Energy Harvesting in Heterogenous Networks with Hybrid Powered Communication Systems

(*invited paper*)

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***Abstract*—In this paper, we investigate energy efficient and energy harvesting (EH) in heterogeneous networks (HetNets) where all base stations (BSs) are equipped to harvest energy from renewable energy sources, e.g., solar. We consider a hybrid power supply of green (renewable) and traditional micro-grid, such that traditional micro-grid is not exploited as long as the BSs can meet their power demands from harvested and stored green energy. Therefore, our goal is to minimize the network-wide energy consumption subject to users' certain quality of service and BSs' power consumption constraints. As a result of binary BS sleeping status and user-cell association variables, proposed is formulated as a binary linear programming (BLP) problem. Two cases based on the knowledge level about future renewable energy (RE) statistics are investigated: (i) an online knowledge case where future RE statistics are unknown, (ii) an offline knowledge case where future network's statistics are a priori perfectly estimated. A green communication algorithm based on binary particle swarm optimization is implemented to solve the problem with low complexity time.**

***Index Terms*—Energy harvesting, sleeping strategy, binary particle swarm optimization.**

I. Introduction

Energy saving is considered as one of the critical research problems that has been discussed in green communication over the last few years. In recent years, energy efficiency has emerged as a major concern in the operation of cellular heterogenous networks (HetNets). Dynamic base station (BS) ON/OFF switching, also known as BS sleeping strategy, is shown to be highly useful in reducing energy consumption of cellular HetNets [1], [2]. The BSs are turned off during periods of low traffic and the small number of active users are offloaded to a nearby BS. As a result, the power consumption of lightly loaded BSs can be reduced or completely eliminated depending on the sleep state of the turned off BS. In [2], the impact of turning off macrocell BSs on the energy efficiency of the HetNet is studied while keeping the small cell BSs active. Several robust and efficient schemes for BS ON/OFF switching have been proposed in literature [3], [4]. For instance, in [3], three different approaches for small cell BS switching in HetNets are discussed. The ON/OFF status of the small cell BSs is controlled by either the detection of active users by the small cell BSs, wake-up signals by the core network, or wake-up signals by the users. In [4], the authors have introduced two modes to cater for the short and long idle periods of the users. It is shown that dense HetNets can be used t achieve higher capacity and performance while simultaneously reducing energy consumption. BS sleeping strategies for single tier cellular networks are investigated in [5], [6]. In [5], an energy saving algorithm, that turns off the BSs one by one and measures the network impact considering the load increments of the neighboring BSs, is proposed. In [6], an algorithm based on simulated annealing search is shown to provide considerable energy savings with insights on the deployment of small cell BSs. In [7], the authors presented a complete framework for a smart-grid powered LTE system based on evolutionary algorithms.

Replenishing a new battery or recharging it using traditional wired charging method is not feasible always (e.g., sensors located on mountains or in forests). Therefore, energy harvesting (EH) has been considered as one of the most effective and robust solutions to protract the lifetime and sustainability of wireless networks [8]. Many promising practical applications that use EH nodes have been discussed recently, such as, emerging ultra-dense small cell deployments, point-to-point sensor networks, and far-field microwave power transfer [9].

One of the limitation of the EH is the discontinuity of the power generation which affects reliability of the service. In [10], the authors consider hybrid powering BSs connected to different micro-grids that cooperate to minimize the total power cost by optimizing their resources allocation. The authors assume that each micro-grid can purchase back-up power from the main grid when needed, in order to ensure a reliable service to the the users. In this work, we consider a downlink EH HetNets system where each BS is equipped to harvest from renewable source. The contribution of this work can be summarized as follows

- Considering a hybrid power supply sources consisting of green (renewable) and traditional micro-grid, such that traditional micro-grid is not exploited as long as the BSs can meet their power demands from harvested and stored green energy.
- Formulating an optimization problem aims to minimize the network-wide energy consumption over a certain time slots. The goal is to optimize the BS sleeping and user-cell association variables under BS's maximum power constraint, maximum BS's storing energy constraint, and user's quality-of-service (QoS) constraint.
- Two cases depending on the knowledge level about future RE generation are investigated:
  1) The online case: in this case, future RE generation statistics are unknown. a binary linear programming (BLP) problem is formulated to optimize the BS sleeping status and user-cell association.
  2) The offline case: this case assumes that the future statistics of the network are perfectly and estimated.

