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Energy-Efficient Solutions For Green Mobile Networks

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To my parents, my brother and my whole family

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Abstract

In recent years, with the growing demand for ubiquitous connectivity and new services, and the rapid growth of the Internet and data center traffic, the energy consumed by Information and Communication Technology (ICT) systems is increasing. The focus on the energy performance of ICT is driven by macro trends related to Economy, Ecology and Engineering.
Economy is tightly connected to cost control in the telecommunication industry where the primary focus lay on energy related operating expense. Hence, mobile operators are more and more motivated to seek "green" approaches that reduce the energy consumption of mobile cellular networks.
Ecology has a clear connection to regulatory aspects based on a societal wish to reduce climate impact as well as national security political aspects like dependence of imported energy supply.
The fundamental aspect of Engineering refers primarily to the technical innovation possibilities opening up when new technical challenges are introduced: it is important both for the scientific community and industry in general to take these challenges seriously, to state a good example in terms of technical solutions and also to demonstrate the claims of the ICT sector to positively impact other sectors shares of global greenhouse gas (GHG) emissions, known as the "enablement effect" of ICT.
This thesis focuses on the emerging research topic "green (energy-efficient) mobile networks" that has drawn huge attention recently from both academia and industry. This topic is highly motivated due to important environmental, financial and quality-of-experience (QoE) considerations. The term "green" emphasizes the environmental dimension of the proposed solutions. Hence, it is not sufficient to present a cost-effective solution unless it is eco-friendly.
As base stations (BS) are responsible for the large amount of energy consumed in cellular networks, energy efficient BS sleep mode techniques have the potential to save a significant amount of energy. However, assuming that BSs are able to alternate between sleeping and active states as frequently as possible may have a negative impact on network reliability, shortening BS lifetime.
In this thesis a multiobjective optimization framework which is aimed at minimizing the power consumption and the number of BS sleep mode switchings in typical and heterogeneous cellular networks (HetNet) is proposed, by jointly considering Quality of Service (QoS) requirements. Both the optimization procedure and the network planning complexity considerably in-

creases when heterogeneous networks with a mix of cell sizes are considered. With the introduction of small cell overlays, the macro cell network becomes over-provisioned due to the offload of traffic by means of small cells. The proposed sleep mode solution aims at reducing the energy consumption of the network by jointly optimizing the amount of management operations related to the addition of low-power base stations. The trade-off between power consumption, sleep mode switchings and performance of the network is shown for different energy saving solutions and traffic load cases.

Moreover, the concern about energy efficiency has been growing rapidly also for manufacturers and researchers of Professional Mobile Radio (PMR) systems, like Terrestrial Trunked Radio (TETRA), which have been designed to provide voice and data services to professional users. The future convergence of PMR to the LTE system introduces a new topic in the research discussion about the energy efficiency of wireless systems.

In this thesis the feasibility of energy efficient solutions for current and potentially future PMR networks is discussed, by providing a mathematical formulation of power consumption in TETRA base stations and assessing possible business models and energy saving solutions for enhanced mission-critical operations.

The final part of the thesis addresses green approaches for weather monitoring. Nowadays, the air quality is getting worse in highly anthropized environments: this phenomenon stimulates a high level of interest within the scientific community and public opinion because of the known strong relationship between exposure to many air pollutants and increased adverse effects on the human health. Developments in communication technologies allow more remote, real-time weather monitoring and access. The use of plants as biosensors represents a new reliable approach for ozone monitoring. In comparison with the traditional monitoring systems, the use of biosensors has the advantage to show us the real impact of pollutants on living organisms, thus providing additional data to the electronic instruments.

In this thesis an automatic method of analysis of plant electrical signals for ozone critical levels detection is introduced, based on the fundamentals of correlation theory. The proposed detection algorithm represents a novel monitoring method for detecting critical levels of ozone concentrations.

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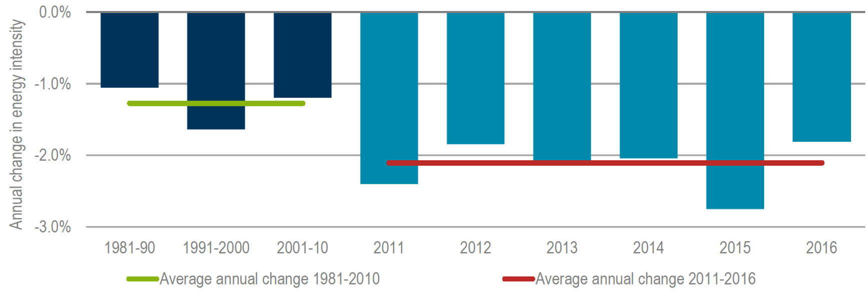
Chapter 1

Introduction

1.1 Energy efficiency: world energy perspective

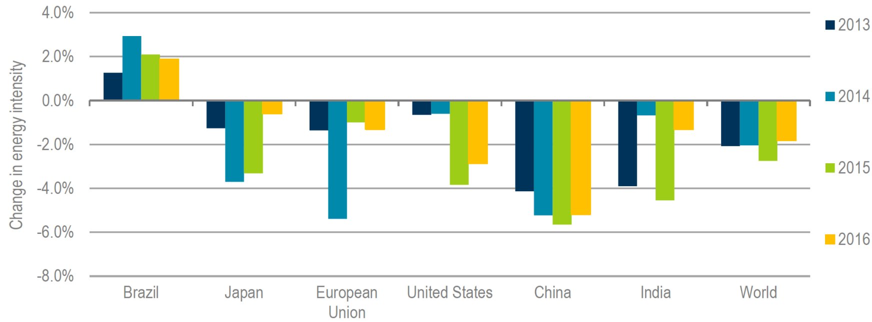
Energy efficiency stands at a crossroads today. Strong efficiency gains continued to be made in 2016 [18], even as energy prices fell. But at the same time, governments are not coming up with new policies fast enough, relying on existing regulations instead, precisely at the time when a pipeline of new efficiency policies should be coming into force. There is a risk that efficiency gains could take a step back. This issue is all the more important when you consider the impact that efficiency is already having on the global energy system. Notably, improved energy intensity has been the biggest factor behind the recent flattening of global greenhouse gas (GHG) emissions. The arguments for stronger action on energy efficiency have never been clearer. The world continued to generate more value from its energy use in 2016. Global energy intensity, measured as the amount of primary energy demand needed to produce one unit of gross domestic product (GDP), fell by 1.8% in 2016. Since 2010, intensity has declined at an average rate of 2.1% per year, which is a significant increase from the average rate of 1.3% between 1970 and 2010 (Figure 1.1). The improvement in intensity varies widely across countries and regions, with China once again having the most significant impact on global trends (Figure 1.2). This is avoiding huge amounts of energy use, generating financial savings for consumers and holding back the growth in GHG emissions. Despite these positive impacts, there is no



Note: Energy intensity is calculated as primary energy demand per USD 1 000 of GDP in 2016 prices at purchasing power parity.
Sources: Adapted from IEA (2016a), *World Energy Outlook 2016*; and IEA (2017a), *World Energy Statistics and Balances 2017* (database), www.iea.org/statistics.

Figure 1.1: Annual changes in global primary energy intensity, 1981-2016 [18]

room for complacency. Policy performance is mixed and new policy implementation slowed significantly in 2016. The current level of efficiency gains will erode quickly if the pace of policy delivery does not accelerate. The decline in global energy intensity means that the world is able to produce more GDP for each unit of energy consumed, an energy productivity bonus. In 2016, the world would have used 12% more energy had it not been for energy efficiency improvements since 2000, equivalent to adding another European Union to the global energy market (Figures 1.3-1.4). In emerging economies, energy efficiency gains have limited the increase in energy use associated with economic growth. Without efficiency, total energy use among the member countries of the International Energy Agency (IEA) would still be increasing. Instead, efficiency has led to a peak in total energy use in 2007, and a subsequent fall to levels not seen since the 1990s. Falling energy intensity is the main factor behind the flattening of global energy-related GHG emissions since 2014. Lower energy intensity, driven largely by efficiency improvements, is combining with the ongoing shift to renewables and other low-emission fuels to offset the impact of GDP growth on emissions. Technological innovation is creating new opportunities for progress on efficiency. Digitalization is beginning to have a significant impact on the energy sector and energy efficiency is emerging as a key arena for innovation. It is creating exciting new opportunities for integrated solutions where efficiency and renewable energy work together to deliver clean energy outcomes at the



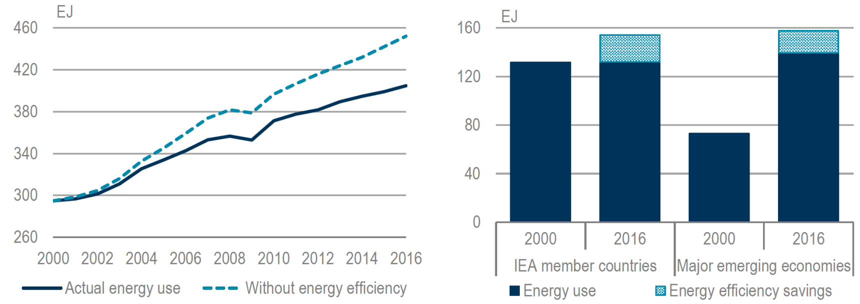
Sources: Adapted from IEA (2016a) *World Energy Outlook 2016*; and IEA (2017a), *World Energy Statistics and Balances 2017* (database), www.iea.org/statistics.

Figure 1.2: Change in primary energy intensity in selected countries and regions [18]

lowest cost. As business models adapt to the digital energy world, so too must policy.

1.2 Environmental, social and economic benefits of ICT

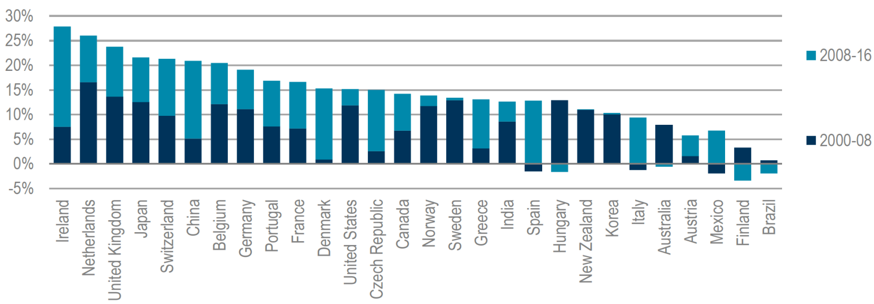
Information and Communications Technology (ICT) can play a fundamental role in helping to meet one of the global economy's most pressing challenges: sustaining economic growth while protecting the planet. In order to achieve that, it is essential that we cut the historical link between every unit of additional global GDP and the greenhouse gas emissions (CO_{2e}) we emit in the process, economy wide. So far, this has proved elusive. The core argument of SMARTer2030 report [17], looking to 2030, is that ICT can allow us to continue to grow economically while holding emissions at 2015 levels and generating numerous social benefits. In particular it shows that ICT's footprint could fall to 1.97% of global emissions by 2030, due to a range of investments companies in the sector have been making to reduce their footprint and to the expected increase in the efficiency of end-user-devices. Propelled by much greater access to broadband internet across the world and by the falling costs of smart phones and end-user devices gener-



Notes: Global energy savings are a combination of improvements in IEA member countries, the six major emerging economies analysed, plus the rest of the world, which represents 26% of global energy use. Energy savings for the rest of the world are estimated by applying the ratio of efficiency improvements to intensity gains observed in emerging economies to the gains in intensity observed in these other countries.

Sources: Timmer et al. (2015), *World Input Output Database* (database), www.wiod.org; IEA (2017c), *Mobility Model* (database) www.iea.org/etp/etpmodel/transport; and IEA (2017d), *Energy Technology Perspectives 2017* (Residential Model); IEA (2017a), *World Energy Statistics and Balances 2017* (database), www.iea.org/statistics; and IEA (2017e), *Energy Efficiency Indicators* (database), www.iea.org/statistics.

Figure 1.3: Energy use with and without energy savings from efficiency improvements globally (left) and by country grouping (right) [18]



Sources: Adapted from IEA (2017e), *Energy Efficiency Indicators* (database), www.iea.org/statistics/topics/energyefficiency/; Timmer et al. (2015), *World Input Output Database* (database), www.wiod.org; IEA (2017c), *Mobility Model* (database), www.iea.org/etp/etpmodel/transport; IEA (2017d), *Energy Technology Perspectives 2017* (Residential Model); and IEA (2017a), *World Energy Statistics and Balances 2017* (database), www.iea.org/statistics.

Figure 1.4: Percentage improvement in the efficiency effect for select countries, 2000-16 [18]

ally, we are witnessing nothing short of a revolution in the growth of new, disruptive business models. A decade ago, few would have guessed that a technology firm would be able to become the largest hotelier in the world within seven years without building a single hotel or guesthouse. Or that a technology start-up could use a single smartphone application to build a 40 billion dollars taxi business in six years without owning one car. And these trends are now extending out to the traditional public sector: healthcare, education and transport, bringing huge opportunities in the way we interact with service providers and with each other. This is set to accelerate. At the same time, as an increasingly affluent generation of consumers and citizens around the world becomes fluent with digital technology, even able to co-create their own solutions, it is becoming evident that ICT can improve lives and empower citizens, from megacities to some of the most remote locations on earth. ICT-solutions can help businesses around the world to continue to grow without putting our environment at risk. Of course, there are policy mechanisms needed, along with the actions businesses and consumers themselves need to take. But the good news is that ICT can do much more than generate revenue, cut costs and reduce emissions. ICT-enabled solutions can also vastly improve the lives of people all over the world, from people living in some of the most remote rural villages in East Africa, to telecommuters living in an affluent metropolis. By connecting the unconnected to the new economy, ICT can also contribute to addressing human development challenges like extreme poverty and a lack of access to essential services like healthcare, education and banking. With smartphones and broadband connections becoming ubiquitous, more and more people will gain access to such services, effectively raising their health outcomes and their income potential. A rapid increase in the adoption of devices like tablets and smartphones, as well as services like cloud computing, broadband networks and data centers, will result in additional emissions from ICT. Holding down the ICT-sector's own emissions as the number of devices increases is extremely important (Figure 1.5).

Greening is not merely a trendy concept, but is becoming a necessity to bolster social, environmental, and economic sustainability. Naturally, green communications have received much attention recently. As mobile network infrastructures and mobile devices proliferate, an increasing number of users rely on cellular networks for their daily lives. As a result, mobile networks are among the major energy hogs of communication networks and their contri-

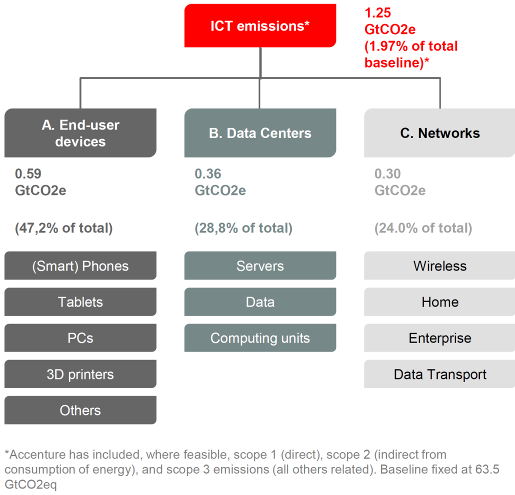


Figure 1.5: Environment - ICT emissions footprint (2030) [17]

bution to global energy consumption is increasing fast. Therefore, greening of cellular networks is crucial to reducing the carbon footprint of ICT. As a result, the field is attracting tremendous research efforts from both academia and industry.

1.3 Need for green networks

In response to the increasing demand for wireless communication services during the past decade, there has been wide deployment of wireless access networks [89]. By definition, a wireless access network is a wireless system that uses base stations (BSs) and access points (APs) to interface mobile terminals (MTs) with the core network or the Internet [34]. Hence, the main components of a wireless access network are BSs/APs and MTs [32]. BSs/APs are mainly in charge of radio resource control and user mobility management, and provide access to the Internet. MTs are equipped with processing and display capabilities, and provide voice services, video streaming, and data applications to mobile users. Currently, MTs are provided with multiple radio interfaces, and mobile users can connect to different networks, such as cellular networks, wireless local area networks (WLANs), and wireless metropolitan area networks (WMANs), and enjoy single-network and/or

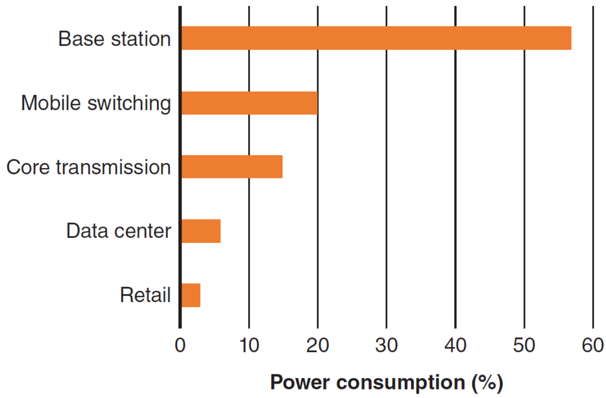


Figure 1.6: Breakdown of power consumption of a wireless cellular network [77]

multi-homing services [83,85,88]. From the network operator side, BS is the main source of energy consumption in the wireless access network [34]. The breakdown of a cellular network's typical power consumption is depicted in Figure 1.6, which shows that almost 57% of the operator's total power consumption is in the BS [34, 35, 69]. Worldwide, there are about 3 million BSs, which consume in total 4.5 GW of power [29]. From the user side, it has been estimated that there exist roughly 3 billion MTs in the world with a total power consumption of 0.2-0.4 GW [111]. Such high energy consumption of wireless access networks has triggered environmental, financial, and quality of experience (QoE) concerns for both network operators and mobile users. From an environmental standpoint, the telecommunications industry is responsible for 2% of the total CO_2 emissions worldwide, and this percentage is expected to double by 2020 [87]. As shown in Figure 1.7, the mobile communications sector has contributed 43% of the telecommunication carbon footprint in 2002, and this contribution is expected to grow to 51% by 2020 [149]. Furthermore, the MT rechargeable batteries' expected lifetime is about 2-3 years and manifests in 25,000 t of disposed batteries annually, a factor that raises environmental concerns (and financial considerations for the mobile users as well) [132]. In addition, the high energy consumption of BSs and MTs is a source of high heat dissipation and electronic pollution [113]. From a financial standpoint, a significant portion of a service provider's annual operating expenses is attributed to energy

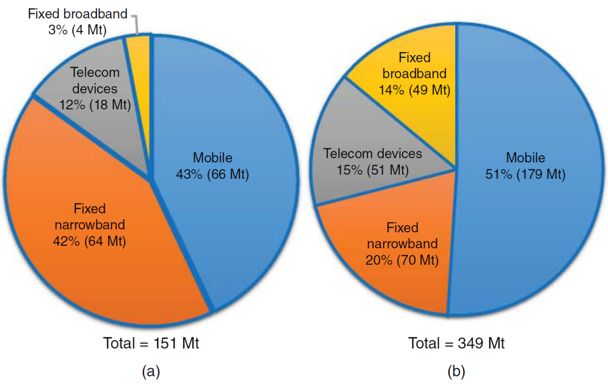


Figure 1.7: Carbon footprint contribution by the telecommunications industry: (a) 2002 and (b) 2020 [5]

costs [126, 146]. Technical reports have indicated that the cost of energy bills of service providers ranges from 18% (in mature markets in Europe) to 32% (in India) of the operational expenditure (OPEX) [57, 82]. The energy expenses reach up to 50% of the OPEX for cellular networks outside the power grid [38, 151]. The aforementioned concerns have triggered increasing demand for energy-efficient solutions in wireless access networks. Research efforts carried out in this direction are referred to as *green network solutions*. The term 'green' confirms the environmental dimension of the proposed approaches. Therefore, a cost-effective solution that is not eco-friendly is not attractive. For instance, having a cost-effective electricity demand schedule for a network operator that relies on different electricity retailers, in a liberated electricity market, is not considered a green solution if it does not ensure that the proposed solution is also eco-friendly in terms of the associated carbon footprint [30]. The objectives of the green wireless communications and networking paradigm are, therefore, (i) reducing energy consumption of communication devices and (ii) taking into account the environmental impacts of the proposed solutions. In order to develop and analyse a green networking solution, an appropriate definition of energy efficiency and consumption for network operators and mobile users should be formulated. This definition should account for the power consumption, throughput, traffic load models, and conflicting performance metrics for network operators and mobile users.

The rest of this thesis is organized as follows. Chapter 2 is dedicated to building the necessary background, providing a technical description of state-of-the-art developments in greening of mobile networks from a networking perspective. It discusses fundamental networking technologies that lead to energy-efficient mobile networks. Chapter 3 presents a multiobjective optimization framework aimed at minimizing the power consumption and the number of BS sleep-mode switchings in cellular networks, by jointly considering QoS requirements. These requirements are expressed in terms of a required bit rate for each mobile terminal. The framework deals with network management, such as the number of BSs that should be switched on, considering common diurnal patterns of the traffic demand. Chapter 4 introduces some energy saving solutions for HetNet scenarios in which macro and micro cells coexist. The MIQP optimization technique is used to minimize the power consumption together with the number of BS sleep mode operations of both macro and micro cells. The trade-off between power consumption, sleep mode switchings and performance of the network is shown for different energy saving strategies. Chapter 5 focuses on the feasibility of energy efficient solutions for current and potentially future Professional Mobile Radio (PMR) networks, by providing a mathematical formulation of power consumption in Terrestrial Trunked Radio (TETRA) base stations and assessing possible business models and energy saving solutions for enhanced mission-critical operations. Chapter 6 presents an innovative monitoring technology that is used to detect ground-level ozone pollution and is based on the deployment of a network of wireless devices which are connected to a collection of plants and are used as biosensors. The proposed detection algorithm represents a novel monitoring method for detecting critical levels of ozone concentrations. Finally, Chapter 7 summarizes the contribution of the thesis and discusses avenues for future research.

Chapter 2

Green mobile networks

This chapter is intended to provide a technical description of state-of-the-art developments in greening of mobile networks from a networking perspective. It discusses fundamental networking technologies that lead to energy-efficient mobile networks. These technologies include heterogeneous networking, multi-cell cooperation, mobile traffic offloading, traffic load balancing and energy consumption models.

2.1 Energy efficient multi-cell cooperation

As cellular network infrastructures and mobile devices proliferate, an increasing number of users rely on cellular networks for their daily lives. Mobile networks are among the major energy guzzlers of ICT infrastructure, and their contributions to global energy consumption are accelerating rapidly because of the dramatic surge in mobile data traffic [23, 38, 68, 77]. This growing energy consumption not only escalates the operators' operational expenditure (OPEX) but also leads to a significant rise of their carbon footprints. Therefore, greening of mobile networks is becoming a necessity to bolster social, environmental, and economic sustainability [55, 70, 104, 134]. The energy consumption of a cellular network is mainly drawn from BSs, which account for more than 50% of the energy consumption of the network. Thus, improving energy efficiency of BSs is crucial to green cellular networks. Taking advantage of multi-cell cooperation, energy efficiency of cellular networks can be improved from three perspectives. The first is to reduce the

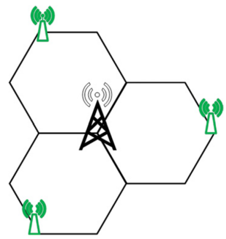


Figure 2.1: Scenario 1: One SCBS per macro site

number of active BSs required to serve users in an area [122]. The solutions involve adapting the network layout according to traffic demands. The idea is to switch off BSs when their traffic loads are below a certain threshold for a certain period of time. When some BSs are switched off, radio coverage and service provisioning are taken care of by their neighboring cells. The second aspect is to connect users with green energy efficient BSs. Through multi-cell cooperation, off-grid BSs enlarge their service areas while on-grid BSs shrink their service areas [75, 76, 174]. The third aspect is to exploit coordinated multi-point (CoMP) transmissions to improve energy efficiency of cellular networks [79]. On the one hand, with the aid of multi-cell cooperation, energy efficiency of BSs on serving cell edge users is increased. On the other hand, the coverage area of BSs can be expanded by adopting multi-cell cooperation, thus further reducing the number of active BSs required to cover a certain area.

2.2 Heterogeneous networking

The energy consumption of mobile networks scales with the provisioned traffic capacity. On deploying a mobile network, two types of BSs may be deployed. They are macro BSs (MBSs) and small cell BSs (SCBSs). As compared with SCBSs, MBSs provide a larger convergence area and consume more energy. SCBSs are deployed close to users, and thus consume less energy by leveraging such proximity. Owing to a small coverage area, in order to guarantee traffic capacity in an area, a very large number of SCBSs must be deployed. The total energy consumption of the large number of SCBSs may exceed that of the MBSs. Hence, in order to improve the energy efficiency of the network, a mixed deployment of both MBSs and SCBSs is

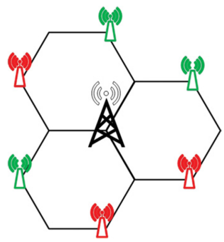


Figure 2.2: Scenario 2: Two SCBSs per macro site

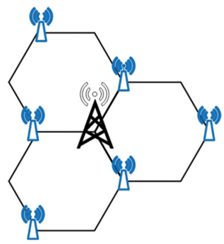


Figure 2.3: Scenario 3: Three SCBSs per macro site

desirable. In general, there are two SCBS deployment strategies: deployed at cell edges and at traffic hot spots. The users located at the edge of a macro cell usually experience bad radio channels due to excessive channel fading. In order to provide service to these users, MBSs could increase their transmit power, but this will result in a low energy efficiency. In a heterogeneous network deployment, SCBSs can be deployed at the edge of macro cells as shown in Figures 2.1-2.4. Depending on the traffic capacity demand, different SCBS deployment strategies can be adopted. For example, when the traffic capacity demand is relatively low, one SCBS may be deployed at the edge of a macro cell to serve the cell edge users as shown in Figure 2.1. As the traffic increases, additional SCBSs can be deployed at the cell edge as shown in Figures 2.2 and 2.3. When the traffic capacity demand is very high, additional SCBSs should be deployed. For example, five SCBSs are deployed for enhancing the energy efficiency of serving cell edge users in Figure 2.4. The number of SCBSs that are deployed to enhance the energy efficiency of serving users located at the edges of macro cells should be optimized based on traffic capacity demand at the cell edge. When the traffic capacity demand in mobile networks is inhomogeneous, deploying SCBSs at the edges

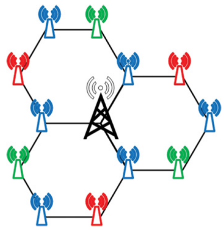


Figure 2.4: Scenario 4: Five SCBSs per macro site

of macro cells may not be optimal. Instead, SCBSs can be deployed in areas where there is high traffic capacity demand such as shopping areas, stadiums, and public parks. We define such areas as hotspots. Owing to proximity to the users, SCBSs can provide very high capacity at hotspots and serve the traffic demand with low energy consumption. In order to deploy SCBSs at traffic hotspots to enhance energy efficiency, the distribution of traffic capacity demand should be understood from network measurements. In addition, the traffic capacity demand should be localized so that a large portion of the traffic demand can be offloaded to SCBSs. In the ideal case, MBSs are only serving users with high moving speed while all the other users are served by SCBSs. If the high traffic demand occurs indoors, the indoor deployment of SCBSs can significantly enhance the energy efficiency of mobile networks.

