Cooperative Small Cell HetNets With Dynamic Sleeping and Energy Harvesting

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***Abstract*—This paper considers a heterogenous wireless cellular network (HetNet) where many small base stations (SBS) coexist. SBSs can be deactivated and put to sleep to save energy and are equipped with two power sources, harvested energy (HE) and a grid power source, where an SBS will use its available HE to serve the associated users first. Then, the SBS will request any shortage of its energy from other active or deactivated SBSs that have a surplus of HE. Finally, if there is still an energy shortage, the SBS will use power drawn from the grid. This transfer of energy is facilitated through the use of the promising smart grid (SG)technology. We investigate the grid energy minimization problem by optimizing both the transmission power and activation/deactivation (dynamic sleeping) of the SBSs. However, since the formulated problem is a mixed integer nonLinear problem (MINLP), generalized Benders decomposition (GBD) is used to decompose the problem into two subproblems: user association and energy harvesting which are solved iteratively. Further, a new heuristic approach is proposed that provides a computationally efficient algorithm to solve and optimize the user association and energy harvesting problems of the system model. This approach uses network centrality to develop a measuring parameter, base station centrality (BSC), of SBS centrality in the network. BSC is presented to mark the SBSs that have the most potential to be deactivated without affecting the quality of service (QoS) of users. Finally, extensive simulations are performed to verify the superiority of the proposed BSC-based strategy over GBD in terms of operational cost.**

***Index Terms*—Energy efficiency, 5G, energy harvesting, smart grid, dynamic sleeping, generalized benders decomposition, network centrality.**

I. Introduction

THE RAPID increase in wireless users equipment (UEs) is boosting demand for higher data rates and better coverage. However, higher data rates require higher energy consumption, which increases the CO2 emission caused by the wireless communication networks in addition to increasing the operational cost (OPEX) [1]. Recently, energy harvesting has been considered one of the promising solutions for sustainable wireless communications. Energy Harvesting technology converts ambient energy to electric energy. Such technology can be used in cellular networks to help reduce OPEX and the carbon footprint of wireless networks [2]. For example, a solar panel with an area of 0.6 m^2 can harvest up to 500 W with a 14% conversion efficiency [3], an energy level can sustain the operation of SBSs through power management.

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

Several researches have dealt with powering cellular BSs with renewable energy sources. In [5] and [3] the authors highlighted the importance of combining renewable energy systems and SG to develop energy-efficient wireless networks. In [6] the authors formulated a constrained optimization problem to minimize the total cost incurred by cellular networks operators by harvesting and transferring energy through SG. Additionally, the authors of [7]–[10] used dynamic sleeping to activate and deactivate BSs to minimize the energy drawn from the grid. In [8] the authors formulated 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 [9] considered a model where SBSs are powered solely by HE and grid energy is optimized by Macro Base Station (MBS) active probability and SBS transmission power. In [10] the authors considered a cognitive radio (CR) system and formulated a constrained optimization problem to maximize throughput by optimizing the power allocation from the renewable energy and SG.

The authors in [12] considered the stochastic process of energy harvesting of the remote radio heads (RRHs) to develop an online resource allocation algorithm, which maximized user utility while ensuring the sustainability of each RRH in cloud-RANs.

However, none of the previous studies considered utilizing the harvesting source of deactivated SBSs to reduce the power acquired from the grid. In this work, deactivated SBSs will keep harvesting and injecting the energy into the SG to aid other SBSs and increase the network efficiency. Moreover, other SBSs will forward their extra HE into the SG to other SBSs. The goal of this work is to minimize the power driven from SG by exploiting HE as much as possible. Therefore, in

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order to benefit from the HE 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 QoS, we set a minimum required rate for every user that the network should not violate. The main contributions of this work are as follows:

1) We formulated an optimization problem to minimize the energy driven from the network by utilizing HE and dynamic sleeping of SBSs. The problem is formulated such that it drives the network to deactivate as many SBSs as possible to minimize their energy consumption and to benefit from their harvesting capability.
2) The formulated problem is MINLP which is NP-hard, so we decomposed the problem into two subproblems: a convex nonlinear problem for solving the continuous variables of the harvesting energy and a mixed integer linear problem (MILP) for solving the user association and dynamic sleeping. Then we used GBD algorithm to solve the two subproblems iteratively for an optimal solution.
3) We proposed a new computationally efficient algorithm (BSC) which is based on network centrality to solve and optimize the dynamic sleeping, user association, and energy harvesting of the system model.
4) Finally, we supported our proposed algorithm with extensive simulations to verify its superiority over the GBD in terms of operational cost.