- Proposing a low complexity green optimization approach based on binary particle swarm optimization (BPSO) algorithm to find a near optimal solution and compare it with the well known genetic algorithm (GA) [11].

II. System Model

In this paper, we investigate a time-slotted system of a finite period of time divided into $b = 1, .., B$, time slots of equal duration T_b.

A. Network Model

We consider a half duplex downlink transmission of three-tiers HetNets consisting of a macrocell tier, microcell tier, and smallcell tier with a total of $L+1$ BSs (i.e., a single macrocell BS and L combined BSs of micro base stations (MBSs), and small base station (SBSs)). The locations of all BSs are modeled by an independent homogeneous Poisson Point Process (PPP). We consider a hybrid power supply micro-grid sources consisting of a green grid (GG) and a traditional grid (TG). The former uses renewable sources to generate the electric power, while the latter uses classical sources to generate the electric power. Each BS is connected to the GG so that can provide help in energy when needed.

The GG has the ability to purchase a back-up power from traditional grid (TG) that is controlled by control unit (CU) when needed as shown in Fig. 2.

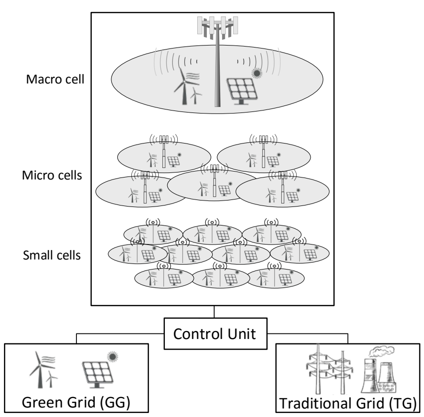

Fig. 1: System model of hyprid EH.

Denoted U^b as the total number of users in the network during time slot b. We denote by $\bar{U}_l$, the maximum number of users that can be served by a BS l, where index $l = 0$ for macrocell BS and $l \geq 1$ for other BS tiers, such that $\bar{U}_l \ll \bar{U}_0$. These numbers reflect the BSs' capacities due to available number of frequency carriers and/or hardware and transmit power limitations. In order to avoid the co-channel interference, we assume that all the channels shared the spectrum orthogonally between the BS. Finally, we assume that the a user is served by at most one BS (either macrocell BS, MBS, or SBS).

In general, we assume that the communication channel between two nodes x and y at time slot b is given as follows

$$h_{xy}^b = \sqrt{d_{xy}^{-\alpha}} \tilde{h}_{xy}^b, \tag{1}$$

where d_{xy} is the Euclidean distance between the nodes x and y, α is a pathloss exponent, and $\tilde{h}_{xy,b}$ is a fading coefficient with a coherence time slot T_b sec. Without loss of generality, all channel gains are assumed to be constat during T_b.

B. Base Station Power Model

Since the energy arrivals and energy consumption of the BSs are random and their energy storage capacities are finite, some BSs might not have enough energy to serve users at a particular time. Under such scenario, it is preferred that some of the BSs are kept OFF and allowed to recharge while their load is handled by the neighboring BSs that are ON. On the other hand, dynamic base station switching-ON/OFF can help in ensuring power saving of HetNets by reducing the traditional (non-renewable) power consumption of BSs that have a heavy energy usage mainly during low traffic period.

Each BS can be set in either of two operational modes: active mode (AM) and sleep mode (SM). The decision to toggle the operational state from one to another is taken centrally (i.e., the decision is taken by some central entity based on the current load offered to the network). In the AM, the BS is serving a certain number of users, thus, the BS radiated power can be expressed as

$$P_l^{\mathrm{BS}} = \sum_{u=1}^{U_l} P_{l,u}, \tag{2}$$

that corresponds to the sum of the radiated power over all users U_l connected to a certain BS l.