2.3 Mobile traffic offloading

Mobile traffic offloading, which is referred to as utilizing complementary network communications techniques to deliver mobile traffic, is a promising technique to alleviate congestion and reduce the energy consumption of mobile networks. Based on the network access mode, mobile traffic offloading schemes can be divided into two categories. The first category is infrastructure based mobile traffic offloading, which refers to deploying SCBSs, for example, pico BSs, femto BSs and WiFi hot spots, to offload mobile traffic from MBS [71, 72]. SCBSs usually consume much less power than MBSs. Therefore, offloading mobile traffic to SCBSs can significantly enhance the energy efficiency of mobile networks [47, 55]. However, the lack of cost-effective backhaul connections for SCBSs often impairs their performance in terms of offloading mobile traffic and enhancing the energy efficiency of mo-

bile networks. The second category is ad-hoc based mobile traffic offloading, which refers to applying device-to-device (D2D) communications as an underlay to offload mobile traffic from MBSs. By leveraging Internet of Things (IoT) technologies, smart devices within proximity are able to connect with each other and form a communication network. Data traffic among the devices can be offloaded to the communication networks rather than delivering through MBSs. Moreover, in order to reduce CO_2 footprints, mobile traffic can be offloaded to BSs powered by green energy such as sustainable biofuels, solar, and wind energy [73, 74, 76, 174]. In this way, green energy utilization is maximized, and thus the consumption of on-grid energy is minimized.
In this section, we briefly overview the related research on mobile traffic offloading and the solutions for user-BS associations in heterogeneous mobile networks.

2.3.1 Infrastructure based mobile traffic offloading

In infrastructure based mobile traffic offloading, the mobile traffic is offloaded to either pico/femto BSs or WiFi hot spots. Deploying pico/femto BSs improves the spectral and energy efficiency per unit area of cellular networks, and thus reduces the network congestion and energy consumption of cellular networks. Traffic offloading between pico/femto BSs and the MBS is achieved by adapting user-BS associations. Kim *et al.* [95] proposed a user-BS association to achieve flow level load balancing under spatially heterogeneous traffic distribution. Jo *et al.* [92] proposed cell biasing algorithms to balance traffic loads among pico/femto BSs and the MBS. The cell biasing algorithms perform user-BS association according to the biased measured pilot signal strength, and enable traffic to be offloaded from the MBS to pico/femto BSs. WiFi hot spots are also effective in terms of offloading mobile traffic. Lee *et al.* [99] pointed out that a user is in WiFi coverage for 70% of the time on average, and if users can tolerate a two hour delay in data transfer, the network can offload about 70% of cellular traffic to WiFi networks. Balasubramanian *et al.* [25] proposed to offload the delay tolerant traffic such as email and file transfer to WiFi networks. When WiFi networks are not available or experiencing blackouts, data traffic is quickly switched back to 3G networks to avoid violating the applications' tolerance threshold.

2.3.2 User-BS associations in heterogeneous mobile networks

Heterogeneous networking is a promising network architecture which may significantly enhance the spectral and energy efficiency of mobile networks. One of the most important issues in heterogeneous cellular networks is to properly associate mobile users with the serving BSs, referred to as the "user-BS association problem". In heterogeneous cellular networks, the transmit power of SCBSs is significantly lower than that of MBSs. Thus, mobile users are more likely to be associated with the MBS based on the strength of their received pilot signals. As a result, SCBSs may be lightly loaded, and do not contribute much to traffic offloading. To address this issue, many user-BS association algorithms have been proposed [39, 92, 95]. Kim *et al.* [95] proposed a framework for user-BS association in cellular networks to achieve flow level load balancing under spatially heterogeneous traffic distribution. Jo *et al.* [92] proposed cell biasing algorithms to balance traffic loads among MBSs and SCBSs. The cell biasing algorithms perform user-BS association according to biased measured pilot signal strength, and enable traffic to be offloaded from MBSs to SCBSs. Corroy *et al.* [39] proposed a dynamic user-BS association algorithm to maximize the sum rate of the network and adopted cell biasing to balance the traffic load among BSs. Fooladivanda *et al.* [61] studied joint resource allocation and user-BS association in heterogeneous mobile networks. They investigated the problem under different channel allocation strategies, and the proposed solution achieved global proportional fairness among users. Madan *et al.* [103] studied user-BS association and interference coordination in heterogeneous mobile networks, and proposed heuristic algorithms to maximize the sum utility of average rates.

2.4 Multi-cell cooperation communications

It has been shown that, with the aid of multi-cell cooperation, the performance of a cellular network in terms of throughput and coverage can be enhanced significantly. However, the potential of multi-cell cooperation to improve the energy efficiency of cellular networks remains to be unlocked. This section gives an overview of multi-cell cooperation solutions for improving the energy efficiency of cellular networks. In particular it introduces traffic intensity aware multi-cell cooperation, which adapts the network lay-

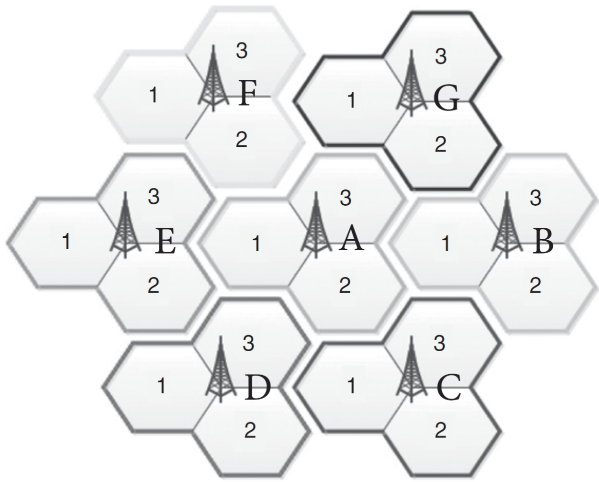


Figure 2.5: Original Network Layout [70]

out of cellular networks according to user traffic demands in order to reduce the number of active BSs.

2.4.1 Traffic intensity aware multi-cell cooperation

The traffic demand of cellular networks experiences fluctuations for two reasons. The first is the typical day-night behavior of users. Mobile users are usually more active in terms of cell phone usage during the day than during the night, and therefore traffic demand during the day is higher than at night. The second reason is the mobility of users. Users tend to move to their office districts during working hours and come back to their residential areas after work. This results in the need for a large capacity in both areas at peak usage hours but in reduced requirements during off-peak hours. However, cellular networks are usually dimensioned for peak hour traffic, and thus most BSs are working at low workload during off-peak hours. Owing to their high static power consumption (the static power consumption of a BS refers to the power consumption of the BS when there are no active users in the coverage of the BS), BSs usually experience poor energy efficiency when they are operating at a low workload. In addition, cellular networks are typically optimized for the purpose of providing coverage rather than for operating at full load. Therefore, even during peak hours, the utilization of

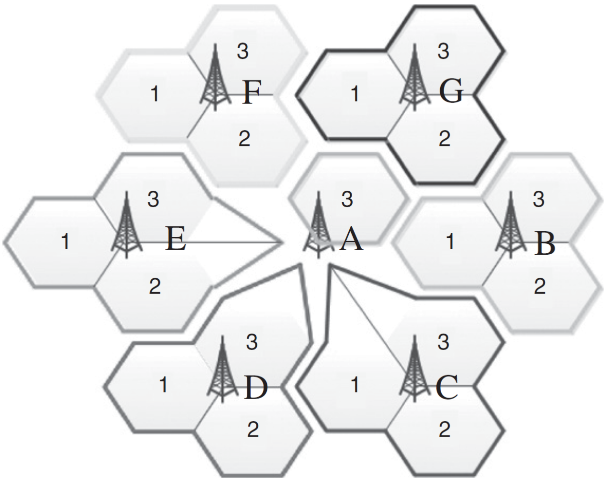


Figure 2.6: BS partially switched off [70]

BSs may be inefficient in terms of energy usage. Adapting the network layout of cellular networks according to traffic demands has been proposed to improve their energy efficiency. The network layout adaptation is achieved by switching BSs on/off dynamically. Figures 2.5, 2.6 and 2.7 show several scenarios of network layout adaptations. Figure 2.5 shows the original network layout, in which each BS has three sectors. For cell A, if most of the traffic demands on it are coming from sector three, and the traffic demands in sectors one and two are lower than a predefined threshold, cell A could switch off sectors one and two to save energy, and the users in the sectors that are switched off will be served by the neighboring cells. In this case, the network layout after the adaptation is shown in Figure 2.6. If traffic demands from sector three of cell A also decrease below the threshold, the entire green cell will be switched off, and the network layout is adapted to the one shown in Figure 2.7. Under this scenario, the radio coverage and service provisioning in cell A are taken care of by its active neighboring cells. When a BS is switched off, the energy consumed by its radio transceivers, processing circuits, and air conditioners can be saved. Therefore, adapting the network layout of cellular networks according to traffic demands can reduce energy consumption significantly. While network layout adaptation can potentially reduce the energy consumption of cellular networks, it must

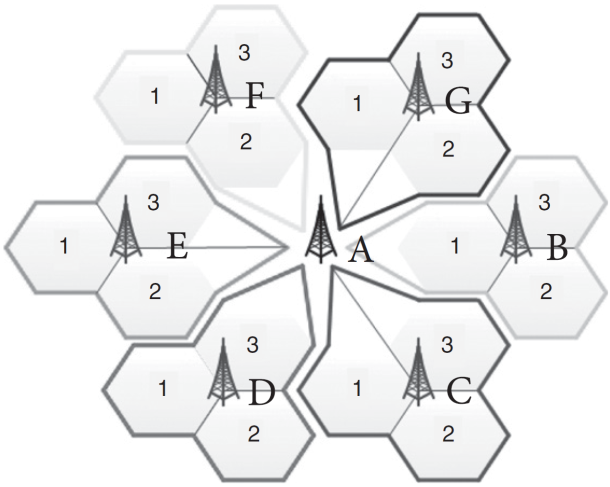


Figure 2.7: BS entirely switched off [70]

meet two service requirements: (1) the minimum coverage requirement, and (2) the minimum quality of service (QoS) requirements for all mobile users. Therefore, in carrying out network layout adaptation, multi-cell cooperation is needed to guarantee service requirements. Otherwise, it will result in a high call blocking probability and a severe QoS degradation. For example, two adjacent BSs may both experience low traffic demands. However, only one BS can be switched off to save energy, and the other BS should be active to sustain the service provisioning in both coverage areas. In this case, if both BSs are switched off according to their own traffic demands, their subscribers will lose connections. Therefore, cooperation among BSs is essential to enable traffic intensity aware network layout adaptation.

Cooperation to estimate traffic demands

Network layout adaptation is based on the estimated traffic demands at individual cells. Traffic demand estimation at individual cells requires the cooperation of neighboring cells. To avoid frequently switching BSs on/off, BSs are switched off only when their traffic demands are less than a predefined threshold for a minimum period, T. Therefore, the estimated traffic demands should represent the traffic demands at individual cells for at least a time period of length T. Hence, traffic demands at a BS consist of three parts: traffic demands from users who are currently attached to the BS, traffic demands from users who will be handed over to other BSs, and traffic demands from users who will be handed over to the BS from its neighboring BSs. While the first two components can be measured and estimated by individual BSs, the estimation of the third component requires cooperation from neighboring cells. Two reasons contribute to the handover traffic from neighboring cells. The first is user mobility. A user's motion including the direction and velocity can be measured by various signal processing methods. Therefore, individual BSs can predict (1) how many users will hand over to other cells in the near future, and (2) to which cells these users are highly likely to hand over. Such information is important for their neighboring BSs to estimate their traffic demands. The second reason for handover traffic is the switching off of neighboring BSs. If one of the neighboring cells is switched off, the users under its coverage will hand over to its neighboring cells, thus increasing the traffic demands of the neighboring cells. Therefore, cooperation among radio cells is important for traffic demand estimation at individual cells.

Cooperation to optimize switching off strategy

With traffic demand estimation, cellular networks optimize the switching on/off strategies to maximize the energy saving while guaranteeing users' minimal service requirements. Currently, most of the existing switching on/off strategies are centralized algorithms, which assume that there is a central controller that collects the operation information of all BSs and optimizes network layout adaptations. Three methods have been proposed to determine which BSs to switch off. The first is randomly switching off BSs with low traffic loads. This method mainly applies to BSs in the night zone where few users are active. The method randomly switches off some BSs to save energy, and the remaining BSs provide coverage for the area. The second method is a greedy algorithm that enforces BSs with higher traffic loads to serve more users, and switches off BSs with no traffic load. The third method is based on the user-BS distance. The required transmission power of BSs for serving users depends on the distance between users and BSs. The longer the distance, the greater the transmission power required in order to meet users' minimal service requirements. Therefore, the user-BS distance can be an indicator for the energy efficiency of cellular networks: the shorter the average user-BS distance, the higher the energy efficiency.

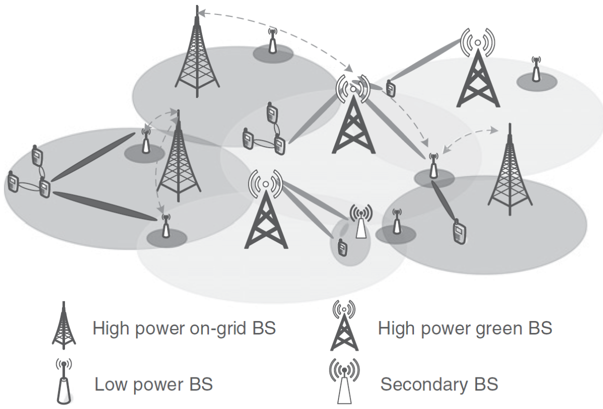


Figure 2.8: Future cellular networks with holistic cooperations [70]

Hence, the algorithm tends to switch off BSs with the longest user-BS distance in order to improve energy efficiency. Centralized algorithms, however, require the channel state information and traffic load information of every cell. Collecting this information centrally may impose tremendous communications overheads, and thus reduce the effectiveness of centralized algorithms in improving energy efficiency. Therefore, distributed algorithms are favored especially for heterogeneous networks, which consist of various types of cells such as macro cells, micro cells, pico cells, and femto cells. To enable distributed algorithms, individual cells may cooperatively form coalitions and share channel state information and traffic load information. Based on the shared information, individual BSs optimize their operation strategies to minimize the total energy consumption of the BS coalition.

This section has discussed how to reduce the energy consumption of cellular networks via multi-cell cooperation. It focuses on traffic intensity aware multi-cell cooperation, in which multiple cells cooperatively estimate traffic demands, and the network layout is adapted based on the estimated traffic demands. Through network layout adaptation, the number of active BSs can be reduced, thus reducing the energy consumption of the network. With advances in cellular network and communications techniques, future cellular networks will be heterogeneous in terms of both network deployments and communications techniques as shown in Figure 2.8. Regarding network deployments, a heterogeneous network refers to deploying a mix of high power

BSs and low power BSs in order to satisfy traffic demands of service areas. High power BSs, for example, macro and micro BSs, are deployed to provide coverage to a large area while low power BSs are deployed to provide high capacity within a small coverage area. In terms of technology diversity, heterogeneous networks consist of a variety of technologies such as MIMO, cooperative networking, and cognitive networking. By increasing network diversity, BSs have more cooperation opportunities, and thus can achieve additional energy savings. However, realizing optimal multi-cell cooperation is nontrivial.

2.5 Traffic load balancing in mobile networks

Proliferation of wireless devices and bandwidth-greedy applications are driving the exponential growth of mobile data traffic that is resulting in a continuous surge in capacity demand across mobile networks. The heterogeneous network (HetNet) is one of the key technologies for enhancing mobile network capacity to satisfy capacity demands [20]. In HetNet, low power SCBSs are densely deployed to enhance the spectrum efficiency of the network and thus increase the network capacity. Owing to disparate transmit power and BS capabilities, traditional user association metrics such as the signal-to-interference-plus-noise-ratio (SINR) and the received-signal-strength-indication (RSSI) may lead to a severe traffic load imbalance [20]. Hence, user association algorithms should be well designed to balance traffic loads and thus to fully exploit the capacity potential of HetNet. Balancing traffic loads in HetNet has been extensively studied in recent years [159]. In mobile networks, traffic loads among BSs are balanced by executing handover procedures. In the LTE system there are three types of handover procedures: Intra-LTE handover, Inter-LTE handover, and Inter-RAT (radio access technology) handover [16]. There are two ways to trigger handover procedures. The first is "Network Evaluated" in which the network triggers handover procedures and makes handover decisions. The other is "Mobile Evaluated" in which a user triggers the handover procedure and informs the network about the handover decision. The network decides whether to approve the user's handover request based on the status of radio resources. In 4G and LTE networks, a hybrid approach is usually implemented, where a user measures parameters of the neighboring cells and reports the results to the network. The network makes the handover decision based on the measurements.

Here, the network can decide which parameters should be measured by users. Aligning with the above procedures, various traffic load balancing algorithms have been proposed to optimize the network utilities [20,21,92,95,168]. The most practical traffic load balancing approach is the cell range expansion (CRE) technique, which biases users' receiving SINRs or data rates from some BSs to prioritize these BSs in associating with users [41]. Owing to the transmit power difference between MBSs and SCBSs, a large bias is usually given to SCBSs to offload users to small cells [20]. By applying CRE, a user is associated with the BS from which they receive the maximum biased SINR or data rate. Although CRE is simple, it is challenging to derive the optimal bias for BSs. Singh *et al.* [145] provided a comprehensive analysis on traffic load balancing using CRE in HetNet. The authors investigated the choice of the bias value and its impact on SINR coverage and downlink rate distribution in HetNet. Jo *et al.* [92] proposed cell biasing algorithms to balance traffic loads among MBSs and SCBSs. These cell biasing algorithms perform user-BS association according to biased measured pilot signal strength, and enable traffic to be offloaded from MBSs to SCBSs. The traffic load balancing problem can also be modeled as an optimization problem and solved by convex optimization approaches. Ye *et al.* [168] modeled the traffic load balancing problem as a utility maximization problem and developed distributed user association algorithms based on primal-dual decomposition. Kim *et al.* [95] proposed an α-optimal user association algorithm to achieve flow level load balancing under spatially heterogeneous traffic distribution. The proposed algorithm may maximize different network utilities, for example, traffic latency and network throughput, by properly setting the value of α. Corroy *et al.* [39] proposed a dynamic user-BS association algorithm to maximize the total rate of network and adopted cell biasing to balance traffic loads among BSs. In addition, game theory has been exploited to model and solve the traffic load balancing problem. Aryafar *et al.* [21] modeled the traffic load balancing problem as a congestion game in which users are the players and user association decisions are the actions. Pantisano *et al.* [130] formulated the traffic load balancing problem in backhaul constrained SCNs as a one-to-manymatching game between SCBSs and users, and proposed a distributed algorithm based on a deferred acceptance scheme to obtain a stable match for mobile users. The above solutions, though they effectively balance traffic loads to maximize network utilities, do not consider energy efficiency as a performance metric in balancing traffic loads.

The dense deployment of SCBSs may incur excessive energy consumption. Enhancing energy efficiency is also a critical task for next generation mobile networks [70, 77]. Although SCBSs consume less power than MBSs, the number of SCBSs will be orders of magnitude larger than those of MBSs for a large scale network deployment. Hence, the overall power consumption of SCNs will be phenomenal.
In addition, most existing solutions optimize traffic load balancing in a mobile network with the assumption that the air interface between BSs and mobile users is the bottleneck of the network. This assumption is generally correct for BSs whose deployments are well planned. However, in the case of the potentially dense deployment of SCBSs, various suboptimal backhaul solutions may be adopted, for example, xDSL, non-line-of-sight (NLOS) microwave, and wireless mesh networks, rather than the ideal backhaul approach provided by optical fiber and LOS microwave [121]. As a result, backhaul, rather than BSs, may become the bottleneck of SCNs. To alleviate backhaul constraints, content caching techniques have been exploited to enable caching popular content in BSs to reduce backhaul traffic loads [116, 137, 144, 161]. Therefore, it is desirable to optimize user association in consideration of backhaul constraints and the performance of BSs' content cache systems in SCNs.

2.5.1 Traffic models

Some energy-efficiency and consumption models are defined on the basis of the temporal fluctuations in the traffic load. In addition, different green approaches can be adopted at different traffic load conditions. Furthermore, some green approaches rely on the temporal and spatial fluctuations in the traffic load to save energy. For instance, in order to determine the sleep duration of a BS or MT, traffic models are used to probabilistically predict the idle period duration. Moreover, the performance evaluation of the green approaches should be carried out using an appropriate traffic model. Consequently, it is necessary to gain a better understanding of the different traffic load models proposed in the literature before introducing energy efficiency and consumption models as well as green solutions. Overall, the traffic modelling can be categorized into two classes, as shown in Figure 2.9. The first class is referred to as the static model and assumes a fixed set of MTs, M, that communicate with a fixed set of BSs, S [31, 65, 101, 102, 114, 115, 123, 129, 170]. The static model suffers from sev-

<table>
<tr><th colspan="5">Model</th><th>Comments</th></tr>
<tr><td colspan="5">Static</td><td>It does not capture the MT mobility and the traffic dynamics</td></tr>
<tr><td rowspan="8">Dynamic</td><td rowspan="3">Spatial</td><td colspan="3">Regional traffic load density</td><td>It defines a location -based traffic load density</td></tr>
<tr><td colspan="3">Stochastic geometry</td><td>BSs and MTs are located according to a homogeneous Poisson point process</td></tr>
<tr><td colspan="3">FSMC</td><td>It models the spatial distribution of MTs within a cell</td></tr>
<tr><td rowspan="5">Temporal</td><td colspan="3">Long-scale</td><td>The model captures traffic fluctuations over the days of the week</td></tr>
<tr><td rowspan="4">Short scale</td><td rowspan="2">Flow-level</td><td>Poisson-exponential</td><td>It models call arrivals as a Poisson process and call departures as an exponential distribution</td></tr>
<tr><td>FSMC</td><td>The number of calls within a cell is represented by a state in a Markov chain</td></tr>
<tr><td rowspan="2">Packet-level</td><td>Infinite buffer</td><td>It models the number of backlogged packets in an MT buffer with infinite capacity</td></tr>
<tr><td>Finite buffer</td><td>It models the number of backlogged packets in an MT buffer with finite capacity</td></tr>
</table>

Figure 2.9: Summary of different traffic models [83]

eral limitations. First, it does not consider the mobility of MTs in terms of their arrivals and departures. Second, it does not capture the call-level or packet-level dynamics in terms of call duration, packet arrival, and so on. On the other side, the second class, which is referred to as the dynamic model, captures the spatial and temporal fluctuations of the traffic load, and is discussed next in detail.

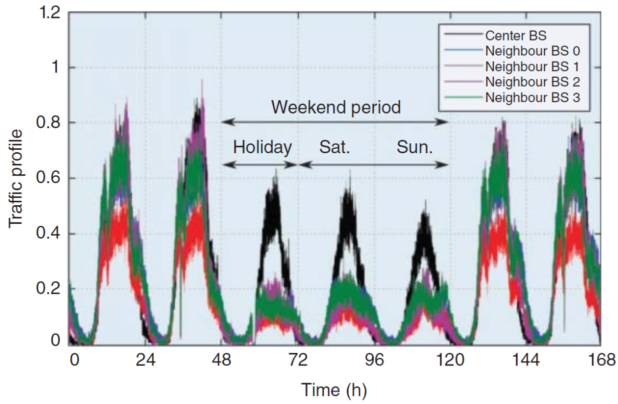


Figure 2.10: Spatial and temporal traffic fluctuations [122]

2.5.2 Traffic fluctuation modelling

Studies have indicated that traffic is quite diverse even among closely located BSs, as shown in Figure 2.10 [74, 122]. As a result, different models have been proposed in the literature to reflect the spatial fluctuations in call traffic load [146, 148, 173]. Location-based traffic load density is one approach to capture traffic spatial fluctuations [148]. In this context, a geographical region is covered by a set S of BSs and the region is partitioned into a set of locations. An alternative approach, which is more suitable for a design stage, defines the locations of BSs based on the stochastic geometry theory [146]. Two different time scales can capture the temporal fluctuations in the traffic load [23, 87]. The first time scale is a long-term one that reflects the traffic variations over the days of the week. Such a model can help in evaluating different energy-efficient approaches for network operators, as it captures both high and low call traffic load conditions. The second time scale is a short-term one that reflects the call (packet) arrivals and departures of the MTs. Such a model plays a vital role in evaluating energy-efficient resource allocation schemes for MTs and BSs.

Long-term traffic fluctuations

Real call traffic traces demonstrate a sinusoidal traffic profile in each cell, as shown in Figure 2.10 [122, 126]. During daytime (11 am-9 pm), traffic is much higher than that during nighttime (10 pm-9 am) [74,126]. Furthermore,

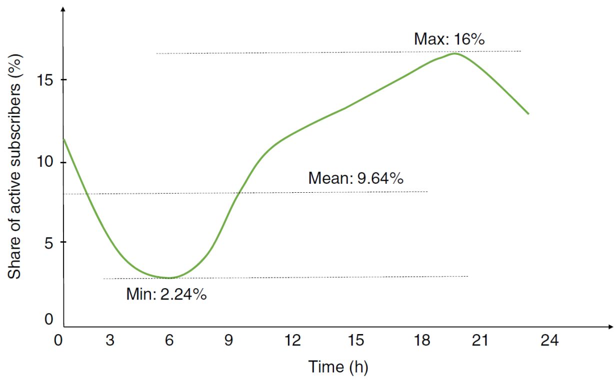


Figure 2.11: Average daily data traffic profile in a European country [23]

during weekends and holidays, the traffic profile, even during the peak hours, is much lower than that of a normal week day [126]. The traffic profile during a weekday is 10% less than its peak value 30% of the time, and this increases to 43% of the time during weekends [126]. This behaviour can be captured using an activity parameter $\psi(t)$, which specifies the percentage of active subscribers over time t, as shown in Figure 2.11 [23]. Denote p as the population density of users per km^2, N as the number of operators (each being able to carry $1/N$ of the total traffic volume), and M_k as the fraction of subscribers with an average data rate r_k for terminal type k (e.g. smart phone and tablet). Hence, the traffic demand, in bits per second per km^2, is given by

$$A(t) = \frac{p}{N}\psi(t) \sum_k M_k r_k. \tag{2.1}$$

Studies have indicated that the traffic load difference between two consecutive days for 70% of the BSs is less than 20% [74]. As a result, the long-term fluctuations in call traffic load can be estimated from the historical mobile traffic records; that is, the activity parameter $\psi(t)$ and the average data rate r_k can be inferred in practice from historical data.

