ENERGY EFFICIENCY ANALYSIS AND MODELING OF COGNITIVE AND HETEROGENEOUS WIRELESS NETWORKS

by

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ABSTRACT

ENERGY EFFICIENCY ANALYSIS AND MODELING OF COGNITIVE AND HETEROGENEOUS WIRELESS NETWORKS

The surging energy costs and the environmental consequences of energy generation and exploitation have put energy efficiency aspect of wireless systems into focus in an unprecedented manner. Moreover, the capacity expectations and requirements for wireless networks have been relentlessly increasing with the adoption of new services and sophisticated wireless terminals. In this thesis, we evaluate cognitive and heterogeneous wireless network paradigms from energy efficiency perspective that has become vital due to the above mentioned phenomena. We specifically focus on energy efficiency analysis and modeling of these systems for realizing the “green networks” objective. We first provide a comprehensive account of energy efficiency of wireless networks. At a cross-sectional level, we consider cognitive radios (CR) paradigm which is affecting all facets of wireless data communications. The CR concept is evaluated from the “energy-efficient operation” and “energy efficiency enabler” perspectives. At the microscopic level, we focus on small cells, namely femtocells, and propose a new networking paradigm called cognitive femtocell networks (CFN). We analyze them in terms of energy efficiency via our analytical model and compare their performance with that of macrocell-only networks as well as traditional femtocell networks.

ÖZET

HETEROJEN VE BİLİŞSEL KABLOSUZ AĞLARIN ENERJİ VERİMLİLİĞİ ANALİZİ VE MODELLEMESİ

Artan enerji fiyatları ile enerji üretim ve tüketiminin çevresel sonuçları, kablosuz ağların enerji verimliliğini daha önce görülmemiş şekilde önemli hale getirmiştir. Buna ek olarak, yeni servislerin ve gelişmiş kablosuz cihazların yaygınlık kazanmasıyla kablosuz ağların gereksinimleri ve kapasite beklentileri durmaksızın artış göstermektedir. Bu tezde bilişsel ve heterojen kablosuz ağ paradigmaları, yukarıda bahsedilen olgulardan dolayı önemli bir hale gelen enerji verimliliği perspektifinden incelenmektedir. "Yeşil ağlar" hedefini hayata geçirebilmek için özellikle enerji verimliliği analizi ve bu ağların modellenmesi konusuna odaklanılmaktadır. İlk olarak kablosuz ağlarda enerji verimliliği konusunu kapsamlı bir şekilde ele alıyoruz. Kesitsel düzeyde, kablosuz veri iletişimini tüm yönleriyle etkileyen bilişsel radyo (CR) paradigmasını inceliyoruz. Bilişsel radyo kavramını "enerji-verimli operasyon" ve "enerji verimliliğini sağlayıcı" perspektiflerinden değerlendiriyoruz. Mikroskopik düzeyde ise küçük hücrelere yani femto-hücrelere odaklanıyor ve bilişsel femto-hücre ağları (CFN) adı verilen yeni bir ağ paradigması öneriyoruz. Bu ağı analitik modelimiz aracılığıyla enerji verimliliği perspektifinden değerlendirerek başarımını geleneksel femto-hücre ağları ve sadece makro-hücrelerden oluşan bir ağ ile karşılaştırıyoruz.

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LIST OF SYMBOLS

C_c	Throughput at a cognitive femtocell user
C_m	Throughput at a macrocell user
C_f	Throughput at a femtocell user
E_{CFN}	Energy consumption of a Cognitive Femtocell Network
E_{FN}	Energy consumption of a femtocell network
E_{MN}	Energy consumption of a macrocell network
E_f^{rx}	Enery consumption of a femtocell user due to data reception
E_f	Total enery consumption of a femtocell user
E_f^i	Enery consumption of a femtocell user due to idling
F_C	Frequencies available at a cognitive femtocell base station
F_F	Frequencies available at a femtocell base station
F_M	Frequencies available at a macrocell base station
F_{CR}	Number of cognitive frequencies that are at the possible use of cognitive femtocells
N_F	Number of femtocell base stations
N_C	Number of cognitive femtocell base stations
n_m	Number of macrocell users
n_p	Number of primary users
n_f	Number of femtocell users
n_c	Number of cognitive femtocell users
N_0	Noise power at the receiver
P	Received signal power
P_C^{bh}	Backhaul power consumption at the cognitive femtocel base station
P_C^{in}	Input power at the cognitive femtocel base station
P_C^{out}	Output power at the cognitive femtocel base station
P_C^s	Sensing power consumption at the cognitive femtocel base station

P_C^i	Idling power consumption at the cognitive femtocel base station
P_d	Probability of detection
P_f	Probability of false alarm
P_c^{rx}	Enery consumption of a cognitive femtocell user due to data reception
P_c^{cs}	Enery consumption of a cognitive femtocell user due to channel switching
P_c^i	Enery consumption of a cognitive femtocell user due to idling
R	Radius of the macrocell base station coverage
r	Radius of a (cognitive) femtocell base station coverage
S	The amplitude of the transmitted signal
T_s	Sensing period
W	Channel bandwidth

δ_F	Average number of channel switching per time slot
λ_c	Probability that a cognitive femtocell user has downlink traffic
λ_m	Probability that a macrocell user has downlink traffic
λ_f	Probability that a femtocell user has downlink traffic
η	Energy efficiency
η_{CFN}	Energy efficiency of a Cognitive Femtocell Network
η_{FN}	Energy efficiency of a Femtocell Network
η_{MN}	Energy efficiency of a Macrocel Network

LIST OF ACRONYMS/ABBREVIATIONS

AAA	Accounting, Administration and Authorization
AWGN	Accounting, Administration and Authorization
BAU	Business-As-Usual
BS	Base Station
CAGR	Compound Annual Growth Rate
CAPEX	Capital Expenditures
CFR	Crest Factor Reduction
CF	Cognitive Femtocell
CFBS	Cognitive Femtocell Base Station
CFN	Cognitive Femtocell Network
CFU	Cognitive Femtocell User
CMOS	Complementary MetalOxide Semiconductor
CR	Cognitive Radio
CRN	Cognitive Radio Network
DSA	Dynamic Spectrum Access
DSL	Digital Subscriber Line
DVB-SH	DVB
DVS	Dynamic Voltage Scaling
ECO	Eco-sustainable
ECR	Energy Consumption Rating
EDC	Efficient Duty Cycle
EE	Energy Efficiency
EM	Electromagnetic radiation
ERG	Energy Reduction Gain
EV	Electric Vehicle
FBS	Femtocell Base Station
FCC	Federal Communications Commission
FN	Femtocell Network

FU	Femtocell User
GeSI	Global e-Sustainability Initiative
HARQ	Hybrid Automatic Repeat Request
HetNet	Heterogeneous Networks
HPA	High Power Amplifier
ICT	Information and Communications Technology
ITU	International Telecommunication Union
IEEE	Institute of Electrical and Electronics Engineers
IMS	IP Multimedia Subsystem
LTE	Long Term Evolution
MAC	Medium Access Control
MBS	Macrocell Base Station
MU	Macrocell User
OTT	Over-The-Top
OFDM	Orthogonal Frequency Division Multiplexing
OPEX	Operational Expenditures
PA	Power Amplifier
PAPR	Peak-to-Average Power Ratio
P2P	Peer-to-Peer
PHY	Physical layer
PU	Primary User
PSM	Power-Saving Mode
QoS	Quality of Service
REM	Radio Environment Map
RF	Radio Frequency
RFIC	Radio Frequncy Integrated Circuit
SON	Self-Organizing Network
SDR	Software-Defined Radio
SU	Secondary User
SINR	Signal to Interference plus Noise Ratio
SIP	Session Inititation Protocol

TVWS	TV White Space
VLSI	Very Large Scale Integration
WLAN	Wireless Local Area Network
VNI	Visual Network Index
WSDB	White Space DB
WSN	Wireless Sensor Networks
4G	Fourth Generation

1. INTRODUCTION

Mobile broadband explosion and upcoming broadband wireless standards are putting a heavy burden on mobile networks for serving a traffic explosion in parallel with new services and multimedia-rich content. The emerging diverse range of services and modalities bring forth new players and factors such as OTT (Over-The-Top) service providers (e.g. Skype and YouTube) and P2P (Peer-to-Peer)-based content sharing, which heavily tax the network resources [1]. According to Cisco VNI forecast, by 2017, global mobile data traffic will reach 11.2 exabytes per month (134 exabytes annually); growing 13-fold from 2012 to 2017 [2]. This forecast is depicted in Figure 1.1 for different regions of the world. It is expected that mobile video will represent 66% of all mobile data traffic and 45% of global mobile data traffic will be offloaded to fixed networks. Additionally, tablets will account for more than 12% of global mobile data traffic and 4G connections will account for 45% of global mobile data traffic by 2017. Therefore, worldwide mobile network operators are struggling to ramp up their capacity and are drawn to upgrade their own network to the latest standards for mobile broadband (e.g. Long Term Evolution, LTE). However, the network operators generally cannot charge for these high bandwidth services while the network resources are stretched to provide adequate QoS levels. In other words, this trend is in contrast with the decline in average revenue per user and their profitability, and the fast adaptation of new standards. In that regard, novel technologies and mechanisms are crucial since the wireless networks are expected to provide much higher capacity in an adaptive manner and to scale more flexibly in time and space.

This huge increase in mobile data traffic implies another profound challenge in addition to meeting service requirements: the drastic surge in energy consumption. Energy consumption of man-made systems has been a major issue due to environmental consequences of energy production and surging energy costs [3]. For instance, in Japan, network power consumption in 2025 is predicted to be 13 times the 2006 level, especially due to the anticipated increase in traffic volume with broadband services and machine-to-machine bursty traffic originating from cloud computing [4]. By 2008

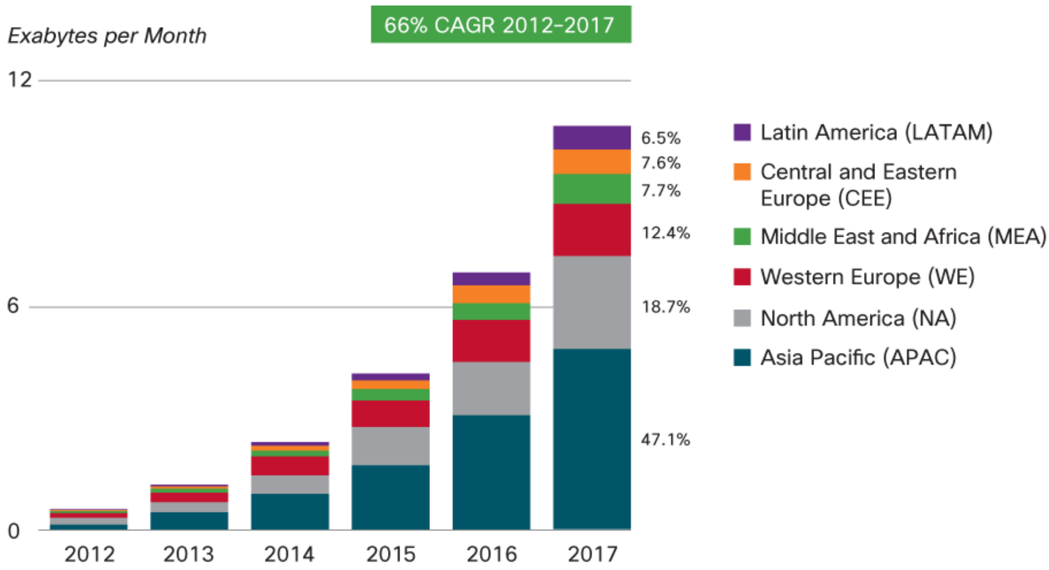


Figure 1.1. Global mobile data traffic forecast by region (source: Cisco VNI Mobile Forecast 2013, CAGR: compound annual growth rate).

figures, it was estimated that 3% of worldwide energy consumption was caused by the ICT infrastructure that generated about 2% of the worldwide CO_2 emissions [5]. Therefore, it is paramount to devise algorithms and solutions for more energy-efficient network operation [6]. In that regard, energy efficiency is an important requirement for any emerging mobile network or standard.

In this thesis, we consider an important part of this wide research topic and focus on cognitive and heterogeneous wireless networks. The heterogeneous network architecture is shown in Figure 1.2. In the next chapter, we discuss and elaborate on the general issue of energy efficiency in wireless networks. We then delve into the connection between energy efficiency and cognitive radios (CR) in the following chapter. Cognitive radio paradigm that emerged in late 1990s [7] changes the traditional spectrum access and management that is based on licensing and strict regulations to a more dynamic scheme that facitates the use of unused spectrum in an opportunistic manner. In this scheme, a CR equipped with various sensors such as sensors for spectrum sensing can detect the spectrum opportunities that are licensed but not used at a time and geographical location. In CR context, the actual owners of the spectrum are called *primary users* (PU) and opportunistic users are called *secondary users* (SU) or cognitive radios (CR). This access paradigm is referred to as *Dynamic Spectrum*

Access (DSA). DSA improves spectrum efficiency by letting CRs use PU bands that stay idle. However, DSA regulations necessiate that this opportunistic access of SUs must not harm the PU communications. CRs can ensure this requirement by performing spectrum sensing or accessing the PU occupancy information through the Radio Environment Maps (REM), the entity that stores or derives spectrum use information at a geographical location [8]. In addition to DSA capability, other important aspects of CRs are self-awareness, environment awareness, and adaptive operation which we call cognitive functionalities in general. A CR is self-aware such that it has the knowledge of its internal states, e.g. hardware or user requirements. It is environment-aware thanks to its sensors so that it can consider the restrictions of this environment, e.g. radio frequency environment. By the help of the *cognitive engine*, an entity that implements various reasoning and learning mechanisms, CR can adapt to the environment and can select the best mode of operation. Cognitive functions in wireless network nodes are beneficial for leveraging intricate trade-offs among energy efficiency, performance and practicality. There are two fundamental but entangled aspects of CRs in green communications context: leveraging CRs for energy efficiency and operation of CRs with energy efficiency. In practice, these two objectives overlap since the improvement of energy efficiency with CRs require efficient CRs, whereas efficient wireless communications require cognitive abilities at different network components and protocols. However, there are intrinsic challenges such as hardware complexity, algorithmic problems and design trade-offs. In Chapter 4, we present and discuss these issues to highlight the case of CRs for green wireless communication systems. Additionally, some fundamental trade-offs that emerge from these challenges and their impact on greening communications via cognitive functions are outlined.

Similar to CRs, another approach is the deployment of small cells. Femtocell networks improve frequency reuse in residential or small indoor areas via low-power miniaturized access points, also known as *femtocell base station* (FBS). The FBS located typically a few tens of meters away from the user device can maintain high signal quality at the user as opposed to farther away macro-BS (MBS) with poor signal quality [9]. An FBS serves the users inside its coverage area through the licensed spectrum as an extension of the cellular operator's network. These devices are also

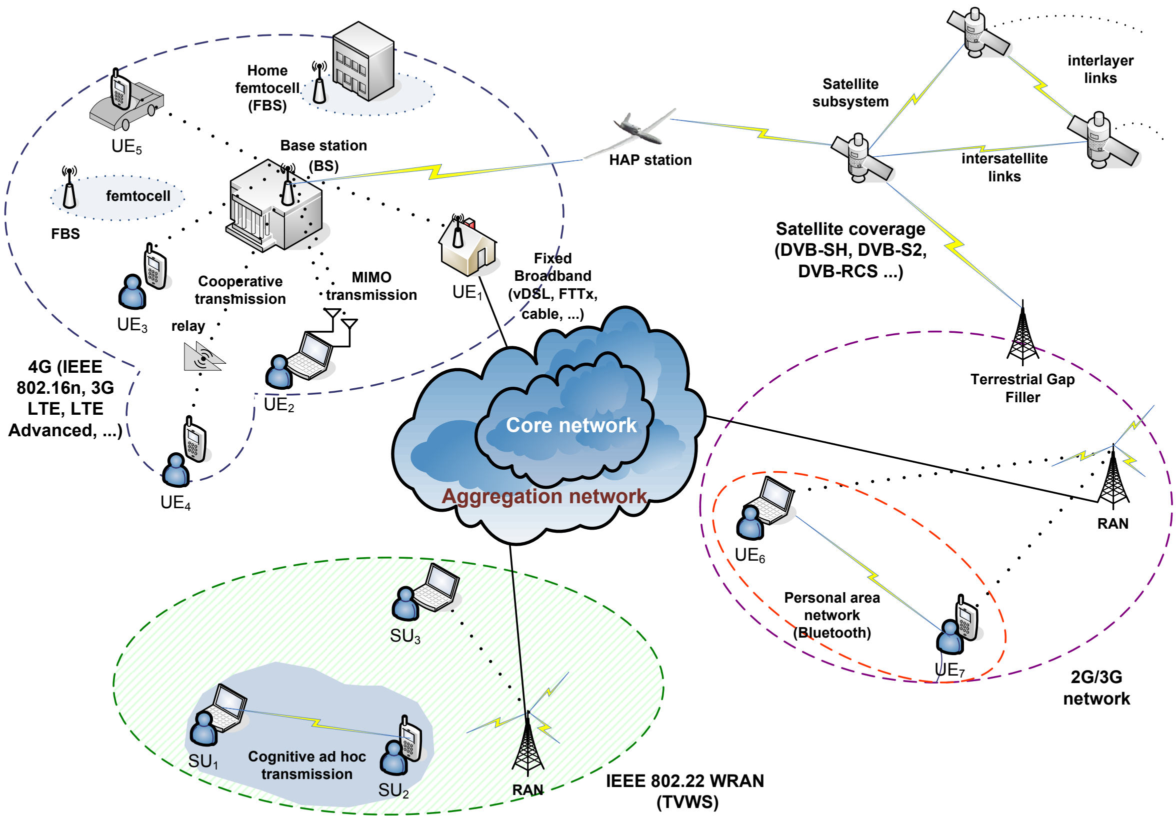


Figure 1.2. The heterogeneous wireless network architecture entailing different network types and technologies.

referred to as *home base stations* as they have all the functionalities those of an MBS but in a scaled-down version due to smaller coverage: coverage area, number of users being served, transmission power, and equipment cost. Providing high quality services indoors is paramount to the operators as a significant portion of voice traffic (50%) and over 70% of data traffic originate from indoors [10]. In Chapter 5, we define and propose a femtocell-based cognitive radio architecture for enabling multi-tiered opportunistic access in next-generation broadband wireless systems. This architecture denoted as *cognitive femtocell network (CFN)* combines the conventional femtocell idea with infrastructure-based overlay cognitive network paradigm. It consists of FBSs with cognitive radio capabilities, or cognitive capabilities in general [11,12]. FBSs with these capabilities are called cognitive FBSs and referred to as CFBS. Although the cognitive capabilities may have different interpretations in different domains, the main rationale is that CFBSs are supposed to analyze, adapt to and learn from the operating RF environment. In that regard, we can enumerate the following interwoven concepts: dynamic spectrum access (DSA) and spectrum management, self-organization without human involvement, traffic prediction-based opportunity usage, transmit-power control, and energy-efficient operation. The complex interaction among these properties implies a complex setting for CFN research. We highlight the drawbacks and advantages of the proposed network structure with a discussion on research directions for cognitive femtocell architecture. We also provide experimental results to illustrate a general proof of concept for this new modality.

CFN concept is promising as a potential component of future heterogeneous networks. However, the ongoing mobile traffic explosion is also expected to result in higher energy consumption and larger carbon footprint which is a major challenge against green communications objective. Thus, energy efficiency has become a key research focus for these systems. In Chapter 6, we analyze the introduction of cognitive femtocells into wireless networks from energy efficiency perspective. We develop an analytical model for such CFN-deployed heterogeneous networks and evaluate the impact of CFN proliferation on energy consumption discussing the relevant tradeoffs and practical issues.

1.1. Contributions and Thesis Outline

In this thesis, we are concerned with issue of energy efficiency in next generation networking paradigms, understanding the operation of the networks from an energy efficiency perspective and then designing more energy-efficient systems with new architectures and protocols for this purpose. The contributions of this thesis can be listed as follows:

(i) Energy efficiency and wireless networks (Chapter 3): A complete analysis of wireless networks from the energy efficiency perspective spanning from wireless devices to networks/systems is performed. We identify fundamental trade-offs, energy efficiency (EE) metrics, energy consumption sources and applicable EE improvement approaches. Moreover, the potential energy efficiency factors and directions are explored.

(ii) A through discussion of various aspects of CRs for energy efficiency and energy efficiency for CRs (Chapter 4): The two prominent objectives of leveraging CRs for energy efficiency and operation of CRs with energy efficiency are analyzed. The emerging trade-offs due to these two objectives are elaborately laid out and discussed, which provides a solid starting point for novel green CR research.

(iii) Cognitive Femtocell Architecture (Chapter 5): We propose a new network architecture that embraces cognitive radio functionalities at the femtocell devices in a macrocell network that additionally deploys femtocell base stations. To the best of our knowledge, our work is the one of the first proposals of the "cognitive femtocell concept" and it has lead to many follow up research papers. We present this concept in Chapter 5. Our research shows that this new architecture can be beneficial for both CRs and macrocell networks. We also list various cognitive functionalities that can be implemented at femtocells for more efficient networking. In addition to being the frontier work on this new paradigm, our work differs from the followers in a way that we also provide a new CR operation principle through femtocells. In our work, we let CRs to get service through CFBS which have higher spectrum detection reliability due to more advanced sensing hardware.

(iv) A novel analytical model for energy efficiency analysis of CFN proliferation (Chapter 6): The contribution of our work in that chapter is two-fold. First, we propose an analytical model to derive the energy consumption and throughput of three networks: a macrocell-only network, a macrocell network that also deploys femtocells, and a cognitive femtocell network consisting of a macrocell, various femtocells, and cognitive femtocells. Second, we analyze the energy efficiency and throughput for heterogeneous network settings. We compare the energy efficiency and throughput performance of these three networks under increasing number of users and increasing number of cognitive femtocells. Benefits and drawbacks of cognitive capabilities at small cells is not yet explored adequately from an energy efficiency viewpoint [13]. Our research shows that CFNs do not only improve throughput but also improve the energy efficiency of the network, if the interference among the network entitites is kept controlled.

In this thesis, we consider energy efficiency improvement techniques at the "soft level", which implies algorithmic, protocol or system design approaches for wireless systems and networks. The "hard level" approaches such as hardware design or circuit-level improvements are not investigated although these are also critical tools for energy efficiency. In the next chapter, we provide some background on the abovementioned networking paradigms. Chapter 3 presents the topic of energy efficiency in wireless networks discussing fundamental aspects such as energy efficiency metrics. Chapter 4 provides a general framework for greener wireless networks by applying the cognitive capabilities while Chapters 5 and 6 focus on CFNs. Finally, Chapter 7 concludes this thesis by summarizing our key contributions in addition to a discussion on possible future directions.

2. RELATED WORK

In this chapter, we provide the related background and work on each contribution listed in Chapter 1. The general topic of energy efficiency in wireless networks is conveyed in Chapter 3. Therefore, it is not covered in this chapter to prevent a redundant presentation.