In the SM, the BS l consumes power equal to γ_l. The sleep mode is a reduced power consumption state in which the BS in not completely turned off and can be readily activated. Although the BS is not radiating power in this mode, elements such as power supply, baseband digital signal processing, and cooling are still active. Therefore, the BS keeps consuming power unless it is in a state of complete shutdown. For simplicity, the total power consumption of BS l can be approximated by a linear model as follows [12]

$$P_l = \begin{cases} \alpha_l P_l^{\mathrm{BS}} + \beta_l, & \text{for AM,} \\ \gamma_l, & \text{for SM,} \end{cases} \tag{3}$$

where a_l corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses and b_l models an offset of site power which is consumed independently of the average transmit power.

We denote by $\boldsymbol{\epsilon}^b$ a binary matrix of size $L+1 \times U$. Its entries $\epsilon_{l,u}^b$ is equal to 1 if user u is allocated to BS l at time b and 0 otherwise.On the other hand, a dynamic ON/OFF switching mechanism is considered to turn off redundant MBSs and SBSs whenever it is possible. More specifically, BS l can be turned off during low traffic periods and the small number of active users are offloaded to nearby BSs A binary vector $\boldsymbol{\pi}^b$ of size $L \times 1$ is introduced to indicate the status of each BS l. Its entries π_l^b equal to 1 if BS l is in AM during time slot b and 0 otherwise. Note that in order to ensure that the users can not be connected to a BS in the SM, then, the following condition should be respected

$$\epsilon_{l,u}^b \leq \pi_l^b, \quad \forall l = 1, ., L, \forall u = 1, ., U, \forall b = 1, ., B. \tag{4}$$

In this paper, we always keep the macrocell BS active (i.e., π_0^b, $\forall b = 1,..,B$) to ensure coverage and minimum connectivity in this typical HetNet (i.e., one macrocell BS surrounded by multiple of MBSs and SBSs). In the case of multiple macrocell BSs covering a bigger geographical area, macrocell BSs could be turned off and cell breathing mechanisms can be employed to ensure connectivity [13].

C. Energy Harvesting Model

In this paper, we assume that each BS can harvest from RE in both AM and SM. We model the RE stochastic energy arrival rate as a random variable Φ Watt defined by a probability density function (pdf) $f(\varphi)$. For example, for photovoltaic energy, Φ can be interpreted as the received amount of energy per time unit with respect to the received luminous intensity in a particular direction per unit solid angle. In general, the energy consumption of the BS l during time slot b can be expressed as

$$E_0^b = T_b \left(\alpha_0 \sum_{u=1}^{U} \epsilon_{0,u}^b P_{0,u} + \beta_0 \right), \quad l = 0 \tag{5}$$

$$E_l^b = T_b \left(\pi_l^b \left[\alpha_l \sum_{u=1}^{U} \epsilon_{l,u}^b P_{l,u} + \beta_l \right] + (1-\pi_l^b)\gamma_l \right), \quad l \geq 1, \tag{6}$$

By using (4), we can re-write (6) as follows

$$E_l^b = T_b \left(\alpha_l \sum_{u=1}^{U} \epsilon_{l,u}^b P_{l,u} + \pi_l^b \beta_l + (1-\pi_l^b)\gamma_l \right), \quad l \geq 1, \tag{7}$$

The harvested energy in BS l and GG at the end of time slot b, are given respectively by

$$H_l^b = T_b \eta_l \varphi_l^b, \tag{8}$$

$$H_g^b = T_b \eta_g \varphi_g^b, \tag{9}$$

where η_l and η_g are the energy conversion efficiency coefficient of the RE at BS l and GG, respectively, where $0 \leq \eta_l, \eta_g \leq 1$. Notice that the current stored energy in BS l and GG depend on both the current harvested energy during slot time b and the previously stored energy during previous slots. Therefore, he stored energy in BS l at the end of time t is given by

$$S_l^b = \left[S_l^{b-1} + H_l^b - E_l^b - E_{le} \right]^+, \tag{10}$$

where E_{le} is the leakage energy during T_b. $[x]^+ = \max(0,x)$.