Short-term traffic fluctuations

Two categories can be distinguished for short-term traffic fluctuation models, namely call (flow)-level and packet-level models. Call (flow)-level models are useful in designing and evaluating green resource scheduling mechanisms at both BSs and MTs under high call traffic load. For myopic resource allocation solutions, the call arrivals are modelled using a Poisson process with rate λ, and the call durations are represented by an exponential distribution [40, 87, 100]. Dynamic resource allocation solutions rely on finite-state Markov chain (FSMC) to model traffic dynamics in terms of call arrivals and departures [173]. In a low call traffic load condition, packet-level traffic models are useful in designing and evaluating green resource solutions (on-off switching) at the BSs and MTs, through modelling the BS/MT buffer dynamics in terms of packet arrival and transmission [96, 109]. Such models are used to investigate the optimal on-off switching mechanisms for the radio interfaces of MTs to achieve energy-efficient (green) communications at a low call traffic load condition.

2.6 Network energy consumption modelling

Understanding the dynamics of energy consumption of mobile networks is essential for designing and optimizing green mobile networks. Base stations, which consist of multiple components such as antennas, power amplifiers, radio frequency transceivers, baseband processing units, power supply units, and cooling units, account for the major energy consumption of a mobile network. In general, a BS's power consumption can be modeled as the sum of its static power consumption and its dynamic power consumption. The static power consumption is the power consumption of a BS without any traffic load. The dynamic power consumption refers to the additional power consumption incurred by the traffic load in the BS, which can be well approximated by a linear function of the traffic load or the output radio frequency power [23].The BS power consumption model can be adjusted to model the power consumption of either MBSs or SCBSs by incorporating and tweaking the BS's static power consumption and the linear coefficient that reflects the relationship between the BS's dynamic power consumption and its traffic load. Following the fluctuations in traffic load, this section summarizes different definitions that have been proposed in the literature to assess energy consumption of wireless networks. Towards this end, it presents different throughput and power consumption models for BSs.

2.6.1 Throughput models

The utility obtained from the wireless network in exchange for its consumed power is expressed most of the time in terms of the achieved throughput. In this context, we first introduce the concepts of aggregate BS capacity C_s, area spectral efficiency T_s, and user-achieved data rate R_m. The BS aggregate capacity C_s for BS s is measured using Shannon's formula as follows [39]:

$$C_s = B_s \log_2 \det(I + PH). \tag{2.2}$$

where B_s denotes the total bandwidth of BS s, I represents the unit matrix, P is the transmission power vector of BS s to every MT m in service, and H stands for the channel gain matrix between BS s and each MT m, which accounts for the channel's fast fading, noise, and interference affecting the radio transmission. The BS capacity C_s in (2.2) is measured in bits per second (bps). At a low call traffic load condition, the area spectral efficiency T_s provides a better representation of the BS's attained utility than the BS's aggregate capacity since it accounts for the coverage probability, which matters the most at such a condition [74]. Specifically, T_s measures the BS throughput while considering the coverage probability. Denote $\Pr\{\gamma_{x\to u} > \zeta\}$ as the success probability of the signal-to-noise ratio (SNR) γ received by an MT at location u from a given BS at some location x satisfying a certain QoS threshold ζ. Averaging the success probability $\Pr\{\gamma_{x\to u} > \zeta\}$ over the propagation range to location u yields the coverage probability $\mathbb{P}_s(\zeta)$. For BS s, the area spectral efficiency T_s measured over a unit area is expressed as

$$T_s = \mathbb{P}_s(\zeta) \log_2(1 + \zeta). \tag{2.3}$$

2.6.2 Power consumption models

In the literature, different models are proposed to capture the power consumption of a network, as summarized in Figure 2.12. The total power consumption P_n of a wireless access network n, from the network operator perspective, can be captured using the aggregate power consumption of the network BSs. Recently, in addition to the BS power consumption, more emphasis is put on the backhaul power consumption, due to the information exchange among BSs for cooperative transmission/networking. Next, we will outline the different power consumption models proposed for BSs and backhauls. For a large-cell BS (MBS), Figure 2.13 illustrates the power

	Model			Comments
BS	Operation only	Large-cell	Ideal	The BS consumes no power when idle, that is, the BS consists only of energy proportional devices
			Realistic	The model captures the BS traffic load independent power consumption
		Femto -cell	Load independent	The BS power consumption does not depend on the offered traffic load
			Load dependent	The BS power consumption relies on traffic load, packet size, and has an idle part
		Including temporal fluctuations		The model accounts for full load, half load, and idle traffic conditions
		Backhaul power consumption		The model defines power consumption for micro-wave and optical fiber backhaul links
	Operation and embodied			Besides the operation power, it accounts for the consumed energy in BS manufacturing and maintenance
MT	Transmission power only	Without power amplifier efficiency		The model does not account for the transmitter power amplifier efficiency
		With power amplifier efficiency		The model accounts for the transmitter power amplifier efficiency
	Including circuit power	Constant		The circuit power consumption is given by a constant term independent of the bandwidth and data rate
		Bandwidth scale		The circuit power consumption scales with the MT assigned bandwidth
		Data rate scale		The circuit power consumption scales with the MT achieved data rate
	Including reception power			Besides the transmitter and circuit power consumption, the model also accounts for the receiver power consumption

Figure 2.12: Summary of different power models proposed in the literature [86]

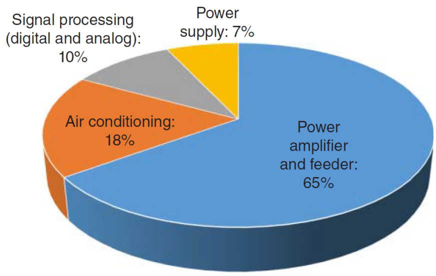


Figure 2.13: Percentage of power consumption at different components of a large-cell BS [86]

Hardware component	Power consumption (W)	Percentage (%)
Microprocessor Associated memory Backhaul circuitry	1.7 0.5 0.5	26.4
FPGA Associated memory Other hardware functions	2 0.5 1.5	39.2
RF transmitter RF receiver RF power amplifier	1 0.5 2	34.3

Figure 2.14: Power consumption profile for a femto-cell BS [86]

consumption percentage of different components of the BS. Furthermore, the power consumption profile of a femto-cell BS is shown in Figure 2.14. According to Figure 2.13 and 2.14, the following facts turn out:

- The signal processing part is responsible for most of the power consumption in a femto-cell BS as opposed to a large-cell BS (namely, 65.6% and 10% for femto and large-cell BSs, respectively).
- The radio frequency (RF) transmission/reception power consumption in a femto-cell BS is almost half of that of a large-cell BS, with only 19.6% of the power consumed in the femto-cell BS power amplifier as opposed to 65% in a large-cell BS.

In the literature, different models are adopted to represent the BS power consumption P_s. For a large-cell BS, the simplest model is an ideal load-dependent representation, which assumes that the BS consumes no power in its idle state, that is, the BS consists of energy-proportional devices [148].

Hence, the BS power consumption can be expressed as

$$P_s = \rho P_{ts}. \tag{2.4}$$

where ρ stands for the system traffic load density, and P_{ts} denotes the BS's transmitted power. The major limitation with such a model is that it is unrealistic, as the power consumption of some BS components in reality is not load-dependent, as shown in Figure 2.13 (e.g. power supply and air conditioning). To capture the power consumption of both load-dependent and load-independent components in the BS, a more sophisticated model assumes the following expression [23]:

$$P_s = \frac{\dfrac{P_{ts}}{\xi(1-\sigma_{\text{feed}})} + P_{\text{RF}} + P_{\text{BB}}}{(1-\sigma_{\text{DC}})(1-\sigma_{\text{MS}})(1-\sigma_{\text{cool}})}. \tag{2.5}$$

where P_{RF} represents the RF power consumption, P_{BB} denotes the baseband unit power consumption, ξ is the power amplifier efficiency, and σ_{feed}, σ_{DC}, σ_{MS}, and σ_{cool} stand for the losses incurred by the antenna feeder, DC-DC power supply, main supply, and active cooling, respectively. The model (2.5) is further approximated using a linear (affine) function for simplicity [30,87, 146,148,151]. The affine function consists of two components to represent P_s. The first term is denoted by P_f and represents a fixed (load-independent) power component that captures the power consumption at the power supply, cooling, and other circuits. The second term is a load-dependent component. The affine model is expressed as:

$$P_s = \Delta_s P_{ts} + P_f, \tag{2.6}$$

where Δ_s is the slope of the load-dependent power consumption. For a femto-cell BS, the power consumption model is described by Deruyck *et al.* [46]:

$$P_s = P_{\text{mp}} + P_{\text{FPGA}} + P_{\text{tx}} + P_{\text{amp}}, \tag{2.7}$$

where P_{mp}, P_{FPGA}, P_{tx} and P_{amp} denote the power consumption of the microprocessor, field-programmable gate array (FPGA), transmitter, and power amplifier, respectively. While the power consumption model in (2.7) captures most of the components in Figure 2.14, it does not exhibit any dependence on the call traffic load. Experimental results in [141] have pointed out the dependence of the femto-cell BS power consumption on the offered load and the data packet size. Consequently, the power consumption model for a femto-cell BS is expressed by Riggio and Leith [141]:

$$P_s = P_d(q, l) + P_f, \tag{2.8}$$

where $P_d(q, l)$ represents the BS power consumption, which depends on the traffic load q [Mbps] and packet size l [bytes], and P_f stands for the idle power consumption component. In order to capture the temporal fluctuations in the call traffic load, a weighted sum of power consumptions at different traffic load conditions (full load, half load, and idle conditions) is considered [77]:

$$P_{s,\text{total}} = 0.35P_{\text{max}} + 0.4P_{50} + 0.25P_{\text{sleep}}, \tag{2.9}$$

where P_{max}, P_{50}, and P_{sleep} denote the full rate, half rate, and sleep mode power consumption, respectively. The weights in (2.9) are determined statistically based on the historical traffic records. Recently, cooperative networking among different BSs and APs in the heterogeneous wireless medium is regarded as an effective approach to enhance the network's overall capacity and reduce the associated energy consumption [83–85, 88, 89]. However, this approach relies on information exchange among different BSs and APs, such as channel state information (CSI), call traffic load, and resource availability, which are carried mainly over the backhaul connecting these BSs and APs together. Hence, more emphasis is given to the backhaul design and its power consumption. Three types of backhaul solutions can be distinguished, namely copper, microwave, and optical fibre. The most common choice for backhaul is the copper lines [44]. Microwave backhauls are deployed in locations where it is difficult to deploy wired (copper) lines. Also, optical fibre backhauls are mainly used in locations with high traffic due to their high deployment cost. Current research is focusing mainly on the power consumption of microwave and optical fibre links, as they can support the current high data rates. In its simplest form, the microwave (wireless) backhaul power consumption is expressed as [44]:

$$P_{\text{BH}} = \frac{C_{\text{req},s} P_{\text{mw}}}{C_{\text{mw}}}, \tag{2.10}$$

where $C_{\text{req},s}$ and C_{mw} represent the BS's required backhaul capacity and the microwave backhaul total capacity (100 Mbps), respectively, and P_{mw} denotes the associated power consumption (50 W). However, the model in (2.10) does not account for many features of the backhaul. To gain a better

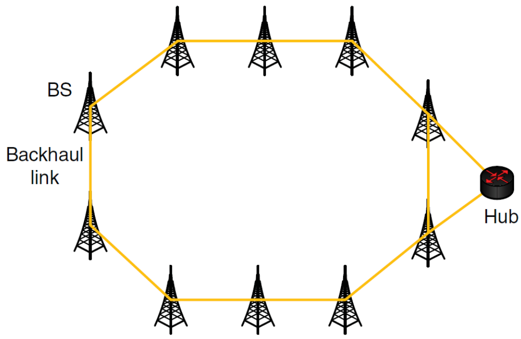


Figure 2.15: Different backhaul topologies [117]: (a) ring topology

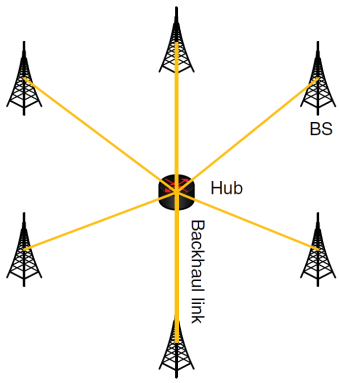


Figure 2.16: Different backhaul topologies [117]: (b) star topology

understanding of the power consumption of backhauls, we first provide a brief description of the backhaul structure and associated topologies.

As shown in Figures 2.15, 2.16 and 2.17, each BS is connected to one or more BSs via a backhaul link. All traffic from BSs is backhauled through a hub node (traffic aggregation point) [117]. Any BS in the network can serve as such a hub node. In general, more than one aggregation level (hub node) can be present. Each hub node is connected to a sink node, which, in turn, is connected to the core network. A BS is equipped with a switch if more than one backhaul link originates or terminates at this BS. Following this description, the microwave backhaul power consumption is expressed as [44]:

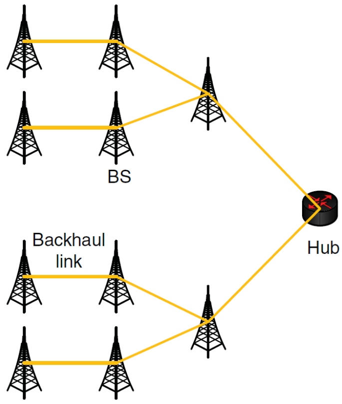


Figure 2.17: Different backhaul topologies [117]: (c) tree topology

$$P_{\mathrm{BH}} = P_{\mathrm{sink}} + \sum_{s=1}^{S} P_{\mathrm{BH},s}, \tag{2.11}$$

where P_{sink} is the power consumption at the sink node, $P_{\mathrm{BH},s}$ denotes the power consumption associated with the backhaul operations at BS s, and S stands for the total number of BSs. The following relationships hold:

$$P_{\mathrm{BH},s} = P_s(C_{\mathrm{req},s}) + P_{\mathrm{switch},s}(A_s, C_{\mathrm{req},s}), \tag{2.12}$$

$$P_{\mathrm{sink}} = P_{\mathrm{sink}}(C_{\mathrm{req,sink}}) + P_{\mathrm{switch,sink}}(A_{\mathrm{sink}}, C_{\mathrm{req,sink}}), \tag{2.13}$$

where $C_{\mathrm{req},s}$ and $C_{\mathrm{req,sink}}$ represent the required backhaul capacity for BS s and the sink node, respectively. The variable A denotes the number of microwave antennas, P_s and P_{sink} represent the power consumed for transmitting and receiving backhaul traffic for BS s and the sink node, respectively, and P_{switch} models the BS/sink switch power consumption. On the other hand, for an optical fibre backhaul, the power consumption is expressed as [44]:

$$P_{\mathrm{BH}} = \left\lceil \frac{S}{\max N_{\mathrm{DL}}} \right\rceil P_{\mathrm{switch}} + SP_{\mathrm{DL}} + N_{\mathrm{UL}} P_{\mathrm{UL}} + \sum_{s=1}^{S} c_s, \tag{2.14}$$

where $\max N_{\mathrm{DL}}$ stands for the maximum number of downlink interfaces available at one aggregation switch, P_{DL} denotes the power consumption due to one interface of a switch, N_{UL} and P_{UL} represent the total number of uplink interfaces and power consumption of one uplink interface, and c_s denotes the power consumption of a pluggable optical interface, which is used to connect a BS to the switch at the hub node. A limitation with the models (2.4)-(2.11) is that they focus mainly on the BS's operation power. In a more general model, the BS's total consumption is described in terms of the BS's operating energy and embodied energy, E_o and E_e, respectively. The BS's embodied energy represents 30-40% of the BS's total energy consumption [82] and accounts for the energy consumed by all the processes associated with the manufacturing and maintenance of the BS. Over the BS's lifetime, the embodied energy is calculated as 75 GJ [82]. It consists of two components. The first component refers to the initial embodied energy E_{ei}, while the second one stands for the maintenance embodied energy E_{em}. The initial embodied energy comprises the energy used to acquire and process raw materials, manufacture components, and assemble and install all BS components. The initial embodied energy is accounted for only once in the initial BS manufacturing process. The maintenance embodied energy includes the energy associated with maintaining, repairing, and replacing the materials and components of the BS throughout its lifetime. Thus, the BS's total energy consumption (in joules) throughout its lifetime is given by Humar *et al.* [82]:

$$E_b = E_e + E_o = (E_{ei} + E_{em}) + E_o, \tag{2.15}$$

where $E_{em} = P_{em}T_{\mathrm{lifetime}}$, with P_{em} and T_{lifetime} representing the BS's maintenance power and lifetime, respectively. $E_o = P_oT_{\mathrm{lifetime}}$, where P_o is defined in terms of the BS's operating power described by (2.4)-(2.9). The model in (2.15) is useful in quantifying the BS's total power consumption during the network design stage, for example, while designing a multi-tier wireless network. Also, a similar expression can be derived for the backhaul energy consumption in (2.10)-(2.14), which when added to (2.15) can be used to calculate the overall network energy consumption.

In order to develop and analyse a green network solution, an appropriate definition of energy efficiency and consumption for network operators and mobile users should be adopted.

In addition, the green network solution should satisfy some target (and possibly conflicting) performance metrics. Therefore, this chapter was dedicated to energy efficiency and consumption definitions, as well as power consumption, throughput, and traffic load models for network operators and mobile users, along with conflicting performance metrics. After having introduced the necessary background concepts in this chapter, the next chapter investigates a framework for optimizing energy utilization in mobile networks.

Chapter 3

On the trade-off between energy saving and number of switchings in green cellular networks

In this chapter, we propose a multiobjective optimization framework aimed at minimizing the power consumption and the number of BS sleep-mode switchings in cellular networks, by jointly considering QoS requirements. These requirements are expressed in terms of a required bit rate for each mobile terminal. The framework deals with network management, such as the number of BSs that should be switched on, considering common diurnal patterns of the traffic demand. The optimization technique proposed in this paper is mixed-integer quadratic programming, which solves the joint power allocation and user association problem while also considering optimized bandwidth allocation schemes. The trade-off between the conflicting objectives, as well as the performance analysis in terms of the throughput and energy consumption of the network, is shown for different traffic load cases. [1]

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[1]This chapter has been published as "On the trade-off between energy saving and number of switchings in green cellular networks" in *Wiley Transactions on Emerging Telecommunications Technologies, in press, 2017* [50].

3.1 Introduction and state of the art

The electricity consumption of the telecommunication networks is forecasted to increase exorbitantly by 150% from 20 TWh in 2011 to 50 TWh in 2020. The biggest growth is expected for the mobile networks due to the immense growth of mobile data traffic by a factor 30 caused by the more intensive use of mobile internet services [138]. These are enabled by more capable mobile networks (LTE and LTE-A technologies) as well as an increasing number of mobile devices with significant computing power (smartphones, tablets).
In order to gain extra commercial benefits and reduce operating expense, mobile operators are more and more motivated to seek "green" approaches that reduce the energy consumption of mobile cellular networks. Therefore, it is essential to consider how to decrease the energy consumption, especially the energy consumption of BSs, in order to fulfil the technical goals of future networks, such as higher user data rates, improved coverage with uniform user experience and reduced end-to-end latency. The goal of improving energy efficiency (EE) and reducing the operational costs of a cellular network puts forward a large variety of critical objectives, often coupled in a conflicting manner. Since the proper design of future networks is characterized by an increasing diversity of requirements and use cases, we need to focus on the communication infrastructure and improve versatility, scalability and adaptability of current networks. These challenges can be addressed by developing a precise and specific problem formulation, in order to design new optimization tools that can flexibly handle multiple objectives, trade-off analysis and adaptive designs.
Recent studies have explored adaptive radio resource management (RRM) solutions to save energy and improve network utilization efficiency. When the spatial traffic distribution is non-uniform and time-varying, dynamic coverage management may be introduced to exploit traffic variations. Dynamic switch on/off of coverage overlaid cells in low traffic is an example. By this solution the BS activity could be adapted to the traffic demand avoiding the waste of energy due to the peak dimensioning [105,119,142,143]. In particular ultra-dense BS deployment makes sleep mode operations more desirable, by exploiting small coverage areas and more random traffic patterns. For traffic fluctuations between day and night, macro sleep or deeper sleep can be enabled. However, for medium to high traffic hours deep sleep is not possible. Therefore, in the time domain a finer granularity of sleep mode has been introduced, identified as cell discontinuous transmission (DTX) [62].

This solution is enabled by the particular structure of the LTE frame and allows the transceiver deactivation (sleep mode) during the idle time slots. Thus, the cell coverage is not affected by the sleep mode, since the signalling symbols are always transmitted at the same power level. Cell DTX feature does not require specific decisions to be taken regarding when to sleep and traffic offloading [62, 78, 160]. However, the savings that can be achieved are limited with respect to deep long term sleep. For the long term sleep, in order to maximize the energy savings, the association between users and BSs can be considered as an optimization variable together with bandwidth allocated to each user [34]. As a matter of fact, an energy saving can be introduced by increasing the bandwidth per user and, consequently, reducing the BS transmission power if the target data rate per user is fixed [156]. Such a solution is known as bandwidth expansion mode (BEM) and can be applied when resource usage is light, i.e. in low load conditions.
In [106, 107] analytical models are developed to identify optimal fixed BS switch-off times as a function of the daily traffic pattern. According to the authors, the extra energy saving gained by multiple switch-offs over single switch-off is only marginal. Dynamic sleep mode schemes generally require more switching operations as compared to fixed schemes, especially with highly variable traffic patterns. Therefore, a fundamental trade-off to be considered is between more energy saving in sleep mode and the cost of switching operations, which includes extra power for monitoring and switching, overhead, delay constraints, and impact on the operational lifetime of BSs [36]. One common problem with current research in this area is that most work implicitly assume that BSs are able to alternate between sleeping and active mode as frequently as possible. Although the most recent BSs have already been designed for frequently entering sleep modes, still most of the current BSs in use today were designed foreseeing only occasional change of state, otherwise the negative impact in terms of failure rate of BS components would be dramatic [37].
It is worth mentioning that BS sleeping might negatively impact QoS requirements of the system because of decreasing capacity, unless specific remedial actions are adopted concurrently [150]. Nonetheless, because sleep mode techniques are based on current architecture, they have the advantage of being easier to test and implement as no replacement of hardware is required and the performance can be evaluated by computer simulation. A potential deficiency of existing studies using this approach is over-simplified models

and assumptions [164]. Power control is a RRM solution for energy saving which aims at minimizing the BS transmission power with a given QoS target for the served users. The benefit of power control is not only in the energy reduction but also in neighbour cell interference management [155, 163]. In [155] the authors propose an optimization framework to maximize the quantity of transmitted bits per energy unit. Such a solution looks at the energy efficiency maximization, but does not consider a QoS target for each user. Moreover, in [163] transmission power for an OFDM communication is minimized without considering any constraint on power model.
By combining some of these approaches, different optimization strategies have been proposed. A pricing algorithm is evaluated in [169] to solve user association problem and minimize area power consumption, also considering interference: therein, mobile terminal rates are fixed and bandwidth is equally allocated to users regardless of their received signal strength. The user association is a fundamental aspect of sleep mode strategies: it implies associating mobile end users with BSs in an energy efficient way. Users originally connected to BSs that went asleep need to be associated with new active BSs, ensuring the QoS requirements during BS sleeping operations. It's worth noticing that simply associating a user to the closest BS may be sub-optimal with random traffic distribution [135, 148]. In [80] the power supply per LTE frame is minimized by assigning a suitable transmission power and rate for each link, without considering the mapping problem and a minimum rate value to ensure QoS. QoS constraints are considered in [81, 139, 167]. In [81] the power allocation per user is optimized aiming at energy per bit minimization with a bit error rate constraint to guarantee the QoS. A lower bound on user data rate is set in [167] where BS transmission power and user rate are optimized in order to maximize the energy efficiency in terms of "bit per Joule". The system model considers a single cell scenario where the effect of neighbouring interference and users mapping are not considered. In [139] a two-step algorithm aiming at minimizing energy consumption by properly assigning subcarriers and power to users is proposed. Such a solution considers a very simple bandwidth division among served users and does not take advantage of BEM in order to reduce the unfairness in the perceived data rate.
In general, there is no available closed form expression to show the direct relationship between transmit power and QoS and user experience measures, such as service latency or user perceived throughput. Therefore, the investi-

gation of simplified but approximate models is accomplished in order to provide insights for practical system design. On the other hand, user scheduling and resource allocation solutions are needed to control the operation point that maximizes network power efficiency while balancing the heterogeneous QoS requirements. Furthermore, heterogeneity is also a key aspect of future networks as outlined in the project Mobile and Wireless Communication Enablers for the Twenty-twenty Information Society (METIS), whose goal is to lay the foundation for the beyond 2020 5G mobile and wireless system. For instance, the combination of different access points, traffic loads and radio access technologies, makes the network highly heterogeneous. Hence, the same deployment strategy cannot be used everywhere and the same RRM solution cannot be used throughout the day with very different network conditions. At the same time network designers need to consider heterogeneous user conditions, because the mobility scenario and specific path loss of a user determines its quality of service. The different requirements or objectives cannot be treated separately, since they are coupled, often in conflicting ways, so that improvements in one objective end up impairing the others. These aspects call for design and optimization frameworks that handle multiple objectives and support the selection of the best attainable operating point [19, 27, 35, 64, 125, 136].

In this chapter an energy efficient and adaptive cellular network configuration strategy with QoS requirements is proposed: a given service rate is guaranteed to mobile terminals; if sufficient bandwidth resources are available, mobile users can obtain higher rates than the target value since their received power must be greater than the terminal sensitivity threshold. The cost of rearranging the network when traffic demand changes is taken into account by considering the number of BS switchings, defined as the number of active/inactive state transitions in a twenty-four hour period. In order to design an effective BS switching mechanism, two issues must be addressed, namely the user association problem and BS operation. The BS on/off switching is coupled with the user association problem. In developing the energy-efficient user association mechanism, the adopted approach aims to balance the trade-off between network energy consumption and the number of switching operations, while accounting for the user target QoS constraints. This case assumes a multiobjective optimization problem with a weighting factor. When the weighting factor equals zero, the user is associated to the BS that maximizes the network energy efficiency performance. As the weighting factor increases, the user association decision pays more attention to the network operation and maintenance costs, in terms of switching operations. In the simulation scenario the traffic demand varies during the hours of a day: the problem of network dimensioning with multi-hour traffic is addressed by determining how much capacity is needed to handle demands at all times. Furthermore, the bandwidth blocks are not uniformly assigned but according to the spectral efficiency of the overall user associations, saving more resources for the users experiencing lower signal quality and including the benefits provided by BEM. The derived optimization framework is based on Mixed Integer Quadratic Programming (MIQP): within this framework the user association problem is iteratively solved, together with the decision variables for the BSs activity. Moreover, the user bandwidth, the rate assignments as well as the transmit power of each active BS are determined. Adapting the network configuration during the day with a minimum number of switching operations allows to reduce signalling traffic and handover operations. Since the implementation of a power saving strategy should consider multiple conflicting objectives, this work extends the results presented in [135] by introducing a multiobjective optimization framework, designed to manage the network configuration over a daily pattern of traffic demands. In order to present the trade-off and performance study a per "traffic load" class analysis is introduced, considering three traffic conditions: low, medium and high traffic load.

