QoS-Aware CAPEX Minimization in Urban Off-Grid Radio Access Networks

Gianluca Rizzo
HES SO Valais, Switzerland
gianluca.rizzo@hevs.ch

Marco Ajmone Marsan
Politecnico di Torino, Italy and Institute IMDEA Networks, Spain
ajmone@polito.it

***Abstract*—Network densification is currently seen as one of the key techniques enabling Radio Access Networks (RANs) to meet the performance and functional requirements of the 5G paradigm in urban areas. Avoiding the connection of small cells to the power grid facilitates their deployment and reduces both capital and operational expenditures (CAPEX and OPEX). In this paper, we propose an approach to enable net-Zero Energy Networking (ZEN) in urban scenarios, based on dynamically managing the operating point of Base Stations (BSs), so as to drastically decrease their overall energy requirements. More specifically, we formalize the problem of optimizing the CAPEX of a ZEN, while guaranteeing quality of service (QoS) and a given level of service availability. Optimization is over power system parameters (solar panel area, battery capacity) as well as over BS power levels and user association over time. We propose a practical algorithm for the derivation of QoS-aware spatio-temporal strategies in terms of user association and BS power allocation, which, for a given expected pattern of renewable power generation, minimize the probability of service unavailability due to power shortage. Through extensive simulations using measured data, and realistic BS deployments, we show that our algorithm leads to substantial reduction in CAPEX, and to feasible power system requirements.**

I. Introduction

The reduction of the carbon footprint of Radio Access Networks (RANs) has recently received a lot of attention from the research community. Indeed, for Mobile Network Operators, a large share of operational expenditures (OPEX) is represented by power supply costs. On the one side, research in this area has produced system- as well as device-level techniques to reduce the amount of energy required to operate a RAN [1]. In particular, sleep-mode algorithms, by tuning the operating point of each base station (BS) in the network, have shown a potential for greatly reducing energy consumption, by adapting it to the amount of traffic served at each time instant. However, such approaches do not consider constraints on available energy.

More recently, operators have considered the possibility of equipping BSs with dedicated renewable energy sources (RES). Besides reducing operational expenditures, RES are important for network deployments in those countries where power supply from the grid is either not available at all, or only intermittently available. A second important example is given by extremely dense (up to hundreds of units per km^2) small cell deployments in future urban 5G RANs, covering the most crowded portions of megacities. In addition to high OPEX, such high BS densities lead to high deployment costs, mainly due to BSs power wiring (assuming wireless backhaul).

Powering such small cells exclusively through RES (the so-called net-Zero Energy Networks, or ZEN) poses several challenges, mainly related to the inherent volatility of RES production patterns [2], [3]. Such volatility could induce a decrease in service availability, and is generally coped with either through a conservative dimensioning of the RES power supply [4], [5], and/or by connecting BSs to the grid [6], [7], [8], [9]. However, in contexts where the connection to the power grid is too expensive, and where available space for photovoltaic (PV) panels and batteries is tightly constrained, such solutions are not feasible.

In this paper we tackle the issue of cost-effective and feasible dimensioning of ZEN, by using system-level approaches similar to those proposed for grid-powered RANs. Our key idea is to mitigate the effects of spatio-temporal fluctuations in RES power production on power supply dimensioning (and hence on network CAPEX), and on service availability, through BS coordination, and load transfer between neighboring BSs, by acting on user-to-BS associations, and on BS transmit powers. This enables feasible and cost-effective solutions for those settings in which connectivity to the grid is not possible.

Our contributions are as follows. First, we formalize the problem of optimizing the CAPEX of a ZEN, over PV panel area and battery capacity, as well as over BS power levels and user association during a reference time interval, while guaranteeing a minimum throughput to each user, as well as a target value for blocking probability and for probability of service unavailability due to power shortages. Second, we propose a practical algorithm for the derivation of a CAPEX-optimal configuration of RES power supply for each BS in a ZEN, and of a set of optimal strategies for tuning the operating point of the network (in terms of number of active BSs, BS transmit power, and user association, at any point in time). Such strategies guarantee that the target QoS levels are met, while keeping the probability of service outage due to power shortage below a predefined threshold.

Through extensive simulations using measured data, and realistic BS deployments, we assess the performance of our algorithm, show that it leads to substantial reduction (up to 70% in a realistic scenario from an Italian operator) in CAPEX and to feasible PV panel and battery installation requirements.

This paper is organized as follows. In Section II we present the system model. In Section III we formulate our optimization problem, and in Section IV we present a heuristic for its solution. In Section V we present numerical results, and Section VI we discuss some related works. Section VII concludes the paper.

II. System Model

We consider a set $\mathcal{N}$ of N base stations (BSs) covering a given service area. We assume their location is given. All BSs are off-grid, and equipped with batteries and a renewable power source. We consider in particular solar powered BSs, as PV panels are usually better suited to urban settings, though our approach can be easily extended to BS powered by any other source. Whenever the power produced by solar panels is not sufficient to operate a BS, the BS draws power from the battery. All surplus power produced is stored in the battery, as long as there is available capacity, otherwise it is discharged. We assume BSs to be partitioned into a set $\mathcal{L}$ of L groups, with each BS group $l \in \mathcal{L}$ being powered by the same PV panels, of area A_l, and batteries, of total capacity B_l. This accounts for settings where BSs are co-located, or within a short distance of each other.

We assume the total CAPEX of such network to be dominated by the cost of batteries, of solar panels and of network equipment.In particular, we are interested in minimizing those components of the CAPEX of the network which depend on renewable power supply. We assume hence that the CAPEX of our network, for a reference lifetime corresponding to the average lifetime of a BS, can be expressed as

$$\sum_{l \in \mathcal{L}} \left(U^{sol} A_l + U^{bat} B_l + U_l^{bs} \right)$$

where U_l^{bs} is the sum of the costs of all BS for the l-th BS group, U^{sol} is the cost of solar panels per m^2, and U^{bat} is the cost of battery per unit capacity. Note that the battery lifetime is typically relatively short (around 500 cycles for lead-zinc batteries [5]). Hence U^{bat} includes the cost of battery replacement for the reference BS lifetime.

We consider the downlink of the access network, as we assume uplink has a minor effect on energy consumption of BSs. We consider the case of QoS-sensitive traffic, such as voice or video, requiring a minimum throughput of R_0 bits/sec (though our approach can be easily extended, e.g. to several traffic classes, requiring different minimum throughput guarantees). Note that QoS guarantees in terms of throughput also imply guarantees on delay, provided that the overall resource utilization is kept below a predefined level. User requests are assumed to arrive randomly and independently in time and space, as a Poisson process, and to remain in the system for a holding time with mean μ^{-1}. The arrival process of user requests in a wireless access network and the solar radiation typically follow spatio-temporal patterns which exhibit periodicity on several temporal scales (days, weeks, years)[5], making them predictable to a large extent. Hence, instead of considering the network operation over its whole lifetime, we focus on a time interval, the *operational window*, of duration corresponding to an integer multiple of such periods (e.g. one or more days, or a week), and generally much shorter than the network lifetime. The intensity of the request arrival process and the profile of solar radiation in the operational window are assumed to be conservative estimates over the whole lifetime, based on past data and taking into account projected traffic growth.

