

# Optimal Control of Wake Up Mechanisms of Femtocells in Heterogeneous Networks

L. Saker, S.E. Elayoubi, R. Combes, T. Chahed

**Abstract**—We study, in this work, optimal sleep/wake up schemes for the base stations of network-operated femto cells deployed within macro cells for the purpose of offloading part of its traffic. Our aim is to minimize the energy consumption of the overall heterogeneous network while preserving the Quality of Service (QoS) experienced by users. We model such a system at the flow level, considering a dynamic user configuration, and derive, using Markov Decision Processes (MDPs), optimal sleep/wake up schemes based on the information on traffic load and user localization in the cell, in the cases where this information is complete, partial or delayed. Our results quantify the energy consumption and QoS perceived by the users in each of these cases and identify the tradeoffs between those two quantities. We also illustrate numerically the optimal policies in different traffic scenarios.

**Index Terms**—Mobile networks, green communications, sleep/Wakeup modes, optimal control.

## I. INTRODUCTION

THIRD Generation (3G) wireless technology and beyond keeps improving since the first releases of the 3G standards by 3GPP. In particular, 3GPP Release 10 which specifies LTE-Advanced (LTE-A) [1] introduces several significant improvements over previous LTE Release 9, notably the possibility of a Heterogeneous Network (HetNet) setting. The HetNet aspect we consider in this work is related to the deployment of femto cells, for the purpose of offloading a part of the traffic of the primary macro network.

Studies on the energy footprint of mobile networks in general and 3G LTE systems of concern to our present work in particular, indicate that as high as 80% of the energy consumed by the overall mobile network is actually consumed by base stations [2]). And so, control and optimization of energy consumption at base stations should be at the heart of any *green* radio engineering scheme.

An important set of works on green radio has then been dedicated to the reduction of the transmitted power of the base stations; the idea is to find the minimal transmission power that ensures coverage and capacity (see for instance [3] and [4]). This approach is essential for reducing the exposure of persons to electromagnetic radiations. However, alone, these schemes are not sufficient to reduce the energy consumption of wireless networks as a large part of energy consumption remains even for low output power. This is due to the load-independent components of the energy consumption and the presence of pilot channels that make low load resources totally inefficient

in terms of energy. This is also the reason that makes energy-aware load balancing techniques not so efficient (an average reduction of the energy consumption of 5% has been observed in [5]).

In dense urban areas, base stations are deployed very close to each other, and so, coverage cells overlap with each other. This overlapping provides an opportunity to put some base stations into sleep mode, reducing thus their energy consumption and, consequently, that of the whole network. This is even more true in the case of femto cells as they are deployed within macro base station coverage cells. This is the aim of the present work where we investigate optimal control of a sleep/wake up mechanism for femto cells in a heterogeneous setting, based on traffic load and user localization in the cell.

We specifically propose to switch OFF femto cells when the cell is not heavily loaded and the macro base station can handle the overall traffic alone, without degrading the users Quality of Service (QoS). As traffic load increases in the cell, one or more femto cells will be switched ON, in a centralized manner, by the macro base station, depending on the information this latter has about the traffic load and user localization. This information can be complete, partial or yet delayed, and may result in different wake up control schemes and subsequent system performance. This is what makes the wake up mechanism more complex to study and implement than the sleep one, because the latter is always carried out in the presence of complete information. And this is the focus of the present work where we derive optimal control policies for wake up mechanisms using Markov Decision Processes (MDPs) along with appropriate variants corresponding to the different levels and nature of information on traffic load and user localization [6].

Many works studied capacity issues of femto cells deployment (see, for instance, [7] and the references therein). They mostly compare the average throughput achieved with and without the presence of femto cells. Although these works give interesting insights into the problem, they do not, however, integrate the dynamic behavior of users, in terms of random arrivals and departures after finite duration service, and its impact on the system capacity and the user-perceived QoS. We focus, in this work, on the Erlang-like capacity gains that are expected from deploying femto cells. By Erlang-like capacity, we mean the maximal traffic intensity that can be served by the network with a target QoS, taking into account the dynamics of arrivals and departures of the users to the system.

As of energy consumption in mobile networks, the energy consumption of base stations has not been classically considered as a constraint when designing Joint Radio Resource Management (JRRM) schemes. The aim was always to ensure higher spectral efficiencies and better QoS (see, for instance,

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[8][9]). A large interest has been dedicated to energy savings at the User Equipment (UE) so as to preserve the user's battery by reducing the amount of energy that is not useful for transmitting information. Consequently, many sleep mode schemes for UEs have been proposed in the literature. For instance, in [10], optimal sleep mode parameters have been derived depending on the traffic pattern for mobile WiMAX devices. Authors in [11] assessed the performance of discontinuous transmission schemes for UMTS.

Fewer works considered sleep mode in the context of femto cells. Particular attention has been given to the sleep mode in indoor access points [12][13][16], where intelligent wake up mechanisms have been proposed. These works focus mostly on the hardware involved in the activation/deactivation mechanisms, and propose algorithms with the ability of putting femto cells in a low-power sleep mode when traffic is low. In [12], out-of-band low consumption radio modules have been used in order to awaken WiFi access points when a call arrives. However, this solution introduces a low power radio module within both the UE and the access point, which is not realistic in LTE commercial deployments. As of femto cell sleep mode, authors in [16], present three strategies to activate femto cells, where wakeup decisions are taken either by the femto cells, the core network or the user. For femto cell centric approaches, also presented in [13], hardware modifications are needed in order to define a "sniffer" that detects variations in the macro cell activity; this approach again introduces a new hardware in the femto cells and is out of scope of this work. In the core-centric approach, wakeup commands are sent by the network to the femto cell. This approach assumes complete traffic localization information and is close to the scheme we consider in Section III. [16] also proposes a UE-centric wakeup mechanism, similar to that of [12] with an out-of-band additional radio module.

The remainder of this paper is organized as follows. We describe, in Section II, our heterogeneous system and the sleep/wake up mode we propose for such a setting and give a Markovian formulation relating traffic, capacity and energy consumption. Section III is dedicated to the control of the sleep/wake up mechanism in the case of complete information on load and user localization by the base station. Section IV is devoted for the case of partial and delayed information. Section V contains our numerical and simulation results. Section VI eventually concludes the paper.

## II. SYSTEM DESCRIPTION AND SLEEP/WAKE UP MODES

### A. System

We consider a network composed of classical macro base stations, in a cellular deployment, as shown in Figure 1. Within the coverage area of each macro base station, a set of  $F$  femto cells are deployed, forming a second layer of femto cells, operated by the same operator. We assume that the macro base stations ensure complete coverage, as this is the case in dense urban areas where femto cells are likely to be deployed as hotspots of large capacity for the purpose of offloading traffic from the macro cells. They are likely to be connected to the macro base station via a (logical) interface<sup>1</sup>, as we assume

<sup>1</sup>X2 interface in LTE networks.