2.1. CRs and Energy Efficiency

An important survey focusing on CRs and EE is [6] constituting the main content of Chapter 4. Most of the work in the literature on CR regarding EE has focused on minimization of energy consumption due to spectral sensing in CRs [14]. Since there is a direct trade-off between enegy consumption burden of sensing and reliability, this topic has been studied in that context. In [15], a tradeoff between the sensing duration and the transmission duration is investigated for maximizing the throughput. The system has sensing diversity, i.e. each user may have different sensing durations. Then, the tradeoff is designed for each single user. Energy-efficient spectrum sensing schemes are proposed for this setting. Spectrum sensing in cognitive sensor networks is studied in [16] to minimize the energy consumption subject to the constraints on both detection probability P_d and false alarm probability P_f. In [17], a cluster-and-forward based spectrum sensing scheme is proposed to save energy. In [18], a novel metric is proposed to evaluate the average sensing EE of CR networks. Moreover, an efficient terminal-assignment strategy for coordinated spectrum sensing is proposed and evaluated. The above works focus on the energy consumption due to sensing and reporting local sensing data. However, it is crucial to consider a more integrated approach and to investigate the energy consumption of sensing, reporting and transmission jointly [14]. A more comprehensive treatment of this subject is provided in Chapter 4.

Table 2.1. Related work on CFN.

Topic	**Related works**
Survey and general issues	[19, 20]
Resource allocation	[12]
Interference management	[21–23]
Opportunistic access	[24, 25]
Energy efficiency	[13]

2.2. Cognitive Femtocell Networks (CFN)

Femtocells improve the spectrum efficiency via improving the frequency reuse in small areas, e.g. home coverage. However, the biggest challenge in efficient femtocell operation is the interference between the layers - macrocell layer and the femtocell layer, and among the femtocells in the femtocell layer. To tackle or mitigate its detrimental effects of this interference, sensing of the frequency use as performed in cognitive radios can be beneficial for a more informed selection of the operation frequency at each femtocell. We call these FBSs equipped with various cognitive capabilities as *Cognitive Femtocells* (CF) and refer to them as CFBS. The related CFN work in the literature is summarized in Table 2.1 and discussed below.

Advantages of facilitating CR capabilities at the FBSs are manifold [19]. Femtocells use the spectrum band owned by the macrocell operator in either orthogonal manner or in the co-channel allocation, the first resulting in inefficient spectrum usage and the second in interference issues. A CFBS can discover the spectral opportunities in its neighborhood by applying various spectrum sensing policies. Then, it can apply an environment-aware resource allocation such that both the co-layer and cross-layer interference are kept in non-disruptive levels. These policies can dynamically operate based on parameters such as traffic requirements, user locations, traffic density, spectral opportunity prediction, and maximum allowed transmission power levels [20]. Hence, higher spectral capacity is available for the femtocell services. In the literature, CF concept is mostly accepted as a promising solution for tackling interference created by the femtocells. Since CRs possess radio scene awareness, they enable CFBS to select the channels that are not in use. This opportunistic operation is called interference avoidance [26]. One of the very recent papers on cognitive femtocells [26] provide a brief overview of interference avoidance, cancellation, and alignment schemes facilitated by CFBSs. This paper also demonstrates a CR-enabled FBS architecture that consists of spectrum state database (also a part of cognitive engine), cognitive module (e.g., consisting of spectrum sensing block at PHY and traffic estimation block at higher layers), and a self-configuration module (e.g., implementing spectrum handover, sharing, and transmission configuration functionalities). In [12], Zhang *et al.* formulate the downlink spectrum sharing problem in cognitive radio femtocell networks, and employ decomposition theories to solve the problem. The experimental results indicate that CR enabled femtocells could achieve much higher capacity than the femtocell networks which do not employ agile spectrum access.

In CFNs, offloading some portion of transmission on the femtocell operator bands to vacant CR bands decreases the interference on the operator frequencies and this in turn increases the system capacity. Since a wider bandwidth is available to the users compared to the conventional femtocells operating under static spectrum access mechanism, average interference for each frequency band decreases. This enhancement is fundamental since femtocells are deployed by the users with no prior frequency planning. Due to lack of careful resource planning as done by the operator deployed base stations, femtocells may experience the challenge of uncontrolled interference [27]. Hence, it is paramount to provide efficient interference management. In [21], Bennis *et al.* devise a game theory and stochastic approximation based approach in order to combat with femto-to-macrocell cross-tier interference. The proposed algorithm relies on the observations of the signal to interference plus noise ratio (SINR) of all active communications in both macro and femtocells when they are fed back to the corresponding base stations. The experimental results indicate that CR enabled femtocells could achieve much higher capacity than the femtocell networks which do not employ agile spectrum access [12]. Similarly, Adhikary *et al.* [24] propose a system where femtocells can decode the macrocell control channel and then exploit the unassigned time and frequency slots for their opportunistic transmission. Thus, the femto-macro interference can be reduced with the proposed cognitive approach. In [22], Lien et al. leverage the cognitive radio technology in order to mitigate cross-tier interference in femtocell networks. A strategic game for resource management is proposed for autonomous femtocell networks avoiding any modification on existing infrastructures. Interference management for wireless networks containing femtocells with CR technology is also studied in [23]. Attar *et al.* investigate on how to mitigate co-channel interference for LTE networks and propose two game-theoretical mechanisms. In [28], Liang *et al.* consider the incumbent GSM networks in the context of cyber-physical systems. Drawing on statistical analysis of real-scene measurements, they propose an Efficient Duty Cycle (EDC) model to accurately characterize the GSM white space to realize cognitive femtocells.

Tighter cooperation and coordination among network tiers is also possible for utilizing the trade-off between interference and throughput. In [25], Urgaonkar et al. investigate two different models of opportunistic cooperation between secondary (femtocell) users and primary (macrocell) users in cognitive femtocell networks. In both models, the secondary users must make intelligent cooperation decisions as they seek to maximize their own throughput subject to average power constraints. By providing controlled interference management, CRs can improve the system capacity in both femtocell coverage and the macrocell footprint. The handover rate and cell coverage area can be tuned in an adaptive manner with cooperative cognitive engines utilized by network nodes. This is also related to the self-organization capability which improves the network organization with easier deployment and less management burdens. This capability is critical since femtocells are deployed by the users with no prior frequency planning.

2.3. Energy Efficiency of Cognitive Femtocells

There has been relatively little CFN related research on energy efficiency compared to other femtocell topics. However, these next-generation systems are also supposed to be evaluated from the green communications perspective as other network types have been. Because this envisaged mode of environment-friendly operation is critical not only for protecting the environment, but also for the very benefit of the cellular operators. A substantial amount of operational expenses of cellular network operators is caused by energy consumption in radio access network. Hence, operators will also benefit from energy-efficient systems and infrastructure. In this vision, FBSs operating with lower power owing to the receiver-transmitter proximity have better energy-efficiency and are already accepted as green devices. Similarly, CRs supporting energy-efficient operation, e.g. cognitive power control, have significant potential towards green communications [6]. It is now imperative to have an energy cost perspective in the design and operation of wireless communications. However, to the best of our knowledge, the energy efficiency of CFNs is an overlooked issue. Hence, there is very limited research [29]. Diffferent from this general cognitive femtocell research, a more recent work on CFNs focusing specifically on energy efficiency is [13] where Xie *et al.* develop a game theoretic approach for energy-efficient resource allocation. They formulate this problem as a Stackelberg game in heterogeneous CR networks. Moreover, different from our work, they assume that both MBS and FBS have CR capabilities. Authors propose an energy efficient spectrum sharing scheme for CFNs that also adapt transmission power of the femtocell. In the considered system, in addition to intelligence at femto-layer, macrocell-layer is also CR-enabled. This CR-enabled macrocell BS (CBS) buys spectrum from the primary networks with some offered price. Then, CBS allocates this spectrum to either femtocells or directly to users in its own coverage. In both cases, transmission power is adapted to maximize the energy efficiency.

A CFBS can dynamically change both its own transmission power and assign appropriate transmission powers to users in its coverage. This energy-aware power assignment obviously improves the energy efficiency at both ends of the communication. This dynamic operation is based on various factors: traffic requirements, traffic activity level, interference environment, and battery levels, to name a few. For instance, a CFBS depending on its traffic conditions can drop its transmission power and even close down in case there are not active users in its coverage. Especially in case of residential closed subscriber groups, during some certain time periods (e.g. nights or working hours), there may be no traffic activity. In those cases, via learning algorithms or threshold based algorithms (e.g. if there is no activity for t time period, than CFBS switches to sleep mode), a CFBS can switch off. This mode of operation is greener than the traditional hard switch on-off operation [19]. Using this approach, Ashraf *et al.* design a user activity detection scheme at femtocells that improves energy efficiency of the femtocells by letting them switch off in case of no active calls [30].

While CRs can empower femtocell networks with their embedded intelligence and advanced operation functions, they also induce diverse challenges of hardware and software complexity in addition to the management of more complicated systems [19]. The incumbent challenges of CRs apply to the context of femtocell integration: spectrum sensing and PU detection, efficient protocols for cognitive operation and new business models are the most apparent challenges that need considerable effort for efficient fusion of the CR paradigm and femtocell networks. CFNs should be evaluated from an energy efficiency perspective if they are to be adopted as a part of heterogeneous green cellular networks. In this thesis, we analyze the effect of CFBS proliferation on the energy efficiency of cellular networks. We setup a general system model with relevant cognitive capabilities and investigate the overall system performance under various conditions.

Our work differs from these two papers in that we provide a general framework to assess the energy efficiency performance of a macrocell network that in addition to macrocell users is composed of various combinations of the following two small cells: femtocells and cognitive femtocells. We do not delve into physical layer specifications etc. but rather give a system level analysis for an understanding of the most general deployments of macrocells, femtocells, and cognitive femtocells.

3. ENERGY EFFICIENCY AND GREEN COMMUNICATIONS CONCEPT IN WIRELESS NETWORKS

Although the proliferation of wireless networks has been going on for many years, explicit concern about their energy-efficient operation has recently gained unprecedented importance. This issue is related to six fundamental drivers in wireless communications:

- Smaller form-factor devices with more advanced services and applications
- More mobility and more ad hoc settings
- The requirement of more complex and diverse capabilities for facilitating ubiquitous and immersive communications experience
- The emergence of green communications concept and environmental issues related to energy generation/consumption and sustainable development
- Operational expenditure reduction via minimization of energy usage
- The widening gap between the level of improvements in energy storage capabilities (i.e. batteries) and the rapid advances in power-efficient circuit design

Energy efficiency is a fundamental constraint in the operation and design of communication networks consisting of battery-operated devices while it is even more challenging in some wireless networks where energy may be entirely non-renewable such as wireless sensor networks (WSN) [31]. For instance, satellites are operated by solar panels or batteries which are limited in energy capacity. Moreover, non-terrestrial space platforms are supposed to utilize much less intense solar radiation operating under more hostile conditions. In a WSN which is typically composed of battery-operated sensor nodes with restricted and non-rechargeable energy resources, network lifetime is limited by the energy use of the sensor nodes. Hence, how energy is used for transmission, reception and related functionalities is the principal factor affecting the network lifetime [32]. In addition to the energy being the primary limiting resource for wireless networks, the network lifetime related to the energy use for transmitting and processing is also a significant performance metric [33]. Considering these factors, energy efficiency must be considered in every aspect of network design and operation, not only for individual network segments, but also for the communication of the entire network [34]. Energy efficiency and power control are vital for wireless network performance, for example, in terms of throughput and delay. Choice of transmission power affects many factors such as energy, success probability, delay, interference, and buffer overflow [35].

The fundamental concept of wireless communications is based on the theory of exchanging electromagnetic signals among wireless network nodes [36]. The conventional network topology models usually treat links as binary-natured, i.e. there is a connection or not. However, this model does not fit to the nature of wireless networks since the signal strength at a specific distance is a decreasing function of the distance from the source of the signal. Therefore, instead of a binary-natured link concept, a relative concept is more appropriate. The signal strength at a distance r denoted by $S(r)$ is calculated according the radio propagation formula below [31]:

$$S(r) = Sr^{-\alpha} \tag{3.1}$$

where S is the amplitude of the transmitted signal, r is the distance from the transmitter, $S(r)$ is the amplitude of the received signal at distance r, and α is a parameter whose value ranges from 2 to 4. This nonlinear characteristic incurs nonlinearity advantages: multihop performing better compared to single hop transmission in terms of energy cost. In other words, more hops utilized in an efficient way during a transmission will cause smaller energy expenditure. However, the peculiar characteristics of wireless transmission does not allow for such a straight-forward conclusion. There is also the additional processing overhead for each intermediate node. In general, although processing energy of a node is smaller than the transmission energy, it may manifest its effect for low rate codes and penalty for large number of hops [33]. Also, broadcasting is different since it entails one-to-many information flow with single downlink wireless transmission. The network scale (the physical separation and number of nodes in the network) is an important factor since it determines the system operation point for these factors.

Transmission power control is one of the mechanisms that can be considered in the scope of energy efficiency. It is motivated from two prospective benefits: energy savings via transmission power minimization and capacity improvement due to interference avoidance [37]. As an illustration, we discuss how the transmission power is intricately associated with the reliable transmission of a single packet [38]. For any particular link $<i, j>$ between a transmitting node i and a receiving node j, let $P_{i,j}$ denote the transmission power. Any signal transmitted is affected by two different factors: attenuation due to the medium, and interference with ambient noise at the receiver. The attenuation is proportional to r^{α} as noted in Equation 3.1. The bit error rate associated with a particular link is essentially a function of the ratio of the received signal power to the ambient noise. For additive white Gaussian noise (AWGN) channel and point-to-point transmission, Shannon's capacity formula provides the achievable rate as

$$R = W \log_2 \left(1 + \frac{P}{WN_0}\right) \tag{3.2}$$

where W is the channel bandwidth (Hertz), P is the received signal power (Watts) and N_0 is the noise power at the receiver (assuming interference is included), respectively. In the constant-power scenario, $P_{i,j}$ is independent of the characteristics of the link $<i, j>$ and is a constant. In this case, a receiver located further away from a transmitter will suffer greater signal attenuation (proportional to r^{α}) and will, accordingly, be subject to a larger bit-error rate. Moreover, this scenario results in the same amount of energy being consumed at the transmitting node (over a given time) regardless of whether the receiving node is in the outer portion of the range of the transmitter or in the immediate vicinity of the transmitting node [37].

In the variable-power scenario, transmitter only sends with the power needed for their intended receiver to satisfy some link performance target via taking advantage of source and destination proximity. In other words, a transmitter node adjusts $P_{i,j}$ to ensure that the strength of the (attenuated) signal received by the receiver is independent of r and is above a certain threshold level. This is the idea of transmission power control which exploits these dynamic factors such as transmitter-receiver distance and channel variations, and thus provides both higher capacity via interference avoidance and more energy-efficient operation. It is also related to dynamic coverage management at the network level, which aims to exploit traffic variations in cellular networks [39]. However, due to wireless channel characteristics, attaining transport efficiency via this mechanism is not clear-cut. There are channel impairments such as multipath effects and fading, delay due to propagation and processing, and disruptions in network topology. This point-to-point analysis becomes inadequate when a networked set of transceivers is considered in a network setting. Moreover, when energy efficiency is considered, one has to consider other factors such as processing overhead in addition to transmission power. Therefore, energy optimization in wireless networks is a complicated issue even when the fundamental concept of power control is considered.

The energy minimization problem in wireless communications should be considered in all aspects from physical layer (PHY) functionalities to application layer approaches. Broadly speaking, main motive for attaining energy efficiency is twofold. First, in the design of newly emerging state-of-the-art systems, energy consumption must be considered through all phases of their design from system conception to the device and technology level. Second, systems should be managed efficiently from the power viewpoint while they are in operation [40]. Low-power techniques vary depending on the level of the design targeted, ranging from semiconductor technology to the higher levels of abstraction. These abstraction levels are classified as algorithm, architecture, register transfer, gate, and transistor levels. Figure 3.1 shows various levels of hierarchy that should be considered for low-power designs. There may also be couplings among various layers of communication protocol stacks. For instance, there exists a value (with respect to the fast fading) of the average Signal to Noise Ratio (SNR) which maximizes the energy efficiency of a communication link between two wireless

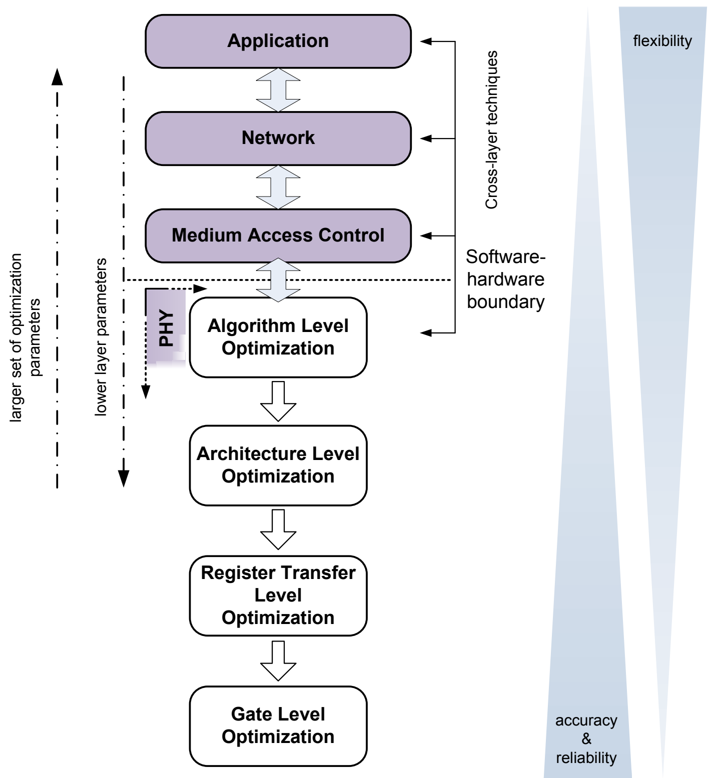


Figure 3.1. Optimization levels for energy minimization.

nodes. As it is shown in [41], the existence of this maximum is strictly related to use of retransmission-based error recovery mechanisms at link layer. These cross-layer issues are discussed in Section 3.3.2.

The higher levels of design abstraction shown in Figure 3.1 provide larger amounts of power reduction for chip designs. In higher levels of abstraction, such as algorithm level, designers have a greater degree of freedom to implement low-power design techniques. Hence, power-optimization process is the most effective method in higher levels of abstraction [42]. As we move toward the lower levels, the amount of power savings becomes less significant and the speed of power optimization becomes slower. Lower level power-optimization techniques are more accurate; however, they are not as applicable as higher level methods. Table 3.1 illustrates the amount of power savings for various optimization levels in CMOS based hardware according to [43].

Table 3.1. Power-saving percentage per optimization level.

Optimization Level	**Power-Saving Percentage**
Algorithm Level	75%
Architecture Level	50%-75%
Register Transfer Level	15%-50%
Gate Level	5%-15%
Transistor Level	3%-5%

3.1. Energy Efficiency Metrics

The requirements of EE metrics at the component, equipment, and system/network level are significantly different. EE metrics for components are relatively straightforward to define and most of them have been well established [44]. It is more complicated to define an EE metric for equipment and system/network. The equipment and networks are more complex systems entailing heterogeneous components. Moreover, they operate in different environments under diverse conditions such as load or channel characteristics. In the literature, there are various energy efficiency metrics considering different aspects of energy consumption and wireless communications. However, in the fundamental sense, energy efficiency is formally defined as the number of bits that can be successfully transmitted with unit energy consumption [45]. In other words, it is the ratio of total throughput to the energy consumed for the transmission of this information. *Bits-per-Joule capacity* introduced in [46] serves as a metric for assessing the energy efficiency performance of a network. According to Shannon's capacity formula as stated in Equation 3.2, *Bits-per-Joule* metric can be calculated as

$$B_e = \left[W \log_2 \left(1 + \frac{P}{W N_0} \right) \right] / P \tag{3.3}$$

Similarly, *energy-per-bit* (E_b) [45] measures the energy required to transmit a single bit. Energy consumed for a single bit transmission is the power consumed during the transmission time (t_b) of this bit. Using Shannon's capacity formula, t_b equals to the inverse of channel capacity R as:

$$t_b = \frac{1}{R} = \left[W \log_2 \left(1 + \frac{P}{WN_0} \right) \right]^{-1} \tag{3.4}$$

From Equation 3.4, energy per bit is calculated as:

$$E_b = Pt_b = (2^{\frac{1}{Wt_b}} - 1)WN_0 t_b \tag{3.5}$$

As shown in Equation 3.5, energy consumption is a function of power consumption. Therefore, the latter is mostly considered as a parameter to be optimized for improving the energy efficiency and used as a metric for measuring the energy efficiency performance.

We define throughput per unit bandwidth $\nu = R/W$, the following relation can be obtained linking E_b and throughput R:

$$E_b/N_0 = (2^{\nu} - 1)\nu \tag{3.6}$$

The relationship of energy and performance based on Equation 3.6 is plotted in Figure 3.2. It can be obtained that for a fixed amount of data, the energy consumption decreases with the decreasing data rate since E_b decreases [14]. However, the conventional per-bit energy consumption in information theory does not always represent the energy efficiency in practical wireless networks. The energy efficiency is context-dependent, e.g. interference from other system, traffic load, etc.

Energy Consumption Rating (ECR) Initiative [47] has proposed the Energy Consumption Rating (ECR) metric for assessing the energy efficiency of a system. ECR is

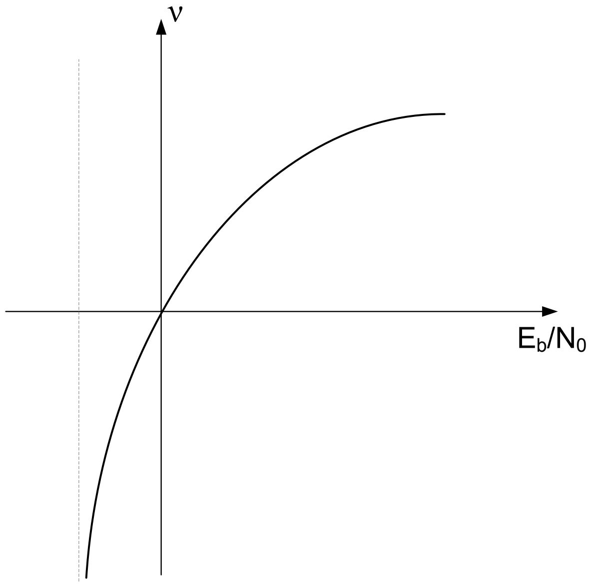


Figure 3.2. The transmission rate as a function of energy efficiency.

given by:

$$ECR = \frac{E}{T} \tag{3.7}$$

where E and T are the energy consumption and effective throughput [48], respectively. ECR provides an absolute measure as the ratio of E and T for different scenarios in communication networks [14]. However, to evaluate transmit energy efficiency, the ECR should consider the overall energy consumption per information bit that is successfully transported over the network and is thus measured in units of joules per bit [49]. In other words, rather than solely focusing on transmit power and resultant ECR, the metric should identify the energy efficiency holistically. An example is provided in [49]: A typical LTE base station sector might operate over a bandwidth of 10 MHz with an average spectral efficiency of 1.5 b/s/Hz, thus achieving an average data rate of 15 Mb/s. If a base station antenna transmits 8 W of RF power, the RF ECR value (considering only transmit energy consumption) for this system would be 0.53 J/b. However, if the total power budget of the base station (e.g., 450 W) is shared among 3 sectors (i.e., 150 W/sector) the ECR value for one sector would increase to 10 J/b.

