Radio Planning of Energy-Aware Cellular Networks

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Abstract

The role of the Information and Communication Technology sector on productivity and economic growth is constantly increasing and, due to its pervasiveness, the ICT power consumption can no longer be ignored. Some energy-aware models and approaches have already been proposed for cellular networks, they aim at reducing power expenditures while decreasing network operators costs. However, the focus is on management issues such as switching on and off network elements based on traffic levels, not on considering that an effective energy-efficient operation largely depends on the decisions taken at the design stages. To fill this gap, we propose a joint design and management optimization approach, which tries to limit energy consumption while guaranteeing connection quality constraints for every user and minimizes operators Capex and Opex. We show that including energy costs in Opex and taking into account energy management strategies at the design stages produce more energy efficient and versatile topologies than when Capex only is considered.

I. Introduction

We are witnessing a growing interest in the area of green networking given the importance of environmental and energy related issues for the Internet and Communication Technologies sector. In fact, it has been reported [10] that the ICT percentage with respect to the world energy expenditures range from 2% to 10%. Of particular concern is the consumption of the cellular wireless system, both for its increasing pervasiveness that pushes for more wireless infrastructure and for the well known fact that Base Stations are particularly energy-hungry, representing over 80% of the power used in the radio segment.

Despite the novelty of the problem, the research community has already produced interesting models and approaches to deal with the issues of energy-savings in cellular networks. Most studies have focused on the *network operation* aspects, in particular on *management* issues mainly aiming at switching off parts of the network when the traffic load decreases [5], [18], [9]. However, an important issue that has not been explored in the literature is that an effective energy-efficient operation depends on the type of Base Stations deployed and the coverage structure of the network and hence on radio planning decisions taken during the design phase. Since the coverage of the service area must be ensured at all times, the level of flexibility offered by the network topology is an important factor to be able to switch some Base Stations on and off to dynamically adapt the network capacity to the traffic load without violating coverage constraints. While concerns for climate change is the main push for research on efficient technology developments, network operators are as well interested in reducing the energy consumption of their networks for economic reasons. Two are the cost categories that mobile operators have to meet: capital investments related to radio equipment, license fees, site buildouts and installation of equipments, commonly identified as

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Capital Expenditures (*Capex*) and running costs, such as transmission, site rentals, marketing terminal subsidies and operation and maintenance (Operational and Management Expenditures, *Opex*) [15]. The challenge in terms of energy-aware modeling is to be able to convey both type of costs and energy issues in a single modeling framework.

The objective of this paper is therefore to fill that gap and present, to the best of our knowledge for the first time, an energy-aware joint design and management problem aiming at maximally limiting energy consumption while reducing both Capex and Opex categories. Among other things, we want to evaluate the impact of having such a modeling approach when compared with more traditional Capex optimization at the planning stages.

This article is divided as follows. In Section II some general green networking papers and some of the most relevant articles that are specifically related to wireless green networking are surveyed. In Section III the relevant issues related to the design of energy efficient wireless networks are discussed and the general approach proposed is presented. The mathematical preliminaries to understand the proposed model and the assumptions made are also presented in Section III, where the propagation model, the traffic variations in time and the different types of Base Stations considered into the model are exposed and discussed. The model itself, based on mathematical programming, is presented in Section IV. The resolution approach and numerical results are presented in Section V. Note that an important part of the presentation is to be able to test the model with appropriate instances, which is not a straightforward matter. Therefore, we have produced an instance generator that is also explained in this Section. Section VI concludes the paper and presents some ideas for further work.

II. Related Work

The literature on general green networking is quickly expanding since the seminal work by Gupta and Singh [11]. Some authors have been concerned with virtualization, others with the development of energy-aware Ethernet, others with evaluating the Internet consumption and with proposals to reduce it (for a review see [21]). However, must of the work has focused on wireline networks despite the fact that the wireless system is highly responsible for the increase in energy consumption.

It must be said that wireless systems engineers have always been concerned with energy issues, since the portability nature of the network, being cellular, ad-hoc or sensor oriented, made it a real challenge in terms of coverage and battery life. Therefore, there is a very large body of literature focused on energy-efficient *devices* or energy-aware *protocols* (an excellent report on the issues affecting wireless energy consumption can be found in [13]). However, the literature on green networking planning and operation is recent and scant. Moreover, as briefly mentioned in the introduction, most articled have dealt with management rather than design issues.

In the area of Wireless Local Area Networks (WLANs) network management strategies based in the concept of resource on-demand (RoD) have been proposed [14]. An analytical model for evaluating the effectiveness of RoD strategies has been proposed in [19]. Management strategies for energy saving in solar powered wireless MESH networks based on IEEE 802.11 are presented in [24].

As far as cellular networks are concerned, in [5], given the network topology and a fixed traffic demand, the authors evaluate the possibility of switching off some nodes in order to minimize the total power consumption, always complying with connectivity and Quality of Service (QoS) constraints. However, in [5] no traffic variations in space or time were considered. Now, since cellular systems are often dimensioned to satisfy the QoS constraints under peak traffic conditions, the traffic reduction in some portions of the network can be exploited in order to allow further and substantial power savings. In [18], deterministic traffic variations over time were taken into account, the purpose was to characterize the amount of energy saved by reducing the number of active access devices when they are not fully utilized. It is shown that energy savings of the order of 25 - 30% are possible for several regular cell topologies. In [4] the authors show that it is possible to switch off some UMTS NodeBs in urban areas during low-traffic periods, while still guaranteeing quality of service constraints in terms of blocking probability and electromagnetic exposure limits.

In [9], it is shown that merely controlling the transmitted power does not allow big energy savings since the energy consumption mainly depends on the on-off states of the BSs. Thus, the authors consider a random traffic distribution and dynamically minimize the number of active BSs to meet the traffic variations in both space and time dimensions. An optimization approach for dynamically managing the energy consumption of wireless networks switching on and off access stations in different periods of time (like different hours of the day) is proposed in [16].

Differently from the papers mentioned above, our goal is not to manage the energy consumption of operating wireless networks, but rather defining a radio planning approach to design wireless networks where the efficiency of energy management can be maximized and the operational costs due to energy minimized.