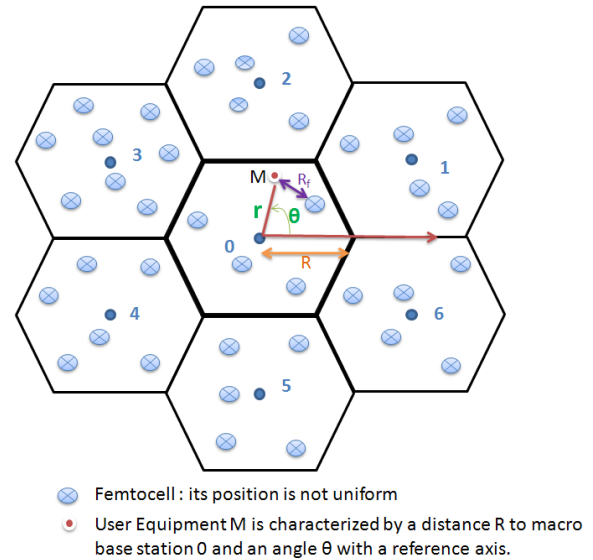


Fig. 1. A regular uniform hexagonal network configuration with femto cells.

that femto cells are in open access (so as to be used, again, by operators for the purpose of offloading traffic). In this case, the X2 interface is mandatory, either physically or logically. In the case of home deployed femto cells, this interface is logical and information is sent from the macro cell to the femto cell through the S1 interface. This case can be handled through the delayed information case we study in this paper.

When femto cells are deployed, users that are within the range of a femto cell can detect the presence of two base stations: macro and femto, and are connected to the one offering them the best Signal to Interference plus Noise Ratio (SINR). Users who are still connected to the macro base station are subject to new sources of interference which reduce their peak throughputs. They, however, enjoy more resources as they now share the macro cell resources with a fewer number of users. As of the users who are offloaded to the femto cells, they have larger peak throughputs as they are close to their serving base station. However, interference is generated between macro and femto layers, as illustrated in Figure 2.

In this context, we study the following sleep/wakeup mechanism: when the cell is not highly loaded and the macro base station can alone handle the traffic while offering users satisfactory QoS, the femto cells are switched OFF. As the load increases, one or more femto cells have to be switched ON, depending on the load and localization of traffic.

This sleep/wake up mode is controlled, in a centralized way, by the macro base station which makes decisions about activating/deactivating femto cells based, again, on the information it has about the traffic load and user localization. This information can be completely known, partially known or delayed, resulting in different system models and performance, as will be detailed next.

### B. Model

Let  $s_t$  be the process describing the evolution of the system state and  $\mathcal{S}$  be the state space.

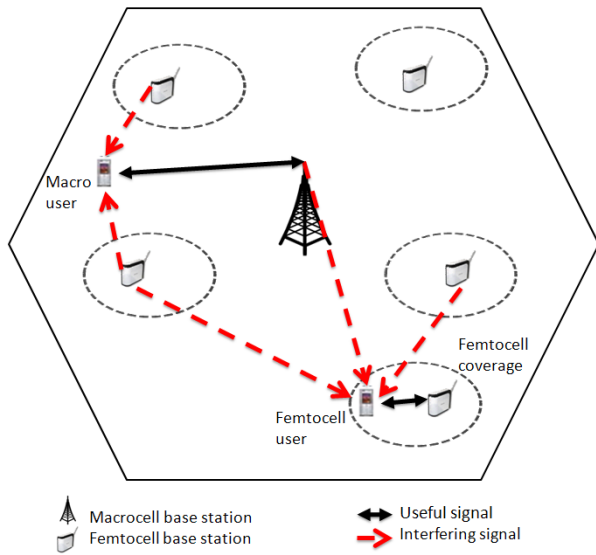


Fig. 2. Interference from a femto cell to a user served by a macro cell and from a macro cell to a user served by a femto cell.

We denote by  $\mathbf{a} = (a_1, \dots, a_F)$ , the vector describing the status of femto cells, with  $a_j = 0$  if femto cell  $j$  is deactivated and  $a_j = 1$  otherwise. Let  $D_i^j(\mathbf{a})$  be the throughput of users of class  $i$  in the area covered by cell  $j$ , where a user class refers to its radio conditions (channel gains experienced by the user), when the vector of activated femto cells is  $\mathbf{a}$ .

In order to ease the understanding, we rearrange the positions of the users in the cell so that the positions that are only covered by the macro base station are numbered from 1 to  $N_0$ , followed directly by the positions covered by femto cell 1, femto cell 2 and so on, as shown in Figure 2. Let  $N_j$  be the number of locations, i.e.; classes, associated with femto cell numbered  $j$ . The state space can be written as:

$$\mathbf{s} = \underbrace{(n_1^0, \dots, n_{N_0}^0)}_{macro}, \underbrace{(n_1^1, \dots, n_{N_1}^1, \dots, n_1^F, \dots, n_{N_F}^F)}_{femto\ 1 \dots femto\ F} \quad (1)$$

where the superscript indicates the cell (0 for the macro cell and  $j \in [1, F]$  for femto cell numbered  $j$ ) and the subscript indicates user class  $i$  covered by cell  $j$ .

Knowing this state, the users that are connected to the different base stations generate a certain load  $\rho_j(\mathbf{s}, \mathbf{a})$  for base station  $j \in \{0, \dots, F\}$  in state  $\mathbf{s}$  (0 indicating the macro cell and  $j \in [1, F]$  the different femto cells). The energy consumption of a base station depends on its load and is given by [15]:

$$E_j(\mathbf{s}, \mathbf{a}) = P_{cst} + \rho_j(\mathbf{s}, \mathbf{a}) \frac{P_j^{max}}{w} \quad (2)$$

where  $w$  is the direct current to radio frequency conversion factor,  $P_j^{max}$  is the radio frequency output power of the power amplifier of base station  $j$ ,  $P_{cst}$  is the fixed power consumption of the radio module (transceiver) that is due to transport and processing units<sup>2</sup>.

When the sleep/wakeup mode is implemented, we define frontiers within the state space; each time these frontiers are

crossed, a subset of femto cells is activated or deactivated.  $\mathcal{S}$  is thus split between subspaces  $\mathcal{S}_{\mathbf{a}}$ , each corresponding to a combination of activated femto cells  $\mathbf{a}$ . The sleep/wake up mode corresponds to switching ON or OFF some femto cells each time the frontier between the different subspaces is crossed in a direction or another.