If new schemes/techniques are proposed to improve EE in a network, it is crucial to employ appropriate metrics to examine the potential energy savings. For that purpose, the relative measure of energy reduction gain (ERG) is defined as:

$$ERG = 1 - \frac{ECR_1}{ECR_0} \tag{3.8}$$

where ECR_0 and ECR_1 denotes the ECR of the base and updated system, respectively.

While analyzing the energy consumption of a network in order to assess the energy efficiency, energy dissipation is mostly considered only in a narrow context, i.e. energy consumption of the devices in the network for transmission and related actions. For instance, energy consumed in a wireless sensor network is calculated as the sum of energy consumed by the nodes in the network only for sensing, communication, and data processing [34]. Energy expenditure for maintaining the infrastructure or deploying the sensors are mostly ignored. For a more accurate energy efficiency analysis, a communication system should be analyzed from a broader perspective ranging from system level to component level [50], and from manufacturing process to the maintenance of the system. Besides, alternative metrics considering not only the throughput capacity or energy consumption performance of the system but also spectral efficiency (*bits per Joule per Hertz*), other QoS related metrics and spatial efficiency (*bits per Joule per unit area*) are yet to be widely adopted for a more accurate and holistic energy efficiency analysis [50].

3.2. The Composition of Energy Consumption in Wireless Communications

According to [51], the European Commission DG INFSO report in [52] estimated European telcos and operators to have an overall network energy requirement equal to 14.2 TWh in 2005, which will rise to 35.8 TWh in 2020 if no green network technologies will be adopted. These trends are depicted in Figure 3.3. According to [5], the Global e-Sustainability Initiative (GeSI) weighed the carbon footprint of networks and related

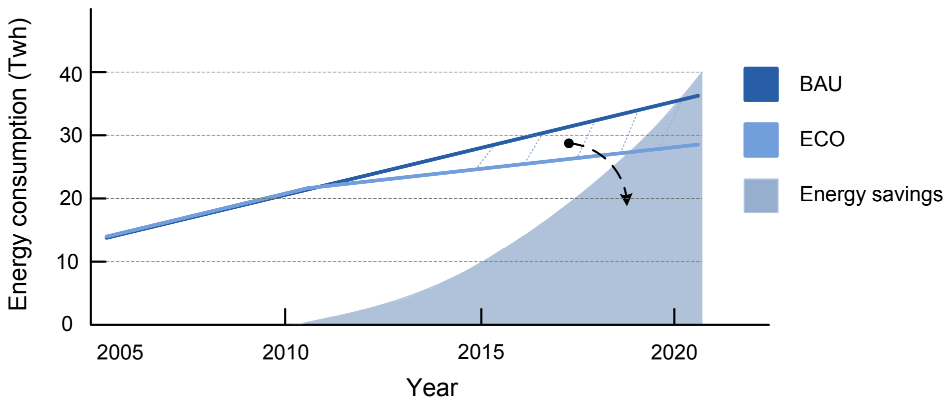


Figure 3.3. Energy consumption estimation for the European telcos network infrastructures. Two scenarios are considered:"Business-As-Usual (BAU) vs. Eco-sustainable (ECO) in addition to the resultant cumulative energy savings between the two scenarios [51]. Source: European Commission DG INFSO report [52].

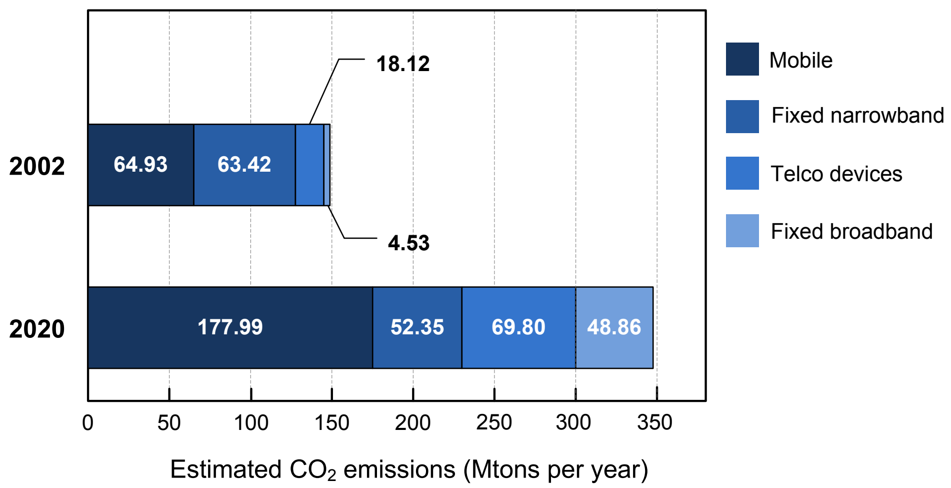


Figure 3.4. GeSI CO_2 emission estimation [51]. Source: Smart 2020 report [5].

infrastructures at about 320 Mtons of CO_2 emissions in 2020. In 2002, network infrastructure for mobile communication generated the leading greenhouse contribution weighing for more than 40% upon the overall network carbon footprint. The 2020 estimation suggests that mobile communication infrastructures will represent more than 50% of network CO_2 emissions as shown in Figure 3.4. Moreover, it is noted that the energy costs accounts for almost 18% of a mobile operator's operational expenditures (OPEX) [53]. Therefore, EE is not just a responsibility for environmental protection but also an opportunity in terms of economic benefits [54]. Careful analysis of the energy consumption of a mobile network (as in [55]) provides the pointers on where the energy saving potential is concentrated, namely access and core networks. For instance according to [55], BSs account for the largest portion of power consumption followed by mobile switching, core transmission, data centers and retails. Therefore, power consumption analysis of radio access network is of significant importance for greener networks. Lately, ways of improving energy efficiency and thus decreasing power consumption have been at the interest of many ICT companies [49]. As a first line of defense, new BS deployments can be avoided by making efficient use of the existing infrastructure [4]. To this goal, traffic optimization (caching) and efficient scheduling by making use of the temporal characteristics of network flows can be employed as well as applying systemic energy-saving techniques exploiting network-wide advances [6].

Different wireless network segments have different peculiarities and requirements. A typical example is the *network scale* factor. Traffic adaptation via sleep mechanisms and dynamic voltage scaling (DVS) do not work well with small-scale networks such as WLANs since they have a large number of diverse nodes with sporadic traffic generation and transfer with relatively low volume (i.e. sparsity in time and space). However, metro and access networks neither have device operating ratios low enough to make sleep control and DVS effective nor optical nodes usage justified (low traffic volume) unlike the core network. A negative consequence is the lack of feasibility for more efficient optical packet switching instead of electrical routers [4]. For satellite networks, these factors emerge in both settings: for relaying services (point-to-point backhauling) the number of nodes is very limited with high duty-cycles for the link. For the access scenarios, the system has more nodes that are geographically spread and with various channel conditions and applications, which make the resource allocation and power control more challenging. Therefore, flexibility and adaptability to different circumstances are critical for any green communications scheme to attain widespread and effective applicability.

3.2.1. Network Node Centric Analysis

The main sources of energy consumption are distributed among various components in a wireless device. A typical wireless device is shown in Figure 3.5. The dominant factors are transmission, processing and maintenance such as cooling. The PHY layer plays a very important role in wireless communications due to the chal-

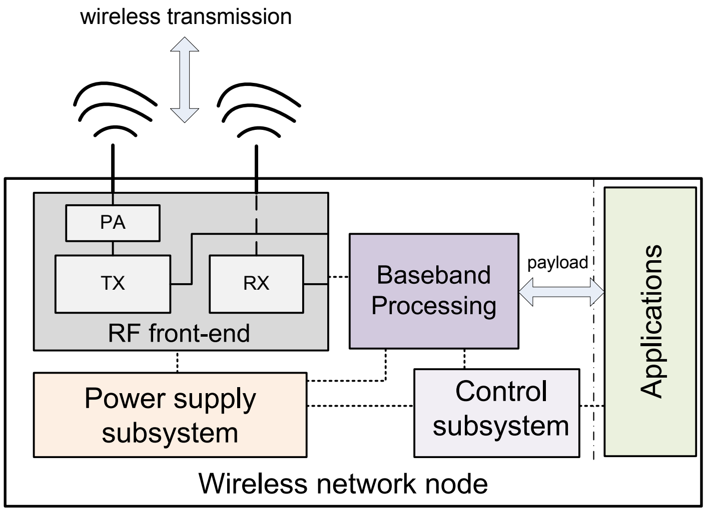


Figure 3.5. Block diagram of wireless network node focusing on radio subsystem.

lenging nature of communication medium. The power consumption of wireless devices heavily relies on the PHY layer. Therefore, energy can be saved in mobile devices by shutting down system components when inactive. The medium access control (MAC) layer manages wireless resources for PHY layer and directly impacts overall network performance. By utilizing various information related to a node (traffic characteristics and requirements, queue states as well as channel states), mechanisms implemented at MAC can determine the operation mode of a node: some time periods can be scheduled as idling or shutdown periods and better energy management can be provided. This type of operation requires a tight coordination among the layers such that a user can wake up as it needs to transmit or receive [45]. Regarding the efficiency provided via the hardware, ubiquitous VLSI-based optimizations have increased the energy efficiency performance of wireless networks. These solutions entail various advances such as RFICs with lower power consumption, smaller idle mode costs and better support for transceiver wake up/sleep/active cycles [56].

3.2.1.1. Sources of Power Dissipation in CMOS Devices. Since most of today's designs are based on CMOS technology, the first step toward power reduction is to analyze the sources of power dissipation in such devices. Power consumption sources in digital CMOS circuits are divided into three main categories [43]:

- Static power dissipation (P_{static}): It is caused by leakage currents and subthreshold currents.

- Short-circuit power dissipation ($P_{short\ circuit}$): It depends on the amount of short-circuit current flowing to ground.
- Dynamic power dissipation ($P_{dynamic}$): It is due to charging and discharging of parasitic capacitive loads of interconnects and devices in the circuit during its operation.

The contribution of these three parameters to the total power consumption is basically additive and shown below:

$$P_{total} = P_{static} + P_{dynamic} + P_{short\ circuit} \tag{3.9}$$

CMOS devices have very low static power dissipation and most of the energy in them is used to charge and discharge load capacitances (dynamic power dissipation). Dynamic power dissipation is of larger magnitude compared to the short-circuit and static powers. Hence, it is considered as the basic component of power consumption of a CMOS device.

From a system-level perspective, the power consumption of a CMOS based silicon can be roughly parametrized into [51]:

$$P = CV^2 f \tag{3.10}$$

where P is the active power consumption, C the capacitance of CMOS circuit, and V and f are the operating voltage and frequency values, respectively. It is worth noting that V and f are related since they need to be directly proportional for a correct working of the CMOS silicon. Clearly, configuring (i.e. decreasing) the operating frequency and the voltage of a processor, or throttling its clock, provides a performance-consumption trade-off, allowing the reduction of the power consumption and of heat dissipation at the price of slower performance. Specifically, power scaling capabilities allow dynamically reducing the working rate of processing engines or of link interfaces. This is usually accomplished by tuning the clock frequency and/or the voltage of processors, or by throttling the CPU clock (i.e., the clock signal is gated or disabled for some number of cycles at regular intervals).

3.2.1.2. The Power Amplifier (PA). In a RF frontend or even an equipment, the power amplifier is the main source of power consumption. According to [57], the power amplifiers in a GSM BS turn 22% of total input energy into heat. The efficiency of power amplifier η is defined as the ratio of effective output power to input power [44]:

$$\eta = \frac{P_{output}}{P_{input}} \tag{3.11}$$

PA is a critical source of power consumption in a typical transmitter. Since nonlinear distortion in circuitry of a wireless system is due to its power limitations (limited power supply), it is most evident in the components handling the highest signal levels, which are typically PAs used for wireless transmission [58]. In other words, transmission power amplifiers have nonlinear transfer functions. This nonlinearity is characterized by amplitude conversion (AM/AM) and phase conversion (AM/PM) [59]. Equations 3.12 and 3.13 give an example of a typical traveling wave tube (TWT) model used in satellite communications, where $A(r)$ and $\Phi(r)$ are the AM/AM and AM/PM conversions, respectively [60]:

$$A(r) = \frac{2r}{1+r^2} \tag{3.12}$$

and

$$\Phi(r) = \frac{r^2}{1 + r^2} \tag{3.13}$$

where r is the amplifier input signal amplitude. The nonlinearity of the structure implies the challenge to quasi-linear operation of PAs.

For real wireless systems, PAs enforce practical hardware constraints on the energy performance limits theoretically achievable via optimizations. For instance, the typical energy conversion efficiency of a power amplifier in current base stations is estimated to be less than 40 percent [39]. Efficiency optimization of PA is also desirable due to its high cost and complexity. In case the modulated signal can enforce less requirements on the linearity of the PA, lower cost transmitters can be designed. This in turn leads to simpler (hence lower cost) surrounding components in addition to less requirements on cooling. Furthermore, battery lifetime can be increased which is crucial for battery-operated hand-held devices [61].

For increasing the base station efficiency, improving the efficiency of the PA and antenna, as well as optimizing the power transfer between them is instrumental. One possible approach for PA is to use the Class J amplifier [62], which relies on fundamental and second harmonic tuning to achieve high efficiencies, while maintaining the linear operation. In the case of the antenna, exploiting highly efficient dual-polarized patch antenna elements is an option [49]. In addition, a system level approach is to shut down a power amplifier when the transmitter is idle. Another energy saving solution is to place PA next to the transmitter antennas in order to minimize feeder cable losses. This design is also beneficial to decrease the cooling related energy consumption.

Wideband PA design is especially important for cognitive and heterogeneous networks since it is necessary for multi-mode and multi-standard operation that reduces the complexity and size of the modules. This is also beneficial for infrastrucutre sharing which allows cooperation among network operators, improving resource utilization and leading to substantial OPEX and CAPEX savings.

3.3. The Emerging Factors and The Potential Approaches for Energy Efficiency in Wireless Networks

In this section, we present an investigation of some emerging factors/approaches in wireless networking with an envisaged impact on the energy efficiency. They can also be interpreted as potential elements in energy efficiency toolbox for green networks.

3.3.1. Cognition in Networks

Cognitive radio networks can enable advanced energy consumption minimization schemes in wireless nodes. Energy awareness is the first step to this goal. That is to say, a node with capability of modeling or estimating its energy consumption can determine the potential points for energy optimization. This requires sensing data and computational schemes based on learning. Additionally, advanced middleware support for realizing an efficient energy management and measurement, and profiling of energy consumption in wireless networks are of fundamental importance for improving energy efficiency. CRs can enable all these tasks since CRs are promised to be self-aware: the CR knows the source of its power supply, the remaining power source as well as energy efficiency performance of alternative adaptation schemes [6]. CRs encompass the sensor and computational infrastructure for enabling these capacities.

3.3.2. Cross-layer Design: The Paradigm Shift

The conventional layered protocol stack where each layer performs some defined functionalities, only allows the adjacent layers to communicate via some primitives. Figure 3.6 depicts this layered approach for TCP/IP stack. Organization of these functionalities and tasks confined into the layers not only eases the management of the system but also facilitates better understanding of the overall system. This architectural principle has facilitated the rapid proliferation of diverse applications that constitute the Internet ecosystem. Moreover, reusability of some parts of the protocol

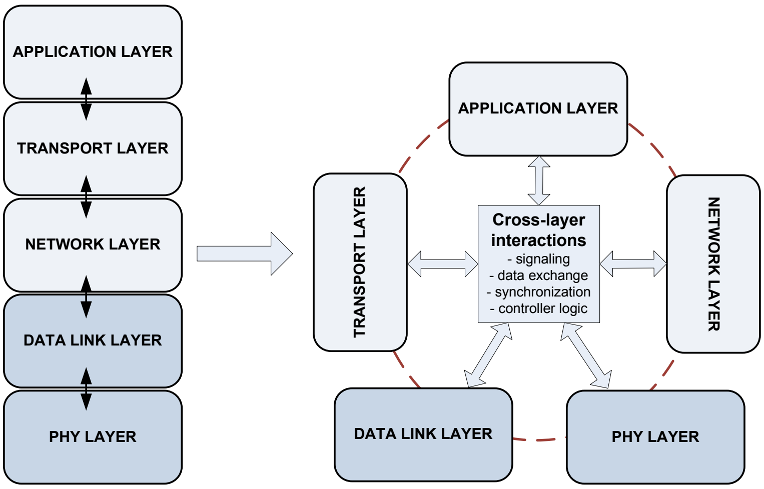


Figure 3.6. Traditional TCP/IP layered protocol stack vs. cross-layer protocol stack.

stack (e.g. same lower layers can be used for a wide range of applications) is increased by this layered architecture, which in turn enhances the utility of the network architecture. Layering typically simplifies network design and leads to robust scalable communication protocols [63]. On the contrary, layering happens to be suboptimal because each layer has insufficient information about the internal and external parameters since the information is not shared among the protocol layers. The interface between the layers is pre-defined and static leading to inflexibility, and is independent of individual network constraints and application requirements [64]. This shortcoming is highly evident for energy efficiency case in heterogeneous networks. In monolithic design approaches, systems are carefully designed and implemented with specific hardware to perform at the maximal efficiency for specific applications [65]. However, heterogeneous and cognitive networks operate under very uncertain and dynamic circumstances. Therefore, cross-layer design is highly beneficial in these systems.

As opposed to restrictions in the interactions between the adjacent layers in layered approach, the cross-layer design (Figure 3.6) expands the functionalities of the layers by enabling the non-adjacent layer interactions [66]. It aims to achieve optimal performance by allowing sharing of information across several layers. By the extended sharing of information, each layer has wider information about the network when compared to layered approach. However, several concerns are evident regarding the flexibility, inter-operability, proliferation and even the performance of the cross-layer design. Since it violates the abstraction of the lower layers to the upper layers, it leads to dependencies between various layers. This in turn, leads to challenges in the cross-layer protocol design. All dependency relations must be clearly identified between the layer pairs and then the design framework must be drawn. Therefore, the simplification in the layered protocol approach leaves its place to many challenges in the cross-layer approach.

Since optimizing energy consumption requires in-depth analysis of the low-level radio hardware meanwhile measuring performance is only possible by taking the characteristics of the protocol stack into account, energy management problem requires a cross-layer solution approach [67]. A typical example is the monitoring and prediction of energy efficiency for supporting the decision making processes in the network equipment [14]. This capability is required in a network-wide setting. On the infrastructure side, network nodes may optimize their energy consumption using different control dimensions such as switching to different network interfaces, adaptive sleep cycles, application-specific policies, and class based policies to avoid sacrificing the QoS of important users. Cross-layer signaling is necessary to exchange the relevant sensory and control information among layers and thus act in a cross-layer manner. Heterogeneous and cognitive networks will operate in dynamic environments where a single energy management solution is not sufficient. Thus, flexible cross-layer solutions are necessary [56]. Potential cross-layer interactions for a network node are shown in Figure 3.7.

Careful attention should be paid to the design of layers in a heterogeneous network in order not to disrupt the basic layering principles and prevent the unstable system behavior. Cross-layer design methodologies that rely on interaction between the different protocol layers, is promising for addressing inherent challenges such as energy efficiency and for providing reliable and high-quality end-to-end performance in wireless communications. However, cross-layer protocol design imposes many challenges in the protocol design and implementation; increase in the layer interdependencies, more complex protocol design, and stability issues. Therefore, great attention and research on the novel cross-layer techniques are required.

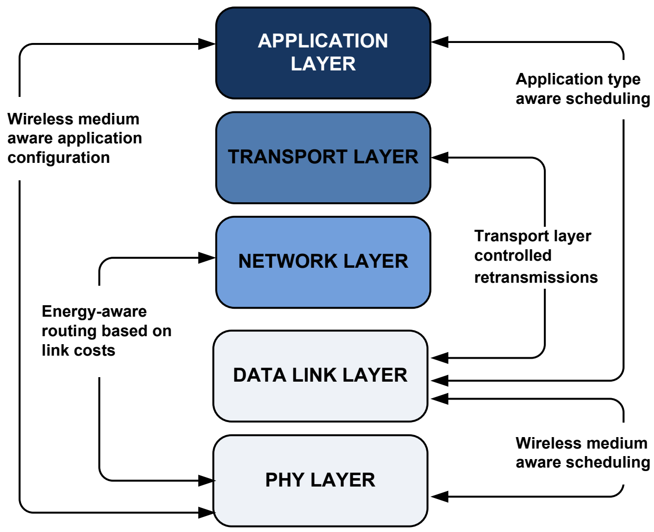


Figure 3.7. Cross-layer mechanisms for energy efficiency. The signaling and information exchange between non-adjacent layers facilitate cross-layer optimization of energy consumption.

3.3.3. Increasing Heterogenity: Plural Networks

Future mobile networks are expected to involve systems that are based on different technologies, such as WiFi, 2G/3G, WiMAX, LTE, and satellite networks [68]. International Telecommunication Union (ITU) has defined integrated and hybrid networks in the framework of Next-Generation Networks in order to address this heterogeneous environment [69]. The cooperation of different wireless communication systems enables design and runtime optimizations to provide these services in the most energy-efficient way, taking into account QoS requirements, signal quality (coverage), and traffic congestion conditions. In this regard, these integrated and hybrid networks so called *Heterogeneous Networks (HetNets)* are posed to be both a challenge and a facilitator for energy-efficient communications.

In this context, HetNet concept relies on the use of multiple types of radio access infrastructure such as macrocells, small cells (picocells, femtocells), relays and distributed antennas in a wireless network in order to offer wireless coverage in an environment with a wide variety of wireless coverage zones. These network architectures may be either operator-deployed and/or consumer-deployed [70]. By deploying these additional network nodes within the local-area range and bringing the network closer to end-users, HetNets are envisaged to improve spatial reuse and coverage enhancing data rates, while retaining the seamless connectivity and mobility of cellular networks [71]. For the realization of such converged networks, a multitude of issues pertaining to transmission efficiency, resource allocation and management, mobility management, and seamless connectivity have to be addressed [72].

To exploit the advantages of these integrated systems, a flexible multimode radio is essential. A multimode radio communication terminal is a tunable device for communicating over multiple radio interfaces [73]. Multimode devices with multi-wireless interfaces are important since they are potentially more open to DSA schemes and cognitive capabilities can be achieved via firmware upgrades in a flexible manner. For multimode devices, there is the additional parameter of selecting which interface to utilize in addition to conventional energy optimization problems. Because a fast interface can send data with less energy per bit since it takes shorter to transmit. However, it may incur a larger wakeup cost. As a result, the multimode structure adds another control dimension to the conventional radio structure. Additionally, the available hardware layout of these devices introduce different dimensions of energy consumption optimization. Overall, the cost and reward structure for opportunistic operation is more complex since different interfaces have different properties such as power consumption per bit, wakeup cost, throughput and channel characteristics [36].