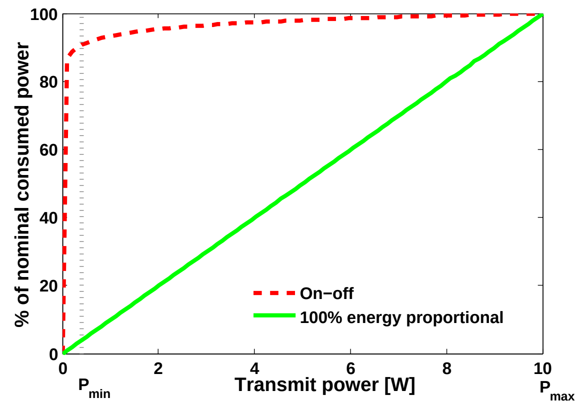

Figure 1: Examples of BS energy model with $P_{max} = 10W$.

A. Energy model

We assume that the total energy consumed by our network can be modulated both by turning off BSs (*sleep modes*) and by tuning the operating point of each BS, by varying its transmit power between P_{min} (typically larger than zero, as we assume that idle BSs are turned off) and P_{max}. We consider the operational window to be partitioned into a set $\mathcal{M}$ of M time slots, generally of different duration, within each of which the network configuration (i.e. the set of active base stations and the transmit power of each base station) does not vary. Duration and number of time slots are typically determined by the overhead introduced by the configuration changes, in terms of time required to switch on/off a base station, to reassign users to BSs, among others. Let $P_{n,m}$ be the transmit power of BS n in the m-th time slot. Coherently with results from measurements (see [10]), we assume the following model for the energy consumed by the n-th BS in the m-th slot, of duration T_m:

$$E_{n,m}(P_{n,m}) = \left(\theta_n^0 + \theta_n^1 P_{n,m} + \theta_n^2 log(\alpha_n P_{n,m} + \beta_n) \right) T_m \quad (1)$$

Parameters θ_n^0, θ_n^1, and θ_n^2 enable modeling of different types of macro and micro BSs. By varying the ratio $\frac{\theta_n^1 + \theta_n^2}{\theta_n^0 + \theta_n^1 + \theta_n^2}$ we can vary the amount of *energy proportionality* of a BS, i.e. that fraction of total consumed power which depends, through the transmit power, on the amount of traffic served. In Fig. 1 we have plotted the BS energy curve for the on-off case, as well as for a 100% energy proportional case. The steep increase in power consumption for low values of transmit power models the jump in power consumption between sleep mode (or off state) and active transmit state. Note that the transmit power at which the slope of the energy model decreases sharply can be tuned by acting on

parameters α_n and β_n, in order to match the minimum transmit power P_{min}.
Finally, with each BS n and time slot m we associate an estimate $S_{n,m}$ of the PV power produced per m^2, averaged over the slot duration, at the location of that BS.

B. User association and BS service model

We use a class-based user association policy, characterized in each time slot m by the association vector $\mathbf{f}_m = \{f^n_{k,m}\}_{n\in\mathcal{N},k\in\mathcal{K}}$. $f^n_{k,m}$ is the fraction of user requests belonging to class k that are associated with and served by BS n during the m-th time slot. Such user association policy can be implemented by partitioning users within a class according to some performance metric, or in a randomized fashion, according to the distribution induced by the association fractions.

We assume BSs monitor the user population in the network over a training period. Each user measures the channel gain (averaging out fast fading) to each BS in the system, and reports the vector of gains to their serving BS. The path gain vectors are then aggregated into a set $\mathcal{K}$ of K classes (using a clustering algorithm such as k-means [11], for instance) so that all members of a class share similar path gains and capacities to the different BSs. For each class k, we define a representative gain vector $\mathbf{g}_k = \{g^n_k\}_{n\in\mathcal{N}}$ where g^n_k is the estimate of the path gain between a user in class k and BS n. Future users can be classified by BSs based on some notion of distance between their path gain vector and the representative path gains of the classes.

For each class k, we denote by $\lambda_{k,m}$ the mean request arrival rate into that class during the m-th slot. We assume that each BS is assigned a frequency band. The maximum rate at which a BS can transmit to a user is modeled as a function of the received signal to interference plus noise ratio (SINR). The capacity from BS n to a user in class k, $C^n_k(\mathbf{P}_m)$, where $\mathbf{P}_m = \{P_{n,m}\}_{n\in\mathcal{N}}$ is given by Shannon's formula approximated for the high SINR regime:

$$C^n_k(\mathbf{P}_m) = W \log_2\left(\gamma \frac{P_{n,m} g^n_k}{e_0 + \sum_{j\in\mathcal{I}_n} P_{j,m} g^j_k}\right) \qquad (2)$$

Here, $\gamma \leq 1$ is a scaling factor to model the gap between current modulation and coding schemes and the Shannon upper bound. $\mathcal{I}_n \subseteq \mathcal{N}\setminus n$ denotes the set of co-channel, interfering BSs. We assume additive white Gaussian noise with power spectral density e_0. W is the channel bandwidth. We only consider large-scale propagation effects, as we model the long-term data rates received by users, and shorter time-scale effects such as small-scale fading are averaged out. As the service discipline at the BS ensures that all users receive identical throughput, R_0, the design QoS parameter is blocking probability. Assuming that no user receives more resources than the guaranteed throughput R_0, is a conservative assumption from the energy viewpoint, given the structure of the energy model - except for the fully energy proportional case.

Table I: Notation

$\mathcal{N}$	Set of all the N base stations in the considered area
$\mathcal{L}$	Set of all the L base station groups
$\mathcal{K}$	Set of all the K classes of users
$\mathcal{M}$	Set of all the M time slots in the operational window

The estimate for the fraction of time that BS n would have to devote to a user from class k is given by $R_0/C^n_k(\mathbf{P}_m)$. The utilization of BS n at time t, $\rho_n(t)$, is the fraction of time that the BS must transmit in order to serve all users associated to it. A new user request arriving at time t, and assigned to BS n by the user association policy, can be served only if the fraction of time which the BS has to devote to the new user is less than $1-\rho_n(t)$, i.e., if its throughput requirements can be met. Otherwise, we assume the request to be blocked.

III. Problem formulation

As we assume BS number and location to be given, the optimization of the CAPEX of the network consists in minimizing the total PV panel area and battery capacity while serving users within the target values of blocking probability. Our approach to such a minimization consists in jointly identifying a QoS- and energy-aware operational strategy (in terms of user association and transmit power) valid for the whole lifetime of the network, and a configuration of the power supply system which is capable of delivering the energy required by the strategy, while minimizing the network CAPEX. Such minimization is performed under the constraint that the probability of service unavailability in the network due to power shortage lies below a target value. As we will see, this condition produces strategies in which BSs support each other, by shifting load in response to a shortage of power.

The periodicity of temporal variations of traffic and of solar radiation makes it possible to simplify such an optimization problem. Indeed, such periodicity allows focusing the optimization over the operational strategy on a time interval (operational window) which is a multiple of the period of the relevant patterns, and which is shorter than the expected network lifetime.

