f}$ will be calculated in details in the following section, where the constraints and requirements posed by the MNOs and the third-party are given within the optimization framework.

The distinctive cases for the satisfaction curves are given below:

- *Non-tolerant MNO (Point A).* For the non-tolerant MNO, the outage tolerance function is convex, with $\delta < 1$.
- *Average-tolerant MNO (Point B).* There is a linear relation between the bidding strategies and the outage-tolerance of the MNOs, by substituting $\delta = 1$ in Eq. (6.13).

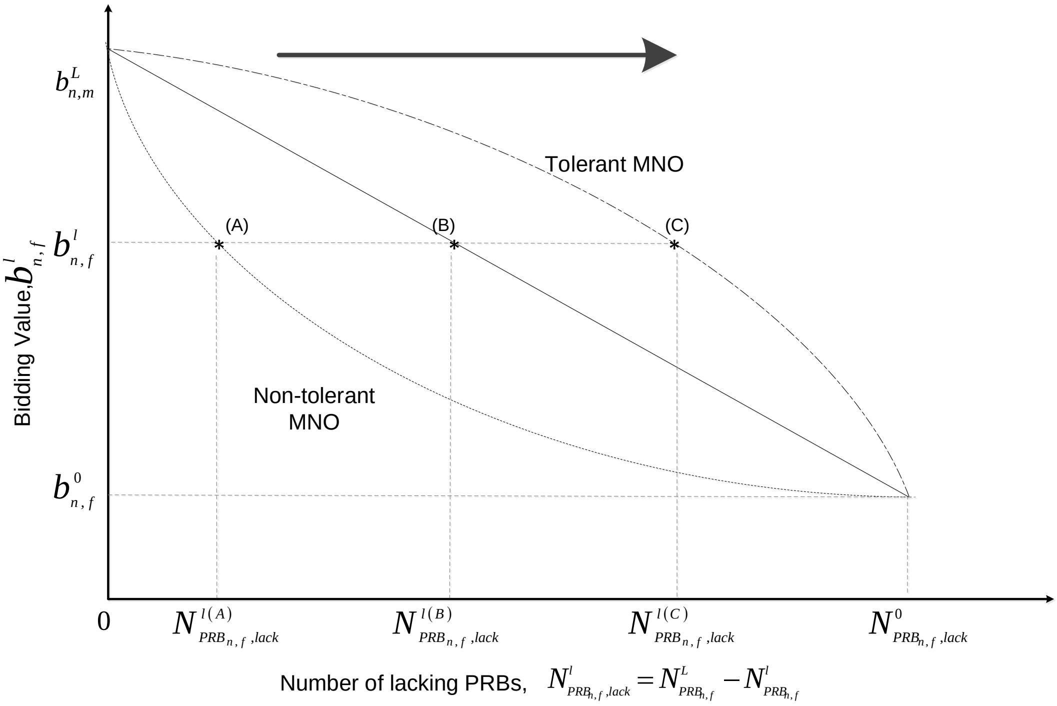


FIGURE 6.5: Bidding strategy versus tolerance function

- *Tolerant MNO (Point C).* For the tolerant MNO, the satisfaction function is concave, with $\delta > 1$.

The parameter δ may obtain a wide range of values. The selection of a value equal to $\delta << 1$ corresponds to a strictly non-tolerant MNO, who decreases its bid requests very fast. In contrast, a very high value of this indicative parameter (i.e., $\delta >> 1$) would lead to very slowly decreasing bidding values, and thus, to a very tolerant operator.

6.3.3 Auction Formulation

By employing the properties of combinatorial auction theory, we formulate the problem of the opportunistic offloading as an auction. Each MNO $n \in \mathcal{N}$ places the corresponding bid pairs, $B^l_{n,f}$. Having received the bids, the third-party selects the subset of MNOs that maximizes the desired goals of all the involved participants in the auction. We define $x^l_{n,f}$ as a binary decision variable that indicates whether the corresponding bidder (MNO n) is winner ($x^l_{n,f} = 1$) or not ($x^l_{n,f} = 0$) in the corresponding SC_f and for the lth bidding value.

The cost of using the SC infrastructure and the increased energy consumption, are the main objectives that should be investigated: the maximization of the profits (the economic objectives of both the third-party and the MNOs), and the minimization of the energy consumption (the energy objective). The interaction of these competing objectives motivates the use of an auction mechanism. In continuation, a detailed analysis of the objectives of each party is presented.

6.3.3.1 The third-party's objective:

The third-party aims at *maximizing its profit* by leasing high volumes of SCs capacity at increased prices. The profit is defined as the difference of the MNOs' winning bids minus its expenses (CapEx and OpEx). We define the financial gain of the SC network, CG_{SC}, as:

$$f_1(\mathbf{x}) = CG_{SC} = \sum_{n\in\mathcal{N}}\sum_{f\in\mathcal{F}}\sum_{l\in\mathcal{L}} x^l_{n,f}\cdot b^l_{n,f} - F\cdot C_{SC}, \tag{6.14}$$

where C_{SC} is the cost of a SC, corresponding to the sum of its CapEx and the traffic-dependent OpEx. For the calculation of the cost of the SCs, the cost model presented in Section 5.3.1 is employed.

To ensure its objective, the third-party introduces a minimum profit, which is described as a function of its total costs:

$$CG^{min}_{SC} = y\cdot F\cdot C_{SC},\ \ y > 0. \tag{6.15}$$

Given the minimum profit, calculated by Eq. (6.15), we estimate the reservation price, which is defined below:

Proposition 1. *The reservation price is defined as the minimum price that a seller would be willing to accept for leasing the corresponding bandwidth:*

$$b^l_{res,n,f} = \frac{N^l_{PRB_{n,f}}}{N^{max}_{PRB}}\cdot y\cdot F\cdot C_{SC}. \tag{6.16}$$

Proof. The third-party is willing to share its resources among the MNOs based on proportional fairness. However, the third-party also wants to ensure that a minimum profit gain will be achieved. To that end, it calculates a reservation price, which is the minimum price that the third-party will accept from an MNO to lease a specific bandwidth. The maximum number of PRBs that the nth MNO can offload to the fth SC of the third-party is given by:

$$N^l_{PRB_{n,f}} = \frac{b^l_{res,n,f}\cdot x^l_{n,f}}{\sum_{n\in\mathcal{N}}\sum_{l\in\mathcal{L}} b^l_{res,n,f}\cdot x^l_{n,f}}\cdot N^{max}_{PRB}. \tag{6.17}$$

Finally, by using the Eq. (6.15) and the Eq. (6.17) in the Eq. (6.14), the reservation price for offloading traffic and using $N_{PRB^l_{n,f}}$ is calculated. □

The reservation price in Eq. (6.16) is not the price that the MNOs will propose to lease their requested capacity, though it is a threshold price that the third-party uses in order to eliminate all the offers that are less than the accepted. The reservation price can either be announced or be unknown to the MNOs. The reservation price means that the seller would rather withhold the capacity if the proposed bids are too low (i.e., lower than the reservation price) and given this price the auction process can be accelerated, since the set of prices that are lower than the reservation price can be discarded.

6.3.3.2 The MNOs' objective:

The objective of each MNO is the *maximization of its financial profits*. The maximization of the profits of the nth MNO is defined as the revenue from switching off its BS minus the winning bids for leasing the requested capacity from the third-party. Therefore, the profit (cost gain) can be written as:

$$f_2(\mathbf{x}) = CG_n = C_{BS} \cdot x_n - \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} x_{n,f}^l \cdot b_{n,f}^l, \tag{6.18}$$

with,

$$x_n = \prod_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} x_{n,f}^l, \forall n \in \mathcal{N}, \tag{6.19}$$

and C_{BS} being the cost of a BS, whose model is also presented in Section 5.3.1, provided that:

$$\sum_{l \in \mathcal{L}} x_{n,f}^l \in \{0, 1\}, \forall n \in \mathcal{N}, \forall l \in \mathcal{L}. \tag{6.20}$$

At this point, let us recall that an operator is able to switch off its BS, if it wins in an auction in all the SCs, a condition that is represented by the product in Eq. (6.19). The product is equal to 1 when the nth MNO wins in F auctions in the equally numbered SCs, otherwise it is 0.

The MNOs are willing to participate in the auction and lease bandwidth resources from a third-party, if they guarantee a minimum profit gain, at the same time. Consequently, they introduce a minimum profit, which is described as a percentage of their total costs:

$$CG_n^{min} = z \cdot C_{BS},\ 0 < z < 1. \tag{6.21}$$

The bidding strategy of the MNOs, along with the proposed bids, depend on the minimum profit gain and the operation costs of the BSs. However, the cost gain can be attained, if and only if, the nth MNO wins in F auctions and is able to lease the requested capacity. In addition, since we consider uniform traffic in the macro cell, we conclude that the bids in the different SCs must be equal and proportional to the corresponding traffic. Thus, the maximum bid price for offloading the traffic in the fth cell is calculated as:

$$b_{n,f}^L = \frac{(1-z) \cdot C_{BS}}{F}. \tag{6.22}$$

Similarly, the minimum bidding price is a proportional value of the maximum one, given by the following equation:

$$b_{n,f}^0 = v \cdot \frac{(1-z) \cdot C_{BS}}{F}, \tag{6.23}$$

where $v \in (0, 1)$. The bidding values of the remaining $L-1$ levels can be calculated based on Eq. (6.13), depending on the maximum bid value and the relation between the outage tolerance of the MNOs and the discount they can be offered for the lower requested bandwidth.

6.3.3.3 Overall objective:

The overall objective of the network is the *minimization of the energy consumption*. This can be attained by reducing the number of active BSs, given that the BSs are responsible for the major part of energy consumption in the network. We define the network energy consumption, $\mathbb{E}[E]$, as follows:

$$f_3(\mathbf{x}) = \mathbb{E}[E] = \sum_{n \in \mathcal{N}} \mathbb{E}[E_{BS_n}] \cdot (1 - x_n) + F \cdot \mathbb{E}[E_{SC}], \tag{6.24}$$

where $\mathbb{E}[E_{BS_n}]$ and $\mathbb{E}[E_{SC}]$ represent the BS and SC energy consumption, respectively.

The combinatorial auction formulation should include all the objectives of the participating entities. In order to capture the tradeoff between the objectives, multiobjective optimization [105] is employed. Multiobjective optimization is the discipline that focuses on the resolution of problems involving the simultaneous optimization of several objectives. The target is to find a subset of acceptable solutions according to a set of objectives. In general terms, the objectives may be conflicting, and consequently, a single global optimum may not exist. Hence, the notion of an optimum set $\mathbf{x}^*$ becomes very important. Some relevant definitions are given next.

Definition 1. *Given the three objectives, $f_1(\mathbf{x})$, $f_2(\mathbf{x})$, and $f_3(\mathbf{x})$, and provided that $\mathbf{x}_1$ and $\mathbf{x}_2$ are two decision variables, then $\mathbf{x}_1$ is said to be the Pareto dominant, and is denoted as $\mathbf{x}_1 \succeq \mathbf{x}_2$, if and only if $f_i(\mathbf{x}_1) \geq f_i(\mathbf{x}_2)$, $\forall i \in \{1, 2, 3\}$, and $f_j(\mathbf{x}_1) > f_j(\mathbf{x}_2)$, for at least one index $j \in \{1, 2, 3\}$*

Definition 2. *$\mathbf{x}^*$ is said to be Pareto optimal (or non-dominated), if there is no other $\mathbf{x}$, so that $\mathbf{x}$ dominates $\mathbf{x}^*$. The set of all Pareto optimal solutions in the decision space is called the Pareto optimal set and the image of the Pareto optimal set in the objective space is called the Pareto optimal front.*

Provided the aforementioned definitions, the ILP multiobjective optimization problem can be formulated as follows.

Definition 3. *The allocation problem is to determine the optimal solution $\{x^l_{n,f}\}$, $\forall n \in \mathcal{N}$, $\forall f \in \mathcal{F}$, and $\forall l \in \mathcal{L}$ that maximizes the distinctive incentives of the* *involved parties in the auction formulation, subject to capacity and offloading targets:*

$$\textbf{P1:} \quad \max \left[\; CG_{SC}, \quad CG_n, \quad -\mathbb{E}[E] \; \right] \tag{6.25}$$

$$\text{s.t.}$$

$$\sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}} x^l_{n,f} \cdot N^l_{PRB_{n,f}} \leq N^{max}_{PRB}, \forall f \in \mathcal{F}, \tag{6.26}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,f} \in \{0,1\}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \tag{6.27}$$

$$b^l_{n,f} \geq b^l_{res,n,f}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \forall l \in \mathcal{L}, \tag{6.28}$$

$$x^l_{n,f} \in \{0,1\}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \forall l \in \mathcal{L}. \tag{6.29}$$

The constraint in Eq. (6.26) ensures that the total number of allocated resources does not exceed their availability, constraint (6.27) ensures that only one bid of the nth MNO in the fth SC can be the winning bid among the l different ones, constraint (6.28) ensures that the bids are higher than the reservation price and the constraint (6.29) ensures the integrality of the binary variable. The objectives of the proposed optimization formulation are contradictory. For example, the maximization of the third-party income does not imply the BSs switching off, whereas the energy consumption objective does not ensure the third-party's interests. In addition, the maximization of the third-party financial gains may lead to additional economic losses from the MNOs' perspective, since the maximization of this objective may lead to a resource allocation that does not imply the BSs deactivation.

Exploiting the fact that the BSs are responsible for the major part of the energy consumption, the third objective of the problem, $f_3(\mathbf{x})$, can be transformed into a constraint. Hence, energy consumption is minimized when the maximum number of MNOs are able to switch off their BSs after winning in M auctions, a condition represented by the product in Eq. (6.19). Thus, the problem **P1** is transformed into a simpler formulation in Eq. (6.30) and, at the same time, the energy consumption objective is not neglected, in contrast to former works [77], where only the maximization of the third-party's income is considered. The equivalent problem is shown below:

$$\textbf{P2:} \quad \max \left[\; CG_{SC}, \quad CG_n \; \right] \tag{6.30}$$

$$\text{s.t.}$$

$$\prod_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{n,f} \in \{0,1\}, \forall n \in \mathcal{N}, \tag{6.31}$$

$$\sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}} x^l_{n,f} \cdot N^l_{PRB_{n,f}} \leq N^{max}_{PRB}, \forall f \in \mathcal{F}, \tag{6.32}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,f} \in \{0,1\}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \tag{6.33}$$

$$b^l_{n,f} \geq b^l_{res,n,f}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \forall l \in \mathcal{L}, \tag{6.34}$$

$$x^l_{n,f} \in \{0,1\}, \forall n \in \mathcal{N}, \forall f \in \mathcal{F}, \forall l \in \mathcal{L}. \tag{6.35}$$

The objective function (6.30) aims at maximizing the financial gain of both the third-party and the MNOs. Constraint (6.32) ensures that an operator either wins in one auction in the F SCs (and switches off its BS) or loses in all the auctions (keeps its BS active). Thus, this constraint ensures the minimization of the energy consumption given by the Eq. (6.24), since the third-party selects the resource allocation that leads to the highest number of switched off BSs, while at the same time, achieves the increase of its income. Constraints (6.32),(6.33), (6.34) and(6.35) are the same as constraints (6.26), (6.27), (6.28) and (6.29), respectively.