III. Problem Formulation and Solution

In this section, we formulate and solve optimally two optimization problems, based on the knowledge level of the RE generation, aiming to minimize the network's energy consumption during the B time slots. The first optimization problem corresponds to the online case where the mobile operator manages its BSs time slot by time slot without any prior information about the future RE generation. The second one corresponds to the offline case with full information about the future RE generation where all the decisions variables are simultaneously optimized for the B time slots. The offline case is a not realistic case. In this study, it is used as a benchmark scenario for comparison with online case or as an approximation of the case where RE energy uncertainty is almost negligible. The achievable data rate of user u served by BS l at a given time b is given by

$$R_{l,u}^b = \log_2 \left(1 + \frac{P_{l,u} \, |h_{l,u}^t|^2}{\mathcal{N}_0} \right) \tag{11}$$

where $\mathcal{N}_0$ is the noise power density.

A. Online Optimization Problem

In this case, we assume that the mobile operator is not aware about the future RE generation(i.e., φ_l^b and φ_g^b are known during b only). Therefore, optimization problem that aims to minimize the total consumed energy at each time slot b is formulated as follows

$$\underset{\pi_l^b, \epsilon_{l,u}^b \geq 0}{\text{minimize}} \quad E_c^b = \sum_{l=0}^{L} E_l^b(\pi_l^b, \epsilon_{l,u}^b) - S_l^b(\pi_l^{b-1}, \epsilon_{l,u}^{b-1}) \tag{12}$$

subject to:

$$\sum_{u=1}^{U} \epsilon_{l,u}^b P_{l,u} \leq \bar{P}_l, \quad \forall l = 0,.,L, \tag{13}$$

$$\sum_{l=0}^{L} \epsilon_{l,u}^b R_{l,u}^b \geq R_0, \quad \forall u = 1,.,U, \tag{14}$$

$$S_l^{b-1}(\pi_l^b, \epsilon_{l,u}^b) + H_l^b \leq \bar{S}_l, \quad \forall l = 0,.,L, \tag{15}$$

$$\sum_{u=1}^{U} \epsilon_{l,u}^b \leq \bar{U}_l, \quad \forall l = 0,.,L, \tag{16}$$

$$\sum_{l=0}^{L} \epsilon_{l,u}^b \leq 1, \quad \forall u = 1,.,U, \tag{17}$$

$$\epsilon_{l,u}^b \leq \pi_l^b, \quad \forall l = 1,.,L, \forall u = 1,.,U, \tag{18}$$

where constraint (13) and (14) represent the maximum allowable transmit energy of BS l and user QoS, respectively. Constraint (15) forces the total energy stored in the battery of a BS l during the time slot b to be less than the battery capacity denoted by $\bar{S}_l$. Constraints (16) and (17) to satisfy the backhauling condition and to ensure that each user is served by at most one BS, respectively.

Notice that, this optimization problem will be solved at the beginning of each time slot. Hence, the optimal solutions for such a problem can be determined using simplex method with Gurobi/CVX interface [14].

B. Offline Optimization Problem

In this case, we assume that the mobile operator can perfectly predict the future RE generation ahead of time. This case can be considered as a useful benchmark to compare with the online case. Therefore, the objective function becomes the minimization of the total energy consumption of the network during all B time slots.

$$\underset{\pi_l^b, \epsilon_{l,u}^b \geq 0}{\text{minimize}} \quad E_c = \sum_{b=1}^{B} \sum_{l=0}^{L} E_l^b(\pi_l^b, \epsilon_{l,u}^b) - S_l^b(\pi_l^{b-1}, \epsilon_{l,u}^{b-1}) \quad (19)$$

subject to:

$$\sum_{u=1}^{U} \epsilon_{l,u}^b P_{l,u} \leq \bar{P}_l, \quad \forall l = 0, ., L, \forall b = 1, ., B, \quad (20)$$

$$\sum_{l=0}^{L} \epsilon_{l,u}^b R_{l,u}^b \geq R_0, \quad \forall u = 1, ., U, \forall b = 1, ., B, \quad (21)$$