The impact of several regular cell layouts on the power consumption of mobile radio networks considering varying numbers of micro base stations per cell in addition to conventional macro sites has been investigated in [22]. It is shown that on the considered layouts, the use of micro base stations has a limited effect on the power consumption. Differently from this work, we do not limit our analysis to regular layouts and we propose an optimization approach that can be used with arbitrary topologies and propagation scenarios.

III. Preliminaries

This section is devoted to preliminary modelling considerations that must be explained in order to properly introduce the model in Section IV. We first present the reasoning behind the joint design and management of energy-aware cellular networks. Then, we present the models and assumptions we used for traffic variations, different types of base stations, and channel propagation. However, note that our optimization approach is general and not limited to these models since traffic values, base station characteristics and propagation coefficients are input parameters. The models are used only for giving concrete examples through numerical results.

A. Joint Design and Management of Energy-aware Cellular Networks

From an energy saving point of view, a radio coverage obtained using small cells served by base stations with low power is considered more efficient than adopting macro cells with large radii created by high power base stations. This is because when decreasing the radius of the cell the energy consumption usually decreases faster than the increase of the number of base stations required to cover the area, even if differences may be observed in the devices depending on the wireless technology and the components adopted. On the other hand, from a deployment cost point of view, the effect is opposite since fixed costs per installation site tend to prevail.

We argue that, when energy management is considered, the level of flexibility offered by the network topology is also important for adapting the capacity of the cellular system to the varying traffic load, switching on and off some base stations or adapting their emission power. Indeed, providing enough network capacity is not the only constraint to be considered since the full coverage of the service area must be ensured at all time. Therefore, the availability of a potentially large number of network configurations consisting in a set of active base stations providing full coverage with different capacity and energy consumption levels is the key issue that enables energy management strategies in cellular networks. For this reason, a cellular coverage based on small cells only may not be the best option also from an energy efficiency point of view since all cells are necessary for proving full coverage and they cannot be switched off when traffic is low. On the other hand, a combination of cells with different sizes can potentially offer a flexible coverage topology able to adapt to different traffic scenarios. This is also in line with the need of most operators to use a mix of 2G (like GSM/GPRS) and 3G (like UMTS/HSPA) technologies, and soon also 4G (like LTE) with different frequencies and coverage ranges.

We believe that in order to take into account the important issue of energy management when planning the radio coverage of a cellular network, an optimization approach that jointly considers both the network design based on Capex and Opex costs as well as energy management according to different traffic distributions is absolutely necessary. These two issues are interdependent due to the fundamental role that the management mechanism has in defining the energy cost and hence the Opex.

Planning a wireless access network roughly deals with finding positions and configuration settings for network devices, while matching service requirements, possibly stated as given constraints (including budget ones). Consolidated models and solution methodologies have already been proposed for different wireless systems ranging from 2G [20] and 3G [1] cellular networks to Wireless LANs hot spots [2].

A common approach to the coverage optimization problem resorts to discrete mathematical programming models [6]. A set of *Test Points* (TPs), representing end users, are identified in the service area. TPs can be considered as traffic centroids, where a given amount of traffic (usually expressed in Erlang or bit per second) is requested [25]. Instead of allowing the positioning of BSs anywhere in the service area, a set of *Candidate Sites* (CSs) where the BSs can be installed is identified. Since we can evaluate (or even measure in the field) the signal propagation between any pair of TP and CS, the subset of TPs covered by a sufficiently strong signal is assumed to be known for a BS installed in any CS. The coverage problem results in the classical minimum cost set covering problem [20].

Let S denote the set of CSs, where a BS can be installed, For each CS j, $j \in S$, let the set K_j index all the possible configurations of the BS that can be installed in j. Since the installation cost and the traffic capacity may vary with the BS configuration (e.g., its maximum emission power and device type), an installation cost γ_{jk} and a traffic capacity c_{jk} are associated with each pair of CS j and BS configuration k. Let I denote the set of TPs generating a traffic demand d_i. The propagation information can be summarized in the coverage coefficient a_{ijk}, which is equal to 1 if a BS installed in CS j with configuration k can cover TP i, and is equal to 0 otherwise. Such parameters can be gathered from a survey of the site to be planned, or using automatic tools for the prediction of the actual propagation conditions.

Binary decision variables y_{jk} are adopted to define if a BS with configuration k is actually installed in CS j ($y_{jk} = 1$) or not ($y_{jk} = 0$). Additional assignment variables x_{ijk} define if a TP i is associated to a BS located in CS j ($x_{ij} = 1$), or not ($x_{ij} = 0$).

A commonly adopted formulation of the radio planning problem with coverage constraints is:

$$\min \quad \sum_{j \in S} \sum_{k \in K_j} \gamma_{jk} y_{jk} \tag{1}$$

$$\sum_{j \in S} x_{ij} = 1 \quad \forall i \in I \tag{2}$$

$$\sum_{k \in K_j} y_{jk} \leq 1 \quad \forall j \in S \tag{3}$$

$$x_{ij} \leq \sum_{k \in K(j)} a_{ijk} y_{jk} \quad \forall i \in I, \forall j \in S \tag{4}$$

$$\sum_{i \in I} x_{ij} d_i \leq \sum_{k \in K_j} y_{jk} c_{jk} \tag{5}$$

$$y_{jk} \in \{0, 1\} \quad \forall j \in S, k \in K_j \tag{6}$$

$$x_{ij} \in \{0, 1\} \quad \forall i \in I, \forall j \in S. \tag{7}$$

Objective function (1) aims at minimizing total installation costs, while constraints (2) ensure that all TPs are assigned to one BS, and constraints (3) that one configuration at most is selected in CS j. Obviously, crucial constraints are (4), stating that a TP i can be assigned to a CS j with configuration k only if it is covered by a BS that is actually installed, and capacity constraints (5) that limit the traffic assigned to installed base stations.

Starting from this radio planning model we introduce the following innovative features to produce an energy-aware design and management model:

- We modify the objective function to include not only base station installation costs (Capex) but also operational costs (Opex) assuming that their variable part is mainly due to the energy cost, which is largely confirmed by data available from mobile operators worldwide;
- We redefine variables and constraints to include in the model the energy management mechanism that, based on a set of traffic scenarios related to different time periods of the day, can switch on and off base stations and modify their emission power;
- We include the energy consumed by the management mechanism into the objective function component of the operational cost and use a tradeoff parameter to define the relative importance of Capex and Opex in the optimization process;
- We jointly consider radio planning and energy management in order to obtain the network planning that minimize deployment and operational costs.

