Cooperative Small Cell HetNets with Sleeping and Energy Harvesting

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Abstract— This paper considers a heterogenous network Het-Net where a macro base station (MBS) coexists with many small base stations (SBSs). SBSs can be deactivated and put to sleep to save energy and are equipped with two power sources, harvested energy (HE) source and a power grid source, where first the SBS will use its available HE to serve the associated users. Then, the SBS will request any shortage of its energy from other active or deactivated SBSs which have surplus of HE. Finally, if there is still shortage in energy, the SBS will use the power drawn from the grid. This transfer of energy is facilitated through the use of the promising technology of the smart grid (SG). We investigate the grid energy minimization problem by optimizing both the transmission power and activation/deactivation (Dynamic Sleeping) of the SBSs. Moreover, a decomposition of the problem into a convex optimization problem and users association according to the best SINR is proposed. Then, we derived a closed form of the optimal transmission power and use the IPOPT algorithm to find the Lagrangian variables. The results clearly show the advantages of our model operational strategy.

Index Terms—Energy Efficiency, 5G, Energy Harvesting, Smart Grid, Sleeping strategy.

I. INTRODUCTION

The rapid increase in the wireless access devices is boosting the demands for higher rates and better coverage. However, higher rates require higher energy consumption, hence increasing the CO2 emission caused by the wireless communication networks [1]. Recently, energy harvesting has been considered as one of the promising solutions for sustainable wireless communications. Energy Harvesting (EH) technology converts the ambient energy to electric energy. Such technology can be used in cellular networks to help reduce the carbon footprint of wireless networks [2]. For Example, a solar panel with .6 square meter, can harvest up to 500 watts with conversion efficiency of 14% [3]. Such energy level can sustain the operation of small cells with power management.

On the other hand, the advanced technology of smart grids (SG) made energy cooperation between wireless networks different components feasible. The concept of SG can be regarded as as an electric system that uses information and two-way power flow in an integrated fashion to achieve an efficient and sustainable system [4]. Exploiting such technology could provide enormous opportunities for wireless networks. One approach is by utilizing the SG to transfer harvested energy from on BS to another, with high transfer efficiency.

Several researches have dealt with powering cellular BSs with renewable energy sources. In [5], [6], the authors highlighted the importance of combining renewable energy systems and the smart grid for developing an energy efficient cellular network. In [7], the authors formulated a constrained optimization problem in order to minimize the total cost incurred by the Cellular Networks operators, by harvesting and transferring the energy through the SG. Additionally, the authors of [8]-[10], used the dynamic sleeping to activate and deactivate BSs in order to minimize the energy drawn from the grid. In [9] they formulate an optimization problem for the system, and due to the problem's NP-hardness, they proposed a greedy decomposition to tackle the problem. On the other hand, the authors of [10] considered a model where the small BSs are powered solely by harvested energy, and minimized the grid energy by optimizing the Macro BS active probability and Small BSs transmission power.

However, none of the previous studies considered utilizing the harvesting source of the sleeping Small BSs to reduce the power acquired from the grid. In this work, the deactivated BS will keep harvesting then injecting the energy to the SG to aid other SBSs and increase the network efficiency. Moreover, other SBSs will forward their extra RE into the SG to other SBSs. The goal of this work is to minimize the power driven from the grid by exploiting the harvested energy as much as possible. Therefore, in order to benefit from the RE and minimize the power driven from the grid, our model will push the network to deactivate as many SBSs as possible and utilize the sleeping SBSs in harvesting energy. However, to ensure quality of service, we set a minimum required rate for every user that the network should not violate.

This paper is organized as follows: Section II describes the proposed Energy Harvesting system model. The problem formulation with the proposed decomposition is given in Section III. Section IV discusses the selected numerical results of the simulation. Finally, the paper is concluded in Section V.

II. SYSTEM MODEL

We consider a heterogenous network where a Macro BS (MBS) and several Small BSs (SBSs) co-exist. The MBS is deployed to provide coverage while the SBSs are deployed to provide higher quality of service (QoS) for users. MBS and SBSs operate in different frequency bands e.g., OFDMA, and therefore, there is no interference between them. However, between the SBSs interference is considered, since reusing the available resource provides higher throughput.

Fig.(1) shows the architecture of the network where SBSs are equipped with energy harvesting methods (solar panels for example.) and are serving users under their coverage. Moreover, every SBS is connected to the Smart Grid with a two way connection.