3.3.4. Virtualization and Cloudification of Mobile Networks

Virtualization is one of the primitives that are widely adopted in ICT infrastructure for improving energy efficiency and reducing the carbon footprint. Modern network equipment already include some virtualization primitives, which allow different logical routers over a single physical platform [51]. However, they are generally conceived for being used in simple VPN-like applications. This notion results in a coupling between logical nodes and physical platforms where a logical network entity can usually work on a specific hardware platform.

As noted in [51], research on router virtualization render the possibility of realizing novel virtualization paradigms, which allow logical instances to be migrated among different physical platforms without suffering service interruption and losing any packets [74]. In perspective, such kind of primitives can be adopted for adapting the number of active physical platforms or aggregating logical entities with respect to traffic volumes and network requirements. This capability is closely related to network topology control and adaptation approach discussed in Section 3.3.5. Logical instances, able to move among different hardware platforms, provide another opportunity for turning off hardware platforms or consolidating functionalities on energy-efficient hardware without causing degraded user experience and network instabilities since the network as an entity becomes a logical infrastructure as well. However, this flexibility requires substantial research efforts to be realized. In this respect, virtualization primitives embedded in network equipment constitute the capability framework for novel network-wide and energy-aware control criteria to dynamically re-configure networks and related equipment. For the mobile network, network virtualization enables dynamic provisioning of virtual network segments to provide different services to different customer groups.

Another approach is to utilize cloud computing concept, especially for computation off-loading. It is very effective for enhancing the computational power and battery life of resource-constrained devices such as mobile user devices [75]. Remote execution via online services running in the cloud permits transposition of computation from battery-powered mobile devices or power-inefficient network nodes in order to utilize "economies of scale" on more energy-efficient hardware. However, this scheme is beneficial when processing overhead is more dominant compared to communication counterpart such as video processing.

3.3.5. Network and Topology Flexibility

Power saving mechanisms based on network and topology control are currently founded on the extension of traffic engineering and routing criteria [51]. In this area, the basic idea is to adapt the network capacity in terms of links and nodes to the actual traffic volumes. Researchers propose to reduce the network energy requirements by switching off unused links and nodes. Thus, the main objective of these studies is to move traffic flows among network nodes in order to find the minimum number of network resources (i.e., links and nodes), guaranteeing the best trade-off between end-to-end network performance and overall power consumption. This approach is closely related to virtualization paradigm discussed in the previous section since virtualization enables "fluidic networks" where communication functionalities can easily migrate, activate or shut-down at different physical network locations.

For the emerging mobile networks, Self-Organizing Networks (SON) concept is also critical in network and topology control [76]. SON concept implies that network entities are active agents and they interact among themselves to reduce the cost of installation and management by through automated mechanisms focusing on self-configuration, self-optimization and self-healing, which constitute the three main phases of the SON cycle [77]. This new type of networks is expected to be widely deployed in 4G networks since small cell proliferation is going to increase with new spectrum bands at high frequencies, capacity requirements and higher peak data rates. This paradigm creates another energy efficiency potential in wireless networks.

3.4. Summary

Energy efficiency and power control are vital for wireless network performance. In this chapter, we have presented background on energy efficiency in wireless networks discussing fundamental aspects such as energy efficiency metrics and the composition of energy consumption. We also discussed emerging developments in wireless networks which are expected to have an impact on energy efficiency related research. In the following chapters, we focus on this subject and energy efficiency following this general background build-up.

4. COGNITIVE RADIOS AND GREEN WIRELESS COMMUNICATIONS

We need energy efficient systems in order to protect our environment, cope with global warming, and facilitate sustainable development. However, telecommunications data volume increases approximately by an order of 10 every 5 years, which results in an increase of the associated energy consumption by approximately 16-20% per annum [78]. For instance, in Japan, network power consumption in 2025 is predicted to be 13 times the 2006 level, especially due to the anticipated increase in traffic volume with broadband services and machine-to-machine bursty traffic originating from cloud computing [4]. While the use of Information and Communications Technology (ICT) is considered to be a facilitator for global energy savings (teleworking, smart logistics, smart buildings, etc.), the volume of network traffic will also increase which leads to a challenging trade-off. Specifically, the computing and communication systems are regarded as key components for reducing the environmental footprint in other environments such as utility grids and transportation systems and also for greening services and utilities. However, by 2008 figures, it is estimated that 3% of the world-wide energy consumption is caused by the ICT infrastructure that generates about 2% of the world-wide CO_2 emissions [5].

A major portion of this expanding traffic has been migrating to mobile networks and systems. Thus, optimizing the energy-efficiency of wireless communications not only reduces environmental impact, but it also cuts overall network costs and helps to make communication more practical and affordable in a pervasive setting. For instance, in many portable devices, 30% of the energy consumption is due to wireless network interfaces [56]. With the expanding domination of multimedia services/traffic in wireless networks, the spectrum requirements and computational burden on these mobile devices are also toughening in contrast to the perpetual trend of equipment miniaturization. Considering all these points, energy-wise optimization of all aspects of wireless communications, ranging from equipment manufacturing to core functionalities, is paramount. Accordingly, the green networks and communications approach which call for a holistic energy-wise optimization of communication systems have spurred a substantial stream of new research activity.

Cognitive radio (CR) is a promising paradigm proposed to cope with the spectrum scarcity problem that has emerged as a result of increased need for anytime-anywhere connectivity [79]. Briefly, CR (also called *smart radio*) is defined as a wireless radio device that can adapt to its operating environment via sensing in order to facilitate efficient communications [80]. A CR, with its built-in intelligence and cognitive capabilities, can sense the radio spectrum, locate spectrum holes and opportunistically access them as long as the licensed users (also called *primary users*, PUs) do not use the band. Moreover, it can facilitate multi-mode radio interfaces that can operate in multiple standards with its adaptation property. However, there are many challenges in realizing the CR concept. Briefly, detecting spectrum holes reliably and vacating the spectrum bands immediately as a PU appears in the CR band are difficult problems that are yet to be solved exquisitely. CRs open up new control dimensions for green wireless communications with their agility and adaptation properties.

Cognitive abilities that refer to a wide range of properties from spectrum sensing to learning-empowered adaptive transmission in wireless network nodes are beneficial for leveraging intricate trade-offs between energy efficiency, performance and practicality. Nodes coupled with these cognitive functionalities, known as *cognitive nodes*, can improve network performance by environment-aware and self-aware operation capabilities. However, there are intrinsic challenges such as hardware complexity, algorithmic problems and design trade-offs. These issues can be classified into two broad groups: *CR inherent problems*, e.g. efficient sensing and spectrum access, and *interworking issues* entailing communications networks themselves and other infrastructural segments such as smart grids [78]. However, it is envisaged that adaptive and optimal operation via cognitive nodes will benefit the overall ICT and the relevant interconnected systems. In this work, we present and discuss these points to highlight the case of CRs for green wireless communication systems. Moreover, we outline the fundamental trade-offs for greening wireless communications via cognitive functions in order to convey the challenges against this objective.

The rest of the chapter is organized as follows: The next section presents a brief background on energy efficiency issues of wireless networks. We then discuss the benefits of CR for energy efficient wireless communications in Section 4.2. Section 4.3 presents some fundamental trade-offs for greening communications via cognitive functions and their impact on energy efficiency. Finally, Section 4.4 concludes the chapter.

4.1. Energy Efficiency Perspective for Wireless Networks

The typical power consumption profile for an European mobile network operated by a global cellular operator is shown in Figure 4.1 according to [55]. This diagram conveys the prime targets for energy savings: access and core networks. To control the increasing power consumption in these domains, the green networks and energy efficiency are now more important than ever. Accordingly, many ICT companies have announced voluntary targets for substantial energy consumption and CO_2 emission reductions for the coming years [78]. In that sense, system-wide energy savings in ICT and ICT empowered systems are crucial. However, this is not a trivial task with a multidimensional setting of various factors such as hardware complexity, algorithmic problems and design issues. As the first line of defense, the mobile operators can avoid upgrades and green-field deployments via better utilization of incumbent infrastructure [4]. A typical approach towards this goal is to play with the temporal characteristics of the traffic: tools for this aim are traffic optimization (caching) and more efficient scheduling of network flows. Moreover, systemic energy-saving techniques exploiting network-wide advances such as generally applicable routing and switching algorithms and evolving device technology can be employed.

Different wireless network segments have different peculiarities and requirements. A typical example is the *network scale* factor. Traffic adaptation via sleep mechanisms and dynamic voltage scaling (DVS) do not work well with small-scale networks such as WLANs since they have a large number of diverse nodes with sporadic traffic generation

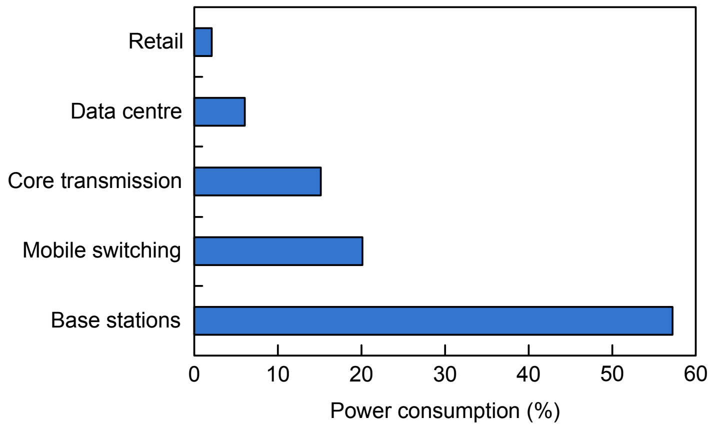


Figure 4.1. Typical breakdown of power consumption in a mobile operator [55].

and transfer with relatively low volume (i.e. sparsity in time and space). However, metro and access networks neither have device operating ratios low enough to make sleep control and DVS effective nor optical nodes usage justified (low traffic volume) unlike the core network. A negative consequence is the lack of feasibility for more efficient optical packet switching instead of electrical routers [4]. Therefore, flexibility and adaptability to different circumstances are critical for any green communications scheme to attain widespread and effective applicability.

The key points related to different network segments are shown in Figure 4.2 and described below. There are energy efficiency approaches addressing different subnetworks such as better power control between end-user devices and access nodes, and generally applicable solutions such as low-power VLSI based network equipment.

4.1.1. Endpoint Devices and Access Network

"Greening" wireless access networks depends on a multitude of factors such as network scale, incumbent standards' capabilities, and cost efficiency. From the end-user perspective, the increasing energy disparity between increasing communication demands and relatively sluggish increase in energy storage capabilities shortens system lifetime and complicates cooling mechanisms. The design of energy-efficient systems needs to encompass RF components, adaptive physical layer algorithms, the MAC protocol and the network layer while taking into account environment and application constraints [56]. The key factors improving energy efficiency in this domain can be

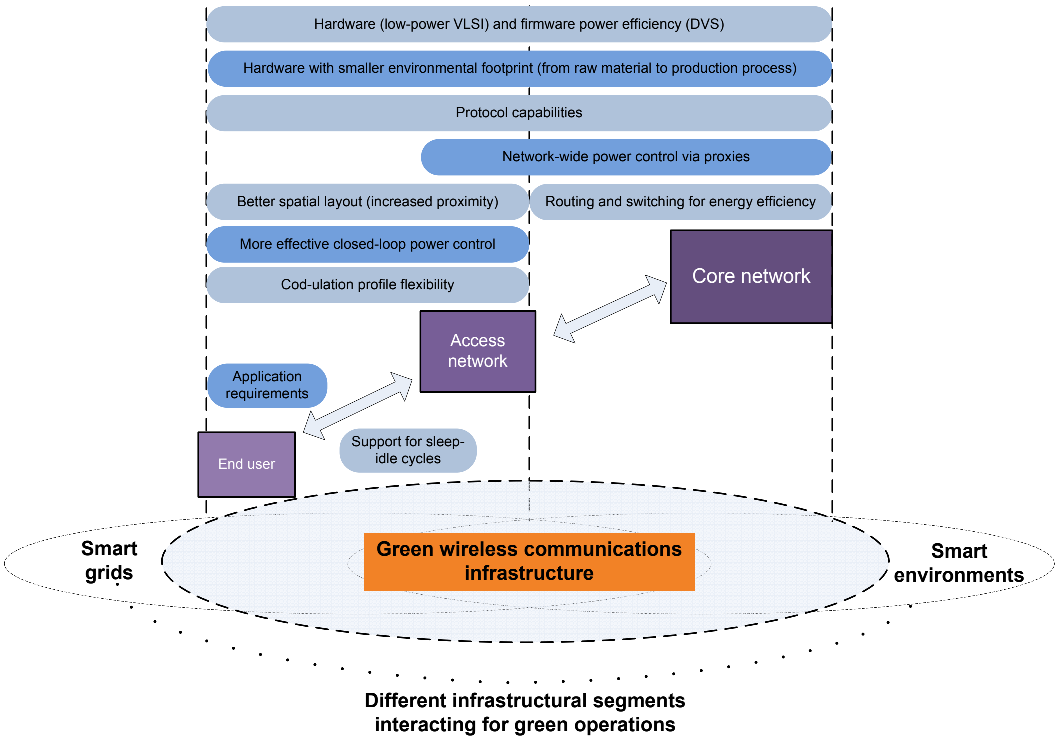


Figure 4.2. General interworking view and mechanisms/advances for greener wireless communications. As the network is traced from the edge towards the core, the number of network devices decreases while the operating ratio and traffic volume increase due to traffic aggregation.

listed as:

- *Base station (BS) architectural enhancements* - According to publicly available data, BS power consumption account for approximately 200 to 500 GWh per year per operator in some European countries [81]. Modern state-of-the-art 3G LTE and WiMAX BSs do not require the "forced" cooling function and instead use passive cooling [55] which provides drastic power savings. The total power consumption of a site without power supply and active cooling/air conditioning can be 20-25% lower according to the energy consumption model in [82].
- *Protocol and middleware support for energy efficiency* such as power saving via radio access controller driven sleep and granular closed-loop power control benefit both access infrastructure and end devices. For instance, to reduce energy consumption in the wireless local network interface, the energy-saving mechanisms defined by IEEE 802.11b called power-saving mode (PSM) are instrumental. PSM is a general approach that works at the wireless link layer between the access point

and the client and switches the wireless node to a lower-power sleep mode when data is not being received or transmitted. For multicarrier transmission schemes such as OFDM, one of the major drawbacks of is the high peak-to-average power ratio (PAPR) of the transmitted signal. If the peak transmit power is limited by either regulatory or application constraints, the protocol middleware is supposed to reduce the average power allowed under multicarrier transmission. That requirement imposes intrinsic power control mechanisms in these systems, which benefits energy efficiency.

- *Hardware advances related to RF components* - The high power amplifier (HPA) is a crucial element of the radio transmitter chain. These analog components are not ideal due to a limited linear range leading to nonlinear distortions in case of out-of-range operation. Particularly, they consume a large portion of energy in RF circuitry during transmission. Better and flexible HPAs and the increase in power efficiency of baseband processing circuits enhance the efficiency of wireless transceivers. For this purpose, signal conditioning algorithms, like crest factor reduction (CFR) for decreasing the PAPR and digital predistortion for increasing the PA linearity, must be applied in order to keep the PA operation closer to saturation [82]. Moreover, load adaptive CFR combined with adaptive power supply of the PA and power supplies optimized for variable input power are instrumental in the analogue chain.
- *Support from applications* via application layer signalling towards other layers such as instantaneous data rate demand and service requirements enable control optimization in a cross-layer setting. This is enabled by firmware and application support resident on the mobile terminals.

4.1.2. Core Network

For any wireless network, the backplane of interconnecting wired network is also critical for energy-efficient operation in addition to the network edge which contains access nodes and user equipment. Energy-efficient routers, switches, servers and communication hardware contribute largely to the consumption in the operator's IP backbone network [4] as shown in Figure 4.1.

- *Impact of energy-efficient computing technologies on core network nodes* - Processing nodes such as call/session control servers, IMS servers, and AAA servers (service network) have benefited from the energy efficiency advances in common IT infrastructure.
- *The proliferation of flat all-IP mobile networks* - Next generation systems such as 3G LTE and WiMAX facilitates a flat all-IP network. This leverages the general advances in low-power, low-cost routers and server equipment [4]. For instance, IEEE P802.3az Energy Efficient Ethernet (EEE) has been standardized in IEEE Std 802.3az-2010, which was approved September 30, 2010 [83]. EEE uses a Low Power Idle mode to reduce the energy consumption of a link when no packets are being sent. In addition, novel IP-based routing/switching schemes enable the harvesting of general advances in communication infrastructure.
- *Network level sleep-mode technologies* - Controller nodes (e.g. proxy server techniques controlling the sleep-active cycles of network nodes according to traffic load) dynamically configure the operational mode of network nodes according to traffic characteristics. Proxy is an intermediate node that intercepts the communication transparently acting as the destination node in order to improve the performance of communication. *Proxying* for energy efficiency is the use of a low-power entity allowing a high-power device to go to sleep and thus save power while still maintaining its network presence [84]. The proxy enables a host to transition into and out of sleep transparently to the network. Use of a proxy requires no infrastructure changes such as changing existing protocols, or maintaining state in routers or switches.
- *Optical switching and routing* - Electronic packet-by-packet processing consumes vast amount of energy consumption for high throughput [85]. Packet routing account for about 37% of all power consumption of routers and optical routers are more efficient in that sense [4]. Therefore, with the increasing number of high bandwidth applications, the usage of all-optical network solutions increases. However, energy consumption of optical networks is also an important issue that

has to be addressed in parallel [86]. In that respect, energy saving both exploiting the traffic characteristics for reducing the number of in-line system components and switching off active optical links especially during low traffic periods can be achieved.

However, there is still room in the core network for new improvements. From the CR perspective, injection of more cognitive capabilities into core network nodes is posed to provide additional savings. This will enable reconfigurable network nodes operating at different points on the energy-performance curve.

4.1.3. Network-wide Enhancements

The next generation mobile communication standards such as 3G LTE and IEEE 802.16m incorporate a multitude of capabilities and techniques that enhance spectral efficiency (bits/Hz/area) and energy efficiency. For instance, MIMO transmission and reception, adaptive modulation and coding, advanced antenna techniques such as beamforming, MAC enhancements such as Hybrid ARQ (HARQ), advanced resource allocation and packet scheduling techniques [87] all provide opportunities to improve power efficiency of these wireless systems. The mechanisms in emerging communication protocols such as WiMAX sleep cycles, DVB-SH efficiency due to energy-aware design, and LTE power saving mechanisms provide new optimization parameters.

On the hardware side, ubiquitous optimizations based on VLSI and circuit design progress have improved the efficiency of wireless network nodes. These can be listed as RFICs with less power consumption and better support for transceiver wake up/sleep/active cycles as depicted in Figure 4.3, and smaller idle mode overhead [56]. Two driving factors have improved the overall consumption of network hardware: DVS and low power VLSI implementations with advances in LSI fabrication and reduction of driving voltage. However, wireless transceivers have different characteristics which require novel RFIC system models. In the access network side, sleep mode in BSs for traffic adaptation at different scales are possible: At macro level, carrier shutdown, sector shutdown, and adaptive coverage can provide adaptive power usage while at

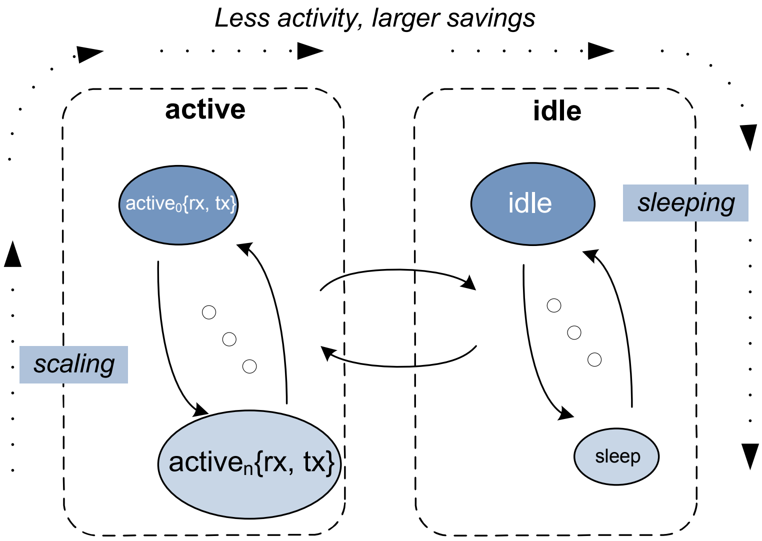


Figure 4.3. Adaptive sleep and active modes for network nodes. The wireless node can utilize dynamic voltage scaling for transmit (tx) and receive (rx) interfaces in active mode. It can also adapt to different activity levels while being idle.

the micro level, total BS shutdown can optimize energy consumption (e.g. a femtocell BS shuts its interface down in case of user non-existence.) Additionally, repeaters and relays which operate at the physical layer can improve spectral efficiency without increasing power consumption [88]. BS design enhancements such as RF amplifier location also improve power efficiency.

Another approach may be to take advantage of spatial network layout and thus increase proximity advantage. As the typical network nodes for this purpose, home BSs, i.e. *femtocells*, are posed to be a good candidate as the supporting infrastructure in that regard [11]. Deployed at the homes or small-area public places, femtocells are low-power plug-and-play BSs providing connectivity to the cellular operator's network via a digital subscriber line (DSL) router or cable modem Femtocell concept has been developed to improve spatial coverage with increasing reuse without introducing much complexity and cost. The main premise behind femtocell is to increase transmitter-to-receiver proximity to improve system capacity via higher quality links and more spatial reuse [89], thereby providing a cost-effective solution for better user experience against poor indoor coverage. Femtocells enable greener wireless access in four factors: More local optimizations, less power consumption, less electromagnetic (EM) pollution, and better resource utilization. We elaborate on femtocells and energy efficiency in

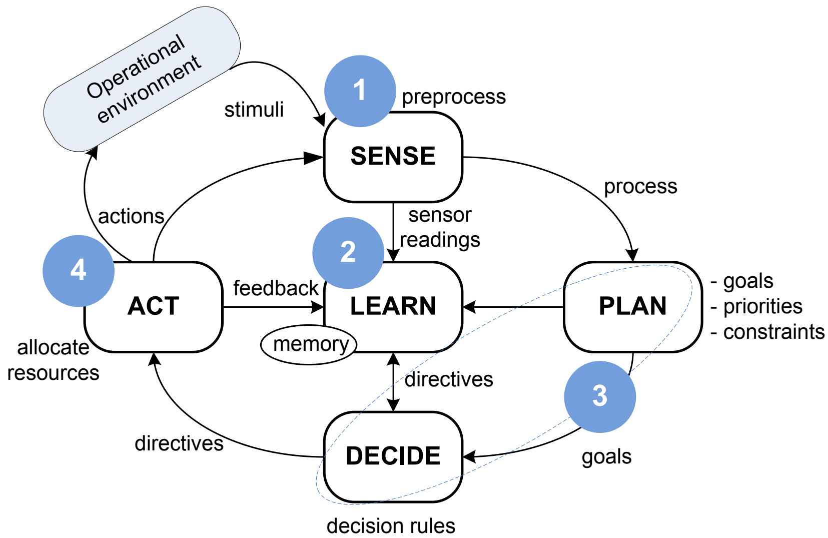


Figure 4.4. Cognition cycle: CR is an active entity performing a cognition cycle entailing actions such as sense, act and decide which can be utilized for energy efficiency in networks.

