Energy Cooperation for Sustainable Base Station Deployments: Principles and Algorithms

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***Abstract*—Energy self-sufficiency is of prime importance for future mobile networks. The design of energy efficient and possibly self-sustainable base stations is key to reduce their impact on the environment, and diminish their operating expense. As a solution to this, we advocate base station deployments featuring energy harvesting and storage capabilities. Each base station can acquire energy from the environment, promptly use it to serve the local traffic or keep it in its storage for later use. In addition, a power packet grid (DC power lines and switches) is utilized to enable energy transfer (*energy routing*) across base stations, compensating for imbalance in the harvested energy or in the load. Most of the base stations are offgrid, i.e., they can only use the locally harvested energy and that transferred from other network elements, whereas some of them are ongrid, i.e., they can also purchase energy from the electrical grid. We formulate the optimal energy allocation and routing as a convex optimization problem with the goals of improving the energy self-sustainability of the network, while achieving high energy transfer efficiencies under dynamic load and energy harvesting processes. An optimal assignment based on the Hungarian method is also presented. Our numerical results reveal that the proposed convex policy: (i) substantially improves the energy self-sustainability of the system, (ii) decreases its outage probability to nearly zero, even when a small number of base stations are connected to the electrical grid, and (iii) the amount of energy purchased from the electrical grid per served user is respectively decreased of three and eight times with respect to using the Hungarian policy and a scenario where the energy exchange among base stations is not permitted.**

***Index Terms*—Energy harvesting, energy routing, energy allocation, energy self-sustainability, power packet grids, future mobile networks.**

I. Introduction

Mobile Internet services have become ubiquitous. ITU estimated that 750 millions households are currently online and that there exist almost as many mobile subscribers as people in the world (around 6.8 billions) [1]. The trend is of a further increase in the traffic demand, in the number of offered and connected devices, especially mobile. However, this massive use of Information and Communications Technologies (ICT) is increasing the amount of energy drained by the telecommunication infrastructure and its footprint on the environment. Forecast values for 2030 are that 51% of the global electricity consumption and 23% of the carbon footprint by human activity will be due to ICT [2]. Besides, energy bills are also becoming a major problem for network operators, whose revenues are decreasing due to an ever increasing OPerating EXpense (OPEX): for example, it has been calculated that the energy bill matches the cost of the personnel needed to run and maintain the network, for a western Europe company in 2007 [3]. Hence, energy efficiency and, possibly, self-sufficiency is becoming a priority for any future development in the ICT sector.

In this paper, we advocate future networks where small base stations will be densely deployed to offer coverage and high data rates, and energy harvesting hardware (e.g., solar panels and energy storage units) will be installed to power network elements [4]. Within this scenario, base stations will be capable of acquiring energy from the environment, use it to serve their local traffic and *transfer* it to other base stations to compensate for imbalance in the harvested energy or in the load. Energy transfer is thus a prime feature of these networks and can be accomplished in two ways: (i) through Wireless Power Transfer (WPT) or (ii) using Power Packet Grid (PPG) [5]. For (i), previous studies [6] have shown that its transfer efficiency is too low for WPT to be a viable solution, but (ii) looks promising. In analogy with communications networks, in a PPG a number of power *sources* and power *consumers* exchange (Direct Current, DC) power in the form of "packets", which flow from sources to consumers thanks to power lines and electronic switches. The energy routing process is controlled by a special entity called *energy router* [7]. Following this architecture, a local area packetized-power network consisting of a group of energy subscribers and a core energy router is presented in [8]. In this paper, the authors devise a strategy to match energy suppliers and consumers, seeking to minimize the mismatch between the energy generation and demand.

An energy sharing framework is presented in [9], where the harvested energy is modeled as a packet arrival process, the storage as a packet queue and the energy consumption as a queue of loads, i.e., one or multiple servers. These three components of the PPG are interconnected through power switches. In [10], the packets take the form of current pulses with fixed voltage and duration. Each energy packet is equipped with an encoded header, containing the information about the destination identity (i.e., its address), which is used to route it through the PPG.

Along the same lines, energy sharing among Base Stations (BSs) is investigated in [11] through the analysis of several basic multiuser network structures. A two-dimensional and directional water-filling-based and offline algorithm is put forward to control the harvested energy flows in time and space (among users), with the objective of maximizing the system throughput for all the considered network configurations. In [12], the authors introduce a new entity called *aggregator*, which mediates between the grid operator and a group of BSs to redistribute the energy flows, reusing the existing power grid infrastructure: one BS injects power into the aggregator and, simultaneously, another one draws power from it. This solution does not consider the presence of energy storage devices, and for this reason some of the harvested energy can be lost if none of the base stations needs it at a certain time instant. The proposed algorithm tries to jointly optimize the transmit power allocations and the transferred energy, maximizing the sum-rate throughput for all the users.

