Energy Efficiency Impact of Cognitive Femtocells in Heterogeneous Wireless Networks

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ABSTRACT

The recent surge in mobile broadband traffic has been accompanied by diminishing revenues per bit and spectral bottleneck for mobile cellular networks. For this purpose, cognitive radio concept embedded in smaller cells, i.e. cognitive femtocell networks (CFNs), 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 (EE) has become a key research focus for these broadband access systems. In this work, we analyze the introduction of cognitive femtocells into wireless networks from energy efficiency perspective. We propose an analytical model for such CFN-deployed heterogeneous networks and evaluate the impact of CFN proliferation on energy consumption discussing the relevant trade-offs and practical issues. We observe two fundamental findings: 1- CFN is beneficial for improving EE. 2- The resultant EE gains are dependent on intricate factors entailing femtocell deployment density, CFBS proliferation rate, sensing period selection and interference management.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design–*Wireless communication*

Keywords

Cognitive radio, femtocells, enegy efficiency.

1. INTRODUCTION

The wireless network capacity has recently been under a great demand with the emerging novel user devices, services and concepts such as mobile multimedia clouds, machine-to-machine communications, mobile cloud-based gaming, smart grid communications, and vehicular networks. In order to provide higher spectral efficiency and to improve network capacity, research on new techniques and innovations including cognitive radios, more cells with heterogeneous networks, cooperation, smart antennas, and PHY/MAC techniques such as Multiple-Input-Multiple-Output (MIMO) are being pursued by the communications research communities. In spectrum reuse based approaches, instead of macrocells that allocate the spectrum resources in wide coverage areas, smaller size cells (e.g., microcell, picocells) with a better spectrum reuse capability have been proposed as a solution to spectrum scarcity. In that sense, femtocells deployed at the customer premises with a coverage area of a few tens of meters are accepted as a promising technology [1]. Besides, femtocells can overcome the challenge of poor indoor coverage in a cost-effective manner by providing a high quality short-distance link to the user equipment. Another promising technology in meeting the excessive demand for the spectrum is cognitive radio (CR). CRs equipped with advanced spectrum analysis and access capabilities can analyze the radio spectrum and transmit optimally on the bands that are not occupied by the actual owners of the spectrum (i.e. primary users, PUs). Hence, new spectrum resources are created [2]. By harnessing the advantages of these two technologies, *cognitive femtocells* present new opportunities for higher quality services, especially for indoor operation. Moreover, mobile users outdoors in the coverage of macrocell base station (BS) also benefit from these technologies since the operator can serve the indoor users easily via femtocell base stations.

While researchers have been seeking new ways of increasing spectral efficiency and network capacity, ecological research has identified the destructive environmental effects of increasing energy consumption. This critical impact has put the wired and wireless communication networks under focus regarding their energy and carbon footprint. Besides, energy efficiency consideration in communications and networking has gained unprecedented importance due to the increasing energy costs with harder access to energy resources. Therefore, it is imperative to have an energy cost perspective in the design and operation of wireless communications.

In this work, we discuss cognitive femtocell networks (CFNs) from energy efficiency perspective and examine the related challenges and trade-offs. The contribution of our work 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 femto-

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Table 1: Related Work on CFN.

Topic	Related works
Survey and general issues	[4, 5]
Resource allocation	[6]
Interference management	[8, 11, 12]
Opportunistic access	[9, 10]
Energy efficiency	[3]

cells. 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 [3]. 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 paper is organized as follows: Section 2 presents related work and potential capabilities that can be integrated to femtocells. Section 3 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 4 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 broadband heterogenous networks by comparing its performance with alternative setups that do not entail cognitive femtocells. Finally, Section 5 concludes the paper.