The multiobjective problem **P2** belongs to the class NP-Complete since it is equivalent to the 0-1 knapsack problem, which is a well-known problem in combinatorial optimization. For the NP-hard problems, an optimal solution is difficult to be found due to the large number of variables [105]. In order to overcome the high complexity of multiobjective problems, metaheuristic methods have become a very active research area and several algorithms have been proposed. Through the use of metaheuristcs, the problem can be solved efficiently and quickly for a relatively small number of MNOs and SCs [106]. In the investigated network configuration with 5 MNOs and 15 SCs [59], the solution is found very quickly. The metaheuristic algorithm (also sometimes called genetic) that finds the Pareto optimal solution for our multiobjective optimization problem works on a set of possible combinations of the decision variables [105]. The basic definition of the Pareto Front is that it consists of exactly those point solutions that are not dominated by any other point. The different objectives cannot be optimized simultaneously. Thus, first the solutions that maximize the MNOs's income and the third party's economic gains are calculated separately. Obviously, these solutions that maximize the cost gains of the MNOs and the third-party always belong to the Pareto Front, and in fact, they are its endpoints. A simple algorithm to find the other solutions (if any) on the Pareto Front begins by sorting the solutions according to one of the objectives - e.g., third party's income. The algorithm then starts with the point with the maximum gain for the third party and continues to the successive solutions in order of increasing third party's cost until the solutions with higher cost gain value for the operators is found. This solution is then added to the Pareto Front and the search is restarted from it.

6.3.4 Pricing Strategy

Having defined the ILP model, we now illustrate the payment rule, which is of crucial importance for the realization of the auction for the third-party. The VCG payment induces all the users to reveal their actual valuations for the requested bandwidth. In VCG mechanism, the third-party charges the bidders (MNOs) with a price for the requested capacity. For example, an MNO who requires large bandwidth will have to pay a high price, since its request results in dissatisfying other MNOs who lose in the auction because of the limited capacity resources and will not be able to offload their traffic.

Let us denote by $p^l_{n,f}$ the price paid by the MNO n to the third-party for the allocated capacity of the fth SC. Thus, the payoff function for bidder n that represents the difference between the price paid by bidder n and its true valuation can be expressed by:

$$\mathcal{U}^l_{n,f} = \begin{cases} u^l_{n,f} - p^l_{n,f}, \text{if MNO } n \text{ is selected,} \\ \quad 0, \qquad\qquad \text{otherwise.} \end{cases} \tag{6.36}$$

The payment rule for each MNO $i \in \mathcal{N}$ can be formally defined as follows:

$$p^l_{i,f} = \sum_{n \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \left(x^l_{n,f}\right)^{\{-i\}} \cdot b^l_{n,f} - \sum_{n \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} x^l_{n,f} \cdot b^l_{n,f}, \tag{6.37}$$

where the first term is the aggregate valuation of the allocated resources, $\left(x^l_{n,f}\right)^{\{-i\}}$, when MNO i does not participate at all in the auction. The second term is the aggregate valuation of the allocation $x^l_{n,f}$ of all MNOs other than i, when i participates in the auction.

Next, we prove that our optimized auction mechanism possesses three important properties: *i*) truthfulness, *ii*) individual rationality, and *iii*) low computational complexity.

Proposition 2 (Truthfulness). *The payment rule defined in Eq. (6.37) satisfies the individual rationality property.*

Proof. To prove the truthfulness, we compare two cases: *Case 1*, where the MNO i bids $b^l_{i,f} = u^l_{i,f}$ and the solution of the problem (6.30) is $x^l_{i,mf}$, and *Case 2*, where the MNO i bids $\left(b^l_{i,f}\right)' = \left(u^l_{i,f}\right)'$ and the corresponding solution is $\left(x^l_{i,f}\right)'$. In addition, let $\left(x^l_{n,f}\right)^{\{-i\}}$ denote the solution to the same problem, considering that MNO i does not participate in the auction, thus forcing $x^l_{i,f} = 0$, $\forall f \in \mathcal{F}$ in the problem. Note that $\left(x^l_{n,f}\right)^{\{-i\}} = \left(\left(x^l_{n,f}\right)^{\{-i\}}\right)'$.

Given the Eq. (6.36) and (6.37), the utility of i, when it bids $u^l_{i,m}$, is equal to:

$$U^l_{i,f} = \sum_{n \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} x^l_{n,f} \cdot u^l_{n,f} - \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \left(x^l_{n,f}\right)^{\{-i\}} \cdot u^l_{n,f}, \tag{6.38}$$

whereas, when the MNO declares $\left(u^l_{i,f}\right)'$, the utility is equal to:

$$\left(U^l_{i,f}\right)' = \sum_{n \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \left(x^l_{i,f}\right)' \cdot \left(u^l_{n,f}\right)' - \sum_{n \in \mathcal{N}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \left(x^l_{n,f}\right)^{\{-i\}} \cdot u^l_{n,f}. \tag{6.39}$$

Since, $x^l_{n,f}$ is the solution that maximizes the objective function (6.30), we have:

$$\sum_{k \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} x^l_{k,f} \cdot u^l_{k,f} \geq \sum_{k \in \mathcal{N} \backslash \{i\}} \sum_{f \in \mathcal{F}} \sum_{l \in \mathcal{L}} \left(x^l_{k,f}\right) \cdot \left(u^l_{k,f}\right)', \tag{6.40}$$

thus, $U^l_{i,f} \geq \left(U_{i,f}\right)'$, and the MNO i cannot increase its utility by bidding unilaterally untruthfully. Therefore, bidding $u^l_{i,f}$ is always a weakly dominant strategy. $\square$

Proposition 3 (Individual Rationality). *The payment rule defined in Eq. (6.37) satisfies the individual rationality property and all bidders are guaranteed to obtain non-negative utility.*

Proof. As we have proved that our scheme is truthful, $b^l_{n,f} = u^l_{n,f}$, $\forall n \in \mathcal{N}$, and the utility of a winning operator is $U^l_{n,f} = 0$, which is always a non-negative value, proving the individual rationality. □

Proposition 4 (Low Complexity). *The allocation optimization problem can be solved in polynomial time.*

Proof. In Section 6.3.3, we have shown that our auction-based problem can be solved in polynomial time, either for small networks through the resolution of **P1** and **P2** problems. □

6.4 Performance Metrics Analysis

In this section, we provide the analytical models for the calculation of the network throughput and energy efficiency, when the auction-based switching off algorithm is applied.

The network traffic is depicted in Fig. 6.2(a) and consists of data traffic with constant bit rate R. We assume that for each node k (BS_n or SC_f)[3], data sessions are Poisson generated processes with rate $\lambda^{(k)}$ and have exponential service time, denoted by $1/\mu^{(k)}$. Hence, we model the operation of the node k as a Markov chain. Each state of the system is characterized by the number of active data sessions, denoted by d. The maximum number of simultaneously served data sessions is $D^{BS} = CR_{BS}/R$ and $D^{SC} = CR_{SC}/R$ for the BSs and the SCs, respectively, given that CR_{BS} and CR_{SC} refer to the BS and SC bandwidth, respectively. By defining $D = \{D^{BS}, D^{SC}\}$, the balance equation is:

$$p_d^{(k)} = \begin{cases} \left(\dfrac{\lambda^{(k)}}{\mu^{(k)}}\right)^d \cdot \dfrac{1}{d!} \cdot p_0^{(k)}, d = 0, 1, ..., D, \\ 0 \qquad\qquad\qquad\qquad , d \geq D, \end{cases} \tag{6.41}$$

where $p_0^{(k)}$ represents the state probability that the node k remains idle, and it is calculated as:

$$p_0^{(k)} = \left(\sum_{d=0}^{D} \left(\frac{\lambda^{(k)}}{\mu^{(k)}}\right)^d \cdot \frac{1}{d!} \right)^{-1}. \tag{6.42}$$

In continuation, employing the steady state probabilities of the Markov chain, we define and calculate the key performance metrics for both the individual nodes and the whole network. We focus on the night zone, with duration t_{night}.

[3] We assume that k corresponds to a BS_n or a SC_f. Thus, $k = \{BS_n, SC_f\}$.

6.4.1 Throughput

The expected throughput $\mathbb{E}[T_{BS_n}]$, $\mathbb{E}\left[T_{SC_f}\right]$, for the BS_n and SC_f, respectively, is defined as the average number (over all possible states of the system) of served sessions in the system multiplied by the transmission rate of the session and is calculated as:

$$\mathbb{E}[T_{BS_n}] = \sum_{d=0}^{D^{BS}} d \cdot R \cdot p_d^{(BS_n)}, \text{and} \tag{6.43}$$

$$\mathbb{E}\left[T_{SC_f}\right] = \sum_{d=0}^{D^{SC}} d \cdot R \cdot p_d^{\left(SC_f\right)}. \tag{6.44}$$

where $p_d^{(BS_n)}$, and $p_d^{\left(SC_f\right)}$ are the steady state probabilities for the given traffic load rate $\lambda^{(BS_n)}$, and $\lambda^{\left(SC_f\right)}$, respectively.

In continuation, we calculate the throughput for the network of N MNOs and the M SCs, after the application of the algorithm. We define as $\lambda'^{(SC_f)} = \sum_{i \in \mathcal{N}_{OFF}} \lambda^{(i)}$, with $\mathcal{N}_{OFF} \subseteq \mathcal{N}$, the subset of operators that switch off their BSs, the new average traffic load of the SC_f, which is equal to the traffic of the switched off BSs that must be served by SC_f. Thus, the total throughput of the network is:

$$\mathbb{E}[T] = \sum_{n \in \mathcal{N}} \mathbb{E}[T_{BS_n}] \cdot (1 - x_n) + \sum_{f \in \mathcal{F}} \mathbb{E}\left[T'_{SC_f}\right], \tag{6.45}$$

where $\mathbb{E}\left[T'_{SC_f}\right]$ is the average throughput of the mth SC when it serves the traffic $\lambda'^{(SC_f)}$.

6.4.2 Energy Efficiency

The expected energy efficiency $\mathbb{E}[\eta_\epsilon^{(BS_n)}]$ of a BS_n is defined as the ratio of the average transmitted bits $\mathbb{E}[B_{BS_n}]$ over the average energy $\mathbb{E}[E_{BS_n}]$:

$$\mathbb{E}[\eta_\epsilon^{(BS_n)}] = \frac{\mathbb{E}[B_{BS_n}]}{\mathbb{E}[E_{BS_n}]}. \tag{6.46}$$

The average transmitted bits during the night zone can be calculated by multiplying the average throughput given in Eq. (6.43) with the duration of the night zone t_{night}:

$$\mathbb{E}[B_{BS_n}] = \mathbb{E}[T_{BS_n}] \cdot t_{night}. \tag{6.47}$$

To calculate the average energy consumption, we should take into account the power consumed by the BS for operation and transmission, consisting of three components: *i*) the constant power P_{cnst}, consumed by an active BS for operations such as cooling, antenna feeding, etc, *ii*) the idle power P_{idle}, which is the power consumed when the BS remains idle, i.e., when there are no ongoing traffic sessions, *iii*) the transmission power for serving the ongoing traffic sessions corresponding to each state $p_d^{(BS_n)}$, considering that P_{tx} denotes the transmission power for serving a single data session. Hence, the average energy consumption during the night zone t_{night} is:

$$\mathbb{E}\left[E_{BS_n}\right] = \left(P_{cnst} + P_{idle} \cdot p_0^{(BS_n)} + \sum_{d=0}^{D^{BS}} P_{tx} \cdot d \cdot p_d^{(BS_n)}\right) \cdot t_{night}. \tag{6.48}$$

Accordingly, the expected energy efficiency $\mathbb{E}[\eta_\epsilon^{(SC_f)}]$ for the SC_f is defined as:

$$\mathbb{E}[\eta_\epsilon^{(SC_f)}] = \frac{\mathbb{E}\left[B_{SC_f}\right]}{\mathbb{E}\left[E_{SC_f}\right]}, \text{with} \tag{6.49}$$

$$\mathbb{E}\left[B_{SC_f}\right] = \mathbb{E}\left[T_{SC_f}\right] \cdot t_{night}, \text{and} \tag{6.50}$$

$$\mathbb{E}\left[E_{SC_f}\right] = P_{SC} \cdot t_{night}, \tag{6.51}$$

where the power of a SC, P_{SC}, is slightly dependent on the traffic, in contrast to the power of a BS that is significantly dependent on the traffic load. Thus, a constant value for the SC power is employed.

Finally, the total network energy efficiency is defined as:

$$\mathbb{E}[\eta_\epsilon] = \frac{\mathbb{E}\left[B\right]}{\mathbb{E}\left[E\right]}, \text{with} \tag{6.52}$$

$$\mathbb{E}\left[B\right] = \sum_{n\in\mathcal{N}} \mathbb{E}\left[B_{BS_n}\right] \cdot (1 - x_n) + \sum_{f\in\mathcal{F}} \mathbb{E}\left[B'_{SC_f}\right], \tag{6.53}$$

and

$$\mathbb{E}\left[E\right] = \sum_{n\in\mathcal{N}} \mathbb{E}\left[E_{BS_n}\right] \cdot (1 - x_n) + \sum_{f\in\mathcal{F}} \mathbb{E}\left[E'_{SC_f}\right], \tag{6.54}$$

where $\mathbb{E}\left[B'_{SC_f}\right]$ and $\mathbb{E}\left[E'_{SC_f}\right]$ are the transmitted bits and the energy consumption of the fth SC, when serving traffic equal to $\lambda'^{(SC_f)} = \sum_{i\in\mathcal{N}_{OFF}} \lambda^{(i)}$.

6.5 Performance Evaluation

This section is composed of three parts. In the first subsection, we explain the simulation scenario employed both for the multiobjective optimization and the system level simulations. The second subsection presents the results regarding the estimation of the Pareto Front for the multiobjective optimization solved by using the Matlab tools and, finally, the last part shows a performance comparison between the proposed scheme and two state-of-the-art proposals with the development of a custom-made C simulator for the network operation.