A. Energy Harvesting Model For SBSs

Let f = 1, ..., F denote the set of the SBSs that are randomly distributed in the macro cell coverage area, while



Fig. 1: A network with SBSs powered by renewable energy and connected to a smart grid.

u = 1, ..., U and c = 1, ..., C denote the set of a randomly distributed users covered by the SBSs and the set of available resource blocks in the network, respectively. Moreover, we consider a time slotted system with fixed duration τ , and n = 1, ..., N denote the index of the slot number. Furthermore, every user is assumed to be associated with only one SBS.

The SBSs harvest energy from a renewable source (e.g. wind, solar... etc), where the amount of harvested energy for every SBS f and time slot n is denoted by $hr_f[n]$ and it follows the truncated Gaussian distribution [11]. Moreover, every SBS is equipped with a battery to store its harvested energy with a maximum capacity of B_{max} with battery level at time slot n is B[n]. However, due to the stochastic nature of the energy harvesting, every BS is connected to a nonrenewable energy source to compensate for the renewable energy shortage. In other words, every SBS is set to use the energy from renewable source first, and then request power form the grid. However, the promising technology of Smart grid which allows a two-way flow of power [4], can be used here to transfer the harvested energy between SBSs, i.e., the SBS with surplus harvested energy will transfer it to other SBSs that suffer from renewable energy deficit. Therefor, at the end of every time slot, the SBS will either transfer the surplus of its harvested energy or request energy from other SBSs to compensate its deficit. If the energy surplus of the other SBSs cannot match the energy demand of the SBS with the shortage, then the SBS will request a non-renewable energy from the smart grid directly. Hence, every SBS is equipped with two power sources: the non-renewable power from the grid and the power from the renewable sources. Therefore, the transmission power between user u and BS f using resource block c, during the time slot n is: $p_{fu}^c[n] = p_{fu,g}^c[n] + p_{fu,r}^c[n]$, where $p_{fu,q}^{c}[n]$ is the power drawn from the grid and $p_{fu,r}^{c}[n]$ is the power drawn from the renewable source (including the energy transferred from other SBSs).

Let $\lambda_f[n]$ and $\mu_f[n]$ denote the amount of the harvested energy the BS f is injecting into or receiving from the smart grid at the end of slot n, respectively. The the amount of the harvested energy that is transferred into the smart grid equals the harvested energy that is drawn from the smart grid, where

Table I: List of Notations



 η is the transfer efficiency.

$$\mu_f[n] = \eta \lambda_f[n] \tag{1}$$

Therefore, at time slot i = 1 the battery will be zero, and at the end of every slot i = 1, 2, ...N the battery storage will be the sum of the harvested energy subtracting the transmission power and the transferred energy $0 \le B_f[i] \le B_{max}$, where $B_f[i]$ is defined as:

$$B_f[i] = \sum_{n=2}^{i} hr_f[n] - \sum_{n=1}^{i} \sum_{u=1}^{U} p_{uf,r}^c[n]\tau - \sum_{n=1}^{i} \lambda_f[n] \quad (2)$$

B. User Association and Achievable Rate

Let x_{uf}^c be a binary indicator that is equal to 1 if user u and SBS f are associated using resource block c, or 0 otherwise. Also, let z_{fu} be a binary indicator that is equal to 1 if user u is associated with SBS f, or 0 otherwise. y_f indicates the SBS on/off status, where $y_f = 0$ if the SBS is OFF (where there are no users associated with it), and $y_f = 1$ if the SBS is ON. However, a deactivated SBS will keep harvesting energy and injecting it into the smart grid to serve other active SBSs.

Moreover, the interference at a user u which is associated with SBS f from all other SBSs at a time slot n will be:

$$I_{uf}^{c}[n] = \sum_{j \neq u}^{U} \sum_{i \neq f}^{F} p_{ji}^{c}[n] h_{ui}^{c}[n],$$
(3)

Then, the signal to interference and noise ratio SINR for every user is:

$$\gamma_{uf}^{c}[n] = \frac{p_{uf}^{c}[n]h_{uf}^{c}[n]}{I_{uf}^{c}[n] + \omega N_{0}},$$
(4)

where $h_{uf}^c[n]$ denotes the channel gain from SBS f to user u using resource block c at time slot n, ω is the available bandwidth for every channel, and N_0 is the channel noise spectral density which is assumed to be Additive White Gaussian Noise AWGN, and ωN_0 is the noise variance σ^2 . Thus, the data rate for every user using a single channel will be as follow:

$$R_{uf}^c[n] = \omega \log(1 + \gamma_{uf}^c[n]) \tag{5}$$

and this requires predicting the harvestable energy and channel conditions. 2. Optimization for every slot separately, and this is not globally optimal, but more realistic.