3.2 System model and problem formulation

A typical LTE system deployment is considered with a given bandwidth and a set of resource blocks as represented in Figure 3.1. A set of omnidirectional BSs provides the radio access to a certain number of user equipments (UEs), as determined by a daily profile of traffic demands [22]. Each base station must allocate the available bandwidth resources among the associated transmitting users by assigning the proper amount of physical resource blocks (PRBs) and guaranteeing their QoS in terms of bitrate on an hourly basis. The UEs request a constant bitrate and are served at the same time. Let $\mathcal{B} = \{BS_1, ..., BS_N\}$ and $\mathcal{U} = \{UE_1, ..., UE_M\}$ be respectively the set of N deployed base stations and the set of M users which have to be served respectively. The binary variable x models the association between BSs and

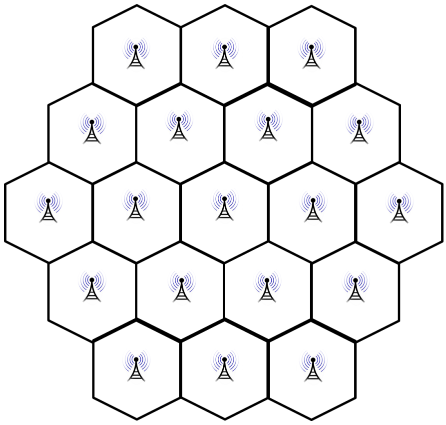


Figure 3.1: The considered BS deployment

UEs, as in the following:

$$x_{ij} = \begin{cases} 1 & \text{if UE } j \text{ is served by BS } i \\ 0 & \text{otherwise} \end{cases} \qquad i \in \mathcal{B},\, j \in \mathcal{U}. \tag{3.1}$$

Assuming π_{ij} as the power assigned for transmission between BS i and UE j and w_{ij} is the bandwidth assigned by BS i to UE j, the data rate achieved by UE j is:

$$\rho_j = \sum_{i \in \mathcal{B}} x_{ij} w_{ij} \log_2(1 + \gamma_{ij}) \tag{3.2}$$

where γ_{ij} is the SINR experienced by UE j served by BS i. The transmission power of each BS i is calculated as $P_i = \sum_{j \in \mathcal{U}} \pi_{ij} x_{ij}$. Therefore, the SINR γ_{ij} is

$$\gamma_{ij} = \frac{\pi_{ij}\sigma_{ij}x_{ij}}{\frac{w_{ij}}{W}\left(\sum_{k=1}^{N} P_k \sigma_{kj} \zeta_k (1 - x_{kj}) + W N_0\right)} \tag{3.3}$$

where σ_{ij} is the channel loss between BS i and UE j, W is the total available bandwidth at BS and N_0 is the Additive White Gaussian noise spectral density. The activity status of each BS is modelled by the binary variable ζ, so that:

$$\zeta_i = \begin{cases} 1 & \text{if BS } i \text{ is active} \\ 0 & \text{if BS } i \text{ is in SLEEP mode} \end{cases} \qquad i \in \mathcal{B}. \tag{3.4}$$

Table 3.1: Given data for the considered problem

Parameter	Value
N	number of deployed base stations
M	number of users
$\mathcal{B} = \{BS_1, ..., BS_N\}$	set of N deployed base stations
$\mathcal{U} = \{UE_1, ..., UE_M\}$	set of M users which have to be served
R_t	Data rate target for each UE
P_{MINj}	sensitivity of UE j
P_{MAX}	maximum allowed BS transmission power
N_p	number of available PRBs at BS
W_p	bandwidth of a single PRB
W	total available bandwidth at BS
σ_{ij}	channel loss between BS i and UE j

Note that in (3.3) the received interference is weighted by the effective fraction of bandwidth assigned to UE. Such a choice is justified by the need to consider the effect of allocating different portions of bandwidth to each UE.

Given the system model and the data reported in Table 3.1, the goal of the problem is to minimize the global power consumption P_c by limiting at the same time the number of BS switchings S during daily traffic variations, reflected in the change of state of the deployed BSs and monitored by ζ.

Let $\mathcal{T} = \{t_1, ..., t_L\}$ be the set of L traffic demands during the day in terms of UEs to be served. At every time $t \in \mathcal{T}$ the two objective functions are then calculated as:

$$P_c^{(t)} = \sum_{i=1}^{N}[(a\sum_{j=1}^{M}\pi_{ij}x_{ij} + P_0)\zeta_i^{(t)} + (1-\zeta_i^{(t)})P_{sleep}], \tag{3.5a}$$

$$S^{(t)} = \sum_{i=1}^{N}[\zeta_i^{(t)}(1-\zeta_i^{(t-1)}) + \zeta_i^{(t-1)}(1-\zeta_i^{(t)})] \tag{3.5b}$$

where parameters a, P_0 and P_{sleep} are the slope of the dynamic consumption, the fixed consumption and the sleep mode consumption, respectively [23]. Considering the activity status transitions of each BS in response to the changing traffic demand, (3.5b) keeps track of the number of sleep mode switchings triggered by energy efficiency policies.

Assuming λ as the weighting factor between the two conflicting objectives, the optimization problem is formulated in (3.6a)-(3.6h).

$$\min_{\pi,x,\zeta} \quad (P_c + \lambda S) \tag{3.6a}$$

$$\text{s.t.} \quad \sum_{j=1}^{M} x_{ij} \leq N_{PRB}, \quad \forall i \in \mathcal{B}, \tag{3.6b}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} = M, \quad \forall j \in \mathcal{U}, \tag{3.6c}$$

$$\sum_{i=1}^{N} x_{ij} = 1, \quad \forall j \in \mathcal{U}, \tag{3.6d}$$

$$c_{ij} \leq \frac{\pi_{ij} \cdot \sigma_{ij}}{P_{MINj}}, \quad \forall i \in \mathcal{B} \quad \forall j \in \mathcal{U}, \tag{3.6e}$$

$$c_{ij} - x_{ij} \geq 0, \quad \forall i \in \mathcal{B} \quad \forall j \in \mathcal{U}, \tag{3.6f}$$

$$\zeta_i \leq x_{ij}, \quad \forall j \in \mathcal{U} \quad \forall i \in \mathcal{B}, \tag{3.6g}$$

$$\sum_{j=1}^{M} \pi_{ij} \leq P_{MAX}, \quad \forall i \in \mathcal{B}. \tag{3.6h}$$

Constraint (3.6b) is for the BS capacity limitation, since a BS cannot assign more than available bandwidth elements N_{PRB}. Constraints (3.6c) and (3.6d) ensure that each UE must be covered by at least one BS and can be connected to only one BS at a time. Constraint (3.6e) is the key for assuring the QoS: the binary variable c_{ij} equals to 0 if $\pi_{ij}\sigma_{ij} \leq P_{MINj}$; hence, for a given UE, constraint (3.6e) will define the set of potential BSs that can provide the minimum received power, P_{MINj}. Then, introducing constraint (3.6f), only one of the BSs in this set is selected. The activity status of a base station is linked to the user associations by constraint (3.6g). Finally, constraint (3.6h) sets the limit on the maximum BS transmission power.
The product of bounded variables in the objective function defines a general MIQP problem. It is well-known that MIQP is NP-hard, trivially because it contains Mixed-Integer Linear Programming (MILP) as a special case. In order to solve the optimization problem the MIQP model has been built in IBM ILOG CPLEX®solver [28], in which the optimal solution is obtained with an iterative method.
Since the optimization problem defines the linear combination of global power consumption and number of BS switchings, the two entities have been normalized in order to be compared and weighted by λ.

Algorithm 1 Power Control (Closest BS Mapping)

Given: x_{ij}, w_{ij}, P_{MINj} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$, P_{MAX}, R_t;
Return: P_i $\forall i \in \mathcal{B}$; P_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$;

```
1: for all i ∈ B do P_i^(0) ← P_MAX
2: repeat
3:    for all i ∈ B do
4:       Calculate π_ij as in (3.7) and (3.8) ∀j ∈ U
5:       P_i ← ∑_{j∈U} π_ij x_ij ∀j ∈ U
6:    end for
7: until convergence
8: Update π_ij as in (3.8) ∀i ∈ B ∀j ∈ U
9: Update P_i to the maximum allowed value ∀i ∈ B
```

A complete list of the considered parameters and their symbols is reported in Table 3.1.

3.3 Network optimization solutions

3.3.1 Power control and bandwidth adaptation

Power control is a well known solution to decrease the global energy consumption by acting on the reduction of inter cell interference [81, 155]. In this work a power control algorithm that is similar to the one presented in [171, 172] is considered, in order to extend that solution to a multichannel scenario with minimum and maximum power constraints[2]. As shown in Algorithm 1, this power control algorithm takes as input a UE-BS association and a bandwidth assignment for each UE and provides iteratively the optimum BS transmission power which can guarantee the target data rate for each UE. The proof of optimality can be found in [171].

The core of the optimum power control algorithm is to calculate at each iteration n the power transmitted by a BS to a certain UE as

$$\pi_{ij}^{(n)} = \frac{w_{ij} 2^{\frac{R_t}{w_{ij}}}}{W \sigma_{ij}} \left(\sum_{k \in \mathcal{B}} P_k^{(n-1)} (1 - x_{kj}) \sigma_{kj} + W N_0 \right) \tag{3.7}$$

---

[2]For the proof of convergence in iterative power control algorithm, please see [172], pp. 163-171.

Algorithm 2 Bandwidth allocation

Given: σ_{ij}, P_i, π_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$ **Return**: w_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$;

Set $n_{PRB} = 0$ $\forall j \in \mathcal{U}$
for all $i \in \mathcal{B}$ **do**
  repeat
    for all $j \in \mathcal{U}$ **do**
      Calculate ρ_j as in (3.2)
      if $x_{ij} = 1$ AND $\rho_j < R_t$ **then**
        increment n_{PRB}
        $w_{ij} = n_{PRB} W_{PRB}$
      end if
    end for
  until all PRBs are assigned or R_t is reached by all served UEs
end for
if any residual PRB and all UEs are satisfied **then**
  share equally residual PRBs
end if

where R_t is the target data rate, i.e. the QoS constraint for each UE. The initial condition is such that $\sum_j \pi_{ij}^{(0)} = P_{MAX}$ for all $i \in \mathcal{B}$. Note that the power assigned to a BS P_i cannot be greater than the maximum allowed power P_{MAX}: in that case the power P_{MAX} is divided equally among each UE to indicate the UEs under outage. Moreover the received power for each UE j cannot be smaller than the sensitivity P_{MINj}: in that case the power which is transmitted by a BS to a certain UE is adjusted by the following equation:

$$\pi_{ij} = max\left(\frac{P_{MINj}}{\sigma_{ij}};\ \pi_{ij}\right). \tag{3.8}$$

Bandwidth assignment to each served UE is a task that can be solved in different ways by radio network operators (RNOs) depending on their policies. A RNO could give more priority to the UEs experiencing the best channel conditions in order to maximize the throughput. The assignment of bandwidth resources is crucial especially when the resources are limited. When an energy saving strategy is applied and the network capacity is reduced by putting a subset of BSs into sleep mode, a certain QoS level should be guaranteed to each served UE. Fairness between served UEs is also a key issue that can be introduced by giving more resources to the UEs experiencing the worst channel conditions. Such a solution enables the use of bandwidth expansion mode in order to reduce the BS transmission power. Algorithm 2 presents a possible solution to assign bandwidth in order to achieve fairness among UEs in terms of QoS, i.e. user data rates.

3.3.2 Network configuration management optimization

The fundamental approach of the optimization problem is to recognize the existence of multiple objectives, such as guaranteed rate for all the users, network power consumption, number of BS switchings, and number of simultaneously active BSs. A key assumption is that these objectives are not ordered, so they are studied considering that in multicriteria optimization problems there are only subjectively optimal solutions. In order to minimize the power consumption in a cellular network, a first optimization strategy is proposed. The problem is iteratively solved for three variables: association between BS and UE, bandwidth assignment and power allocation. In particular, a suitable BS-UE association allows saving power by decreasing the number of BSs that are not serving traffic and that can be deactivated or put in sleep mode. In order to limit the cost of switching operations, the number of power state transitions of BSs is also taken into account in the optimization process. By adopting the joint bandwidth and power allocation scheme a further gain is introduced, reducing the transmission power and decreasing the inter cell interference. The deactivation and power reduction of the BSs are allowed only if no outage is introduced, i.e. the target QoS is satisfied for each served UE. The optimization framework is composed of (i) MIQP solver of the user association problem obtaining the optimized active subset of BSs, (ii) bandwidth allocation scheme, (iii) power control algorithm, used to control the feasibility of the UE to BS mapping derived in (i) by identifying the eventual outages. The MIQP optimization refers to the problem formulated in (3.6a)-(3.6h). The output of this step is the mapping x_{ij} between BSs and UEs, the power transmitted by each BS to each connected UE π_{ij} and the set of active BSs ζ_i. Then in the second step the bandwidth is allocated to each UE by the respective serving BSs. The bandwidth allocation is performed following Algorithm 2. The MIQP model is solved by IBM ILOG CPLEX®solver [28]. Since the model cannot manage directly the QoS for each UE because of its non-linearity, two approaches are proposed in order to avoid any outage. Such approaches are (i) Power consumption minimiza-

Algorithm 3 MinPower

Given: σ_{ij}, P_{MINj} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$, P_{MAX}, λ;
Return: x_{ij}, w_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; ζ_i, P_i $\forall i \in \mathcal{B}$; P_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$

```
Solve MIQP
Solve bandwidth allocation as in Algorithm 2
```

Algorithm 4 MinPower-QoS

Given: σ_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; , P_{MAX}, P_{MINj}, λ;
Return: x_{ij}, w_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; ζ_i, P_i $\forall i \in \mathcal{B}$; π_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$

repeat
  Execute MinPower algorithm (Algorithm 3)
  Execute Power Control algorithm (Algorithm 1)
  Data rate (ρ_j) calculation as in (3.2) $\forall j \in \mathcal{U}$
  for all $j \in \mathcal{U} \backslash$satisfied UEs **do**
    $P_{MINj} \leftarrow P_{MINj} + \delta$
  end for
until no outages

tion assuming an interference controlled scenario (*MinPower*); (ii) Iterative power consumption and BS sleep mode switching minimization to guarantee QoS (*MinPower-QoS*). The *MinPower* scenario assumes a good planning or a perfect inter cell interference cancellation (ICIC) solution, but it could be also the reference condition for rural areas. If the rate of each user is only dependent on the SNR, the only variable to be taken into account is the power received by the serving BS. On the other hand, if the interference cannot be neglected, the *MinPower* algorithm cannot guarantee the required QoS, as shown in Algorithm 3, and some outages could arise. Therefore, this algorithm represents an optimum lower bound for the network optimization in terms of global power consumption. In order to avoid the data rate outages and reduce the impact of switching operations *MinPower-QoS* is introduced in Algorithm 4. It combines the optimum power control and the *MinPower* approaches in an iterative framework. In particular *MinPower* is executed in order to obtain the optimum set of active BSs, the optimum mapping and the bandwidth assignment and to minimize the power consumption, as well as the number of switch on/off operations, while the feasibility of this solution is controlled by the Power Control procedure, as shown in Algorithm 4. If some data rate outages occur, the power of the users which do not satisfy the target QoS is iteratively increased by a δ value in order to identify new active BS sets with a better mapping. In order to design the network which aims at minimizing the power consumption, but also reduces the number of necessary BS switchings throughout a daily pattern of traffic demands, we characterize the attainable objective set of suboptimal solutions by computing a discrete set of λ sample points. As λ increases, the priority of reducing network operation and maintenance costs also increases.

3.3.3 Algorithmic complexity

In this section, the worst case performance of each algorithm is studied as a function of the number of users M, and the number of base stations N.

Power Control (Closest BS Mapping): The initialization step requires N assignments. The algorithm cycles through the list of base stations, which requires N iterations, with, at most, M assignments and M evaluations in each iteration. The final updates require MN assignments. The algorithm complexity is $\mathcal{O}(MN^2 + MN)$.

Bandwidth allocation: The algorithm iterates N times, and each stage requires M evaluations and M comparisons. The algorithm complexity is $\mathcal{O}(MN)$.

MinPower: The MIQP problem is NP-hard. This means that, in worst case, the solution time grows exponentially with the number of integer variables, but MIQP can easily be reformulated as a convex MIQP. This is true for example when all products are between a binary variable and a bounded variable. Unfortunately, the worst case complexity is still exponential and the number of combinations necessary to enumerate, and solve an optimization problem, is problem dependent. CPLEX uses branch and cut algorithm, based on branch and bound, in order to work in polynomial time when the number of constraints is small enough [28].

MinPower-Qos: The dominant part of the algorithm is the execution of *MinPower* algorithm, so the worst case complexity is still exponential. The second half of the algorithm, which involves *Power Control* and QoS target satisfaction, can be shown to be $\mathcal{O}(MN^2 + MN)$. Once again, the use of pre-processing techniques in CPLEX branch and cut algorithm can provide a solution to the optimization problem in polynomial time [28].

Table 3.2: Simulation parameters [7]

Parameter	Value
Deployment	19 BS, hexagonal grid, wrap-around
Intersite distance	500 m
Path loss	$15.3 + 37.6\log(d[m])$ (3GPP Typical Urban)
Shadow fading	std dev 8 dB
Indoor loss	20 dB
Bandwidth	5 MHz (25 PRBs)
Carrier frequency	2GHz
Max BS P_{TX}	20 W
UE sensitivity	-90 dBm
Noise PSD	-174 dBm/Hz
Target user data rate	512 Kbps
Power consumption	$a = 4.7$ $P_0 = 130$ W $P_{sleep} = 13$ W

3.4 Simulation results

In order to evaluate the power consumption savings due to the base station sleep mode mechanism and the transmission power adaptation, the proposed solution, namely, *MinPower-QoS*, is compared to upper bound and lower bound solutions. As an upper bound, the *Closest BS Mapping* is considered, adopting Algorithm 1, based on power control with closest BS mapping and equal bandwidth assignment to each UE. BSs which are not serving any UE are put on sleep mode. As a lower bound, the optimum energy saving solution *MinPower* is used. Moreover, in order to assess the trade-off between network energy consumption and the number of switching operations in *MinPower-QoS*, different λ values have been considered. Simulation parameters and path loss model are reported in Table 3.2 [7]. If a UE cannot achieve the data rate target, the minimum received power threshold, defined as P_{MINj} in constraint (3.6e), is increased by $\delta = 1$ dB in each iteration of *MinPower-QoS*, solving the MIQP model with this new setting. Increasing P_{MINj} by one unit at every step of the optimization process guarantees the fulfillment of QoS requirements for each network user. The number of active UEs that are randomly placed in the playground has been set considering the daily traffic profile of Figure 3.2. The trend of the UE requests shows a typical daily oscillation of the traffic, that is consistent with average profiles available in literature [22]. The maximum number of active UEs at busy hours in the considered area of 3 km^2 is equal to 230, i.e. 75 UEs/km^2. It corresponds to the maximum number of UEs that can be managed by the *Closest BS Mapping* solution without any capacity outage, representing the

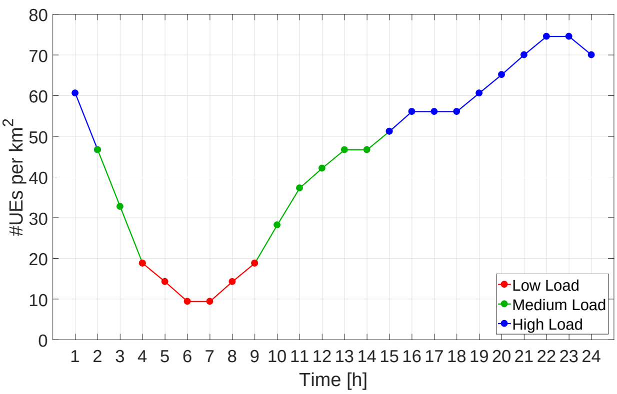


Figure 3.2: Daily traffic pattern

maximum load of the cellular network. Three traffic load classes have been derived from the maximum traffic load, considering 20, 50 and 75 UEs/km^2 as peak values for low, medium and high traffic load respectively. As shown by the research activities of the EARTH Project [22], the daily variation of the number of active users is analogous to the daily variation of the traffic and small-scale short-term evaluations fail to capture the energy efficiency of the entire network, since the load situation of a network varies radically over the time of a day and a week. Therefore each single stage of the iterative process can represent a snapshot of the current network, and using average traffic statistics, the impact of user mobility can be neglected in the simulation scenario.

The results are obtained by statistical analysis of 50 simulation runs with a 95% confidence interval. In Figure 3.3(a) the UE satisfaction rate is depicted starting from optimum *MinPower* solution as first iteration. From this figure, it is possible to note also the impact of the number of active UEs on the number of iterations before affording 0 outages. While *MinPower* experiences outages, *MinPower-QoS* converges to 0 outage performance after a number of iterations that depends on the number of UEs, i.e. the network traffic load. Each iteration corresponds to a solution in the search space for the MIQP model which stops when it reaches a minimum power solution with 0 outages. The cumulative transmission power vs the number of iterations is also depicted in Figure 3.3(a). Active UEs are satisfied when mapping and received power allow to reach the target QoS. Among the feasible solutions,

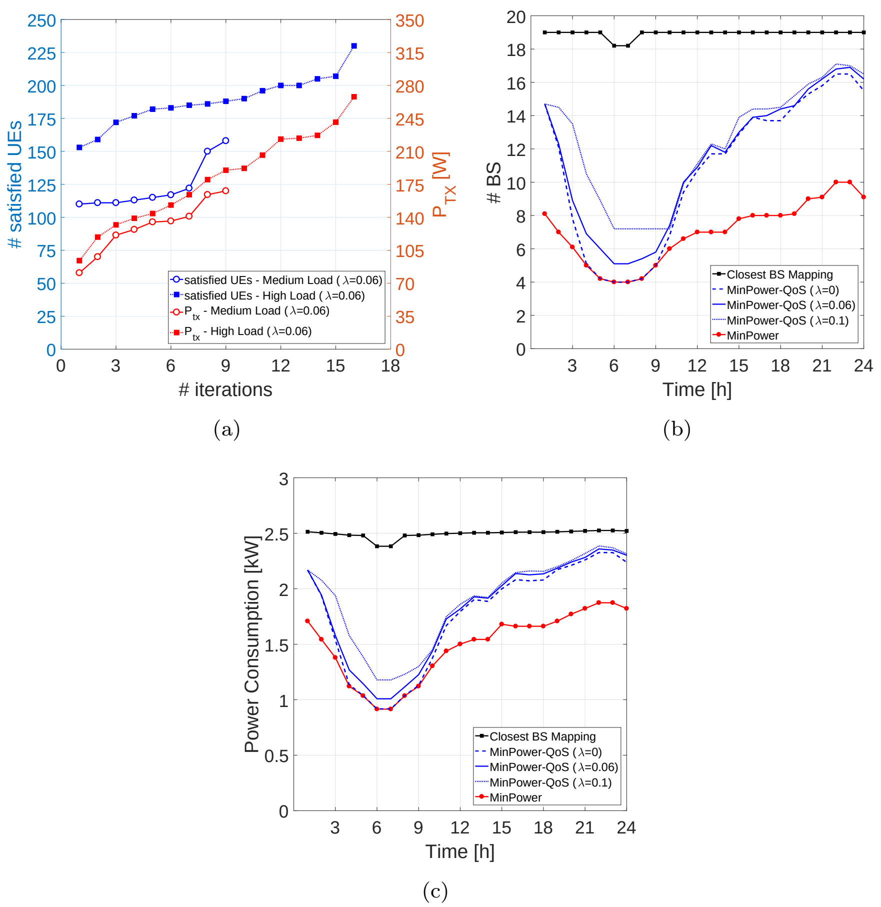


Figure 3.3: Simulation results: (a) satisfied UEs and cumulative transmission power of active BSs vs number of iterations in *MinPower-QoS*; (b) active BSs vs time of day; (c) global power consumption vs time of day

the one minimizing the global power consumption is chosen. Particularly, even if the proper mapping is obtained by increasing the BS transmission powers, this trend can be harmful for some UEs at the cell edge because of the interference level. Therefore, the cumulative transmission power of the active BSs is directly proportional to the number of UEs, as shown in medium and high load cases, but is also dependent on the current subset of active BSs at every step of the optimization process. On the other hand a lower number of UEs requires less iterations to reach the solution. Figure 3.3(b) presents the comparison of the number of active BSs for *MinPower-QoS*, with different λ values, with respect to the other solutions, i.e., *Closest BS Mapping* and *MinPower*. From the figure the behaviour of the proposed solution is evident: when no optimization on the number of BS switchings is applied ($\lambda = 0$) the number of active BSs is the same as in *MinPower* case in low load hours. On the other hand, by increasing the weight of BS switchings in the optimization process, the number of active BSs ends up being more stable. Because of the QoS requirements, the slope of *MinPower-QoS* is higher than *MinPower*: as expected, the *MinPower-QoS* converges to *Closest BS Mapping* when the number of active UEs increases at busy hours. This result is enforced by Figure 3.3(c) where the total power consumption versus time is depicted. It is interesting to see that in the interference limited scenario under high load, *MinPower-QoS* can still have power savings over the *Closest BS Mapping* algorithm due to its flexibility in user association and bandwidth allocation. On the other hand, for the minimum load demand the performance of *MinPower-QoS* is close to the energy consumption optimum lower bound represented by *MinPower*. More in detail, the impact of the weighting factor λ in *MinPower-QoS* optimization process can be highlighted. The solution with an intermediate value of $\lambda = 0.06$ has a remarkable performance from the power consumption perspective, by maintaining a good compromise in terms of power saving during peak and off-peak hours. Such a behaviour can be explained by a more flexible management of the radio resources that allows a lower number of active BSs and a lower transmission power. On the other hand, when the weight of λ increases, the adaptability of the network configuration is reduced in terms of switching operations and the total power consumption inevitably gets higher, especially in low load hours. More details about this trend are provided in Figure 3.4. The results achieved by *MinPower-QoS*, in terms of daily energy consumption and daily number of BS sleep mode switchings, are shown for

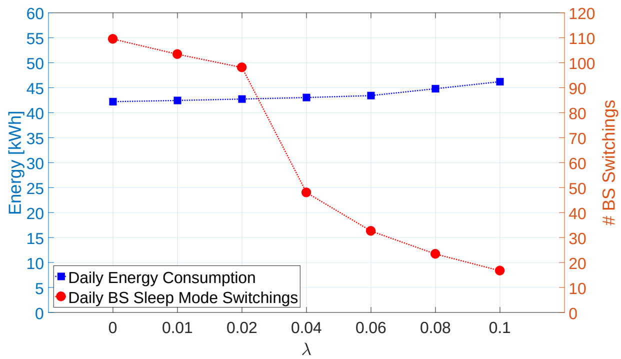


Figure 3.4: Daily energy consumption vs number of BS switchings in *MinPower-QoS*

the set of discrete values $\lambda \in \{0, 0.01, 0.02, 0.04, 0.06, 0.08, 0.1\}$. When $\lambda = 0$ the optimization framework obtains the best energy saving solution at the expense of a greater number of BS sleep mode switchings. The introduction of the multiobjective optimization approach with weighting factor λ on the other side drastically reduces the number of sleep mode transitions, consuming more energy with higher values of λ. In particular the optimal trade-off is guaranteed by the $\lambda = 0.06$ case, which consumes 3% more energy to the benefit of 70% less daily number of BS switchings with respect to the $\lambda = 0$ case. Since the optimization model is based on reaching the best solution with 0 outages, it is important to remind that the introduction of λ does not alter the satisfied UEs target, while searching for the best attainable BS subset, as shown in Figure 3.3(a). Moreover in Figure 3.5 the running time for *MinPower-QoS* algorithm is plotted as a function of the number of users with 3 different values of λ. Measurements were performed on a system featuring an Intel Centrino Core 2 Duo E6600 CPU running at 2.20 GHz and 4 GB RAM. The proposed method requires tens of seconds in medium to high traffic load cases. Although the running time increases as the growth of user population, the impact of the optimization process in terms of reduced number of BS switchings moderately affects the performances with higher values of λ.