6.5.1 Simulation Scenario

The simulation scenario corresponds to a dense HetNet deployment, such as a university campus or an urban area. More specifically, our scenario focuses on a cell served by the BSs of $N = 5$ MNOs [59] and $M = 15$ SCs that cover the whole cell area and are uniformly distributed. In our experiments, we consider various scenarios, where the operators have different traffic volumes (i.e., ρ), different bidding strategies (i.e., non-tolerant, linear and tolerant), different cost requirements (i.e., z), and different bidding levels (i.e., L). The system level simulations are based on Monte Carlo experiments and the presented results focus on the night zone for the duration of one year. Note that the results are calculated for the case of one macro cell, but they can be easily extended to more extended configurations. Furthermore, we consider the period of one year, since during the duration of a year the traffic load of a MNO is considered to be stable [107]. The set of parameters used in simulations is provided in Table 6.2.

TABLE 6.2: Simulation Parameters for MAS

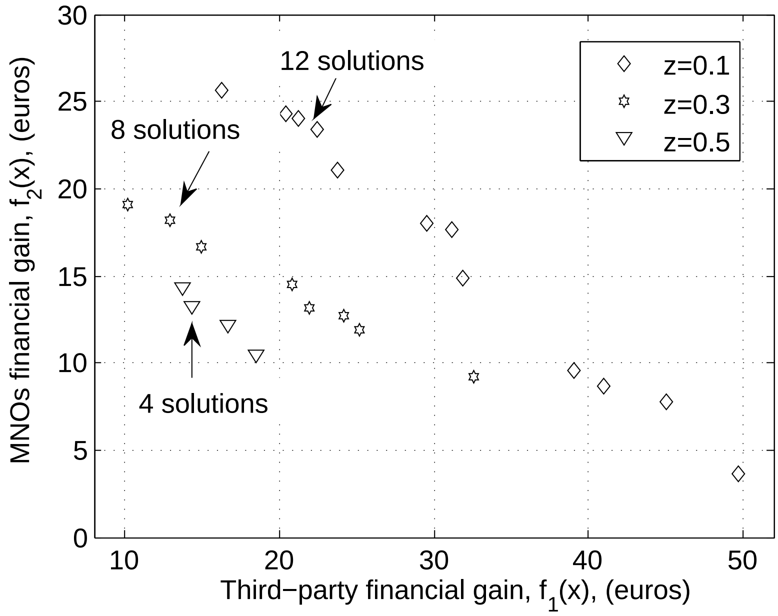
Parameter	**Value**
Number of MNOs, N	5
Number of SCs, F	15
Traffic load, *Load*	Fig. 6.3
BS antenna gain, G_{BS}	14 dBi
SC antenna gain, G_{SC}	5 dBi
Pathloss exponent, γ	4
Noise power, P_{noise}	-174 dBm/Hz
BS transmission power, $P_{tx,BS}^{max}$	46 dBm
SC transmission power, $P_{tx,SC}^{max}$	30dBm
Maximum number of PRBs, N_{PRB}^{max}	50
BS bandwidth, CR_{BS}	20 MHz
SC bandwidth, CR_{SC}	5MHz
δ	[0.5, 1.5]

To assess the performance of our scheme, we compare the proposed Multiobjective Auction-base Switching off strategy (referred as MAS in the rest of the paper), to two benchmark solutions: *i*) an auction-based switching off scheme, where the income of the third-party is the one and only objective to be maximized (referred as ISO) [77], and *ii*) a baseline scenario with Full Operational Topology (FOT), where none of the BSs is switched off.

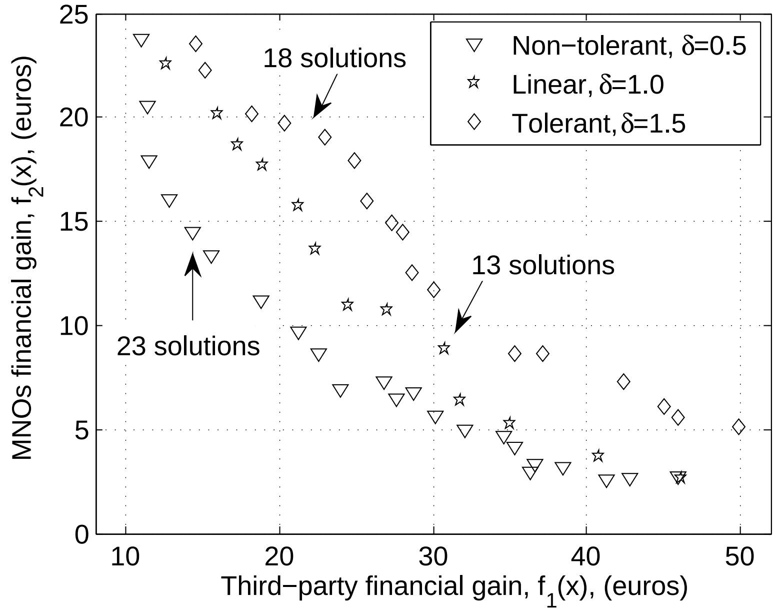
6.5.2 Estimation of the Pareto Front

In this section, we present the Pareto Front analysis. In this set of experiments, we assume that the five operators have the same traffic volume equal to the maximum possible traffic load, i.e., $\rho_n = 1$. In addition, we assume that each MNO submits three different bids, corresponding to $L = 2$, to the third-party.

Fig. 6.6 illustrates the Pareto Front solutions achieved by solving the proposed multiobjective problem for different minimum financial gains with the same bidding strategy (Fig. 6.6(a)) and different bidding strategies with the same minim profit requirement (Fig. 6.6(b)). In both figures, the third-party's annual financial gain that can be attained by leasing its resources to one MNO is represented in the x-axis and the annual economic profits of one MNO are given in y-axis.



(a) Estimated Pareto Front for multiple MNOs' requirements, $L = 2$ and linear bidding strategy



(b) Estimated Pareto Front for multiple bidding strategies, $L = 2$ and $z = 0.1$

FIGURE 6.6: Estimation of Pareto Front solutions

In Fig. 6.6(a), the set of non-dominated solutions is shown for linear bidding strategy. Note that the stochastic search performed by means of the genetic algorithm succeeds in estimating a full Pareto Front for the given parameters of the studied problem. As expected, in all the different cases, the higher the third-party's income ($f_1(\mathbf{x})$), the lower the financial gain of the MNOs ($f_2(\mathbf{x})$). Thus, the Pareto Front is monotonically decreasing, meaning that the improvement of one objective leads to deterioration of the other objective, and there is no feasible solution that leads to the maximization of all the objectives. A second observation relies on the motivation of the MNOs to maximize their economic gains, a fact that can be explored through the parameter z that reflects the requirements of the the minimum profit gain of an operator, denoted in Eq. (6.21). As it is plotted in the figure, the greedy behavior of the MNOs for higher cost gains (case: $z = 0.5$) leads to lower income for the third-party and at the same time, fewer solutions can be achieved. This result is of significant importance, since a greedy behavior from the MNOs' perspective will produce lower bids that may not be accepted by the third-party, and thus, the MNOs will not be able to offload their whole traffic. Hence, a switching off strategy will not be achieved and both the MNOs and the third-party will suffer with economic losses and inefficient use of capacity. The selection of a proper value of the parameter z helps the operators to decide whether it is profitable for them to bid or not, by taking into account their financial needs, and by observing Fig. 6.6(a), we conclude that lower values of z lead to higher income for the two involved parties. To provide further insights for our approach, let us add at this point that in a realistic scenario with a large number of macro BSs, the cost gains for the MNOs and the third-party are significantly higher. For example, in the central area of London [108], where 500 BSs are deployed and owned by one MNO, when we apply our proposed switching off technique, the economic gain may reach up to $\sim$ 12.500 € for the MNO and up to $\sim$ 25.000 € for the third-party.

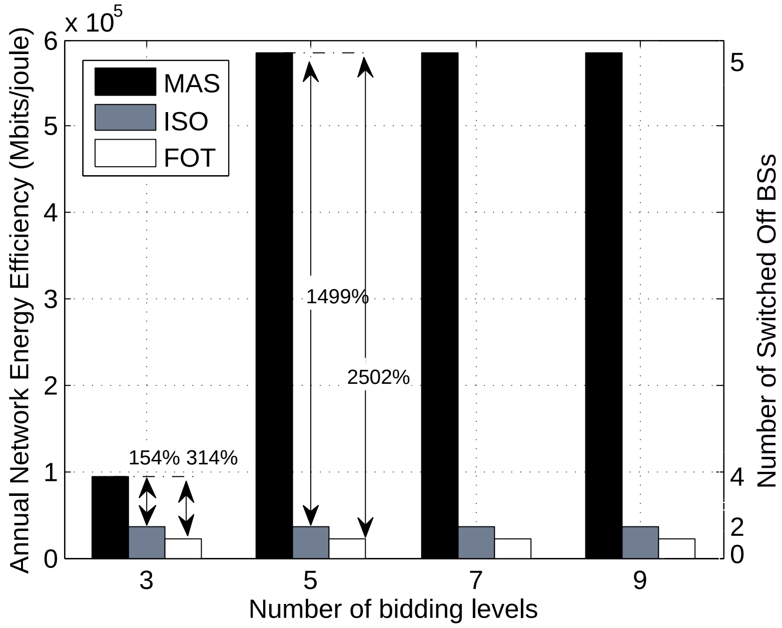
In continuation, Fig. 6.6(b) illustrates the Pareto Front by examining different bidding strategies for the case of $z = 0.1$. Again, we observe that the attained solutions are decreasing monotonically, thus, proving the contradiction between the objectives. In addition, as we can see, the more tolerant the bidding strategy of the MNOs, the higher financial gains for the involved parties. This important insight can be easily explained by taking into account the fact that a non-tolerant MNO is more greedy, and thus, it offers lower bids for the requested capacity than a tolerant one, as illustrated in Fig. 6.5. As a consequence, the third-party may lose its incentive to lease the offered bandwidth, and the economic benefits will be reduced for the operators and the SC network. It is worth noting that the tolerant bidding strategy offers better solutions due to the leasing of more resources and the switching off of higher number of BSs, while the linear bidding strategy implies an intermediate solution between the extreme cases. Hence, along with the minimum guaranteed profit, the bidding strategy is also an important indicator that affects the decision of MNOs on bidding.

6.5.3 Numerical Results

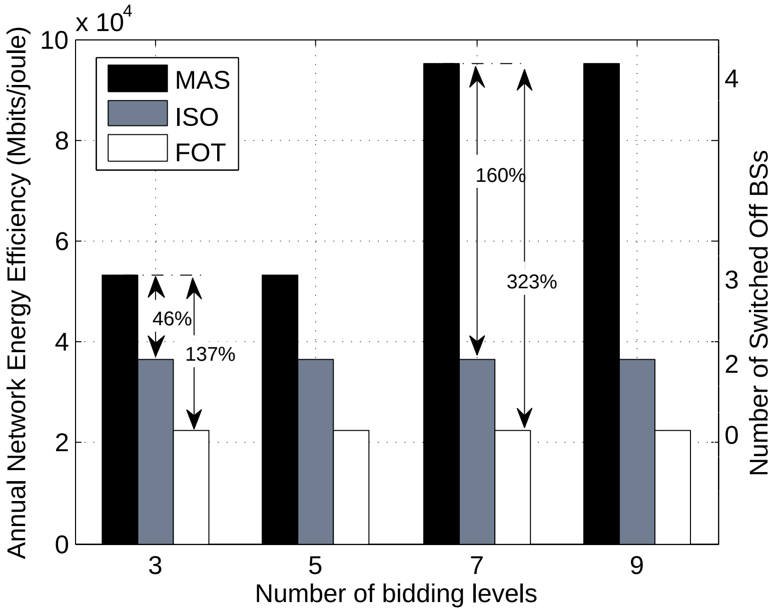
This section includes the performance results with regard to telecommunication - oriented (network throughput and energy efficiency) and cost - oriented (annual cost and income gains) metrics. In this set of experiments, we study a more realistic scenario, where the operators have different traffic volumes and, thus, different requirements and outcomes, when our proposed algorithm is applied. According to recent studies by Marsan and Meo [59], in most European countries, there are usually up to two telecommunication companies holding the major part of the market share, up to two smaller operators serving an intermediate portion of the users, and finally, up to one smaller company with a very small slice of the market. By exploiting these interesting findings, we consider the scenario, where two MNOs (i.e., BS_1 and BS_2) are fully loaded ($\rho_1 = \rho_2 = 1.0$), two operators (i.e., BS_3 and BS_4) have relatively lower traffic with $\rho_3 = \rho_4 = 0.7$, and the fifth MNO (denoted by BS_5) has very low traffic ($\rho_5 = 0.3$). The results presented below, are calculated for an operating point on the Pareto Front that is assumed to satisfy all the involved parties in the auction. We would like to highlight that the selection of a solution among the Pareto Front solutions either can be derived through agreements between the involved parties or another distinguished entity may select the operating point among the Pareto Front solutions.

6.5.3.1 Telecommunication Metrics:

Fig. 6.7 presents the network energy efficiency versus L for a tolerant (Fig. 6.7(a)) and a non-tolerant (Fig. 6.7(b)) bidding strategy. The number of switched off BSs of every algorithm is also shown in the plot (right y-axis), along with the percentage gains in terms of energy efficiency of our approach compared to the state-of-the-art works. First, we observe that the energy efficiency achieved by the MAS scheme increases with the number of levels for tolerant and non-tolerant bidding, since a biggest variety of the proposed bids (higher number of levels) implies a higher number of choices for the resource allocation. Another important remark is that MAS significantly outperforms the baseline scenario, FOT, (where no BS is switched off), as well as the ISO algorithm. The gains compared to the ISO scheme are remarkably high, reaching up to 1499% and 160% for tolerant and non-tolerant bidding, respectively. Compared to the FOT, the gains are even higher. The better performance of our proposal in terms of energy efficiency is justified by the higher number of switched off BSs, as this is highlighted also in the plots. As we have already mentioned in Section 6.3.3, the goal of our proposal lies in maximizing the energy efficiency, an objective neglected in the auction-based works of the literature, where only the maximization of the third-party's income was considered. The optimal resource allocation implemented by the third-party takes into account the constraint of the energy consumption minimization that eventually leads to a lower number of active BSs. Comparing the behavior of our algorithm in the two figures, it can be observed that the tolerant bidding strategy achieves more considerable gains with respect to the non-tolerant bidding, mainly due to the deactivation of many underutilized BSs in the network. These results emphasize the role of the bidding strategy and the number of bidding levels on the achievable energy efficiency, thus providing the necessary insights to the MNOs in order to select the most appropriate strategy based on their interests. In Fig. 6.8, the conclusions of Fig. 6.7(b) and in Fig. 6.7(a) are better illustrated, since the comparison between the three schemes and the different bidding strategies is more clearly shown. Finally, we should mention that the results of linear bidding are not shown here for simplicity, given that the achieved gains range between the two aforementioned cases. Finally, we should mention that the results of linear bidding are not shown here for simplicity, given that the achieved gains range between the two aforementioned cases.