If the state is equal to  $\mathbf{s}$ , the load of the different cells will depend on  $\mathbf{a}$  and will be denoted by  $\rho_j(\mathbf{s}, \mathbf{a})$  (for instance, the macro cell will serve the users that are in the coverage area of deactivated femto cells, and its load increases). The energy consumption knowing that the vector of activated femto cells is  $\mathbf{a}$  will be:

$$E_j(\mathbf{s}, \mathbf{a}) = [P_{cst} + \rho_j(\mathbf{s}, \mathbf{a}) \frac{P_j^{max}}{w}] \mathbf{1}_{\{a_j=1\}}(\mathbf{a}) \quad (3)$$

where  $\mathbf{1}_{\{a_j=1\}}$  is the indicator function equal to 1 if femto cell  $j$  is ON and to 0 otherwise.

### III. COMPLETE INFORMATION

In this section, we suppose that complete information about the positions of users in the cell is available to the base station when taking the decision. This corresponds to the case of complete traffic localization information, for instance in the presence of GPS equipment at the mobile terminals. The case of partial or inexistent localization information is treated in the next section. Note that complete information about the traffic served by a femto cell is always available at the macro base station, as this information may be exchanged on the X2 interface; the problem of lack of localization information only appears when the aim is to wake up a deactivated femto cell, and not when to put it into sleep.

In order to optimize the sleep/wake up policy, we define a Continuous Time Markov Decision Process (CTMDP) that associates to each state an action and corresponding transition probabilities and rewards. The controller observes the current state  $\mathbf{s}$  of the network and associates a set of possible actions  $\mathcal{A}_{\mathbf{s}}$  to it, taken upon arrival to it from the previous state. Knowing a given action  $\mathbf{a}$ , an instantaneous reward  $r(\mathbf{s}, \mathbf{a})$  is associated to this state. This cost function has to be an increasing function of energy and a decreasing function of QoS. The corresponding formal representation is as follows [25]:

$$(\mathcal{S}, \mathcal{A}, (\mathcal{A}_{\mathbf{s}}, \mathbf{s} \in \mathcal{S}), \tilde{q}(\mathbf{s}'|\mathbf{s}, \mathbf{a}), r(\mathbf{s}, \mathbf{a}))$$

Note that the set of possible actions  $\mathcal{A}$  reduces to a subset  $\mathcal{A}_{\mathbf{s}}$  for particular states.

A policy  $P$  associates an action  $\mathbf{a}(\mathbf{s}|P)$  to state  $\mathbf{s}$ . Let  $\mathbf{Q}$  be the transition matrix of the initial, non controlled, process, with  $q(\mathbf{s}, \mathbf{s}')$  the transition rate between states  $\mathbf{s}$  and  $\mathbf{s}'$  in  $\mathcal{S}$ . The transition rates of the controlled process  $\tilde{q}(\mathbf{s}'|\mathbf{s}, \mathbf{a})$  can be derived as follows:

- Some elements of the transition matrix  $\tilde{\mathbf{Q}}$  of the CTMDP can be obtained based on  $\mathbf{Q}$ . For instance:
  - the transitions due to the arrivals of new calls to the system.
  - the transitions due to mobility of users between different regions of the cell, served by the macro base station or by the femto cell.
  - the transitions due to the departure of real time calls.

<sup>2</sup>Note that this dependence on load is more obvious in a macro base station than in a femto cell, as the transmitted power of this latter is very low.

Note that, in [18], it has been shown how to take into account the mobility of users within different regions of a cell, depending on the average velocity of users and the topology of the system.

- Some transitions are different from the ones in  $\mathbf{Q}$  as they depend on the state of femto cells (active or in sleep mode). This is the case of termination of elastic calls, as their durations depend on their throughputs. The new departure rates will depend on the throughputs  $D_i^j(\mathbf{a}(\tilde{\mathbf{s}}|\mathbf{P}))$ , but also on the spectrum sharing policies. We will show next how to derive these rates in an LTE network.

Note that, by construction, we define the policy as a function of the actual state. The decision of switching ON or OFF a resource is thus taken by observing the actual state only. If the initial process  $(s_t, \mathbf{Q})$  is Markovian, the controlled process  $(\tilde{s}_t, \mathbf{a}_t, \tilde{\mathbf{Q}})$  is Markovian as well.

#### A. MDP resolution

If the action is allowed to change whenever the state changes, we can use an equivalent Discrete Time Markov Decision Process (DTMDP) for the above-mentioned CTMDP to find an optimal controller. We, specifically, consider a DTMDP with finite state space  $\mathcal{S}$ , and for each  $s \in \mathcal{S}$ , we denote by  $\mathcal{A}_s$  the finite set of allowed actions in that state. This DTMDP can be found by uniformization and discretization of the initial process as follows [6]:

- When all the transition rates in matrix  $\mathbf{Q}$  are bounded, the sojourn times in all states are exponential with bounded parameters  $q(\mathbf{s}|\mathbf{s}, \mathbf{a})$ .  $\sup_{\mathbf{s} \in \mathcal{S}, \mathbf{a} \in \mathcal{A}_s} q(\mathbf{s}|\mathbf{s}, \mathbf{a})$  thus exists, and we can find a constant  $\nu$  verifying:

$$\sup_{\mathbf{s} \in \mathcal{S}, \mathbf{a} \in \mathcal{A}_s} [1 - p(\mathbf{s}|\mathbf{s}, \mathbf{a})]q(\mathbf{s}|\mathbf{s}, \mathbf{a}) \leq \nu < \infty \quad (4)$$

with  $p(\mathbf{s}|\mathbf{s}, \mathbf{a})$  the probabilities of staying in the same state after the next event.

- We can thus define an equivalent, uniformized process with state-independent exponential sojourn times with parameter  $\nu$ , and transition probabilities:

$$\tilde{p}(\mathbf{s}|\mathbf{s}', \mathbf{a}) = \begin{cases} 1 - \frac{[1-p(\mathbf{s}|\mathbf{s}, \mathbf{a})]q(\mathbf{s}|\mathbf{s}, \mathbf{a})}{\nu} & \mathbf{s}' = \mathbf{s} \\ \frac{p(\mathbf{s}|\mathbf{s}', \mathbf{a})q(\mathbf{s}|\mathbf{s}', \mathbf{a})}{\nu} & \mathbf{s}' \neq \mathbf{s} \end{cases}$$

These two processes, the original and the uniformized one, are equal in distribution.