$$S_l^{b-1}(\pi_l^b, \epsilon_{l,u}^b) + H_l^b \leq \bar{S}_l, \quad \forall l = 0, ., L, \forall b = 1, ., B, \quad (22)$$

$$\sum_{u=1}^{U} \epsilon_{l,u}^b \leq \bar{U}_l, \quad \forall l = 0, ., L, \forall b = 1, ., B, \quad (23)$$

$$\sum_{l=0}^{L} \epsilon_{l,u}^b \leq 1, \quad \forall u = 1, ., U, \forall b = 1, ., B, \quad (24)$$

$$\epsilon_{l,u}^b \leq \pi_l^b, \quad \forall l = 1, ., L, \forall u = 1, ., U, \quad (25)$$

Notice that the constraints (20)-(25) are similar to the constraints (13)-(18) except that they have to be satisfied for all time slots $b = 1, .., B$.

The offline problem can be also solved using simplex method with Gurobi/CVX interface [14].

C. Special case

The communication channel is assumed to be a block fading channel with a coherence time T_c second. Therefore, the scheduling and user-cell association can be assumed to be taken over a short time scale. While, the operational state of the switching ON/OFF of the BSs can be taken over a long time scale, where each long time slot consists of multiple short slots. Hence, the problem can be solved by optimizing only $\epsilon_{l,u}^b$ at the beginning of the short time slot and optimizing both π_l^b and $\epsilon_{l,u}^b$ at the beginning of the long time slot.

IV. Low Complexity Algorithm

The formulated BLP optimization problems given in Section III is considered as NP-hard problem due to the existence of the binary variables, hence, we propose to employ a meta-heuristic algorithm, namely BPSO.

The BPSO algorithm was firstly developed in 1997 by J. Kennedy and R. Eberhart [15]. The idea is inspired from swarm intelligence, social behavior, and food searching by a flock birds and a school of fish. The main advantages are summarized as follows: (i) BPSO presents a simple search process and is easy to implement with few parameters to manipulate (e.g., such as the number of particles and acceleration factors for BPSO), (ii) it requires low computational cost attained from small number of agents, and (iii) it provides a good convergence speed [16]. Then, we propose to compare its performances with the well known evolutionary GA [11].

A. Binary Particle Swarm Optimization (BPSO)

The BPSO starts by generating N particles $\boldsymbol{\lambda} = [\pi_1^1, .., \pi_L^B, .., \epsilon_{1,1}^1, .., \epsilon_{L,U}^B]$;$n = 1, .., N$ of size $L + (L+1)U \times 1$ for online case (solved for each time slot b) and $LB + (L+1)UB \times 1$ for offline case to form an initial population $\mathcal{S}$. Then, it determines the minimum energy consumed by each particle that satisfy the QoS by solving the optimization problem. Then, it finds the particle that provides the best solution for this iteration, denoted by $\boldsymbol{\lambda}^{\text{best}}$. In addition, for each particle n, it saves a record of the position of its previous best performance, denoted by $\boldsymbol{\lambda}^{(\text{n,local})}$. Then, at each iteration i, BPSO computes a velocity term $V_m^{(n)}$ corresponding to element m in $\boldsymbol{\lambda}$ as follows:

$$V_m^{(n)}(i) = \Omega V_m^{(n)}(i-1) + \psi_1(i) \left(\lambda_m^{(\text{n,local})}(i) - \lambda_m^{(n)}(i) \right) + \psi_2(i) \left(\lambda_m^{\text{best}}(i) - \lambda_m^{(n)}(i) \right), \quad (26)$$

where Ω is the inertia weight and ψ_1 and ψ_2 are two random positive numbers ($\psi_1, \psi_2 \in [0, 2]$) generated for each iteration i [15]. Then, it updates each element i of a particle $\boldsymbol{\lambda}^{(n)}$ as follows:

$$\lambda_m^{(n)}(i+1) = \begin{cases} 1 \text{ if } r_{\text{rand}} < \Psi\left(V_m^{(n)}(i)\right), \\ 0 \text{ otherwise.} \end{cases} \quad (27)$$

