Energy-Efficient Planning and Management of Cellular Networks

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***Abstract*—We study base stations energy-efficient management algorithms in a cellular access network taking into account different planning strategies. To provide energy savings, sleep modes are adopted at the Base Stations (BSs). We propose two switch-off strategies that are based either on the cell load or the BS coverage overlap. Our results show that energy savings between 10% and 30% can be achieved also for the deployment already planned to be energy-efficient, while even higher savings are achievable with the other deployments. Moreover, we find that both the proposed switch-off strategies obtain similar results, suggesting that the order at which the BSs are switched-off, and the set of BSs selected to be switched off, do not change significantly the average estimation of potential energy savings. Furthermore, on a realistic case study, comparisons are made between the results obtained by using deterministic channel estimation models and empirical formulations.**

I. Introduction

In recent years, energy consumption has become one of the most challenging issues among the ICT (Information and Communications Technology) community. Both economical aspects, such as high electricity bills for operators and environmental concerns, are driving the market to investigate more and more advanced energy-efficient solutions. Concerning the networking sector, one of the most promising approaches to reduce the energy consumption of networks and networking equipment is given by the use of sleep modes. In the specific case of cellular networks, it has been shown that Base Stations (BSs) are often under-utilized during low intensity traffic periods [1], [2], [3], [4]. Thus, letting BSs enter sleep mode during low traffic periods is shown to be an efficient solution that allows to save a significant amount of energy [4], [5]. Besides BSs switch-off, sleep modes can be enabled also considering different options, ranging from the reduction of the number of active transmitters [6], to the switch-off of a whole network, when coverage is provided by other technologies of the same operator, or when several operators offer coverage in the same service area [7], by allowing customers to roam from the network that switches off to one that remains on. However, to the best of our knowledge all previous works assume either regular topologies [2], [5] (i.e., square, hexagonal and circular cells) or a given planning driven by operators policies [3], [4].

However, a natural question is then how much the planning strategy affects the sleep mode performance. For example, is it useful to apply sleep modes to a deployment already planned to be energy-efficient? And, also, is it possible to define simple policies that allow to switch off BSs under different deployments? The answer to these questions is the goal of this paper. We first consider three network planning strategies: the first one minimizes the number of transmitters, the second one minimizes the power consumption, while the third one is a combination between the previous two strategies. Specifically, we focus on a real urban environment in the center of London and we leverage on genetic algorithms to find deployments for each of the considered network planning strategies. Given the generated deployments, we evaluate the energy savings achievable when sleep modes are implemented and users traffic varies over time. Our aim is to find the minimum set of BSs to be powered on to satisfy a given traffic demand. We apply different heuristic algorithms for deciding which BSs to be switched off. Our main findings show that energy savings between 10% and 30% can be achieved also for the deployment already planned to be energy-efficient, while even higher savings can be achieved with the other deployments.

Concerning the switch-off strategies, we find that all heuristics are able to save a large amount of energy, suggesting that the order at which the BSs are switched-off, and, possibly, the set of BSs selected to be switched off, do not change significantly the estimation of potential energy savings.

Finally, we compare the results obtained with a sophisticated propagation model based on ray tracing techniques against results deriving from an empirical propagation model. The comparison suggests that the models lead to similar performance predictions in terms of energy savings, with the empirical model that slightly overestimates the power consumption with respect to the ray tracing model. Thus, simple propagation models can be adopted to have a rough estimation of the energy savings that can be achieved with the use of sleep modes, while ray tracing based propagation models are more effective during the actual network planning phase, for example, to find potential users' locations where coverage cannot be guaranteed.

The rest of the paper is organized as follows. We first describe the scenario and the main assumptions in Section II. The radio planning strategies are detailed in Section III.

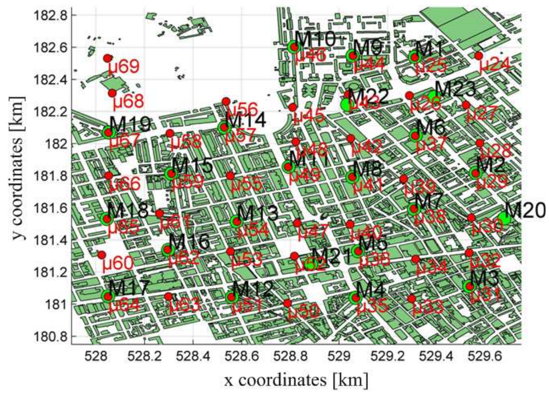

Fig. 1. The area under investigation with 23 Macros and 46 Micro stations. The points denote possible antenna placements. The urban environment is in vector format for the ray tracing code and represents a district of zone 1 of city of London.

Section IV illustrates the BSs switch-off strategies that we propose. We present our main findings in Section V. Finally, conclusions are drawn in Section VI.

II. Scenario and Assumptions

An area *A* of central London is under investigation representing a real district, with the urban environment described by a vector format database (*A* is [1.8 x 1.8 Km]). Within *A* there is a set *S* of 69 possible sites, as shown in Fig. 1.