We now work with the DTMDP. We use the following notations: for  $t \in \mathbb{N}$ , let  $s_t, a_t, r_t$  and  $c_t$  denote, respectively, the state, action, reward and cost at time  $t$  of the DTMDP. Let  $\mathcal{P}_{s,s'}^a = \mathbb{P}[s_{t+1} = s' | s_t = s, a_t = a]$  denote the transition probabilities,  $\mathcal{R}_{s,s'}^a = \mathbb{E}[r_{t+1} | s_t = s, s_{t+1} = s', a_t = a]$  the expected reward associated to the transitions and  $\mathcal{C}_{s,s'}^a = \mathbb{E}[c_{t+1} | s_t = s, s_{t+1} = s', a_t = a]$  the cost incurred by the transitions. Let  $C_{max}$  be the maximal admissible cost.

A policy is a mapping between a state and an action; applying policy  $P$  can be written as  $a_t = P(s_t)$ ,  $t \in \mathbb{N}$ . We denote by  $\mathcal{P}$  the set of policies. We restrict our attention to deterministic policies only, and for a general constrained MDP, the optimal policy is randomized [20]. The reason

for this restriction to deterministic policies is implementation simplicity [21].

*Definition 1:* Given a discount factor  $\gamma \in [0, 1)$  and initial state  $s$ , we define the discounted value  $V_\gamma^P(s)$  and discounted cost  $C_\gamma^P(s)$  of a policy  $P$  starting at  $s$  by:

$$V_\gamma^P(s) = (1 - \gamma) \mathbb{E}_{P,s} \left[ \sum_{t \in \mathbb{N}} r_t \gamma^t \right] \quad (5)$$

$$C_\gamma^P(s) = (1 - \gamma) \mathbb{E}_{P,s} \left[ \sum_{t \in \mathbb{N}} c_t \gamma^t \right] \quad (6)$$

where  $\mathbb{E}_{P,s}$  is the expectation with respect to the probability generated by policy  $P$ , starting at  $s$ , i.e.,  $s_0 = s$ .

Blackwell [22] gives the following results on optimal policies.

- Theorem 1:* (i) For a discounting rate  $\gamma \in [0, 1)$  and penalization  $\mu \geq 0$ , there exists a policy  $P_{\gamma,\mu}^*$  which maximizes  $(V_\gamma^P(s) - \mu C_\gamma^P(s))$ ,  $\forall s$ .
- (ii) There exists a policy  $P_{1,\mu}^*$  and  $\gamma_0$  such that  $P_{\gamma,\mu}^* = P_{1,\mu}^*$  for  $\gamma_0 \leq \gamma < 1$ . We will call such a policy a Blackwell optimal policy.
- (iii) We also have that  $(V_\gamma^{P_{\gamma,\mu}^*}(s), C_\gamma^{P_{\gamma,\mu}^*}(s)) \xrightarrow{\gamma \rightarrow 1^-} (V_{1,\mu}^*(s), C_{1,\mu}^*(s))$ . Furthermore:

$$V_{1,\mu}^*(s) = \lim_{T \rightarrow +\infty} \mathbb{E}_{P_{1,\mu}^*,s} \left[ \frac{1}{T} \sum_{1 \leq t \leq T} r_t \right] \quad (7)$$

$$C_{1,\mu}^*(s) = \lim_{T \rightarrow +\infty} \mathbb{E}_{P_{1,\mu}^*,s} \left[ \frac{1}{T} \sum_{1 \leq t \leq T} c_t \right] \quad (8)$$

The last part of the theorem states that to obtain a policy which is optimal for the average cost criteria with infinite time horizon, it is sufficient to find an optimal policy for the discounted cost criteria, providing that the discount factor  $\gamma$  is close enough to 1. This is essential since we are interested in the average cost criteria, for example to find a policy which is optimal in the sense of blocking probability or mean delay.

Finally, in the model we are considering, every policy makes the underlying Markov chain ergodic. Hence,  $(V_{1,\mu}^*(s), C_{1,\mu}^*(s))$  does not depend on the starting state  $s$ , and we will write  $(V_{1,\mu}^*(s), C_{1,\mu}^*(s)) = (V_{1,\mu}^*, C_{1,\mu}^*)$ .

The following result gives a method to find the optimal policy, subject to constraints on the average cost.

*Theorem 2:*  $\mu \rightarrow C_{1,\mu}^*$  is non increasing.

*Proof:* Let  $s \in \mathcal{S}$ ,  $0 \leq \mu_1 \leq \mu_2$  and  $\gamma_0$  such that  $P_{\gamma,\mu_1}^* = P_{1,\mu_1}^*$  and  $P_{\gamma,\mu_2}^* = P_{1,\mu_2}^*$ ,  $\gamma_0 \leq \gamma < 1$ .

Then, by the definition of  $P_{\gamma,\mu_1}^*$  and  $P_{\gamma,\mu_2}^*$ :

$$\begin{aligned} V_\gamma^{P_{\gamma,\mu_2}^*}(s) - \mu_1 C_\gamma^{P_{\gamma,\mu_2}^*}(s) &\leq V_\gamma^{P_{\gamma,\mu_1}^*}(s) - \mu_1 C_\gamma^{P_{\gamma,\mu_1}^*}(s) \\ V_\gamma^{P_{\gamma,\mu_1}^*}(s) - \mu_2 C_\gamma^{P_{\gamma,\mu_1}^*}(s) &\leq V_\gamma^{P_{\gamma,\mu_2}^*}(s) - \mu_2 C_\gamma^{P_{\gamma,\mu_2}^*}(s) \\ (\mu_2 - \mu_1) C_\gamma^{P_{\gamma,\mu_2}^*}(s) &\leq (\mu_2 - \mu_1) C_\gamma^{P_{\gamma,\mu_1}^*}(s) \\ C_\gamma^{P_{1,\mu_2}^*}(s) &\leq C_\gamma^{P_{1,\mu_1}^*}(s) \\ C_{1,\mu_2}^* &\leq C_{1,\mu_1}^* \end{aligned} \quad (9)$$

which completes the proof.  $\blacksquare$

*Corollary 1:* Assume that there exists  $\mu^*$  such that  $C_{1,\mu^*} = C_{max}$ . Then  $P_{1,\mu^*}^*$  is the policy which maximizes  $V_{1,\mu^*}^*$  subject to  $C_{1,\mu^*} \leq C_{max}$ .