The CAPEX optimization problem therefore translates into finding, for given estimated patterns of request arrivals $\boldsymbol{\lambda} = \{\lambda_{k,m}\}_{k\in\mathcal{K},m\in\mathcal{M}}$ and of solar power production $\mathbf{S} = \{S_{n,m}\}_{n\in\mathcal{N},m\in\mathcal{M}}$ in the operational window, a configuration of power supply system (in terms of panel areas $\mathbf{A} = \{A_l\}_{l\in\mathcal{L}}$ and battery capacities $\mathbf{B} = \{B_l\}_{l\in\mathcal{L}}$) which minimizes CAPEX, and a network operational strategy $(\mathbf{P}, \mathbf{f})$ (i.e. a set of transmit powers $\mathbf{P} = \{\mathbf{P}_m\}_{m\in\mathcal{M}}$ and of user association policies $\mathbf{f} = \{\mathbf{f}_m\}_{m\in\mathcal{M}}$) which can be sustained by the power supply system while achieving the target value of blocking probability. Such strategy will then be valid for any time interval within the network lifetime, of the same duration as that of the operational window, and such that $\boldsymbol{\lambda}' \leq \boldsymbol{\lambda}$ and $\mathbf{S}' \geq \mathbf{S}$.

Our optimization variables are hence $\mathbf{A}$, $\mathbf{B}$, $\mathbf{P}$ and $\mathbf{f}$. A last set of optimization variables is given by the battery load at the beginning of the observation window, $\mathbf{b}_0 = \{\mathbf{b}_{l,0}\}_{l\in\mathcal{L}}$. Indeed, for the operational strategy resulting from our optimization to be applicable periodically (with a period equal to the operational window), the strategy must be such that the load of a battery at the end of the operational window must not be inferior to its load at the beginning of that time interval. Hence, minimizing over $\mathbf{b}_0$ lowers the energy requirements of the optimal strategy.

The estimate of blocking probability due to fluctuations in user arrivals can be computed by using a multidimensional version of the Erlang B formula ([12], [13]). We consider each BS in turn, and discretize the time requirements of each class as well as the total capacity of the BS. We choose the total number of (discrete) channels available to each BS n, Π_n, as a suitably large constant. The number of channels required for BS n to serve class k in the m-th slot is $\tau_k^{n,m} = \left\lceil \frac{R_0}{C_k^n(\mathbf{P}_m)} \right\rceil$. The offered traffic from class k to BS n is $O^n_{k,m} = f^n_{k,m}\nu_{k,m}$, where $\nu_{k,m} = \lambda_{k,m}\mu^{-1}$ is the *class load*, i.e. the mean number of requests from class k being served in the network in the m-th slot. The *relative probability* $q(j,m,n)$ that j of the n-th BS channels are occupied is defined recursively as

$$q(j,m,n) = \sum_{k=1}^{K} O^n_{k,m}\tau_k^{n,m}\frac{q(j-\tau_k^{n,m},m,n)}{j}$$

with $q(0,m,n) = 1$ [13]. By normalizing the $q(j,m,n)$ for $j = 1,\ldots,\Pi_n$, we finally obtain the probability distribution function of the total number of busy channels at the n-th BS. This allows computing an estimate the blocking probability of each class at the n-th BS in slot m. Let $\boldsymbol{\lambda}_\mathbf{m} = \{\lambda_{k,m}\}_{k\in\mathcal{K}}$. An estimate of the blocking probability in the network during the m-th slot, $BP(\mathbf{P}_m, \mathbf{f}_m, \boldsymbol{\lambda}_m)$, is finally derived by computing, from $\mathbf{f}_m$ and $\boldsymbol{\lambda}_m$, estimates of the fraction of a BS traffic that originates from each class, and of the fraction of the total traffic served by each BS.

As for solar power supply, for each time slot m and BS group l, we assume to know the standard deviation $\sigma_{l,m}$ of the estimation error of the solar power produced per m^2 during slot m at the location of the l-th BS group. For ease of computation, we assume such estimation error to be Gaussian with zero mean. Additionally, we assume the error to be independent for each BS. This is a reasonable assumption if we assume that estimation of power production takes into account all macroscopic natural mechanisms, so that the error can be modeled as a noise due to local shadowing effects or local variations in cloud thickness, for instance. Let $E_{l,m}(\mathbf{P}_m)$ be the energy consumed by the l-th group during slot m. I.e. $E_{l,m}(\mathbf{P}_m) = \sum_{n\in l} E_{n,m}(P_{n,m})$, with $E_{n,m}(P_{n,m})$ given by (1), and where $n \in l$ indicates all BSs which are part of the l-th group. The expected battery load at the end of the m-th slot at the l-th group can be expressed recursively as $b_{l,m}(\mathbf{P}, A_l, B_l) = \min(b_{l,m-1}(\mathbf{P}, A_l, B_l) + S_{l,m}A_l - E_{l,m}(\mathbf{P}_m), B_l)$. The probability of not running out of power in the whole network during the observation window can be estimated as function of the product of the CDFs of the battery load at the end of the m-th time slot, over all BS groups and time slots. If δ is the maximum acceptable value of such probability, we impose that

$$\prod_{l\in\mathcal{L},m\in\mathcal{M}} \frac{1}{2}erfc\left(\frac{-b_{l,m}(\mathbf{P}, A_l, B_l)}{\sigma_{l,m}A_l\sqrt{2}}\right) \geq 1-\delta \qquad (3)$$

As blocking due to energy shortage is likely to take place when and where peaks of traffic occur, it might have a heavy impact on perceived quality of service. Hence we assume δ to be much smaller than the target value of blocking probability η_0. In this way, the overall blocking in the network is dominated by the stochastic fluctuations in request arrivals, and it can be reliably estimated using the procedure described. Our CAPEX minimization problem can be formulated as follows:

Problem 3.1:

$$\min_{\mathbf{A},\mathbf{B},\mathbf{P},\mathbf{f},\mathbf{b_0}} \sum_{l=1}^{L}\left(U^{sol}A_l + U^{bat}B_l + U_l^{bs}\right) \qquad (4)$$

Subject to:

$$\begin{aligned}
&Constraint\ (3);\\
&\forall l\in\mathcal{L}, \quad 0 \leq A_l \leq A_l^{max}, \quad 0\leq B_l \leq B_l^{max} && (5)\\
&\forall m\in\mathcal{M}, \quad BP(\mathbf{P}_m, \mathbf{f}_m, \boldsymbol{\lambda}_m) \leq \eta_0 && (6)\\
&\forall m\in\mathcal{M},\ k\in\mathcal{K}, \quad \sum_{n=1}^{N} f^n_{k,m} = 1 && (7)\\
&\forall n\in\mathcal{N},\ k\in\mathcal{K}, m\in\mathcal{M},\\
&\qquad f^n_{k,m} \geq 0 && (8)\\
&\qquad (C_k^n(\mathbf{P_m}) - R_0)f^n_{k,m} \geq 0 && (9)\\
&\qquad f^n_{k,m}P_{min} \leq f^n_{k,m}P_{n,m} \leq f^n_{k,m}P_{max} && (10)\\
&\forall l\in\mathcal{L},\ m\in\mathcal{M}, \quad b_{l,m}(\mathbf{P}, A_l, B_l) \geq 0 && (11)\\
&\forall l\in\mathcal{L}, \quad b_{l,M}(\mathbf{P}, A_l, B_l) \geq b_{l,0} && (12)
\end{aligned}$$

For each BS group, the upper bounds A_l^{max} and B_l^{max} in constraint (5) are determined by constraints related to maximum acceptable form factor (maximum available surface, or volume, maximum weight) at the location of the installation. Constraint (6) forces the estimated blocking probability in each time slot to be not larger than a target value η_0. Condition (7) imposes that the sum of all fractions relative to a same class to be equal to one (that is, all users from that class are assigned to a BS), while condition (8) descends directly from the definition of class fractions. (9) is a coverage constraint, requesting that each BS can serve at least a single user from any class assigned to it. (10) requires the transmit power of all active BSs (i.e., all BSs serving at least one class) to be between P_{min} and P_{max}. Thus, any inactive BS can have zero transmit power and hence enter sleep mode.