There are two types of base station deployments, namely the *macrocells* with 3 sectors per site and the *microcells* with 1 sector only. We define $M_a \subset S$ and $M_i \subset S$ the set of macrocells and microcells, respectively. The number of possible macrocells and microcells sites is 23 and 46, respectively. Each site j is defined by the following parameters: (i) position in Cartesian coordinates $\{x_j, y_j\}$, (ii) BS type (micro or macro), (iii) height H_j above ground, (iv) maximum transmission power P_j^{max}, (v) the antenna gain G_j. Note that in the initial site positions there are locations in which macrocell and microcell site can coexist. However, in the final network topology it is not possible to power on a macrocell and a microcell at the same position.

Users and their properties are modeled with the user equivalent definition. Let U be the set of users over the area A. N_U is the total number of users.[1] Each user $u_i \in U$ is defined by the position $\{x_i, y_i\}$, the antenna gain g_i, and the type of service, i.e., voice, video or web service. We assume fixed positions for users. The bit rate and minimum signal to noise ratio threshold ($E_b/I_0 = \delta_i$) are defined as $R_i = 12$ kbps, $\delta_i = 5$ dB for voice, $R_i = 64$ kbps, $\delta_i = 2.5$ dB for video and $R_i = 144$ kbps, $\delta_i = 2$ dB for web service. Moreover, the positions $\{x_i, y_i\}$ are uniformly distributed in A and different randomly generated snapshots are examined. Finally, we define the coverage of a site as the area where the signal to noise ratio requirements are met and the received signal strength is higher than a minimum sensitivity.

[1]During the planning phase N_U is kept constant. The variation of this parameter is considered during the management phase, i.e., when sleep modes are applied.

A bigraph is used to model the affinity of user equivalents to sites $G(U, S)$ which is undirected with vertex set $V\{U \cup S\}$ such that there is an edge if and only if user *u* is under the coverage umbrella of site *j*. Denoting with $\gamma_{ij}^{\downarrow}$ the downlink signal to noise (interference) ratio between user i and site j, the coverage umbrella is defined by the condition $\gamma_{ij}^{\downarrow} \geq \varphi_i$, being φ_i a minimum threshold. The affinity graph describes possible associations of users to sites. A subgraph of the affinity graph named as association graph represents the real association of users to the site based on the best server and soft handoff procedure. Since we are dealing with the downlink case only,[2] notation $^{\downarrow}$ is omitted in all formulations. A user i is assumed to be assigned to the "best server" base station from the available set of possible base stations, denoted by the following equation:

$$\arg\max_{j \in S} (G_j + g_i + L_{ij} + P_j^{max})^{dB} \geq \varphi_i^{dB} \tag{1}$$

where L_{ij} denotes the path loss between base station j and user i. A user is covered and, thus, assigned to the set of users C_j, if and only if the following condition is satisfied:

$$\gamma_{ij} = \frac{L_{ij} G_j g_i p_{ij}}{n + \omega L_{ij} G_j g_i (P_j - \nu_i p_{ij}) + \sum\limits_{k \in S, k \neq j} L_{ik} G_k g_i P_k} \geq \varphi_i \tag{2}$$

where φ_i is the minimum threshold, n is the thermal noise, ω and ν_i are the orthogonality factor and voice activity, respectively. Finally, $P_j = \sum\limits_{i \in C_j} \nu_i p_{ij} + p_j^p$ denotes the required transmission power of the base station to serve the covered users. Parameter p_j^p characterizes the power of the control channels which are approximately the 15% of the total power P_j^{max} [8]. The required transmission power p_{ij} to serve user i from BS j is computed assuming a perfect SINR power control [8]:

$$p_{ij} = \delta_i \nu \frac{R_i}{R_c L_{ij}} [(1-w) P_j^{max} L_{ij} G_j g_i + \sum_{k \neq j} L_{ik} G_k g_i P_k + n] \tag{3}$$

where R_c is the UMTS chip rate (3.84Mcps).

Moreover, capacity is usually power limited due to the bounded maximum transmission power of the site:

$$\sum_{i \in C_j} \nu_i p_{ij} + p_j^p \leq P_j^{max} \tag{4}$$

Capacity is also associated to the maximum amount of data traffic a site can handle:

$$\sum_{i \in C_j} x_{ij} R_i \leq T \tag{5}$$

where $x_{ij} = 1$ if user i is connected to site j and 0 otherwise, $T = 14$ Mbps if $j \in M_a$ and $T = 4$ Mbps if $j \in M_i$.

[2]Note that we leave for future work the analysis for the uplink case, both in the planning and in the management phases.

TABLE I
WALFISH-IKEGAMI PROPAGATION MODEL: PARAMETERS SETTING.