We can now give a straightforward numerical method to find the optimal controller. Using the results of Section II-B, we can calculate  $\mathcal{P}_{s,s'}^a$ ,  $\mathcal{R}_{s,s'}^a$ , and  $\mathcal{C}_{s,s'}^a$   $s \in \mathcal{S}, s' \in \mathcal{S}, a \in \mathcal{A}_s$  in closed form. Then, for a fixed  $\gamma$  and  $\mu$ , we can find the optimal policy  $P_{\gamma,\mu}^*$  by value iteration [19]. For  $\gamma < 1$  close enough to 1, value iteration yields  $P_{1,\mu}^*$  using the previous result on Blackwell optimality. We can then find  $\mu^*$  by dichotomy, since  $\mu \rightarrow C_{\gamma^{1,\mu}}^*$  is non increasing.

## B. Application to LTE networks

We consider, for instance, the case of elastic traffic in LTE networks. In this case, the heterogeneity in radio conditions translates into a larger service time for cell edge users. The service rate is state-dependent and the transitions between states  $\mathbf{s} = (n_1^0, \dots, n_{N_0}^0, n_1^1, \dots, n_{N_1}^1, \dots, n_1^F, \dots, n_{N_F}^F)$  and  $\mathbf{s}' = (m_1^0, \dots, m_{N_0}^0, m_1^1, \dots, m_{N_1}^1, \dots, m_1^F, \dots, m_{N_F}^F)$ , are given by:

$$\tilde{q}(\mathbf{s}'|\mathbf{s}, P) = \begin{cases} \lambda_i^j & m_i^j = n_i^j + 1 \\ \frac{n_i^j D_i^j(\mathbf{a}(\tilde{\mathbf{s}}|P))}{\sigma \sum_{i \in C(i,j|\mathbf{a}(\tilde{\mathbf{s}}|P))} \sum_{i=1}^{N_j} n_i^j} & m_i^j = n_i^j - 1 \\ n_i^j \nu_{i \rightarrow i'}^{j \rightarrow j'} & m_{i'}^{j'} = n_{i'}^{j'} + 1, \\ & m_i^j = n_i^j - 1 \end{cases}$$

where  $\lambda_i^j$  is the arrival rate of new users of class  $i$  to station  $j$  (denoted area  $(i, j)$ ),  $\sigma$  is the average file size, and  $C(i, j|\mathbf{a}(\tilde{\mathbf{s}}|P))$  is the set of areas in the cell that share the same resources with users of class  $i$  in station  $j$ , knowing policy  $P$  that deactivates some femto cells in state  $\mathbf{s}$ .  $\nu_{i \rightarrow i'}^{j \rightarrow j'}$  is the mobility rate from area  $(i, j)$  to area  $(i', j')$ , as calculated in [18]. The system is Markovian if the arrival rates are Poisson, the file size is exponentially distributed [17] and the dwell times in each region are also exponentially distributed. The MDP can be solved as indicated in the previous sub-section. The QoS is, here, related to the throughput received by users: a target throughput is fixed and a large proportion of users (say 90%) must achieve this target.

*Remark:* In a network without sleep mode, the cell can be modeled as a network of Processor Sharing (PS) queues and its evolution can be described by the overall number of users in each base station  $n_j = \sum_{i=1}^{N_j} n_i^j$ . The steady-state probabilities have a product form, given by the BCMP theorem [23]. When the sleep mode is implemented, the BCMP conditions are no longer verified (the arrival rates to the different cells depend on the state of other cells) and a complete MDP resolution is needed.

## IV. CONTROL WITH INCOMPLETE INFORMATION

In the previous section, we showed how to derive optimal controllers for sleep/wakeup mode in an ideal case where complete traffic load and localization information is available when taking the decisions. This is however not realistic in a real setting where mobile terminals are not all equipped with GPS receivers. This lack of information may cause blind decisions that lead to capacity and energy consumption

problems. For instance, in the case of real-time services, when the load increases and we choose to activate a femto cell that cannot offload a large amount of traffic, all the available resources may saturate and new arrivals and handover requests will be blocked due to erroneous actions. In the case of elastic calls, their throughput will degrade, leading to longer download times and possible queue instability.

We study in this section sleep/wakeup mechanisms in the case of incomplete information: partial and delayed, and show how to derive optimal controllers in these two cases.

### A. Partial information

When the state of the system is only partially observable, this corresponds to a Partially Observable MDP (POMDP) [6]. In particular, the macro base station knows about the number of users that are connected to it and the number of users that are connected to active femto cells, but has only partial, or sometimes even no traffic localization information. The available information for state  $\mathbf{s}$  under policy  $P$  is thus  $n_j$  for all cells  $j$  such that  $a_j(\tilde{\mathbf{s}}|P) = 1$  where  $\tilde{\mathbf{s}}$  is the observation. The observation of the system is thus composed of the aggregate load information and the history of actions that determine the vector of active femto cells  $\mathbf{a} = (a_1, \dots, a_f)$ , with  $a_j = 1$  if femto cell  $j$  is active and equal to 0 otherwise, and is given as:

$$\tilde{\mathbf{s}} = f(\mathbf{s}, \mathbf{a}) = \{n_j | a_j = 1\}$$

where  $n_j$  is the overall number of users in the region covered with cell  $j$ . Let  $\tilde{\mathcal{S}}$  be the observation space.

In addition to this aggregate load information, additional traffic localization information can be available when taking the wake up decision<sup>3</sup>. This information can be, for instance, derived from inaccurate localization methods, based on localization algorithms such as triangulation methods [24], or by exploiting traffic information in neighboring sites in a cellular system. This can be expressed by a belief function  $b(\mathbf{s}|\tilde{\mathbf{s}})$ , expressing the guess that the macro base station makes about the hidden state  $\mathbf{s}$ , knowing  $\tilde{\mathbf{s}}$ . Formally,  $b(\cdot)$  is a function from  $\tilde{\mathcal{S}}$  to the space of probability distributions on  $\mathcal{S}$  that gives the likelihood of all states  $\mathbf{s} \in \mathcal{S}$ , knowing  $\tilde{\mathbf{s}} \in \tilde{\mathcal{S}}$ . The case of no traffic localization information corresponds to  $b(\cdot)$  being the uniform distribution over  $\mathcal{S}$ , while the complete localization information corresponds to the Dirac probability function on the hidden state.

Knowing state  $\tilde{\mathbf{s}}$  and based on the belief functions  $b(\cdot)$ , the system takes action  $\tilde{\mathbf{a}}(B(\tilde{\mathbf{s}}))$ , where  $B(\tilde{\mathbf{s}})$  is the hidden state of maximal belief given by:

$$B(\tilde{\mathbf{s}}) = \arg \max_{\mathbf{s}} b(\mathbf{s}|\tilde{\mathbf{s}})$$

Note that when several hidden states have the same belief, the choice is made randomly among them.