In this paper, we consider the aforementioned scenario where all the BSs are equipped with solar harvesting hardware and energy storage units. They are all connected through a PPG. Moreover, some of them are connected to the electrical grid (referred to as *ongrid*), whereas the remaining ones are *offgrid* and, in turn, rely on either the locally harvested energy or on the energy transfer from other BSs. Since the BSs have a local energy storage, they can accumulate energy when the harvested inflow is abundant. Some of the surplus energy can also be transferred to other BSs to ensure the self-sustainability of the cellular system. The energy distribution is performed using the PPG infrastructure, where a centralized energy router is responsible for deciding the power transfer/allocation among BSs over time. For the harvested energy, we use real solar data from [13], whereas the BS load is modeled according to [14]. We formulate the energy routing problem through convex optimization, proposing an optimal power allocation strategy with the main goal of *promoting the self-sufficiency of the BS system*. This is accomplished by draining energy from *energy rich* BSs, while maximizing the transfer efficiency of the energy routing process. An approach based on the *Hungarian method* [15] is also presented and the two algorithms are numerically evaluated and compared with a scenario where BSs have energy harvesting and storage capabilities, but energy routing is not permitted. Numerical results, obtained with real-world harvested energy traces, show that the convex optimization approach keeps the outage probability to nearly zero for a wide range of traffic loads. Also, in the best cases, the amount of energy purchased per served user is reduced of one third with respect to the Hungarian-based allocation method and of almost eight times as compared to the case where the transfer of energy among base stations is not allowed.

The paper is organized as follows. In Section II, we describe the network scenario. The energy allocation problem is described in Section III, where the proposed solutions are also presented. Routing and scheduling policies are addressed in Section IV. The numerical results are presented in section V, and final remarks are given in section VI.

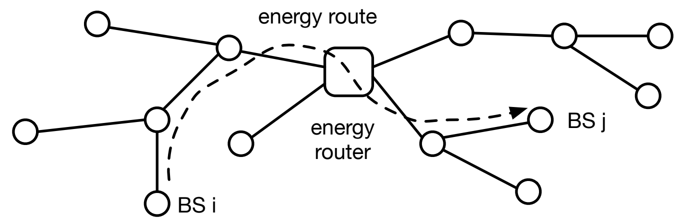

Fig. 1. Power packet grid topology example.

II. System Model

We consider a mobile network comprising N BSs, where each of them has energy harvesting capabilities, i.e., a solar panel, an energy conversion module and an energy storage device. Some of the BSs are ongrid and, in turn, can also obtain energy from the electrical grid. These are termed *ongrid* BSs (set $\mathcal{N}_{\rm on}$). The remaining BSs are *offgrid* (set $\mathcal{N}_{\rm off}$). The proposed optimization process evolves in slotted time $t = 1, 2, \dots$, where the slot duration is *one hour* and corresponds to the time granularity of the control. Note that the slot duration can be changed without requiring any modifications to the following algorithms.

A. Power Packet Grids

A PPG is utilized to distribute energy among the BSs. The grid architecture is similar to that of a multi-hop network, as shown in Fig. 1, where circles are BSs and the square is the energy router, which is in charge of making energy routing and power allocation decisions. According to [8], BSs are connected through Direct Current (DC) power links (electric wires) and the transmission of energy over them is operated in a Time Division Multiplexing (TDM) fashion. Energy transfer occurs by first establishing an *energy route*, which corresponds the sequence of power links between the energy source and the destination. Each power link can only be used for a single energy trading operation at a time. Power distribution losses along the power links follow a linear function of the distance between the source and the destination [8]. They depend on the resistance of the considered transmission medium and are defined by [16]:

$$R = \frac{\rho \ell}{A}\,, \tag{1}$$

where ρ is the resistivity of the wire in $\Omega \mathrm{mm}^2/\mathrm{m}$, ℓ is the length of the power link in meters, and A is the cross-sectional area of the cable in mm^2. Finally, in this paper we consider PPGs with a single energy router in the center of the topology. A number of trees originate from the router and each hop is assumed to have the same length ℓ, i.e., the same power loss.