Carrier frequency	2000 MHz
Macro BS height	30 m
Micro BS height	5 m
Mobile users height	1.7 m
Roof height for Macro BS	27 m
Roof height for Micro BS	5 m
Angle between incidences coming from BS and road	90°
Building separation	10 m
Roads width	10 m

A. Power consumption model

We model the total power consumption of a BS j as a linear equation:

$$W_j = bP_j + c \tag{6}$$

where b is the scaling factor of transmission power P_j, and c takes into account the fixed power consumed independently on the transmission power [9]. We consider two different sets of values for the parameters b, c: we refer to f_1 as the power profile 1 that uses the values reported in [9], and f_2 as the power profile 2 that uses the values in [10]. Note that f_1 uses values typical of UMTS networks, while f_2 is related to LTE networks. We set:

1) f_1: $b_{Ma} = 22.6$, $c_{Ma} = 412.4$; $b_{Mi} = 5.5$, $c_{Mi} = 32$;
2) f_2: $b_{Ma} = 15.9$, $c_{Ma} = 712.2$; $b_{Mi} = 6.2$, $c_{Mi} = 106$.

B. Channel Estimation Models

To compute the path loss L_{ij} at each test point in the considered deployments, we use two propagation models: the empirical propagation model of Walfish-Ikegami [11] and a realistic model based on ray tracing. Both models are described in the following.

1) Empirical Propagation Model: The well-known Walfish-Ikegami model is a statistical model that considers only characteristic parameter values and disregards the topographical configuration of buildings, see [11] for details. We set the model's parameters so as to consider a metropolitan environment where no Line-of-Sight (LOS) exists. For completeness, we report the other model parameters in Table I.

2) Ray Tracing Approximation: Path loss L_{ij} and received signal strength are computed according to a 3D ray tracing algorithm using multiple reflections from building facets and multiple slope Uniform Theory of Diffraction (UTD) technique [12], [13]. The adopted ray tracing model is based on a database preprocessing method [14] which guarantees high speed and low CPU demands. The field computation is based on a multiple slope UTD solution where higher order field terms sustain field continuity around the shadow boundaries of the scenario. The total field comprises a summation of multiple reflections, diffractions and combination of the both mechanisms. An example of the predicted received field and the user association is presented in Fig. 2.

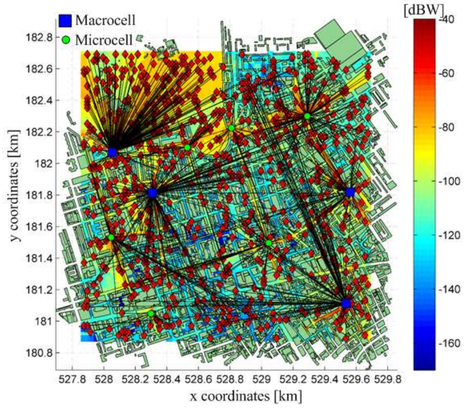

Fig. 2. Received power, based on ray tracing results, and user association to base stations for a given snapshot of the network.

III. RADIO PLANNING STRATEGIES

The radio planning incorporates the channel prediction algorithm (ray tracing) coupled with an evolutionary optimization technique (the genetic algorithm). The radio planning algorithm searches the state space of the feasible solutions and converges to a network topology which is derived under a specific optimization target. For the purpose of our investigation we investigate three strategies:

- minimum transmitters (TX)
- minimum power consumption (MP)
- hybrid network (H)

TX strategy corresponds to the typical mobile operator's strategy for low CAPEX (CAPital EXpenditure); the objective is to minimize the number of deployed base stations and provide Quality of Service (QoS) over a predefined area. The MP strategy corresponds to energy efficiency and low OPEX (OPerating EXpense) imposed to the administrative domain of the mobile operator; the objective is to minimize the total energy consumption and provide QoS over the examined area and it can be considered as a minimum Joule/bit strategy. The hybrid strategy is a combination of the above.

We apply the presented strategies considering two operational states of the network, corresponding to peak traffic and off-peak traffic. The intuition is to provide to the BS management algorithm the deployment computed for the peak traffic. The algorithm then switches off some BSs according to the current traffic. However, we provide also to the management algorithm the set of BSs that has to be always powered on to guarantee a minimal QoS, computed for the off-peak traffic. In the following we detail first the peak traffic planning, then the off-peak planning is described.

A. Peak Traffic Planning

During the first step of planning the optimization algorithm defines the network topology for the peak traffic condition adopting one among the strategies TX, MP or H.

More formally, let $U^{max} \subset U$ be the set of users during peak hour, with cardinality N^{max}. Let Q_i a binary operator indicating if Eq.(2) is satisfied for each user $i \in U^{max}$.

Additionally, let $a_j \in \{0,1\}$ be binary variables which take the value of 1 if BS j is powered on. Let P_j^{max} be discrete variables indicating the maximum transmission power of BS j. In particular, we assume $P_j^{max} \in \{0, 10, 20, 30, 40, 50\}$W for macro BS and $P_j^{max} \in \{0, 1, 2, 3, 4, 5\}$W for micro BS. Finally, let $x_{ij} \in \{0,1\}$ be binary variables which take the value of 1 if user i is connected to BS j.