This paper is an extension of [11] with the following are extensions made to the conference paper:

1) The original optimization problem is decomposed into two subproblems: a convex nonlinear problem and a mixed integer linear problem (MILP), where the GBD algorithm is used to solve the two subproblems iteratively for an optimal solution.
2) The BSC algorithm, which is to solve the dynamic sleeping, user association and energy harvesting of the system model is introduced to overcome the optimal solution complexity.
3) The results are reproduced with different scenarios covering the differences between the optimal algorithm and GBD and the proposed solution. Also, larger network topology is used to represent more realistic situations.

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. In Section IV user association and dynamic sleeping is proposed using centrality analysis. Section V discusses selected numerical results of the simulation. Finally, the paper is concluded in Section VI.

II. System Model

This paper considers HetNets where several SBSs co-exist in a designated area. The deployment of SBSs is a promising solution to provide higher QoS for users. However, between the SBSs interference is considered, since the SBSs are deployed in a densed environment and the reusing the available resource provides higher throughput.

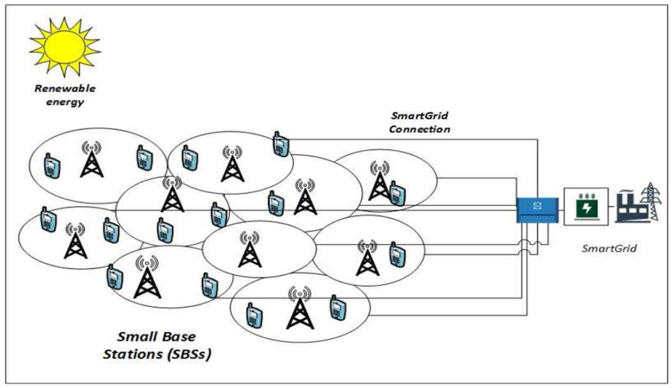

Fig. 1. A network with SBSs powered by renewable energy and connected to the SG.

Fig. 1 shows the architecture of the network where SBSs are equipped with EH technology (e.g., solar panels); each SBS serves UEs under its coverage; and every SBS is connected to the SG with a two-way connection.

A. Energy Harvesting Model For SBSs

Let $f = 1, \ldots, F$ denote the set of the SBSs that are randomly distributed in the macro cell coverage area of $\mathbb{A}$, while $u = 1, \ldots, U$ and $c = 1, \ldots, C$ denote the set of a randomly distributed users covered by the SBSs and the set of available resource blocks in the network, respectively. We consider a time slotted system with fixed duration τ; $n = 1, \ldots, N$ denotes the index of the slot number; and every UE is assumed to be associated with only one SBS.

Every SBS is equipped with two power sources: non-renewable power from SG and power from renewable sources (e.g., wind, solar). The SBSs harvest energy from a renewable source, where the amount of HE for every SBS f and time slot n is denoted by $hr_f[n]$ and it follows normal distribution. Normal Distribution is used as a distribution of the average harvested energy levels by invoking the central limit theorem, where the sum of a large number of independent and identically distributed (i.i.d) variables asymptotically becomes a normal distribution. However, since the harvested energy cannot have negative values we omitted values below certain levels [16].

Every SBS is equipped with a battery to store its HE with a maximum capacity of B_{max} where battery level at time slot n is $B[n]$. However, due to the stochastic nature of energy harvesting, every SBS is connected to a non-renewable energy source to compensate for any renewable energy shortage. In other words, every SBS is set to use the energy from a renewable source first and then request power form the grid. However, because SG technology allows a two-way flow of power [4], it can be used here to transfer HE between SBSs. In other words the SBS with surplus HE will transfer it to other SBSs that suffer from renewable energy deficits. Therefore, at the end of every time slot, an 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