B. Harvested Energy Profile

Solar energy generation traces have been obtained for the city of Chicago using SolarStat [13]. For the solar modules, the commercially available Panasonic N235B photovoltaic technology is considered. Each solar module features a total of 25 solar cells leading to a panel area of $0.44\,\mathrm{m}^2$, which is deemed practical for installation in a urban environment, e.g., on light-poles. As discussed in [13] and [4], the energy harvesting inflow is generally bell-shaped with a peak around mid-day, whereas the energy harvested during the night is negligible. However, there may be a high variability in the harvested energy among the BSs due to the orientation of their solar panel and to differences in the surrounding environment (trees, buildings, etc.). The amount of energy harvested $H(t)$ by the generic BS $n = 1, \dots, N$ in time slot t is obtained as:

$$H(t) = u_{(0,r)} h(t)\,,\; t = 1, 2, \dots\,, \tag{2}$$

where $u_{(0,r)}$ is sampled from the uniform probability distribution function (pdf) $U(0, r)$, defined in the open interval $(0, r)$. Here, $u_{(0,r)}$ is referred to as shading factor, and is used to model the (possibly differing) harvested energy amounts across BSs. Instead, $h(t)$ returns the (hourly) harvested energy income, which is computed as in [13] and is the same for all BSs. A random experiment is executed for each BS n at the beginning of each time slot t, using Eq. (2). The resulting harvested energy trace is referred to as $H_n(t)$.

C. Traffic Load and Power Consumption

It is commonly accepted and confirmed by empirical measurements that the energy consumption of base stations is time-correlated and daily-periodic [4]. In this paper, we use the typical daily load profile in Europe from [14], which allows tracking the number of mobile users that are to be served by a BS across a day. Given the load $\rho \in [0, 1]$, intended as the percentage of the total bandwidth that the BS allocates to serve the users in its cell, the BS energy consumption is obtained using the linear model in [4]. In addition, as we describe shortly below, starting from a common load pattern, we differentiate the load experienced by each BS introducing some randomness. This creates some imbalance in the load distribution, which is key to assess the effectiveness of the proposed optimization strategies. Specifically, the hourly traffic load $L_n(t)$ of BS $n = 1, \dots, N$ represents the number of users that are served by the BS in time slot t, and is computed as follows. First, for each BS n and time t, the load is generated according to the following equation:

$$L(t) = \mathtt{round}\left(u_{(a,b)} d(t)\right)\,,\; t = 1, 2, \dots\,, \tag{3}$$

where $\mathtt{round}(\cdot)$ returns the integer that is nearest to the argument, $u_{(a,b)}$ is a random value sampled from $U(a, b)$, the uniform pdf in the open interval (a, b), a and b are the minimum and maximum number of users in a BS cell, and $d(t) \in [0, 1]$ represents the daily load profile, which is defined as the percentage of active users in one BS cell in hour t and is taken from [14]. Note that $d(t)$ is common to all the BSs, and $L_n(t)$ is obtained for each BS n performing a random experiment for each time slot t, using Eq. (3). At this point, the load of BS n in slot t is approximated as $\rho_n(t) = L_n(t)/L_{\max}$, where $L_{\max}$ represents the maximum number of users that can be served (serving capacity). The energy consumption (energy outflow) of this BS, referred to as $O_n(t)$, is finally obtained using $\rho_n(t)$ with the BS energy consumption model in [4] (see Eq. (1) in that paper).

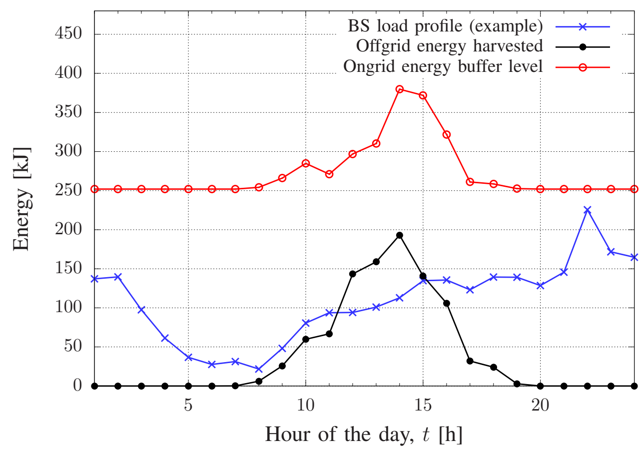

Fig. 2. Example energy traces: energy harvested profile (black line), BS load profile (blue line) and energy buffer level for an ongrid BS ($B_{\mathrm{up}} = 250\,\mathrm{kJ}$).

D. Energy Storage Units

Energy storage units are referred to in what follows as *energy buffers*. The energy buffer level for BS $n = 1, \dots, N$ is denoted by $B_n(t)$ and two thresholds are defined, B_{up} and B_{low} respectively termed the *upper* and *lower* energy threshold, with $0 < B_{\mathrm{low}} < B_{\mathrm{up}} < B_{\max}$, where $B_{\max}$ is the energy buffer capacity. For the results in this paper we used $B_{\max} = 360\,\mathrm{kJ}$, which corresponds to a battery capacity of $100\,\mathrm{W\,h}$ (small size Li-Ion battery). For an offgrid BS, i.e., $n \in \mathcal{N}_{\mathrm{off}}$, $B_n(t)$ is updated every time slot (hour) as:

$$B_n(t+1) = B_n(t) + H_n(t) - O_n(t) + T_n(t)\,, \tag{4}$$

where $T_n(t)$ is the amount of energy that is transferred, which can either be positive (BS n is a consumer) or negative (BS n acts as a source). Note that the objective of our optimization in Section III is to find $T_n(t)$ for all t as a function of all the other system parameters. Also, $B_n(t)$ is the energy buffer level at the beginning of time slot t, whereas $H_n(t)$, $O_n(t)$ and $T_n(t)$ are the energy harvested, the energy that is locally drained and the energy transferred in the time slot (from t to $t+1$), respectively. The energy level of an ongrid BS $n \in \mathcal{N}_{\mathrm{on}}$ is updated as:

$$B_n(t+1) = B_n(t) + H_n(t) - O_n(t) + T_n(t) + \theta_n(t)\,, \tag{5}$$

where the new term $\theta_n(t) \geq 0$ represents the energy purchased by BS n from the electrical grid *during* hour t. The behavior of a BS is determined by the energy level in its energy buffer. Specifically, if $B_n(t) \geq B_{\mathrm{up}}$, the BS behaves as an *energy source*, and is thus eligible for transferring a certain amount of energy $T_n(t)$ to other BSs. In this work, we assume that if the total energy in the buffer at the end of the current time slot t is $B_n(t) < B_{\mathrm{up}}$ and the BS n is ongrid, then the difference $\theta_n(t) = B_{\mathrm{up}} - B_n(t)$ is purchased from the electrical grid in slot t, as an ongrid BS must always be a source, i.e., in the position of transferring energy to other BSs. If instead $B_n(t) \leq B_{\text{low}}$, the BS behaves as an *energy consumer*. From the above assumptions, it descends that in this case the BS can only be offgrid and its energy demand amounts to $d_n(t) = B_{\text{low}} - B_n(t)$, so that its energy buffer would ideally become equal to the lower threshold B_{low} by the end of the current time slot. Note that, this can only be strictly guaranteed if $H_n(t) - O_n(t) \geq 0$: however, since $B_n(t)$ is measured at the beginning of time slot t, whereas $H_n(t)$ and $O_n(t)$ are only known at the end of it, the amount of energy that the BS demands $d_n(t)$ (still at the beginning of the time slot) cannot explicitly depend on them. Although we may use estimates of $E[H_n(t) - O_n(t)]$ to get more accurate results, this approach is left for future work. In Fig. 2, we plot a typical load pattern (blue curve), the harvested energy by an offgrid BS (black curve) and $B_n(t)$ for an ongrid BS (red curve). Note that an ongrid BS maintains the buffer level equal to B_{up} when no energy is harvested, whereas its buffer $B_n(t)$ grows beyond B_{up} around mid-day where there is an energy surplus due to the harvesting process.

III. Problem Formulation

In this section, we propose an optimal energy allocation strategy whose objective is to make the offgrid BSs as self-sustainable as possible. This is achieved by transferring some amount of energy from rich energy BSs to those offgrid base stations that are energy consumers (whose buffer level is below B_{low}). Note that maximizing energy transfer efficiency in the energy routing process is also important, and will be explicitly modeled in the objective functions of Section III-B.

A. Notation

We use the indices i and j to respectively denote an arbitrary energy source and a consumer. $\mathcal{X}_s = \{1, \dots i, \dots, I\}$ and $\mathcal{X}_c = \{1, \dots j, \dots, J\}$ are the set of BS acting as sources and consumers, respectively. With e_{ij} we mean the total available energy from the source $i \in \mathcal{X}_s$ to the consumer $j \in \mathcal{X}_c$, in matrix notation we have $\boldsymbol{E} = [e_{ij}]$. Note that e_{ij} is the energy that would be available at the consumer BS j and, in turns, it depends on i, j and on the distribution losses between them, i.e., on the total distance that the energy has to travel (see Section II-A). Vector $\boldsymbol{D}$, with elements d_j, represents the energy demand from each consumer $j \in \mathcal{X}_c$. g_{ij} represents the number of hops in the energy routing topology between source $i \in \mathcal{X}_s$ and consumer $j \in \mathcal{X}_c$, in matrix notation we have $\boldsymbol{G} = [g_{ij}]$. Also, we assume that all hops have the same physical length. Finally, with $x_{ij} \in [0, 1]$ we mean the fraction of e_{ij} that is allocated from source $i \in \mathcal{X}_s$ to consumer $j \in \mathcal{X}_c$, in matrix notation $\boldsymbol{X} = [x_{ij}]$.