We show that the proposed model can be solved to the optimum for realistic size networks and that it allows to get an interesting insight on the coverage and topology characteristics of energy-efficient wireless networks. The model proposed is presented in Section IV.

B. Traffic Variation Behavior

Intuitively it can be said that traffic intensity varies as a natural effect of users'daily habits. For example, it has been measured that mobile traffic presents its peak between noon and 4 pm. and that there is a significant decrease in the late evenings. Moreover, in a typical business area, the traffic pattern is almost the same from Monday to Friday but it decreases during the weekend [12].

In order to account for the main fluctuations, but neglecting the differences that occur between working and weekend days, we consider an approximated daily traffic pattern based on the measurements presented in [12] and [17]. According to this profile, the whole day is split in time periods, each one gathering smaller intervals (hours) in which the users behaviour can be assumed unchanged.

Let T be the ordered set of the different time periods. Let $h(t)$ represent the length of period $t \in T$. Each period is expressed in hours and it lasts

$$h(t) = e(t) - o(t), \tag{8}$$

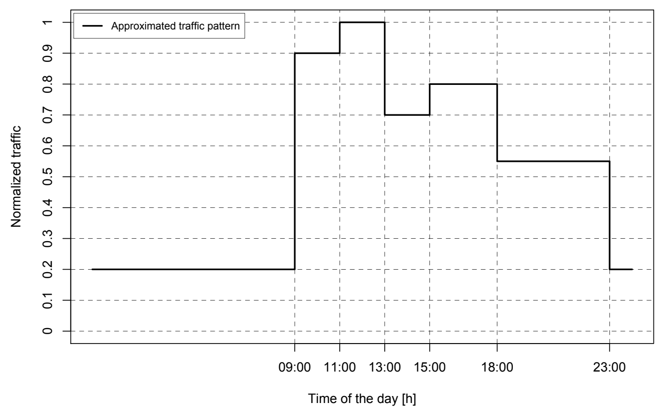

Fig. 1: Approximated traffic profile of analyzed mobile network.

where $e(t)$ and $o(t)$ are, respectively, the end and the beginning times of period $t \in T$. Note that the end of the previous time period $e(t-1)$ is equal to the beginning of the new one $o(t)$, so that there is no time gap between adjacent periods and the summed duration of all periods is equal to the number of hours in a day. In this paper, we have assumed a total of six time periods.

Observing Figure 1, the progress of the approximated traffic profile defines active users percentages in every time instance. So, in order to comply with the outlined pattern, our traffic distribution is modelled as follows.

Let us recall the previously defined set of traffic aggregation points, called Test Points (TPs). We assumed that only a group of TPs can provide real traffic, while the others are only used in the network dimensioning phase. For each traffic centroid, we calculate a random traffic value ranging from 0 to 10 Erlangs. This value represents the maximum traffic (in Erlang) that the TP can generate. Then, depending on the time period, the maximum traffic value is multiplied by the normalized traffic (that is to say, the active users percentage) typical of every instance.

C. Base Station Categories

The discussion about which Base Station size deployment can offer much economic and energy saving is a common topic in literature [8], [15]. Each BS category has different performances in terms of cell range and reliability and consequently different impact on Capital and Operational and Management Expenditures. In light of that, the total cost structure of a radio access network is closely related to the quantity and types of different access points employed to obtain the required network capacity and coverage.

With respect to energy expenditures, it is often believed that efficiency improvements can be achieved through high density deployments of small and low power BSs, compared to network topologies featuring low density deployment of high power BSs. In fact, although micro sites cover smaller areas, these generally provide much higher Signal to Interference and Noise Ratios (SINR) due to shorter propagation distances; besides, accordingly to the coverage area sizes, micro BSs have lower energy consumption [8].

From an economic standpoint, small BSs imply a low cost for equipment, site lease and installation, while macro BSs are clearly more expensive because of the higher output power, capacity and required reliability. On the other hand, the cost per user can be lower in case of bigger BSs due to fixed costs not directly related to the capacity of the BS, which can be divided between many users.

In this paper we allowed the joint low and high power Base Stations deployment, which can change in time in order to comply to traffic variations: thus, we tried to achieve the complete coverage of the interested area and limit the energy (and consequently, economic) waste due to low traffic periods.

Three Base Stations types are employed, each one transmitting at a different maximum power. Considering the values provided by GSM standard [7] as reference, we selected the following configurations:

- *Macro BS*. Emitted power of $43\ dBm$, corresponding to a maximum coverage radius of about $9500\ m$;
- *Micro BS*. Emitted power of $20\ dBm$, corresponding to a maximum coverage radius of about $1300\ m$;
- *Pico BS*. Emitted power of $15\ dBm$, corresponding to a maximum coverage radius of about $825\ m$.

In order to limit unnecessary power expenditures, we introduced the possibility of using only a percentage (70%, 60% or 50%) of the maximum transmitted power allowed for the specific category. In our model we call *configurations* the different Base Stations types and *power levels* the percentages described above. Moreover, every BS can be switched off and enter in the stand-by mode in case of very low traffic profile.

As displayed in Table I, realistic values of consumed power and capacity are derived for every couple of BS configuration-power level. The former, measured in decibels, takes into account the mean power consumption of the equipment that occurs per sector, such as power amplifier, transceiver, signal generator and AC-DC converter, and the equipment that occurs only once, such as the air conditioning and the microwave link (responsible for communications with the backhaul network). The latter, expressed in Erlangs and computed by setting the desired blocking probability to 0.02, quantifies the maximum traffic volume which can be addressed by a single BS.

It is worth pointing out that the design approach we proposed is general and can be used with any mix of BS types and technologies. The example values above have been used only to obtain numerical results in realistic scenarios.

D. The Propagation Model

In real scenarios, deterioration of transmitted signal quality is commonly assumed to be due to three different causes: path loss, slow fading (also named shadowing) and fast fading. However, for the sake of simplicity, in this paper we concentrate on the effect of path loss and shadowing.