The optimization problem for the planning strategy TX is defined as:

$$TX \rightarrow \min \sum_{j \in S} a_j \tag{7}$$

subject to:

$$\sum_{i \in U^{max}} Q_i = \eta N^{max} \tag{8}$$

$$\sum_{i \in C_j} \nu_i p_{ij} + p_j^p \leq P_j^{max} \quad \forall j \tag{9}$$

$$\sum_{i \in C_j} x_{ij} R_i \leq T \quad \forall j \tag{10}$$

$$P_j^{max} \leq B a_j \quad \forall j \tag{11}$$

Eq.(7) minimizes the total number of BSs powered on. Eq.(8) imposes to serve at least ηN^{max} users, with $\eta = 95\%$. Eq.(9) bounds the power needed to serve the current set of users to be smaller than the maximum transmission power. Eq.(10) bounds the total data traffic T for each BS. Finally, Eq.(11) imposes to switch on a BS if the transmission power is larger than 0, adopting the big-M method, being B a large constant.

For the planning strategy MP, the optimization problem can be defined as for TX with the following objective function:

$$MP \rightarrow \min \sum_{j \in S} W_j \tag{12}$$

with W_j denoting the total power consumption of BS j, which is a function of the transmission power (see Eq.(6)).

Finally, the hybrid planning H is a combination of the above topologies obtained with a heuristic approach that is described in Section III-C.

For each strategy, we denote as D the set of BSs powered on at the end of the peak traffic planning step, i.e., $D = \{j | a_j = 1 \quad \forall j\}$.

B. Off-Peak Traffic Planning

During this step the planning for low traffic is computed, starting from the planning D of the peak hour. The intuition here is to select a subset of BSs $MD \subset D$ that has to be always powered on to satisfy the minimum traffic and coverage constraints. Thus, the BSs that are included in MD can not be powered off at all. The problem can be formulated as the TX planning, but in this case set D is used instead of the entire set of locations S. More formally, let $U^{min} \subset U$ be the subset of off-peak users, with cardinality N^{min}. We then define the low traffic planning problem as:

$$\min \sum_{j \in D} a_j \tag{13}$$

subject to:

$$\sum_{i \in U^{min}} Q_i = N^{min} \tag{14}$$

$$(9), (10), (11) \qquad \forall j \in D \tag{15}$$

with control variables a_j, P_j^{max}, x_{ij} defined as previously.

The network topologies that are modeled following this procedure correspond to the networks that are capable to satisfy coverage and QoS for the minimum expected traffic conditions.

Finally, we define the set of flexible base stations FD as $FD = D \setminus MD$, i.e., the base stations that can be potentially switched off.

C. Genetic Algorithm Optimization

A genetic algorithm (GA) optimization technique is used to search for the feasible solutions and converge to the near optimum one satisfying the constraints of the problem. The GA used is similar to the one presented in [15]. We refer the reader to [15] for a detailed description of the algorithm. In brief, each gene includes as decision variables a_j, P_j^{max}, and the type of BS (micro or macro). Additionally, the GA implements different techniques to improve the solution quality, including a single point crossover technique, elitism, and a liner penalty function. However, the GA does not converge to a single optimum solution but it provides a set of near optimum solutions in the final generation. Since the initial population of the GA is randomly generated, the final solutions are not always the same. We have therefore performed 100 independent runs of the GA and at each run, the chromosome with the best fit function (objective function) is selected and stored. For each network strategy (TX, MP and H), the solution with the best performance is chosen. In particular, for the hybrid scenario H the network topology derived from MP and composed by the least number of base stations is selected.

We have then run the GA algorithm under high and low traffic conditions. Table II reports the main results for the three network planning strategies. As expected, the TX strategy produces a network with a small number of high power macrocell stations. On the other hand the MP strategy converges to a network with a large number of low power microcell stations. Finally, the hybrid strategy requires a balanced number of macros and micros to provide the QoS in the area. In general, energy efficiency is achieved when the network comprises a large number of microcell stations, optimally placed within the area A, following the same observations derived in [9].

IV. Base Station Management

Given the BS set selected during the planning phase, we rely on the possibility to put some BS into sleep mode, so that the current traffic is sustained by the base stations that remain powered on. When a BS is powered off, its power consumption is negligible. Thus, our aim is to adapt the current

TABLE II
PLANNING RESULTS

Planning	Set	Number of Macrocells	Number of Microcells
TX	High Traffic	5	1
	Low Traffic	2	-
	Flexible BSs	3	1
MP	High Traffic	1	14
	Low Traffic	1	7
	Flexible BSs	-	7
H	High Traffic	4	6
	Low Traffic	2	3
	Flexible BSs	2	3

Algorithm 1 Pseudo-code description of the proposed heuristics.

```
sort_BS(BS_array, order_type);
for j = 1; j ≤size(BS_array); j++ do
    if BS_array[j].id ∈ FD then
        disable_BS(BS_array[j]);
        user_coverage=compute_coverage(BS_array);
        BS_capacity=compute_capacity(BS_array);
        if (check_coverage(user_coverage) == false) ||
        (check_capacity(BS_capacity) == false)) then
            enable_BS(BS_array[j]);
        end if
    end if
end for
```

network capacity to the actual traffic, while guaranteeing an adequate QoS to users. In this way, energy savings can be achieved by leaving powered on the minimal subset of BSs to satisfy a given traffic demand.