Chapter 5 and Chapter 6.

4.2. Benefits of Cognitive Radios for Green Wireless Communications

According to FCC (FCC NPRM, Dec 17, 2003, ET-03-108), "A cognitive radio is a radio that can change its transmitter parameters based on interaction with the environment in which it operates." This interaction may involve active negotiation or communications with other spectrum users and/or passive sensing and decision making within the radio. To this end, a CR is supposed to perform an envisaged cognitive operational cycle shown in Figure 4.4. CR *senses* its electromagnetic operational environment by its sensors. After processing these sensory readings that represent the state of the environment, CR *plans* and *decides* on its actions considering its goals, priorities and constraints. With these self-awareness and environment-awareness capabilities, a CR can select the best strategy meeting its goals. Upon deciding on the most appropriate strategy, CR *acts* accordingly. All steps interact with the embedded learning module. In other words, a CR *learns* from its experiences which also makes it *smart*. The energy efficiency related functionalities should be embedded in these flows, and also these processes themselves should be made energy-efficient.

CR has been proposed as a general approach for higher efficiency in wireless communication systems. Moreover, from the green perspective, spectrum is a natural resource which should not be wasted but be shared. CRs enable this paradigm with smart operation and agile spectrum access. But they also have to be optimized on the way to green communications. There are two related aspects of CRs in the green networks perspective: achieving energy efficiency in CR (this paradigm enables a more prevalent optimization) and energy efficiency via cognitive radio (capabilities.)

The energy management problem, in its most general formulation, is a multidimensional optimization problem which consists of dynamically controlling the system to minimize the average energy consumption under some performance constraint(s) [90]. In general, the related objective of energy efficiency can be measured as *number of transmitted data bits per Joule of energy*. Since CRs mostly apply a periodic sensing scheme in order to evade any interruptions to the reappearing PUs, each frame is divided into two main parts: sensing and transmission. In general, the longer the sensing duration, the better the sensing accuracy. However, it shortens the duration available to transmission. Hence, sensing and transmission scheduling should be performed providing a balance between the sensing accuracy and transmission efficiency. Taking this issue from the energy perspective especially for battery-limited CRs, CRs can decide on the best sensing and transmission duration considering this problem as an energy-efficiency maximization problem subject to PU interference restrictions. Similarly, power allocation over a number of channels can improve the energy-efficiency in multi-channel CRs. A CR with a limited power budget can allocate its restricted resources considering the energy-efficiency of each channel [91].

The evolution and interaction of green communications and the cognitive networks are shown in Figure 4.5. The advent of cognitive end devices (CRs and wired nodes) and smart core/access network nodes such as cognitive femtocells constitute a meta-infrastructure forming smarter ICT via cognitive capabilities which can be denoted as *cognitive networks*. This interconnected structure provides a pervasive enabler for green systems and services such as smart utility networks (e.g., smart grids), smart ambient environments (home, workplace, enterprise, etc.), and smart transportation systems. In this work, we focus on the general optimization problem of operational consumption after the wireless communication system is deployed, but not the entire system lifecycle of manufacturing, deployment, and operations as the green networks approach considers. To that end, the capabilities of CRs enable a diverse set of energy efficiency optimizations in different communication settings:

- *Intelligence support for energy efficiency functionalities* Models for energy consumption estimation require sensory data and computational schemes based on learning for accurate operation. Moreover, sophisticated middleware support for energy management and measurement, and profiling of energy consumption in wireless networks are crucial for attaining energy efficiency. Power supply and energy efficiency awareness is possible with CRs since the CR knows the source of its power supply, the remaining battery life, and the energy efficiency of alternative adaptation schemes [92]. CRs encompass the sensor and computational infrastructure for enabling these capacities.
- *Energy savings via duty-cycle optimization and robustness in ad hoc settings* For mobile ad hoc networks, the infrastructure-less and mobile system setup leads to rapid changes in the network topology and thus causes the issue of constantly forming and breaking communication links. This difficulty is also critical for the lifetime of the network since mobile ad hoc networks comprise energy-limited nodes [93]. Dynamic spectrum access in CRs can alleviate this problem via various mechanisms such as switching to the backup channels, estimation of the further link qualities, and acting accordingly, since it is inherently designed with these considerations. On the other hand, CRs may be subject to link disruptions due to unexpected PU appearance in the transmission band. The service disruptions due to spectrum unavailability should be minimized since the constant cost of having the system ready for communication can be eliminated and longer sleep opportunities can be created for network devices. CRs facilitate duty-cycle optimization since they perform agile spectrum access.
- *Network layer capabilities* CRs can utilize energy-aware vertical and horizontal handovers with support from the access infrastructure. They can select the most

appropriate network not just according to the physical layer conditions and available bandwidth, but also with a consideration of energy cost. For instance, in the mesh mode, they can optimize routing and switching for energy efficiency.

- *Cross-layer optimizations* The energy management problem lends itself to a cross-layer solution approach, as measuring performance requires taking into account the characteristics of the protocol stack, whereas optimizing energy expenditure relies on the detailed knowledge of the low level radio hardware [90]. Cognitive network devices with their assumed machine learning and control frameworks are inherently more apt to cross-layer optimizations since these functionalities have to interact with different layers of the system. These communication systems will operate in dynamic environments where a single energy management solution is not sufficient. Thus, flexible cross-layer solutions are necessary [56].

The applications in cognitive networks will be able to interact with the radio for more flexible and adaptive operation. This functionality enables context-aware operation in the lower layers under application driven smart schemes. On the infrastructure side, network nodes with cognitive capabilities may optimize their energy efficiency using different control dimensions such as switching to different network interfaces, adaptive sleep cycles, application specific policies, and class-based policies to avoid sacrificing QoS of important users (Figure 4.3).

- *Enabler for ubiquitous efficiency optimizations* The interaction with other utility networks such as end-points for "smart grids" and "smart transportation systems" will provide new opportunities for optimization of these networks. A typical example is distributed power generation and consumption that will become more common with the proliferation of home fuel cells, small-scale renewable energy sources and high peak-to-average resource demands such as in electrical grids when plug-in hybrids and electric vehicles (EVs) are charged overnight [78]. CRs can provide support for two-way information flows in the next generation grids. For these grids, smart meters that provide accurate real time information on consumption to the user and the utility company are critical. Moreover, distributed and micro-scale power generation infrastructure requires pervasive networking for control and monitoring. Various communication standards such as Zigbee have been considered for communication among these elements in the home network and the wide area network (towards the grid operator). However, these systems generally face two main issues: *coverage* and *interference* [94]. Using cognitive networks such as TV white space (TVWS) based IEEE 802.22 can provide a feasible solution to these issues. In particular, given the relatively low data rates involved in smart metering communications within each home, a single (or even a small sub-channel) TVWS channel could be assigned for such applications in order to provide whole-home coverage. Moreover, they can support wider area communication between smart meters, microgrids and utility control centers.

- *Physical layer capabilities* In the physical layer, beamforming (exploiting antenna directionality) for reducing power requirement and interference for a given range and data rate is possible. An example in that regard is major issue of the PAPR of the transmitted signal in multicarrier transmission schemes such as OFDM. The CR sensors provide data support for power efficient PAPR reduction techniques. Furthermore, the cognitive mobile devices will have the intelligence to select the most energy efficient PHY profiles based on the present channel state via learning and estimation. However, this requires hardware support with more complex signal processing and comes with some typical issues such as hidden node problem and MAC design [95].

- *Bandwidth-energy trade-offs* According to Shannon's law, there is a direct trade-off between bandwidth and power efficiency. Therefore, with agile spectrum access and smart operation, CRs may prefer bandwidth expansion to minimize power consumption in valid operational opportunities without sacrificing throughput. These communication theoretic trade-offs provide tools to mitigate energy consumption issue.

- *Simpler and more efficient evolution paths* The software defined nature of CR allows the modification of energy saving schemes in operation (runtime) much more easily (e.g. novel sleep mechanisms, operational profile mappings computed offline and updated [56]). This also enables more autonomous operation and self configuration for network nodes. This is in line with the 4G evolution path where the flat network architecture incurs a paradigm shift towards intelligent radio access network.

- *Smaller impact on human health* The increase in the number of wireless infrastructure nodes such as base stations and mobile terminals has increased the awareness of the public about EM radiation. Avoiding EM pollution via the proper use and sharing of spectrum resources for protecting the human health [96] addresses the public health concerns due to EM radiation originating from wireless systems. This is due to the Shannon's capacity formula, which translates into the trade-off relation between transmit power P and signal bandwidth W for a given transmission rate, R, as

$$P = WN_0(2^{\frac{R}{W}} - 1) \tag{4.1}$$

It can easily be seen from the above expression that when no limit is imposed on the bandwidth, the minimum power consumption goes down to $N_0R\ln 2$ [39]. OFDM based next generation systems such as LTE provide more flexibility compared to GSM and UMTS for dynamic spectrum adjustment. These communication theoretic trade-offs among bandwidth, throughput and energy consumption performances can be balanced for attaining a desirable balance between these parameters.

- *Longer lifetime for wireless equipment* Another important feature of CRs is their ability to provide upgradeable and longer lifetime radio equipment for the wireless communications infrastructure [97]. For the commercial end-user devices, this is very important. Because the lifetime of consumer devices are shortening with the increasing pace of new communication and application capabilities. For cellular networks such as 2G/3G/LTE systems, the user device lifetime is around 1-2 years which results in a rapid cycle of device replacement and high energy footprint due to manufacturing processes [98]. For the military domain, software upgradability and reconfigurability for flexibility and low cost of ownership is essential since this type of applications is characterized by long-lifetime acquisitions although missions and technical requirements vary at a faster scale. CR capabilities will also be applicable to satellites from the

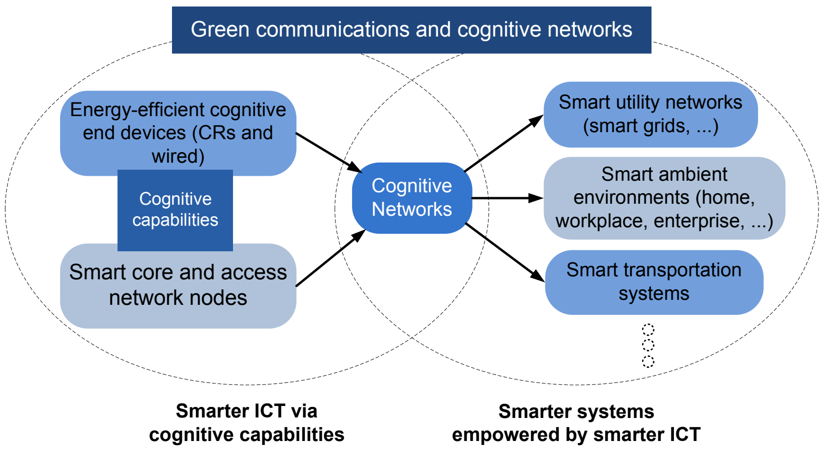


Figure 4.5. Proliferation of cognitive networks for the ultimate goal of "greening" of ICT and ICT empowered functionalities.

SDR perspective where SDR enables remote upgrades of communication capabilities and possibly mission expansion/upgrades during the lifetime of a satellite [99]. User equipment lifetime is longer since firmware updates allow support of new protocols and features without disposal of these devices. This is critical since the disposal of equipment contributes to the enormous electronic waste (e-waste) issue and leads to waste of energy and natural resources used for production, logistics, and deployment in the first place. This is against the goal of energy efficiency and environmental-friendly operation for wireless networks.

4.3. The Emerging Tradeoffs: The Virtue of Being Smart or The Comfort of Being Simple-minded?

The wireless communications systems typically operate under very volatile conditions due to dynamic propagation environment and diverse application requirements. By carefully adapting the system to these dynamics at runtime and capitalizing on the energy scalability features of the system, substantial energy savings are possible compared to conventional design. For CR systems, a major challenge is to enable low energy reconfigurable radio implementations that are suited for physically-limited mobile terminals and competitive with fixed hardware implementations. As noted in [90], a cross-layer cognitive controller functional block can intelligently configure the platform runtime controllable parameters depending on the context. For that functionality, it depends on proper monitors of the radio environment such as access network detection, channel state information, spectrum scanning information, and interference metric, and of the user needs and profiles as input signals.

The functionalities listed for CRs generally require more advanced hardware and software with a larger environmental footprint for attaining the overall environmental or cost-wise gains. Therefore, the fundamental trade-off for adoption of these mechanisms is the complexity introduced into systems vs. the gain towards greening of these systems. This leads to the figurative case of "being smart" vs. "being simple-minded." Moreover, CRs will have to couple efficient energy management and efficient spectrum usage. Consequently, some fundamental trade-offs for greening wireless communications via cognitive functions emerge. They can be listed as:

- *Computational complexity vs. energy consumption* - All the capabilities which rely on computation such as data processing and learning listed in Section 4.2 incur an energy consumption penalty [100]. This trade-off particularly resides on Stage 2 (Learn) and 3 (Plan and Decide) of the cognition cycle. Machine learning algorithms and decision theoretic frameworks may have high complexity with a corresponding energy burden. Spectrum sensing and agile access require energy consumption and may incur additional complexity. Therefore, it is important to optimize the energy cost without sacrificing performance (i.e. to reduce complexity) for energy-efficient cognitive radios. The relevant costs must be outweighed by the energy efficiency gains provided by the cognitive network. The analysis of this trade-off is an important research topic.
- *Penetration vs. performance* - In system design, the higher performance you target, the more exotic solutions you may end up with. That "alienation" factor may negatively affect the compatibility of novel CR based systems and impede their penetration into deployed networks. This general issue is also related to the trade-off described next since it is closely linked to the standardization and regulatory perspective. This trade-off is especially coupled to the Stage 1 (Sense) and 4 (Act) of the cognition cycle. Because these stages specify the interfaces

and interactions with the external systems and convey potential interoperability issues. The need to detect and/or generate a wide range of waveforms in any band also imposes a challenging requirement for the specification of the underlying reconfigurable radio.

- *Market exposure vs. regulatory lag* - The proliferation of innovative communication systems directly depends on the regulatory timeliness and support for attaining wide market exposure. The standardization for cognitive networking has been going on in various efforts, most notably IEEE 802.22, IEEE DYSPAN Standards Committee, IEEE 1902 and ECMA-392. The regulatory drive for power-awareness in the design, configuration and management of networks, and in the design and implementation of protocols are crucial for the adoption of CRs on the way to green networks. Therefore, the regulatory lag determines the market exposure of smart radios in green wireless communication context.
- *Hardware complexity vs. financial cost* - Reconfigurable wireless terminals, constituting the infrastructure for CRs, entail software defined radio (SDR) based digital baseband engine and reconfigurable analog front-end circuits. Energy gains can be achieved using energy-scalable design paradigms in the baseband processing algorithms, advanced digital control in the baseband component or flexible power amplifiers [90]. The energy efficiency capabilities also necessitate more complicated and expensive hardware, which is a general issue for CRs, not just in the energy efficiency context. This phenomenon has been a practical obstacle against the proliferation of agile and smart radio concepts since their inception. This trade-off is effective on all the stages of the cognition cycle.
- *Spectrum sensing vs. less overhead* - Spectrum sensing is pure overhead with energy consumption. However, sensing strategy directly determines the spectrum opportunities and thus the performance of dynamic spectrum access. Therefore, the more frequent the spectrum sensing, the more transmission opportunities. This in turn causes higher energy consumption. Another challenge in waveform detection and spectrum sensing lies in the requirement to simultaneously sense and communicate [90]. The large dynamic range due to signals, noise, and interference poses a significant challenge for low power terminal implementation.

Moreover, even performance measurement for decision support is problematic since it is not trivial which energy and quality metrics are suitable as controller input.

These interconnected trade-offs are in general applicable both to communication systems that are optimized for energy efficiency via cognitive functionalities and to CRs themselves. The key notion in that context is that significant energy savings are possible by continuously adapting the energy-scalable CR to the actual environment conditions while satisfying performance constraints. This requirement points to a system-level approach exploiting cross-layer interactions among different layers in order to carry out integrated energy management and pervasive energy consumption optimization.

4.4. Summary

The benefits of green wireless communications outweigh the drawbacks for the mobile operators. The research for green communications is an interdisciplinary field since it depends on advances in myriad areas from computer architecture to networking/communications standards. It requires the parallel effort of optimizing cognitive networks and optimization of other systems via cognitive networks and cognitive capabilities in general. The CRs are supposed to couple energy efficiency with efficient spectrum usage for supporting green communications. The vast applicability of CR based optimization in home, enterprise and data center environments brings up many opportunities as well as challenges and open problems towards these goals. It should be noted that "to consume only when necessary" (spectrum, energy, hardware) is in contrast with the consumer society tendencies promoted by the cultural logic of late capitalism. However, this approach is crucial to cope with global warming and to enable global sustainable development. In this chapter, we have presented and discussed CRs from the perspective of green wireless communications. We have also outlined the issues and trade-offs entangled with fusion of cognitive dimension and wireless systems. In Chapter 5, we define a novel small-cell network, namely Cognitive Femtocell

Network (CFN), which builds on the notions of CR and femtocell. Subsequently, we focus and expand the general CR analysis in this current chapter for that specific type of CRN and elaborate on its energy efficiency in Chapter 6.

5. COGNITIVE FEMTOCELL NETWORKS: AN OVERLAY ARCHITECTURE FOR LOCALIZED DYNAMIC SPECTRUM ACCESS

The need for anytime-anywhere service access over wireless networks has spurred a great demand for wireless radio resources. Additionally, the emerging web-based services such as *YouTube* and *Facebook* require broadband access due to the multimedia-rich content. Hence, efficient spectrum utilization is of great concern for two reasons: providing spectrum opportunities for emergent technologies/services and utilizing already crowded lower frequency bands with better spectrum efficacy. Dynamic spectrum access (DSA) facilitates the so-called *cognitive radio (CR)* devices to analyze the spectrum bands and access them if unoccupied until the arrival of an incumbent transmitter. In CR terminology, a primary user (PU) refers to a user who has higher priority or legacy rights for utilizing a specific part of the spectrum whereas a secondary user (SU) equipped with CR exploits the unused parts of this spectrum in such a way that PU communications are not disturbed. Since a PU has the right to access the spectrum depending on its contract with its service provider whenever it needs, a CR node must vacate those primary bands as fast as possible. Otherwise it would harm the primary communications which is a violation of CR operation rules. However, it is non-trivial for an SU to detect the existence of a higher priority PU in these spectrum bands of interest [101]. This requirement is challenging since there is usually no interaction between the primary and secondary (cognitive) networks. In order to detect the spectrum opportunities or the PUs, SUs sense the spectrum with its sensors. Depending on sensor readings and spectrum decision algorithm, SU decides on the state of a frequency band as *idle* or *busy*.

Reliable PU detection is the fundamental step in the realization of DSA and the opportunistic use of white spectrum. Depending on the PU signal knowledge and the radio environment, various transmitter detection schemes can be applied such as matched filter detection and energy detection [101]. A detection scheme must be reliable such that some degree of probability of detection (P_d) must be met, e.g. 0.9 in IEEE 802.22 [102] which is the first CR based wireless network standard. Moreover, probability of false alarm (P_f) which is defined as the probability that the detection scheme incorrectly declares the spectrum as occupied when it is not, should be sufficiently low. In case of false alarm, these spectrum holes can not be identified for SU use thereby resulting in lower spectrum efficiency. Performance of primary signal detection schemes may significantly degrade in case of severe channel impairments. In order to cope with this issue, robust spectrum sensing can be achieved by cooperation among SUs at the expense of message exchange overhead and cooperation delay. SUs can share their local sensing data with other SUs. Moreover, an infrastructure based solution with more advanced capabilities and network-wide knowledge can improve the system performance. The gain vs. overhead trade-off must be considered in designing such collaborative techniques.

In addition to reliable PU detection issues, there are other difficulties for wide acceptance of CRs such as deployment of new infrastructure for access control, hardware support, security/privacy issues, and network management. Reusing the existing infrastructures for tackling with these issues provides cost-efficiency and ease-of-deployment. Home base stations, i.e. *femtocells*, are posed to be a good candidate as the supporting infrastructure in that regard. Deployed at the homes or small-area public places, femtocells are low-power plug-and-play base stations providing connectivity to the cellular operator's network via a broadband connection such as digital subscriber line (DSL) or cable [103]. Femtocell concept has been developed to improve spatial coverage with increasing reuse at the expense of affordable complexity and cost. Considering the fact that around 40 percent of mobile usage is originating from the homes, femtocells providing better user experience indoors are attracting the interest of various parties [104]. The main premise behind femtocell is to increase transmitter-to-receiver proximity to improve system capacity via higher quality links and more spatial reuse [89], thereby providing a cost-effective solution for better user experience against poor indoor coverage. However, this requires the deployment of additional infrastructure and network changes. In this chapter, we define and propose a femtocell-based CR architecture for enabling multi-tiered opportunistic access

Table 5.1. Advantages and disadvantages of CR and femtocells from the viewpoints of operator and user.

	Operator		User	
	Advantages	Disadvantages	Advantages	Disadvantages
Femtocell	• Better coverage/capacity • Cost optimization • Higher subscriber satisfaction • Higher macrocell reliability • Better spatial correlation between capacity need and infrastructure	• Deployment cost • Management complexity • More complicated network evolution • Security issues due to IP connectivity • QoS issues due to IP backhauling	• Low-power transmission (longer battery lifetime) • Higher bandwidth • Better indoor signal reception • Cheaper services	• Deployment and operational costs • Burden on broadband connection for backhauling
Cognitive Radio	• Spectrum opportunities for newcomer operators • Better utilization of radio resources • Revenue generation by spectrum leasing and auctioning	• Provision of PU transparent services • SU/PU differentiation • Resource management and allocation	• Autonomous and adaptive operation • Environment aware spectrum access • Cheaper services • Multi-mode operation	• Hardware support for spectrum sensing and transmission in various bands • Hardware complexity • Spectrum sensing overhead

in next-generation cellular broadband wireless systems. This architecture combines the conventional femtocell idea with infrastructure-based overlay cognitive radio network (CRN) paradigm. Table 5.1 summarizes the challenges and opportunities of these two concepts from both the network operator's and user's perspective. For the former, the most significant advantage of femtocells is the better indoor coverage and increased spectral efficiency leading to reduced capital and operational costs. However, this necessitates a more complicated network structure with quality-of-service (QoS) and security issues. For the user, femtocells provide higher bandwidth with lower power consumption at the cost of new device installment and a broadband backhaul connectivity. Similarly, application of DSA in CRs increases the spectral efficiency and eases the penetration of new operators with novel wireless services. For the user, CR facilitates more autonomous operation with more cost-effective and personalized services. For both parties, it induces diverse challenges of hardware and software complexity in addition to the management of more complicated systems. The integrated network architecture aims to cover the best practices of femtocells and CRNs at the cost of challenges of these two concepts. This "cognitive femtocell" idea also leads to a simpler and easier proliferation of CR into the practical systems.