TABLE I
LIST OF NOTATIONS USED THROUGHOUT THE PAPER

Notation	Description
f	SBS index.
u	User index.
c	Resource block index.
n	Time slot index.
τ	Duration time of every slot.
B_{max}	Maximum battery capacity.
$p_{fu}^c[n]$	Transmission power from f to u by c.
$B_f[n]$	Battery level of SBS f during slot n.
$\lambda_f[n]$	Injected energy into the SG by f during n.
$hr_f[n]$	HE for every SBS during n.
$\mu_f[n]$	Drawn energy from the SG by f during n.
$\lvert h_{fu}^c[n]\rvert$	Channel gain between f and u by c during n.
η	The transfer efficiency of the SG.
ν_f	Indicates if all users associated with SBS f are offloadable.
ϕ_f	The total number of SBSs that f can offload its associated users to them.
x_{fu}^c	The binary association between f and u through c.
y_f	The SBS f ON/OFF status.
ω	Available bandwidth for every channel.
E_b	The energy consumption of the SBS basic circuit.

the shortage, then the SBS will request non-renewable energy from the smart grid directly. 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 $p_{fu,g}^c[n]$ is the power drawn from the grid and $p_{fu,r}^c[n]$ is the power drawn from the renewable source including HE transferred from other SBSs.

Let $\lambda_f[n]$ and $\mu_f[n]$ denote the amount of HE the BS f is injecting into or receiving from SG at the end of slot n, respectively. Then 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 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 $i = 1, 2, \ldots, N$ the battery storage will be the sum of the harvested energy subtracting the transmission power and the transferred energy $0 \leq B_f[i] \leq B_{max}$, where $B_f[i]$ is defined as:

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

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 sleeping SBS will keep harvesting energy and injecting it into the smart grid to serve other active SBSs.

The time-varying distance between the fth SBS and the uth user can be expressed as follows:

$$d_{uf}[n] = \left\|\tilde{l}_u[n] - l_f\right\| \quad \forall u \in U, \quad \forall f \in F \tag{3}$$

where the $\tilde{l}_u[n]$ and l_f are the $x - y$ coordinates for the predicted location of the user at time slot n, and the fixed location of the SBS, respectively. It follows from (3) that the channel power gain can be modeled as:

$$|h_{uf}^c[n]|^2 = \frac{\beta_0}{d_{uf}^{\alpha}[n]} = \frac{\beta_0}{\left\|\tilde{l}_u[n] - l_f\right\|^{\alpha}} \tag{4}$$

where β_0 denotes the channel gain at the reference distance of $d_0 = 1$m, and α is the path loss exponent.

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

$$I_{uf}^c[n] = \sum_{j \neq u}^{U}\sum_{i \neq f}^{F} p_{ji}^c[n]|h_{ui}^c[n]|^2, \tag{5}$$

then, the signal to interference and noise ratio (SINR) for every user is:

$$\gamma_{uf}^c[n] = \frac{p_{uf}^c[n]\left|h_{uf}^c[n]\right|^2}{I_{uf}^c[n] + \omega N_0}, \tag{6}$$

where 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:

$$R_{uf}^c[n] = \omega \log\Big(1 + \gamma_{uf}^c[n]\Big) \tag{7}$$

Equation is a lower bound on the capacity that can be asymptotically approached by using long channel codes and treating interference as noise. Selecting an exact coding and modulation technique is out of the scope of this paper, but we implicitly assume that a technique that can approximately achieve (7) is being used.

III. PROBLEM FORMULATION

In this section, an optimization problem that minimizes the non-renewable energy consumption of the transmission power for a cooperative HetNets 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 HE 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 $\mathcal{F}$:

$$\underset{p_{uf}^c[n],\lambda_f[n],\mu_f[n],y_f,z_{uf},x_{uf}^c}{\text{Minimize}} \sum_{f,u,n,c=1}^{F,U,N,C} p_{fu,g}^c[n]\tau + \sum_{f=1}^{F} E_b y_f \tag{8}$$

$$\text{subject to} \quad \sum_{f}^{F}\sum_{c=1}^{C} x_{fu}^c R_u^{min} \leq \sum_{f=1}^{F}\sum_{c=1}^{C} x_{fu}^c R_{fu}^c[n], \quad \forall u, \forall n \tag{9}$$