III. PROBLEM FORMULATION

In this section, an optimization problem, which minimizes the non-renewable energy consumption of the transmission power for a cooperative heterogenous network is formulated. First, we formulate a problem where users association, sleeping strategy and energy minimization are performed within a single optimization problem. There are two problems, the first is optimizing over N slots and this requires predicting the harvestable energy and channel conditions, where the second is optimizing for every slot separately, and this is not globally optimal, but more realistic, hence we focus on the second problem in this paper. The problem can be stated as follows: given the number of users and SBSs, the problem will solve the user association, sleeping strategy and power consumption, then at every time slot the optimization problem will recalculate the users association and the transmission power, while not changing the status of the SBSs, this will help simplify the problem since the time slot is relatively very short. However, due to the non-convexity of the problem we present a more tractable and a convex approximation where we decouple the users association and sleeping strategy from the energy minimization.

We can then mathematically state the main optimization problem as below:

Problem \mathcal{F} :

$$\underset{p_{uf}^{c}[n],\lambda_{f}[n],\mu_{f}[n],y_{f},z_{uf},x_{uf}^{c}}{\text{Minimize}} \sum_{f,u,n,c=1}^{F,U,N,C} p_{fu,g}^{c}[n]\tau + \sum_{f=1}^{F} E_{b}y_{f}$$
(6)

subject to

$$\sum_{f}^{F} \sum_{c=1}^{C} x_{fu}^{c} R_{u}^{min} \leq \sum_{f=1}^{F} \sum_{c=1}^{C} x_{fu}^{c} R_{fu}^{c} [n], \qquad \forall u, \forall n \ (7)$$

$$\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu,r}^{c}[n]\tau \le B_{f}[n-1] + \mu_{f}[n], \qquad \forall f, \forall n, (8)$$

$$B_f[n] \le B_{max} \qquad \qquad \forall f, \forall n, \ (9)$$

$$\mu_f[n] = \eta \lambda_f[n] \qquad \qquad \forall f, \forall n, \ (10)$$

$$\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \le P_{f}^{max} \qquad \forall f, \forall n, (11)$$

$$\sum_{u=1}^{U} x_{fu}^c \le 1 \qquad \qquad \forall f, \forall c, (12)$$

$$\sum_{f=1}^{F} z_{uf} = 1, \qquad \qquad \forall u, \ (13)$$

$$\frac{\sum_{c=1}^{C} x_{uf}^c}{\# of Us} \le z_{uf} \le \sum_{c=1}^{C} x_{uf}^c, \qquad \forall f, \forall u, (14)$$

$$\frac{\sum_{u=1}^{U} z_{uf}}{\# of SBSs} \le y_f \le \sum_{u=1}^{U} z_{uf}, \qquad \forall f, (15)$$

Constraint (7) represents the QoS for every user. The constraints from (8) to (11) are dealing with energy transfer and cooperation between SBSs, while constraints from (12) to (15) are dealing with the users association and SBSs sleeping strategy. Constraint (8) represents the energy consumption causality where the BS cannot use energy more than what is available. Constraint (9) limits the battery capacity. Constraint (10) is for energy conservation, where the total injected energy into the smart grid equals the total received energy by all BSs. Constraint (11) limits the maximum allowed transmission power for every BS.

Constraint (13) represents the users' association with the FBSs, where every user is associated with a single FBS and no user is allowed to associate with more than that. Constraint (14) evaluates z_{uf} , where if there is at least one user u that is associated with the SBS f, then z_{uf} is one, or zero otherwise. Similarly, constraint (15) captures the sleeping strategy of the variable y_f , where if there is at least one user associated with the FBS f then this FBS is kept on, otherwise it will be turned off.

However, due to the coupling of the user associations and sleeping strategy with energy harvesting, the above problem is clearly intractable and difficult to solve. Since we have three binary variables $(y_f, z_{fu}, \text{ and } x_{fu}^c)$ with four different indices (f, u, and c), the time needed to find the optimal solution will increase exponentially as the network size increases linearly. This is due to the fact that the problem is a Mixed Integer NonLinear problem (MINLP), for which there is no efficient algorithm for solving it. Therefore, we present an approximation (Γ), where we decouple the users association and sleeping strategy from the rest of the problem, and perform the users' association according to the highest SINR for all users. Thus, the rest of the problem will be a convex optimization problem as follow:

Problem Γ :

$$\begin{array}{l} \underset{p_{uf}[n],\lambda_{f}[n],\mu_{f}[n]}{\text{Minimize}} \sum_{f=1}^{F} \sum_{n=1}^{N} \sum_{u=1}^{U} p_{fu,g}^{c}[n]\tau + E_{b}y_{f} \\ \text{subject to} \\ \sum_{f}^{F} \sum_{c=1}^{C} x_{fu}^{c} R_{u}^{min} \leq \sum_{f=1}^{F} \sum_{c=1}^{C} x_{fu}^{c} \tilde{R}_{fu}^{c}[n], \\ (8) - (11) \end{array} \qquad \forall u, \forall n \\ \end{array}$$

where $\tilde{R}_{fu}^{c}[n] = \omega \log(1 + \frac{p_{uf}^{c}[n]h_{uf}^{c}[n]}{\sigma^{2}})$ The problem (Γ) is convex, since the objective function (16)

The problem (1) is convex, since the objective function (16) is linear and all the constraints are convex [12]. Therefore, we can use the lagrangian to obtain the optimal solution of (16). The Lagrangian of (16) is given in (17), where $\alpha_u[n], \rho_f[n], \zeta_f[n], \xi_f[n], \beta_f[n]$ are the lagrangian multipliers.

(16)

The Karush-Kuhn-Tucker (KKT) conditions for problem (Γ) is as follows:

$$\mathcal{L} = \sum_{f,n,u,c=1}^{F,N,U,C} p_{fu,g}^{c}[n]\tau + \sum_{f=1}^{F} E_{b}y_{f} + \sum_{u=1}^{U} \sum_{n=1}^{N} \alpha_{u}[n] \bigg[-\sum_{f=1}^{F} \sum_{c=1}^{C} R_{fu}^{c}[n] + \sum_{f}^{F} x_{fu}^{c} R^{min} \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \rho_{f}[n] \bigg[B_{f}[n] - B_{max} \bigg] + \sum_{f,n=1}^{F} \sum_{u,c=1}^{N} \zeta_{f}[n] \bigg[\sum_{u,c=1}^{U,C} p_{fu,r}^{c}[n]\tau - B_{f}[n-1] - \mu_{f}[n] \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \xi_{f}[n] \bigg[\mu_{f}[n] - \eta\lambda_{f}[n] \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] - P_{f}^{max} \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] - P_{f}^{max} \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] - P_{f}^{max} \bigg] \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] - P_{f}^{max} \bigg] \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] - P_{f}^{max} \bigg] \bigg] \bigg] + \sum_{f=1}^{F} \sum_{n=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} p_{fu}^{c}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{C} \beta_{f}[n] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{F} \sum_{c=1}^{T} \sum_{u=1}^{N} \beta_{f}[n] \bigg[\sum_{u=1}^{U} \sum_{c=1}^{T} \beta_{f}[n] \bigg] \bigg] \bigg] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{c=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{u=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{u=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{u=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{u=1}^{T} \beta_{f}[n] \bigg[\sum_{u=1}^{T} \sum_{u=1}^{T$$

$$\frac{\partial \mathcal{L}}{\partial p_{fu,g}^{c}[n]} = \tau - \alpha_{f}[n] \Big[\frac{\omega h_{fu}^{c}[n]}{\sigma^{2} + p_{fu}^{c}[n] h_{fu}^{c}[n]} \Big] + \beta_{f}[n] = 0$$
$$\forall f, \forall u, \forall c, \forall n$$

(18)

$$\frac{\partial \mathcal{L}}{\partial p_{f_{u,r}}^c[n]} = -\alpha_f[n] \Big[\frac{\omega h_{f_u}^c[n]}{\sigma^2 + p_{f_u}^c[n] h_{f_u}^c[n]} \Big] - \rho_f[n] \tau$$
(19)
+ $\zeta_f[n] [\tau - (n-1)\tau] + \beta_f[n] = 0 \quad \forall f, \forall u, \forall c, \forall n$

$$\frac{\partial \mathcal{L}}{\partial \lambda_f[n]} = -\rho_f[n] + \zeta_f[n] - \eta \xi_f[n] = 0 \qquad \forall f, \forall n \quad (20)$$

$$\frac{\partial \mathcal{L}}{\partial \mu_f[n]} = -\zeta_f[n] + \xi_f[n] = 0 \qquad \forall f, \forall n \ (21)$$

Using (18)-(19), the closed form expressions for the transmission power can be obtained as follows:

$$p_{fu,g}^{c*}[n] = \frac{\alpha_u[n]\omega ln2}{(\tau + \beta_f[n])} - \frac{\sigma^2}{h_{fu}^c[n]} - p_{fu,r}^c[n]$$
(22)

$$p_{fu,r}^{c*}[n] = \frac{\alpha_u[n]\omega ln2}{\tau(\zeta_f[n](n-1) - \rho_f[n]) + \beta_f[n]} - \frac{\sigma^2}{h_{fu}^c[n]} - p_{fu,g}^c[n]$$
(23)

Note that the optimal powers are functions of the Lagrangian multipliers. To find the optimal Lagrangian multipliers, the Interior Point Algorithm for Large Scale Nonlinear Programming, Interior Point OPTimization (IPOPT) was used [13].