(11) requires expected battery load at the end of each time slot in each BS group to be non negative. Finally, as discussed, condition (12), by imposing the expected battery load at the end of the operational window to be not inferior than the load at the beginning of the window, makes it possible to replicate periodically the strategy for the whole

network lifetime.

IV. A Practical Algorithm

Problem 3.1 has non-convex, non-separable constraints and hence, to the best of our knowledge, it cannot be solved efficiently. In the present section we describe our heuristic to solve Problem 3.1, consisting in breaking the original problem into subproblems which can be solved efficiently.

Our heuristic is divided into two stages. The first stage derives a set of spatio-temporal strategies $(\mathbf{P}, \mathbf{f})$ which minimizes the total energy consumed by the network during the operational window. The second stage, based on such strategies, determines that configuration of the renewable power supply system which minimizes the total network CAPEX, over solar panels area and battery capacity.

A. Stage one: Derivation of optimal operation strategies

The goal of the first stage of our algorithm is to find the most energy efficient network operation strategy $(\mathbf{P}, \mathbf{f})$ allowed by constraints on installable solar panel area and battery capacity, and achieving the target value of blocking probability η_0. Hence, for the dimensioning parameters of the renewable power supply, we assume for all l, $A_l = A_l^{max}$, $B_l = B_l^{max}$, and $b_{l,0} = B_l^{max}$.

The problem of minimizing the total energy consumed in the network during the operational window over transmit powers $\mathbf{P}$ and user association vectors $\mathbf{f}$ is nonconvex and nonlinear. To solve this problem, we propose an iterative procedure in which two sub-problems are solved in tandem at each iteration. The first sub-problem, given a user association policy, determines the optimal BS transmit powers. The second one, given such transmit powers, finds a complementary user association policy that enables the reduction of the overall energy consumption over the operational window.

In order to obtain a problem formulation which we can solve efficiently, instead of directly constraining blocking probability, we control it indirectly, by imposing an upper bound to mean BS utilization. Indeed, by controlling BS utilization we tune the amount of spare resources available at each BS for absorbing the effects of stochastic fluctuations in request arrivals, and therefore the probability that a new request gets blocked. Hence, instead of constraint (6) we consider the following one:

$$\forall n \in \mathcal{N},\ m \in \mathcal{M}, \quad \bar{\rho}_{n,m}(\mathbf{P}_m, \mathbf{f}_m) \leq 1 - \epsilon_m \tag{13}$$

where $\bar{\rho}_{n,m}$ is the mean utilization of the n-th BS in the m-th slot, given by:

$$\bar{\rho}_{n,m}(\mathbf{P}_m, \mathbf{f}_m) = \sum_{k=1}^{K} \frac{R_0}{C_k^n(\mathbf{P}_m)} \nu_{k,m} f_{k,m}^n$$

Here, $\nu_{k,m} f_{k,m}^n$ is the mean number of requests in the system belonging to class k served by BS n under the association policy $\mathbf{f}_m$ during the m-th slot. $\frac{R_0}{C_{k,m}^n(\mathbf{P}_m)}$ is the estimated fraction of time required for BS n to serve a request from class k during that slot. By controlling BS utilization (i.e. by tuning ϵ_m for each slot $m = 1, \ldots, M$) we control blocking probability. Since blocking probability is a decreasing function of the utilization gap ϵ_m, our iterative heuristic finds the value of ϵ_m (lying between 0 and 1) that induces the target blocking probability, by performing a binary search over the valid range of ϵ. Note that such approach could also be applied to control indirectly, to some extent, delay and jitter.

Let us now describe in detail our iterative heuristic. At each iteration, Sub-problem 1 and 2 are solved in tandem. Let $(\mathbf{P}(i), \mathbf{f}(i))$ represent the optimized strategy, and for each slot $m \in \mathcal{M}$ let ϵ_m be the utilization gap. We focus in the sequel on the optimization carried out in the $(i+1)^{\text{th}}$ iteration.

1) Optimizing over BS transmit powers: The optimized total energy consumed at iteration $i+1$, is given by the value of the objective function after solving the sub-problem formulated below, and is denoted by $\Phi(i+1)$.

Problem 4.1 (Sub-problem 1):

$$\Phi(i+1) = \min_{\mathbf{P}(i+1)} \sum_{l \in \mathcal{L}, m \in \mathcal{M}} E_{l,m}(\mathbf{P}(i+1)) \tag{14}$$

Subject to:

$$\sum_{l \in \mathcal{L}, m \in \mathcal{M}} log\left(\frac{1}{2} erfc\left(\frac{-b_{l,m}(\mathbf{P}(i+1), A_l^{max}, B_l^{max})}{\sigma_{l,m} A_l^{max} \sqrt{2}}\right)\right) \geq$$
$$\geq \log(1-\delta) \tag{15}$$

$$\forall n \in \mathcal{N},\ m \in \mathcal{M},\ \bar{\rho}_{n,m}(\mathbf{P}_m(i+1), \mathbf{f}_m(i)) \leq 1 - \epsilon_m \tag{16}$$

$$\forall l \in \mathcal{L},\ m \in \mathcal{M}, \quad b_{l,m}(\mathbf{P}(i+1), A_l^{max}, B_l^{max}) \geq 0 \tag{17}$$

$\forall n \in \mathcal{N},\ k \in \mathcal{K},\ m \in \mathcal{M},$

$$R_0 + R_\Delta - C_k^n(\mathbf{P}_m(i+1)) \leq \frac{R_\Delta f_\Delta}{f_{k,m}^n(i)} \tag{18}$$

$$P_{min} + P_\Delta - P_{n,m}(i+1) \leq \frac{P_\Delta f_\Delta}{f_{k,m}^n(i)} \tag{19}$$

$$\forall n \in \mathcal{N},\ m \in \mathcal{M}, \quad 0 \leq P_{n,m}(i+1) \leq P_{max} \tag{20}$$

Note that constraints (9) and (10) in Problem 3.1 are active only if the corresponding fraction is non-zero. In order to obtain estimates of the sensitivity of the power consumption to the user association policy (which we use in sub-problem 2), we modify these constraints as shown in Problem 4.1, where $R_\Delta, f_\Delta, P_\Delta$ are small constants. The iterative algorithm ensures that none of the fractions $f_{k,m}^n(i)$ are less than f_Δ at the input to the above sub-problem. The modified constraints are equivalent to the original ones when $f_{k,m}^n(i) = f_\Delta$, and get more stringent as $f_{k,m}^n(i)$ grows. When $f_{k,m}^n(i) = 1$, the requirements on the class capacity and power exceed the original ones by $R_\Delta(1 - f_\Delta)$ and $P_\Delta(1 - f_\Delta)$ respectively.