where r_{rand} is a pseudo-random number selected from a uniform distribution in $[0, 1]$ and Ψ is a sigmoid function for transforming the velocity to probabilities and is given as:

$$\Psi(x) = \frac{1}{1 + e^{-x}}. \quad (28)$$

Algorithm 1 Proposed Solution using BPSO Algorithm

$i = 1$.
Generate an initial population $\mathcal{S}$ composed of N random particles $\boldsymbol{\lambda}^{(n)}$, $n = 1 \cdots N$.
while not converged **do**
  for $n = 1 \cdots N$ **do**
    Compute the corresponding consumed utility function $E_c^{(n)}(i)$.
  end for
  Find $(n_j, i_j) = \arg\min_{n,i} E_c^{(n)}(i)$ (i.e., n_j and i_j indicate the index and the position of the particle that results in the minimum energy consumption). Then, set $E_c^{\text{best}} = E_c^{(n_j)}(i_j)$ and $\boldsymbol{\lambda}^{\text{best}} = \boldsymbol{\lambda}^{(n_j)}(i_j)$.
  Find $i_l = \arg\min_i E_c^{(n)}(i)$ for each particle n (i.e., i_l indicates the position of the particle n that results in best local utility). Then, set $\boldsymbol{\lambda}^{(\text{l,local})} = \boldsymbol{\lambda}^{(n)}(i_l)$.
  Adjust velocities and positions of all particles using (27).
  $i = i + 1$.
end while

These steps are repeated until reaching convergence by either attaining the maximum number of iterations or stopping the algorithm when no improvement is noticed. Details of the proposed optimization approach are given in Algorithm 1.

B. Genetic Algorithm

The performances of the proposed BPSO algorithm is compared to those of the well-know GA. In our genetic based approach, we generate randomly N particles $\boldsymbol{\lambda}^{(n)}$, $n = 1 \cdots N$

of size $L+(L+1)U \times 1$ for online case (solved for each time slot b) and $LB+(L+1)UB \times 1$ for offline case to form an initial population $\mathcal{S}$. Then, it determines the minimum energy consumed by each particle that satisfy the QoS by solving the optimization problem. After that, the algorithm selects $\tau (1 \leq \tau \leq N)$ strings that provide the minimum consumed energy and keeps them to the next population while the $N-\tau$ remaining strings are generated by applying crossovers and mutations to the τ survived parents. Crossovers consist in cutting two selected random parent strings at a correspond point which is chosen randomly. The obtained fragments are then swapped and recombined to produce two new strings. Then, mutation (i.e., changing a bit value of the string randomly) is applied with a probability p [17]. This procedure is repeated until reaching convergence or reaching the maximum number of iterations.

After solving the optimization problem, the total cost of the non-renewable energy consumed is equal to the cost of the energy consumed by all BSs that exceeding the available harvested energy stored at time b and given by

$$\mathcal{C}^b = \left[\sum_{l=0}^{L} \left[E_l^b - S_l^{b-1} \right]^+ - S_g^{b-1} \right]^+ \tag{29}$$

where S_g^{b-1} is the stored energy at the GG at the end of time slot $b-1$. Therefore, the total cost over multiple time slots is given by $\mathcal{C} = \sum_{b=1}^{B} \mathcal{C}^b$.

V. Simulation Results

In this section, selected numerical results are provided to evaluate the performance of the EH HetNets systems. Selected BSs transmit their messages periodically every $T_b = 60$ sec. All the fading channel gains adopted in the framework are assumed to be independent and identically distributed (i.i.d) Rayleigh fading gains. The efficiency transmission and conversion ratios are set to $\eta_l = \eta_g = 0.3$, respectively. The target data rate user (R_0), the number of MBSs and SBSs are 10 bits/s/Hz, 4 and 8, respectively, unless otherwise stated. The noise power is taken to be $N_0 = \mathcal{N}\mathcal{W}$, where $\mathcal{N} = -174$ dBm/Hz and $\mathcal{W} = 180$ KHz. The power consumption parameters are selected according to the energy aware radio and network technologies (EARTH) model for macrocell BS, MBSs, SBSs, are given, respectively [12] as follows: $\alpha_l = \{4.7, 2.6, 4\}$ W and $\beta_l = \{130, 56, 6.8\}$ W. The other power consumption parameters for MBSs and SBSs are given respectively by $\gamma_l = \{39, 2.9\}$ W. The maximum transmit power levels for the for macrocell BS, MBSs, SBSs, are set, respectively, to $\bar{P}_l = \{46, 38, 20\}$ dBm.