The rest of the chapter is organized as follows: The next section presents a brief background on femtocell networks in addition to technical challenges. We then introduce the cognitive femtocell (CF) concept with a summary of network elements and their functionalities that will be integrated to a conventional next-generation cellular femtocell network. Section 5.3 provides experimental results on the throughput performance of the introduced femtocell overlay network. Section 5.4 discusses the technical challenges and open research directions for the presented architecture. Finally, Section 5.5 concludes this chapter.

5.1. Technical Challenges

Sensing the spectrum and finding the access opportunities is not a trivial task in CRs. There are numerous sensing methods that can be applied depending on the system requirements and the network architecture. For instance, SUs can utilize their local sensing information or can make use of the exchanged sensing data of their neighbors. Sensing can be performed synchronously network-wide, or each SU can have its own sensing schedule. It can also be done by external auxiliary entities rather than the SU network itself to avoid its burden on the SU. In this regard, sensor networks have been proposed as an external network for assisting the CRs in analyzing the spectrum and finding the white spaces. For instance, Sensor Network aided Cognitive Radio (SENDORA) [105] concept aims to address various operational scenarios in the next-generation cognitive networks by the help of wireless sensor networks. Although it is a novel approach to alleviate a challenging issue, it has the drawback of requiring additional infrastructure of sensors that are resource-constrained.

Accessing the spectrum usage list from a central database is an alternative approach that eases the task of spectrum sensing. This approach can be applied to the systems with slowly changing bands such as TV bands. With the global shift from analog TV to digital TV, a vast amount of TV bands are being opened for free use. The PUs using these bands are broadcasters, authorized TV devices and wireless microphones. In the USA, Federal Communications Commission (FCC) accepts the management of white spaces and protection of PUs by a white space database (WSDB) approach [106]. WSDB keeps the up-to-date spectrum availabilities by applying secure and trusted registration of devices. This approach is viable and efficient since TV bands are relatively static. On the other hand, for more dynamic and frequently changing spectrum bands, it can be challenging. Latency in getting the available spectrum information via database access and thus accuracy of that information are the relevant drawbacks of this approach. Femtocell infrastructure already being deployed can mitigate this reliable spectrum sensing problem.

Femtocells can be utilized for residential (private) use and thus only registered users can be served by a femtocell. Alternatively, operators may install femtocells in public places, e.g. shopping malls or cafes, and any subscriber inside the coverage region can access femtocell. The first case is referred to as *closed access* whilst the latter is *open access*. Open access use-case has to tackle with securely providing access to the network resources. Moreover, it may result in excessive signalling for providing handover between adjacent femtocells or between femtocells and the macrocell in case of high user mobility. In *hybrid access* which is a combination of these two access schemes, a portion of femtocell resources are allocated to the residential registered users whilst the remaining is available for the open access [107]. Since femtocells are mostly user-installed devices, their positions are determined by users, as opposed to cellular base stations (BSs) that are deployed after a detailed capacity and performance planning [108]. Hence, femtocells can result in interference between the neighboring femtocells and underlaying macrocells leading to a capacity reduction and performance degradation [109]. Most widely-applied interference mitigation techniques are advanced power adaptation and synchronization signaling between femtocells. Furthermore, there are alternative approaches using other methods. For instance, Li *et al.* [110] work on femtocells that are capable of sensing the spectrum and allocate the spectrum minimizing the interference based on the spectrum sensing results.

Another challenge is the control of QoS in the broadband IP access which is usually DSL. This is more of a challenge if the femtocell and backhaul broadband access are provided by different operators. In addition, scalability is an important issue related to the deployment of femtocells [108]. This is crucial especially for hierarchical cellular systems such as 2G networks. However, the next-generation broadband wireless access systems 3G LTE and IEEE 802.16 WiMAX follow a different network architecture and employ a flat network where the access nodes are more autonomous and intelligent leading to more sophisticated network edge. This is a fundamental factor for femtocells in our setting since we consider this kind of network and assume more autonomous and capable spectrum managing entities. In other words, this trait strengthens the applicability of our approach.

From the economic point of view, the cost burden of femtocells requires a different model for distributing costs to the relevant parties. Financial analysis of femtocell networking has been provided in [89]. Considering the cost aspect, a different economic model can be created by altering femtocells into more advanced entities via introducing controlled changes for cognitive radio networking. An open access femtocell that provides service to secondary users registered to an operator's network can charge less

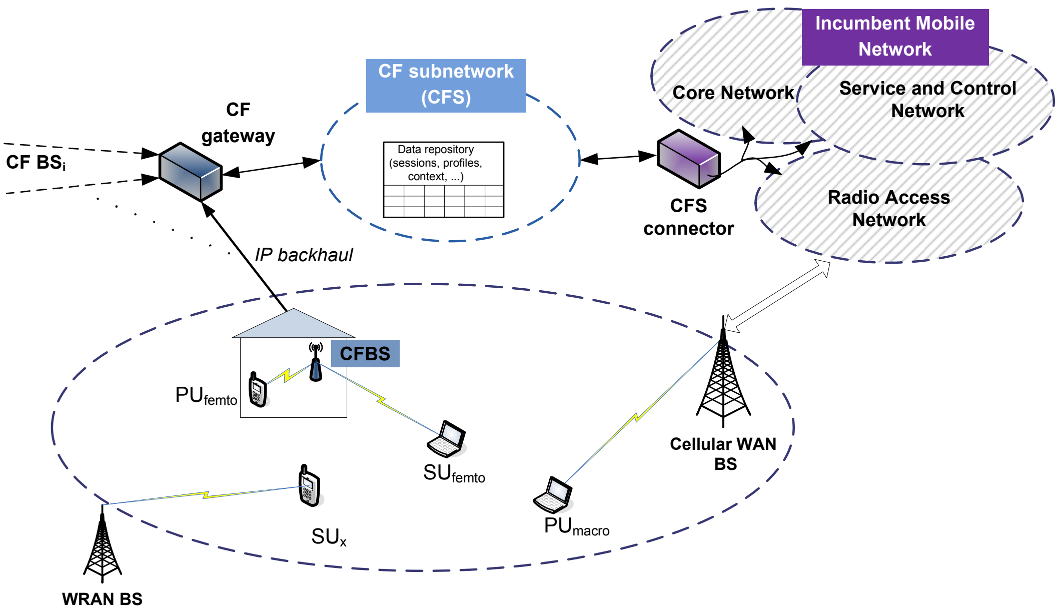


Figure 5.1. Cognitive femtocell network architecture with network subsystems, SUs and PUs (femtocell and macrocell) having various access modes.

to its incumbent users, proportional to how much it allows its resources for the use of SUs. The idea of opportunistically allocating resources of a femtocell facilitates the SUs get service by the help of femtocell's cognitive capabilities and enables efficient spectrum usage and lower prices for PUs.

Femtocell BS based on a software defined radio architecture can update both its firmware and application software, thereby can adapt to changing environment and network requirements. This also enables more autonomous operation and self configuration for femtocell BSs. This is in line with the 4G evolution path where the flat network architecture incurs a paradigm shift towards intelligent radio access network [111].

5.2. Cognitive femtocell: Small-scale distributed system for cognitive network proliferation

We propose an extension to the conventional femtocell concept for enabling cognitive operation for dual-mode handsets. Proposed network architecture is depicted in Figure 5.1. In this setting, the standard indoor coverage expansion idea for femtocell is still intact and operational. We use the term *cognitive femtocell base station* (CFBS)

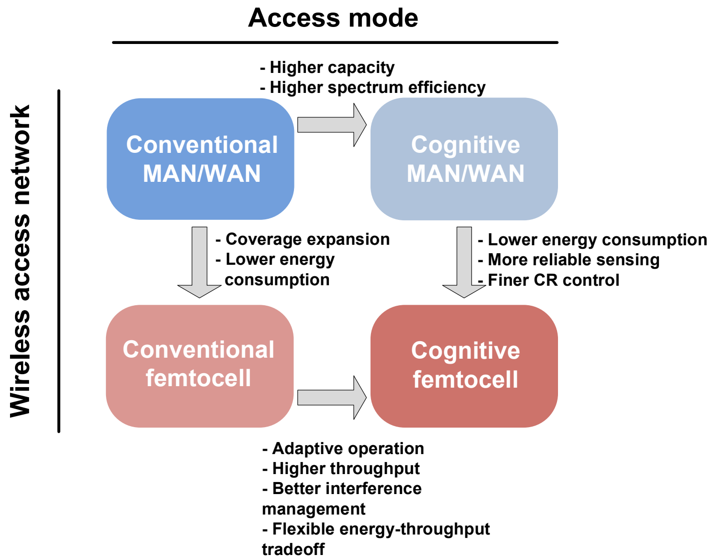


Figure 5.2. Access modes and networks matrix.

for the device, which is a simplified low-power network entity that utilizes broadband cellular technology (3G LTE/WiMAX) with IP backhaul through a local broadband connection, such as digital subscriber line (DSL), cable, or fiber [108]. It is coupled with relevant CR capabilities such as spectrum sensing, interference management, and efficient resource allocation via learning and adapting to the operating environment. CFBS acts as a conventional femtocell base station (FBS) that provides backhauling services to the users in its coverage region. CFBS accesses the operator's network via wired broadband IP connection. The wide area network used for cognitive exploitation is assumed to be 3G LTE or IEEE 802.16 WiMAX. Moreover, CFBS is responsible for local sensing and is connected to a separate cognitive femtocell subnetwork (CFS) for infrastructure resident functionalities such as user rights, service provisioning, profile management and charging in the cognitive domain.

In order to control interference on the femtocells in vicinity and underlaying macrocell, CFBS constructs the radio environment map (REM) of the femtocell by sensing its operating environment. Since femtocell coverage region is in the order of tens of meters, the interference per frequency band can be assumed to be uniform in its coverage region due to spatial correlation. In order to serve the SUs with a service request, CFBS authorizes the SUs with low bit rate control signalling via a standard protocol such as Session Initiation Protocol (SIP) [112]. SUs and CFBS are assumed to be multi-radio and multi-interface. For instance, a personal area network (PAN) interface such as Bluetooth can be utilized for signaling. The dual-mode assumption is realistic due to the wide availability of PAN access on current mobile handsets and integrated multinetwork access points (APs) for femtocells. However, a software update in the handsets for supporting the cognitive mode is necessary. This update should provide the required protocol modifications and application level tools for configuration and management of this mode by the user.

This architecture is beneficial for both the femtocell and cognitive operation in different aspects. Advantages of this system layout are manifold:

- Less SU interference and better spectrum access due to better sensing capability
- Better spectrum utilization for incumbent operator
- New business models where opportunistic spectrum access is integrated as a primary service
- The incumbent mobile network does not have to change significantly.
- The architecture enables the establishment of Mobile Virtual Network Operators (MVNOs) for providing localized cognitive access with different pricing schemes (i.e. CFS can belong to to another operator (MVNO) working with multiple operators.)
- Larger and better coverage due to conventional femtocell idea
- Since the infrastructure will be supplied and maintained by the user(s), an incentive in terms of free or cheaper service shall be provided.
- Femtocell traffic aggregation can be performed in the CFS, and thus the incumbent network does not have to handle numerous femtocells in the radio network controller's functionality.

With an advanced sensing unit, CFBS monitors its operating radio environment. We assume that CFBS can scan and allocate the frequency ranges of multiple operators hence enabling the multi-operator service deployment. Via periodic spectrum sensing, CFBS can locate the spectrum opportunities that are not utilized by any PUs in its region and the neighboring femtocells. Depending on the PU traffic requests and spectrum opportunities available for SUs, CFBS manages resource allocation. The cognitive femtocell networking facilitates SUs and PUs operate in various access modes. Service access can be either directly to the MAN/WAN network or via the femtocell BS. Access modes are summarized in Figure 5.2. Compared to conventional MAN/WAN access, access through the cognitive counterpart provides higher capacity via exploiting the spectrum opportunities more efficiently. Conventional femtocell access facilitates coverage expansion and operation with lower energy consumption. Cognitive femtocell access adds diverse enhancements to conventional access modes, namely adaptive operation, higher throughput, better interference management and flexible energy-throughput tradeoff.

This architecture also allows more advanced machine learning and fingerprinting based spectrum sensing. Since CFBS manages the traffic backhauling from the PUs and allocation of spectrum opportunities to the SUs, it can train itself on the traffic pattern of both PUs and SUs. Traffic prediction and modeling is a fundamental capability in order to allocate spectrum opportunities efficiently [101]. Briefly, if CFBS had the exact knowledge of current and future spectrum usage pattern, then it would be trivial to make allocation of white spaces. SUs would access the spectrum whenever there is no traffic and would vacate the band just before the spectrum band is occupied. Although, this exact knowledge is impossible, it can be estimated utilizing accumulated information and applying various prediction methods. For instance, in [113, 114] CR nodes estimate the residual idle and busy times of primary WLAN channels using the theory of alternating renewal processes. In this model, each PU channel is considered to follow up and down periods in a renewal cycle that correspond to busy and idle channel states, respectively. In [115], CRs estimate the call arrival rate and call holding time using an algorithm which exploits the periodicity of the PU traffic process.

Signaling flow among SUs, CFBS and CFS is depicted in Figure 5.3. First, SU performs ranging in order to associate with the CFBS (Step 1). Upon receiving the request from SU, CFBS queries the SU database residing in the CFS. If the SU can be registered in the network, then CFBS authorizes the SU into the network (Step 2). Next, when SU requests frequency (Step 3), CFBS checks REM that is constructed by

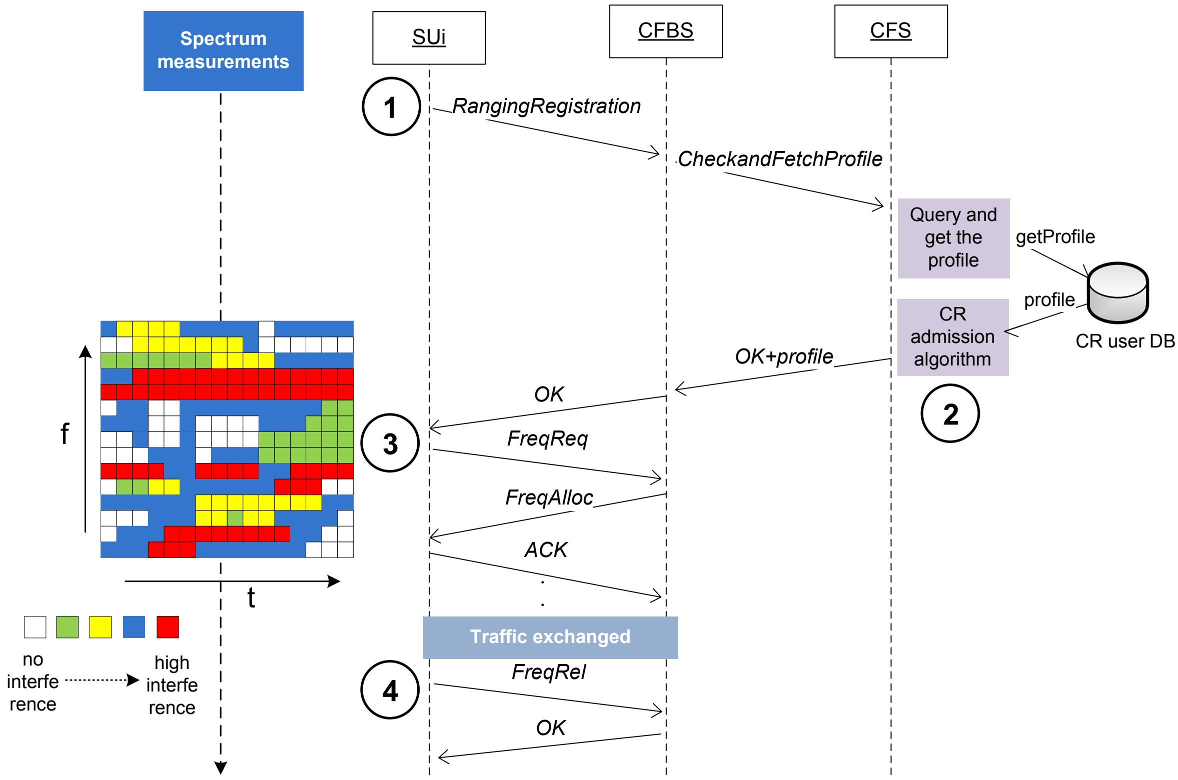


Figure 5.3. Access control signaling among SU, CFBS and CFS.

periodic spectrum measurements and updated according to the PU activities. State of a channel centered at frequency f Hz at the time slot i is represented by $S(f, i)$. The state of the channel can be either busy or idle depending on the measured energy and the PU detection threshold. REM can be represented as a two-dimensional array as in Figure 5.3. The spectrum measurements at a time slot t for the available channels (f_1 to f_n) are stored in REM. Assuming an energy-detector as the PU detection scheme, CFBS decides on the state of the channel. REM also stores the previous measurements in a time window and thereby CFBS can exploit this data for learning the spectral environment. Therefore, this architecture enables the CFBS to predict the PU traffic activities and allocate channels accordingly. Finally, SU can start transmission. CFBS enforces policies based on profile for service and QoS provisioning fetched from the user database of the CFS operator. After allocating the channels for opportunistic use, the resource usage is transmitted to the central authority for charging and monitoring.

After completing its transmission, SU releases the channel (Step 4). If a PU reappears in the channel during SU's transmission, SU is forced to perform spectrum hand-

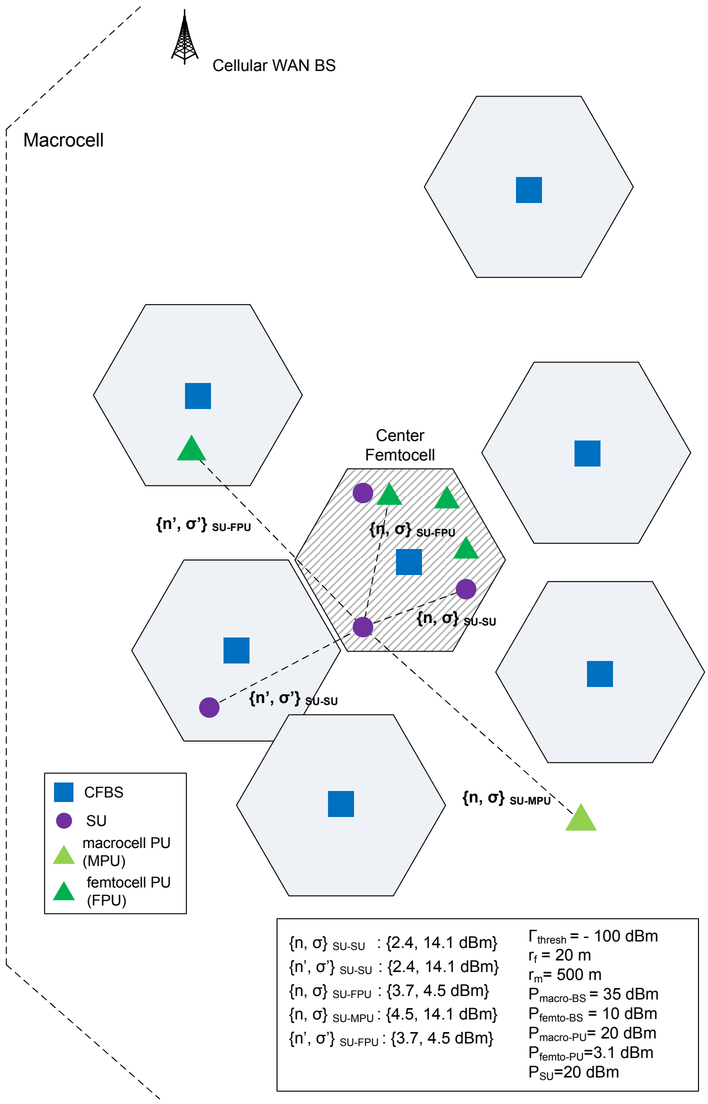


Figure 5.4. Simulation setup with three SUs in center femtocell coverage and the relevant system parameters.

off. Depending on the spectrum availability, it can be allocated either another primary or a secondary frequency channel. In this work, we do not address CR MAN/WAN access mechanisms after SU frequency allocation.

5.3. Experimental Results

In this section, we provide interference and throughput performance of cognitive femtocell networks via system-level simulations in order to demonstrate the potential benefits described earlier. We assume that the broadband cellular network (BWN) operates at 2.1 GHz carrier frequency with channels of 10 MHz bandwidth. Femtocell

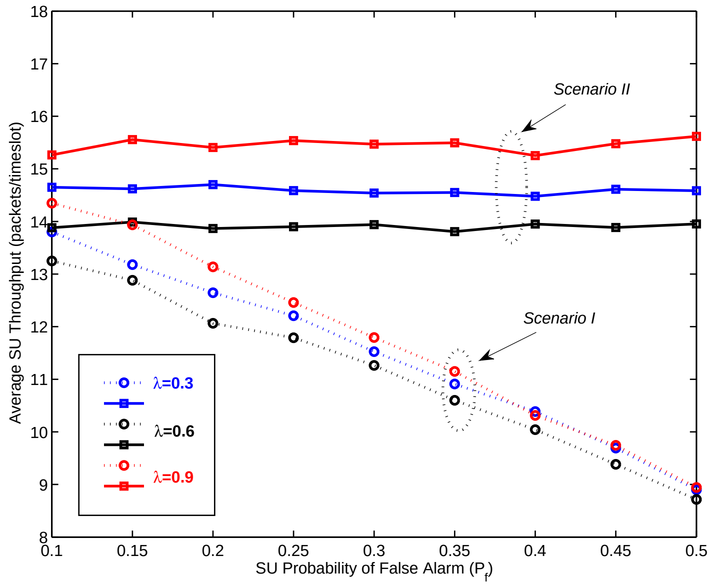


Figure 5.5. SU throughput performance vs. SU probability of false alarm. SU throughput decreases with increasing P_f in Scenario I. However, macro-PU and femto-PU throughput values are slightly affected.

users are stationary, therefore the channel is assumed to be stationary. A lognormal path loss model is used between every node in the network. The transmission power P_t of macro-PU, femto-PU, SU, femto-BS and macro-BS are 20, 3.1, 20, 10 and 35 dBm, respectively. Mobility is not considered in the experiments since we do not focus on the handover and inter-femtocell user management which is a general femtocell issue. In the simulation setup, we focus on a single macro-BS coverage with radius r_m=500 m, whereas the femtocell radius is r_f=20 m. We suppose a frequency reuse factor of 1, which is the general case for 3G LTE and WiMAX systems.

Figure 5.4 illustrates the network deployment model employed in the experiments. The simulation area comprises a two-tiered and tessellated femtocell distribution. In each femtocell footprint, there are three SUs and three femto-PUs. There are seven femtocells deployed in a confined region inside the macrocell to simulate a realistic network setup. These femtocells are scattered around a center femtocell in a randomized fashion (random distance and angular orientation). The macro-users are spectrally orthogonal while the femto-PUs use overlapping frequencies with them. However femto-PUs in the same femtocell use non-overlapping frequencies. Additionally, we assume the availability of two more frequencies for modeling the effect of multi-operator frequency sensing and allocation capability of CFBS.