2. RELATED WORK

There has been relatively little CFN related research on energy efficiency compared to other femtocell topics. However, these next-generation systems are supposed to be evaluated from the green communications perspective since a substantial amount of operational expenses of mobile broadband networks is caused by energy consumption in radio access network. Hence, network operators will also benefit from energy-efficient systems and infrastructure. In this vision, femtocell base stations (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 [2]. The related work in the literature is summarized in Table 1 and discussed below. Advantages of facilitating CR capabilities at the FBSs are manifold [4]. 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 cognitive FBS (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 [5]. Hence, higher spectral capacity is available for the femtocell services. In [6], 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 [7]. Hence, it is paramount to provide efficient interference management. In [8], 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 [6].

Considering opportunistic access, Adhikary *et al.* [9] 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. Similarly, Urgaonkar *et al.* investigate two different models of opportunistic cooperation between secondary (femtocell) users and primary (macrocell) users in cognitive femtocell networks [10]. In [11], Lien *et al.* leverage the CR technology in order to mitigate crosstier 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 [12]. Attar *et al.* investigate on how to mitigate co-channel interference for LTE networks and propose two game-theoretical mechanisms.

In [13], 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. Diffferent from this general cognitive femtocell research, a more recent work on CFNs focusing specifically on energy efficiency is [3] where Xie *et al.* develop a game theoretic

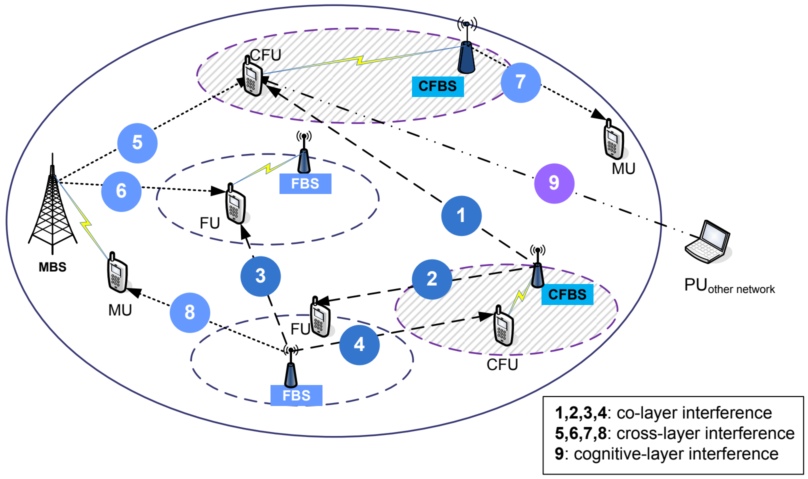


Figure 1: System model and the relevant interference effects on network entities.

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 macrocell base station (MBS) and FBS have CR capabilities.

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 [4]. 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 the next section, 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.

3. 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 CRs.

The heterogenous network under focus that is illustrated in Fig. 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 (albeit drawn differently in Figure 1 for better illustration purposes) with a circular 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

Table 2: Energy consumption components for each entity.

Entity	Tx	Rx	Backhaul	Sensing	Idling
MBS	+				
FBS	+		+		+
CFBS	+		+	+	+
MU		+			+
FU		+			+
CFU		+			+

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, we present our approach to calculate these energy consumption and related capacity values. Table 2 lists all energy consumption components associated with each entity.

3.1 Downlink Energy Consumption Model

In this section, we present our model for each component: MBS, FBS, CFBS, MU, FU, and CFU. We use the model introduced in [14] for base station transmission energy consumption. 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 [14]. Additionally, we include the backhaul energy consumption since it may substantially affect the energy efficiency figures especially for small cells [15]. Effect of backhauling at the MBS is skipped since both scenarios -with and without small cells- already have this cost.

3.1.1 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}.

3.1.2 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:

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

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

3.1.3 CFBS energy consumption

At a time slot, a CFBS may be in one of the three states: it transmits downlink traffic to CFUs, it switches to idle mode if there is no downlink traffic, or 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:

$$E_C = \frac{E_C^s + (T_s - 1)(\lambda_c E_C^t + (1 - \lambda_c) E_C^i)}{T_s}. \tag{2}$$

3.1.4 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* [16]. 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:

$$E_c = \frac{P_c^i + (T_s - 1)(\lambda_c (P_c^{rx} + P_c^{cs} \delta_F) + (1 - \lambda_c) P_c^i)}{T_s} \tag{3}$$

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.