While the above problem is a non-convex optimization in $\mathbf{P}(i+1)$, we use a transformation of variables similar to [14], and use the logarithmically transformed power vector $\hat{\mathbf{P}} = \log(\mathbf{P}(i+1))$ as the decision variables. Moreover, we consider the logarithm of constraint (3). Under this transformation, using the same procedure as in [14] it is easy to see that the feasible region, as well as the objective function is a convex function of $\hat{\mathbf{P}}$. As a result, Sub-problem 1 is convex in $\hat{\mathbf{P}}$, and can be solved efficiently. We denote the Lagrange multipliers (assumed to be all positive) at the optimum associated with constraints (16) as $x_\rho^{n,m}$, with the coverage constraints (18) as x_{Cov}^{nkm} and with the minimum power constraints (19) as x_{Pow}^{nkm}.

2) Optimizing over user association policy: In Sub-problem 2, our goal is to optimize over user association policy in a way that enables the energy consumption of the network to be further reduced in the following iteration. The objective function is chosen as:

$$X(\mathbf{f}(i+1)) = \sum_{n\in\mathcal{N},k\in\mathcal{K},m\in\mathcal{M}} f_{k,m}^n(i+1)\cdot \\ \cdot\left(\frac{-x_\rho^{n,m}R_0\nu_{k,m}}{C_k^n(\mathbf{P}_m(i+1))}+\frac{x_{\text{Cov}}^{nkm}R_\Delta f_\Delta}{(f_{k,m}^n(i))^2}+\frac{x_{\text{Pow}}^{nkm}P_\Delta f_\Delta}{(f_{k,m}^n(i))^2}\right) \tag{21}$$

Such function is a weighted sum of the user association fractions. The weights are a linear combination of the relaxation factors in constraints (16), (18) and (19), each multiplied by the sensitivity of the total consumed energy for that constraints. As a result, each weight is the sensitivity of the total energy consumption to the respective user association fraction. Hence, by minimizing (21) over association fractions, we change the constraints in Sub-problem 1 (which depends also on association fractions) in the next iteration in a way which enables energy consumption to be further reduced, allowing the optimization over BS powers to make the fastest progress.

Problem 4.2 (Sub-problem 2):

$$min_{\mathbf{f}(i+1)}X(\mathbf{f}(i+1))$$

Subject to:

$\forall n\in\mathcal{N}$,$\forall k\in\mathcal{K}$, $\forall m\in\mathcal{M}$,

$$(C_k^n(\mathbf{P}_m(i+1))-R_0)f_{k,m}^n(i+1)\geq 0 \tag{22}$$

$$(P_{n,m}(i+1)-P_{min})f_{k,m}^n(i+1)\geq 0 \tag{23}$$

$$f_{k,m}^n(i+1)\geq 0 \tag{24}$$

$\forall n\in\mathcal{N}$, $m\in\mathcal{M}$,

$$\bar{\rho}_{n,m}(\mathbf{P}_m(i+1),\mathbf{f}_m(i+1))\leq 1-\epsilon_m \tag{25}$$

$$\forall k\in\mathcal{K},\, m\in\mathcal{M},\ \sum_{n=1}^N f_{k,m}^n(i+1)=1 \tag{26}$$

Note that Sub-problem 2 is a linear problem in the fractions, and can be solved efficiently. It is guaranteed to have a feasible solution when parametrized with the optimal BS transmit powers obtained from Sub-problem 1, since the user association vector used to define Sub-problem 1 remains a feasible solution in Sub-problem 2.

3) The iterative heuristic: The overall iterative procedure for stage one is summarized in Algorithm 1. For each array of values of $\boldsymbol{\epsilon}=(\epsilon_1,\ldots,\epsilon_M)$, we start by setting $\Phi(0)=\infty$ as the initial starting point, and choose for each time slot one or more random (feasible) user association vector. If no feasible starting point is found, we conclude that no satisfactory policy exists for the given array $\boldsymbol{\epsilon}$. Otherwise, the values of the utilization gap in each time slot are updated according to a binary search algorithm. The algorithm stops when either the target blocking probability is achieved in every time slot, or no feasible solution $(\mathbf{P}(i),\mathbf{f}(i-1))$ has been found.

Note that after each iteration, the value of overall energy consumption decreases. Since this is a bounded quantity, the algorithm is guaranteed to converge. Iterations stop when the decrease in energy consumption between two consecutive iterations falls below a preset threshold.

Thanks to the shape of the power consumption model (Section II) and in particular to its change in slope at P_{min}, the iterative procedure tends to associate users to BSs with a high value of transmit power, "pushing" BSs with low traffic to values of transmit power below P_{min}. For 100% energy proportional base stations (an idealization, given current technological possibilities), instead, the algorithm tends to balance load among BSs. In any case, BSs whose transmit power falls below P_{min} do not serve any user request, and they can therefore be turned off. The final optimal consumed power is then computed by setting to zero the contributions from those BSs which are turned off.

Since the minimization of total energy consumed in the operational window is not a convex problem, the stage 1 iterative heuristic we described does not necessarily converge to a global optimum. However, such algorithm can be tried with few random starting points, and the best solution can be chosen to obtain a better approximation of the global optimum.

Algorithm 1 Stage one: BS powers and user association vector

$j=1$;
repeat
  $i=1$;
  repeat
    Solve Sub-problem 1 for $\mathbf{P}(i)$ and $\Phi(i)$ given $\mathbf{f}(i-1)$ and $\boldsymbol{\epsilon}(j)$;
    Solve Sub-problem 2 to find $\mathbf{f}(i)$ given $\mathbf{P}(i)$ and $\boldsymbol{\epsilon}(j)$;
    Set $f_{k,m}^n(i)=0$, if $f_{k,m}^n(i)<f_\Delta$;
    $\forall k,m$, scale fractions, such that $\sum_{n=1}^N f_{k,m}^n(i+1)=1$;
    $i=i+1$;
  until $\frac{\Phi(i-1)-\Phi(i)}{\Phi(i-1)}$ is above its threshold **and** both sub-problems admit a feasible solution
  if a feasible $(\mathbf{P}(i),\mathbf{f}(i-1))$ is found **then**
    Compute estimate of blocking probability $BP(\mathbf{P}(i),\mathbf{f}(i-1),\epsilon(j))$
    Compute $\boldsymbol{\epsilon}(j+1)$ from $\boldsymbol{\epsilon}(j)$
  else
    return No feasible solution has been found;
  end if
  $j=j+1$;
until Blocking probability is larger than η_0 **and** $\frac{\boldsymbol{\epsilon}(j+1)-\boldsymbol{\epsilon}(j)}{\boldsymbol{\epsilon}(j)}$ is above its threshold
return $\mathbf{P}(i),\mathbf{f}(i-1)$;

B. Stage two: CAPEX minimization

When stage one is completed successfully, its output is a set of transmit powers and of user association strategies for the considered operational window $(\mathbf{P},\mathbf{f})$, ensuring that the target blocking probability is met for all its duration. In the second stage of our heuristic, we look for the CAPEX-optimal configuration of the power supply system (solar power and battery) capable of supporting the optimal spatio temporal strategy derived.