In order to evaluate the overall throughput performance of the proposed solution, Figure 3.6 shows the results obtained in terms of daily power consumption and aggregate daily throughput. While *MinPower* is able to heav-

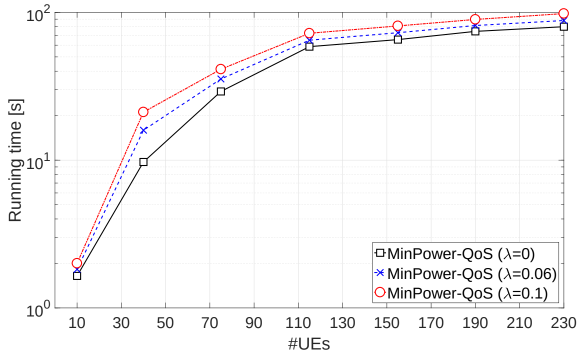


Figure 3.5: Running time as a function of number of users in *MinPower-QoS*

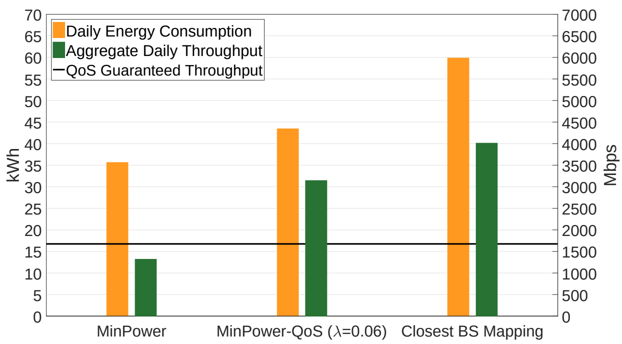


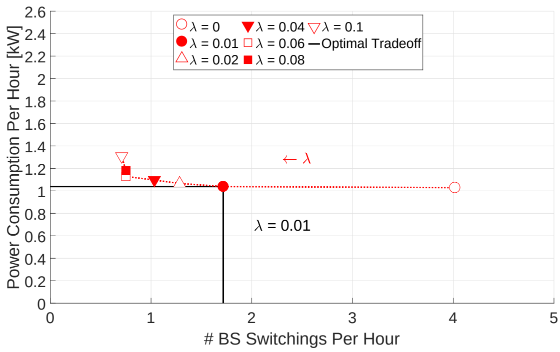
Figure 3.6: Daily energy consumption and aggregate throughput

ily reduce the amount of consumed power, the lack of QoS requirements causes a huge loss in terms of overall throughput achieved by users. On the other hand, *MinPower-QoS* can obtain an acceptable throughput performance, holding up to the *Closest BS Mapping* reference case and delivering major energy savings at the same time.

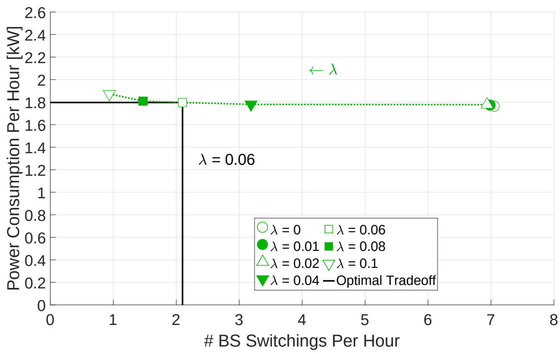
In Figure 3.7 the optimization solutions obtained by *MinPower-QoS* are divided in three subsets, corresponding to low, medium and high traffic load periods, as highlighted in Figure 3.2. The introduction of the weighting factor λ in the optimization process allows to heavily reduce the number of switching operations during the day, particularly at off-peak hours, when the network degree of adaptability is higher. Note that with lower values of λ, the power consumption sligthly changes until no optimization is applied in terms of switching operations ($\lambda = 0$); on the other hand, employing the highlighted optimal λ values the hourly number of BS switchings drops below one-half of the peak value in low load case and below one-third of the peak value in medium and high load cases. Consequently, the optimal network configuration can be obtained, affording the coverage and QoS requirements with minimum number of BS switchings.

Such a solution is able to reduce the signalling and handover traffic overhead related to the joint BS on/off switching and user association strategy, as well as the impact on operations and maintenance activities, which involve operational performance, monitoring and control of site operations. Moreover it can be seen that the impact of λ factor is more evident when the network is in low load conditions: by adopting the minimum weight value $\lambda = 0.01$ in the optimization process the power saving obtained by *MinPower-QoS* can be preserved, without increasing the number of active BSs. Conversely, in order to obtain an optimal performance for all the network configuration requirements, in medium and high load cases an higher value of λ is necessary: for $\lambda = 0.06$ not only the number of BS switchings is highly reduced, but also the number of active BSs and the network power consumption are optimized at busy hours with respect to the $\lambda = 0$ reference case.

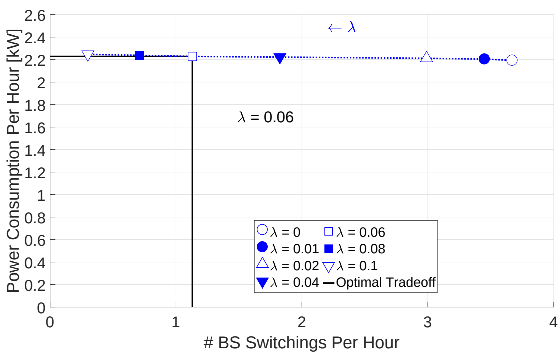
Considering the trade-off between energy consumption and network performance, the optimization process of *MinPower-QoS* is shown to be particularly effective when the network is not heavily loaded, as depicted in Figure 3.8(a): the proposed solution in fact guarantees a comparable energy use as in *MinPower* strategy, without compromising the network throughput performance. Moreover, the flexible management of user association and



(a)

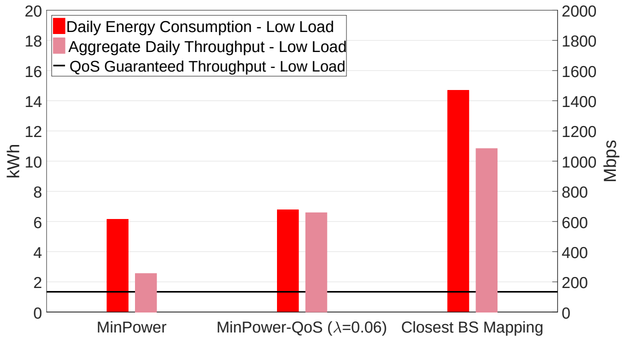


(b)

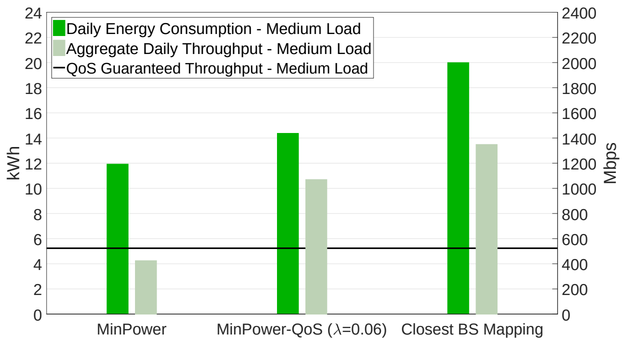


(c)

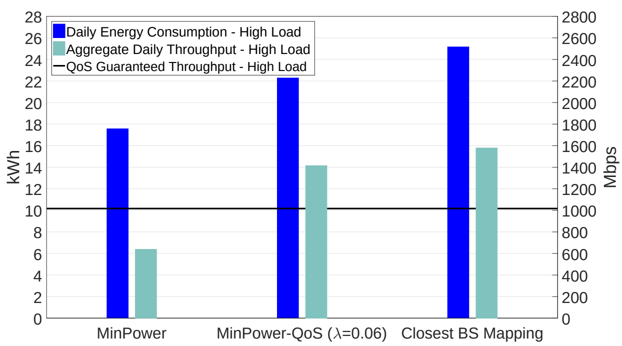
Figure 3.7: Optimal trade-off between power consumption and number of BS switchings: (a) low load hours; (b) medium load hours; (c) high load hours



(a)



(b)



(c)

Figure 3.8: Throughput and energy consumption analysis: (a) low load hours; (b) medium load hours; (c) high load hours

bandwidth distribution of *MinPower-QoS* allows to greatly exceed the QoS target throughput, even in heavily loaded network scenarios, as shown in Figure 3.8(b) and Figure 3.8(c).

3.5 Conclusion

This chapter has presented a novel multiobjective optimization framework, which allows to study and solve the network power consumption minimization problem, guaranteeing QoS target requirements and minimum number of BS switchings. The results for interference limited scenarios and average daily traffic loads are shown. By putting the cells into sleep mode, up to 60% power savings can be achieved at off-peak hours with respect to the basic scheme. Furthermore, the proposed *MinPower-QoS* methodology affords performance very close to the optimum solution, particularly for low traffic load scenarios. By optimizing the network configuration a 70% reduction of BS switch on/off operations can be reached in a day with 3% more energy expense. More in detail, considering daily traffic variations, significant savings can be obtained when the traffic is below 35% of the maximum load. Above that level, in medium to high traffic load, 25% and 10% power savings are still obtainable, but other energy efficiency features can be preferred instead of deep sleep.

Chapter 4

Energy efficient optimization of a sleep mode strategy in heterogeneous cellular networks

In this chapter we propose some energy saving solutions for HetNet, by jointly considering QoS requirements. We focus on the HetNet scenario in which macro and micro cells coexist. The MIQP optimization technique is used to minimize the power consumption together with the number of BS sleep mode operations of both macro and micro cells. The trade-off between power consumption, sleep mode switchings and performance of the network is shown for different energy saving strategies. [1]

4.1 Introduction

The search fo green network solutions should be taylored to the proposed architectures for the future mobile systems such as the heterogeneous networks, where cells of different sizes effectively coexist. The combination of different access points, traffic loads and radio access technologies, makes the network highly heterogeneous. Hence, the same deployment strategy cannot be used everywhere and the same RRM solution cannot be used throughout

[1] This chapter has been published as "Energy efficient optimization of a sleep mode strategy in heterogeneous cellular networks" in *Proc. of IEEE European Conference on Networks and Communications (EuCNC), 2017* [49].

the day with very different network conditions.
In this chapter an energy efficient and adaptive cellular network configuration strategy with QoS requirements is investigated. The solution is based on the use of traffic forecast in order to allow the base stations to know the traffic behavior in their coverage area. A given service rate is guaranteed to mobile terminals and the cost of rearranging the network when traffic demand changes is taken into account by optimizing the actual number of BS switchings, defined as the number of active/inactive state transitions in a twenty-four hour period. As highlighted in [120], the forecast approach requires a lower number of switch on/off operations with respect to the procedure which is based on instantaneous traffic measurements; as a result, the control traffic and handover operations are also reduced. This work extends the results presented in [135] by considering a multiobjective optimization framework, designed to inspect the network sleep mode operation cost over a daily pattern of traffic demands. Introducing a mix of cell sizes and generating a heterogeneous network adds to the complexity of the optimization procedure and network planning. With the introduction of small cell overlays, the macro cell network becomes over-provisioned due to the offload of traffic by means of small cells. One strategy for the network operator is to keep the existing macro cell BSs as they are, until the natural growth in user demand catches up with the spare capacity. This approach does not offer the most efficient energy saving solution since it may take a long time for growth in user demand to increase sufficiently. Alternatively, the network operator can re-optimize the existing macro cell network in response to small cell deployment. Performing this optimization will make the overall network more energy efficient and reduce network OPEX over the long term. The proposed sleep mode solution aims at reducing the energy consumption of the network by jointly optimizing the amount of management operations related to the addition of low-power base stations. The small cells can improve network performance and service quality by offloading from the large macro cells, but a negative effect is the increased interference on the downlink experienced by the user. These questions call for handling the network deployment in a more efficient way, by closely reexamining its requirements. The optimization problem formulation assumes weighting factors between the conflicting objectives of reducing the power consumption while narrowing down sleep mode operations. Both macro and micro cells subsets are jointly considered in the sleep mode scheme of the optimization process, allowing to avoid

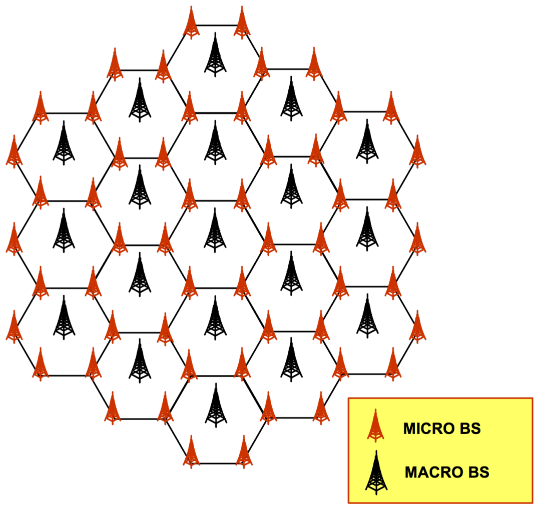


Figure 4.1: Considered het-net scenario

overlapping coverage.

4.2 System model and problem formulation

A LTE-based network of two different layers of hexagonal cells is considered, as shown in Figure 4.1. The first layer is composed of a set of 19 macro cells, while the second layer is formed by 54 micro cells surrounding the first macro cell layer. Both macro and micro base stations are equipped with omnidirectional antennas. According to [6], for each cell the following power model is considered:

$$P_c = \begin{cases} a \cdot P_{tx} + P_0, & \text{if BS is ON} \\ P_{sleep}, & \text{if BS is OFF} \end{cases} \tag{4.1}$$

In particular the value of a, P_0 and P_{sleep} are related respectively to the variable power consumption, the fixed power consumption of the active base station and the fixed power consumption of the base station on sleep mode. These parameters are set as described in Table 4.1 for a typical LTE system. Regarding the traffic generation, each user in the interested area requests a constant bitrate data stream: if the target data rate value is reached, the

Table 4.1: Power consumption model parameters

BS type	a	P_0	P_{sleep}
Macro BS	4.7	130 W	75 W
Micro BS	2.6	56 W	39 W

Table 4.2: Given data for the considered problem

Parameter	Value
N	number of deployed base stations
M	number of users
$\mathcal{B} = \{BS_1, ..., BS_N\}$	set of N deployed base stations
$\mathcal{U} = \{UE_1, ..., UE_M\}$	set of M users which have to be served
P_{MINj}	sensitivity of UE j
P_{MAX}	maximum allowed BS transmission power
R_t	datarate target for each UE
N_p	number of available PRBs at BS
W	total available bandwidth at BS
W_p	bandwidth of a single PRB
σ_{ij}	channel gain between BS i and UE j

quality of the link is assumed to be acceptable. Each user can be served by macro and micro base stations, but can be connected to only one base station at a time. In [6] the variations of traffic data during the day are modeled with a daily pattern related to the percentage of active users during the day and the global number of subscribers in a certain area. In this work the average number of simultaneous users at busy hour has been fixed and then calculated following this pattern for the rest of the day. The number of simultaneous users is assumed to follow a Poisson distribution with a different mean at each hour. The users are uniformly distributed in the considered area. In order to exploit the het-net scenario in terms of effective macro/micro cell sleep mode transitions, a suitable traffic forecast technique is considered [119].
Given the system model and the data reported in Table 4.2, the goal of the problem is to minimize the global power consumption P_c while controlling the number of BS sleep mode switchings S during daily traffic variations.

Let $\mathcal{B} = \{BS_1, ..., BS_N\}$ and $\mathcal{U} = \{UE_1, ..., UE_M\}$ be respectively the set of N deployed base stations and the set of M users which have to be served. The binary variable x represents the association between BSs and

UEs, as in the following:

$$x_{ij} = \begin{cases} 1 & \text{if UE } j \text{ is served by BS } i \\ 0 & \text{otherwise} \end{cases} \qquad i \in \mathcal{B},\, j \in \mathcal{U} \tag{4.2}$$

Assuming π_{ij} as the power assigned for transmission between BS i and UE j and w_{ij} as the bandwidth assigned by BS i to UE j, the data rate achieved by UE j is:

$$\rho_j = \sum_{i \in \mathcal{B}} x_{ij} w_{ij} \log_2(1 + \gamma_{ij}) \tag{4.3}$$

where γ_{ij} is the SINR between BS i and UE j. The transmission power of each BS i can be calculated as $P_i = \sum_{j \in \mathcal{U}} \pi_{ij} x_{ij}$. Therefore, the SINR γ_{ij} is

$$\gamma_{ij} = \frac{\pi_{ij} \sigma_{ij} x_{ij}}{\frac{w_{ij}}{W} \left(\sum_{k=1}^{N} P_k \sigma_{kj} \zeta_k (1 - x_{kj}) + W N_0 \right)} \tag{4.4}$$

where σ_{ij} is the channel gain between BS i and UE j, W is the total available bandwidth at BS and N_0 is the noise spectral density. The activity status of each BS is modeled by the binary variable ζ:

$$\zeta_i = \begin{cases} 1 & \text{if BS } i \text{ is active} \\ 0 & \text{if BS } i \text{ is in SLEEP mode} \end{cases} \qquad i \in \mathcal{B} \tag{4.5}$$

Let $\mathcal{T} = \{t_1, ..., t_L\}$ be the set of L traffic demand forecasts during the day in terms of UEs to be served. At every time $t \in \mathcal{T}$ the two objective functions are then calculated as:

$$P_c^{(t)} = \sum_{i=1}^{N} [(a \sum_{j=1}^{M} \pi_{ij} x_{ij} + P_0) \zeta_i^{(t)} + (1 - \zeta_i^{(t)}) P_{sleep}] \tag{4.6a}$$

$$S^{(t)} = \sum_{i \in \mathcal{B}} [\zeta_i^{(t)} (1 - \zeta_i^{(t-1)}) + \zeta_i^{(t-1)} (1 - \zeta_i^{(t)})] \tag{4.6b}$$

where parameters a, P_0 and P_{sleep} are the slope of the dynamic consumption, the fixed consumption and the sleep mode consumption, respectively [23]. Considering the activity status transitions of each macro and micro BS in response to the changing traffic demand, eq. (4.6b) keeps track of the number of sleep mode operations triggered by the energy efficiency policies. We assume two weighting factors, λ_M and λ_m, in the energy efficiency optimization process, in order to control the number of macro and micro BS subsets' sleep mode operations, S_M and S_m, respectively. The optimization problem is formulated in (4.7a)-(4.7h).

$$\min_{\pi,x,\zeta} \quad (P_c + \lambda_M S_M + \lambda_m S_m) \tag{4.7a}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} x_{ij} = 1, \quad \forall j \in \mathcal{U}, \tag{4.7b}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} = M, \quad \forall j \in \mathcal{U}, \tag{4.7c}$$

$$\sum_{j=1}^{M} x_{ij} \leq N_{PRB}, \quad \forall i \in \mathcal{B}, \tag{4.7d}$$

$$c_{ij} \leq \frac{\pi_{ij} \cdot \sigma_{ij}}{P_{MINj}}, \quad \forall i \in \mathcal{B} \quad \forall j \in \mathcal{U}, \tag{4.7e}$$

$$c_{ij} - x_{ij} \geq 0, \quad \forall i \in \mathcal{B} \quad \forall j \in \mathcal{U}, \tag{4.7f}$$

$$\zeta_i \leq x_{ij}, \quad \forall j \in \mathcal{U} \quad \forall i \in \mathcal{B}, \tag{4.7g}$$

$$\sum_{j=1}^{M} \pi_{ij} \leq P_{MAX}, \quad \forall i \in \mathcal{B}. \tag{4.7h}$$

Constraints (4.7b) and (4.7c) determine the coverage and the singular association for each UE. Constraint (4.7d) sets the BS capacity limit, in terms of bandwidth elements N_{PRB}. Constraint (4.7e) is fundamental for assuring the QoS: the binary variable c_{ij} equals to 0 if $\pi_{ij}\sigma_{ij} \leq P_{MINj}$; hence, for a given UE, constraint (4.7e) will define the set of potential BSs that can provide the minimum received power, P_{MINj}. Then, introducing constraint (4.7f), only one of the BSs in this set is selected. The activity status of a base station is linked to the user associations by constraint (4.7g). Finally, constraint (4.7h) sets the limit on the maximum BS transmission power.

4.3 Network optimization solutions

4.3.1 Power control

Power control is a well known solution that is able to decrease the global energy consumption by reducing the inter cell interference. As shown in Algorithm 5, in this work the considered power control algorithm is based on

Algorithm 5 Power Control

Given: x_{ij}; P_{MINj} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; w_{ij}; R_t; P_{MAX};
Return: P_i $\forall i \in \mathcal{B}$; P_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$;

for all $i \in \mathcal{B}$ **do** $P_i^{(0)} \leftarrow P_{MAX}$
repeat
    for all $i \in \mathcal{B}$ **do**
        Calculate π_{ij} as in Eqns. (4.8) and (4.9) $\forall j \in \mathcal{U}$
        $P_i \leftarrow \sum_{j \in \mathcal{U}} \pi_{ij} x_{ij}$ $\forall j \in \mathcal{U}$
    end for
until convergence
Update π_{ij} as in Eqn. (4.9) $\forall i \in \mathcal{B}$ $\forall j \in \mathcal{U}$
Update P_i to the maximum allowed value $\forall i \in \mathcal{B}$

the UE-BS association and the bandwidth assignment for each UE. The target QoS data rate for each UE is guaranteed by the iterative process, which provides the optimum BS transmission power. The proof of convergence can be found in [171]. At each iteration n the power transmitted by a BS to a certain UE is calculated as

$$\pi_{ij}^{(n)} = \frac{w_{ij} 2^{\frac{R_t}{w_{ij}}}}{W \sigma_{ij}} \left(\sum_{k \in \mathcal{B}} P_k^{(n-1)} (1 - x_{kj}) \sigma_{kj} + W N_0 \right) \tag{4.8}$$

where R_t is the target data rate, i.e. the QoS requirement for each UE. The initial condition is $\sum_j \pi_{ij}^{(0)} = P_{MAX}$ for all $i \in \mathcal{B}$. The received power for each UE j must be greater than the sensitivity P_{MINj}: if this is not the case the power which is transmitted by a BS to a certain UE is adjusted by the following equation:

$$\pi_{ij} = max \left(\frac{P_{MINj}}{\sigma_{ij}};\ \pi_{ij} \right) \tag{4.9}$$

4.3.2 Het-net EE optimization

The fundamental approach of the optimization problem is to recognize the existence of multiple objectives, such as guaranteed rate for all the users, network power consumption, number of BS sleep mode operations and number of simultaneously active BSs, both of macro and micro cell subsets. In order to minimize the power consumption in the cellular network, a first

Algorithm 6 Energy Efficiency

Given: σ_{ij}, P_{MAX}, P_{MINj} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$, λ_M, λ_m;
Return: x_{ij}, w_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; ζ_i, P_i $\forall i \in \mathcal{B}$; P_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$

1: Solve MIQP

optimization strategy is proposed. The iterative process solves the problem for three variables: association between BS and UE, bandwidth assignment and power allocation. In order to limit the cost of sleep mode operations, the number of power state transitions of BSs is taken into account in the optimization process. The deactivation and power reduction of the BSs are allowed only if the target QoS requirement is satisfied for each served UE. A MIQP solver has been adopted to perform the optimization procedure that refers to the problem formulated in (4.7a)-(4.7h). The MIQP model is solved by IBM ILOG CPLEX®solver [28]. Since the model cannot manage directly the QoS for each UE because of its non-linearity, two approaches are proposed in order to avoid any outage: (i) Power consumption minimization assuming an interference controlled scenario (*EE*); (ii) Iterative power consumption and BS sleep mode operation minimization to guarantee QoS (*EE Qos*). The *EE* scenario assumes a perfect inter cell interference cancellation (ICIC) solution. If the interference cannot be neglected, the *EE* algorithm cannot guarantee the required QoS and some outages could arise. Therefore, this energy saving solution represents an optimum lower bound in terms of global power consumption. In order to avoid the datarate outages and reduce the impact of sleep mode operations the *EE Qos* strategy is introduced in Algorithm 7. It combines the optimum power control and the *EE* solutions in an iterative method. In particular the *EE* algorithm obtains the optimum set of active BSs and the optimum BS-UE association, while the feasibility of the solution is controlled by the Power Control procedure as shown in Algorithm 7. If some data rate outages occur, the power of the outage users is increased by a δ value in order to look for new active BS subsets and a better association. It is important to emphasize that although the *EE* method provides more energy efficient sleep mode solutions, it incurs control signaling over the network to wake up cells. As an example, a single wake-up control packet could be used to trigger the activation/deactivation of a cell BS. The number of BS sleep mode operations related to the adoption of the energy saving strategies throughout the daily pattern of traffic demand fore-

Algorithm 7 Energy Efficiency with QoS Requirements

Given: σ_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$, P_{MINj}, P_{MAX}, λ_M, λ_m;
Return: x_{ij}, w_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$; ζ_i, P_i $\forall i \in \mathcal{B}$; π_{ij} $\forall i \in \mathcal{B}$, $\forall j \in \mathcal{U}$

```
repeat
    Execute EE algorithm (Algorithm 6)
    Execute Power Control algorithm (Algorithm 5)
    Data rate (ρ_j) calculation as in Eqn. (4.3) ∀j ∈ U
    for all j ∈ U\satisfied UEs do
        P_MINj ← P_MINj + δ
    end for
until no outages
```

casts is considered in the optimization process by computing a discrete set of λ_M and λ_m sample points. λ_M and λ_m introduce a weighting condition between the objective functions calculated in (4.6a), (4.6b) and (4.7a). As λ_M and λ_m increase, also the priority of reducing network operation and maintenance costs increases, for macro and micro BS subsets respectively.