B. Objective Functions

As a first objective, we seek to minimize the difference between the amount of energy offered by the BS sources $i \in \mathcal{X}_s$ and that transferred to the BS consumers $j \in \mathcal{X}_c$. This amounts to fulfill, as much as possible, the consumers' energy demand $\boldsymbol{D}$. At time t, the energy that can be drained from a source i is $B_i(t) - B_{\text{low}}$. Now, if we consider the generic consumer j, the maximum amount of energy that i can provide to j is $e_{ij} = (B_i(t) - B_{\text{low}})a(g_{ij})$, where $a(g_{ij}) \in [0, 1]$ is the attenuation coefficient between i and j, due to the power loss. We thus write a first cost function as:

$$f_1(\boldsymbol{X}, \boldsymbol{E}, \boldsymbol{D}) = \sum_{j=1}^{J} \left(\sum_{i=1}^{I} x_{ij} e_{ij} - d_j \right)^2 , \tag{6}$$

where $i \in \mathcal{X}_s$ and $j \in \mathcal{X}_c$. Due to the existence of a single path between any source and consumer pair, and the fact that each power link can only be used for a single transfer operation at a time, a desirable solution: (i) picks source and consumer pairs (i, j) in such a way that the physical distance (g_{ij}) between them is minimized and (ii) achieves the best possible match between sources and consumers, i.e., uses source i, whose available energy e_{ij} is the closest to that required by consumer j. That is, we would like x_{ij} to be as close as possible to 1. If this is infeasible, several sources will supply the consumer. Through the minimization of the following cost function, the number of hops g_{ij} between sources and consumers is minimized and we favor solutions with $x_{ij} \to 1$:

$$f_2(\boldsymbol{X}, \boldsymbol{G}) = \sum_{i=1}^{I} \left(\sum_{j=1}^{J} - \exp\left(\frac{x_{ij}}{g_{ij}} \right) \right) , \tag{7}$$

in other words, with this cost function we are looking for a sparse solution (i.e., a small number of sources with x_{ij} close to 1. Note that when $x_{ij} \to 1$ and g_{ij} is minimized, the argument x_{ij}/g_{ij} is maximized and the negative exponential is minimized. Also, the exponential function was picked as it is convex, but any increasing and convex function would do.

C. Optimization Problem

At each time slot t, every BS n updates its buffer level $B_n(t)$, using either Eq. (4) or Eq. (5) (note that $B_n(t-1)$, $H_n(t-1)$, $O_n(t-1)$, $T_n(t-1)$ and $\theta_n(t-1)$ are all known in slot t, see Section II). It then decides whether to act as a source or as a consumer in the current time slot. Each source i evaluates e_{ij} for all $j \in \mathcal{X}_c$ through $e_{ij} = (B_i(t) - B_{\text{low}})a(g_{ij})$ and each consumer j evaluates the amount of energy required as $d_j = B_{\text{low}} - B_j(t)$. g_{ij} (power losses) is fixed as it only depends on the topology. At time t, armed with the cost functions in Eq. (6) and Eq. (7), the following optimization problem is formulated:

$$\min_{\boldsymbol{X}} \quad \alpha f_1(\boldsymbol{X}, \boldsymbol{E}, \boldsymbol{D}) + (1 - \alpha) f_2(\boldsymbol{X}, \boldsymbol{G}) \tag{8a}$$

$$\text{subject to:} \quad 0 \leq x_{ij} \leq 1, \qquad \forall i \in \mathcal{X}_s, \forall j \in \mathcal{X}_c, \tag{8b}$$

$$\sum_{j=1}^{J} x_{ij} \leq 1, \qquad \forall i \in \mathcal{X}_s, \tag{8c}$$

where $\alpha \in [0, 1]$ is a weight used to balance the relative importance of the two cost functions and x_{ij} are the decision variables. The first constraint represents the fact that x_{ij} is a fraction of the available energy e_{ij} from source i, and the second constraint means that the total amount of energy that a certain source i transfers to consumers $j = 1, \dots, J$ cannot exceed the total amount of available energy at this source.

For any fixed value of α, Eq. (8) is a convex minimization problem which can be solved through standard techniques. In this paper, we have used the CVX tool [17] to obtain the optimal solution $\boldsymbol{X}^* = [x^*_{ij}]$, which dictates the optimal energy fraction to be allocated from any source i to any consumer j.

D. Solution through Optimal Assignment

Alternatively, the energy distribution problem from sources to consumers can be modeled as an assignment problem, where each source $i \in \mathcal{X}_s$ has to be *matched* with a consumer $j \in \mathcal{X}_c$. This approach can be solved applying the *Hungarian method* [15], an algorithm capable of finding an optimal assignment for a given square $M \times M$ cost matrix, where $M = \max(I, J)$. An assignment is a set of M entry positions in the cost matrix, no two of which lie in the same row or column. The sum of the M entries of an assignment is its cost. An assignment with the smallest possible cost is referred to as *optimal*.