Problem 4.3 (Stage two):

$$\min_{\mathbf{A},\mathbf{B},\mathbf{b_0}} \sum_{l=1}^{L} \left(U^{sol} A_l + U^{bat} B_l + U_l^{bs} \right) \tag{27}$$

Subject to:
Constraints (5), (11), (12);

$$\forall l \in \mathcal{L},$$
$$\sum_{m \in \mathcal{M}} log \left(\frac{1}{2} erfc \left(\frac{-b_{l,m}(\mathbf{P}, A_l, B_l)}{\sigma_{l,m} A_l \sqrt{2}} \right) \right) \geq \frac{\log(1-\delta)}{L} \tag{28}$$

Problem 4.3 is again nonlinear and nonconvex. In order to solve it efficiently, we substitute condition (15)) with (28). That is, we impose an upper bound to the the probability of energy shortage which is the same for all BS groups. This generates a problem which is separable into L problems, each of which involves only three variables, and it can therefore be solved efficiently by exhaustive search. Note that if stage one yields a feasible solution, stage two always admits a feasible solution.

The final output of stage two is an allocation of battery capacity and solar panels area for each BS group, as well as a minimum initial battery load $\mathbf{b_0}$, which minimizes CAPEX while keeping the probability of energy shortage as well as blocking probability below their target maximum values.

V. Numerical evaluation

In this section we assess numerically the performance of our heuristic. To this end, we first characterize it in a simple, controlled setting, with regular BS layout and uniform user distribution. Then we apply our algorithm to a more realistic setup, parametrized with data from an Italian operator.

The maximum BS transmit power is assumed to be 10 W. The carrier frequency and bandwidth of each BS are assumed to be 1 GHz, and 5 MHz, respectively, both values being representative of RANs of today. The noise power spectral density is chosen such that the received SNR equals 10 dB at a distance of 1 km from a BS transmitting at maximum power. We assume a 3 dB SINR backoff in the capacity formula (2). The target value of blocking probability is 2%, with a tolerance of 5% (i.e., between 1.9 and 2.1 %), and the maximum acceptable probability of running out of energy is 0.1%. We assume that the throughput requirement of each user is 120 kb/s (corresponding to medium quality video), and that session durations are exponentially distributed with average equal to 5 minutes. We assume all BSs to have a maximum nominal power consumption of 500 W. Unless otherwise stated, the standard deviation of the estimation error has been set conservatively to 5% of the maximum amount of energy consumed in one hour by one BS. The values of the parameters used in our CAPEX model are taken from [15], and they are around 200 USD for a 200 W peak PV panel (corresponding to an area of 1 m^2), and 200 USD for a 12 V, 200 Ah lead-acid battery. Counting a

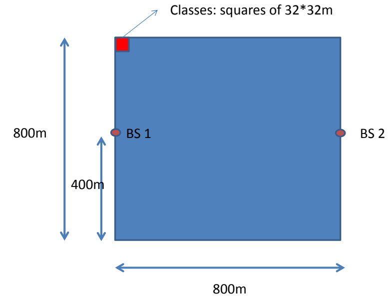

Figure 2: BS and area layout for the baseline setup.

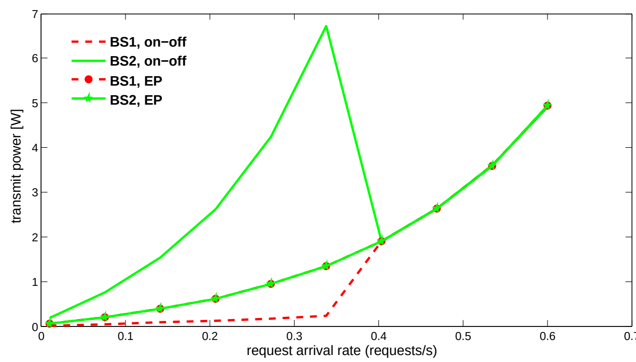

Figure 3: BS transmit power as a function of overall arrival rate for the baseline setup, for the on-off energy model.

battery lifetime of approximately 500 charge cycles, over a time period of 10 years, and conservatively assuming one full cycle per day, the compound price of a single battery with that capacity is 1460 USD.

A. Baseline

The considered scenario for the baseline is depicted in Fig. 2. It consists of two BSs at the opposite ends of a square planar surface, whose side is $800m$ long. We considered a regular grid of 1000 classes inside the area. This scenario can be representative of a crowded area (e.g., a village) in a developing country, with users served by two off-grid BSs. Service request arrivals are assumed to be uniformly distributed within the area.

In a first set of experiments, we consider an observation window consisting of a single time slot. We considered both the 100% EP and the on-off energy models. Fig. 3 shows that in the energy-proportional case, the algorithm shares equally the load between BSs. Conversely, in the on-off case, due to the high cost of keeping a BS on, in low traffic load regime the algorithm puts to very low transmit power (and hence to sleep) one of the two BSs. Indeed, the logarithmic increase in consumed power for low transmit powers leads to a high marginal cost per request in BSs with very low transmit power. This pushes the algorithm to first serve the largest possible amount of users with a single BS, and assign very low load, if any, to the other BS. When traffic load grows to a point that the system cannot satisfy the QoS constraints (in terms of blocking probability) with a single BS, the algorithm allocates users also to the second BS. When this happens, we see that our algorithm

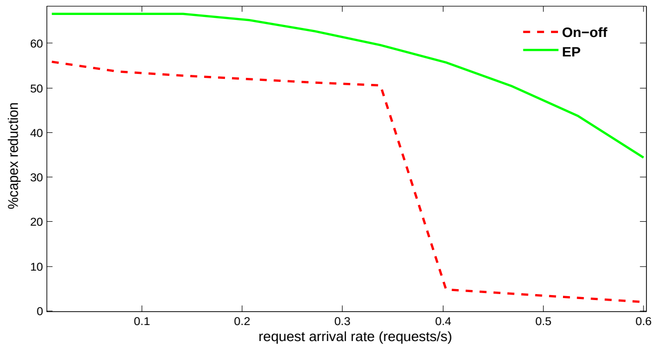

Figure 4: Reduction of network CAPEX as a function of the request arrival rate. Two BSs setup.

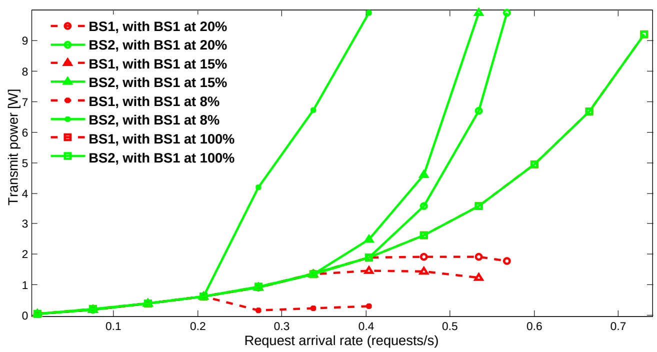

Figure 5: Transmit power of the two BSs, for different values of energy budget for BS 1. BS 2 is endowed with sufficient energy to operate at full transmit power in the considered interval.

balances load (and hence transmit power) between the two BSs. Indeed, with our energy model, the marginal power cost per user request (when the amount of resources required to satisfy it are the same) in the regime where transmit power is larger than P_{min}, changes only marginally between P_{min} and P_{max}. Hence, once a second BS is active, the most efficient allocation (with uniform user distribution) is the one in which every user is served by the closest BS, as it minimizes the average amount of resources allocated to each user.