At each BS, RE is assumed to be generated following Gamma distributions $\Gamma(20,2)$, $\Gamma(12,2)$, and $\Gamma(3,1)$ for macrocell BS, MBSs, and SBS, respectively, where in $\Gamma(x,y)$, x is the shape parameter and y and scale parameter. While for GG, RE is assumed to be generated following a Gamma distribution $\Gamma(25,2)$. The total stored energy at macrocell BS, MBSs, and SBSs cannot exceed $\bar{S}_l = \{50, 12, 6\}$ KJ, respectively, and the battery leakage is set to be $E_{le} = 10\,\text{mJ}$ every T_b. The BPSO is executed with the following parameters: $N = 20$ and $\Omega \in [0,1]$ is a linear decreasing function of the BPSO iterations expressed as follows: $\Omega = 0.9 - \frac{t(0.9-0.2)}{\mathcal{I}}$, where $\mathcal{I} = 200$ is the maximum number of iterations.

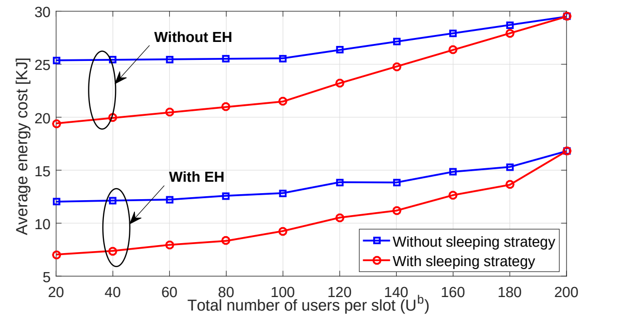

Fig. 2: Average energy cost of $B = 20$ time slots versus total number of users.

Table I: MBSs and SBSs status during multiple time slots

Number of users per b	Active MBSs				Active SBSs			
	m_1	m_2	m_3	m_4	s_1	s_2	s_3	s_4
$U^1 = 100$	$\times$	-	-	$\times$	$\times$	-	$\times$	-
$U^2 = 40$	$\times$	-	-	$\times$	$\times$	-	-	$\times$
$U^3 = 200$	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$	-
$U^4 = 80$	-	$\times$	-	$\times$	-	-	$\times$	-
$U^5 = 140$	$\times$	-	-	$\times$	$\times$	$\times$	-	$\times$
$U^6 = 220$	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$	$\times$
$U^7 = 80$	$\times$	-	-	$\times$	$\times$	-	$\times$	-
$U^8 = 160$	$\times$	$\times$	$\times$	-	-	$\times$	-	$\times$
$U^9 = 160$	$\times$	$\times$	-	$\times$	$\times$	$\times$	$\times$	-
$U^{10} = 60$	-	-	$\times$	-	$\times$	$\times$	$\times$	$\times$

Fig. 2 plots the total average energy cost, which is equal to $\frac{\mathcal{C}}{B}$, for $B = 20$ versus number of users (U^b, $\forall b = 1, .., B$), for online case. This figure investigates the impact of RE with two scenarios: 1) with the proposed EH (i.e., hybrid of RE and TG energy), 2) without EH(the energy depends on the TG energy only). It also investigate the impact of the sleeping strategy (i.e., optimizing $\boldsymbol{\pi}$) on the system performance. we can see that the proposed scheme (with EH and with sleeping strategy) offers a significant amount of energy saving switching over the other scenarios. It should be noted that the sleeping strategy is very useful specially for low traffic period with a considerable energy cost gap. Indeed, for $U^b = 100$ users, the average energy cost can be reduced by around 30% for the EH scenario by going from 13.5 KJ to around 9.5 KJ. However, this gap reduces when number of users increases. This can be justified by the fact that, when the number of users are relatively high, most of BSs should be in the AM in order to satisfy the user QoS.