$$\sum_{u=1}^{U}\sum_{c=1}^{C} p_{fu,r}^c[n]\tau \leq B_f[n-1] + \mu_f[n], \quad \forall f, \forall n, \tag{10}$$

$$B_f[n] \leq B_{max} \quad \forall f, \forall n, \tag{11}$$

$$\sum_{f=1}^{F}\sum_{i=1}^{n} \mu_f[i] = \sum_{f=1}^{F}\sum_{i=1}^{n} \eta\lambda_f[i] \quad \forall n, \tag{12}$$

$$\sum_{u=1}^{U}\sum_{c=1}^{C} p_{fu}^c[n] \leq P_f^{max} \quad \forall f, \forall n, \tag{13}$$

$$\sum_{u=1}^{U} x_{fu}^c \leq 1 \quad \forall f, \forall c, \tag{14}$$

$$\sum_{f=1}^{F} z_{uf} = 1, \quad \forall u, \tag{15}$$

$$\frac{\sum_{c=1}^{C} x_{uf}^c}{\#ofUs} \leq z_{uf} \leq \sum_{c=1}^{C} x_{uf}^c, \quad \forall f, \forall u, \tag{16}$$

$$\frac{\sum_{u=1}^{U} z_{uf}}{\#ofSBSs} \leq y_f \leq \sum_{u=1}^{U} z_{uf}, \quad \forall f, \tag{17}$$

Constraint (9) represents the QoS for every user. The constraints from (10) through (13) are dealing with energy transfer and cooperation between SBSs, while constraints from (14) through (17) are dealing with the users association and SBSs sleeping strategy. Constraint (10) represents the energy consumption causality where the SBS cannot use energy more than what is available. Constraint (11) limits the battery capacity. Constraint (12) is for energy conservation, where the total injected energy into the smart grid equals the total received energy by all SBSs. Constraint (13) limits the maximum allowed transmission power for every SBS.

A. Generalized Bender Decomposition

Due to the coupling of the users associations and the sleeping strategy with energy harvesting, the above problem is clearly intractable. Since we have three binary variables (y_f, z_{fu}, 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 because the problem is MINLP has no efficient algorithm for solving it. Therefore, we propose a decomposition approach where problem ($\mathcal{F}$) is decomposed into two subproblems, the first subproblem includes the integer variables, while the second problem contains the continuous variables.

Generalized Benders Decomposition (GBD) is a well-known method for solving mathematical programming problems with MINLP [13]. GBD is a generalization of the Benders decomposition [14] to include a broader class of problems which can be nonlinear. The duality theory for nonlinear convex problems is exploited to derive the cuts corresponding to those in the original Benders Decomposition. However, GBD requires the optimization problem to be a convex nonlinear problem, which is not the case for problem ($\mathcal{F}$). Hence, ($\mathcal{F}$) is nonconvex problem due to constraint (9), where the SINR inside the log will cause the constraint to be nonconvex.

B. Linearizing QoS Constraint

In this section we derived a concave lower bound of constraint (9) using the first order Taylor series to transfer problem ($\mathcal{F}$) to the standard form in GBD. Therefore, constraint (18) can be written as:

$$\begin{aligned} R_{uf}^c[n] &= \omega\log\left(1 + \frac{p_{uf}^c[n]|h_{uf}^c[n]|^2}{\sum_{j\neq u}^{U}\sum_{i\neq f}^{F} p_{ji}^c[n]|h_{ui}^c[n]|^2 + \omega N_0}\right) \\ &= \omega\log\left(\sum_{u}^{U}\sum_{f}^{F} p_{uf}^c[n]|h_{uf}^c[n]|^2 + \omega N_0\right) \\ &\quad - \omega log\left(\sum_{j\neq u}^{U}\sum_{i\neq f}^{F} p_{ji}^c[n]|h_{ui}^c[n]|^2 + \omega N_0\right) \\ &\geq \omega\log\left(\sum_{u}^{U}\sum_{f}^{F} p_{uf}^c[n]\left|h_{uf}^c[n]\right|^2 + \omega N_0\right) - \hat{R}_{Ty} \end{aligned} \tag{18}$$

where $\hat{R}_{Ty}$ is the first-order Taylor approximation around point ($p_{0ji}^c[n]$), and is as follows:

$$\begin{aligned} \hat{R}_{Ty} &\triangleq \omega log\left(\sum_{j\neq u}^{U}\sum_{i\neq f}^{F} p_{0ji}^c[n]|h_{ui}^c[n]|^2 + \omega N_0\right) \\ &\quad + \sum_{j\neq u}^{U}\sum_{i\neq f}^{F} \frac{\left|h_{ui}^c[n]\right|^2}{ln(2)p_{0ji}^c[n]\left|h_{ui}^c[n]\right|^2 + \omega N_0} \\ &\quad \times \left(p_{ji}^c[n] - p_{0ji}^c[n]\right) \end{aligned} \tag{19}$$

Hence, the approximated concave lower bound of equation (18) will be as follows:

$$\hat{R}_{uf}^c[n] \triangleq \omega\log\left(\sum_{u}^{U}\sum_{f}^{F} p_{uf}^c[n]\left|h_{uf}^c[n]\right|^2 + \omega N_0\right) - \hat{R}_{Ty} \tag{20}$$

Thus, replacing (18) by its approximated concave lower bound $\hat{R}_{uf}^c[n]$ will transfer problem ($\mathcal{F}$) into a convex MINLP, which can be rewritten as follows:

Problem $\mathcal{P}$:

$$\underset{p^c_{uf}[n],\lambda_f[n],\mu_f[n],y_f,z_{uf},x^c_{uf}}{\text{Minimize}} \sum_{f,u,n,c=1}^{F,U,N,C} p^c_{fu,g}[n]\tau + \sum_{f=1}^{F} E_b y_f$$
$$\text{subject to} \quad \sum_{f}^{F}\sum_{c=1}^{C} x^c_{fu} R^{min}_u \leq \sum_{f=1}^{F}\sum_{c=1}^{C} x^c_{fu}\hat{R}^c_{uf}[n], \quad \forall u, \forall n \quad (10)-(17). \tag{21}$$

C. Derivation of the Primal Problem

The problem ($\mathcal{P}$) now falls into the standard forms of GBD problem form, where the problem has two sets for variables. The first is the binary variables (y_f, z_{fu}, and x^c_{fu}) that can be considered as the complicating variables and the second set is the continuous variables ($p^c_{uf}[n], \lambda_f[n], \mu_f[n]$). Therefore, it is much easier to solve problem ($\mathcal{P}$) when the binary variables are fixed. In fact, fixing the binary variables means that problem ($\mathcal{P}$) becomes a convex optimization problem that can be solved efficiently using the Lagrangian method. Consequently, the problem is decomposed into two subproblems, the primal problem and the master problem. The primal problem is a convex nonlinear optimization problem and is formulated as follows:

Problem $\mathcal{L}$:

$$\underset{p^c_{uf}[n],\lambda_f[n],\mu_f[n],}{\text{Minimize}} \quad \mathbb{S} = \sum_{f,u,n,c=1}^{F,U,N,C} p^c_{fu,g}[n]\tau + \sum_{f=1}^{F} E_b \bar{y}_f$$
$$\text{subject to} \quad (10)-(13),\ (20)$$

The goal of solving the primal problem is to find an upper bound for the solution given by Algorithm 1. The problem ($\mathcal{L}$) is convex, since the objective function is linear and all the constraints are convex [17] (Note: the second part of the objective function is constant and has no effect on the final solution.) Therefore, problem ($\mathcal{L}$) can be solved using the Lagrangian to obtain the optimal solution. Hence, the Lagrangian of ($\mathcal{L}$) is given in (22), shown at the bottom of the page, where $[\alpha_u[n], \rho_f[n], \zeta_f[n], \xi_f[n], \beta_f[n]]$ are the Lagrangian multipliers.