(a) Tolerant bidding strategy



(b) Non-tolerant bidding strategy

FIGURE 6.7: Annual network energy efficiency for $z = 0.1$ and different bidding strategies

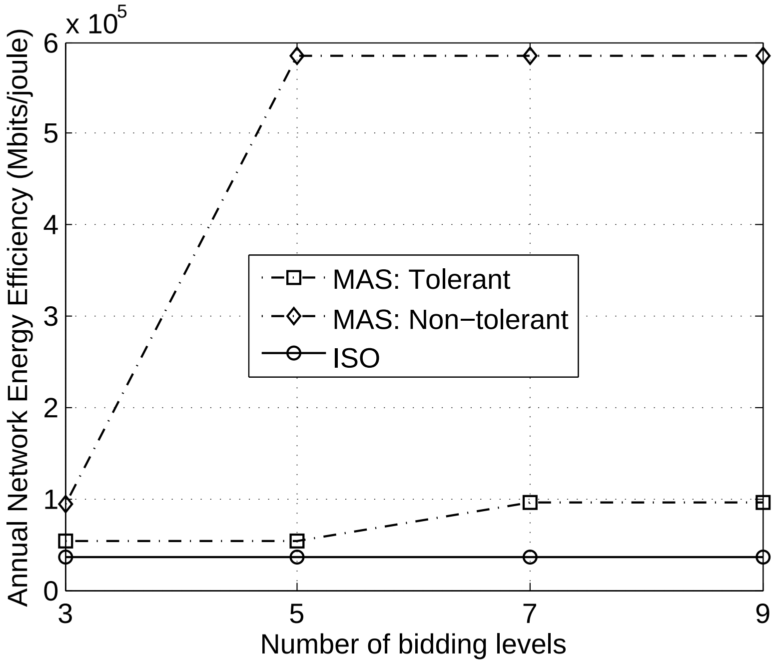


FIGURE 6.8: Annual network energy efficiency for different bidding levels and strategies

Along with the total network energy efficiency performance, it is interesting to study the individual energy efficiency gains of the different MNOs. To that end, the individual gains for the specific (but representative) case of $z = 0.1$ and the two different bidding strategies are quantified in Table 6.3, where interesting conclusions can be extracted. In particular, independently of the bidding strategy and the number of L, the ISO scheme is beneficial only for the group of operators that switch off their BSs, which are always the same (MNO_1 and MNO_2), while the rest of the operators always keep their BSs active. More specifically, the MNOs that switch off their BSs theoretically achieve infinite energy efficiency, as they have their traffic served at zero energy cost, whereas the active operators serve their own traffic without improving their situation. The proposed MAS eliminates this unfairness, by offering the chance to more MNOs to switch off their BSs, providing them with extra incentives to participate in the auction. The individual gains are remarkable and show how our proposal can benefit both the MNOs, along with the whole network.

Despite the importance of the energy efficiency results, the deactivation of the BSs in the network and the traffic offloading to the SCs potentially implies loss of connections. To that end, we study the normalized throughput that represents the percentage of served connections in the system. Fig. 6.9 presents the normalized throughput of the auction-based switching off schemes for different number of bidding levels and different bidding behaviors. It can be observed that, as the number of switched off BSs increases, the MAS approach experiences small losses (around 5% and 3% for tolerant and non-tolerant bidding, respectively). The degraded performance is explained by the high number of deactivated BSs, leading to the service of all the traffic mainly by the SC network (since at most one BS remains active). The MNOs are able to decide whether the throughput performance can

Table 6.3: Operator Energy Efficiency with Respect to the FOT Scheme for $z = 0.1$

	Tolerant bidding				
Algorithm	**MNO$_1$**	**MNO$_2$**	**MNO$_3$**	**MNO$_4$**	**MNO$_5$**
MAS-L = 3	∞	$3 \cdot 10^4$	∞	∞	∞
ISO-L = 3	∞	∞	$2.2 \cdot 10^4$	$2.2 \cdot 10^4$	$1 \cdot 10^4$
MAS-L = 7	∞	∞	∞	∞	∞
ISO-L = 7	∞	∞	$2.2 \cdot 10^4$	$2.2 \cdot 10^4$	$1 \cdot 10^4$
	Non-tolerant bidding				
Algorithm	**MNO$_1$**	**MNO$_2$**	**MNO$_3$**	**MNO$_4$**	**MNO$_5$**
MAS-L = 3	∞	$3 \cdot 10^4$	$2.2 \cdot 10^4$	∞	∞
ISO-L = 3	∞	∞	$2.2 \cdot 10^4$	$2.2 \cdot 10^4$	$1 \cdot 10^4$
MAS-L = 7	∞	$3 \cdot 10^4$	∞	∞	∞
ISO-L = 7	∞	∞	$2.2 \cdot 10^4$	$2.2 \cdot 10^4$	$1 \cdot 10^4$

be sacrificed to achieve energy efficiency, or even small losses are prohibitive (and, thus, a tolerant strategy is not acceptable).

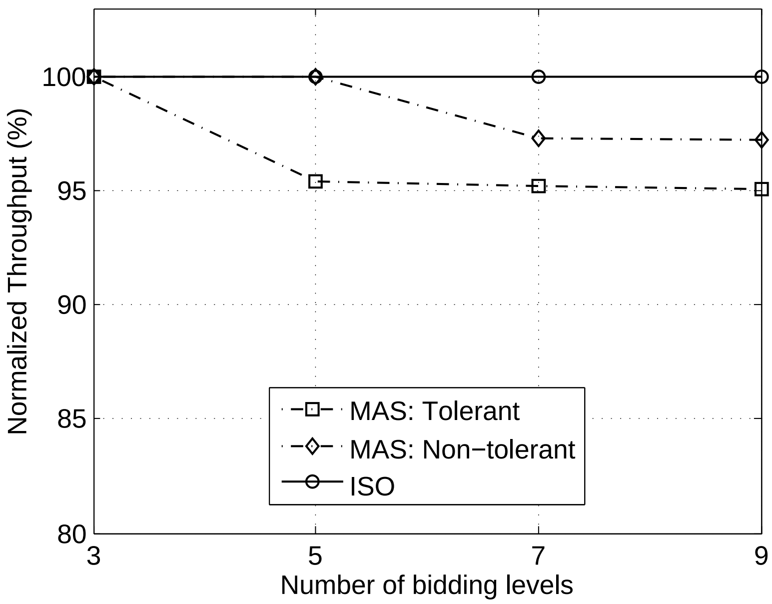


Figure 6.9: Normalized throughput for different bidding levels and strategies

The results in terms of lacking PRBs are given in Fig. 6.10. As it is observed, a larger number of PRBs are lacking, when MAS strategy is applied. In our case, there are different reasons for the degraded throughput performance. The unserved users are either because lower bids (thus, fewer PRBs) are selected or the overall PRBs are not adequate for the total offloaded traffic. However, the impact on the throughput is negligible, as it was shown also in Fig. 6.9.

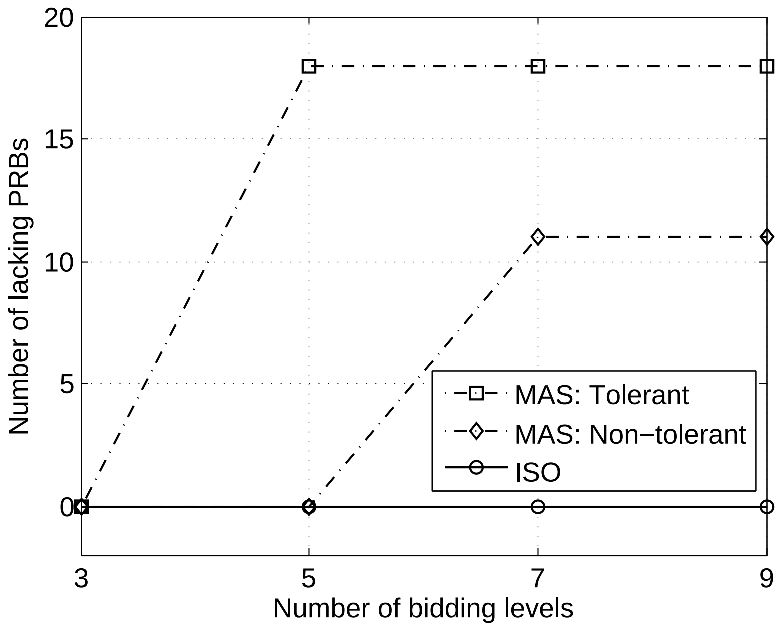


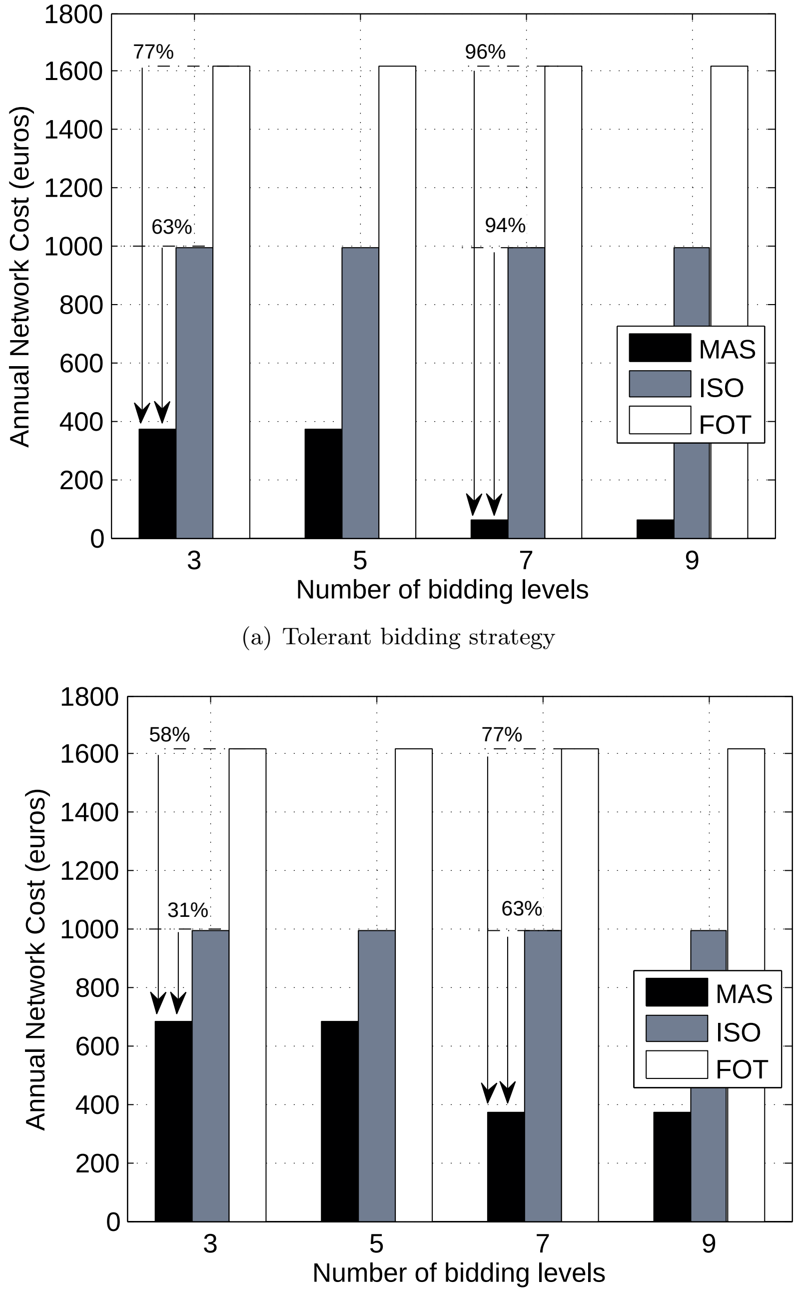
FIGURE 6.10: Number of lacking PRBs

6.5.3.2 Cost Metrics:

The total annual network cost and the individual annual gains for the operators and the third-party, compared to the state-of-the-art algorithm and having as a benchmark the FOT scheme, are presented in Fig. 6.11 and Fig. 6.13, respectively.

The annual network cost is given versus the different number of bidding level values and for the tolerant (Fig. 6.11(b)) and non-tolerant (Fig. 6.11(a)) bidding strategies, respectively. The total cost of the network is the sum of the average cost of all operators and the third-party for the operation of the whole infrastructure (i.e., the active BSs and SCs). The first observation is that the network cost is the same for level pairs ($l = 3$ and $l = 5$) and ($l = 7$ and $l = 9$) for the MAS algorithm, due to the number of switched off BSs that is the same for the two cases. The MAS scheme achieves a considerable reduction up to 94% and 96% for tolerant bidding, when compared to ISO and FOT schemes, respectively, mainly due to the deactivation of many underutilized BSs in the network. For the case of non-tolerant bidding strategy, the cost reduction is lower. This result is explained by the fact that MNOs are more greedy and, in their attempt to increase their economic gains, they do not offer high bids for the requested capacity. As a consequence, the third-party does not accept the allocation of resources to low prices and therefore, some BSs may not be switched off. Concerning the ISO scheme, we observe that the total annual cost is not affected by the different bidding levels, since, in ISO auction, only one bid is offered based on the maximum traffic load expectations and fewer BSs are deactivated.

A clear comparison between MAS, for tolerant and non-tolerant bidding, and ISO is given in Fig. 6.12, where the annual network cost behavior is highlighted.