Table I confirms the sleeping strategy results in Fig 2. In general it can be noted that, activating the MBSs and SBSs essentially depends on the traffic and BS's battery level. For example, as shown in Table I, during low traffic periods e,g., $b = \{2, 4, 7, 10\}$ (i.e., $U^2 = 40, U^4 = 80, U^7 = 80, U^{10} = 60$), the sleeping strategy activate some of BSs and keeps the others in the SM in order to harvest some energy. On the other hand, when the network is more congested e.g., during slots $b = \{3, 6, 8, 9\}$ (i.e., $U^3 = 200, U^6 = 220, U^8 = 160, U^9 = 160$), most of the BSs are in AM.

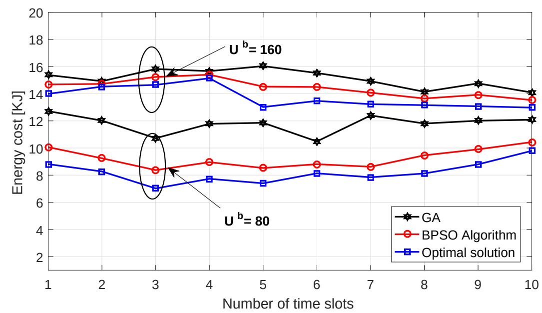

Fig. 3: Comparison between optimal solution with BPSO algorithm and GA. Energy cost versus number of time slot

Under the same setup of Fig. 2, Fig. 3 compares between the optimal solution (obtained using BLP) with BPSO algorithm and the well known GA for different total number of users $U^b = \{80, 160\}$. It can be seen, that the BPSO achieves better performance than GA and close to the optimal solution in both low and high traffic periods. We can notice that both algorithms are close to the optimal when the network is more congested. This can be explained, by knowing that during high traffic period, the network needs to keep most of the BSs in AM, hence, optimizing only the association variable (i.e., $\boldsymbol{\epsilon}$). It is also worth to note that optimizing $\boldsymbol{\pi}$ has more weigh in saving energy that optimizing $\boldsymbol{\epsilon}$ due to the high values of offset power parameter β compare to the amplified power parameter α.

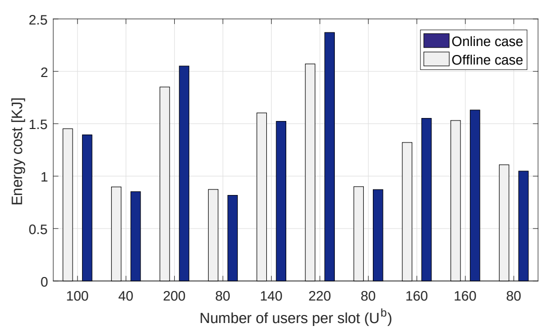

Fig. 4: Comparison between online and offline cases.

Finally, Fig. 4 compares the online case to a benchmark case (i.e., offline case). Fig. 4 plots the total energy cost of the network for both cases versus different numbers of users. Since activating the BSs depends on their battery levels and the traffic status, the offline case can manage the available resources globally and more efficiently. For example, during $b = 7$ (i.e., $U^7 = 80$), the offline case consume more energy by forcing some BSs to be in SM and activate them where the network is more congested, i.e., $U^8 = U^9 = 160$. Although it consumes more energy than the online case, which is around 0.1 kJ, when $b = 7$, the offline case saves more energy, which is around 0.6 kJ, during the next two time slots $b = 8$ and $b = 9$.

VI. Conclusions

In this paper, we proposed a downlink energy harvesting heterogenous networks using hybrid power sources. All the base stations are equipped with a harvested source and can get some energy from green grid or/and traditional grid when needed. We formulated a binary linear optimization problem aiming to minimize the consumed energy over multiple time slots. The problem is solved optimally and compared with two low complexity algorithms. After solving the problem, we investigated, via numerical results, the behavior of the proposed scheme versus various system parameters. Finally, we discussed the effect of sleeping strategy to the system average energy cost.

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