The minimal set of BSs is computed using a centralized algorithm, i.e., we assume that BSs share information like status (on-off), load and capacity with a centralized unit. In particular, two heuristic approaches are proposed. All heuristics start by considering a topology in which all BSs are powered on. Then the algorithm checks iteratively if a given BS (among the ones that can be potentially put into sleep mode) can be turned off. At each iteration, the considered BS is removed from the topology. User coverage and BS capacity are then recomputed on the residual topology. If both coverage and capacity are still fulfilled, then the selected BS is definitively powered off. Algorithm 1 reports a schematic description of the heuristics.

The base station set is first sorted considering a given rule before iterating through all the BSs. We consider the following sorting rules:

- Least-Load (LL)
- Most-Overlapped (OV)

The Least Load (LL) strategy is based on the load sustained by the BSs in the considered deployment. Specifically, the BSs are selected starting from the least loaded one, i.e., the BS that serves the smallest fraction of users, to the most loaded one. The rationale being that low loaded BSs are more likely to be switched off first, avoiding frequent off-on transitions.

The Most-Overlap (OV) strategy takes instead into account the overlapping coverage areas existing among neighboring BSs. The intuition is that, in dense deployments, several BSs are necessary to provide capacity during the peak hours, but they are redundant during low traffic periods. In this case, the BSs are sorted according to decreasing overlapping. For each BS the overlapping is computed as the number of active users that can hear the current BS and at least another BS over the total number of users that can hear the current BS. We say that a user can hear a BS if the SINR threshold requirement on the control channel is satisfied.

A. *Energy Efficiency Metrics*

We first define the network energy consumption when all BSs are always powered on. In particular, we define the energy consumption of the Always-On (AO) scheme for time period Γ as:

$$EC = \sum_{j=1}^{N_{BS}} \int_0^\Gamma W_j(t)dt \tag{16}$$

where $W_j(t)$ is the power consumption of the $j-th$ BS at time t and N_{BS} indicates the total number of BSs of current deployment. We compute $W_j(t)$ for two distinct cases. In the first one $W_j(t)$ is computed assuming that the transmission power $P_j(t)$ adapts to the current traffic based on the number of active users. We refer to this case as EC_A. Then, we consider also the case in which $P_j(t)$ is always equal to the power required to serve the users during the traffic peak. Clearly, this assumption leads to high energy consumption and represents a worst case. We denote this case as EC_{NA}.

Analogously, we can compute the energy consumption EC_s of the network when sleep modes management is applied. Note that in this case $W_j(t)$ is 0 if BS j is powered off.

The energy saving of the sleep mode scheme with respect to an Always-On scheme thus becomes:

$$ES = \frac{EC - EC_s}{EC} \cdot 100[\%] \tag{17}$$

ES_A and ES_{NA} are the energy savings achievable with the sleep mode scheme when energy consumption of the AO scheme is EC_A and EC_{NA}, respectively.

V. PERFORMANCE EVALUATION

We evaluate the performance of our heuristics considering the three different deployment strategies. We start by considering the case in which the traffic varies with a sinusoidal pattern. Fig. 3 (top) reports the normalized traffic profile. Note that the peak corresponds to have 847 active users in the network (i.e., active user density $\rho = 261.4$ users/Km^2), while the lowest traffic intensity corresponds to 40 users. For each time instant, we then randomly select the corresponding fraction of active users. Unless otherwise specified, values are averaged over 50 independent runs for selecting the current set of users.

We first apply the Least-Load (LL) strategy to the three deployments, adopting power profile f_1. Fig. 4 shows the

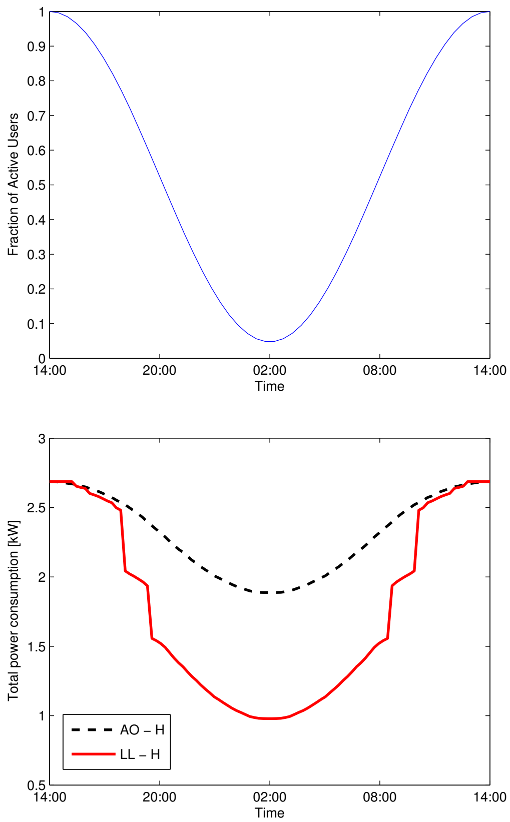

Fig. 3. Normalized sinusoidal traffic profile (top), total power consumption versus time (bottom).