Let $\boldsymbol{C} = [c_{ij}]$ be the cost matrix, where rows and columns respectively correspond to sources i and consumers j. Hence, c_{ij} is the cost of assigning the i-th source to the j-th consumer and is obtained as follows:

$$c_{ij} = \alpha(e_{ij} - d_j)^2 + (1-\alpha)\left(-\exp\left(\frac{1}{g_{ij}}\right)\right), \quad (9)$$

where the first term weighs the quality of the match (the demand d_j should be as close as possible to e_{ij}) and the second the quality of the route. To ensure the cost matrix is square, additional rows or columns are to be added when the number of sources and consumers is not equal. As typically assumed, each element in the added row or column is set equal to the largest number in the matrix.

The main difference between the optimal solution found by solving the convex optimization problem (Eq. (8)) and that found by the Hungarian method is that the latter returns a one-to-one match between sources and consumers, i.e., each consumer can only be served by a single source. On the other hand, for any given consumer the convex solution also allows the energy transfer from multiple sources.

IV. Energy Routing

Next, we describe how the energy allocation x_{ij} is implemented over time. The algorithm that follows is executed at the beginning of each time slot, when a new allocation matrix $\boldsymbol{X}^*$ is returned by the solver of Section III-C. Each hour is further split into a number of mini slots. Given a certain maximum transmission energy capacity $e_{\max}$ for a power link in a mini slot, the required number of mini slots to deliver a certain amount of power $e_{ij}x_{ij}$ between source i and consumer j is obtained as $n_{ij} = \lceil x_{ij}e_{ij}/e_{\max} \rceil$.

Since each power link can be used for a single energy transfer operation at a time, we propose an algorithm that seeks to minimize the number of mini slots that are used. First of all, an energy route for the source-consumer pair (i, j) is defined as the collection of intermediate nodes to visit when transferring energy from i to j. The algorithm proceeds as follows: 1) a route r_{ij} is identified for each source i and consumer j (note that for the given network topology this route is *unique*), 2) the disjoint routes, with no power links in common, are found and are allocated to as many (i, j) pairs as possible, 3) for each of these pairs (i, j), the energy transfer is accomplished using route $r_{i,j}$ for a number of mini slots n_{ij}, 4) when the transfer for a pair (i, j) is complete, we check whether a new route is released (i.e., no longer used and available for subsequent transfers). If that is the case, and if this route can be used to transfer energy for any of the remaining pairs (i', j') (not yet considered), this route is allocated to any of the eligible pairs (i', j') for $n_{i',j'}$ further mini slots. This process is repeated until all source-consumer pairs have completed their transfer.

V. Numerical Results

In this section we show some selected numerical results for the scenario of Section II. The parameters that were used for the simulations are listed in Table I.

The results in Fig. 3 are obtained considering $|\mathcal{N}_{on}| = 3$, a total number $N = 18$ of base stations and 30 users on average per BS. This graph shows the average outage probability $\gamma(t)$ over an entire day, that for each time t is computed as the ratio between the number of BSs whose battery level is completely depleted, and the total number of BSs in the system N. The performance of three methods is shown in the plot: (i) **no energy exchange (NOEE)**, i.e., the BS that are offline only have to rely on the locally harvested energy, (ii) **convex solution (CONV)**, found solving Eq. (8) and (iii) **Hungarian solution (HUNG)**, found through the Hungarian method of Section III-D. As expected, the probability that a BS runs out of service due to energy scarcity is higher when energy cannot be transferred among BSs (NOEE) and is in general very high across the whole day for NOEE and HUNG. Moreover, we see that for the latter schemes γ

TABLE I
System parameters used in the numerical results.

Parameter	Value
Number of BSs, N	18
Cable resistivity, ρ	$0.023\,\Omega\mathrm{mm}^2/\mathrm{m}$
Cable cross-section, A	$10\,\mathrm{mm}^2$
Length of a power link, ℓ	$100\,\mathrm{m}$
Shadowing factor, r	2
Minimum number of users in a BS cell, a	$[5, 65]$
Maximum number of users in a BS cell, b	$[15, 75]$
Maximum energy buffer capacity, $B_{\max}$	$360\,\mathrm{kJ}$
Upper energy threshold, B_{up}	70%
Lower energy threshold, B_{low}	30%
Cost weight, α	0.5
Mini slot duration	$60\,\mathrm{s}$
Maximum transmission energy capacity, e_{max}	90 kJ/mini-slot

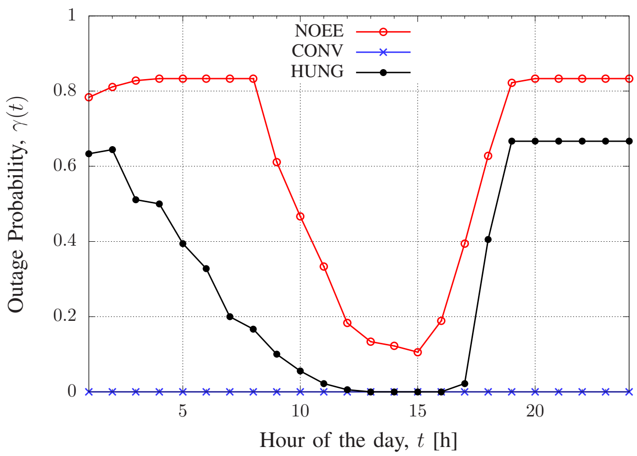

Fig. 3. Outage probability γ over a day.