Policy  $P$  is a mapping between belief and action. This may lead to actions that wake up femto cells with no or low traffic, which incurs additional costs in terms of energy consumption and QoS degradation. As the belief of the states becomes more accurate after the wake up action is taken (the activated femto

<sup>3</sup>complete information is always available when all femto cells are active

cell will establish links with the mobiles within its coverage area and communicate its load to the macro base station), corrective actions may be needed in order to limit the costs.

### B. Delayed information

When we wait for accurate traffic localization information before taking the action, this is equivalent, in modeling, to the case where the decision is taken instantaneously, but takes effect only after some time. The problem of action delay has been studied in a number of control problems, as in [27] for the control of source rates. The main idea when dealing with MDPs with delays is to transform them into equivalent MDPs without delays, as it has been shown in [26].

The CTMDP of Section III has now a new component, the delay  $t_{on}$ . In order to derive the optimal controller in this case, we follow the same approach as in Section III, i.e., by uniformization and discretization. The resulting MDP has the following components:

$$(\tilde{\mathbf{S}}, \mathbf{A}, (\mathbf{A}_{\tilde{\mathbf{s}}}, \tilde{\mathbf{s}} \in \tilde{\mathbf{S}}), \tilde{q}(\tilde{\mathbf{s}}|\tilde{\mathbf{s}}, \mathbf{a}), \tilde{g}(\tilde{\mathbf{s}}, \mathbf{a}), \delta)$$

where  $\delta = T_{on}\nu$  is the (discretized) activation delay. Here, we choose the uniformization rate  $\nu$  such that it verifies (4) and is a multiple of  $\frac{1}{T_{on}}$ . As  $\nu = \delta \frac{1}{T_{on}}$ ,  $\delta$  is an integer verifying:

$$\left[ T_{on} \cdot \sup_{\mathbf{s} \in \mathbf{S}} [1 - p(\mathbf{s}|\mathbf{s}, \mathbf{a})]q(\mathbf{s}|\mathbf{s}, \mathbf{a}) \right] \leq \delta < \infty \quad (10)$$

Indeed, the information necessary for optimal action selection at stage  $i$  is contained in  $\hat{\mathbf{s}}_i = (\check{s}_i, a_{i-\delta}, \dots, a_{i-1})$ , and the state space is  $\hat{\mathbf{S}} = \tilde{\mathbf{S}} \times \mathbf{A}^\delta$ . As of the cost function, it can be defined function of the cost without delay:  $\hat{g}(\hat{\mathbf{s}}, a_i) = \tilde{g}(\check{\mathbf{s}}, a_{i-\delta})$ . It has been also shown in [28] that the discounting factor for the MDP with delays (deterministic or random) is equal to that of the MDP without delays.

Note that the dimension of the states increases with  $\delta$  and the optimal value of  $\nu$  is thus given by:

$$\nu = \frac{1}{T_{on}} \left[ T_{on} \cdot \sup_{\mathbf{s} \in \mathbf{S}} [1 - p(\mathbf{s}|\mathbf{s}, \mathbf{a})]q(\mathbf{s}|\mathbf{s}, \mathbf{a}) \right]$$

When the activation delay is random, the uniformized MDP becomes a Stochastic Delay MDP (SDMDP), with random delay  $\Delta$ . It has been shown in [28] that such an SDMDP reduces to an MDP without delay, with a state space of variable dimensions, depending on the observed delay:

$$\hat{\mathbf{s}}_i = (\check{s}_i, a_{i-\Delta}, \dots, a_{i-1})$$

Note also that the dimension of state  $\hat{\mathbf{s}}_i$  is variable, taking possibly a very large value, we have thus to fix an upper bound  $\bar{\Delta}$  on the delay and stop any (activation) action until the impact of the last one is observed.

## V. RESULTS

In our numerical results, we illustrate the sleep/wake up schemes for an LTE-Advanced network with the following parameters:

- The maximal distance between the macro and Femto cells is set to 450 meters for a cell range equal to 500 meters.
- Trisected sites in a dense urban area are considered. We also consider two types of femto cells: operator-installed

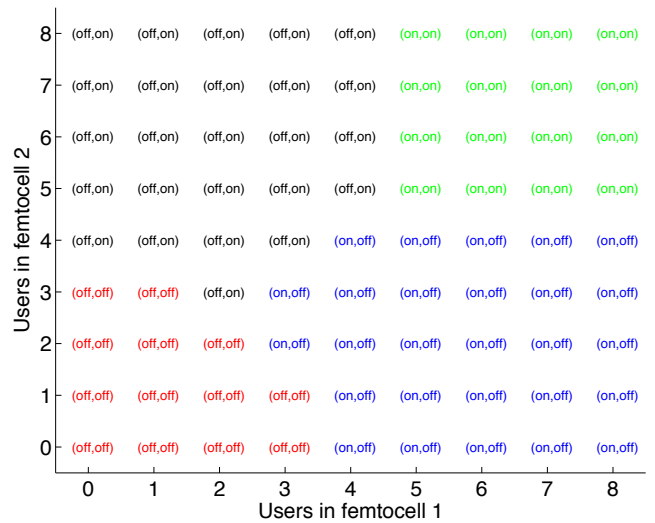


Fig. 3. Optimal policy, 3 users in the region covered only by the macro cell. Red colored regions correspond to both femto cells active, yellow ones correspond to activating femto cell 2 only, blue regions correspond to activating only femto cell 1, while dark blue ones correspond to both femto cells in sleep mode.

outdoor femto cells, with a coverage of 50 meters, and client-installed indoor femto cells with a coverage of 10 meters. We suppose that the number of operator-installed femto cells is small (up to 2 per sector), while the number of client-installed femto cells is large (up to 100 per sector). The scenario is as it appears in Figure 1.

- Macro cells use 10 MHz of spectrum in the 2.6 GHz band, resulting in an average throughput of 27 Mbps for a user that is served alone in the macro cell.
- Femto cells reuse 5 MHz of the macro cell spectrum and offer 15 Mbps on average for users that are served by them (this is again the throughput when there is only one user served by the femto cell).
- As the transmission power of femto cells is low, their energy consumption is load-independent and equal to 50 Watts for outdoor femto cells and 5 Watts for indoor ones.

A target throughput of 500 Kbps is sought. QoS is measured as the proportion of users that have a throughput higher than this target.

The results corresponding to a small number of Femto cells are obtained from numerical resolution of analytical expressions using Matlab, while the results pertaining to a larger number of cells are obtained through event-based simulations the duration of which corresponds to a number of iterations yielding a 95% confidence interval. Decisions take place upon users arrivals and departures.

### A. MDP resolution illustration

The optimal controller is obtained numerically by calculating the transition probabilities, costs and rewards; value iteration is then used to derive the optimal policy satisfying the constraints. More details are given in Section III.A.