(a) Tolerant bidding strategy

(b) Non-tolerant bidding strategy

FIGURE 6.11: Annual network cost for $z = 0.1$ and different bidding strategies

The individual revenue of each operator and the third-party is plotted in Fig. 6.13. We may observe that, similar to the energy efficiency gains, the ISO scheme provides financial gains only to particular operators (MNO_1 and MNO_2), and especially to the MNOs that switch off their networks, whereas the economic gains of the remaining operators are zero compared to the FOT scheme, since these MNOs keep their BSs active and serve their own traffic without having any benefit from the auction. On the other hand, for the proposed MAS approach, more operators are able to have economic benefits, independently of the particular number of levels due to the optimal resource allocation that is attained by our solution,

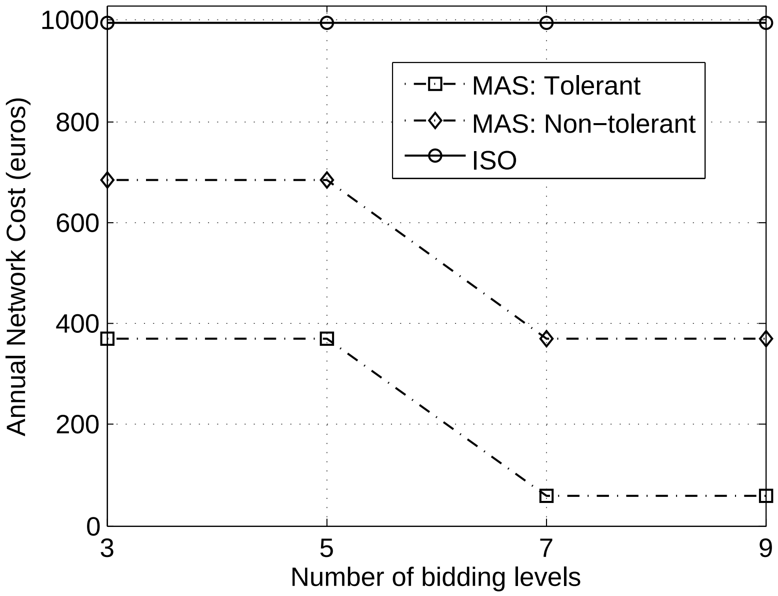
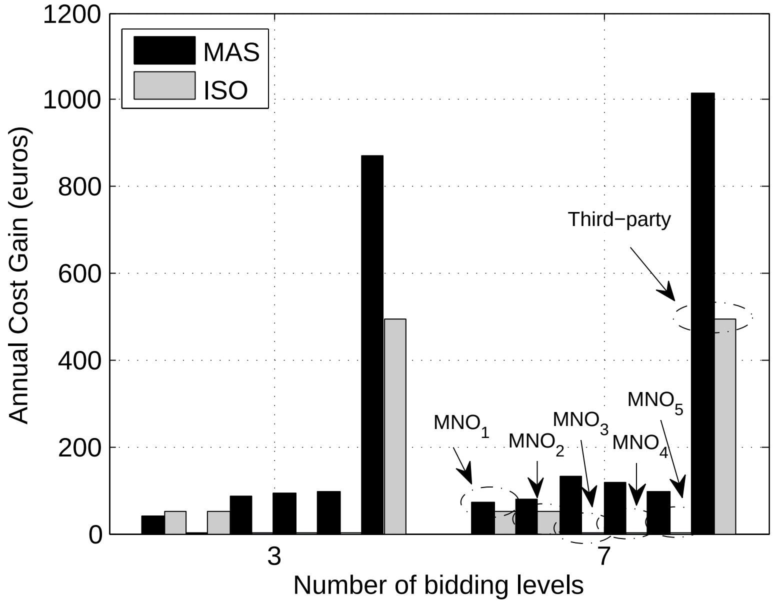


FIGURE 6.12: Annual network cost for different bidding levels and strategies

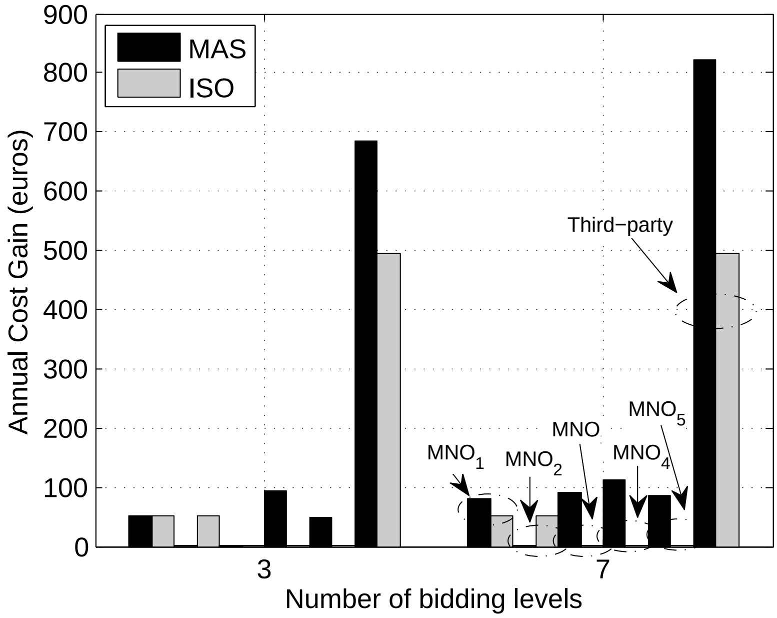
which gives more opportunities to the majority of the MNOs to participate in the auction. Furthermore, as the number of bidding levels increases, the MAS algorithm achieves higher financial gains for the operators due to the higher number of combinations of bids offered. In addition, for the tolerant bidding strategy (Fig. 6.13(a)) the economic gains are higher compared to the non-tolerant behavior (Fig. 6.13(b)).

6.5.4 Discussion

Based on the analysis in Section 6.5.2 and 6.5.3, we have shown that the proposed MAS scheme outperforms the state-of-the-art approaches in terms of energy efficiency (network and individual), annual network cost and individual cost gains. In addition, it achieves balanced results for the MNOs with respect to the individual energy efficiency and cost gains. Furthermore, through a performance assessment, we have identified the significance of the bidding behavior, the number of levels and the parameter z. In particular, higher values of z achieve lower gains for both the MNOs and the third-party. In addition, better performance results are attained in terms of energy efficiency, aggregate network cost, and individual cost gains, when higher number of levels are chosen and through tolerant bidding strategy. Hence, the MNOs should choose the suitable values of L and the bidding strategy depending on their priorities. Finally, we should highlight that, even though minor losses may appear in terms of throughput, the attained benefits with respect to energy efficiency, individual and network cost gains are remarkable and are adequate for giving the necessary incentives to the MNOs and the third-party to apply the proposed auction-based switching off strategy.



(a) Tolerant bidding strategy



(b) Non-tolerant bidding strategy

FIGURE 6.13: Annual cost gain for $z = 0.1$ and different bidding strategies

6.6 Concluding Remarks

This chapter was motivated by the traits of the heterogeneous network configuration and the low utilization of the BSs and the SCs during the night. In addition, the coexistence of multiple operators and third-party networks led to proposing novel switching off algorithms that achieve energy savings and cost reduction. This goal was attained through the deactivation of the underutilized BSs and the auction-based traffic offloading to the SCs. Firstly, we investigated solutions to share the cost of the SC network. These cost sharing techniques provided preliminary results that aim the investigation of switching off solutions. Secondly, by employing an auction-based framework and by exploiting multiobjective tools, we introduced a novel switching off scheme that allows the MNOs reduce their expenditures and achieve significant energy savings. The proposed scheme has been evaluated in terms of throughput, energy and cost efficiency for various traffic conditions and bidding strategies. The results have shown that our proposal can significantly improve the network energy efficiency. Regarding the financial costs/gains, the proposed scheme provides higher cost efficiency and fairness compared to the state-of-the-art algorithms, motivating the operators to adopt game theoretic strategies for their decisions and proceed to leasing agreements with a third-party. After evaluating the merit of the novel strategy, the main conclusions can be summarized as follows:

- The involved parties (MNOs, and third-party) achieved notable improvements by switching off the redundant BSs and offloading the traffic to the SCs.
- The individual objectives of the operators and the third-party are considered in the problem formulation. Thus, our auction-based scheme that is resolved by using multiobjective tools is feasible in competitive environments.
- The use of game theoretic tools in the context of BSs switching off was investigated. The results and experience obtained during the research indicate that appropriate calibration results both in effective optimization and good performance. Thus, in order to keep expressions that capture accurately the behavior of the MNOs, non-cooperative games has been successfully employed. The main advantage of the method resides on the fact that a good picture of the tradeoffs and fair solutions are provided.

Chapter 7

Final Considerations, Conclusions and Future Work

"Projects we have completed demonstrate what we know – future projects decide what we will learn."

Dr. Mohsin Tiwana

The emerging data traffic demand is one of the main concerns of wireless cellular networks. More BSs, data centers and other network equipment are such as microcells, femtocells and picocells are required to support the growth in mobile traffic. Since BSs consume more than half of the total energy in a typical cellular network, the increase in the number of BSs has a significant impact in overall energy consumption. In addition, due to the introduction and popularization of HetNets expenses related to deployment and energy consumption now comprise a large proportion of capital and operational expenditures for service providers and telecommunication companies, in general. It is widely acknowledged that cellular communication networks will have greater economic and ecological impact in the coming years. Seeing this, innovative energy and cost efficient solutions are provided, concentrating on environmental influences of cellular networks, while at the same time these solutions guarantee seamless coverage and excellent QoS to the users.

In current and future cellular technologies, such as LTE and LTE-Advanced, it has been observed that the networks are significantly underutilized during some hours of the day (i.e., especially during the night), and thus, switching off the redundant nodes of the networks has been identified as a key framework to meet the challenges posed by future green networks. Therefore, the objective of this Ph.D thesis has been to make a solid contribution to the theory of switching off strategies and their feasibility for implementation in real-world cellular deployments. Based on the study of the state-of-the-art works, a set of opportunities were identified, and consequently, new methods of analysis, game theoretic strategies, optimization techniques, and guidelines have been presented with the goal of improving the energy efficiency. The current dissertation contributes with solid arguments and novel optimization schemes to make switching off more appealing. The research methodology comprised a combination of mathematical models, game theoretic tools, optimization techniques, and system level simulations.

The novelties presented in this Ph.D thesis include not only the development of energy-aware switching off mechanisms for creating greener networks, but also, efforts towards cost reduction. Thus, the frameworks developed have been successfully applied to investigate robust scenarios under variable conditions and deployments, such as single-operator and multi-operator networks with macro BSs and dense HetNets.

7.1 Summary and Conclusions

This thesis focus on contributing to the global goal of green ICT by improving the energy efficiency of wireless networks. The focus has been put on the design and performance analysis and evaluation of new energy-efficient switching off algorithms for single-operator, multi-operator and heterogeneous wireless networks. The thesis have been divided into one preliminary part and three main parts:

- A preliminary part comprised of Chapter 1 and Chapter 2.
- A first main part comprised of Chapter 3.
- A second main part comprised of Chapter 4.
- A third main part comprised of Chapter 5 and Chapter 6.

The contributions and conclusions of the three main parts are summarized in the following section.

7.1.1 Towards the greening of single-operator networks

The research work presented in this Ph.D. thesis started by investigating energy efficient and flexible algorithms and study the performance and feasibility of three switching off schemes in wireless cellular topologies. The proposed analytical models take into account the network geometry and the traffic load pattern characteristics to decide the switching off behavior of the BSs. The first two mechanisms exploit the impact of the distance parameter between the users and the BSs, along with the traffic load volume to allow the decision of the adequate BSs to be switched off. By means of these two methods, we studied the performance of the network in terms of energy and throughput efficiency in realistic network topologies, without the need for computationally-heavy system level simulations, since simple analytical models are proposed. Significant energy efficiency gains were identified that give the necessary incentives to extend the research analysis in further and more complex network configurations.

Besides the proposal of the simple switching off schemes, there was the need for optimization techniques in realistic deployments. Indeed, the knowledge of network configurations with the static positions of the BSs, along with the predictions and the expectations of the traffic load patterns, provide the necessary incentives to propose centralized optimization solutions. Thus, a novel switching off scheme was proposed. Through the innovative mechanism, the energy efficiency was maximized. The results were of significant importance and proved how fundamental is the application of an optimization technique.

7.1.2 Towards the greening of multi-operator networks

The coexistence of multiple operators in the same geographical area motivated the thesis research to shift towards the investigation of deactivation techniques in environments with BSs, belonging to different MNOs.

The aforementioned issues inserted a new business model, known as infrastructure sharing. Thus, we proposed a roaming-based infrastructure sharing scheme, applicable in multi-operator environments during low traffic periods. Taking into account the rationality of the MNOs and their conflicting interests, we introduced a game theoretic framework that enables the MNOs to make individual switching off decisions for their own BSs, thus bypassing potential complicated service level agreements among them. The employed analytical models were based on realistic assumptions about the network configuration and the traffic patterns. The proposed scheme has been evaluated in terms of throughput, energy and cost efficiency for various traffic conditions and roaming cost values. The results have shown that our proposal can significantly improve the network energy efficiency, guaranteeing at the same time the network throughput in realistic scenarios (i.e., up to four MNOs). Regarding the financial costs/gains, the proposed scheme provides higher cost efficiency and fairness compared to the state-of-the-art algorithms, motivating the operators to adopt game theoretic strategies for their decisions. In our future work, we plan to elaborate on cooperative game theoretic schemes in order to investigate the potential trade offs.

7.1.3 Towards the greening of heterogeneous networks

In the last part of this Ph.D thesis, we investigated the energy and cost efficient solutions that can be applied in heterogeneous environments, where third-party companies and multiple MNOs coexist. The possibility of a third-party that provides a tier of SCs in HetNets can provide significant gains in energy efficiency, but at the same time raises important issues with regard to the SC cost sharing among different operators. Thus, we introduced an accurate cost model for the SCs that takes into account the traffic load for a precise estimation of the energy consumption. In order to effectively share this cost, we investigated four different state-of-the-art cost sharing techniques and we introduced a new hybrid policy that achieves a traffic-aware sharing of the total expenses. Our results highlighted the potential energy efficiency gains in the network, along with the fair sharing of the SC cost that can be achieved through our proposed policy.

In continuation, we proposed a novel auction-based offloading and switching off algorithm that achieves energy savings and cost reduction by encouraging MNOs to offload their traffic to the SCs, and switch off the redundant BSs. Moreover, by employing auction tools and novel bidding strategies, we introduced a switching off scheme that allows the MNOs to reduce their expenditures in multi-operator cellular HetNets. The proposed scheme has been evaluated in terms of energy efficiency and cost metrics for various conditions (different bidding levels and behaviors). The results have shown that our proposal can significantly improve the network energy efficiency, guaranteeing at the same time the network throughput under strict requirements. Regarding the financial costs/gains, the proposed scheme provides higher cost benefits and fairness compared to the state-of-the-art algorithms, motivating the operators to participate in an auction-based offloading. we provided also interesting insights concerning the rules and behaviors that the MNOs should follow when they participate in an auction strategy.

7.2 Future Research Lines

The greening evolution of wireless networks consists of the main contribution of this thesis. However, this Ph.D dissertation is the starting point of many open topics that have not been covered in the state-of-the-art, but they have been identified through the course of the thesis.

In the current context of exponential grow in mobile data traffic, there is a consensus about the next challenge, increasing capacity in a factor 1000x. Among the different challenges that this goal has, providing enhanced user experience and greener and high-quality networks still is a priority. Switching off mechanisms should be extended to fit in the new technological developments.

In the light of the conclusions, future research items with respect to the first part of the thesis on network planning solution in singe-operator marco BSs networks include:

- The theoretical analysis of the proposed switching off algorithms applied in the single-operator environments have been developed considering the Markov chain model for users that generate voice traffic. Therefore, the development of more advanced analytical models considering other classes of traffic (e.g., video, data) would provide a better knowledge of the performance of the proposed algorithms.
- The analysis provided in this thesis has mostly considered homogeneous traffic and static users. Nevertheless, in a realistic scenario, individual characteristics (e.g., position, channel quality) may not be the same for all users or they may change over time. In order to fully exploit the potential of the proposed schemes, it would be necessary to design adaptive algorithms for changing conditions.