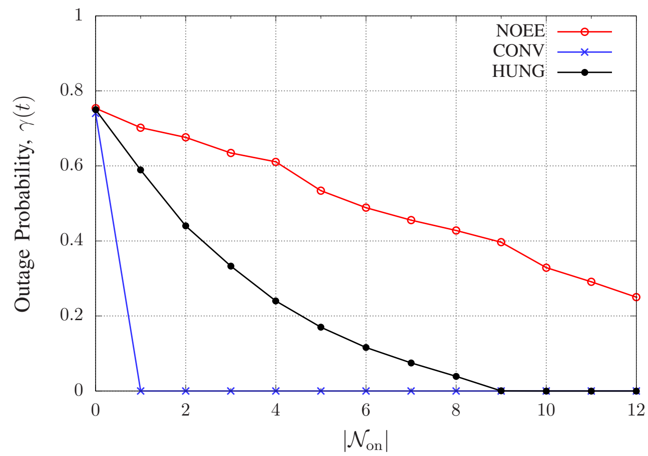

Fig. 4. Outage probability γ *vs* the number of ongrid BS $|\mathcal{N}_{on}|$.

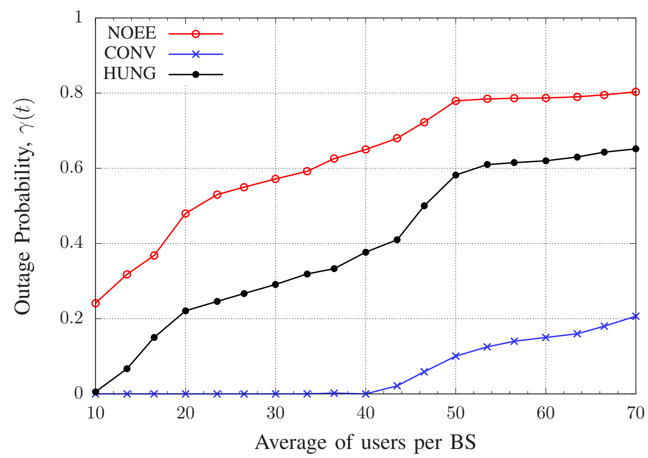

Fig. 5. Outage probability γ *vs* the average of users per BS.

increases when the amount of energy harvested is very little (i.e., night-time). The problem of the Hungarian method is that it returns a matching of source-consumer pairs where each source is allocated to a single consumer and, in turn, some of the BSs will not be allocated in some time slots (due to the imbalance between number of sources and number of consumers). This leads to high outage probabilities for the considered scenario. The convex optimization problem offers a more flexible solution, as it allows the energy transfer from multiple BSs and in different amounts. This translates into a zero outage probability. In Fig. 4, the evolution of the outage probability as the number of ongrid BSs increases is presented, considering an average of 30 active users per BS. Again, the convex solution performs better than the Hungarian one, but nevertheless we see that the same results are attained when the number of ongrid BSs gets equal to the number of offgrid ones. In fact, $N = 18$ and $|\mathcal{N}_{\text{off}}| = N - |\mathcal{N}_{\text{on}}|$, which means that when $|\mathcal{N}_{\text{on}}| = 9$ there is the same number of ongrid and offgrid base stations and, in fact, in this case the Hungarian method also leads to a zero outage. The same occurs as $|\mathcal{N}_{\text{on}}|$ keeps increasing, as $|\mathcal{N}_{\text{on}}| > |\mathcal{N}_{\text{off}}|$. The outage probability γ as a function of the traffic load is shown in Fig. 5 for $|\mathcal{N}_{on}| = 3$ and $N = 18$. As expected, γ is an increasing function of the load. However, CONV starts increasing later than NOEE and HUNG, and does it at a slower pace. Some considerations about the energy use are in order. All the algorithms purchase some energy from the electrical grid, although the way in which they use it differs. With NOEE, the energy purchased in solely used to power the base stations that are ongrid, whereas those being offgrid have to rely on the harvested energy. CONV and HUNG allow some energy redistribution among the base stations. With these algorithms, an energy rich BS may transfer energy to other base stations whose energy buffer is depleted. Note that an energy rich base station may belong to either the ongrid set or to the offgrid one. The latter case occurs when, for instance, one base station experiences no traffic during the day and all the energy it harvests is stored locally. In this case, this base station is energy rich, although it is offgrid and both CONV and HUNG consider it as an energy source for other BSs. We now see the whole base station network as a close system that gathers energy in two ways: 1) harvesting it from the environment and 2) purchasing it from the electrical grid. The harvested energy is basically free (the CAPEX is not considered here) and shall be utilized to the best extent: energy transfer among base stations makes this possible. The energy bought by the online BSs is costly and shall also be utilized as efficiently as possible. Next, we try to assess how efficiently the energy that is purchased by the BS system is utilized to serve the mobile users. To do so, for each hour t, we compute an *efficiency metric* $\eta(t)$, which represents the amount of energy purchased from the electrical system *per successfully served user* in hour t. For its computation, we use the following quantities: $\theta_i(t)$ is the total amount of energy purchased by base station $i \in \mathcal{N}_{\text{on}}$ in hour t, $\gamma_n(t)$ is the outage probability for BS $n \in \mathcal{N}_{\text{on}} \cup \mathcal{N}_{\text{off}}$ in hour t, defined as the fraction of this time slot in which its energy buffer is