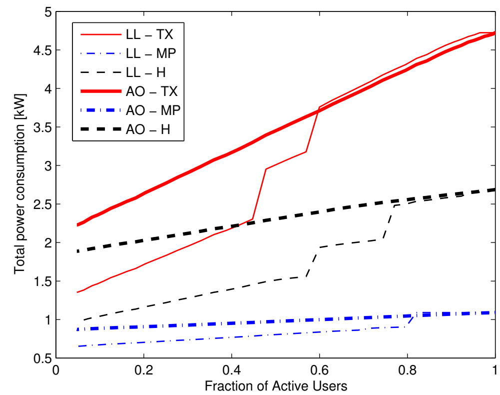

Fig. 4. Power consumption versus the fraction of active users (LL strategy).

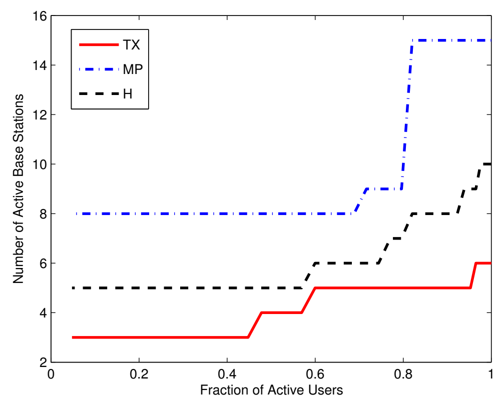

Fig. 5. Number of active BSs versus the fraction of active users (LL strategy).

power consumption of the Always-On scheme (labels 'AO') and the power consumption of the LL strategy versus the fraction of active users, considering the case in which the BS transmission power adapts to the current traffic. When sleep modes are adopted the power consumption of the network is reduced with respect to an Always-On scheme for all the deployments. In particular, the savings achievable with sleep mode become significant when the fraction of active users is lower than the peak, namely about 0.42, 0.8 and 0.58 for deployments TX, MP and H, respectively. As expected, the highest energy saving is obtained with the hybrid deployment H, since it is designed to be a combination between the minimum transmitter and the energy-efficient deployments. Interestingly, the power consumption of the sleep mode scheme is higher than the Always-On scheme when TX is deployed and the percentage of active users is larger than 60%. This is due to the transmission power increase of the BSs that have to remain active and have to cover the users left by the BSs switched-off. Indeed, the number of active BSs decreases from 6 to 4 when the fraction of active users decreases from 1 to about 0.6. This can be observed in Fig. 5 that reports the number of active BSs versus the fraction of active users. Note that the minimum number of BSs needed during low traffic hours (MD) is reached by MP and H, while TX requires an additional base station powered on even with low traffic. In particular, the additional BS is required to fulfill the capacity constraint: this is due to the fact that there are a few BSs, and some users with very high path losses require a large amount of transmission power if the BS is not sufficiently close.

To capture the effect of the traffic profile, bottom plot of Fig. 3 details the power consumption versus time for the deployment H, considering both the Always-On scheme with EC_A and LL heuristic. Interestingly, power consumption of the energy-aware network is half of AO during low traffic hours. Observe also the deep steps affecting the total power when a single BS is switched off and then on again.

To give more insights, Table III reports the energy savings ES_A and ES_{NA} obtained considering the adaptive EC_A and not adaptive EC_{NA} energy consumption, respectively. As expected, higher percentage savings are achieved when the transmission power P_j of the AO scheme does not adapt to current traffic (ES_{NA}). For example, the LL algorithm run over deployment TX is able to save almost 40% of energy.

We then consider power profile f_2. Table IV reports the energy savings with LL. Interestingly, the savings are even larger than f_1 when P_j adapts to the current traffic (ES_A), ranging between 17% and 28%.

In the following, we consider the OV heuristic for BS

TABLE III
ENERGY SAVINGS: LL STRATEGY, POWER PROFILE f_1.

LL strategy	TX	MP	H
ES_A [%]	12.4	13.0	22.8
ES_{NA} [%]	39.4	28.2	41.4

TABLE IV
ENERGY SAVINGS: LL STRATEGY, POWER PROFILE f_2.

LL strategy	TX	MP	H
ES_A [%]	17.1	21.5	28.2
ES_{NA} [%]	33.1	27.3	37.1

management. Fig. 6 and Fig. 7 report the power consumption and the number of active BSs, respectively. Table V shows the energy savings considering power profile f_1. Several considerations hold in this case: (i) overall results are similar to LL, since ES_{NA} saves more energy than ES_A; (ii) OV always selects the minimal number of BSs powered on when traffic is low (differently from LL), suggesting that coverage overlapping is a good choice for deciding the order in which BSs are turned off; (iii) considering deployment TX, the OV strategy allows to save power as soon as the fraction of active users is 0.9, while with the LL strategy, savings can be achieved starting from about 0.6; (iv) when traffic is low the network power consumption is similar for all the deployments, i.e., 0.6-1.0 kW, suggesting that the specific deployment has a rather limited impact in this case, being the OV heuristic able to save a consistent amount of power even for TX and MP.