D. Derivation of the Master Problem

The master problem is derived by fixing all continuous variables and solving the problem with only the binary variables $\mathbb{Z} = [y_f, z_{fu}, x^c_{fu}]$. Thus, the master problem will be a pure binary optimization problem. The master problem goal is to find the lower bound solution of Algorithm (1). Hence, the master problem can be formulated as follows:

Problem $\mathcal{M}$:

$$\underset{y_f,z_{uf},x^c_{uf}}{\text{Minimize}} \quad \nu \tag{24}$$
$$\Gamma\big(\alpha_u[n], \rho_f[n], \zeta_f[n], \xi[n], \beta_f[n]\big) \leq \nu$$
$$\forall \alpha_u[n], \rho_f[n], \zeta_f[n], \xi[n], \beta_f[n] \geq 0, \quad \forall u \in U, \ \forall f \in F,\ \forall n \in N \tag{25}$$
$$\hat{\Gamma}\Big(\hat{\alpha}_u[n], \hat{\rho}_f[n], \hat{\zeta}_f[n], \hat{\xi}[n], \hat{\beta}_f[n]\Big) \leq 0$$
$$\forall \hat{\alpha}_u[n], \hat{\rho}_f[n], \hat{\zeta}_f[n], \hat{\xi}[n], \hat{\beta}_f[n] \geq 0,\ \forall u \in U,\ \forall f \in F,\ \forall n \in N\ (14)-(17) \tag{26}$$

The master problem uses Lagrange equation (22) that is associated with the primal problem to get a lower bound for the solution of Algorithm (1). However, when the solution of the primal problem is not feasible, Algorithm 1 uses Lagrange multipliers for the feasibility problem instead.

$$\begin{aligned}\Gamma\big(\alpha_u[n], \rho_f[n], \zeta_f[n], \xi[n], \beta_f[n]\big) = &\sum_{f,n,u,c=1}^{F,N,U,C} p^c_{fu,g}[n]\tau + \sum_{f=1}^{F} E_b y_f + \sum_{u=1}^{U}\sum_{n=1}^{N}\alpha_u[n]\left[-\sum_{f=1}^{F}\sum_{c=1}^{C}\hat{R}^c_{fu}[n] + \sum_{f}^{F} x^c_{fu}R^{min}\right]\\ &+\sum_{f=1}^{F}\sum_{n=1}^{N}\rho_f[n]\big[B_f[n]-B_{max}\big] + \sum_{f,n=1}^{F,N}\zeta_f[n]\left[\sum_{u,c=1}^{U,C} p^c_{fu,r}[n]\tau - B_f[n-1]-\mu_f[n]\right]\\ &+\sum_{n=1}^{N}\xi[n]\left[\sum_{f=1}^{F}\sum_{i=1}^{n}\mu_f[n] - \sum_{f=1}^{F}\sum_{i=1}^{n}\eta\lambda_f[n]\right] + \sum_{f=1}^{F}\sum_{n=1}^{N}\beta_f[n]\left[\sum_{u=1}^{U}\sum_{c=1}^{C}p^c_{fu}[n] - P^{max}_f\right]\end{aligned} \tag{22}$$

$$\begin{aligned}\hat{\Gamma}\Big(\hat{\alpha}_u[n], \hat{\rho}_f[n], \hat{\zeta}_f[n], \hat{\xi}[n], \hat{\beta}_f[n]\Big) = &\sum_{u=1}^{U}\sum_{n=1}^{N}\hat{\alpha}_u[n]\left[-\sum_{f=1}^{F}\sum_{c=1}^{C}\hat{R}^c_{fu}[n] + \sum_{f}^{F} x^c_{fu}R^{min}\right] + \sum_{f=1}^{F}\sum_{n=1}^{N}\hat{\rho}_f[n]\big[B_f[n]-B_{max}\big]\\ &+\sum_{f,n=1}^{F,N}\hat{\zeta}_f[n]\left[\sum_{u,c=1}^{U,C} p^c_{fu,r}[n]\tau - B_f[n-1]-\mu_f[n]\right]\\ &+\sum_{n=1}^{N}\hat{\xi}[n]\left[\sum_{f=1}^{F}\sum_{i=1}^{n}\mu_f[n] - \sum_{f=1}^{F}\sum_{i=1}^{n}\eta\lambda_f[n]\right] + \sum_{f=1}^{F}\sum_{n=1}^{N}\hat{\beta}_f[n]\left[\sum_{u=1}^{U}\sum_{c=1}^{C}p^c_{fu}[n] - P^{max}_f\right]\end{aligned} \tag{23}$$