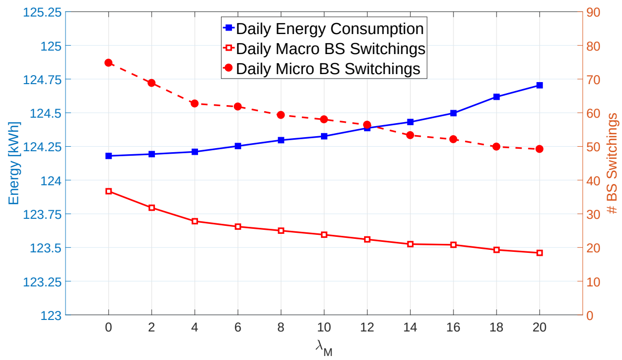
4.4 Simulation results

The proposed energy saving solution, namely, the *EE Qos* strategy, is compared to upper and lower bound solutions. As for the upper bound, the *Closest BS Association* is considered, adopting Algorithm 5, based on power control with closest BS association to each UE. The BSs which are not serving any UE are put on sleep mode. As a lower bound, the optimum energy saving solution *EE* is adopted. Simulation parameters are reported in Table 4.3 [7]. If a UE cannot achieve the data rate target, the minimum received power threshold, defined as P_{MINj} in constraint (4.7e), is increased by $\delta = 1$ dB in each iteration of *EE Qos*, solving the MIQP model with this new setting. The maximum number of active UEs at peak hours is equal to 570. It corresponds to the maximum number of UEs that can be managed by the *Closest BS Association* strategy without any capacity outage, hence representing the maximum load of the cellular network. The results are obtained by statistical analysis of 50 simulation runs with a 95% confidence interval. In Figure 4.2(a) and 4.2(b) the results obtained by *EE QoS* with

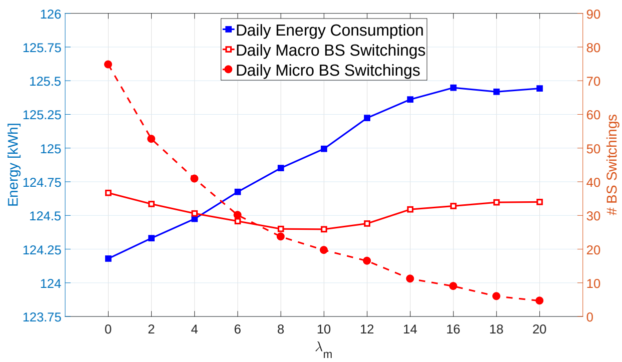
Table 4.3: Simulation parameters [7]

Parameter	Value
Macro BS intersite distance	1000 m
Micro BS intersite distance	500 m
Path loss	$15.3 + 37.6\log(d)$ (3GPP Typical Urban)
Shadow fading	std dev 8 dB
Indoor loss	20 dB
Carrier frequency	2GHz
Bandwidth	10 MHz (50 PRBs)
Max macro BS P_{TX}	20 W
Max micro BS P_{TX}	5 W
Noise PSD	-174 dBm/Hz
UE sensitivity	-90 dBm
Target user datarate	1 Mbps

a set of increasing λ_M and λ_m values respectively are shown. As expected, the introduction of the weighting factors in the optimization process allows to heavily reduce the number of BS sleep mode operations during the day. With $\lambda_M = 20$, the daily energy consumption sligthly rises (0.5 kWh), while the number of macro BS switchings is reduced by half. Note that as λ_M increases, also the number of switchings of micro BS subset decreases. This trend could be explained by the greater efficiency of a more stable network configuration and deployment: switching off some macro cells might bring more energy savings, but on the other hand the increasing number of active micro cells covering macro cells area might have a negative impact in terms of operational costs, especially in high traffic periods. This trend is no longer true if we consider the optimization process of reducing micro BS switching operations: particularly, Figure 4.2(b) shows that when λ_m values are greater than 10, the reduced number of micro cell sleep mode operations causes the negative effect of increasing the number of macro cell sleep mode activations. Given the high number of deployed micro cells, the optimization procedure is able to greatly reduce the number of micro BS switchings: with $\lambda_m = 10$ micro BS sleep mode operations are reduced by three quarters at the cost of a daily energy consumption increase of 0.8 kWh. Based on these results, the values of $\lambda_M^* = 20$ and $\lambda_m^* = 10$ have been considered as optimal weighting factors for *EE QoS* solution. In Figure 4.3(a) the UE satisfaction rate is depicted for the maximum network load, starting from the *EE* solution as first iteration value. It can be noted the impact of the number of active UEs on the number of iterations before the 0 outage objective is achieved. While the *EE* strategy experiences outages, the *EE QoS* solution

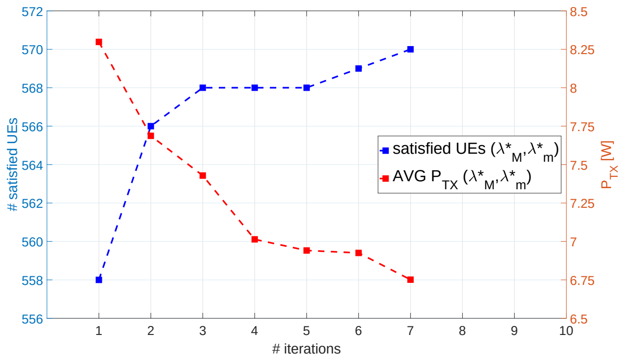


(a)

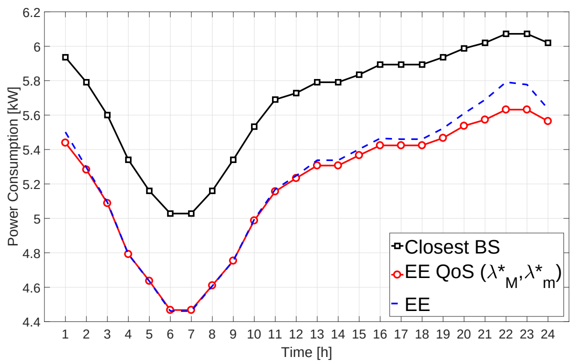


(b)

Figure 4.2: Energy consumption vs BS switchings in the optimization process: (a) Macro BS subset sleep mode operations weighting factor λ_M; (b) Micro BS subset sleep mode operations weighting factor λ_m



(a)



(b)

Figure 4.3: Simulation results: (a) satisfied UEs and average transmission power per active BS vs number of iterations in *EE Qos*; (b) power consumption vs time of day for the implemented solutions

converges to 0 outage performance after a number of iterations that is related to the current network traffic load in terms of users. Each iteration corresponds to a solution in the search space for the MIQP model. The good behaviour of the iterative optimization procedure allows to obtain the target solution in less than 10 iterations even in high traffic load case. The average transmission power vs the number of iterations is also depicted in Figure 4.3(a). Active UEs are satisfied when the mapping and received power allow to reach the QoS target. Among the feasible solutions, the one minimizing the global power consumption is chosen. In particular, even if the proper association is obtained by increasing the BS transmission powers, this trend becomes harmful for cell edge users because of the increasing interference level. In this case it is better to switch on other BSs, reducing the average transmission power together with the total power consumption and the interference. Figure 4.3(b) presents the results in terms of power consumption for *EE QoS* optimization strategy, with respect to the other solutions, i.e., *Closest BS Association* and *EE*. From the figure the behaviour of the proposed solution is evident: by introducing the optimal weights for macro and micro BS sleep mode operations in the optimization process, the number of active BSs ends up being heavily reduced, bringing high energy savings with respect to the *Closest BS Association*. Because of the QoS requirements, the slope of the *EE QoS* solution is slightly higher in high traffic load periods with respect to the *EE* performance: however it is interesting to see that the *EE QoS* results are very close to the optimum lower bound represented by the *EE* strategy. In order to evaluate the overall throughput performance of the proposed solution, Figure 4.4 shows the obtained results in terms of daily power consumption and aggregate daily throughput. While the *EE* strategy is able to allow a bigger reduction of the amount of consumed energy, the lack of QoS requirements causes a huge loss in terms of overall throughput achieved by users. On the other hand, the *EE QoS* solution can obtain an acceptable throughput performance, holding up to the *Closest BS Association* reference case, while guaranteeing fair energy savings. Moreover, the flexible management of user association and radio resources adopted by the *EE QoS* strategy allows to greatly exceed the QoS requirements in terms of target throughput. With an additional 1.5% energy expense, *EE QoS* solution is able to bring up to a 44.3% improvement for the throughput with respect to the *EE* strategy, still guaranteeing up to 8% less energy consumption compared to the *Closest BS Association*.

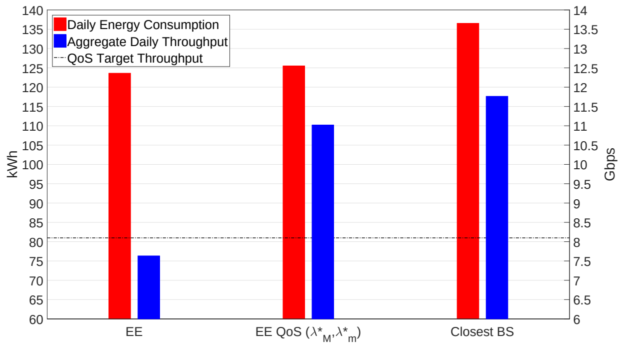


Figure 4.4: Daily energy consumption and aggregate throughput

4.5 Conclusion

In this chapter an energy saving solution for LTE heterogeneous networks is presented and implemented in a multiobjective optimization framework. The energy saving is obtained by adapting the number of active macro and micro base stations to traffic variations. Since each cell needs the knowledge of traffic variations in its coverage area, a traffic forecast technique is used. The network is able to adapt itself to the capacity requested by users at different times of the day, solving the power consumption minimization problem with QoS target requirements and guaranteeing a minimum number of BS sleep mode operations for macro and micro cell subsets. The proposed *EE QoS* strategy affords performance very close to the optimum solution, particularly in terms of active base stations. By optimizing the network configuration in terms of BS sleep mode switchings, this study shows the positive impact of long term sleep solutions in a heterogeneous cellular network scenario, holding down the related signaling and handover traffic overhead as well as the negative impact on operations and maintenance activities, which involve operational performance, monitoring and control of site operations.

Chapter 5

Energy efficiency perspectives of Professional Mobile Radio networks

This chapter focuses on the feasibility of energy efficient solutions for current and potentially future Professional Mobile Radio (PMR) networks, by providing a mathematical formulation of power consumption in Terrestrial Trunked Radio (TETRA) base stations and assessing possible business models and energy saving solutions for enhanced mission-critical operations. The energy efficiency evaluation has been performed by taking into account the traffic load of a deployed TETRA regional network. [1]

5.1 Introduction

Professional Mobile Radio (PMR) systems represent a subset of mobile communications networks which are designed for mission critical communications. Since they provide a mobile wireless service to their users, as in the public radio network case, such systems are mainly addressed to public safety and security organisations to guarantee fail-safe and secure voice and data

[1] This chapter has been presented as "Energy Efficiency Perspectives of PMR Networks" in *Third ETSI Workshop on ICT Energy Efficiency and Environmental Sustainability, 2015* [51] and published in *MDPI Information, vol. 8, n. 1, 2017* [52].

communications. On the other hand, the target requirements of the provided service are quite different than the public case, particularly in terms of system availability, security, resilience and reliability that are typical of mission critical communications [10].
Recently, PMR and public radio systems share common needs and interests. As a matter of fact, the possibility of providing broadband services is taken into account also by the PMR operators and manufacturers who are currently working on extending their systems capabilities. In order to increase the throughput and be able to support broadband services like video communications, LTE is now under investigation as the platform for future PMR systems [67].
Moreover, a greater sensibility toward environmental and energetic issues has been raised in research and the industrial world, and a lot of inherent international research activities have been funded [97,112,127,128]. The energetic costs are one of the major drivers of operational expenditures [26]. At the same time, controlling the cost of energetic waste allows for cutting greenhouse gas emissions, thus reducing air pollution with positive consequences on environment. An energy efficient cellular network can be achieved in multiple ways. First of all, an opportune deployment, taking into account the optimal site location, is needed to minimize the transmission power budget and the number of needed base stations. Moreover, considering that new technologies will be progressively introduced in an already deployed network, the hardware optimization is expected to significantly reduce the current energy waste, especially due to power amplifiers, the most power-consuming devices in a base station's equipment [42]. In this regard, replacing the old network devices with new and less power consuming ones will introduce a substantial energy efficiency gain. However, such energy gain should be further improved through radio resource management solutions aiming at optimizing the network usage with respect to the actual needs. As a matter of fact, the daily power consumption of a base station has a rather constant profile over time with respect to the transmitted traffic, as depicted in Figure 5.1. This behavior justifies the goal of using energy efficiency strategies to shape the power consumption to the actual energy demand. To this aim, many promising radio resource management strategies, mainly focused on power control and power amplifiers' sleep mode, have been proposed [34, 58, 119, 165].

This chapter discusses the feasibility of energy efficient solutions for current and future PMR networks. First of all, a review of the state-of-the-art

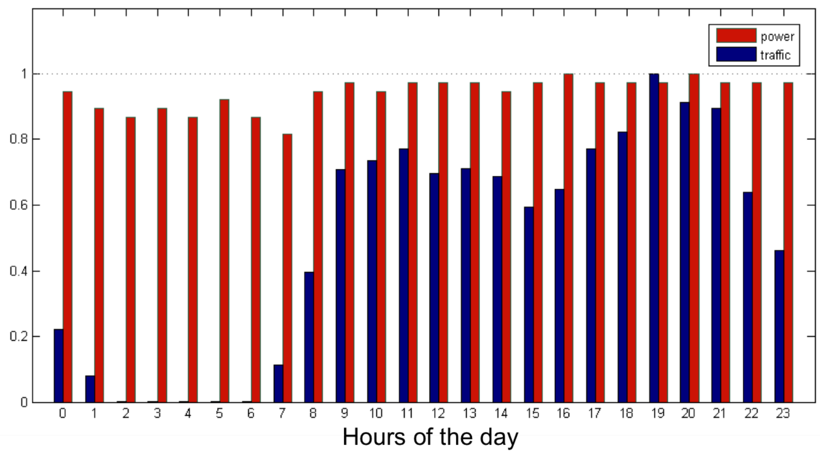


Figure 5.1: Power consumption and traffic of a generic public cellular base station during a day.

of such systems is provided, mainly referring to the most popular system in Europe, which is TETRA. The main TETRA features are described highlighting the evolution to a broadband system through TETRA Enhanced Data Service (TEDS). Moreover, since the availability of IP broadband services will be a PMR target requirement, the feasibility of the transition to a TETRA over LTE system is discussed. In order to evaluate the energy impact of such a system, a TETRA/TEDS power consumption model is introduced, as well as some energy saving radio resource management techniques developed for commercial wireless systems. Then, an evaluation of the energy performance of an optimized TETRA/TEDS system has been done, also taking into account the potential energy efficiency gain, due to hardware improvements and radio resource management flexibility that will be allowed by the transition to an LTE infrastructure. Since the evaluation of power saving solutions should be based on actual network configuration and traffic load scenarios, this work extends the results presented in [45] by introducing a detailed energy consumption analysis focused on the traffic data of a deployed TETRA regional network. Finally, the performance of the considered systems is evaluated both from an economic and an environmental point of view, showing the positive impact of the energy management improvements in current TETRA/TEDS systems and the significant energy saving gain allowed by the LTE platform.

5.2 Present and future PMR systems

PMR systems have been introduced to provide a speech and data two-way radio communication service in non-public networks tailored to the specific professional operational needs. Typically, the main users of such kind of services are military, police and public safety forces, but also private institutions like transportation and logistic companies. The target PMR scenario is represented by the mission critical communications. It is characterized by four key requirements: resilience and highly availability of the infrastructure, reliability of the communications, security and possibility of point-to-multipoint communications to support group calls and messages. A resilient and highly available infrastructure can be obtained by redundant network architecture and fail-safe network elements, allowing a minimum service even if the connection to the infrastructure is not possible or limited. Moreover, the communication is considered reliable if the provided service is accessible and stable. Therefore, the target quality of service must be reached within the entire coverage area and the communication setup must be extremely fast. Security is needed to protect users from malevolent actions like jamming, interception and spoofing, providing features like mutual authentication of terminals, jamming compensations, end-to-end encryption and temporarily terminal disabling. Low power consumption is also needed to reduce the operational costs. Such requirements have been largely implemented in the mobile radio terminals by introducing, for instance, transmission power control in order to increase the battery lifetime [94]. Currently, TETRA [1, 2] is the most widely used PMR standard, providing a reliable infrastructure to support mission critical communications. As depicted in Figure 5.2, the PMR evolution, particularly referring to TETRA, is linked to the commercial radio system evolution since PMR manufacturers cannot afford in-depth research and development budgets to develop next generation PMR mobile radio technologies in parallel to or even ahead of commercial mobile radio manufacturers. Therefore, since its beginning, PMR systems have been exploiting commercial radio systems technologies and standards. The remainder of this section describes the TETRA evolution, starting by the original TETRA system and TEDS, representing the state-of-the-art, and a possible evolution related to the broadband services provided by the 4G commercial

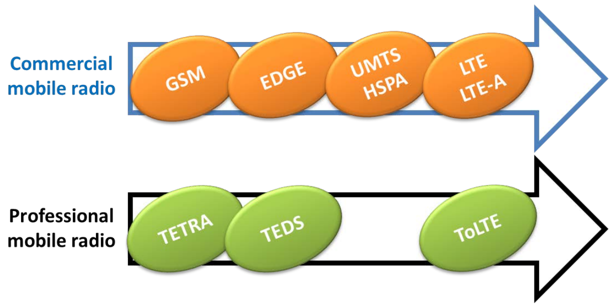


Figure 5.2: Terrestrial Trunked Radio (TETRA) evolution.

standard, identified as TETRA over LTE.

5.2.1 TETRA and TEDS for speech and data communications

TETRA is a multiple access digital system for secure private radio communications. It allows the transmission of high quality voice and low-speed data, and it has been proposed mainly for emergency services, public safety, and, in general, for all the scenarios where a bounded secure area for communications is needed.
The TETRA system has some unique functionalities that cannot be obtained by commercial cellular systems: these features are motivated by the specific purposes of the secure private radio systems with respect to those pursued by widespread cellular technologies. In particular, TETRA offers:

- group calls;
- reduced call set-up time (below 300 ms) with respect to 2G technologies;
- direct mode of operation using other mobile devices as repeaters;
- secure data transmission by end-to-end encryption;
- push-to-talk mode.

As depicted in Figure 5.3, the TETRA architecture is similar to a generic cellular network and includes the following standard interfaces:

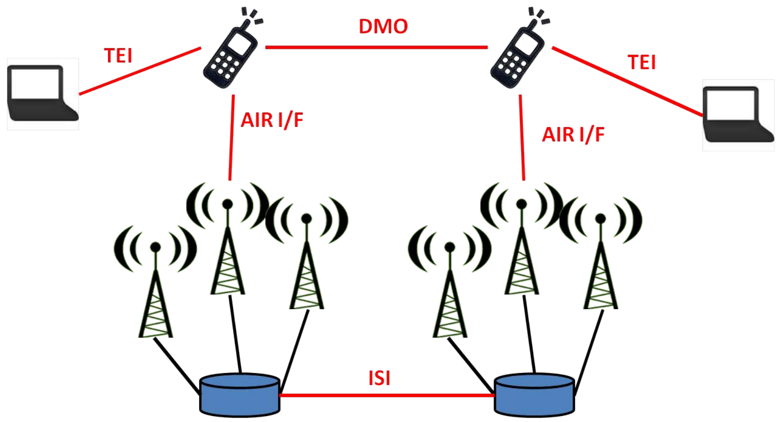


Figure 5.3: TETRA architecture.

- *Air Interface (AIR I/F)*, which ensures the interoperability of terminal equipment of different manufacturers;
- *Terminal Equipment Interface (TEI)* facilitating the independent development of mobile data applications;
- *Inter Systems Interface (ISI)* which allows the interconnection between TETRA networks of different manufacturers;
- *Direct Mode Operation (DMO)* guaranteeing the communication between terminals also beyond network coverage.

A Time Division Multiple Access (TDMA) is used to allocate four time slots, each of which has a duration of 14.167 ms, into a 25 kHz bandwidth carrier. Each time slot represents a full rate channel or, optionally, two half rate channels in order to increase the random access. Frequency division duplexing is used to associate to a time slot the uplink and downlink channels. Data and control information is mapped within each channel and the transmission is done through $\pi/4$-PSK modulation. The physical content of a time slot is organized as a burst, as described in Figure 5.4. At each base station, the first slot of each TDMA frame of one carrier is occupied by the Broadcast Common Channel (BCCH). The remaining time slots of such carriers and, eventually, all the time slots of other available carriers can be assigned to a Traffic Channel (TCH). When a channel is idle because it is not assigned to

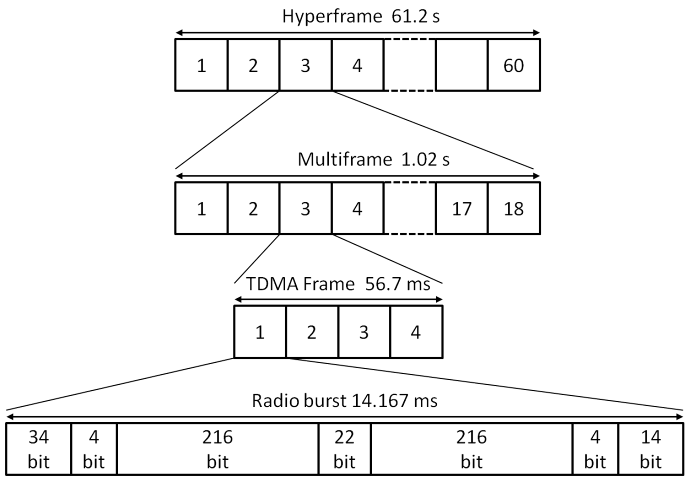


Figure 5.4: TETRA radio frame.

any TCH, a dummy burst is transmitted in order to maintain a continuous bit flow.

The first release of TETRA allows a maximum uncoded data rate of 28.8 kbps. In order to improve this standard to support IP-based multimedia services, TEDS has been introduced taking care of the maximum backward compatibility [124]. TEDS can be considered as an evolution of TETRA system, with improvements focusing on transmission and bandwidth extension, in order to meet the need for higher speed data services. In particular, as reported in Figure 5.5, channels with different bandwidths are available. Allowed bandwidths are 25 kHz, as in the previous release, 50 kHz, 100 kHz and 150 kHz. Moreover the adoption of spectral-efficient multilevel modulation schemes enables the possibility of link adaptation: 4-QAM, 16-QAM and 64-QAM are added to $\pi/4$-PSK scheme, used in the first release of TETRA. In order to detect errors and protect the information, different channel coding schemes have been introduced. By adaptively selecting the opportune modulation, taking into account the needs and the link quality, a throughput beyond 500 kbps can be obtained, as shown in Table 5.1. The TEDS improvements are not only related to physical layer. Classifying data flows into classes allows for negotiation of the opportune quality of service for each flow in terms of throughput, delay, precedence and reliability. Allowed classes are

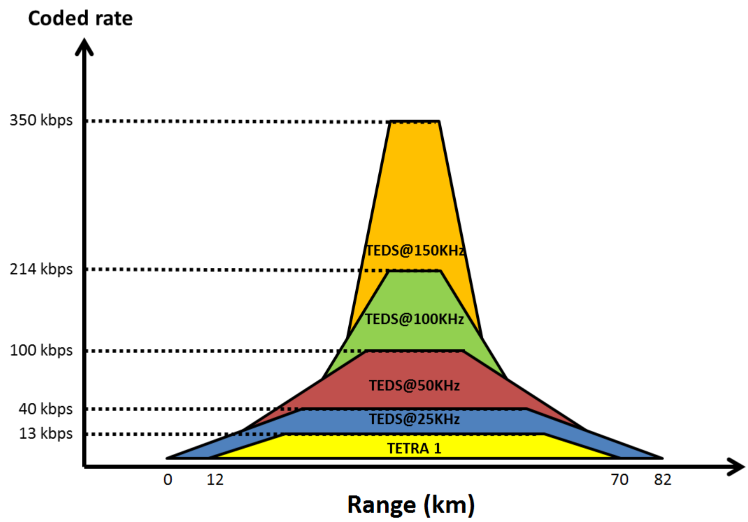


Figure 5.5: TETRA Enhanced Data Service (TEDS) bandwidth and performance.

Table 5.1: Channel coding and TETRA Enhanced Data Service (TEDS) throughput.

	25 kHz	**50 kHz**	**100 kHz**	**150 kHz**
π/4-DQPSK, r = 2/3	15.6 kbps			
π/8-D8PSK, r = 2/3	24.3 kbps			
4-QAM, r = 1/2	11 kbps	27 kbps	58 kbps	90 kbps
16-QAM, r = 1/2	22 kbps	54 kbps	116 kbps	179 kbps
64-QAM, r = 1/2	33 kbps	80 kbps	175 kbps	269 kbps
64-QAM, r = 2/3	44 kbps	107 kbps	233 kbps	359 kbps
64-QAM, r = 1	66 kbps	160 kbps	349 kbps	538 kbps

real-time class for live audio and video transmission, and telemetry class for bursted low capacity transmissions, and background class for file transfer and web applications.

5.2.2 The PMR evolution through the LTE system

Currently, most TETRA manufacturers are looking to the future by implementing a TETRA over LTE system [53,153] in order to provide higher data rate and lower latency services.

LTE is the state-of-the-art standard for commercial mobile communications, providing an all-IP connectivity through an infrastructure designed for very high speed services.
Even if LTE has been developed for commercial use, some work groups in 3GPP have been working on the adaptation of the standard to mission critical communications [59]. In particular, the following items are currently under investigation:

- Group communication and push-to-talk (PTT),
- Proximity based services,
- Network resilience,
- High power user equipments,
- Enhanced Radio Access Network (RAN) sharing,
- Priority and QoS control.