TABLE I: Transmission and consumption features of every couple of BS configuration - power level.

Config.	Config. cost (Euro)	Power level	Transmit power (dBm)	Consumed power (dB)	Capacity (Erl)	Max coverage distance (m)
C1	40000	P1- 100%	43	31.2	26	9396.4
		P2 - 70%	41.5	30.7	26	8233.6
		P3 - 60%	40.8	30.1	26	7776.7
		P4 - 50%	40.0	28.8	26	7268.9
		P5 - 0%	0	3	0	0
C2	22000	P1- 100%	20	27.0	14	1321.6
		P2 - 70%	18.5	26.9	14	1158.1
		P3 - 60%	17.8	26.2	14	1093.8
		P4 - 50%	17.0	25.7	14	1022.4
		P5 - 0%	0	3.0	0	0
C3	15000	P1- 100%	15	22.5	9	862.8
		P2 - 70%	13.5	22.0	9	756.1
		P3 - 60%	12.8	21.3	9	714.1
		P4 - 50%	12	20.5	9	667.5
		P5 - 0%	0	3.0	0	0

A commonly adopted model indicates that the mean path loss increases exponentially with distance [3], [8], [23]:

$$\overline{PL}(d) \propto \left(\frac{d}{d_0}\right)^n, \tag{9}$$

where $\overline{PL}(d)$ is the mean path loss, n is the path loss exponent which indicates how fast path loss increases with distance, d_0 is a close-in reference distance and d is the transmitter-receiver separation distance. Average power path loss is defined as the power loss from the transmitter to the reference distance d_0

$$\overline{PL}(d_0)[dB] = 10\log_{10} P_t - 10log_{10}P(d_0) \tag{10}$$

plus the additional path loss described by (9) in decibels:

$$\overline{PL}(d)[dB] = \overline{PL}(d_0)[dB] + 10n\log_{10}\left(\frac{d}{d_0}\right). \tag{11}$$

where P_t is the power of the transmitted signal. For our model a $1\ m$ reference distance was chosen, and we assume $\overline{PL}(d_0)$ is due to free space propagation from the transmitter to that distance. According to [23], considering antenna gains equal to system cable losses, leads to $31.5\ dB$ path loss at $900\ MHz$ over a $1\ m$ free space path.

Experimental measurements indicate that path loss is log-normally distributed about (11). Hence, path loss at a separation of d meters is better described by

$$PL(d)[dB] = \overline{PL}(d)[dB] + X_\sigma[dB], \tag{12}$$

where X_σ is a zero mean log-normally distributed random variable with standard deviation σ, which can be interpreted as representing the variability of power loss of transmitter-receiver configurations located at different places. Assuming that the distribution of large-scale path loss is log-normal for our data, we need to get the path loss exponent n and standard deviation σ as a function of the general surroundings. In [8] a linear regression was used to compute these values in a minimum mean square error sense for some measured data: from those results, we found that for our problem $n = 2.7$ and $\sigma = 13\ dB$ are the correct values. Once defined the path loss model, the received power at the distance d is calculated as

$$P_r(d)[dB] = P_t[dB] - PL(d)[dB]. \tag{13}$$

In order to verify wether or not a receiver is covered by a BS installed in a Candidate Site (CS), we need to know the power level required at the receiver that allows the connection between the two terminals. Chosen the most common GSM 900, constant receiver sensitivity level (P_{rth}) of $-102\ dBm$ is assumed for all mobile stations, according to ETSI GSM Technical Specification [7].

IV. The Mathematical Model

A. Notational Description

Having described the modeling philosophy as well as the physical details of the system we want to optimize, we need an additional notation to be able to set the mathematical model. For the sake of completeness, some of the notation that was first presented in Section III is also included here.

The notational presentation is divided in model parameters and decision variables:

Model Parameters:

- I_c : Set of TPs that need to be covered. We assume that they do not generate any traffic. This first subset of Test Points (*Coverage* Test Points) helps us provide a basic, fixed coverage of the network even in case of very low traffic profile.
- I_t : Set of TPs that need to be covered and that generate variable traffic. This second subset of Test Points (*Traffic* Test Points) allows the network to “follow” the traffic variations in different time periods.
- S : Set of the available Candidate Sites for the Base Stations.
- K_j : Set of possible configurations for a BS located in site j.
- L : Set of available power levels for a BS installed with configuration k.
- d_{it} : Traffic provided by the Traffic TP i in period t.
- c_{jkl} : Capacity of the BS located in site j with configuration k and power level l.
- γ_{jk} : Installation cost for a BS located in site j with configuration k. This is composed of two parts: the cost ξ_j due to the characteristics of the chosen site (for example, open spaces or buildings) and the cost τ_k

specific for the selected configuration.

ϵ_{jkl} : Power consumption for a BS located in site j with configuration k and power level l.

r_{ij} : Distance between the TP i and the BS located in site j.

β, ϑ : Weight parameters that will be used for trade-off in the objective function.

Finally, to conclude the model parameters, we need to introduce a binary one that summarizes the coverage information for each combination of Coverage or Traffic TP i, CS j, configuration k and power level l:

$$a_{ijkl} = \begin{cases} 1 & \text{if TP } i \in I_c \cup I_t \text{ is covered by a BS} \\ & \text{installed in } j \text{ with configuration } k \\ & \text{and power level } l, \\ & \\ 0 & \text{otherwise.} \end{cases} \tag{14}$$

Decision Variables: The problem of finding the subset of powered Base Stations with minimal cost that ensures coverage and capacity demand of all Test Points can be formulated using three decision variables. The first are those selecting which subset of CSs are chosen in any time interval:

$$z_{jk} = \begin{cases} 1 & \text{if a BS is installed in site } j \text{ with} \\ & \text{configuration } k, \\ & \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

Location and transmission characteristics of any installed BS are defined by the second binary variables:

$$y_{jklt} = \begin{cases} 1 & \text{if a BS installed in site } j \\ & \text{with configuration } k \text{ has} \\ & \text{power level } l \text{ in period } t, \\ & \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

Binary decision variables are also used to explicitly indicate the assignment of Traffic TPs to the active BSs:

$$x_{ijt} = \begin{cases} 1 & \text{if TP } i \in I_t \text{ is assigned to a BS} \\ & \text{installed in site } j \text{ in period } t, \\ & \\ 0 & \text{otherwise.} \end{cases} \tag{17}$$

B. Joint Design and Management Energy Aware Model

Having defined all the parameters and variables, we can now describe the modelling objective and constraints.