In order to illustrate the performance gains introduced by CFBS, two scenarios are compared. In Scenario I, SUs sense the spectrum and access the available frequency bands exploiting their own sensing capabilities. In Scenario II, CFBS manages spectrum sensing and allocation. In both scenarios, as PU detection mechanism, a simple energy detection scheme is assumed with a detection threshold of Γ_{thresh}=-100 dBm. In other words, an SU senses the spectrum and it can detect the existence of the PU if aggregate received power (dBm) at the SU is higher than Γ_{thresh}. We use a discrete-time slot-level system simulation such that at the beginning of each time slot, femto-PUs and SUs generate traffic depending on their traffic activity and generation model. In order to model the worst case, in high load case all femto-PUs and macro-PUs are active and generate traffic. In light load case, traffic activity is generated randomly according to a uniform distribution with an activity factor of λ which stands for the portion of time slots that a user generates traffic. SUs are assumed to have traffic at each time slot such that if there exists a spectrum opportunity, they start transmission.

Each channel is modeled with corresponding channel parameters as depicted in Figure 5.4. In Scenario II, the contribution of transfer of sensing and detection from less-capable SU to more advanced CFBS is modeled as more reliable sensing capability which corresponds to P_d=0.90 and P_f=0.1 which are the typical values of IEEE 802.22. Simulations are run with various SU probability of detection (P_d) and probability of false alarm (P_f) values and under various femto-PU and macro-PU traffic loads. Figure 5.5 illustrates the change in the average throughput with increasing SU P_f. Average throughput is calculated in terms of packets per timeslot and it decreases with increasing P_f in Scenario I. However, in Scenario II, throughput is not affected since spectrum sensing is driven by the CFBS. Femto-PU and macro-PU throughput values are slightly affected in both scenarios. In low activity case where λ=0.3, femto-PU throughput is 6.30 packets/timeslot and macro-PU throughput is 1.29 packets/timeslot in both scenarios. In medium activity and high activity cases (λ=0.6 and λ=0.9, respectively), femto-PU throughput is 12.57 and 18.90 packets/timeslot in Scenario

I and Scenario II. Similarly, macro-PU throughput is slightly higher in Scenario II compared to Scenario I with values 2.81 vs. 2.83 for λ=0.3 and 4.82 vs. 4.90 for λ=0.9.

Next, we investigate the impact of P_d increasing from 0.5 to 0.9 on macro-PU and SU throughput. In case of low P_d values, SU fails to detect an ongoing PU transmission and transmits on an occupied channel. Hence, interference experienced at the macro-PUs increases directly with the decrease in the sensing precision, thereby resulting in low signal-to-noise ratio (SNR) at the macro-PUs. In other words, in these scenarios SUs cause harmful interference to the macro-PUs such that minimum required SNR can not be satisfied for successful packet reception at macro-PUs. This results in packet drops, thereby a decrease around five percent in macro-PU throughput. In Scenario I, SU throughput is slightly higher than Scenario II since SUs access the spectrum more aggressively. In Scenario II, since sensing is more robust (P_d=0.95) and meets the macro-PU restrictions, throughput barely changes in various settings. Experimental results illustrate the benefits of CFBS deployment and indicate that it enhances SU throughput and decreases the interference experienced by the PUs due to more reliable sensing by CFBS.

5.4. Discussions

The research directions and open issues for CF networks can be classified into native topics for CRN and femtocells, and emergent topics due to the integration of these two concepts. The research directions in conventional femtocell aspect are as follows:

Interference management Since femtocells are deployed at the subscriber's premise in ad hoc manner, cellular frequency planning is missing. This usually results in interference issues among nearby femtocells (intra-tier) and between femtocell and the underlaying macrocell (cross-tier). Interference decreases the system capacity and may result in poor user experience. Hence, interference mitigation techniques in both uplink and downlink are crucial [103].

Pricing, business and service models This is a two-fold issue: the pricing of the equipment and the service. In order to compete with Wi-Fi or similar ubiquitous wireless access technologies, femtocell services must be provided with favorable cost options [89]. The capital and operational expenditures should be kept at a reasonable level in order to justify a femtocell solution. Standardization for the femtocell BS protocols and a scalable interface to the operator network is a key factor in that respect.

Backhaul support and net neutrality Since the femtocell is connected to the operator's network via the Internet, providing sufficient user experience can be challenging. QoS requirements of the traffic generated by the femtocell users need to be met via applying various QoS provisioning mechanisms at both the operator's network and the IP network [89]. Net neutrality is an emerging principle where user access networks should not enforce restrictions on traffic content/source/characteristics and on the modalities of communication. This idea is particularly applicable to broadband access networks and thus the traffic generated due to femtocell backhauling. For the case of disparate cellular and wired broadband operator, regulations leading to net neutrality may ease the deployment of femtocells and alleviate the performance bottleneck due to the disfavoring by the access network operator (e.g. DSL or Fiber-To-The-x, FTTx) against the other operator's traffic.

In CR domain, there are various open issues some of which can be listed as follows:

Sensing reliability Providing a simple yet reliable spectrum sensing scheme is still an open problem in CR communications. Radio front-end with a wideband spectrum sensing capability is required at the CR in order to operate in a wide range of spectrum [116]. Additionally, SUs are restricted with low power transmission with a requirement of PU detection at low SNR environments. CR devices must include computational intelligence in order to adapt their sensing mechanisms to a wide-range of spectrum channels that expose differences in nature, e.g. emergency communication bands vs. TV bands [79].

Inter-femtocell interference among PUs and SUs Related to the spectrum sensing issue, SUs must be able to detect the PUs in close proximity with a sufficient probability of detection. Since femtocell coverage is small compared to macrocells, it is easier to detect the PUs in femtocells service area. However, in femtocell setup, PUs operate with low power levels due to short distance between the transmitter and receiver. FBS performing spectrum analysis for guaranteeing non-harmful interference to the neighbors, can share its sensing with the SUs. Thus, SUs using this information in addition to their spectrum sensing outcomes can detect the PUs. However, it is still an issue to vacate a channel in a sufficiently short time in case a PU reappears in band.

Cross-tier cognitive interference among PUs in the macrocell and SUs in the femtocell Macro-PUs geographically residing in the femtocell coverage area or close proximity but being served by the macro-BS raise destructive interference [103]. Since FBS locations are unknown to the service provider, this interference must be managed by the FBSs themselves. Depending on the access method (i.e., open, closed or hybrid) this interference may become even more destructive [107]. High performance yet efficient interference mitigation techniques spanning from power control to spectrum allocation mechanisms should be employed at the femtocells.

The issues due to CR and femtocell integration are more diverse since they entail challenges from both domains. The predominant issues and topics are as follows:

SU and CFBS requirements Hardware and firmware modifications in conventional FBS for providing high-performance spectrum sensing are still to be explored. Namely, fundamental issues can be listed as protocol stack changes, powerful signal analysis methods for reliable wideband spectrum sensing and hardware requirements such as antennas, more advanced RF front-ends and signal processing circuitry. For SU, the substantial changes should be confined to software domain for wider and easier service penetration.

Signalling protocols between SU and CFBS The service registration and control at the application level between SU and CFBS should be done using a low-latency and lightweight protocol. The signalling should be provided through standardized protocols and interfaces that are based on open standards such as SIP. This is an open research topic.

Interworking between CFS and incumbent operator's core network Interworking protocols at signalling and bearer levels to provide interoperability of these two subsystems should be developed [108]. Aggregation at CF gateway should be scalable in order to support the large amount of femtocells connected to CFS. Similarly, CFS connector at the CFS edge should scale both horizontally and vertically, and support different signalling and data interfaces between peers.

Analysis of power efficiency gains via CF architecture The power efficiency is crucial for mobile devices due to limited battery life and restricted form factor. On the network side, power awareness is necessary to minimize costs and environmental impact of network infrastructure, i.e. aiming *green* networks. The gains and tradeoffs introduced with the combination of DSA and spatial proximity of transmitter-receiver pair in femtocells are yet to be explored in more detail.

Business models for open and dynamic access The cost reductions via off-loading the macro network by the femtocell operation and discovering the vacant resources by cognitive capabilities, provide a strong motivation for operators to introduce cognitive femtocell based services. These cost savings can be exploited to provide low-cost voice and data services to the customers. However, more practical and streamlined business models need to be developed by the operators for encouraging the femtocell owners willing to share their resources with SUs. Moreover, charging models and service agreements for cognitive femtocell users are to be defined.

Service aspects-authentication, authorization and accounting (AAA) Service provisioning and access control are inherently complicated in cognitive femtocell networks with opportunistic access enabled over open femtocells. In addition, security and privacy should be provided at a satisfactory degree. This is also challenging since SUs may connect over different femtocells through different broadband operators.

5.5. Summary

The wireless broadband access is spreading on all fronts. Although these access systems address different requirements, the fundamental requirement is to achieve higher spectral efficiency. Femtocells are accepted as promising low-cost and easy-to-deploy candidate for providing small-area indoor coverage and thus increasing spectral efficiency and system capacity. However, this approach has the drawback of increased deployment and operational costs in the infrastructure aspect. Another approach for addressing the requirements of broadband access is dynamic spectrum access. Dynamic spectrum access facilitates the cognitive radio nodes to analyze the spectrum and access the white spaces till the arrival of licensed users.

In this chapter, we study a femtocell-based cognitive radio scheme in order to provide more effective dynamic spectrum access and management. In this system, the cognitive femtocell network utilizes a new service paradigm and transforms the main burden, interference management, into the service enabler itself. SUs are controlled by the femtocell infrastructure to tackle with reliable sensing and service control issues. Cognitive FBSs have spectrum sensing hardware and access the cognitive operator's network to authorize the SUs and apply the required AAA functionalities. We carry out system-level simulations to show the performance gain introduced by the proposed architecture. Simulation results demonstrate that with better sensing capability, FBS discovers the spectrum opportunities more efficiently and allocates them to the requesting SUs in its coverage area. Hence, SU throughput and spectrum access is improved, which also results in less interference to the PUs.

6. ENERGY EFFICIENCY IMPACT OF COGNITIVE FEMTOCELLS IN HETEROGENEOUS NETWORKS

In this chapter, we delve deeper into the cognitive femtocell concept and discuss cognitive femtocell networks (CFNs) from energy efficiency perspective via examining the related challenges and trade-offs. While CRs can empower femtocell networks with their embedded intelligence and advanced operation functions, they also induce diverse challenges of hardware and software complexity in addition to the management of more complicated systems [19]. The incumbent challenges of CRs apply to the context of femtocell integration: spectrum sensing and PU detection, efficient protocols for cognitive operation and new business models are the most apparent challenges that need considerable effort for efficient fusion of the CR paradigm and femtocell networks. CFNs should be evaluated from an energy efficiency perspective if they are to be adopted as a part of heterogeneous green cellular networks. Therefore, our aim is to investigate the interplay between the energy gains achieved by introducing cognitive femtocells with spectrum sensing/discovery capability and the additional energy overhead induced by spectrum sensing and backhauling by these systems. We highlight the cases under which conditions energy efficiency achieved by small cells and increased spectral efficiency compensate for the additional energy consumption by cognitive femtocells.

The remainder of this chapter is organized as follows: Section 6.1 first describes the system model and next proposes an analytical model for calculating the energy efficiency and throughput of a network consisting of a macrocell, various femtocells and cognitive femtocells. Subsequently, Section 6.2 analyzes this cellular heterogeneous network and evaluates the system performance in terms of energy efficiency and throughput. This analysis investigates the effect of CFNs on energy efficiency of cellular heterogenous networks by comparing its performance with alternative setups that do not entail cognitive femtocells. Finally, Section 6.3 concludes the chapter.

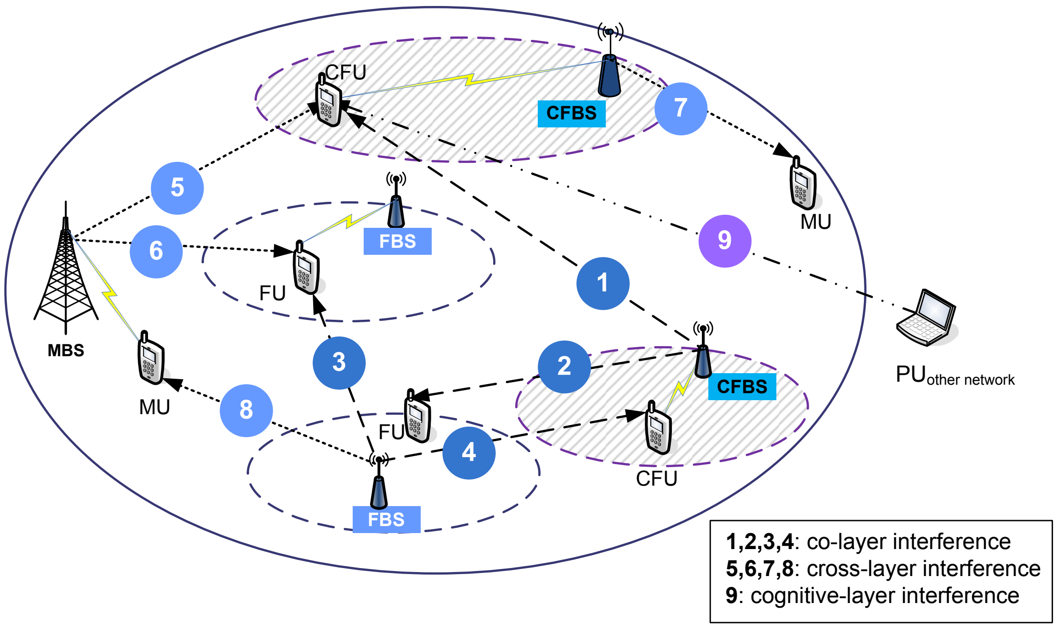


Figure 6.1. System model and and the relevant interference effects on network entities.

6.1. System Model

We describe the heterogeneous wireless system with CFBSs investigated in our work and layout the system model analytically in this section. We assume the availability of fundamental CR capability of dynamic spectrum access at CFBSs as well as capability of detecting user activity in the related coverage area. The latter capability is directly linked to the "environment-awareness" property of cognitive radios.

The heterogenous network under focus that is illustrated in Figure 6.1 consists of three types of cells: cognitive femtocells managed by CFBS, femtocells managed by FBS, and a macrocell managed by MBS. Each of these base stations serves its users: cognitive femtocell users (CFUs), femtocell users (FUs), and macrocell users (MUs), respectively. MBS resides at the center of the cell with a coverage radius of R. The difference between an FU and a CFU is due to the serving base station: an FBS or a CFBS. Both are stationary, hence their channels with the serving CFBS/FBS are assumed to be stationary. CFBSs have the necessary capability of utilizing a wider band than the licensed cellular network (compatible RF frontend and baseband processing). Moreover, the femtocells are synchronized for time-slotted operation. We use the formal definition of energy efficiency - *number of transmitted data (bits) per* *unit energy consumption*- as our performance metric measured in *bits/Hertz per joule.*

Let N_F, N_C, n_f, n_c, n_m denote the number of each entity: FBS, CFBS, FU, CFU, and MU, respectively. A macrocell-only network will have only MUs ($N_C = n_c = N_F = n_f = 0$) whereas a macrocell network with only traditional femtocells has no cognitive entities ($N_C = n_c = 0$). The F_M frequencies are owned by the operator. The MUs operate at these frequencies orthogonally while the FUs and CFUs use overlapping frequencies with them. Additionally, we assume the availability of F_{CR} more frequencies for modeling the effect of multi-operator frequency sensing and allocation capability of CFBSs. Each CFBS/FBS serves to a single CFU/FU in its coverage. We assume that each CFBS performs sensing regularly, once in each T_s time slots. The longer is this period, the lower is the energy consumption for sensing and the lower is the sensing performance. We incorporate the effect of T_s in our system by modeling probability of detection (p_d) and false alarm (p_{fa}) as functions of T_s: p_d decreases while p_{fa} increases with increasing T_s. We will refer to these terms as $p_d(T_s)$ and $p_{fa}(T_s)$ to represent this relationship.

We focus on the downlink transmission, and spectrum sensing and allocation only on the CFBS downlink. There are two main reasons for this: first, the asymmetric nature of user traffic concentrates the transmissions on the downlink. Second, the relatively easier proliferation of CR capabilities through FBS deployment compared to user replacements implies this scenario more likely.

The following notation is used for representing types: C stands for CFBS, c for CFU, F for non-cognitive femto, f for FU, M for MBS, m for MU, and P for primary user. In this network, energy consumption (E) and throughput (C) are calculated as the sum of values by related entities, i.e. total throughput of users in the system opposed to the total energy consumption of all network nodes excluding the licensed users of the primary bands (primary users, PUs) since they are external entities. For the sake of brevity, we use energy and power interchangeably at certain points during analysis since we already consider power consumption per time unit ($P \times T$) leading to an implicit energy consumption value for those specific cases. In the following part,

Table 6.1. Energy consumption components for each entity.

Entity	**Transmission**	**Reception**	**Backhaul**	**Sensing**	**Idling**
MBS	+				
FBS	+		+		+
CFBS	+		+	+	+
MU		+			+
FU		+			+
CFU		+			+

we present our approach to calculate these energy consumption and related capacity values. Table 6.1 lists all energy consumption components associated with each entity.

6.1.1. Downlink Energy Consumption Model

In this section, we present our model for each component: MBS, FBS, CFBS, MU, FU, and CFU. As shown in Table 6.1, MBS consumes energy only for transmission whereas an FBS also has backhaul and idling components for energy consumption. A CFBS has all these components as of an FBS with an addition of component for sensing energy consumption. Since we focus on downlink transmission, all user types consume energy for reception and idling. We use the model introduced in [117] for base station transmission energy consumption[1] . In this model, power consumed for transmission (P^{in}) is a function of transmission power P^{out} and network load. This model accounts for all energy consuming components, e.g., circuitry and feeder losses [117]. Additionally, we include the backhaul energy consumption since it may substantially affect the energy efficiency figures especially for small cells [118]. Considering the fact that backhaul also may change the best operation mode especially for small cell scenarios, we also include backhaul energy consumption in the small cells. Effect of backhauling at the MBS is skipped since both scenarios -with and without small cells- already have this cost.

[1]Throughout the section, we use power and energy consumption interchangebly. Both in fact refer to the power consumption as we consider unit time in our model.

6.1.1.1. MBS energy consumption. MBS energy consumption is due to downlink transmission to the MUs in its coverage. Given the power consumption for transmission is P_M^{in}, total energy consumption equals P_M^{in}.

6.1.1.2. MU energy consumption. Let λ_m denote the probability that an MU has a downlink traffic in a time slot and P_m^i be the idling energy consumption when an MU has no incoming traffic. Since MBS allocates frequencies orthogonally, an MU is assigned a frequency with probability $p = F_M/n_m$, $(F_M \leq n_m)$. Average energy consumption at the MU is:

$$E_m = \lambda_m p P_m^{rx} + (1 - \lambda_m p) P_m^i \tag{6.1}$$

where P_m^{rx} denotes the energy consumption of an MU for receiving the downlink traffic.

6.1.1.3. CFBS energy consumption. At a time slot, a CFBS may be in one of the three states:

(i) it transmits downlink traffic to CFUs,
(ii) it switches to idle mode if there is no downlink traffic, or
(iii) it halts all traffic and senses the spectrum.

Let λ_c denote the probability that a CFU has a downlink traffic in a time slot, and CFBS performs spectrum sensing once in each T_s slots. In the transmission mode, total energy consumption (E_C^t) is the sum of energy consumption due to transmitter and the backhaul equipment: $E_C^t = P_C^{in} + P_C^{bh}$. For sensing and idling modes, energy consumption $(E_C^s$ and $E_C^i)$ becomes $E_C^s = P_C^s + P_C^{bh}$ and $E_C^i = P_C^i$. Then, average CFBS energy consumption becomes:

$$E_C = \frac{E_C^s + (T_s - 1)(\lambda_c E_C^t + (1 - \lambda_c) E_C^i)}{T_s}. \tag{6.2}$$

6.1.1.4. CFU energy consumption. A CFU may be in two states: traffic reception or idling. It receives downlink traffic if it has some incoming traffic and allocated a frequency by the CFBS. It idles if it does not have an incoming traffic or no frequency is allocated for it. Additionally, a CFU idles during sensing periods as CFBS halts transmission and performs sensing. A CFU receives traffic from the serving CFBS at the assigned frequency f. Since discovered spectrum opportunities at the CFBS may be spectrally distant from the operator-owned frequencies, we include the cost of RF antenna tuning, aka *channel switching cost* [119]. Channel switching cost is a linear function of the difference between the current and to be switched frequencies, i.e., $|f - f'|$. Let δ_F be the average number of channel switching, and P_c^i be the energy consumption when a CFU has no incoming traffic. Energy consumption at the CFU is:

$$E_c = \frac{P_c^i + (T_s - 1)(\lambda_c(P_c^{rx} + P_c^{cs}\delta_F) + (1 - \lambda_c)P_c^i)}{T_s} \tag{6.3}$$

where P_c^i, P_c^{rx}, and P_c^{cs} denote the energy consumed by a CFU for idling, reception, and channel switching, respectively.

6.1.1.5. FBS energy consumption. Different from CFBS, an FBS does not perform spectrum sensing. Energy consumption at the FBS is due to transmission, backhaul, and idling.

6.1.1.6. FU energy consumption. An FU different from the CFU operates only on the operator bands which are typically a set of contiguous bands. Hence, channel switching in FUs is negligible compared with the CFUs. Energy consumption at the FU is due to receiving or idling in case of no incoming traffic.

6.1.2. Spectrum capacity calculation

CFBS in a CFN discovers spectrum opportunities via analyzing the spectrum consisting of F_{CR} frequencies. However, sensing process is not totally accurate; a CFBS may fail to detect active PU(s) in the band, called *misdetection*, or may give an alarm that PU exists in the band but it does not, called *false alarm*. Some opportunities might be lost due to false alarm. Taking the effect of false alarm into account, we can model the spectrum capacity of CFBSs in terms of available frequencies. Given that there are F_{CR} frequencies for opportunistic use, and each frequency is idle with probability p_{idle}, then spectrum capacity F_C is the sum of discovered frequencies and the MBS frequencies:

$$F_C = F_{CR} p_{idle}(1 - p_{fa}(T_s)) + F_M \tag{6.4}$$

whereas in a setting with only femtocells sharing the operator's frequencies, spectrum capacity is simply

$$F_F = F_M. \tag{6.5}$$

6.1.3. Interference calculation

Below, we classify the type of interference among the entities into three groups and identify the value of each using the expected distance between the source and the victim of the interference. Let $n_{*,x}$ be the number of entities of `Type *` creating interference to an entity of `Type x`, and $I_{*,x}$ be corresponding interference. We find the number of interferers as $\lambda_* \bar{N}_* / F_*$ where $\bar{N}_*$ is the number of `Type *` nodes excluding the node itself:

$$n_{C,m} = \frac{\lambda_c N_C}{F_C}, \quad n_{F,m} = \frac{\lambda_f N_F}{F_F} \tag{6.6}$$

$$n_{C,c} = \frac{\lambda_c (N_C - 1)}{F_C}, \quad n_{F,c} = \frac{\lambda_f N_F}{F_F} \tag{6.7}$$

$$n_{C,f} = \frac{\lambda_c N_C}{F_C}, \quad n_{F,f} = \frac{\lambda_f (N_F - 1)}{F_F} \tag{6.8}$$

We consider only a single MU receiving at each MBS frequency and a single PU for each primary network frequency. Hence, we can write $n_{P,c} = 1$, $n_{M,c} = 1$, $n_{M,f} = 1$.