More specifically, group communications, PTT and proximity based services, that enable device-to-device (D2D) communications, are the key requirements for public safety mission critical voice services. The work on such subjects has been carrying on within the LTE Release 12 and LTE Release 13 groups [11, 12, 14]. In the framework of these releases, some issues about resilience and RAN sharing are also being discussed. For example, in order to face a disaster causing the failure of some devices, any base station should be able to act alone in connecting the served users with the rest of the network [13]. Moreover, an enhanced flexibility in sharing network resources could allow the adoption of smart radio resource management strategies between critical and non-critical users [15]. As for high power user equipment and priority and QoS control, such features are already provided by the LTE technology and the work that is being carried on is related to future enhancements [3, 8].
Whilst these outcomes will clearly directly affect infrastructure vendors, the market for user equipment, applications and other end-user equipment, and services can be expected to be less impacted. In other words, whether or not the bearer network is owned and operated by the user organization, or services are provided by mobile network operators, users will still require terminal devices and applications. In a standardized market, competition and innovation, as well as economies of scale resulting from the wider global

LTE user equipment ecosystem, can be expected to influence prices. A strong standards-based approach will ensure interoperability between different vendors leading to a competitive equipment market.
Besides the opportunities offered by exploiting the LTE technology for PMR services, the main issue resides in the way such services should be provided. Since there is no commercial interest to develop and integrate all the PMR functionalities over the LTE infrastructure, especially the ones related to security end encryption operations, only private networks should be preferred. Private networks could be self-deployed by the interested organizations for its own activities or provided by a third-party. In both cases, once the LTE system will be compliant with mission critical communications requirements, the main open issue will be the actual channelization, since LTE is designed to operate with bandwidths starting from 1.4 MHz. However, the PMR evolution over the LTE system, i.e., TETRA over LTE, represents a big opportunity for current PMR users to increase the efficiency of their own spectrum usage.

5.3 Power consumption modelling in PMR systems

A TETRA base station is composed of several functional blocks that are depicted in the diagram of Figure 5.6. In particular, the main blocks are baseband unit (BB), radio frequency unit (RF) and power amplifier (PA), which together form the transmission chain. Moreover, the site control unit (SCU) is responsible for the management operations of the considered site. In order to maintain the opportune temperature for the whole site, a cooling system is considered. This system is responsible for cooling down the site environment coping with the temperature increase due to electronic operations, or, conversely, provides a heating function when the devices temperature gets below the operational target. Transformers and rectifiers are needed to adapt the network power in order to feed the base station devices, and their operation is considered in the main supply system.

A TETRA base station power consumption model can be obtained by adapting the one proposed in [23]. The following equation is considered:

$$P_{in} = N_{TRX} \frac{\frac{P_{out}}{\mu_{PA}(1-\sigma_{feed})} + P_{RF} + P_{BB} + P_{SCU}}{(1-\sigma_{DC})(1-\sigma_{MS})(1-\sigma_{cool})}, \tag{5.1}$$

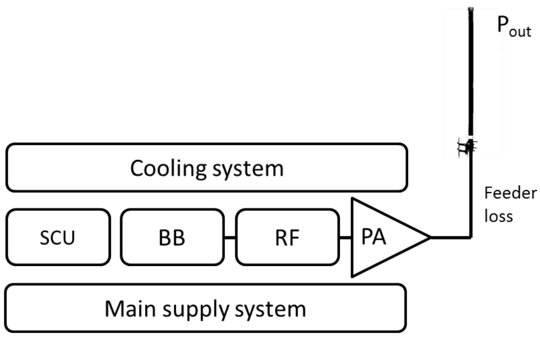


Figure 5.6: TETRA base station model.

where N_{TRX} is the number of transceivers at the base station; P_{out} is the transmission power; P_{BB}, P_{RF} and P_{SCU} are, respectively, the power spent for the base band operation, the RF stage and the site control unit. The feeder loss is modeled by the σ_{feed} parameter and μ_{PA} is the power amplifier efficiency. Finally, σ_{DC}, σ_{MS} and σ_{cool} model the DC loss, i.e., the loss in the transmission chain, the loss in the main supply system and the loss for cooling. The power consumption parameters are summarized in Table 5.2. Equation (5.1) shows that the power consumption in base stations can be divided into a static component and a dynamic component. In particular, the dynamic component is related to the output power: by varying P_{out}, for instance when managing different amounts of traffic, and then the variable part of the total power consumption changes. On the other hand, the static component, represented by P_{BB}, P_{RF} and P_{SCU}, does not significantly change for different P_{out} values, or the variations are negligible. Therefore, the model can be simplified as follows:

$$P_{in} = N_{TRX}(\Delta_p P_{out} + P_0), \tag{5.2}$$

where the PA efficiency and losses effects are included in Δ_p and P_0 takes into account the static BB, RF and SCU power consumption. By considering the parameters in Table 5.2, $\Delta_p = 7.5$ and $P_0 = 280$ W have been assumed.

Table 5.2: TETRA base station power consumption parameters.

Parameter		Value
Transmission power	P_{out}	$[0, 20]$ W
Power Amplifier (PA) efficiency	μ_{PA}	0.25
Radio Frequency (RF) power consumption	P_{RF}	114 W
Baseband (BB) power consumption	P_{BB}	75 W
Site Control Unit (SCU) power consumption	P_{SCU}	23 W
DC loss	σ_{DC}	7.5%
Feeder loss	σ_{feed}	50%
Main supply loss	σ_{MS}	9%
Cooling loss	σ_{cool}	10%

5.4 Energy efficiency strategies for PMR systems

5.4.1 Carrier sleep mode

Because of the impact of fixed power consumption, which is the power spent by the base station even for zero transmission power, the most common energy saving strategy proposed for commercial cellular system is the carrier sleep mode. As a matter of fact, in order to improve the capacity, operators could deploy more than one carrier per cell. As explained in section 5.2, the cell signaling is transmitted just over one carrier, while the other ones only manage the traffic and the dedicated signaling. Therefore, carrier sleep mode works automatically by deactivating the unused carriers; the only carrier that cannot be ever deactivated is the one carrying the cell signaling in order to maintain the coverage of the area. Deactivating a carrier, or putting it on sleep mode, means putting the carrier in a low power consumption state, such that the base station controller can make it operating when needed in a very small time (a few seconds).
By adopting the carrier sleep mode, the power consumption model presented in (5.2) can be modified as follows:

$$P_i = \begin{cases} \Delta_p P_{out} + P_0, & \text{if the } i\text{-th carrier is ON,} \\ P_{sleep}, & \text{if the } i\text{-th carrier is sleeping,} \end{cases} \tag{5.3}$$

where P_{sleep} is the power consumption of the sleep mode state. In this study, $P_{sleep} = 140$ W has been assumed.

The performance of TETRA carrier sleep mode is depicted in Figure 5.7, which shows the energy consumption of a TETRA base station that

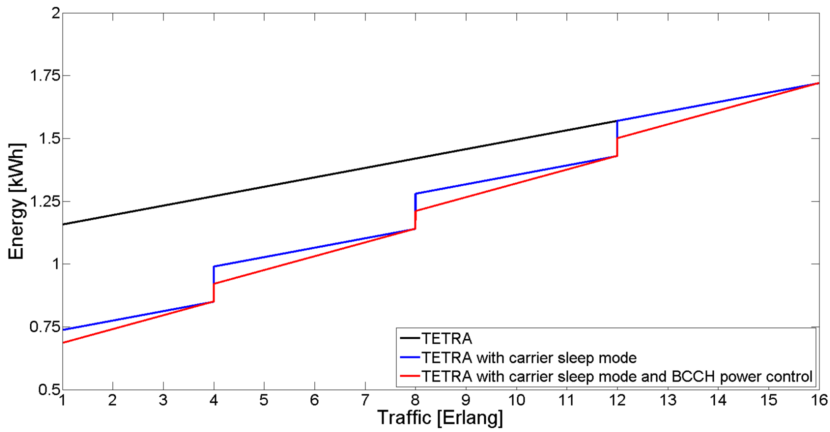
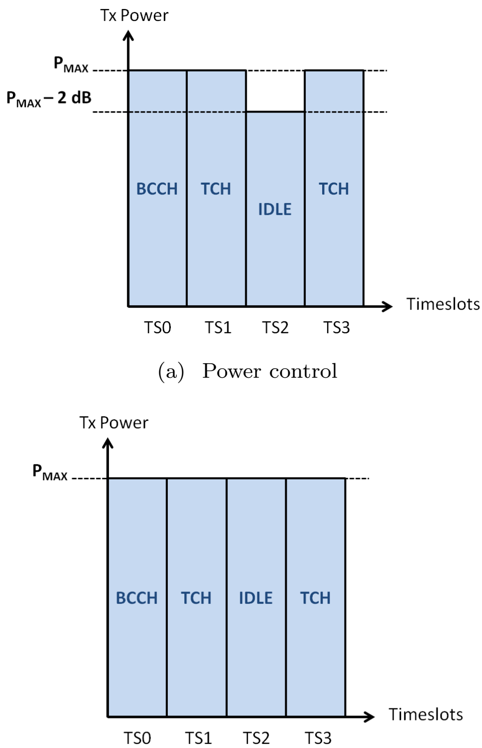


Figure 5.7: Energy consumption versus traffic for TETRA.

is equipped with four carriers as a function of traffic load: the carrier sleep mode, as expected, provides significant energy savings, especially in the case of low traffic load, converging instead to the baseline consumption with peak traffic load.

5.4.2 BCCH carrier power control

Power control is a software based solution that introduces an energy saving mode on the BCCH transceiver. Such a solution reduces the overall power consumption by transmitting dummy bursts on the idle channels, i.e., on the time slots that are not allocated to a TCH, with a power level lower than the maximum transmission power of the BCCH channel. The behaviour of power control is shown in Figure 5.8: note that, in our analysis, a 2 dB power reduction has been considered. In order to keep the cell range unaltered, the BCCH channel is always transmitted at full power. The introduction of power control allows the power consumption to vary according to the served traffic. Figure 5.7 shows the behavior of a TETRA base station power consumption when power control is applied. The largest energy saving is achievable in the case of low traffic load, while for higher traffic load values, the performance of power control converges to the TETRA baseline case. We observe that the gain due to power control on the BCCH carrier is smaller with respect to the impact of carrier sleep mode. Therefore the



(a) Power control

(b) No power control

Figure 5.8: Transmitted signals for power control (**a**) and no power control (**b**) cases.

combined adoption of the two solutions should be supported. In this regard, the proposed power consumption model has been evaluated by statistical analysis, considering a weekly traffic data set of a deployed TETRA regional network and a 95% confidence interval.

Figure 5.9 shows how the considered strategies perform in terms of daily average power consumption. As expected, the application of the carrier sleep mode brings significant energy savings, resulting in a 30% lower power consumption, considering the daily average traffic load of a single TETRA base station. Even if the energy gains achieved by power control on the BCCH carrier are smaller, employing this strategy in combination with the carrier

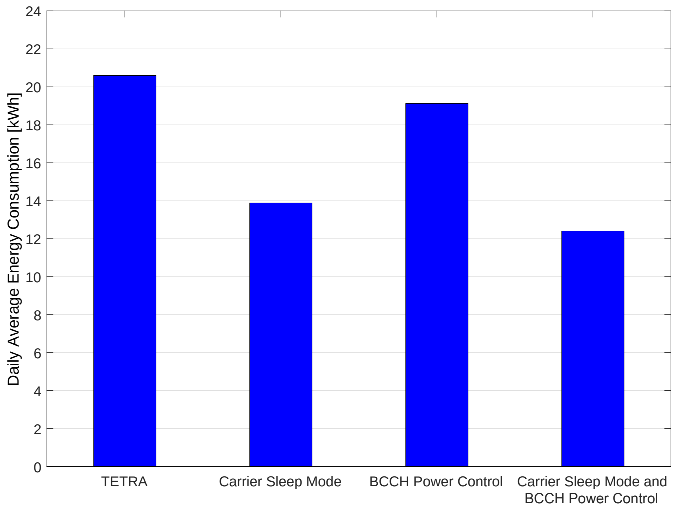


Figure 5.9: Daily average energy consumption of a single TETRA base station.

sleep mode results in an additional 10% saving, showing that the common techniques proposed for commercial cellular standards could actually improve the energy efficiency of PMR systems.

5.5 Technical and economic considerations on energy efficiency of next generation PMR systems

5.5.1 Business models for mobile broadband PMR

When evolving to mobile broadband communications, public safety agencies may choose from numerous business models that will support its specific needs, taking into account existing PMR network operations, available spectrum, regulatory environment and financial resources. It may contract services provided by a mobile network operator (MNO), operate or use a service from a dedicated virtual network over a mobile operator's infrastructure (G-MVNO), build a wholly owned and operated dedicated network, or use a mix of different approaches [9]. Adding LTE mobile broadband capabilities to existing PMR networks in a nondisruptive, cost-effective and energy-efficient way can be complex, with many factors to consider. These include startup costs, operating and capital expenditures (OPEX and CAPEX), expected revenues, available spectrum, existing network equipment, commercial wireless services and the political environment. The following are five possible business models that are proposed to match the trade-off between objectives and constraints.

Contract services through an existing Mobile Network Operator

In this model, the public safety agency simply contracts data subscriptions with an MNO to provide mobile broadband services. Public safety users and consumers share the same spectrum and network. The public safety entity pays a consistent, predictable periodic fee for network access, usually a function of some known factor, such as the number of end users, devices or usage. This arrangement is relatively inexpensive if traffic, the number of users and subscription fees can be low, and fast if MNO LTE service already is available. CAPEX concerns only applications and terminals, which could remain significant if a large number is required. OPEX consists mainly of monthly fees for using the MNO service, and is proportional to the number of users and usage volume. Challenges for the MNO model include no control over four critical requirements: coverage (usually very poor in sparsely populated areas), availability, prioritization and resilience. Typically, little or no support exists for mission-critical features, and gaps in coverage can occur where the population density is low, such as in rural and isolated areas. For mission-critical needs, these issues might be addressed through stringent service level agreements (SLAs) to assure such features as priority access or network redundancy in case of an outage, which may significantly increase the subscription fee. In addition, most MNOs have a monthly data cap and additional fees for excess usage, which can significantly impact OPEX.

Obtain service from a Government Mobile Virtual Network Operator

The MVNO approach has become prevalent in the commercial sector, where branded operators resell bulk-purchased wireless services to consumers while providing their own usage plans, billing and customer support. The MVNO approach can be extended to the support of public safety users. In that case, the MVNO, called a G-MVNO (Government MVNO) provides added-value services (such as user and device management, customer care, end-to-end security, billing and so on) to the public safety users that, in turn, get access to secure broadband data services when the G-MVNO leverages the 4G access network from the MNO. The G-MVNO model offers more control over services and security than the MNO approach, providing a ready-made network for basic public safety needs. It keeps CAPEX moderate (mainly terminals and a few LTE core network nodes). A G-MVNO can manage services and management over a mix of 4G, 3G and PMR platforms for the best possible availability in routine situations and major crisis. It can be configured to combine security, availability, ease of use and economics tailored for public safety, while keeping the effective management of end-to-end data service a first priority. About the cons of this approach, as with the MNO model, a G-MVNO provides no absolute control over coverage (especially in rural areas), availability and assured resilience. In addition, depending on the MNO, it may offer limited support of some critical public safety features, such as direct mode or group calling.

Deploy dedicated network services through a Public-Private Partnership Project

The Public-Private Partnership Project (PPP) business model features a dedicated and standalone LTE network, which is deployed, operated and maintained by an MNO and/or another independent operator. This type of network is typically owned by a telecom operator, which provides the service to the public safety agencies while usually assuming the financial, technical and operational risk of the service offer. One of the key benefits of the PPP model is that the public safety agency is the only entity using the network. CAPEX and OPEX can be reduced through synergies in the reuse of antenna sites, backhaul and technical skills contributed by the private partner. Public safety communications requirements are assured and customized, with full control over such critical specifications as latency, coverage and resilience. The main challenge is that this model requires having access to a dedicated broadband public safety spectrum and negotiating with a partner to invest the upfront CAPEX to build the network. However, many synergies can exist to minimize this upfront investment.

Build, own and operate a dedicated private network

In this model, the public safety agency finances, procures, builds and manages its own network, setting technical requirements for capacity, security, reliability, redundancy and robustness. It takes full responsibility for all network elements and software, and employs in-house personnel to build, manage, operate and maintain the network. The extent of upfront costs depends on the scale of deployment (local, regional or national), whether the network is shared among several entities and/or whether the deployment is scheduled gradually over years or within a shorter time period. The clear advantage with a dedicated LTE network is that it can be designed to match all mission-critical requirements, with the agency having full control over the procurement process. Specifications (such as site hardening, extended coverage and resilience to multiple faults, extreme events, and energy saving solutions) can be tailored to missions, as well as to the agency's future evolution strategy. As with the PPP model, a dedicated network can offset CAPEX and OPEX by operating as a wholesaler where regulations permit, or sharing with other critical users of the public sector such as defense, utilities and transportation agencies. On the other hand, specifying, building and maintaining a dedicated network requires significant upfront investments and technically skilled professionals for network operations. Acquiring dedicated LTE spectrum may require an initial investment or an annual fee. A dedicated spectrum must be cleared of any previous service, usually a slow process in countries where no dedicated spectrum currently exists. Both CAPEX and OPEX typically could be higher in this model. However, CAPEX depends significantly on the spectrum of operations (the lower the spectrum, the lower the number of sites to deploy) and can be planned over multiple years to deploy in critical areas first.

Combine a G-MVNO with a private network (hybrid model)

Given that the spectrum is a scarce resource in many regions, some agencies may elect to build a custom communications network dedicated exclusively to mission-critical services, while conducting less critical back-office operations through commercial operators using the G-MVNO model. This approach can be implemented relatively easily, since LTE is both a technology for commercial carriers as well as the new-generation platform for PMR. This model has the advantage of rapid deployment without having to wait for dedicated broadband spectrum to become available. It enables an agency to handle very high volumes of everyday data traffic while preserving a fully controlled, mission-critical core for emergency situations. It is flexible and positions the agency for future evolution to a fully dedicated network. It allows agencies to make investment efficient by combining a mix of commercial and dedicated spectrum terminals. In addition, when both options are available, the MNO network can be used to offload traffic from the private network that is not mission-critical, preserving key resources for mission-critical traffic and applications. Following this strategy means less than full control over the entire network and its coverage area, and may require mobile transmitters or antennas on some occasions. Developing a hybrid approach also introduces slightly greater complexity to design, operations and financial models, requiring critical consideration and coordination of these elements. Public safety agencies embarking on an LTE deployment project must consider factors such as budget, regulatory issues, internal resource constraints, coverage and reliability targets, available spectrum (frequency band and bandwidth) and number of end users when choosing the best overall design and business model. Agencies should also have a plan for energy management because the wealth of robust data and growth of mobile traffic will offer new ways of conducting operations. Regardless of the model chosen, the network must be defined through an end-to-end service-centric approach.

5.5.2 LTE energy efficiency gain

The actual transition from the traditional TETRA infrastructure to the LTE platform could introduce a significant energy saving gain without considering the adoption of any particular strategy. Referring to the most power consuming stage, that is the RF stage, the main difference between TETRA and LTE is related to modulation types and techniques. In particular, TETRA, as all the systems coming out from 2G cellular technologies, employs constant envelope modulations, which improve the efficiency of power amplifiers thanks to the low peak to average power ratio (PAPR). Recently, several techniques have been proposed in order to increase the PA efficiency. In particular, Envelope Tracking has been found to be the most effective one and has been included in the LTE standard. Envelope Tracking dynamically adjusts the supply voltage to the envelope of the RF input, allowing a better efficiency also for high PAPR modulations, like Orthogonal Frequency-Division Multiplexing (OFDM) used in the LTE system. Looking at the power consumption model, a comparison could be done considering the LTE system reference case provided by the European Seventh Framework Programme (FP7) EARTH project [6]. The reference case has been obtained from the power measurements of a 10 MHz 2×2 LTE base station, and, referring to the linear power model in (5.2), $\Delta_p = 4.7$ and $P_0 = 130$ W have been set.

5.5.3 Radio Resource Management strategies for energy efficiency

Looking at commercial cellular networks, the adoption of efficient radio resource management solutions is one of the most effective ways to reduce the overall energy consumption. As a matter of fact, network dimensioning is peak-load oriented. Therefore, most of the day the traffic is much lower than in peak hours, and a lot of energy gets wasted. The main goal of an energy efficient radio resource management scheme is to adapt the network energy consumption to the actual daily traffic load. The main way to adapt the radio resources to the users' requests is the introduction of base station sleep mode, which gives the system the possibility to put some devices of a base station in a low power state. Referring to the LTE system, several sleep mode techniques have been proposed [34]. In particular, frequency domain, system domain and time domain approaches are under investigation in current research about green wireless access networks. All the solutions focus on putting the RF power amplifiers on low consumption state. Frequency domain solutions are able to manage the available bandwidth at the base station by putting on sleep mode the relative carrier blocks. In order to maintain the same power spectral density, the reduced bandwidth requires less radiated power. Spatial domain solutions derive from the coexistence of multiple radio access technologies, which are allowed by the LTE standard: the global network energy efficiency can be improved by introducing cooperation schemes between the available access technologies. Other spatial domain solutions are reducing antenna number at the base station and dynamically configuring cells in a multicell scenario. Even if such approaches are an attractive solution for commercial LTE cellular networks, characterized by the densification of base stations and cell layers, they are not suitable for PMR networks like TETRA. Therefore, in order to design an energy efficient TETRA over LTE network, just the time domain approaches should be investigated. The most promising time domain solution is identified as cell DTX, a hardware feature based on the deactivation of some components

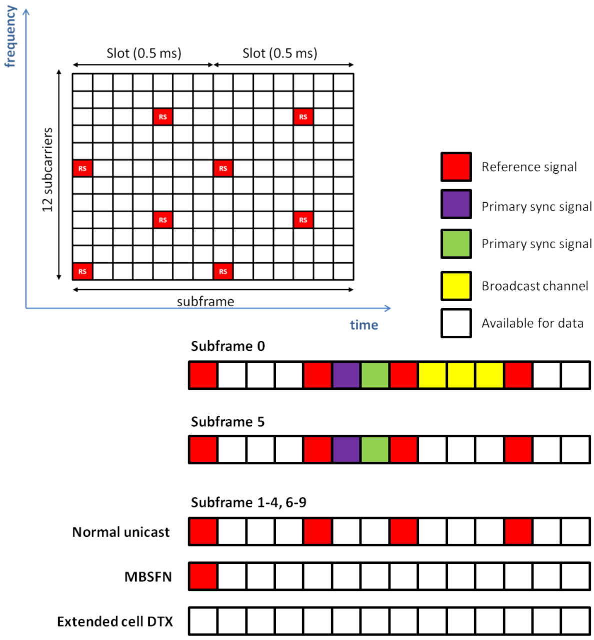


Figure 5.10: Cell DTX: power amplifiers can be put in low power state if there is no downlink traffic.

of a base station when there is no traffic, i.e., during the zero transmission time intervals [152]. As we observed before, if a base station with no traffic can be put into sleep mode, then the idle power consumption will be significantly reduced; in addition, cell DTX acts only when no data or signaling is transmitted, thereby the cell coverage is not affected. As shown in Figure 5.10, only a small fraction of each subframe must be transmitted even if the base station is not managing any traffic flow. In particular, a high cell DTX gain can be obtained using Multicast-broadcast single-frequency network (MBSFN) or extended cell DTX subframes instead of the normal unicast ones [34].

Unlike long term sleep solutions, cell DTX deactivates only some parts of the base station equipment, in order to ensure the immediate activation of the base station upon request. This approach hence allows the energy consumption to adapt to the variation of traffic in a very short time scale. Thanks to these characteristics, cell DTX is able to decrease the baseline power consumption of the base station to $P_s = \delta P_0$, where $0 \leq \delta \leq 1$. The power consumption model presented in (5.2) then can be written as follows:

$$P_{in} = N_{TRX}(\Delta_p P_{out} + (1-\delta)\eta P_0 + \delta P_0). \quad (5.4)$$

Here, η denotes the load of the base station, while $(1-\delta)\eta P_0$ represents the load dependent baseline power consumption, bound to the fast traffic adaptation property of cell DTX. Note that, in the case of $\delta = 1$, the base station does not have the DTX capability, and the power consumption model is the same as the one observed in (5.2). To compare the energy efficiency performance of the advanced TETRA systems and the 4G commercial standard LTE, we consider a volume of traffic 100 times greater than the daily average traffic load of a current TETRA base station. Figure 5.11 displays the performance of the described energy efficiency solutions for TEDS and LTE systems, in terms of daily energy consumption of a single base station. We consider TEDS systems with 50 kHz and 150 kHz bandwidths and assume $\delta = 0.1$ for the case of LTE with cell DTX. We observe that the combination of carrier sleep mode and power control on the BCCH carrier can bring striking energy savings for TETRA network, although the energy efficiency performance of such systems is very far from the performance of the current LTE commercial standard. Despite the high hardware efficiency of LTE system, the introduction of cell DTX helps to further break down the energy consumption of the network by significantly reducing the baseline power consumption of the base stations. Looking at the PMR broadband evolution over the LTE system, such a feature represents a very promising energy saving approach, considering the typical low traffic density of PMR systems, compared to cellular public radiotelephone standards.

From an economic perspective, the results presented in Figure 5.12 show the impact of the power saving features in terms of annual OPEX, considering the scenario of a regional network with 150 base stations and an energy cost of 0.20 Euros per kWh. Adopting advanced energy efficiency strategies in the TETRA network results in significant OPEX savings of up to 70 thousand Euros per year of operation, compared to the current standard technology; this positive trend is also considerable with the introduction of highly efficient cell DTX solutions in LTE networks. Regarding the sustainable development of modern communications systems, the overall network energy saving also guarantees a remarkable reduction in terms of carbon emission of CO_2: considering an average carbon emission of 525 kg of CO_2

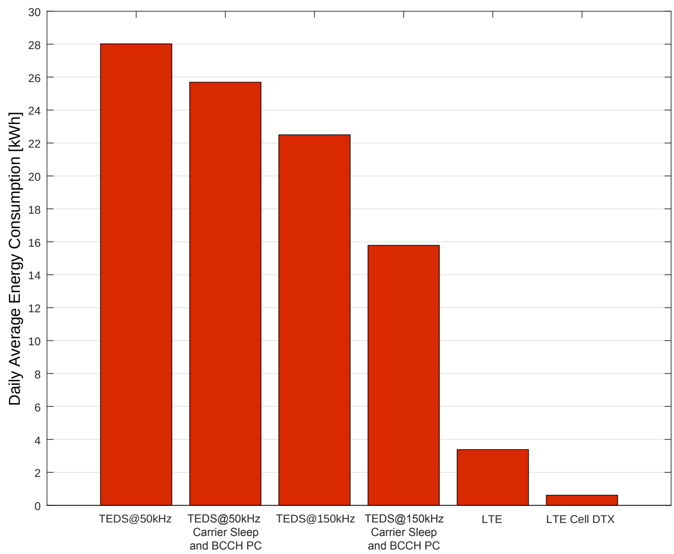


Figure 5.11: Comparison of daily average energy consumption of TETRA and LTE radio base stations.