The objective function:

$$\begin{aligned} \min \quad & \sum_{j\in S}\sum_{k\in K_j} z_{jk}\gamma_{jk} + \\ \beta \sum_{j\in S}\sum_{k\in K_j}\sum_{l\in L}\sum_{t\in T} & \epsilon_{jkl}\cdot h(t)\cdot y_{jklt} + \\ \vartheta \sum_{i\in I_t}\sum_{j\in S}\sum_{t\in T} & x_{ijt}\cdot h(t)\cdot r_{ij} \end{aligned} \tag{18}$$

The objective (18) is composed of three major terms: the installation costs (Capex), the price of the operational and maintenance expenditures (Opex) of the base stations installed in the area and a final term, introduced to guarantee a better connection quality between users and antennas, that induces the model to to try to assign every Test Point to the nearest available Base Station. Note that the model considers that there is a trade off between the three terms that is adjusted by playing with the values of parameters β and ϑ.

Coverage constraints:

$$\sum_{j\in S}\sum_{k\in K_j}\sum_{l\in L} a_{ijkl}y_{jklt} \geq 1 \qquad \forall i \in I_c, t \in T \tag{19}$$

$$x_{ijt} \leq \sum_{k\in K_j}\sum_{l\in L} a_{ijkl}y_{jklt} \qquad \forall i \in I_t, j \in S, t \in T \tag{20}$$

The two constraints above represent two different types of coverage constraints. (19) provide a minimal and constant (over all scenarios) coverage by ensuring that *all* the TPs are within the service area of at least one installed Base Station. On the other hand (20) insure that *traffic* TPs are only assigned to the Base Station they are covered by.

Capacity constraints:

$$\sum_{i\in I_t} x_{ijt}d_{it} \leq \sum_{k\in K_j}\sum_{l\in L} c_{jkl}y_{jklt} \qquad \forall j \in S, t \in T \tag{21}$$

The capacity constraints (21) insure that each active BS can satisfy the traffic demand of the covered traffic TP.

Assignment constraints:

$$\sum_{j\in S} x_{ijt} = 1 \qquad \forall i \in I_t, t \in T \tag{22}$$

The assignment constraints given by (22) impose that every traffic TP is assigned to only one Base Station.

Linking constraints:

$$\sum_{l\in L} y_{jklt} = z_{jk} \qquad \forall j \in S, k \in K_j, t \in T \tag{23}$$

(23) above are linking constraints between variables y and z.

Configuration constraints:

$$\sum_{k\in K_j} z_{jk} \leq 1 \qquad \forall j \in S \tag{24}$$

Configuration constraints (24) impose that at most one configuration is chosen for every CS.

Binary constraints:

$$z_{jk} \in \{0,1\} \qquad \forall j \in S, k \in K_j \tag{25}$$

$$x_{ijt} \in \{0,1\} \qquad \forall i \in I_t, j \in S, t \in T \tag{26}$$

$$y_{jklt} \in \{0,1\} \qquad \forall j \in S, k \in K_j, l \in L, t \in T \tag{27}$$

Finally, (25), (27) and (26) impose the binary values for the decision variables.

V. Resolution Approach

The mathematical model we propose has been programmed using the AMPL programming language and CPLEX solver. In order to test the effectiveness of the model, we needed to generate realistic cellular network instances so that the number of CSs and TPs are similar to the ones that can be found in real networks.

Therefore, an instance generator was designed, implemented in C++ and used as an input for the CPLEX solver. In what follows, we explain the main features of the instance generator.

A. Instance Generator (IG)

IG input: The following is a list of the parameters that are used as an input to start the generation of instances. The Instance Generator takes the following entry parameters: noitemsep

- dimensions of the covered area (length x height),
- number of CSs $|S|$,
- number of Coverage TPs $|I_c|$,
- number of Traffic TPs $|I_t|$,
- range of random traffic for Traffic TPs,
- number and values of possible configurations for the BSs,
- cost of each configuration,
- number and values of possible power levels,
- percentage of transmitted power for each power level,
- consumed power for each couple configuration- power level,
- minimum power needed for a TP to be covered by a BS (receiver sensitivity),
- BS capacity for each couple configuration - power level,

- number of time periods, with starting and ending time,
- percentages corresponding to the daily traffic profile,
- value of the trade-off parameters β and ϑ.

Now that we have stated all the elements that must be taken into account to produce the instance generator, we can present the algorithm.

Instance Generator Algorithm:

- *Reading and random assignment*
  - Read all the input parameters
  - Create random coordinates for all Candidate Sites and Test Points
  - Assign a random cost parameter to each CS
  - Assign, within the chosen range, a random traffic value to each Traffic TP
- *Computation of values*
  - *For every pair of test point and candidate sites (TP, CS)compute*
    - the mutual distance and the related channel attenuation based on the relation (12)
  - *For every possible configuration and power level*
    - Determine wether the pair (TP, CS) is feasible depending on the value of the received power (13).

Thus, the outcome of the instance generator is then a feasible set of traffic and coverage TPs as well as candidate sites that guarantee the feasibility of the instance. In other words, the instance algorithm allows us to find the appropriate a_{ijkl} defined in (14).

In the following subsection, we present results for some *test scenarios*.

B. Experimental Results

TABLE II: Parameters used for generating the test scenarios.

	Scenario Nr.1	Scenario Nr.2
Area Size (m^2)	5000×5000	10000×10000
CSs Number	20	80
Coverage TPs Number	36	121
Traffic TPs Number	30	100
Configurations Number	3	3
Chosen Configurations	C1, C2, C3	C1, C2, C3
Power Levels Number	4	4
Chosen Power Levels	P1, P2, P4, P5	P1, P2, P4, P5

In order to assess the performance of the proposed approach, we considered different test scenarios generated using the IG. The scenarios features are described in Table II. For each scenario, the first entry of the table represents the area size (expressed in squared meters), the second entry is the number of Candidate Sites and next are the Coverage Test Points and the Traffic Test Points randomly placed in the area. Finally, the Table presents the values of the configurations and power levels allowed in each scenario.