We first begin by illustrating the optimal policy (derived in Section III) for an average offered traffic of 35 Mbps/sector.

Figures 3 and 4 show the actions chosen by the optimal policy as a function of the number of users in the two

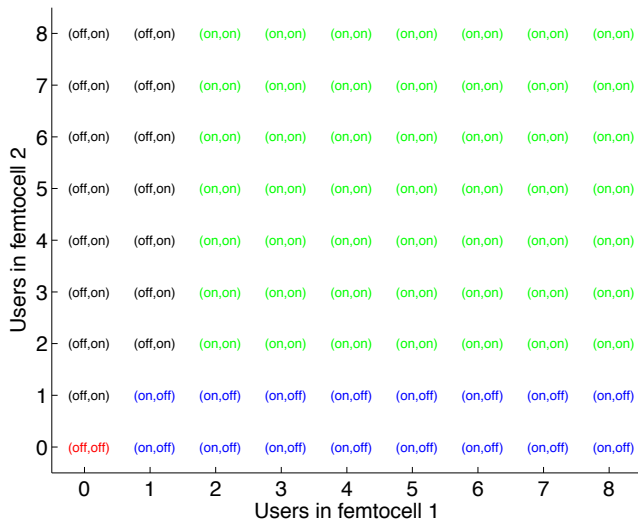


Fig. 4. Optimal policy, 6 users in the region covered only by the macro cell.

femto cells when there are 3 and 6 users in the macro cell, respectively. We can see in both figures that the behavior of the optimal policy is fairly intuitive: when both femto cells are lightly loaded, they both remain shut down and users are served by the macro cell to save energy. When only one femto cell serves more users, it is switched ON, while the other one remains OFF. Finally, when both femto cells are heavily loaded, they are both switched ON, leading to maximal energy consumption to be able to guarantee the target QoS. It is also noted that the optimal policy is symmetrical. Furthermore, we can see that as the number of macro cell users grows (Figure 4), the region in which some femto cells are switched OFF becomes smaller, which is logical since in case of heavy traffic they have to be both activated to offload the macro cell and ensure a good QoS.

### B. Partial versus complete information

We now move to the illustration of the behavior of the optimal policy for 4 different cases:

- 1) No sleep mode, femto cells are always active.
- 2) Sleep/wake up modes with complete traffic localization information.
- 3) Sleep/wake up modes with no information about the localization of users (only aggregate load information is available).
- 4) Sleep/wake up modes with partial traffic localization information.

Figures 5 and 6 illustrate the user-perceived QoS and the overall energy consumption as a function of increasing traffic, respectively. The first observation is that sleep mode reduces energy consumption, even in cases of partial or no information; the reduction being larger with increasing amount of information. However, QoS is reduced when sleep mode is activated, as resources have to be shared between a larger number of users when femto cells are shut down. When traffic localization information is missing, QoS degrades as it is possible to awaken a femto cell that is not able to offload a large part of the macro layer traffic, while the energy consumption increases as activating a wrong femto cell incurs

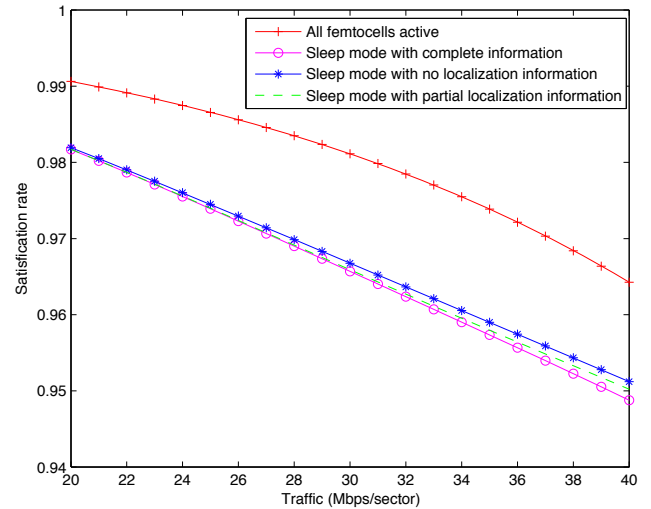


Fig. 5. QoS perceived by the users (partial information versus complete information).

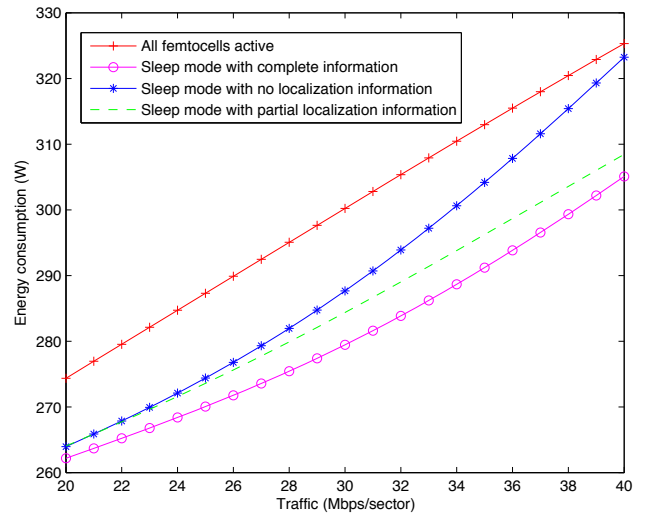


Fig. 6. Energy consumption (partial information versus complete information).

additional costs. Note that these values correspond to the optimal tradeoff between energy consumption and QoS, as determined by the optimal policy.

### C. Delayed information

We now move to the case of accurate localization algorithms that, however, need some delay before delivering the information. We consider an average offered traffic of 35 Mbps/sector and study the impact of longer information delay on the performance (we plot QoS in Figure 7 and energy consumption in Figure 8). The first observation is that, when the delay tends to zero, the scheme corresponds to the one with complete information. However, energy consumption indeed decreases when the localization delay increases, because in this case the Femto cell will be switched ON later. On the other hand, QoS degrades with localization delay, because again the Femto cell takes more time to be switched ON.

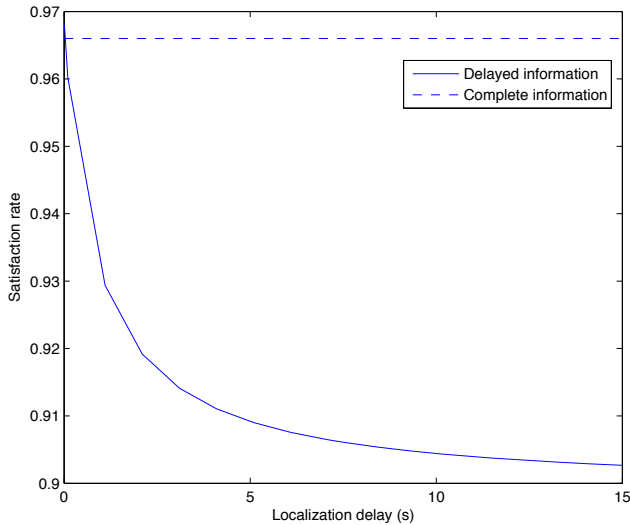


Fig. 7. Evolution of the QoS perceived by the users when the localization delay increases.