In order to evaluate the CAPEX savings enabled by our algorithm, we have compared them with the savings enabled by the optimal configuration (in terms of PV panel area and battery capacity) when transmit power at both BSs is P_{max}, i.e. when no energy-aware tuning of the operating point is in place. Fig. 4 shows that even in absence of (or with very low) load proportionality in the energy model, tuning the operating point of the network allows serving the same amount of requests with less energy, thus potentially saving a substantial amount of CAPEX. This is due to the fact that BSs are able to coordinate and redistribute load in a way which generates savings. Note that in the EP case, the algorithm does not turn off any BS. Hence, the maximum savings are determined by the minimum transmit power allowed.

Those savings are potentially even higher when load is not constant over time and space. Indeed, with varying loads, system-level techniques allow replacing worst-case conservative configurations, designed for serving peak loads over a given time interval, with configurations which adapt over time and space. In this case, our algorithm derives spatio-temporal strategies, through which BSs coordinate over time and space in order to minimize CAPEX, and to keep the likelihood of exhausting power below the target value.

In order to better characterize such CAPEX and energy aware coordination among BSs, we have run a set of experiments in which one of the two BSs (due, for instance, to tighter constraints on installable PV panel area) is allocated only a percentage of the energy required to operate at full transmit power. Fig. 5 shows the results for the energy proportional case, though identical considerations hold for the on-off case. As we can see from the plots, a tight energy constraint at one BS inevitably translates into a decrease in the maximum amount of traffic which can be served by the whole network. However, our algorithm, by shifting load to those BSs with the most available energy, increases the maximum amount of traffic which can be served.

A specific feature of the solution stemming from our algorithm, is that it allows overcoming limitations on the amount of energy available at a given BS and time slot also by moving energy across slots. In order to see this, we have considered the two BSs in an operational window composed by two slots of identical duration. All BSs in slot 1, as well as BS 2 in slot 2 have enough energy to operate at maximum transmit power for the whole slot duration. BS 1 in slot 2 has instead only 8% of that amount. For three different values of arrival rates (and hence three different amounts of energy required to serve users in slot 1) we have varied the arrival rate in slot 2. In Fig. 6 we see that for the largest arrival rate in slot 1, both BSs consume all energy in that slot, and hence cannot save energy for the following slot. When we decrease the arrival rate in slot 1, we see that the energy saved by BS1 in slot 1 is used to increase the maximum amount of energy which BS 1 can consume in slot 2. When BS 1 has consumed in slot 2 all the extra energy unused in slot 1, transmit powers of both BSs in slot 1 adjust in order to allow BS 1 to save more energy for slot 2. However, as we have seen also in Fig. 5 this comes at the cost of supporting a lower maximum amount of traffic in slot 2.

B. Pisa

In order to assess in a more realistic setup the potential CAPEX savings enabled by our heuristic, we have considered a LTE macro setting for which BS locations, antenna orientations, and angular beamwidths, as well as traffic information in terms of number of active calls over time handled by each BS, are derived from the data of a large Italian operator. Though a macro cell case, such setting is still useful for a realistic evaluation of the main features of the algorithm.

The considered geographical area corresponds to the center

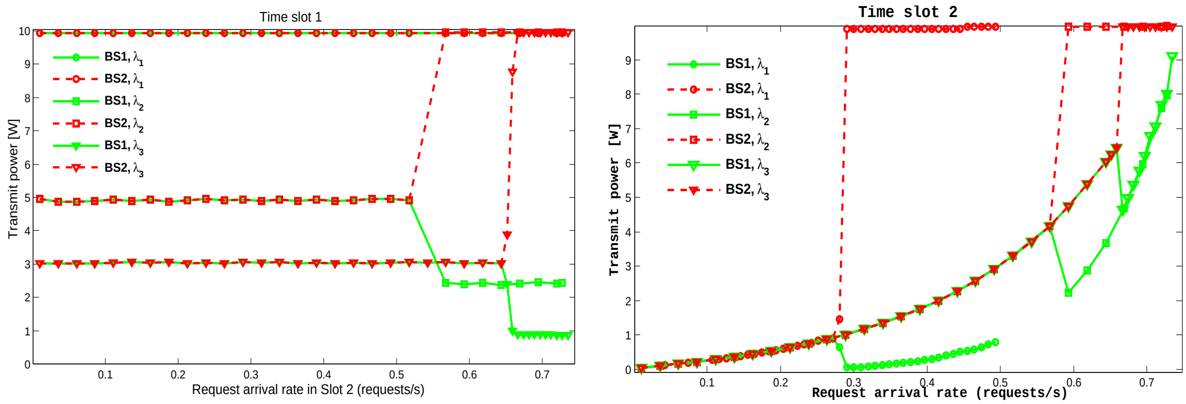

Figure 6: Left: BS Transmit power in slot 1 for three different arrival rates in slot 1 ($\lambda_1 = 0.745$, $\lambda_2 = 0.6$ and $\lambda_3 = 0.5$) in function of arrival rate in slot 2. Right: BS Transmit power in slot 2 in function of request arrival rate. Both BS in slot 1, as well as BS 2 in slot2, are endowed with renewable energy sufficient to run at full transmit power, while BS 1 in slot 1 has only 8% of that amount of energy.

of the city of Pisa, Italy (Fig. 7). The area contains 16 BS sectors which we assume each associated with an independent LTE BS, and distributed over 6 locations. All BSs in a same location are served by the same power supply system, and hence share batteries and solar panels. We adopt the COST 231-Hata model [16], which is widely used to model urban environments, along with lognormal shadowing with a standard deviation of 4 dB, to model propagation conditions. We assume a frequency reuse factor of 3.

We use a spatially inhomogeneous Poisson process to model the spatial load at any given time. In order to determine the spatial intensity of the inhomogeneous Poisson process, we use the call detail records of each BS during a whole day (a week day), averaged over intervals of 30 min. Then we assume all BSs to transmit at the same power, and assign users to the BS with the strongest signal. We further assumed the origin location of calls handled by a BS to be uniformly distributed within their cell.

We assume all BSs to have a maximum nominal power consumption of 500 W, except for the BS with omnidirectional antenna, consuming a maximum of 1500 W. Coherently with models proposed for recent LTE BS HW [1], the energy proportionality ratio (see Section II-A) has been assumed to be 60%.

For the total amount of illumination in a day, we have considered solar data for Pisa from [17] relative to the month with less illumination (December). As for its distribution over the 24 hours, we have assumed a parabolic trend going from 7AM to 5PM, and peaking (with a 100% efficiency) at 12AM. Note that, while reasonably close to reality, such parametrization has as its main objective to allow a crude, first order evaluation of CAPEX savings, while exemplifying the use of our approach. Hence, other effects, such as battery efficiency, have been discarded for the sake of ease of analysis.