The optimization of energy consumption, installation and operational costs was performed using the mathematical model presented in Section IV. For every scenario, we tested different values of the weight parameters β and ϑ: by doing so, we strove to highlight the benefits achieved by jointly minimizing costs and power expenditures in the design and management phases, instead of limiting the optimization at the network planning stage.

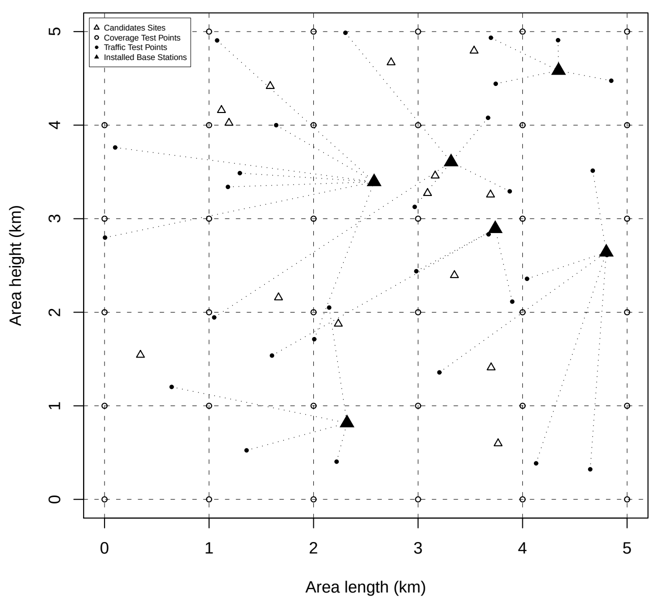

Fig. 2: Scenario 1, $\beta = 0$ - all time periods, and $\beta = 1$ - time period 2.

As an example of the type of results obtained, Figure 2 displays the network provided by the optimization model with $\beta = 0$ (for the cases of $\vartheta = 0.01$ and $\vartheta = 0.001$, which produce the same topology). When $\beta = 0$ only Capex costs are considered and operation costs due to energy expenditures are neglected. As pointed out in the Figure's caption, the same network is also obtained with $\beta = 1$ ($\vartheta = 0.001$ and $\vartheta = 0.0001$) since the Capex component largely prevails in the objective function. We observe that the optimal solution of the design problem includes 6 base stations, all of type $C1$. This is because covering the area with big cells is more convenient from an installation cost point of view (the costs per covered square kilometer are 0.16, 4.14, and 7.46 for BS types $C1$, $C2$, $C3$, respectively).

Given that with $\beta = 0$ the energy cost is not relevant, the energy management part of the model simply keeps base stations on at maximum power in all time periods. With $\beta = 1$, even if the energy-cost component of the objective function is much smaller than the installation cost and it does not impact on the selection of the number of base stations to be deployed, the energy management mechanism is encouraged to modify the topology according to the traffic level by switching on and off base stations and adjusting their power. The topology reported in Figure 2 shows the network topology in time period 2, when traffic is high and all 6 base stations are powered on. While Figure 3 shows the topology during time period 6 when traffic is low and only 2 base stations are kept on (the only two in the figure that have connected TPs).

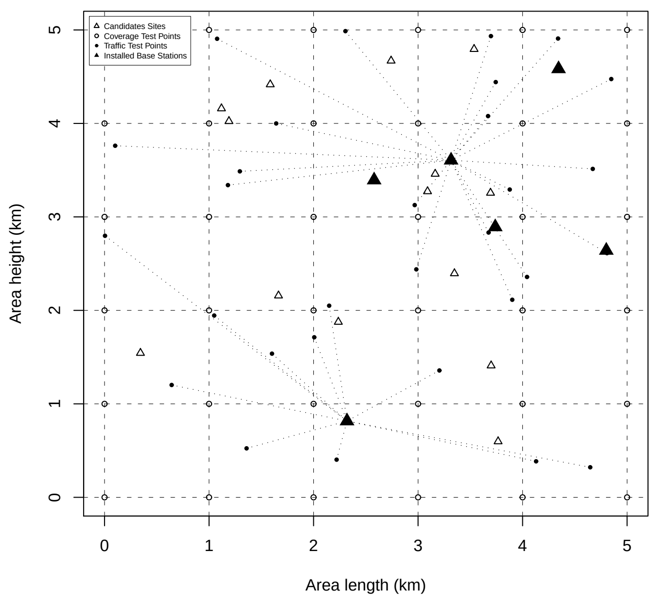

Fig. 3: Scenario 1, $\beta = 1$ - time period 6.

Figure 4 reports the network designed using $\beta = 100000$ ($\vartheta = 100$). With such a high value of β, the Opex component in the objective function is much higher than the Capex one and the optimization process is pushed to select the most energy efficient network topology, regardless of its installation cost. We can see that now more base stations (17) are installed and that several of them are small ones with short coverage range (types C2 and C3). Note also that, even if time period 2 corresponds to the peak traffic scenario, only 16 out of 17 base stations are powered on, which shows the importance of energy management.

In time period 6, which is the one with the lowest traffic load, only 3 out of 17 base stations are used to serve TPs while the others are switched off, as shown in Figure 5. Notably, one of the on cells is a big one, while the other two are small ones.

In Table III we show a summary of the results obtained solving Scenario 1 with different values of β. The Table reports the numerical values of the first two components of the objective function (corresponding to Capex and Opex), the total Energy (given by Opex/β), the number of base stations installed, and the number of base stations powered on during the six time periods with the corresponding average base station utilization. The BSs utilization

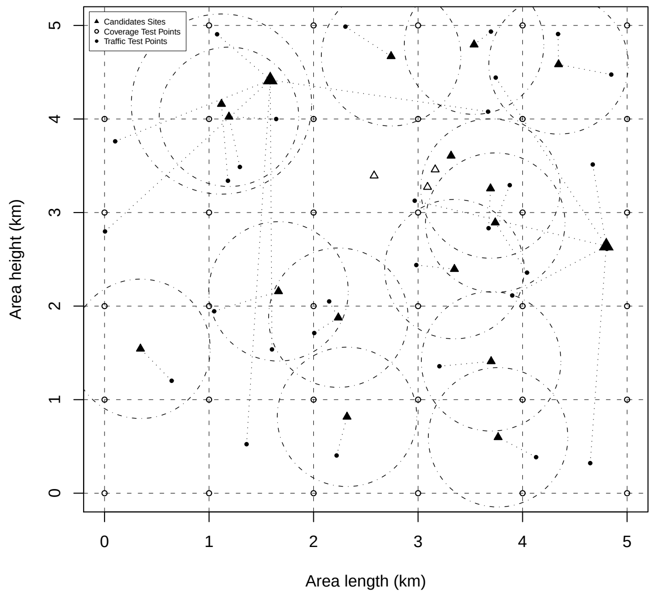

Fig. 4: Scenario 1, $\beta = 100000$ - time period 2.