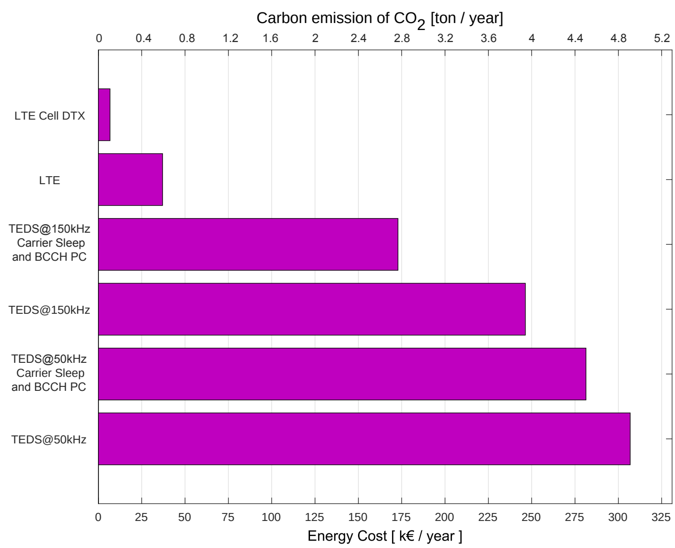


Figure 5.12: Annual energy expenditure and carbon emission of CO_2 for TETRA and LTE networks.

per 1000 kWh, the proposed energy efficiency solutions can save more than 1 ton of CO_2 per year in advanced TETRA networks. In the case of LTE systems, the adoption of cell DTX has an equally great impact, by granting more than 80% reduction of annual carbon emission of CO_2, with respect to the standard LTE network configuration.

5.6 Conclusion

In this chapter, the energy efficiency of PMR systems has been considered. First, the most common PMR system, namely TETRA, has been introduced. After a discussion on the possibility of TETRA system to converge over the LTE platform, a power consumption model for a generic TETRA base station has been proposed. Then, the most effective energy saving solutions have been introduced and evaluated. In particular, the combined adoption of carrier sleep mode and BCCH power control ensures the reduction of TETRA base station baseline power consumption. The future transition to a TETRA over LTE system has then been considered, evaluating the impact of the most promising energy efficiency solutions on a deployed TETRA regional network. Results show significant improvements in terms of capacity and energy efficiency, as well as a positive impact in terms of OPEX and carbon footprint.

Chapter 6

Green Wireless Sensor Network for ozone pollution detection

This chapter describes an innovative monitoring technology that is used to detect ground-level ozone pollution and is based on the deployment of a network of wireless devices which are connected to a collection of plants and are used as biosensors. Such devices retrieve and transmit the electrical activity signals, which are generated within the plants, and use them to monitor environmental conditions. In order to classify the morphology characteristics of plant response to ozone exposure we used a segmentation of time series measurements of the electrical activity of plants before, during and after the stimulation. Then, we extracted the significant deviations from the baseline trend to detect and identify the response to a known stimulus, in terms of correlation coefficient. As a result, the proposed detection algorithm represents a novel monitoring method for detecting critical levels of ozone concentrations. [1]

[1] The work presented in this chapter has been published as "Plant electrical activity analysis for ozone pollution critical level detection" in *Proc. of IEEE 23rd European Signal Processing Conference (EUSIPCO), 2015* [48] and as "A WSN for ground-level ozone monitoring based on plant electrical activity analysis" in *Proc. of IEEE International Wireless Communications and Mobile Computing Conference (IWCMC), 2015* [118].

6.1 Introduction

Atmospheric pollution has become one of the most serious environmental problems of the modern world. Its adverse effects are associated with the degradation of the quality of life, affecting the sustainability of urban ecosystems [91]. The problem of the poor air quality in highly anthropized environments exerts nowadays a high level of interest within the scientific community and public opinion because of the known strong relationship between exposure to many air pollutants and increased adverse effects on human health [98, 108, 110]. Among air pollutants, ozone is one of the most important greenhouse gas [60] with secondary origin, generated in the troposphere through a series of complex photochemical reactions involving solar radiation and ozone precursors, i.e. methane (CH_4), carbon monoxide (CO), volatile organic compounds (VOCs), and nitrogen oxides (NO_x), which are largely emitted from anthropogenic sources [131]. Background O_3 concentrations have risen from $\sim$10 ppb before the industrial revolution [158] to daytime summer concentrations exceeding 40 ppb in many parts of the Northern Hemisphere [157]. Due to its nature of reactive oxidant agent, ozone can generate several negative effects on human health including lung inflammation, reduced lung function, degenerative diseases, age related disorders and eventually cancer [93]. Ozone also acts as a corrosive agent for many materials, surface coatings and buildings [54]. Therefore, it is easy to understand the importance of a proper air quality management and the attention to new reliable approaches for ozone monitoring, such as the use of plants as biosensors. The most common air quality measurements exploit sensors based on the use of physicochemical properties in order to measure the concentrations of air pollutants. In comparison with the traditional monitoring systems, the use of biosensors has the advantage of showing the actual pollutants impact on living organisms, thus providing additional data to the electronic instruments. Moreover, this allows to take into account the concepts of bioavailability, dose and exposure, resulting in a more realistic approach to assess the pollutants impact on environment and human health [56]. An ideal monitoring system should be biologically-based and at the same time practical for wide use. Plants perfectly reflect this feature, being naturally widespread in our environment, easy and cheap to product and to maintain thanks to their self-sustainability. Moreover, plants are more sensitive than humans and animals in terms of physiological reaction to fluctuations of multiple parameters [166]. Because of their sessile nature, plants are indeed continuously exposed to a wide variety of environmental changes to which they are able to respond by adjusting their physiological characteristics to limit possible damages. These remarkable characteristics make plants suitable tools for environmental monitoring. More specifically, morphologicaland anatomical parameters of plants, such as specific leaf area (SLA), stomatal density (SD), and pore surface, have proven to be useful indicatorsof air quality [24]. The observationof necrosis on leaves and coloured spots allow, in certain cases, the identification of pollutant sources. The advantage of this kind of biomonitoring is to allow the follow-up of air quality evolution and the extent of its impact on vast zones at low cost. On the other hand, the interpretation of the results could be made difficult by the influence of other environmental parameters and of the ecosystems heterogeneity, requiring the participation of specialists [56]. Moreover, this kind of analysis can give us just long-term exposure information. In the present study we propose a new approach to use plants as easy and dynamic bio-sensors able to provide real-time data on air quality changes, particularly referring to ozone concentration. Ozone effect on plants determines changes in growth and appearance of visible symptoms (e.g. chlorosis, necrosis) but this response is preceded by a series of biochemical events, the so-called "hidden injury" [140]. All these changes at physiological level are reflected in the generation of electrical signals. It is known from time that plants produce electrical signals when subjected to various environmental stimuli [33, 43, 63, 133]. These electrical signals in essence represent changes in underlying physiological processes influenced by the external stimuli. Since plants react to environmental changes generating responses in the bioelectrical activity, this lead to the possibility to classify external stimuli from the typical electrical signal response [33]. The focus of our work was to find an association between ozone exposure and some typical features in the resulting plant electrical signal, in order to create a classification algorithm able to identify the stimulus. In order to obtain reliable results, automatic response detection and data classification for plant electrical signals are necessary to be developed. Many chapters reported artifact detection methods for EEG and EKG analysis [66,90,154]. Various advanced methods have been applied to detect artifacts in EEG signals, such as independent component analysis (ICA) and support vector machine (SVM) [66], wavelet analysis [90] and autoregressive (AR) model [154]. These methods were appropriate for human biological signals and offline analysis. As for the analysis of plant bio-electrical signals related to environmental changes, the

response detection algorithm needs to be simplified.
In this chapter a correlation based data classification system for plant electrical signal analysis is proposed. A dataset of electrical signals was collected from ligustrum and buxus plants exposed to ozone in controlled conditions. These species have been selected for the study because of their widespread use in urban sites. To automatically segment the signals a derivative-based detection method was designed, similarly to those used in spike detection [162]. Finally, the detected signals were classified based on correlation waveform analysis of plant response to ozone air pollution. The proposed data classification method can be extended for various research purposes by defining weight coefficients and adjusting thresholds.

6.2 Data acquisition

The experiments were performed inside a closed growth chamber, the so-called *iTreeBox*, in order to control the ozone concentration and the other environmental parameters. A picture of the *iTreeBox* chamber is shown in Figure 6.1. Inside the box plants were exposed to standard artificial light conditions by means of LED lights responding to the plants photosynthetic needs (PAR radiation). About 50 cm high plants of *Ligustrum texanum* and *Buxus macrophilla* were used for the experiments and each plant was placed in the chamber to be exposed to ozone stimuli in a controlled environment. Electrical signals were monitored by means of three stainless steel needle electrodes, one placed at the base (reference for background noise subtraction), one in the middle and the other on top of the stem. After some preliminary test, the sampling frequency was set at 10 samples/s for all the recordings. All the experiments were carried out during the day time for about 8 hours and the ozone treatment always started at least one hour after the beginning of the electrical signal acquisition to allow the plant acclimating to the artificial light and the box conditions. Before exposing plants to the pollutant, several acquisitions in natural environment conditions (without ozone stimulus) were performed, in order to monitor the physiological electrical activity of each plant. The main ozone treatment consisted of 1 hour exposure to a constant concentration of 240 $\mu g/m^3$, that is the ozone alert threshold value, as set out in [4]. Moreover, further experiments consisted in exposing the plant to incremental ozone concentrations, in order to simulate more realistic environmental conditions, as in days of summer heat. The ozone was

Figure 6.1: The *iTreeBox* plant growth chamber

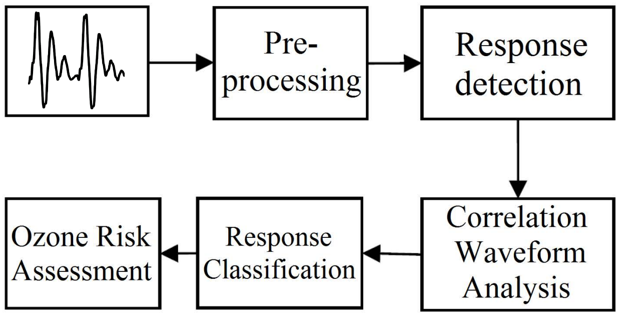


Figure 6.2: Flow chart of the detection algorithm

injected in the chamber with four increasing concentration values (60, 120, 180 and 240 $\mu g/m^3$) every 60 minutes, for a total exposure duration of four hours.

6.3 Data analysis

The proposed detection algorithm of plant response to ozone is designed according to two approaches. The first one is based on a preliminary extraction of significant deviations from a certain baseline trend: in order to correctly identify the response in an automatic way, a derivative-based algorithm has been used. The second step is based on the classification of the ozone risk level by the method of correlation. In all applications we used the signals deriving from the experiments carried out in the *iTreeBox* chamber. The methods were developed under Matlab software. The detailed flow chart of the proposed system is shown in Figure 6.2.

6.3.1 Pre-processing of the plant electrical signal

The reference signals generated by a plant are generally contaminated by different sources of noise. Since most of the energy of such biological signals is concentrated at low frequencies, we applied a low-pass filter, followed in cascade by a moving average filter to further clean the signal. Given the fact that the responses to an ozone stimulus last approximately 60 minutes, the used low-pass filter has a cutoff frequency of 5 mHz.

6.3.2 Plant response detection

In general, in response to an environmental stimulus, the plant electrical activity appears irregular for a certain period of time. We use the different characteristics induced by ozone air pollution to detect the abnormal signal waveform. In order to automatically segment the data and correctly identify the response, we implemented a derivative-based algorithm. Given the voltage signal $V(t)$ and the following parameters vector:

$$P = (A_{dV}, \Delta t_d, S_V) \tag{6.1}$$

a response is defined to occur when the first derivative of the signal decreases below a negative threshold A_{dV}:

$$\frac{dV(t)}{dt} < A_{dV}. \tag{6.2}$$

In order not to associate very quick fluctuations to actual responses, we set another threshold, Δt_d, as a minimum time duration following the onset of the response. This condition enables the accurate detection of long-lasting effects on the plant electrical activity caused by ozone exposure. Based on the supplied data, it has been noticed that the central position of the response is related to the nearest local minimum of the plant voltage signal: if the response voltage initially decreases, after a certain time period it will start to increase in order to restore the pre-stimulation baseline trend. This property was used to estimate the minimum variation in the slopes of the ozone response and set an amplitude threshold, S_V, on the voltage signal. The ozone response is then detected and extracted whenever the difference between the central location of the response, V_c, and the basal voltage V_b, that is the value of the voltage signal preceding the onset of response, exceeds the threshold S_V:

$$|V_c - V_b| > S_V. \tag{6.3}$$

In our approach, the period taken for the plant to stabilize its potential after the stimulus has to be assigned to the same response. Since such a response model has a 60 minutes average duration, the value of V_c is calculated as the local minimum of the voltage signal, while V_b is estimated to be the voltage signal value for the preceding 30 minutes. An example of detected ozone response is depicted in Figure 6.3. A representative ozone response template, constructed by coherent averaging of the respective response segments of the

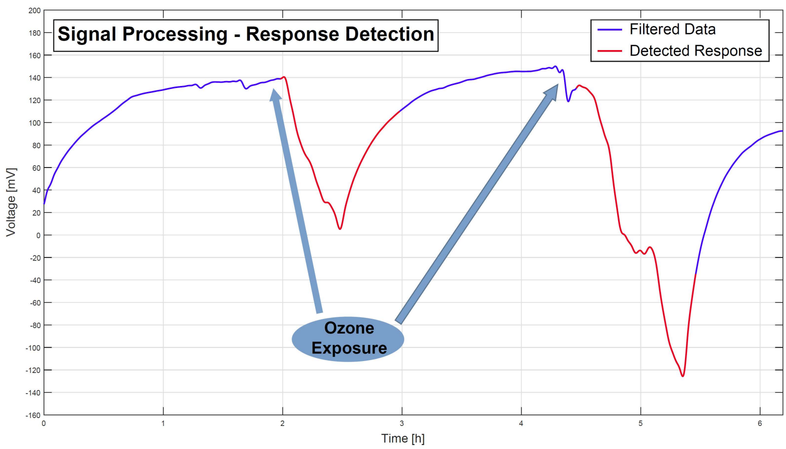


Figure 6.3: Response detection of ligustrum plant signal after ozone exposure

recordings used for the training phase, was employed for subsequent comparison with all the responses detected by the proposed system. A window size of 60 minutes was used, in order to effectively include the long-lasting repolarization phase of the plant signal.

6.4 Correlation waveform analysis for ozone response classification

Cross correlation is a statistical technique which can show whether and how strongly pairs of variables are related. It is an excellent tool to match images and signals with each other. It is robust to noise, and can be normalized for pattern matching. The correlation coefficient is a statistical measure of similarity of two waveforms; it produces a value, ρ, which falls within the range [-1,+1], where +1 indicates a perfect match between signal and template. Mathematically, the correlation coefficient is defined as follows:

$$\rho = \frac{\sum_{i=1}^{N}(t_i - \bar{t})(s_i - \bar{s})}{\sqrt{\sum_{i=1}^{N}(t_i - \bar{t})^2}\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2}} \tag{6.4}$$

where t_i are the template points, s_i are the signal points under analysis, $\bar{t}$ is the average value of the template points, $\bar{s}$ is the average value of the signal points, N is the number of points in the template, and ρ is the performance measure. The correlation coefficient is independent of the relative amplitudes of two signals and independent of any baseline changes. Based on the supplied data, it was observed that the plant response to ozone stimulus is characterized by a specific waveform. The proposed detection system takes advantage of this property to classify the risk level of ozone air pollution by using the correlation coefficient. Several studies have offered guidelines for the interpretation of the size of a correlation. The interpretation of the correlation coefficient depends on the context and purposes. In our study an empirical approach was adopted, by giving numerous plant signals to the system in order to adjust and validate the threshold values of the proposed algorithm. The correlation-based classifier has been implemented to distinguish electrical responses to critical level of ozone exposure by identifying the detected responses with very strong correlation to the template. The corresponding decision rule has been chosen by setting a threshold value of 0.73 on ρ.

6.5 Experimental results

To examine the efficiency of the algorithms, a database of 84 day-long recordings of plant electrical activity was employed. The recordings were chosen to include a broad variety of waveform responses. The database was collected from both ligustrum and buxus plants, including experiments carried out with constant or incremental ozone concentrations exposure, mixed pollutants (ozone and sulphur dioxide), as well as with natural environment conditions. The complete recordings database is summed up in Figure 6.4. The correctness of a classification can be evaluated by computing the number of correctly recognized class examples (true positives, tp), the number of correctly recognized examples that do not belong to the class (true negatives, tn), and examples that either were incorrectly assigned to the class (false positives, fp) or that were not recognized as class examples (false negatives, fn). According to [147], the following performance measures for

Table 6.1: Results from the classification algorithm

	Ligustrum	Buxus	Total Performance
Accuracy	92%	81%	87%
Precision	96%	89%	93%
Sensitivity	89%	77%	84%
Specificity	95%	85%	91%

classification are considered:

$$Accuracy = \frac{tp + tn}{tp + fn + fp + tn} \tag{6.5}$$

$$Precision = \frac{tp}{tp + fp} \tag{6.6}$$

$$Sensitivity = \frac{tp}{tp + fn} \tag{6.7}$$

$$Specificity = \frac{tn}{fp + tn} \tag{6.8}$$

The detection results of the proposed algorithm are listed in Table 6.1. The classification system is shown to be capable of discriminating the response to critical levels of ozone air pollution from the depolarizations induced by effects of natural environmental conditions with 87% accuracy. However, individual thresholds were required for each plant species and were based on the initial training phase. The total performance is high since the achieved precision and specificity are high for the ligustrum plant dataset (96% and 95% respectively), compared to the results of the buxus plant dataset (89% precision and 77% sensitivity). The main advantage of the proposed system resides in the fact that the classification algorithm based on correlation coefficient, by recognizing the degree of similarity between plant electrical signal and template waveform provides a very efficient and innovative monitoring technology for detecting ground-level ozone pollution.

6.6 Conclusion

This chapter has presented an automatic method of analysis of plant electrical signal in order to detect critical level of ozone air pollution. The experimental data were coming from plants exposed to various ozone concentrations in a closed plant growth chamber, specifically designed to recreate

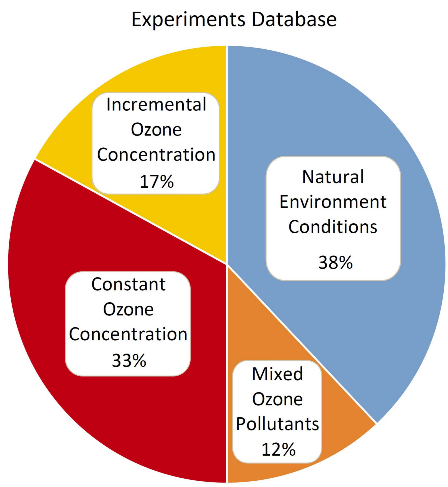


Figure 6.4: Database summary for the 84 day-long test recordings

typical environmental and daylighting conditions. The proposed classification algorithm is based on the correlation theory; it mainly recognizes the degree of similarity between a reference ozone response and the acquired plant electrical signal. Then the decision is made based on the correlation coefficient. The experimental results show that the proposed system achieves over all accuracy of 87%. Moreover the innovative approach to the problem of atmospheric pollution monitoring, based on plant electrical activity analysis, allows the classifier to be easily extended to other major air pollutant classes in future studies.

Chapter 7

Conclusion

This chapter summarizes the contribution of the thesis and discusses avenues for future research.

7.1 Summary of contribution

Wireless communications are undergoing a rapid evolution, wherein the quest for new services and applications motivates the rapid introduction of new technologies into the marketplace. In particular, the wireless communications industry has begun to pursue energy efficient solutions. This thesis provides an overview of energy-efficient wireless communications, with recent contribution to the state-of-the-art, and discusses the most relevant research challenges to be addressed in the future, by introducing some original contributions. The first step presents a multiobjective optimization framework which is aimed at minimizing the power consumption and the number of BS sleep-mode switchings in cellular networks, by jointly considering QoS requirements. These requirements are expressed in terms of a required bit rate for each mobile terminal. The framework deals with network management, such as the number of BSs that should be switched on, considering common diurnal patterns of the traffic demand. The proposed optimization technique is mixed-integer quadratic programming, which solves the joint power allocation and user association problem while also considering optimized bandwidth allocation schemes. The trade-off between the conflicting objectives, as well as the performance analysis in terms of the throughput and energy consumption of the network, is shown for different traffic load

cases. The proposed optimization can obtain up to 60% energy savings during off-peak hours, guaranteeing QoS target requirements. By optimizing the network configuration, a 70% reduction in BS switch on/off operations can be reached in a day with 3% more energy expense.
Moreover, the focus is moved to the HetNet scenario in which macro and micro cells coexist. The MIQP optimization technique is used to minimize the power consumption together with the number of BS sleep mode operations of both macro and micro cells. Results about the trade-off between power consumption, sleep mode switchings and performance of the network show that the proposed optimization can guarantee QoS target throughput for users and significant reduction of 50% for macro and 73% for micro BS respectively daily number of switchings, while still achieving 8% savings in terms of daily energy consumption.
Then the feasibility of energy efficient solutions for current and potentially future PMR networks is considered, by providing a mathematical formulation of power consumption in TETRA base stations and assessing possible business models and energy saving solutions for enhanced mission-critical operations. The energy efficiency evaluation has been performed by taking into account the traffic load of a deployed TETRA regional network: in the considered network scenario with 150 base stations, significant OPEX savings up to 70 thousand Euros per year of operation are achieved. Moreover, the proposed solutions allow for saving more than 1 ton of CO_2 per year.
Finally the study of the relationship between environmental stimuli of atmospheric pollution and electrical responses of plants has been addressed for developing technologies that use plants as organic sensing devices. An automatic method of analysis of plant electrical signals for ozone critical levels detection is proposed, based on the fundamentals of correlation theory. In order to classify the morphology characteristics of plant response to ozone exposure we used a segmentation of time series measurements of the electrical activity of plants before, during and after the stimulation. Then, we extracted the significant deviations from the baseline trend to detect and identify the response to a known stimulus, in terms of correlation coefficient. As a result, the proposed detection algorithm represents a novel monitoring method for detecting critical levels of ozone concentrations.

7.2 Directions for future work

Despite the various effort proposed to analyse and design effective green solutions, many open issues remain to be further investigated. As future research, green solutions should capture the trade-off in energy efficiency among network operators and mobile users, and should be designed to balance such a trade-off. The heterogeneous wireless access medium exhibits great potential in improving energy efficiency while satisfying the QoS of mobile users. A joint bandwidth and power allocation approach results in a significant advantage in energy-efficient communications over the power-only allocation scheme. In joint bandwidth and power allocation for uplink and downlink communications in a heterogeneous networking setting, there are many challenging technical issues that require further studies, including fairness in energy efficiency among users, achieving mutual benefits among network operators, decentralized implementation with reduced signaling overhead, interference management and implementation complexity. As future work, we plan to extend our analysis considering the lifetime degradation introduced by power management strategies. Moreover, we plan to investigate solutions applied to ultra-dense heterogeneous networks for 5G, exploiting in particular the millimeter-wave (mmWave) spectrum, which offers the potential for high-bandwidth communication channels in cellular networks.
As shown in this thesis, energy efficiency has gained in the last decade its own role as a performance measure and design constraint for communication networks, but many technical, regulatory, policy, and business challenges still remain to be addressed before the ambitious 1000-times energy efficiency improvement goal can be reached.

Appendix A

Publications

This research activity has led to several publications in international journals and conferences. These are summarized below.[1]

International Journals

1. **M. Dolfi**, S. Morosi, P. Piunti, E. Del Re. "Energy Efficiency Perspectives of PMR Networks", *MDPI Information*, vol. 8, n. 1, 2017.
[DOI: 10.3390/info8010001]

2. **M. Dolfi**, C. Cavdar, S. Morosi, P. Piunti, J. Zander, E. Del Re. "On the trade-off between energy saving and number of switchings in green cellular networks", *Wiley Transactions on Emerging Telecommunications Technologies*, vol. in press, 2017.
[DOI: 10.1002/ett.3193]

International Conferences and Workshops

1. P. Piunti, **M. Dolfi**, S. Morosi, S. Jayousi, E. Del Re. "Performance evaluation of an energy efficient RRM strategy in heterogeneous cellular networks", in *Proc. of IEEE 25th Annual International Symposium on Personal, Indoor, and Mobile Radio Communication (PIMRC)*, Washington, DC (USA), September 2014.
[DOI: 10.1109/PIMRC.2014.7136411] *3 citations*

[1] The author's bibliometric indices are the following: H-index = 2, total number of citations = 5 (source: Google Scholar on Month 10, 2017).

2. **M. Dolfi**, S. Morosi, P. Piunti, E. Del Re. “Energy Efficiency Perspectives of PMR Cellular Systems”, in *Third ETSI Workshop on ICT Energy Efficiency and Environmental Sustainability*, Sophia Antipolis (France), June 2015.
3. S. Morosi, **M. Dolfi**, E. Del Re, E. Masi, I. Colzi, S. Mancuso, F. Francini, R. Magliacani, A. Valgimigli, L. Masini. “A WSN for ground-level ozone monitoring based on plant electrical activity analysis”, in *Proc. of IEEE International Wireless Communications and Mobile Computing Conference (IWCMC)*, Dubrovnik (Croatia), August 2015.
[DOI: 10.1109/IWCMC.2015.7289171] *2 citations*
4. **M. Dolfi**, I. Colzi, S. Morosi, E. Masi, S. Mancuso, E. Del Re, F. Francini, R. Magliacani. “Plant electrical activity analysis for ozone pollution critical level detection”, in *Proc. of IEEE 23rd European Signal Processing Conference (EUSIPCO)*, Nice (France), August 2015.
[DOI: 10.1109/EUSIPCO.2015.7362821]
5. **M. Dolfi**, S. Morosi, C. Cavdar, E. Del Re. “Energy efficient optimization of a sleep mode strategy in heterogeneous cellular networks”, in *Proc. of IEEE European Conference on Networks and Communications (EuCNC)*, Oulu (Finland), June 2017.
[DOI: 10.1109/EuCNC.2017.7980740]

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