- The design of the maximization switching off scheme in Chapter 3 could be optimized to include more parameters and details. The optimization framework could provide solutions in terms of different constraints and restrictions to provide a wide range of insights about the BSs behavior.

- Related to the previous points, so far, the performance of the switching off solutions, presented in Chapter 3, has been evaluated through analytical framework and with the help of extensive simulations through custom made C simulation environments. An important step forward would be the implementation of the switching off approaches in more sophisticated simulators and testbed frameworks. This would allow a comprehensive performance evaluation in more realistic scenarios, it would permit the practical selection of several parameter values and would, without a doubt, open the road to many interesting experiments.

There are also several open issues regarding the second part of this thesis, focused on infrastructure sharing solutions in multi-operator macro BS networks:

- The game theoretic algorithm proposed in Chapter 4 has shown outstanding gains for the low traffic conditions in multi-operator environments. Apart from the non-cooperative game framework, another possible line of research (i.e., cooperative games) could be investigated. In addition, a different game theoretic utility function that includes the QoE requirements could be examined.

- In line with the previous switching off idea, the analysis and performance evaluations of the GTIS scheme have considered an hexagonal topology with the presence of multiple operators. Thus, further analysis and performance evaluations need to be carried out in more complex topologies, where random deployed BSs are deployed and the proposed mechanism may need some refinements to work well in these scenarios.

Future challenges and open issues concerning the third part of the thesis are summarized in the following key points:

- Concerning the cost sharing techniques, presented in Chapter 5, the robustness of the proposed hybrid solution could be studied and more advanced mechanisms could be proposed to take into account the different parameters and factors of the network topologies and traffic patterns. The fairness indicator can be used to show the importance of the different cost sharing schemes.

- Finally, cooperative solutions, along with the auction-based formulations, should be examined for the switching off algorithms, given in Chapter 6. This idea has not be widely investigated in the literature. Therefore, we could focus on the design of new mechanisms that optimally combine power saving strategies along with the economic reduction of all the involving parties of the HetNets in a cooperative framework.

- The presented results have shown that the proposed network planning algorithms in HetNets can generally improve the energy efficiency of the involved parties but there is still a margin for performance improvement. Future work can be focused on the effort to increase efficiency by further reducing the energy and cost expense through mechanisms such as cooperative sharing or more intelligent resource allocation strategies. Different policies can also be employed for fairness among operators and third-party companies.

- Due to their dense deployment, not all SCs are expected to have a direct connection to the core network. As a result, some SCs will forward their traffic to the neighboring SCs until they reach the core network, thus forming a multi-hop backhaul network. Due to the large number of backhaul links, the backhaul is expected to be one of the main challenges that future HetNets will have to face in the decision of the appropriate BSs to be switched off.

In the three parts of the thesis, we focused on obtaining energy savings, through BS switching off and infrastructure sharing during periods of low activity. Even though, we focused on the future challenges of each part separately, the general goals for future work can be summarized as follows:

- The issue in dynamic BS switching is the temporal granularity. While most of the early work in this area has primarily focused on switching off BSs once a day, it remains to be seen whether finer-grained operation (e.g., on an hourly or even more frequent basis) can improve energy efficiency, particularly in scenarios where traffic patterns are not predictable from day to day. However, this may require more active online monitoring of traffic and increase the complexity of coordination with other cells to ensure coverage.

- Another related question is whether it is more profitable for the BSs to be switched off in a distributed manner or through centralized approaches. The levels of coordination can affect different tradeoffs, such as complexity, information exchange and efficiency of the BS deactivation policy.

- Another novel approach that can play a role in the greening of the networks is the adoption of new technologies that are provided in the 4G and 5G standards. For example, CoMP that has been developed in the context of LTE-Advanced cellular networks could by used for coverage extension when the BSs are turned off.

- In our simplified estimate of energy savings, we considered uniform cell sizes. In 4G/5G systems, because of the required high data rate, cellular towers will be more dense and have varying coverage, with more heterogeneous cells, such as microcells, picocells, and femtocells. While most existing deployment strategies focus on QoS during peak periods, energy savings during off-peak periods should also be taken into account. The concept of heterogeneous nodes can potentially be exploited for energy efficiency, since in the case of light load we can turn off (most of) the SCs. On the other hand, considering energy efficiency introduces additional complexity in network planning and deployment, and thus needs to be further studied.

Concluding, this thesis has advanced the state-of-the-art first by presenting switching off schemes, second, by introduction infrastructure sharing solution and, third, by providing cost and energy effective agreements between different involved parties for various network configurations and scenarios. The three parts of the thesis have provided valuable lessons on green network planning. Even though they have been treated independently throughout this dissertation, it is possible to envision a network were all parts can be combined. The road ahead lies open for further research following the new lines of investigation that have been identified.

Appendix A

Optimization Theory: Background Information

In this Appendix, we present some background theory and general concepts of optimization theory.

Optimization theory is a branch of mathematics which encompasses many diverse areas of minimization and maximization. Optimization theory is the more modern term for operations research and includes the calculus of variations, control theory, convex optimization theory, decision theory, game theory, linear programming, Markov chains, network analysis, optimization theory, queuing systems, etc. The area of optimization has received enormous attention in recent years, primarily because of the rapid progress in computer technology.

Optimization is central to any problem involving decision making and entails choosing between various alternatives. This choice is governed by the desire to make the best decision. The measure of goodness of the alternatives is described by an objective function. Optimization theory and methods deal with selecting the best alternative in the sense of the given objective function. our focus is the optimization problems solved formulated and solved through the methods of Integer Linear Programming (ILP).

The goal of ILP is to determine the values of decision variables that maximize or minimize a linear objective function, where the decision variables are subject to linear constraints. A linear programming problem is a special case of a general constrained optimization problem. In the general setting, the goal is to find a point that minimizes the objective function and at the same time satisfies the constraints. We refer to any point that satisfies the constraints as a feasible point. In a linear programming problem, the objective function is linear, and the set of feasible points is determined by a set of linear equations and/or inequalities.

An ILP in canonical form is expressed as:

$$\max \sum_{j \in \mathcal{J}} c_j \cdot x_j \tag{A.1}$$

s.t.

$$\sum_{j \in \mathcal{J}} a_{i,j} \cdot x_j = b_j, \forall i \in \mathcal{I}, \tag{A.2}$$

$$x_j \geq 0, \forall j \in \mathcal{J}, \tag{A.3}$$

$$x_j \text{ integer}, \forall j \in \mathcal{J}. \tag{A.4}$$

A pictorial representation of a simple linear program with two variables (2 - dimensional representation) and seven inequalities (seven sides of the polygon) is given in Fig. A.1. The set of feasible solutions is depicted in green and forms a polygon. The linear cost function is represented by the red line and the arrow. The red line is a level set of the cost function, and the arrow indicates the direction in which we are optimizing.

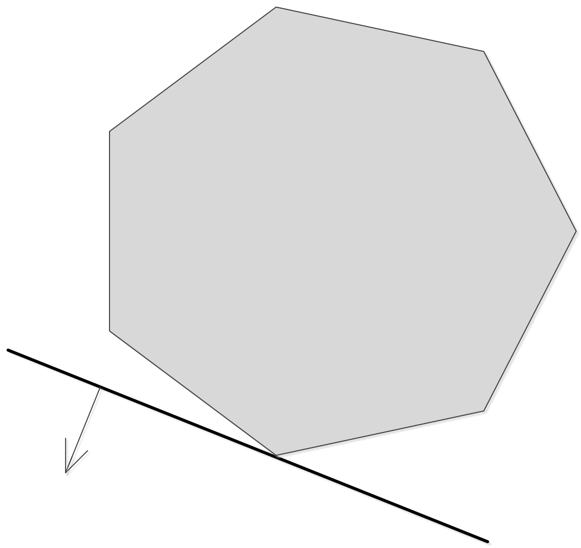


FIGURE A.1: General representation of an ILP program.

Several variations to the above problem are possible; for example, instead of minimizing, we can maximize, or the constraints may be in the form of inequalities. In the following sections, we will employ the properties of ILP in order to provide a maximization solution to the problem of energy waste in wireless cellular networks.

Appendix B

Multiobjective Optimization Theory: Background Information

In this Appendix, we present some background theory and general concepts of multiobjective optimization theory.

Many fields of science have to deal with large scale problems in which acceptable solutions involve simultaneous optimization of several conflicting criteria or objectives. Multiobjective optimization is the discipline that focuses on the resolution of these problems [105].

The target of multiobjective optimization is to find a subset of good solutions ($\mathcal{X}^*$) from a set $\mathcal{X}$ according to a set of criteria $\mathcal{F}$, with cardinality greater than one, typically expressed as mathematical functions, the so-called objective functions. Thus,

$$\mathcal{F} = \{f_i(\mathbf{x}) : \mathbb{R}^n \to \mathbb{R}, i = 1, 2, \ldots, m\}, \tag{B.1}$$

where, f_i represents the ith objective function and $\mathbf{x} \in \mathbb{R}^n$ is the optimization vector containing the n design variables. Therefore, every single $\mathbf{x} \in \mathcal{X}$ is a solution of the multiobjective problem that in general, is defined by:

- A set of n design variables $(x_1, x_2, \ldots, x_n)$ subject to optimization such that $\forall \mathbf{x} \in \mathcal{X}$, $\mathbf{x} = [x_1, x_2, \ldots, x_n]$.
- The domain of each design variable $(\mathcal{X}_1, \mathcal{X}_2, \ldots, \mathcal{X}_n)$ such that $x_i \in \mathcal{X}_i$ and $\mathcal{X} = \mathcal{X}_1 \times \mathcal{X}_2 \times \ldots x \times \mathcal{X}_n$. The set $\mathcal{X}$ is also known as search space or feasible set.
- Constraints among design variables.
- An objective space defined by a function $f : \mathcal{X} \to \mathbb{R}^m$ such that for each $\mathbf{x} \in \mathcal{X}$, $f(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x})]$.

It might well happen that the objectives are in conflict. In this case, improving one of them implies worsening another. It makes no sense talking about a single global optimum, and for this reason, the notion of an optimum set ($\mathcal{X}^*$) acquires especial relevance in the context of multiobjective optimization.

A central element in the theory of multiobjective optimization is the concept of Pareto efficiency. A solution $\mathbf{x}^*$ is element of the set $\mathcal{X}^*$, i.e., it is Pareto efficient, if and only if, there does not exist a solution $\mathbf{x} \in \mathcal{X}$, such that $\mathbf{x}$ dominates to $\mathbf{x}^*$ in the Pareto sense. A solution $\mathbf{x}_1$ dominates in the Pareto sense (is preferred to) another solution $\mathbf{x}_2$, $(\mathbf{x}_1 \succ \mathbf{x}_2)$, if $\mathbf{x}_1$ is better than $\mathbf{x}_2$ in at least one criterion (objective function) and no worse with respect to the remaining ones. In global optimization, it is a convention that optimization problems are defined as minimizations problems [106], and hence, if one criterion f needs to be maximized, then f is redefined as $-f$. Thus,

$$\mathbf{x}_1 \succ \mathbf{x}_2 \Leftrightarrow f_i(\mathbf{x}_1) \leq f_i(\mathbf{x}_2) \wedge \exists j | f_j(\mathbf{x}_1) < f_j(\mathbf{x}_2). \tag{B.2}$$

In this manner, the notion of optimality in the multiobjective context can be formalized as follows: a solution $\mathbf{x}^*$ features Pareto efficiency (is Pareto optimal), and hence, element of $\mathcal{X}^*$, if and only if, there does not exist a solution $\mathbf{x} \in \mathcal{X}$, such that $\mathbf{x}$ dominates $\mathbf{x}^*$. Thus,

$$\mathbf{x}^* \in \mathcal{X}^* \Leftrightarrow \nexists \mathbf{x} \in \mathcal{X} | \mathbf{x} \succ \mathbf{x}^*. \tag{B.3}$$

The set $\mathcal{X}^*$ of Pareto optimal solutions is called optimal nondominated set and its image is known as the optimal Pareto Front. When a multiobjective problem is solved, it is unusual to obtain the optimal Pareto Front due to problem complexity, instead a set of near-optimal solutions is found. Hereafter, for the sake of clarity, it should be understood that the set $\mathcal{X}^*$ contains such near-optimal solutions, and hence, its image, the corresponding Pareto Front, is an estimation of the optimal Pareto Front. These ideas are illustrated in Fig. B.1 for the case where $f = [f_1(x), f_2(x)]$.

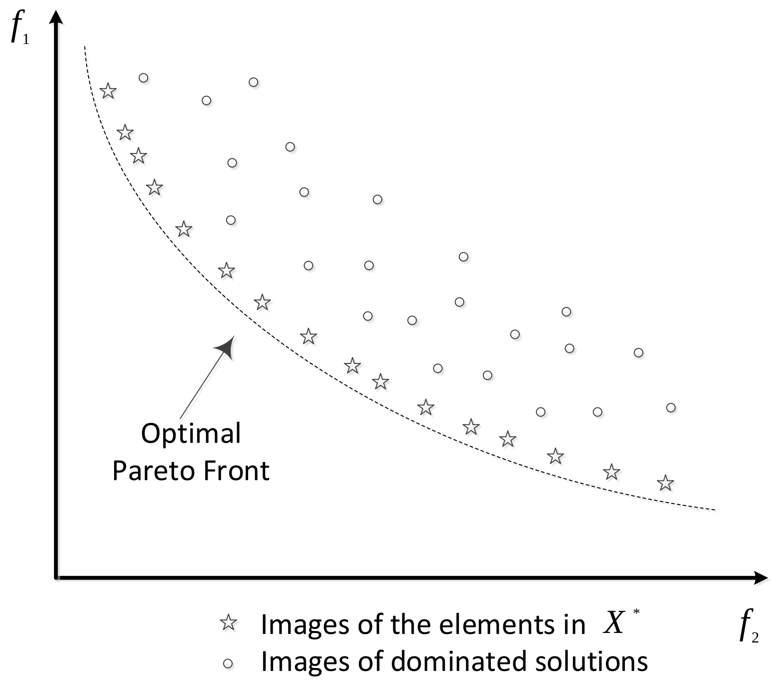


FIGURE B.1: A representation of the Pareto Front.

Any solution in $\mathcal{X}^*$ is optimal in the sense that no improvement can be made on a component of f without worsen at least another of its components. Given this, the estimation of the set $\mathcal{X}^*$ provides a complete picture of the tradeoffs among objective functions, which is desirable in problems such as the optimization of BSs switching off, where reducing the energy consumption and cost expenses always comes at the expense of QoS.

Multiobjective optimization problems, in general, can be expressed in the following form:

$$\min \ f(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_n(\mathbf{x})] \tag{B.4}$$
$$\text{s.t.}$$
$$\mathbf{x} \in \mathcal{X}. \tag{B.5}$$

Solving problems such as the one show in Eq. (B.4) is very difficult for the following reasons:

1. As it was shown, the definition of optimality in multiobjective optimization only allows establishing a partial order [109] between the solutions, which complicates the design of resolution algorithms.
2. The vast majority of multiobjective problems are NP-hard [110].
3. The cardinality of the set $\mathcal{X}^*$ grows exponentially with the number of objectives.