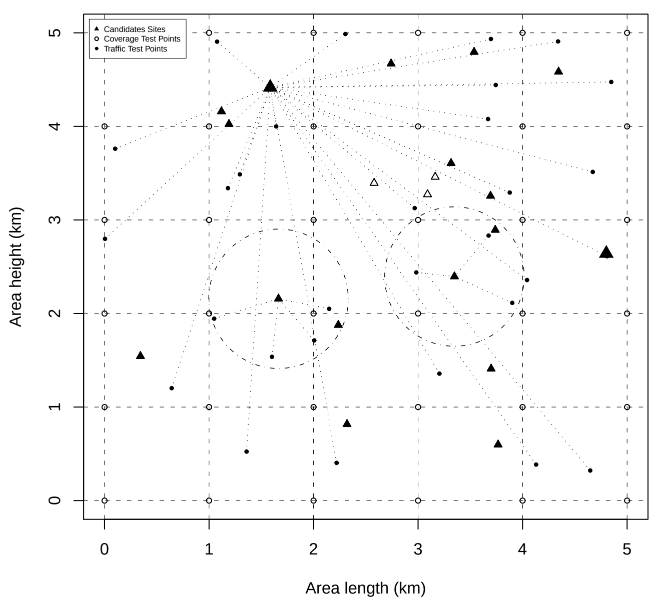

Fig. 5: Scenario 1, $\beta = 100000$ time period 6.

is calculated as

$$\sum_{j \in S} \frac{\sum_{i \in I_t} \sum_{k \in K_j} \sum_{l \in L} \frac{x_{ijt} \cdot d_{it} \cdot 100}{c_{jkl} \cdot y_{jklt}}}{\sum_{k \in K_j} \sum_{l \in L} y_{jklt}}. \tag{28}$$

For this scenario, computation time to solve the problem varies from a few minutes to one hour approximately.

We observe that increasing the value of β, the installation cost as well as the number of base stations increase, while the total energy consumed decreases. With respect to the case of $\beta = 0$ where only installation cost is considered and base stations are always powered on, the Capex increase is 79% with $\beta = 100$ and 131% with $\beta = 100000$, while energy decreases 70% with $\beta = 100$ and 71% with $\beta = 100000$. In this scenario, the value of $\beta = 100$ appears a reasonable compromise between installation cost and energy consumption. Increasing β further provides negligible improvements in energy saving at the price of a remarkable additional installation cost. Obviously, in general the most appropriate value of β depends on many issues including the characteristics of the problem instance and base station types. Consider however, that β basically incorporates two important parameters: i) the energy cost and, ii) the time period over which the network designer wants to compute the operational expenditures in order to compare them with the installation one. Therefore, an analysis of the Pareto optimal solutions with different values of β allows the network designers to select the best option according to the network development policies of the mobile operator.

TABLE III: Scenario 1: Summary of the results with different values of β.

		$\beta = 0$	$\beta = 1$	$\beta = 100$	$\beta = 100000$
		$\vartheta = 0.0001$	$\vartheta = 0.0001$	$\vartheta = 0.01$	$\vartheta = 10$
Capex		384723.7	384723.7 *(0%)*	690577.8 *(+79%)*	888688.5 *(+131%)*
Opex		0	66850.3	4428686.5	4312904078.0
Energy		146479.2	66850.3 *(-54%)*	44286.9 *(-70%)*	43129.0 *(-71%)*
Installed BSs		6	6	13	17
Powered On BSs	Period 1	6 - 88%	6 - 88%	11 - 88%	15 - 77%
	Period 2	6 - 97%	6 - 97%	13 - 87%	16 - 83%
	Period 3	6 - 68%	5 - 82%	11 - 74%	13 - 76%
	Period 4	6 - 78%	5 - 93%	12 - 83%	14 - 83%
	Period 5	6 - 54%	4 - 80%	9 - 82%	9 - 82%
	Period 6	6 - 19%	2 - 58%	2 - 75%	3 - 59%

In Table IV we show the results for Scenario 2, which is a larger instance than the one presented in the first Scenario. Here it can be appreciated that the trend that was found in the results for Scenario1 is even more striking as increase of the energy management term more than double the number of installed BSs, the Capex cost, while producing important reductions in energy consumption.

VI. Conclusion

In this paper we have considered the problem of designing energy efficient wireless access networks. One of the main instruments available to mobile operators to save energy and reduce operational costs is that of dynamically managing the network in order to switch on and off base stations and adjust their emission power according to the varying traffic load in the service area. Therefore, we have proposed an optimization framework that selects base stations to be installed and their configuration and jointly considers this dynamic energy management. The goal of

TABLE IV: Scenario 2: Summary of the results with different values of β.

		$\beta = 0$	$\beta = 1$	$\beta = 100$	$\beta = 100000$
		$\vartheta = 0.0001$	$\vartheta = 0.0001$	$\vartheta = 0.01$	$\vartheta = 10$
Capex		1287673.2	1287673.2 *(+0%)*	2798054.1 *(+117%)*	3096466.0 *(+140%)*
Opex		0	205882.0	15583566.8	15430417906.0
Energy		668029.5	205882.0 *(-69%)*	155835.7 *(-76%)*	154304.2 *(-77%)*
Installed BSs		20	20	52	57
Powered On BSs	Period 1	20 - 87%	19 - 91%	46 - 78%	50 -77%
	Period 2	20 - 97%	20 - 97%	47 - 81%	52 - 79%
	Period 3	20 - 68%	15 - 90%	37 - 76%	39 - 73%
	Period 4	20 - 77%	17 - 91%	40 - 80%	45 - 76%
	Period 5	20 - 53%	11 - 97%	26 - 82%	28 - 81%
	Period 6	20 - 19%	6 - 64%	8 - 69%	8 - 69%

the optimization process is that of minimizing the sum of installation and operational expenditures, where these last ones are determined by energy consumption.