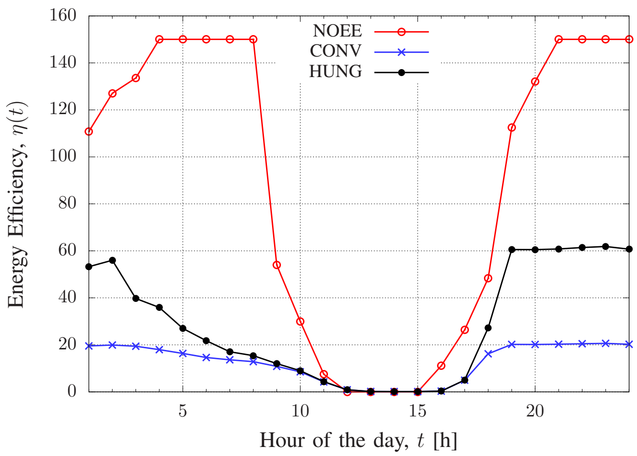

Fig. 6. Efficiency metric $\eta(t)$.

completely depleted. Hence, the efficiency is obtained as:

$$\eta(t) = \frac{\sum_{i \in \mathcal{N}_{\text{on}}} \theta_i(t)}{\sum_{n=1}^{N} ((1 - \gamma_n(t)) L_n(t))} . \quad (10)$$

$\eta(t)$ is shown in Fig. 6 across an entire day for $|\mathcal{N}_{\text{on}}| = 3$, $N = 18$ and 30 active users (on average) per BS. Clearly, good energy allocation schemes have a small $\eta(t)$ (the smaller the better), as this indicates that the energy purchased is put to good use. From this plot, we see that CONV provides much better (smaller) η that the other two schemes. We also see that the highest advantages are obtained in the periods of the day during which the energy harvested is scarce. In fact, from $t = 12$ (midday) to 15 (3 pm) the energy harvested is generally abundant and any solution would do. During these hours ("energy peak hours") the offgrid base stations have no problem (if properly dimensioned) to handle the respective traffic load. The problems arise when the harvested energy is not so abundant, scarce or event absent. In these cases, a good allocation strategy should take advantage of the energy reserve in the energy buffers (accumulated during the energy peak hours) and distribute energy from ongrid or energy rich BSs in a way to keep the power losses small. CONV does a very good job in these respects: in the best cases, the amount of energy purchased per served user is reduced of one third with respect to HUNG and of almost eight times when the transfer of energy among base stations is not allowed (NOEE).

VI. Conclusions

In this paper, we have considered future small cell deployments where energy harvesting and packet power networks are combined to provide energy self-sustainability through the use of own-generated energy and carefully planned energy transfers among network elements. In the considered scenario, besides possessing energy harvesting and storage units, some of the base stations (BSs) are offgrid and receive power from energy rich BSs. Two energy allocation schemes have been proposed, one based on convex optimization and one on the Hungarian method. The objective of the proposed solutions is to (i) maximize the energy transfer efficiency among base stations, while (ii) reducing as much as possible the outage probability, i.e., that offgrid base stations are unable to serve their load due to energy scarcity. Numerical results, obtained with real-world harvested energy traces, reveal that the convex optimization approach is capable of keeping the outage probability to nearly zero for a wide range of traffic loads. In the best cases, the amount of energy purchased per served user is reduced of one third with respect to the Hungarian allocation method and of almost eight times when the transfer of energy among base stations is not allowed.

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