3.1.5 FBS energy consumption

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

3.1.6 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.

3.2 Spectrum capacity calculation

A 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*. While misdetection may result in harmful interference to the PUs already transmitting in the band, false alarm results in spectrum opportunity loss, i.e., lower spectrum capacity. Hence, considering the effect of false alarm, 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:

$$F_C = F_{CR} p_{idle} (1 - p_{fa}(T_s)) + F_M \tag{4}$$

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

$$F_F = F_M. \tag{5}$$

3.3 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. 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 Fig. 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:

$$d = \sqrt{\frac{R}{2}^2 (1 - \cos(\frac{2\pi}{N_C}))}. \tag{6}$$

  Similarly, a CFBS creates interference to the FUs in the femtocells ($I_{C,f}$, link `2` in Fig. 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 Fig. 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 (6): $d = \sqrt{\frac{R}{2}^2 (1 - \cos(\frac{2\pi}{N_C} - \frac{2\pi}{n_m}))}$.

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

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):

$$\begin{aligned} I_m &= n_{C,m} I_{C,m} + n_{F,m} I_{F,m} + N_0 \\ I_f &= n_{C,f} I_{C,f} + n_{F,f} I_{F,f} + n_{M,f} I_{M,f} + N_0 \\ I_c &= n_{C,c} I_{C,c} + n_{F,c} I_{F,c} + n_{M,c} I_{M,c} + \\ &\quad n_{P,c}(1 - p_d(T_s)) I_{P,c} + N_0. \end{aligned}$$

Table 3: Summary of basic variables and parameters.

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 exponent (MBS-CFU, MBS-FU, PU-CFU)	2.8
$\alpha_{FC}, \alpha_{CC}, \alpha_{FF}$	Path loss exponent (FBS-CFU, CFBS-CFU, FBS-FU)	2

We can calculate the theoretical capacity perceived by each user type using Shannon's formula. Since CFUs do not receive traffic during sensing periods, we normalize throughput of CFUs (C_c) accordingly as below:

$$C_m = \frac{F_M}{n_m} \log_2(1 + \frac{P_M^{out}}{I_m}) \tag{7}$$

$$C_c = \frac{T_s - 1}{T_s} \frac{F_C}{n_c} \log_2(1 + \frac{P_C^{out}}{I_c}) \tag{8}$$

$$C_f = \frac{F_F}{n_f} \log_2(1 + \frac{P_F^{out}}{I_f}). \tag{9}$$

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

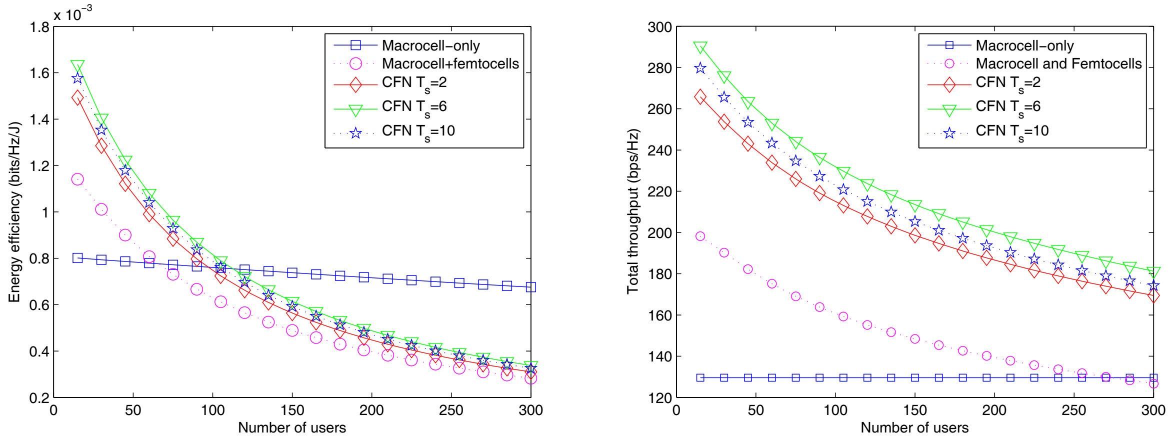
$$\begin{aligned} E =& E_M + n_m E_m + N_C E_C + \\ & n_c E_c + N_F E_F + n_f E_f \end{aligned} \tag{10}$$

$$C = n_m C_m + n_c C_c + n_f C_f \tag{11}$$

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

4. ANALYSIS AND EVALUATION

In this section, we evaluate the effects of CFN on the energy efficiency of heterogeneous mobile networks via system-