We have shown that varying the tradeoff parameter β between installation and operational expenditures, the network topologies that we get through the proposed models have quite different characteristics. Network with a low installation cost are not very efficient from an energy consumption point of view since that tend to use big cells. On the other hand, the most energy efficient networks includes not only small cells with low energy consumption, but also big cells in order to provide to the energy management mechanism enough flexibility to adjust network capacity according to traffic load.

Acronyms

AMPL A Modeling Language for Mathematical Programming

BS Base Station

Capex Capital Expenditures

CS Candidate Site

ICT Information and Communication Technology

IG Instance Generator

Opex Operational and Management Expenditures

QoS Quality of Service

SINR Signal to Interference and Noise Ratio

TP Test Point

References

[1] E. Amaldi, A. Capone, and F. Malucelli. Planning UMTS base station location: Optimization models with power control and algorithms. *IEEE Transaction on Wireless Communications*, 2(5):932–952, September 2003.

[2] S. Bosio, A. Capone, and M. Cesana. Radio planning of wireless local area networks. *IEEE/ACM Transactions on Networking*, 15(6):1414–1427, December 2007.

[3] C.D. Charalambous and N. Menemenlis. Dynamical spatial log-normal shadowing models for mobile communications. *Proceedings of the 27th General Assembly of the International Union of Radio Science*, August 2002.

[4] L. Chiaraviglio, D. Ciullo, M.Meo, and M.A. Marsan. Energy-aware umts access networks. In *WPMC'08*, 2008.

[5] L. Chiaraviglio, M. Mellia, and F. Neri. Energy-aware networks: Reducing power consumption by switching off network elements. In *FEDERICA-Phosphorus tutorial and workshop (TNC2008)*, 2008.

[6] A. Eisenbĺatter and H.F. Geerd. Wireless network design: solution-oriented modeling and mathematical optimization. *Wireless Communications, IEEE*, 13(6):8–14, December 2006.

[7] TS ETSI. 145 005 v9.3.0 (3gpp ts 45.005 version 9.0 release 9). July 2010.

[8] A.J. Fehske, F. Richter, and G.P. Fettweis. Energy efficiency improvements through micro sites in cellular mobile radio networks. In *GLOBECOM Workshops, 2009 IEEE*, pages 1–5, November 2009.

[9] J. Gong, S. Zhou, Z. Yang, D. Cao, C. Zhang, Z. Niu, and P. Yang. Green mobile access network with dynamic base station energy saving. In *IEICE Tech. Rep., IA 2009*, volume 109, pages 25–29, October 2009.

[10] The Climate Group. SMART 2020: Enabling the low carbon economy in the information age. In *2010 State of Green Business*, June 2008.

[11] M. Gupta and S. Singh. Greening of the internet. In *Proceedings of the conference on Applications, technologies, architectures, and protocols for computer communications*, pages 19–26, 2003.

[12] P. Heegaard. Empirical observations of traffic patterns in mobile and ip telephony. *Next Generation Teletraffic and Wired/Wireless Advanced Networking*, pages 26–37, 2007.

[13] H.Karl. An overview of energy-efficiency techniques for mobile communication systems. Technical report, Report of the Working Group 7 âĂIJLow-power broadband wireless communicationâĂİ of the Arbeitsgruppe Mobikom, DLR/BMBF, October 2003.

[14] A.P. Jardosh, K. Papagiannaki, E.M. Belding, K.C. Almeroth, G. Iannaccone, and B. Vinnakota. Green wlans: On-demand wlan infrastructures. *Journal of Mobile Networks and Applications*, December 2008.

[15] K. Johansson, A. Furuskar, P. Karlsson, and J. Zander. Relation between base station characteristics and cost structure in cellular systems. In *Personal, Indoor and Mobile Radio Communications, 2004. PIMRC 2004. 15th IEEE International Symposium on*, volume 4, pages 2627–2631, May 2004.

[16] J. Lorincz, A. Capone, and D. Begusic. Optimized network management for energy savings of wireless access networks. *Computer Networks*, page to appear, 2010.

[17] J. Lorincz, A. Capone, and M. Bogarelli. Energy savings in wireless access networks through optimized network management. In *Wireless Pervasive Computing (ISWPC), 2010 5th IEEE International Symposium on*, pages 449–454, May 2010.

[18] M. A. Marsan, L. Chiaraviglio, D. Ciullo, and M. Meo. Optimal energy savings in cellular access networks. In *Proc. of GreenComm'09*, June 2009.

[19] M. A. Marsan, L. Chiariviglio, D. Ciullo, and M. Meo. A simple analytical model for the energy-efficient activation of access points in dense WLANs. In *e-Energy 2010 - First International Conference on Energy-Efficient Computing and Networking*, April 2010.

[20] R. Mathar and T. Niessen. Optimum positioning of base stations for cellular radio networks. *Wireless Networks*, 6(4):421–428, 2000.

[21] H. Mellah and B. Sansò. Review of facts, data and proposals for a greener Internet. In *Proceedings of Broadnets09*, September 2009.

[22] F. Richter, A.J. Fehske, and G.P. Fettweis. Energy efficiency aspects of base station deployment strategies for cellular networks. In *VTC '09*, 2009.

[23] S.Y. Seidel and T.S. Rappaport. 914 mhz path loss prediction models for indoor wireless communications in multifloored buildings. *Antennas and Propagation, IEEE Transactions on*, 40(2):207–217, February 1992.

[24] T. D. Todd, A. A. Sayegh, M. N. Smadi, and D. Zhao. The need for access point power saving in solar powered wlan mesh networks. *IEEE Network Magazine*, 22(3), May/June 2008.

[25] K. Tutschku. Demand-based radio network planning of cellular mobile communication systems. In *IEEE INFOCOM*, volume 3, pages 1054–1061, 1998.