We then extend our analysis considering a real traffic profile of [16] also used in the EARTH project [17], reported in Fig. 8. This profile can be considered representative of residential areas since the peak is localized during evening/night hours. Fig. 9 shows the power savings achievable with LL over the three deployments considering EC_A. Also in this case, higher power savings are achievable during low traffic periods, being the largest ones obtained for deployment TX. Note that during peak hours the network with LL strategy consumes more power than the Always-On (AO) one, hence the saved power is lower than zero. On the contrary, deployment MP reaches moderate power savings that are almost constant during the whole day. Table VI summarizes the percentage energy savings with the real traffic profile. We can observe that the energy savings are only a bit smaller than the ones achievable with the sinusoidal profile we have used for Table III, ranging between 8% and 38%

Finally, we consider the impact of using different propagation models (PM). Fig. 10 shows the results obtained comparing the ray tracing and the Walfish-Ikegami models

TABLE V
ENERGY SAVINGS: OV STRATEGY, POWER PROFILE f_1.

OV strategy	TX	MP	H
ES_A [%]	19.0	11.6	23.6
ES_{NA} [%]	44.0	27.1	42.0

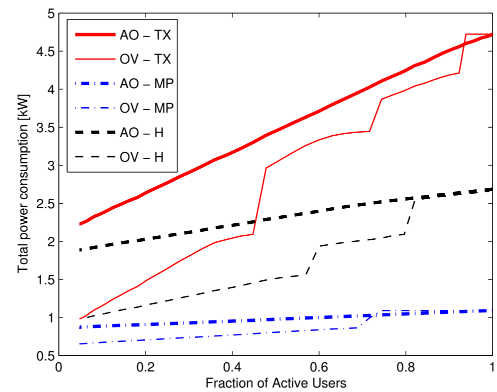

Fig. 6. Power consumption versus the fraction of active users (OV strategy).

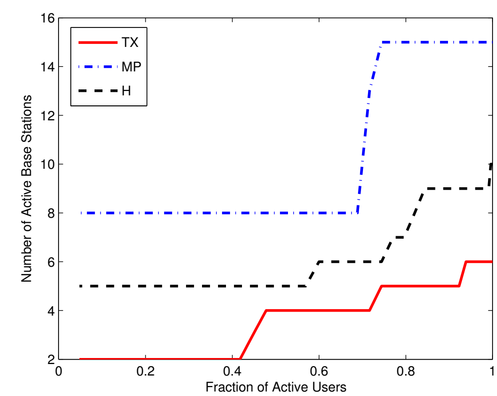

Fig. 7. Number of active BSs versus the fraction of active users (OV strategy).

considering deployment H. We can note that the Walfish-Ikegami model slightly overestimates the network power consumption. Similar considerations hold also for TX and MP deployments (not reported here due to the lack of space). However, in all cases, we observe that overall results do not change significantly considering the two models. This suggests that, in order to estimate the potential energy savings that can be achieved by adopting sleep modes to base stations in cellular networks, it is sufficient to use a simple propagation model. However, more sophisticated propagation models, like the ray tracing one, are more effective during the planning phase.

VI. CONCLUSIONS

In this paper we have assessed the effectiveness of sleep modes techniques coupled with different network planning schemes. We have first considered three network planning strategies that minimize the number of transmitters, the power consumption or a combination of the above. Given the generated deployments, we have proposed different heuristics to select the minimal number of BSs as traffic varies over time. Our main findings have shown that energy savings between 8% and 44% can be achieved on a realistic scenario, depending

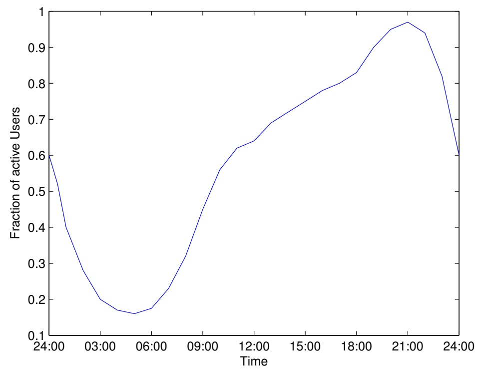

Fig. 8. Real traffic profile: fraction of active users versus time.

TABLE VI
ENERGY SAVINGS WITH A REAL TRAFFIC PROFILE: LL STRATEGY, POWER PROFILE f_1.

LL strategy	TX	MP	H
ES_A [%]	8.4	12.9	20.7
ES_{NA} [%]	33.5	27.2	38.2

on the adopted power profile or strategy. In particular, we have found that energy savings between 11% and 28% are achievable also for deployments already planned for energy efficiency. Finally, we have shown that the energy savings obtained with empirical models are similar to the ones obtained with ray tracing techniques.