(a) Energy efficiency.

(b) Total throughput.

Figure 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.

level simulations based on (10) and (11). 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. In Scenario II, the system has femtocells in the macrocell coverage. Scenario III reflects a CFN scenario, where CFBSs are also deployed in addition to FBSs in the macrocell. System parameters for these settings are summarized in Table 3. 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: $p_d(T_s) = 0.9/(T_s - 1)$ and $p_{fa}(T_s) = 0.1(T_s - 1)$. 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}.

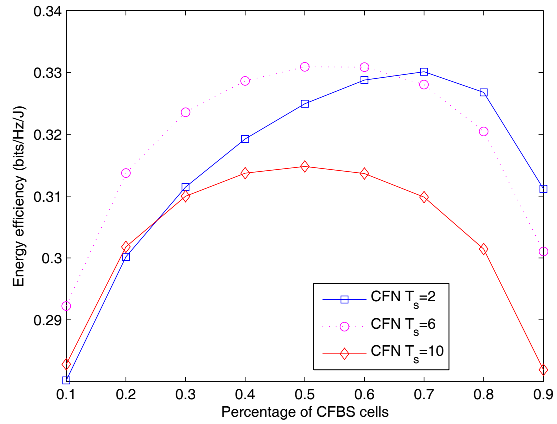
Fig. 2(a) depicts energy efficiency of these three scenarios. In Scenario I, all users are MUs whereas in Scenario II half of the users is MUs and the other half is FUs. In Scenario III, the number of MUs, FUs, and CFUs in the network are equal. This last scenario corresponds to the setting where CFNs 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 tradeoff 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 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 [14].

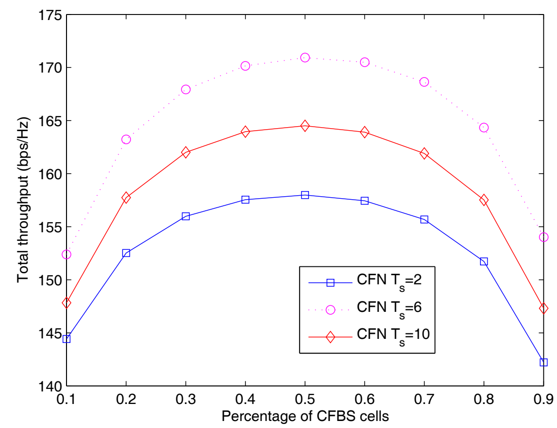
Fig. 2(b) illustrates the change in system throughput. Scenario I exhibits constant throughput, which is expected since the available spectral resources are fixed for this macrocell-only network. For Scenario II, we can see an increased throughput compared to Scenario I. This improvement is brought by 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. Fig. 3(a) and Fig. 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 noncognitive 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.



(a) Energy efficiency.



(b) Total throughput.

Figure 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.

However, under more capable CFBS devices, e.g. devices not only implementing DSA but a set of other cognitive capabilities listed in Section 2, 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.

5. CONCLUSION

In this work, 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. Although we focus on femtocells in our analysis, the developed model can be applied to small cell networks in general with the adoption of corresponding parameter values.

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.

As future work, we plan to consider mobility and incorporate the effects of handovers among network tiers. In our work, we focused only on spectrum sensing at the CFBS as the sole cognitive capability. However, CFBS may also possess other cognitive capabilities such as power adaptation and user-activity based switch-off. The integration of these more advanced CR features into our model is another potential research direction to extend our work.

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