Problem in Eq. (B.4) can be solved encoding the solutions either with real-valued variables (continuous optimization problems) or discrete variables (combinatorial optimization problems). The following discussion applies to both types of problems. The approaches to solve this problem can be classified as follows:

- *Pareto approaches.* The search and selection of solutions is based on the concept of Pareto efficiency. This chapter focuses on this strategy because multiobjective optimization evolutionary algorithms are also based on this approach.
- *Non-Pareto and non-scalar approaches.* These methods use operators to deal with the objective functions separately. Few works have employed this approach. Examples include parallel [111] and lexicographic [112] selection.

Multiobjective (combinatorial or not) optimization problems typically belong to the class NP-Complete [110], and hence, optimality cannot be guaranteed in polynomial time. Therefore, deterministic methods for finding optimal solutions are not an option. Moreover, multiobjective problems with objective functions depending on many (independent) design variables often results in large n-dimensional objective spaces, full of local optima and discontinuities [106]. In the particular case of switching off optimization, n would be proportional to the network size (the number of cells, number of MNOs), which is considerably high even in deployments covering small cities.

Certain algorithms such as gradient based methods are susceptible to be trapped in local optima, while other optimization techniques such as Sequential Quadratic Programming (SQP) based methods [113] require convexity (a very strong assumption in this context) to guarantee convergence. In addition, traditional constrained optimization, in which only one objective function is optimized subject to a set of constraints on the remaining ones, has the drawbacks of 1) limiting the visibility of the whole objective space, and 2) reducing the output to one single network configuration.

Summarizing, the problem under consideration requires of an optimization tool fulfilling the following features:

- It must be able to find good (near-optimal) solutions by efficiently exploring the search space.
- It should operate in an effective manner with multiple criteria and a large number of design variables.
- It should not require strong assumptions on the objective functions such as linearity, convexity, continuity, or differentiability.

Multiobjective optimization evolutionary algorithms [114] fulfill the previous requirements, and hence, their use in cell switching off optimization for large and irregular networks is investigated. Multiobjective optimization evolutionary algorithms are population based metaheuristics that simulate the process of natural evolution. The main advantages of these algorithms are: 1) their black box nature makes them suitable to deal with many practical problems as only few assumptions need to be made on the objective functions, and 2) they incorporate important features such as elitism, convergence, and distribution.

The solution of multiobjective optimization problems has always been of great interest for scientist and engineers working on operations research. Several exact methods have been proposed for solving problems involving two objectives and a small number of design variables such as branch and bound [115] and dynamic programming [116]. However, these methods are not effective for large scale problems with more than two criteria and a high number of design variables. Indeed, for more than two criterion, there are not useful procedures due to the multiobjective nature of the problems and the NP-Complete difficulty [114].

Thus, heuristic methods have become a very popular approach to solve problems involving a large number of design variables and multiple objective functions. These strategies do not guarantee to find the optimal Pareto Front, but a good approximation of it. In this context, the methods can be grouped into two types: on the one hand, the heuristic based algorithms that are problem-specific (heuristics), and on the other hand, high level strategies that can be applied to a large number of multiobjective problems (metaheuristics).

An heuristic can be considered as a part of an iterative optimization algorithm that uses available information to determine 1) which solution candidate should be tested in each iteration, and 2) how next candidates must be produced [106].

However, as heuristics are problem type dependent, they have been used as means to solve specific problems.

A metaheuristic is a method for solving more general classes of problems. They combine objective functions and heuristics in an abstract and hopefully efficient way, usually without utilizing deeper insight into their structure, i.e., by treating them as black-box-procedures [106]. Due to this versatility, metaheuristics have become a very active research area and several algorithms have been proposed. Popular ones include adaptations of classic (single objective) schemes such as Tabu Search [117], Simulated Annealing [118], Particle Swarm Optimization [119], and Evolutionary Algorithms [114]. For instance, a simulated annealing based multiobjective optimization algorithm can be found in [120]. A summary of the methods for solving MO problems is shown in Fig. B.2. A complete and in-depth discussion of metaheuristics and evolutionary computation can be found in [121] and [114].

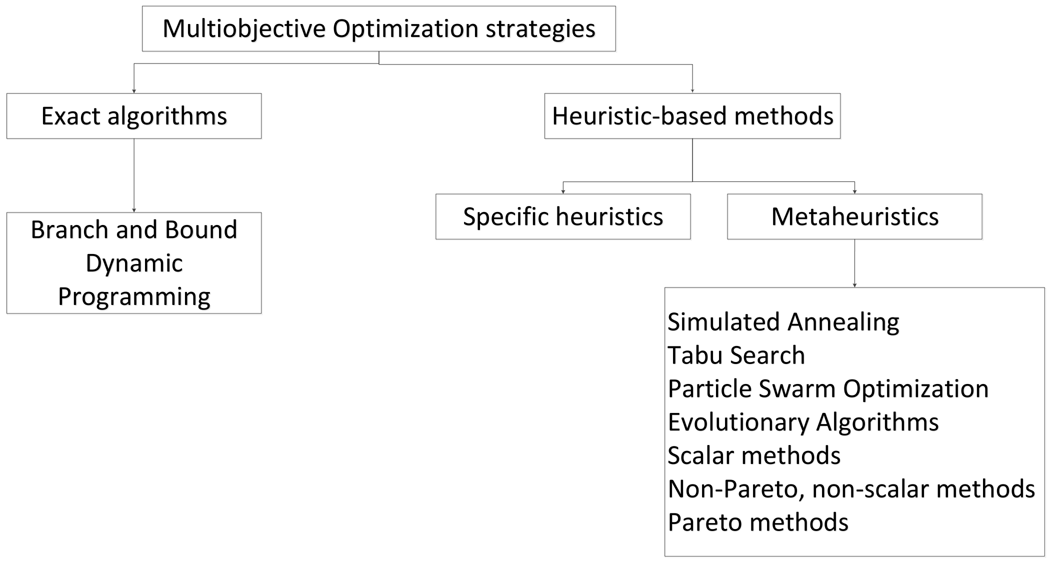


Figure B.2: Methods for solving multiobjective optimization problems.

Bibliography

[1] 5GPPP. 5g vision - the 5g infrastructure public private partnership: the next generation of communication networks and services. *Technical Report*, February 2015. URL http://5g-ppp.eu/wp-content/uploads/2015/02/5G-Vision-Brochure-v1.pdf.

[2] The Climate Group. Smart 2020: Enabling the low carbon economy in the information age. *Technical Report*, 2008. URL http://www.smart2020.org/assets/files/02Smart2020Report.pdf.

[3] S. Carson. Total cost of ownership - creating value for operators. *Presentation Ericsson Capital Markets Day*, May 2007.

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

[5] Global Action Plan. *Report*, December .

[6] Cisco. Cisco visual networking index: Global mobile data traffic forecast update, 2014-2019. *Whitepaper*, February 2015.

[7] T. Loozen, R. Murdoch, and S. Orr. Mobile web watch 2013. accenture. *Technical Report*. URL www.accenture.com.

[8] V12.5.0 3GPP TS 36.300. 3rd generation partnership project; technical specification group radio access network; evolved universal terrestrial radio access (e-utra) and evolved universal terrestrial radio access network (e-utran); overall description; stage 2 (release 12). *Technical Report*, March 2015.

[9] D. Martín-Sacristan, J. F. Monserrat, J. Cabrejas Peñuelas, D. Calabuig, S. Garrigas, and N. Cardona. On the way towards fourth generation mobile: 3gpp lte and lte-advanced. *EURASIP Journal on Wireless Communications and Networking*, (4), March 2009.

[10] L. M. Correia, D. Zeller, O. Blume, D. Ferling, Y. Jading, I. Godor, and L. Van der Perre. Challenges and enabling technologies for energy aware mobile radio networks. *IEEE Communications Magazine*, 48(11), November 2010.

[11] Vodafone group. Sustainability report: Environmental footprint - performance data. 2012. URL http://www.vodafone.com/content/index/about/sustainability/sustainabilityreport/issuebyissue/environmentalfootprint/performancedata.html.

[12] T. Chen, H. Zhang, Z. Zhao, and X. Chen. Towards green wireless access networks. *5th International ICST Conference on Communications and Networking in China (CHINACOM)*, August 2010.

[13] Market Research. Sbi bulletin: Energy efficiency technologies in information and communication industry, 2005-2015. August 2012.

[14] Centre for Energy-Efficient Telecommunications (CEET) Bell Labs and University of Melbourne. The power of wireless cloud. 2013. URL http://www.wballiance.com/wba/wp-content/uploads/downloads/2012/07/16WBA-Industry-Report-2011-Global-Developments-in-Public-Wi-Fi-1.00.pdf.

[15] B. Gammage, D. C. Plummer, E. Thompson, L. Fiering, H. LeHong, F. Karamouzis, C. Da Rold, K. Collins, W. Clark, N. Jones, C Smulders, M. Escherich, M. Reynolds, and M. Basso. Gartner's top predictions for it organizations and users, 2010 and beyond: A new balance. *Gartner Report*, December 2009. URL http://www.gartner.com/id=1268513.

[16] European Commission. Climate change: Commission welcomes final adoption of europe's climate and energy package. *European Commission press release*, December 2008. URL http://europa.eu/rapid/press-releaseIP-09-628en.htm.

[17] M. Stanley. Hopes of growth fade away: A proprietary approach. *Financial analyst report*, October 2004.

[18] G. Fischer. Future challenges in r&d with respect to mobile communication base stations. *FP7 Design WS, Alcatel-Lucent*, January 2008.

[19] L. Suarez, L. Nuaymi, and J. Bonnin. An overview and classification of research approaches in green wireless networks. *EURASIP Journal on Wireless Communications and Networking*, 142:1–18, April 2012.

[20] Alcatel-Lucent. 9900 wireless network guardian. *White paper*, August 2012. URL http://www3.alcatel-lucent.com/wps/DocumentStreamerServlet?LMSG_CABINET=Docs_and_Resource_Ctr&LMSG_CONTENT_FILE=White_PapersGuardian_EN_Tech_WhitePaper.pdf.

[21] T. Frisanco, P. Tafertshofer, P. Lurin, and R. Ang. Infrastructure sharing and shared operations for mobile network operators: From a deployment and operations view. *IEEE Network Operations and Management Symposium (NOMS)*, April 2008.

[22] D. E. Meddour, T. Rasheed, and Y. Gourhant. On the role of infrastructure sharing for mobile network operators in emerging markets. *Elsevier Journal on Computer Networks Journal*, 55(7):1567–1591, May 2011.

[23] Mobile network sharing report 2010-2015, development, analysis & forecasts. *Market Study, Visiongain*, 2010.

[24] L. Gao, G. Iosifidis, J. Huang, and L. Tassiulas. Economics of mobile data offloading. *IEEE International Conference on Computer Communications (INFOCOM)*, April 2013.

[25]

[26] GSMA TM. Base station planning permission in europe 2013. *Report*, December 2013. URL http://www.gsma.com/publicpolicy/wp-content/uploads/2013/05/GSMA_Base_Station_Planning_in_Europe-2013.pdf.

[27] GSMA TM. Mobile infrastructure sharing. *Report*, September 2012. URL http://www.gsma.com/publicpolicy/wp-content/uploads/2012/09/Mobile-Infrastructure-sharing.pdf.

[28] C. E. Jones, K. M. Sivalingam, P. Agrawal, and J. C. Chen. A survey of energy efficient network protocols for wireless networks. *Wireless Networks*, 7(4), January 2001.

[29] Abertis. Abertis reaches an agreement with telefónica and yoigo on the acquisition of a minimum package of 4.227 mobile telephone towers. *Press Release*, August 2013. URL http://www.abertis.com/dyndata/01082013AdquisicionTorresMovilesEN.pdf.

[30] L. Chiaraviglio, D. Ciullo, M. Meo, and M. A. Marsan. Energy-aware umts access networks. *11th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, September 2008.

[31] L. Chiaraviglio, D. Ciullo, M. Meo, and M. A. Marsan. Energy-efficient management of umts access networks. *21st International Teletraffic Congress (ICT)*, September 2009.

[32] M. A. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo. Optimal energy savings in cellular access networks. *IEEE International Conference on Communications Workshops (ICC Workshops)*, June 2009.

[33] M. A. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo. Switch-off transients in cellular access networks with sleep modes. *IEEE International Conference on Communications Workshops (ICC)*, June 2011.

[34] S. Zhou, J. Gong, Z. Yang, Z. Niu, and P. Yang. Green mobile access network with dynamic base station energy saving. *ACM MobiCom*, September 2009.

[35] J. Gong, S. Zhou, Z. Niu, and P. Yang. Traffic-aware base station sleeping in dense cellular networks. *18th International Workshop on Quality of Service (IWQoS)*, June 2010.

[36] K. Samdanis, D. Kutscher, and M. Brunner. Self organized energy efficient cellular networks. *IEEE 21th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, September 2010.

[37] K. Samdanis, T. Taleb, D. Kutscher, and M. Brunner. Self organized network management functions for energy efficient cellular urban infrastructures. *Journal in Mobile Networks and Applications*, 17(1), February 2011.

[38] G. Fusco, M. Buddhikotl, H. Gupta, and S. Venkatesan. Finding green spots and turning the spectrum dial: Novel techniques for green mobile wireless networks. *IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, May 2011.

[39] M. A. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo. A simple analytical model for the energy-efficient activation of access points in dense wlanss. *1st International Conference on Energy-Efficient Computing and Networking (e-Energy)*, April 2010.

[40] A. P. Jardosh, G. Iannaccone, K. Papagiannaki, and B. Vinnakota. Towards an energy-star wlan infrastructure. *8th IEEE Workshop on Mobile Computing Systems and Applications (HotMobile)*, March 2007.

[41] F. Alaca, A. B. Sediq, and H. Yanikomeroglu. A genetic algorithm based cell switch-off scheme for energy saving in dense cell deployments. *IEEE Global Telecommunications Conference Workshops (GLOBECOM Workshops)*, December 2012.

[42] S. Morosi, P. Piunti, and E. D. Re. Sleep mode management in cellular networks: A traffic based technique enabling energy saving. *Transactions on Emerging Telecommunications Technologies, Special Issue: Quality of Experience in Wireless Multimedia Systems*, 24(3):331–341, April 2013.

[43] E. Oh and B. Krishnamachari. Energy savings through dynamic base station switching in cellular wireless access networks. *IEEE Global Telecommunications Conference (GLOBECOM)*, December 2010.