As ongoing work, we are investigating the effects of non-uniform users distribution on the overall savings. Moreover, we will investigate *online* algorithms to dynamically adapt the set BSs powered on following the traffic variation. Finally, we will consider CAPEX/OPEX costs and their impact on the planning and management strategies.

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REFERENCES

[1] J.T. Louhi, *Energy efficiency of modern cellular base stations*, INTELEC 2007, Rome, Italy.

[2] M. Ajmone Marsan, L. Chiaraviglio, D. Ciullo, M. Meo, *Optimal Energy Savings in Cellular Access Networks*, GreenComm'09 - 1st International Workshop on Green Communications, Dresden, Germany, June 2009.

[3] C. Peng, S. B. Lee, S. Lu, H. Luo, H. Li, *Traffic-Driven Power Saving in Operational 3G Cellular Networks*, ACM MobiCom11, Las Vegas, Nevada, USA, September 2011.

[4] E. Oh, B. Krishnamachari, X. Liu, Z. Niu, *Toward dynamic energy efficient operation of cellular network operation*, IEEE Communication magazine, June 2011.

[5] M. Ajmone Marsan, L. Chiaraviglio, D. Ciullo, M. Meo, *Energy-Efficient Management of UMTS Access Networks*, ITC 21 - 21st International Teletraffic Congress, Paris, France, September 2009.

[6] L.i Saker, S. E. Elayoubi, *Sleep mode implementation issues in green base stations*, PIMRC, Istanbul, Turkey, September 2010.

[7] M. Ajmone Marsan, M. Meo, *Energy Efficient Management of two Cellular Access Networks*, ACM SIGMETRICS Performance Evaluation Review, Special Issue on the 2009 GreenMetrics Workshop, Vol. 37, No. 4 (March 2010), pp. 69 – 73.

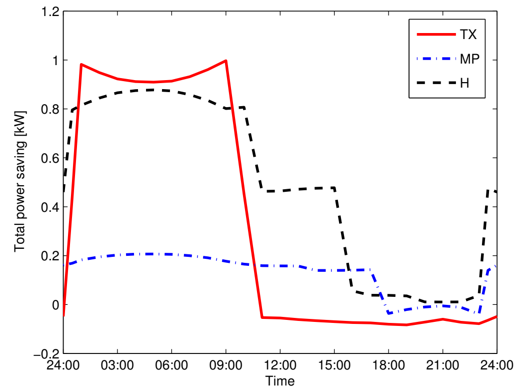

Fig. 9. Real traffic profile: power saving versus time (adaptive power consumption model).

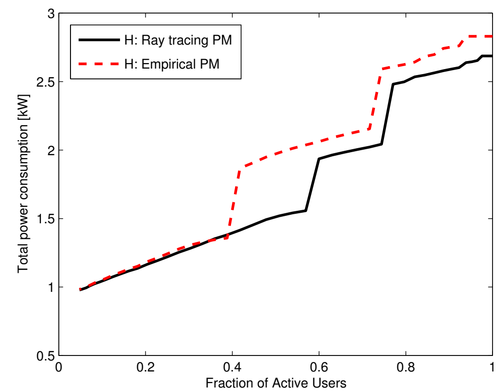

Fig. 10. Propagation models comparisons (LL strategy): total power consumption versus the fraction of active users.

[8] M. J. Nawrocki, M. Dohler, A. H. Aghvami, *Understanding UMTS radio network planning: modeling, planning and automatic optimization*, WILEY, ISBN: 978-0-470-01567-4, 2006.

[9] A. J. Fehske, F. Richter, and G. P. Fettweis, *Energy efficiency improvements through micro sites in cellular mobile radio networks*, in Proc. of IEEE GreenComm, Honolulu, Hawaii, Dec. 2009.

[10] G. Auer, V. Giannini, I. Godor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez., C. Desset, O. Blume, *Cellular Energy Efficiency Evaluation Framework*, GreeNet workshop, in proc. of VTC Spring 2011.

[11] Cost 231 Final Report, http://www.lx.it.pt/cost231/.

[12] G. Koutitas and C. Tzaras, *A Slope UTD solution for a cascade of multishaped canonical objects*, IEEE Trans. Antennas Propag., vol. 54, no. 10, pp. 2969-2976, 2006.

[13] A. Karousos, *The distortion of UWB Signals in the Environment*, PhD Thesis, University of Surrey, 2008.

[14] G. Wolfle, R. Hoppe, and F. Landstorfer, *A fast and enhanced ray optical propagation model for indoor and urban scenarios, based on an intelligent preprocessing of the database*, IEEE Int. Symp. Personal, Indoor and Mobile Radio Comm. (PIMRC), Sept. 1999.

[15] G. Koutitas, *Green Network Planning of Single Frequency Networks*, IEEE Trans. on Broadcasting, vol. 56, no. 4, pp. 541-550, 2010.

[16] Sandvine, *Mobile Internet Phenomena Report*, 2010, http://www.sandvine.com/downloads/documents/2010%20Mobile%20 Internet%20Phenomena%20Report.pdf

[17] EARTH Project, https://www.ict-earth.eu/.