IV. SIMULATION RESULTS

In this section, simulation results are provided to demonstrate the performance of the proposed model in Fig.1. In all simulations (unless stated otherwise.), the time slot duration is set to 100 ms (i.e., $\tau = 100ms$). The available bandwidth $\omega = 5MHz$, the maximum transmission power $p_{max} = 1watt$ and the noise spectral density is $N_0 = 10^{-16}W/Hz$. The energy transfer efficiency $\eta = 0.9$. The initial battery level are set to zeros, while the battery sizes $B_{max} = 6J$. The harvested energy levels are given by a truncated normal distribution with a mean equal to 0.2 and standard deviation is 0.007, the truncated normal distribution is set to have values higher than 0.001 [14].

In Fig.2, we compare the solution of the main problem (\mathcal{F}) as the optimal solution to our proposed approach for (Γ) and to a noncooperative approach (where the deactivated SBSs harvest no energy). In this simulation we have 6 SBSs with

15 users and N = 4. From the figure we can see that using sleeping SBSs to harvest energy and transfer it to other SBSs provide better performance than the noncooperative approach. On the other hand, our approximated approach performs close to the optimal solution of \mathcal{F} . While the optimal took longer times (hours) the approximated approach took much shorter time (seconds). However, for $R_{min} \geq 1Mbps$ the optimal approach performed better since it was able to turn off an extra SBS. However, as the R_{min} increases, the performance of the approximate approach is keeping up with the optimal while the noncooperative approach is increasing fast.



Fig. 2: Comparing the Optimal with The Approximation.

In Fig.3, we investigate the effect of the η parameter and the increase in the R_{min} on the amount of power used from both sources (P_r and P_a). In this simulation we used 10 SBSs (where the optimization problem turned off one of them is used to harvest energy) and 30 users while N = 4. As the results show, for $\eta = 0.9$, the network will rely solely on P_r until the R_{min} reaches 1.3Mbps then we see that the P_q start increasing to provide the necessary power to match the increase of users demands. A similar pattern happens in both $\eta = 0.5$ and $\eta = 0.65$, with lower R_{min} required to trigger the use of power from the grid (P_a) . This is understandable since the lower the efficiency means the lower the energy transferred between SBSs in the network. On the other hand, for lower minimum rate $(R_{min} > 1Mbps)$, P_r for the three scenarios are very close to each other, despite the difference in efficiencies, this is due to the fact that for lower rate almost all SBSs are using their harvested energy and not receiving or transferring it through the network where the η factor will come into effect.



Fig. 3: The Minimum Rate Compared to the Efficiency.

Fig.4 shows the effect of increasing the number of BSs and the number of users on the amount of injected energy λ . As in the figure, we have two trends. First, the increasing number of SBSs will increase the amount of injected energy (λ) into the network. Second, as the number of users in the network increases λ decreases until it becomes almost zero. This can be explained as the number of users increases, the active SBSs will have no energy left to inject into the network, and only the deactivated SBSs that will be injecting energy into the network.



Fig. 4: Number of OFF BSs to the Amount of Injected Energy vs. the Smart Grid.

V. CONCLUSIONS

In this paper, energy harvesting in cooperative SBSs heterogenous networks with dynamic sleeping strategy was investigated, where the deactivated SBSs are cooperating with the rest of the network by harvesting then injecting the energy to the network. Each of the SBSs is equipped with a harvesting device and a finite battery to store the HE. We formulated an optimization problem aiming at minimizing the transmission power driven from the grid under user QoS constraints. Moreover, we proposed a decomposition of the problem into a convex optimization problem and users association according to the best SINR. Then, we calculated the closed form of the optimal transmission power and used the IPOPT algorithm to find the Lagrangian variables. Finally, the results showed the performance superiority over the case with the deactivated SBSs not cooperating with the other active SBSs in harvesting the energy. Additionally, the results showed the benefit of densifying the network of more SBSs, where they will cooperate in adding more HE.

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