[44] J. Lorincz, A. Capone, and D. Begusic. Optimized network management for energy savings of wireless access networks. *Elsevier Journal on Computer Networks*, 55(3):514–540, February 2011.

[45] C. Peng, S. B. Lee, S. Lu, H. Luo, and H. Li. Traffic-driven power saving in operational 3g cellular networks. *ACM 17th Annual International Conference on Mobile Computing and Networking (MobiCom)*, September 2011.

[46] P. Kolios, V. Friderikos, and K. Papadaki. Switching off low utilization base stations via store carry and forward relaying. *IEEE 21th International Symposium on Personal, Indoor and Mobile Radio Communications Workshops (PIMRC Workshops)*, September 2010.

[47] L. Xiang, F. Pantisano, R. Verdone, X. Ge, and M. Chen. Adaptive traffic load-balancing for green cellular networks. *IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, September 2011.

[48] P. Ghosh, S. Das, S. Naravaram, and P. Chandhar. Energy saving in ofdma cellular systems using base-station sleep mode: 3gpp-lte a case study. *National Conference on Communications (NCC)*, February 2012.

[49] G. Cili, H. Yanikomeroglu, and F. Yu. Cell switch off technique combined with coordinated multi-point (comp) transmission for energy efficiency in beyond-lte cellular networks. *IEEE International Conference on Communications (ICC)*, June 2012.

[50] M. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo. Multiple daily base station switch-offs in cellular networks. *4th International Conference on Communications and Electronics (ICCE)*, August 2012.

[51] X. Guo, S. Zhou, Z. Niu, and P. Kumar. Optimal wake-up mechanism for single base station with sleep mode. *25th International Teletraffic Congress (ITC)*, September 2013.

[52] Y. Wu, G. He, S. Zhang, Y. Chen, and S. Xu. Energy efficient coverage planning in cellular networks with sleep mode. *IEEE 24th International Symposium Personal Indoor and Mobile Radio Communications (PIMRC)*, September 2013.

[53] J. Zheng, Y. Cai, X. Chen, R. Li, and H. Zhang. Optimal base station sleeping in green cellular networks: A distributed cooperative framework based on game theory. *IEEE Transactions on Wireless Communications*, PP(99), April 2015.

[54] B. Leng, P. Mansourifard, and B. Krishnamachari. Microeconomic analysis of base-station sharing in green cellular networks. *IEEE International Conference on Computer Communications (INFOCOM)*, May 2014.

[55] M. A. Marsan and M. Meo. Energy efficient management of two cellular access networks. *ACM SigMetrics Performance Evaluation Review*, 37(4): 69–73, March 2010.

[56] M. A. Marsan and M. Meo. Energy efficient wireless internet access with cooperative cellular networks. *Elsevier Journal on Computer Networks*, 55 (2):386–398, February 2011.

[57] E. Oh, B. Krishnamachari, X. Liu, and Z. Niu. Towards dynamic energy-efficient operation of cellular network infrastructure. *IEEE Communications Magazine*, 49(6):56–61, June 2011.

[58] L. Chiaraviglio, D. Ciullo, G. Koutitas, M. Meo, and L. Tassiulas. Energy-efficient planning and management of cellular networks. *9th Annual Conference on Wireless On-Demand Network Systems and Sevices (WONS)*, January 2012.

[59] M. A. Marsan and M. Meo. Network sharing and its energy benefits: a study of european mobile network operators. *IEEE Global Communications Conference, Exhibition & Industry Forum (GLOBECOM)*, December 2013.

[60] G. Fettweis and E. Zimmermann. Ict energy consumption - trends and challenges. *11th International Symposium on Wireless Personal Multimedia Communications (WPMC)*, September 2008.

[61] F. Richter, A. J. Fehske, and G. P. Fettweis. Energy efficiency aspects of base station deployment strategies for cellular networks. *IEEE 70th Vehicular Technology Conference Fall (VTC Fall)*, September 2009.

[62] A. J. Fehske, F. Richter, and G. P. Fettweis. Energy efficiency improvements through micro sites in cellular mobile radio networks. *IEEE Global Telecommunications Conference Workshops (GLOBECOM Workshops)*, December 2009.

[63] F. Richter and G. P. Fettweis. Cellular mobile network densification utilizing micro base stations. *IEEE International Conference on Communications (ICC)*, May 2010.

[64] F. Richter, A. J. Fehske, P. Marsch, and G. P. Fettweis. Traffic demand and energy efficiency in heterogeneous cellular mobile radio networks. *IEEE 71st Vehicular Technology Conference (VTC Spring)*, May 2010.

[65] O. Arnold, F. Richter, G. P. Fettweis, and O. Blume. Power consumption modeling of different base station types in heterogeneous cellular networks. *Future Network and Mobile Summit*, June 2010.

[66] F. Han, Z. Safar, and K. J. R. Liu. Energy-efficient base-station cooperative operation with guaranteed qos. *IEEE Transactions on Communications*, 61 (8):3505–3517, June 2013.

[67] J. Bartelt, A. Fehske, H. Klessig, , G. Fettweis, and J. Voigt. Joint bandwidth allocation and small cell switching in heterogeneous networks. *IEEE 78th Vehicular Technology Conference (VTC Fall)*, September 2013.

[68] Y. S. Soh, T. Q. S. Quek, M. Kountouris, and H. Shin. Energy efficient heterogeneous cellular networks. *IEEE Journal on Selected Areas in Communications*, 31(5):840–850, May 2013.

[69] Nokia. Nokia networks: Solutions. *Report*, February 2015. URL http://networks.nokia.com/portfolio/solutions/heterogeneous-networks.

[70] M. H. Alsharif, R. Nordin, and M. Ismail. A review on intelligent base stations cooperation management techniques for greener lte cellular networks. *Journal of Communications*, 9(12), December 2014.

[71] I. Ashraf, F. Boccardi, and L. Ho. Sleep mode techniques for small cell deployments. *IEEE Communications Magazine*, 49(8):72–79, August 2011.

[72] S. Cai, L. Xiao, H. Yang, J. Wang, and S. Zhou. A cross-layer optimization of the joint macro- and picocell deployment with sleep mode for green communications. *22nd Wireless and Optical Communication Conference (WOCC)*, May 2013.

[73] M. Wildemeersch, T. Quek, C. Slump, and A. Rabbachin. Cognitive small cell networks: Energy efficiency and trade-offs. *IEEE Transactions on Communications*, 61(9):4016–4029, September 2013.

[74] L. Saker, S. E. Elayoubi, R. Combes, and T. Chahed. Optimal control of wake up mechanisms of femtocells in heterogeneous networks. *IEEE Journal on Selected Areas in Communications*, 30(3), April 2012.

[75] D. Tsilimantos, J. M. Gorce, and E. Altman. Stochastic analysis of energy savings with sleep mode in ofdma wireless networks. *IEEE International Conference on Computer Communications (INFOCOM)*, April 2013.

[76] K. Huang and V. Lau. Enabling wireless power transfer in cellular networks: Architecture, modeling and deployment. *IEEE Transactions on Wireless Communications*, 13(2), February 2014.

[77] S. Paris, F. Martignon, I. Filippini, and L. Chen. A bandwidth trading marketplace for mobile data offloading. *IEEE Conference on Computer Communications (INFOCOM)*, April 2013.

[78] W. Dong, S. Rallapalli, R. Jana, L. Qiu, K. K. Ramakrishnan, L. Razoumov, Y. Zhang, and T. Won Cho. ideal: Incentivized dynamic cellular offloading via auctions. *IEEE/ACM Transactions on Networking*, 22(4):1271–1284, August 2014.

[79] S. Paris, F. Martignona, I. Filippini, and A. Capone. A truthful auction for access point selection in heterogeneous mobile networks. *International Conference on Communications (ICC)*, June 2012.

[80] C. Han, T. Harrold, S. Armour, I. Krikidis, S. Videv, P. M. Grant, H. Haas, J. S. Thompson, I. Ku, C. X. Wang, T. A. Le, M. R. Nakhai, J. Zhang, and L. Hanzo. Green radio: Radio techniques to enable energy-efficient wireless networks. *IEEE Communications Magazine*, 49(6):46–54, June 2011.

[81] I. Humar, X. Ge, L. Xiang, M. Jo, M. Chen, and J. Zhang. Rethinking energy efficiency models of cellular networks with embodied energy. *IEEE Network*, 25(2):40–49, March 2011.

[82] V10.0.0 3GPP TR 32.826. 3rd generation partnership project; technical specification group services and system aspects; telecommunication management; study on energy savings management (esm) (release 10), technical report. *Technical Report*, March 2010.

[83] Sandvine. Intelligent broadband networks global internet phenomena report. *Technical Report*, Spring 2011.

[84] UMTS Forum. Mobile traffic forecasts 2010-2020 report. *Report 44*, January 2011.

[85] D. Fudenberg and J. Tirole. Game theory. *MIT Press, 1st ed.*, August 1991.

[86] M.J. Osborne and A. Rubinstein. A course in game theory. *MIT Press, 1st ed.*, July 1994.

[87] Z. Han, D. Niyato, W. Saad, T. Basar, and A. Hjorungnes. Game theory in wireless and communication networks. *1st Edition, Cambridge university press*, January 2012.

[88] W. Rudin. Principles of mathematical analysis. *2nd Edition, New York: MacGraw-Hill*, January 1964.

[89] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y. Dong Yao. Opportunistic spectrum access in unknown dynamic environment: A game-theoretic stochastic learning solution. *IEEE Transactions on Wireless Communications*, 11(4):1380–1391, April 2012.

[90] Y. Xing and R. Chandramouli. Stochastic learning solution for distributed discrete power control game in wireless data networks. *IEEE/ACM Transactions on Networking*, 16(4):932–944, August 2008.

[91] L. Liang and G. Feng. A game-theoretic framework for interference coordination in ofdma relay networks. *IEEE Transactions on Vehicular Technology*, 61(1):321–332, January 2012.

[92] S. Tombaz, A. Vastberg, and J. Zander. Energy-and cost-efficient ultra-high-capacity wireless access. *IEEE Wireless Communications*, 18(5):18–24, October 2011.

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

[94] A. Ghosh, N. Mangalvedhe, R. Ratasuk, B. Mondal, M. Cudak, E. Visotsky, T. A. Thomas, J. G. Andrews, P. Xia, H. S. Jo, H. S. Dhillon, and T. D. Novlan. Heterogeneous cellular networks: From theory to practice. *IEEE Communications Magazine*, 50(6):54–64, June 2012.

[95] C. Beckman and G. Smith. Shared networks: making wireless communication affordable. *IEEE Wireless Communications*, 12(2):78–85, April 2005.

[96] Y. Chen, S. Zhang, and S. Xu. Characterizing energy efficiency and deployment efficiency relations for green architecture design. *IEEE International Conference on Communications Workshops (ICC Workshops)*, May 2010.

[97] Small Cell Forum. URL www.smallcellforum.org.

[98] A. Qureshi, R. Weber, H. Balakrishnan, J. Guttag, and B. Maggs. Cutting the electric bill for internet-scale systems. *ACM Conference on Data Communication (SIGCOMM)*, August 2009.

[99] L. S. Shapley. A value for n-person games. *Annals of Mathematical Studies*, August 1953.

[100] J. Coon, C. P. Dettmann, and O. Georgiou. Full connectivity: Corners, edges and faces. *Journal of Statistical Physics*, 147(4):758–778, May 2012.

[101] H. Holma and A. Toskala. Lte for umts: Ofdma and sc-fdma based radio access. *John Wiley & Sons*, March 2011.

[102] E. Dahlman, S. Parkvall, and J. Skold. 4g lte/lte-advanced for mobile broadband. *Elsevier Ltd.*, May 2011.

[103] 3GPP TR 36.942 V12.0.0. 3rd generation partnership project; technical specification group radio access network; evolved universal terrestrial radio access (e-utra); radio frequency (rf) system scenarios (release 12). *Technical Report*, September 2014.

[104] V. Krishna. Auction theory. *Academic Press, 2nd ed.*, August 2009.

[105] Y. Sawaragi, I. Hirotaka, and T. Tanino. Theory of multiobjective optimization. *Academic Press, Inc., 1st ed., Mathematics in Science and Engineering*, 176, 1985.

[106] T. Weise. Global optimization algorithms - theory and application. *Selfpublished, 2nd ed.*, January 2008. URL http://www.it-weise.de/.

[107] Ericsson. Ericsson mobility report: On the pulse of the networked society. *Technical Report*, November 2014.

[108] Ofcom. Sitefinder: Mobile phone base station database. *Report*, March 2015. URL http://sitefinder.ofcom.org.uk/search.

[109] S. Finch. Transitive relations, topologies and partial orders. *Technical Report*, June 2003. URL http://www.people.fas.harvard.edu/~sfinch/csolve/posets.pdf.

[110] M. R. Gary and D. S. Johnson. Computers and intractability: A guide to the theory of np-completeness (series of books in the mathematical sciences). *WH Freeman and Company, 1st ed.*, January 1979.

[111] B. R. Jones, W. A. Crossley, and A. S. Lyrintzis. Aerodynamic and aeroacoustic optimization of rotorcraft airfoils via a parallel genetic algorithm. *Journal of Aircraft*, 37(6):1088–1096, November-December 2000.

[112] M. P. Fourman. Compaction of symbolic layout using genetic algorithms. *1st International Conference on Genetic Algorithms*, pages 141–153, July 1985.

[113] R. Fletcher. The sequential quadratic programming method. *Springer*, May 2007.

[114] C. A. Coello, G. B. Lamont, and D. A. Van Veldhuizen. Evolutionary algorithms for solving multi-objective problems. *Springer: Genetic and Evolutionary Computation Series, 2nd ed.*, 2007.

[115] T. Sen, F. M. E. Raiszadeh, and P. Dileepan. A branch-and-bound approach to the bicriterion scheduling problem involving total flowtime and range of lateness. *Management Science*, 34(2):254–260, February 1988.

[116] R. L. Carraway, T. L. Morin, and H. Moskowitz. Generalized dynamic programming for multicriteria optimization. *European Journal of Operational Research*, 44(1):95–104, January 1990.

[117] F. Glover. Tabu search: A tutorial. *The Institute of Management Sciences*, pages 74–94, July-August 1990.

[118] S. Kirkpatrick, C. D. Gelatt Jr., and M. P. Vecchi. Optimization by simulated annealing. *Science*, 220(4598):671–680, May 1983.

[119] R. Poli, J. Kennedy, and T. Blackwell. Particle swarm optimization. *Swarm Intelligence*, 1(1):33–57, June 2007.

[120] T. Parks, A. Suppapitnarn, K. A. Seffen, and P. J. Clarkson. A simulated annealing algorithm for multiobjective optimization. *Engineering Optimization*, 33(1):59–85, January 2000.

[121] Michael Pilegaard Hansen. Metaheuristics for multiple objective combinatorial optimization. *PhD thesis, Technical University of Denmark*, March 1998.