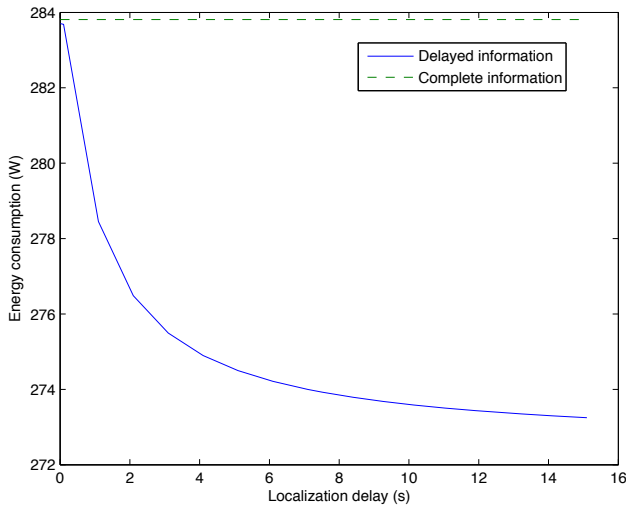


Fig. 8. Evolution of the energy consumption when the localization delay increases.

#### D. Dense deployment of femto cells

In the previous sections, we considered the case of operator-installed femto cells, with a relatively small number of femto cells per macro sector. In this section, we consider the case of client-installed, open access femto cells. This scenario may involve a large number of femto cells per macro sector, as the femto cell market penetration of femto cells increases. These femto cells are generally deployed indoors, with a low power consumption (5 watts per femto cell is considered in the numerical applications). We consider three femto cell densities: 10, 25 and 100 femto cells per sector, and an overall offered traffic of 30 Mbps per sector. Recall that the positions of femto cells are randomly selected in the cell.

As of the numerical analysis, we make use of event-based simulations to simulate the controller, because the state space dimension is too high for a pure analytical resolution. For scalability issues in realistic network deployments with a high

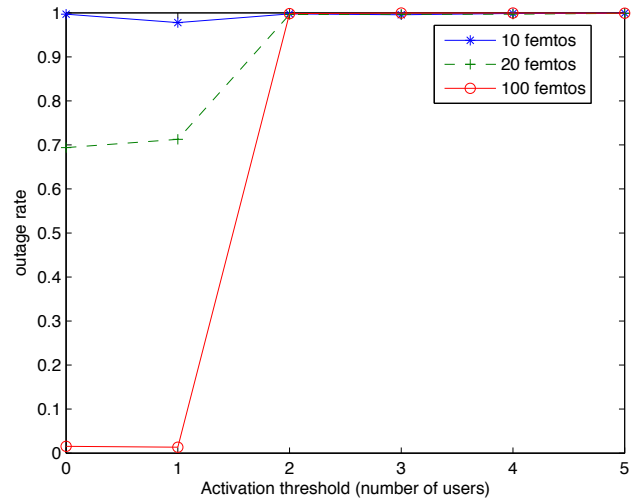


Fig. 9. Evolution of the QoS perceived by the users function of the activation threshold

density of femto cells, we consider a threshold-based policy.

We plot in Figures 9 and 10 the satisfaction rate of users and the overall energy consumption in the network composed of macro and femto cells, as a function of the activation threshold. This latter is defined as the number of users in the femto cell coverage area above which the activation decision is taken. We only illustrate the complete information case as the aim is to study the impact of a high density of femto cells on the performance. Note that a threshold of 0 corresponds to a network without sleep mode, whereas a larger threshold corresponds to a more aggressive sleep mode.

Let us first discuss the first point (activation threshold=0), corresponding to the baseline case (no sleep mode). As expected, as we consider a constant overall traffic, the larger the number of femto cells in the network, the higher is the energy consumption and the better is the QoS (low outage rate). When the activation threshold increases, femto cells are put into sleep mode more frequently, leading to a lower energy consumption, but to a worse QoS (higher outage rate). All the values converge to the same value when the activation threshold is too high (femto cells are always put in sleep mode). Figures 9 and 10 also show that an activation threshold of 1 is optimal, as it reduces drastically the energy consumption (up to 170% for the 100 femto cell case), without a large impact on QoS.

## VI. CONCLUSION

We developed, in this paper, optimal sleep/wakeup schemes in heterogeneous networks, composed of macro and femto base stations. The aim was to reduce the energy consumption of the network while preserving QoS. The scenario studied, in this paper, is the dense urban case where macro cells ensure complete coverage, but femto cells form hotspots of large capacity and are used to offload parts of the macro layer traffic. Both macro and femto base stations are controlled by the same operator.

We have, first, shown how to derive optimal policies in the case where complete traffic localization information is present when taking the decision, using control theory. We, next,



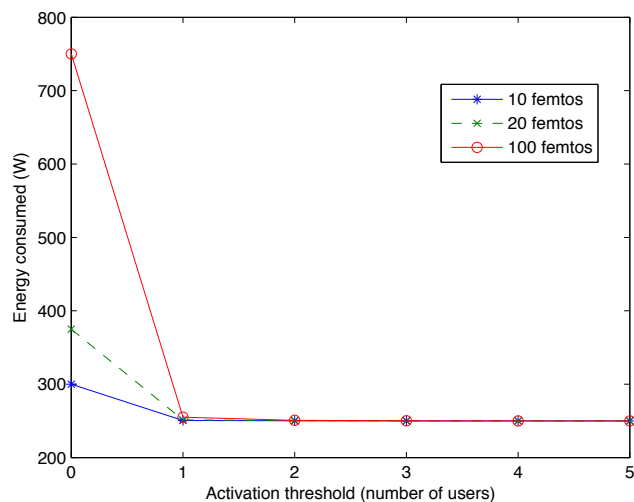


Fig. 10. Energy consumption function of the activation threshold

discussed more realistic cases where localization information is not available at all, or only partially, or yet delayed. We have shown how to apply MDP theory in these cases, with partially observable states or with delayed actions.

As of future works, we intend to study distributed sleep/wakeup schemes in extremely dense networks composed of only femto cells, and derive optimal controllers with limited communication between cell sites.

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