- *Co-layer Interference:* A CFBS creates interference to the CFUs receiving at the same frequency in the coverage of other CFBSs. This effect is marked as `1` in Figure 6.1. This interference equals to $I_{C,c} = P_C^{out} d^{-\alpha}$ where d is the average distance to the closest CFBS and α is the path loss exponent of the link between the CFBS and the CFU. Assume that N_C CFBS are uniformly deployed at angular separation $\frac{2\pi}{N_C}$ and at a distance $\frac{R}{2}$ away from the center of the cell on the average. In this network, d can be calculated using the law of cosine as follows:

$$d = \sqrt{\frac{R^2}{2}(1 - \cos(\frac{2\pi}{N_C}))}. \tag{6.9}$$

  Similarly, a CFBS creates interference to the FUs in the femtocells ($I_{C,f}$, link `2` in Figure 6.1), FBS to FUs in neighboring cells ($I_{F,f}$, link `3`), and FBS to the CFUs ($I_{F,c}$, link `4`). All are calculated similar to $I_{C,c}$.

- *Cross-layer Interference:* Interference between macro-layer and femto-layer is called cross-layer interference. In the downlink, BS generates interference to the user receiving at the same frequency in the other layer: MBS to the CFUs/FUs and CFBS/FBS to the MUs. The effects marked with `5,6,7,` and `8` in Figure 6.1 correspond to these interference types, respectively. Average distance between the MBS and a CFU/FU is $d = \frac{R}{2}$. Average distance between a CFBS/FBS and an

MU is calculated similar to inter-CFBS distance calculation in Equation 6.9:

$$d = \sqrt{\frac{R^2}{2}(1 - \cos(\frac{2\pi}{N_C} - \frac{2\pi}{n_m}))}. \tag{6.10}$$

- *Cognitive Layer Interference:* CFBS may experience/create severe interference from/to the external primary networks at F_{CR} bands. This interference is significantly high in case of misdetection compared to the opportunistic use of the spectrum after successful discovery of the idle bands. This effect is depicted as link 9. The distance between the source and the victim of the interference is:

$$d = \sqrt{\frac{R^2}{2}(1 - \cos(\frac{2\pi}{N_C} - \frac{2\pi}{n_p}))}. \tag{6.11}$$

Interferences at an MU (I_m), at an FU (I_f), and at a CFU (I_c) under a certain probability of detection $p_d(T_s)$ are calculated as follows considering all three types of the interference and the background noise (N_0):

$$I_m = n_{C,m}I_{C,m} + n_{F,m}I_{F,m} + N_0 \tag{6.12}$$

$$I_f = n_{C,f}I_{C,f} + n_{F,f}I_{F,f} + n_{M,f}I_{M,f} + N_0 \tag{6.13}$$

$$I_c = n_{C,c}I_{C,c} + n_{F,c}I_{F,c} + n_{M,c}I_{M,c} + n_{P,c}(1 - p_d(T_s))I_{P,c} + N_0. \tag{6.14}$$

We can calculate the theoretical capacity perceived by each user type using Shannon's formula. Since we are mainly concerned with the relative performance comparison of different scenarios and the effect of CFN proliferation, we assume that the channel bandwidth is 1 Hz for the sake of simplicity. This setting also allows the performed analysis to be network-technology independent. Therefore, the results may also be interpreted as "per frequency unit capacity".

Since CFUs do not receive traffic during sensing periods, we normalize throughput of CFUs (C_c) accordingly as below:

$$C_m = \frac{F_M}{n_m}\log_2(1+\frac{P_M^{out}}{I_m}) \tag{6.15}$$
$$C_c = \frac{T_s-1}{T_s}\frac{F_C}{n_c}\log_2(1+\frac{P_C^{out}}{I_c}) \tag{6.16}$$
$$C_f = \frac{F_F}{n_f}\log_2(1+\frac{P_F^{out}}{I_f}). \tag{6.17}$$

Finally, energy consumption (E) and capacity (C) are calculated as the total energy consumption and throughput of all entities in the network as follows:

$$\begin{aligned} E =& E_M + n_mE_m + N_CE_C + \\ & n_cE_c + N_FE_F + n_fE_f \end{aligned} \tag{6.18}$$
$$C = n_mC_m + n_cC_c + n_fC_f \tag{6.19}$$

Using the derived network capacity and energy consumption values, energy efficiency η is calculated as $\eta = \frac{C}{E}$.

6.2. Analysis and Evaluation

In this section, we evaluate the effects of CFN on the energy efficiency of heterogeneous mobile networks via system-level simulations. In order to analyze the energy efficiency tradeoffs emerging with the introduction of CFBSs, we analyze three scenarios:

- In Scenario I, there are no femtocells but just the macrocell serving the cellular users. This scenario is also referred to as `macrocell-only` scenario.
- In Scenario II, the system has femtocells in the macrocell coverage. This scenario is referred to as `macrocell+femtocells` scenario.

- Scenario III reflects a CFN scenario, where CFBSs are also deployed in addition to FBSs in the macrocell. This scenario is referred as `CFN` scenario.

Table 6.2. Summary of basic variables and parameter values.

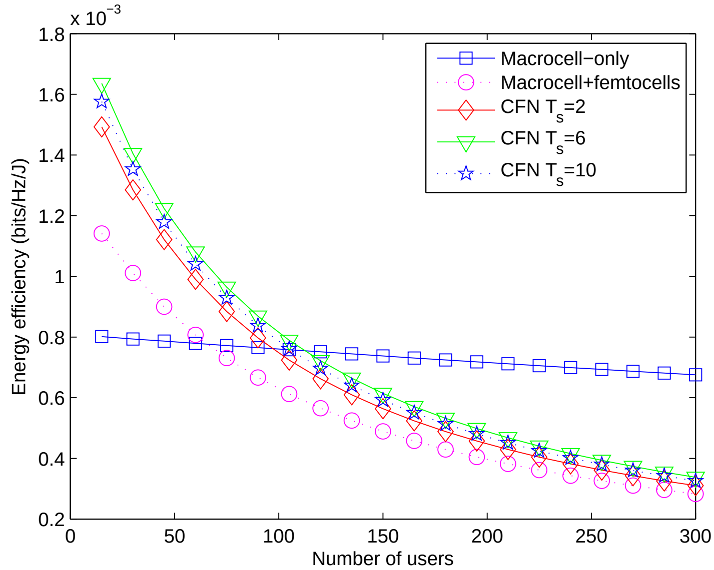
Parameter	**Explanation**	**Value**
R	Radius of macrocell	500 m
P_C^{out}, P_F^{out}, P_M^{out}	Transmission power of CFBS, FBS, and MBS	30, 30, 46 dBm
P_C^i, P_C^{bh}, P_C^s	CFBS power of idling, backhaul, and sensing	500, 100, 600 mW
P_m^i,P_m^{rx}	MU idling and receiving power	200, 600 mW
P_c^i,P_c^{rx}	CFU idling and receiving power	200, 300 mW
δ_F	Average number of channel switching	5
F_M, F_{CR}	Number of MBS and CR frequencies	10, 5
p_{idle}	PU probability of being idle	0.6
λ_f, λ_m, λ_c	Traffic probability of FU, MU, and CFU	0.6
$\alpha_{MC}, \alpha_{MF}, \alpha_{PC}$	Path loss exponential (MBS-CFU, MBS-FU, PU-CFU)	2.8
$\alpha_{FC}, \alpha_{CC}, \alpha_{FF}$	Path loss exponential (FBS-CFU, CFBS-CFU, FBS-FU)	2

System parameters for these settings are summarized in Table 6.2. For calculating distances in different scenarios for specific number of users, we take an initial random setting as our reference and calculate distances from the presented distance formulas. Since the nodes become closer with increasing number of users N, we scale distance values based on our reference model. We model the performance decrease in sensing with increasing sensing period as follows:

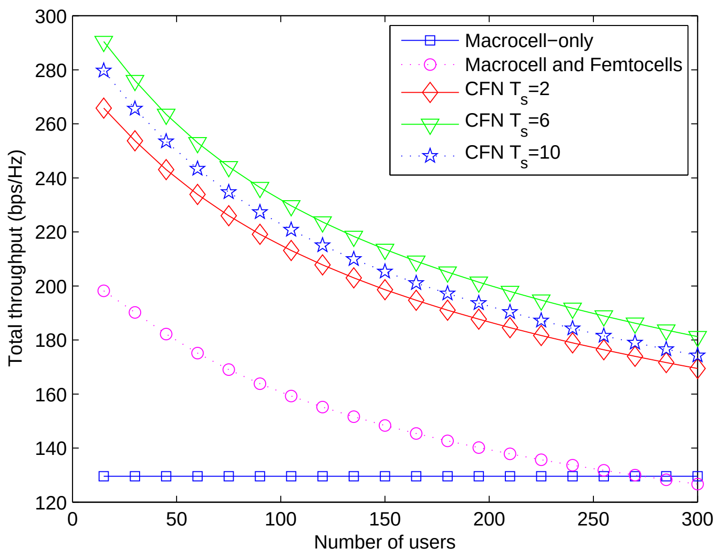
$$p_d(T_s) = 0.9/(T_s - 1) \text{ and } p_{fa}(T_s) = 0.1(T_s - 1). \tag{6.20}$$

However, please note that any non-increasing function of T_s can be integrated into our evaluation for calculating p_d and non-decreasing function of T_s for calculating p_{fa}.

Figure 6.2(a) depicts energy efficiency of these three scenarios. In Scenario I, all users are MUs whereas in Scenario II half of the users is MUs and the other half is FUs. In Scenario III, the number of MUs, FUs, and CFUs in the network are equal. This last scenario corresponds to the setting where CFNs are deployed into the network leading to a heterogeneous network of macrocells, conventional femtocells and cognitive femtocells. For this scenario, we set T_s to 2, 6, and 10 time slots to see the effect of sensing period. With increasing number of users, the energy efficiency of all scenarios decreases as expected. In general, CFN attains higher energy efficiency for typical settings. This is due to the additional bandwidth utilized via DSA. While CFN outperforms Scenario I and Scenario II, Scenario II generally outperforms Scenario I. This supports the proposition that deploying small cells to a macrocell improves energy efficiency, and adding cognitive capabilities to these femtocells further improves the performance. The CFN scenario with $T_s = 6$ performs as the best one. This result shows the trade-off between energy/throughput consumption of sensing vs. its accuracy. The performance loss suffered by Scenario II and Scenario III is greater with increasing user density leading to lower performance after an intersection point with Scenario I at $N = 100$ and $N = 150$, respectively. After a certain point, CFBS and FBS become so dense that their interference degrades the network performance. Although, macrocell-only scenario has lower bandwidth and lacks frequency reuse, it attains higher energy efficiency due to its interference-free operation principle. We infer from this figure that effective interference management schemes have to be applied for femtocell and cognitive femtocell scenarios in order to realize their potential. Additionally, the backhaul power consumption in FBSs and CFBSs, albeit not having a significant share in total energy consumption for low number of nodes, may have an effect on the total energy efficiency of the network. In order to investigate the sensitivity of energy efficiency to spectrum sensing overhead, we also considered the case where spectrum sensing requires higher power consumption, setting $P_C^s = 1800\ mW$ instead of $600\ mW$. Our analysis revealed that energy efficiency did not change significantly because power consumption for transmission dominates the power consumption for sensing in the considered model due to periodic sensing. Hence, we can infer that efficient use of the transmission power is more significant for better energy efficiency compared to the sensing energy



(a) Energy efficiency of the system.



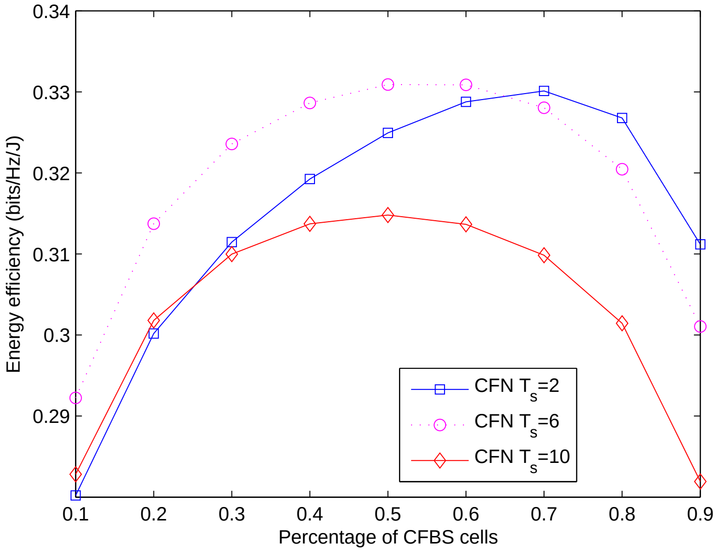
(b) Total throughput of the system.

Figure 6.2. Comparison of three scenarios. Scenario I: Macrocell only network, all users are MUs; Scenario II: FBSs are added to the macrocell network. Half of the users are MUs and the other half are FUs; Scenario III: MBS, FBS and CFBS are deployed in the macrocell. There are equal number of MUs, FUs, and CFUs in the network.

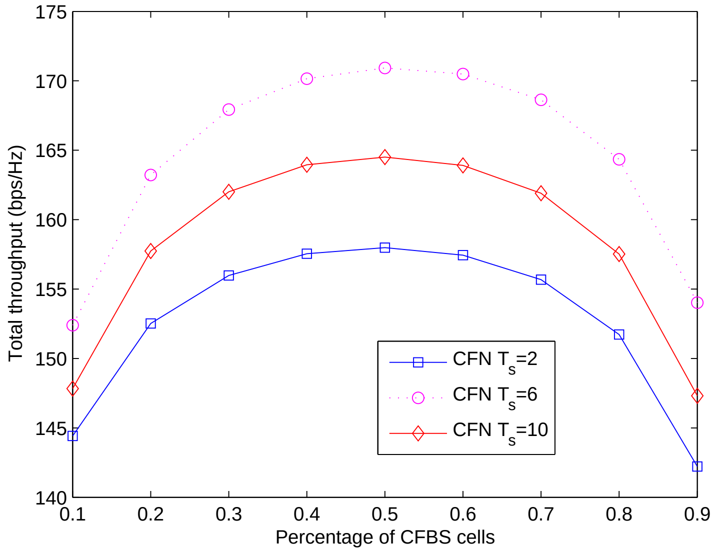
consumption. This result is in accordance with the widely articulated importance of power control and optimization for the energy efficiency of wireless networks in the literature [117].

Figure 6.2(b) illustrates the change in system throughput. Scenario I exhibits constant throughput, which is expected since the available spectral resources are fixed for this macrocell-only network. For Scenario II, we can see an increased throughput compared to Scenario I. This improvement is brought by the femtocells that can reuse the frequency resources of the macrocell. However, while this frequency reuse does not result in significant throughput loss for low femtocell density, it leads to lower throughput converging to that of the macrocell-throughput under denser femtocell deployments. As observed in other works, dense deployments of small cells have the challenge of interference management and if not controlled (as in the considered system) this issue leads to major throughput loss. The spectrum utilization in cognitive manner for Scenario III hits an interference wall resulting in diminished capacity due to collisions and missed opportunities. As we considered a quiet period for sensing, i.e., all transmission is halted and sensing is performed, the more frequent the sensing is, the less time remains for transmission. Additionally, the longer the sensing period is, the higher the energy consumed for sensing is. On the other hand, sensing more frequently improves sensing accuracy and hence discovered spectrum capacity for the cognitive femtocells. This phenomenon can be interpreted as "do not sense too much or too little" to traverse an optimal curve between sensing accuracy and sensing related resource consumption (spectrum or energy). This figure corroborates this intricate trade-off since Scenario III with $T_s = 6$ maintains the highest throughput among all Scenario III cases. Additionally, similar to Scenario II, CFN suffers from increasing interference for denser deployments in general, regardless of the sensing period value.

The performance of Scenario III depends on the sensing accuracy of the radios which is represented in the T_s related p_d and p_{fa} values. Obviously, one fundamental improvement for such a CR system would be to enhance the sensing scheme in terms of accuracy and energy consumption. This has two interrelated benefits: better sensing allows for shorter sensing periods while energy-efficient sensing modules decrease energy consumption per sensing time. Such fundamental enhancements would also improve the overall system performance. The analytical results also indicate the sensitivity of this type of systems to user densities. Next, we investigate the impact of CFBS proliferation. In this scenario, there is a constant number of users in MBS coverage (i.e., 300 users), and 100 of them are MUs. The remaining users are served by FBS or CFBS based on the number of deployed CFBSs. We increase the density of deployed CFBSs from 0.1 corresponding to 10% of small cells being cognitive femtocells, to 0.9. Figure 6.3(a) and Figure 6.3(b) depict the impact of increasing CFBS deployment for $T_s = 2, 6$, and 10 time slots. We observe that deploying more CFBSs initially increases the capacity and energy efficiency. Scenario with $T_s = 2$ time slots has lower throughput and energy efficiency as it consumes half of the operation time for sensing. However, as density increases, this scenario achieves higher energy efficiency compared to the cases with $T_s = 6$ and 10 time slots. Basically, higher sensing accuracy achieved by short T_s results in lower energy consumption. We also observe that there is an optimal percentage of CFBS which leads to peak performance. In other words, this result demonstrates that adding cognition to the non-cognitive FBS devices improves the energy efficiency as well as throughput initially. However, after some point this cognitive operation results in throughput loss due to overheads in sensing. When there is a huge demand for the discoverable PU spectrum resources, disproportionate time loss in agressive sensing by all CFBSs degrades the performance improvement facilitated via discovered spectrum capacity. Hence, under such a scenario not all the devices but some portion of the FBSs should utilize dynamic spectrum access. Please note that our system does not employ any cooperation between the CFBSs which leads to this conclusion. However, under more capable CFBS devices, e.g. devices not only implementing DSA but a set of other cognitive capabilities such as power adaptation or interference alignment [26], then turning more FBS into CFBS would further improve the system performance. This analysis renders the improved benefits attainable with a robust and efficient selection/adoption of cognitive capabilities for deployment in network elements.



(a) Energy efficiency of the system.



(b) Total throughput of the system.

Figure 6.3. Effect of CFBS proliferation. Number of MUs are kept constant and remaining users are served by either FBS or CFBSs. Number of deployed CFBSs is increased from 10% to 90% of the small cells.

6.3. Summary

In this chapter, we have analyzed the impact of introducing cognitive radio capability - spectrum sensing and opportunistic access - into femtocells as a practical application of cognitive radio concept. Cognitive Femtocell Networks (CFNs), a heterogenous network consisting of femtocells enriched with CR capabilities, are promising as next-generation cellular radio systems integrating the advantages of two emerging radio concepts: cognitive radios and small cells. We have provided a general analytical approach to model the energy efficiency and capacity of a heterogenous network - a macrocell-only network, a macrocell network with femtocells, and a network consisting of macrocell, femtocells and cognitive femtocells. We have highlighted the benefits of coupling these two concepts via our system model.

Our analysis illustrates the trade-offs related to the adoption of CFNs from the energy efficiency perspective. In general, CFNs improve energy efficiency and throughput of the network. On the other hand, it incurs additional sensing overheads, which may yield higher energy consumption if performed in a wasteful manner. Our results show this tradeoff between sensing accuracy and energy efficiency. We also observe that under high cognitive femtocell density with uncontrolled cross- and co-layer interference, a macrocell only network performs better. Hence, CFNs have to apply interference management and control schemes to be less sensitive to node density and to be more robust to heavy network load.

7. CONCLUSION

7.1. Summary of Key Contributions

This thesis aims to provide an understanding of energy efficiency challenges and some practical solutions for them in next generation wireless networking paradigms.Although due to the common traits of wireless technologies, most of the discussions, analysis, and solutions provided in this thesis can be considered as relevant to wireless networks in general, we have focused on cognitive radio networks and cognitive femtocell networks (CFNs).

This thesis contributes to the research both on energy efficiency and wireless networks as follows:

- We have provided an analytical discussion of EE in wireless networks and identified fundamental trade-offs, EE metrics, energy consumption sources and applicable EE improvement approaches.
- We have presented an elaborative discussion on the current state of the art in green networking paradigm and highlighted directions for greener communications via cognitive radio functionalities.
- We have proposed a new type of network so called *cognitive femtocell network* (CFN) that brings two networking paradigms together – cognitive radio and femtocells – in order to tackle the "artificial" spectrum inefficiency and low quality communications indoors by enjoying the benefits of these two paradigms. In addition to a new network architecture named as CFN, we provide an elaborate discussion on possible enhancements that can be applied at femtocells for both better spectral efficiency and energy efficiency. Furthermore, in our model we have shown how secondary users can benefit from getting service through femtocells rather than performing spectrum sensing with a lower sensing reliability.
- We have designed a simple yet efficient analytical model to investigate the energy efficiency benefits brought by cognitive femtocells to the macrocell-only networks

by capturing the operation principles of macrocell networks as well as macro-femto networks and cognitive femtocell networks. Limiting our attention to the system level only, e.g., spectrum capacity and interference at a cognitive femtocell, femtocell and a macrocell, we have shown that femtocells improve throughput compared to a macrocell-only network by better utilizing the macrocell frequencies in a small locality. Next, we have demonstrated that cognitive femtocells further improve the spectrum efficiency as well as the energy efficiency of the network under normal network density. For a very densely deployed cognitive femtocell network, the detrimental effects of the interference begin to dominate the spectral efficiency benefits achieved by cognitive femtocells. Therefore, our analysis consistent with the previous works has shown that interference management is substantial for cognitive femtocell networks.

7.2. Future Directions

The envisaged future directions entail the core paradigms that we have covered in this thesis work, namely CRs and CFNs.

In Chapter 5, we designed a cognitive femtocell network that deploys CR-enabled femtocells. However, the considered cognitive functionality was minimal, i.e., spectrum sensing and resource allocation. A more advanced cognitive femtocell device can apply various functionalities such as traffic prediction or power adaptation. Such cognitive femtocells with more advanced capabilities are essential to realize the real potential of cognitive femtocells.

In Chapter 6, we provided an analytical model for evaluating the energy efficiency of cognitive femtocell networks. However, we have not considered any interference management schemes neither at femtocells nor at cognitive femtocells. The lack of this mechanism showed itself as the decreasing performance with increasing cognitive femtocell density. The first interesting direction we envision is embedding various interference management schemes and then analyzing the added benefits. In this more advanced system, it is evident that energy efficiency will improve. However, quantifying this improvement can show the further improvements at cognitive femtocells. Another future work can be to simulate the proposed system with more detailed features, e.g. mobility of users, and compare it with the analytical model.

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