We assumed an operational window starting at 12PM and lasting 24h, subdivided into seven time slots. The choice of time slots number and duration has been done in order to obtain an acceptable accuracy of spatio-temporal patterns, while minimizing the number of network reconfigurations. In each time slot, we have set the values of mean illumination and mean request arrival rate equal to, respectively, the average and the maximum (over the 30-min average) over the time slot duration.

The results of our heuristics are summarized in Fig. 8. Results are compared with a CAPEX optimized for a configuration with no tuning of the BS operating point. The reduction in CAPEX of the power supply system of the ZEN is of 69%, slightly larger than the reduction in the total energy consumed during 24h (62%). The larger CAPEX saving is due to BSs sharing resources within each group, which compensates the (generally) larger battery costs due to differences in BS consumed energy between consecutive slots. The differences in savings among BSs are to be attributed to the spatio temporal inhomogeneities in traffic load, which play a major role in determining the outcome of the algorithm, despite its tendency to balance load uniformly across BSs. Indeed, in the considered scenario, the service provided by some of the BSs cannot be completely substituted by the service provided by other BSs. Such aspect, which limits the maximum achievable CAPEX savings with our approach, should hence be taken into account when deciding number, position and antenna orientation of BSs in a clean-slate ZEN.

In order to verify that blocking probability in our network is within the target range of values, we have run a set of event-driven simulations with the powers and user association policy resulting from the optimization. Results have confirmed that our approach estimates accurately the blocking probabilities resulting from our policies, and that the proposed algorithm is able to find efficient network configurations while achieving the target blocking probability.

All the computations were executed under Matlab on a laptop with a 2.80 GHz Intel core 2 duo processor and 4 GB of RAM. We have run stage 1 of our heuristic with three random starting points. The heuristic required

Figure 7: Location, antenna orientation, and angular beamwidth for the considered BSs in downtown Pisa. The red point indicates an omnidirectional antenna.

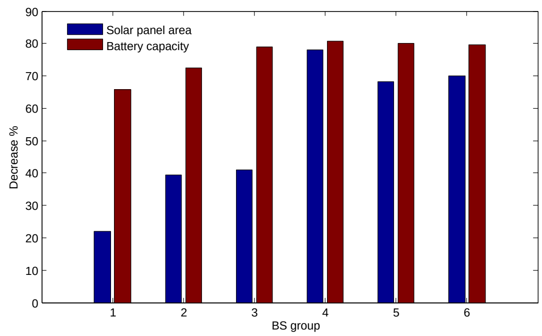

Figure 8: Percentage of decrease in total panel area and battery capacity with respect to the CAPEX-optimal configuration without sleep modes.

on average 4 iterations to converge for a given value of blocking probability. In the most computationally involved setup (Pisa, with 16 BSs and 1000 classes), a complete run of the whole heuristic took 40 minutes of CPU time, while taking only 30 seconds for the two BSs, two slots case.

VI. Related Work

The adoption of RES in RANs has been investigated for some time in both the energy and the networking fields [9], [18], [8]. Only a few papers, however, looked at the allocation of resources to a group of RES-powered BSs, also accounting for user-to-BS association. [9] investigates resource management in RANs where BSs are equipped with energy harvesting devices, but also connected to the power grid. An optimization problem is formulated which minimizes the energy drawn from the power grid by adapting the BSs on-off states, the active resource blocks, and the renewable energy allocation, while meeting a predefined QoS constraint in terms of blocking probability. In this case, user-to-BS associations are accounted for, but not optimized. [8] considers a RAN comprising both macro BS and pico BS, the latter consuming much less power. The authors minimize the on-grid power consumption over user associations, also optimizing QoS in terms of traffic delivery latency.

VII. Conclusions

We investigated the problem of the optimal dimensioning of net-zero energy RANs in urban areas, which use sleep modes for BSs in low traffic conditions. Our optimization aims at reducing the RAN CAPEX for PV panels and batteries under QoS constraints in terms of minimum throughput, blocking probability, and service outage due to lack of power. Results show that very significant reductions in energy consumption can be achieved, which translate in substantial savings in CAPEX and feasible PV panel and battery installation requirements.

References

[1] L. B. et al., "Dynamic resource provisioning for energy efficiency in wireless access networks: A survey and an outlook," *IEEE Communications Surveys Tutorials*, vol. 16, no. 4, pp. 2259–2285, 2014.
[2] H. Al Haj Hassan, L. Nuaymi, and A. Pelov, "Renewable energy in cellular networks: a survey," in *Online GreenCom*, pp. 1–7, IEEE, 2013.
[3] A. M. Aris and B. Shabani, "Sustainable power supply solutions for off-grid base stations," *Energies*, vol. 8, no. 10, pp. 10904–10941, 2015.
[4] M. A. Marsan, G. Bucalo, A. Di Caro, M. Meo, and Y. Zhang, "Towards zero grid electricity networking: Powering bss with renewable energy sources," in *ICC 2013*, pp. 596–601, IEEE, 2013.
[5] M. Meo, Y. Zhang, R. Gerboni, and M. A. Marsan, "Dimensioning the power supply of a lte macro bs connected to a pv panel and the power grid," in *ICC 2015*, pp. 178–184, IEEE, 2015.
[6] D. Valerdi, Q. Zhu, K. Exadaktylos, S. Xia, M. Arranz, R. Liu, and D. Xu, "Intelligent energy managed service for green base stations," in *GLOBECOM Workshops*, IEEE, 2010.
[7] G. Merei, C. Berger, and D. U. Sauer, "Optimization of an off-grid hybrid pv–wind–diesel system with different battery technologies using genetic algorithm," *Solar Energy*, vol. 97, pp. 460–473, 2013.
[8] T. Han and N. Ansari, "Green-energy aware and latency aware user associations in heterogeneous cellular networks," in *GLOBECOM*, pp. 4946–4951, IEEE, 2013.
[9] J. Gong, J. S. Thompson, S. Zhou, and Z. Niu, "Base station sleeping and resource allocation in renewable energy powered cellular networks," *Communications, IEEE Transactions on*, vol. 62, no. 11, pp. 3801–3813, 2014.
[10] G. e. a. Auer, "How much energy is needed to run a wireless network?," *Wireless Communications, IEEE*, vol. 18, pp. 40 –49, Oct. 2011.
[11] M. Anderberg, *Cluster Analysis for Applications*. Academic Press, 1973.
[12] Kleinrock, *Queueing Systems, Vo. I: Theory*. John Wiley and Sons, 1975.
[13] T. Janevski, *Traffic analysis and design of wireless IP networks*. Artech House, 2003.
[14] M. Chiang, "Balancing transport and physical layers in wireless multihop networks: jointly optimal congestion control and power control," *IEEE JSAC*, vol. 23, pp. 104 – 116, Jan. 2005.
[15] D. Feldman, "Photovoltaic pricing trends: historical, recent, and near-term projections," *NREL Technical Report*, 2014.
[16] M. Hata, "Empirical formula for propagation loss in land mobile radio services," *IEEE Transactions on Vehicular Technology*, vol. 29, pp. 317 – 325, Aug 1980.
[17] NREL, "Pvwatts calculator." http://pvwatts.nrel.gov/, 2016.
[18] T. Han and N. Ansari, "On optimizing green energy utilization for cellular networks with hybrid energy supplies," *Wireless Communications, IEEE Transactions on*, vol. 12, no. 8, pp. 3872–3882, 2013.