Algorithm 1 Generalized Bender Decomposition

1: Input: f; u; n; c; $h_{fu}^{c}[n]$; $hr_f[n]$; R_{min}; P_{max}; ωN_0; ϵ
2: Initialize: y_f^0; x_{fu}^{0c}; z_{fu}^0; $i=0$; $UB=\infty$; $LB=-\infty$; $\Delta=\infty$
3: **while** $\Delta \geq 1$ **do**
4: Solve the primal NLP problem [$\mathcal{L}$] and let the solution be: $\bar{\mathbb{T}}^{[k]} = [\bar{p}_{uf}^{c}[n]^{[k]}, \bar{\lambda}_f[n]^{[k]}, \bar{\mu}_f[n]^{[k]}]$ and the multipliers: $\bar{\mathbb{Q}}^{[k]} = [\bar{\alpha}_u[n]^{[k]}, \bar{\rho}_f[n]^{[k]}, \bar{\zeta}_f[n]^{[k]}, \bar{\xi}[n]^{[k]}, \bar{\beta}_f[n]^{[k]}]$
5: Set $UB = \bar{\mathbb{S}}^{[k]}$
6: **if** $\bar{\mathbb{T}}^{[k]}$ is feasible **then**
7: **if** $UB - LB \leq \epsilon$ **then**
8: $\mathbb{T}^* := \bar{\mathbb{T}}^{[k]}$
9: $\mathbb{Q}^* := \bar{\mathbb{Q}}^{[k]}$
10: **else**
11: $k = k+1$
12: **end if**
13: **else**
14: Solve the feasibility problem and find the lagrangian multipliers $\hat{\mathbb{Q}}^{[l]}$
15: $l = l+1$
16: **end if**
17: Solve the Master MIP problem [$\mathcal{M}$] and let the solution be: $\bar{\mathbb{Z}}^{[k]} = [\bar{y}_f^{[k]}, \bar{z}_{fu}^{[k]}, \bar{x}_{fu}^{c[k]}]$
18: Set $LB = \bar{\mu}^{[k]}$
19: **if** $UB - LB \leq \epsilon$ **then**
20: $\mathbb{Z}^* := \bar{\mathbb{Z}}^{[k]}$
21: $\Delta = 0$
22: **else**
23: Go to step 4
24: **end if**
25: **end while**
26: Output: $\mathbb{T}^*, \mathbb{Z}^*$

feasibility problem is stated as follows:

$$\text{Problem } \mathcal{U}: \quad \underset{p_{uf}^c[n], \lambda_f[n], \mu_f[n], \kappa}{\text{Minimize}} \quad \kappa \quad \text{subject to} \quad (10)-(13),\ (20). \tag{27}$$

Thus, Algorithm 1 is presented to solve the optimization problem iteratively between the master $\mathcal{M}$ and primal $\mathcal{L}$ problems. First, we initialize feasible points for the binary variables: [y_f^0, z_{fu}^0, and x_{fu}^{0c}] along with other parameters. Second, the convex subproblem ($\mathcal{L}$) is solved generating an optimal solution $\bar{\mathbb{T}}^{[1]} = [\bar{p}_{uf}^c[n], \bar{\lambda}_f[n], \bar{\mu}_f[n]]$ and the multipliers $\bar{\mathbb{Q}}^{[1]} = [\bar{\alpha}_u[n], \bar{\rho}_f[n], \bar{\zeta}_f[n], \bar{\xi}[n], \bar{\beta}_f[n]]$, then, this solution is set as the upper bound of the algorithm. However, if the primal problem ($\mathcal{L}$) is infeasible, the algorithm then solves the feasible problem ($\mathcal{U}$) and sets its solution as the upper bound. The second step is to solve the master problem ($\mathcal{M}$) with any efficient Integer Linear algorithm applying the solution of the primal problem ($\mathcal{L}$) : $[\bar{\mathbb{T}}, \bar{\mathbb{Q}}]$ from the first step. Then we set the binary solution of the master problem's output to be the lower bound. On every iteration the algorithm evaluates the difference between the *UB* and *LB* and if the difference is greater than ϵ, then the algorithm uses the solution of the binary variables from the master problem ($\mathcal{M}$) to solve the revised primal ($\mathcal{L}$) problem and repeat the previous steps. The algorithm iterates until the termination condition is met. It is shown in [13] that the GBD algorithm terminates in a finite number of steps.

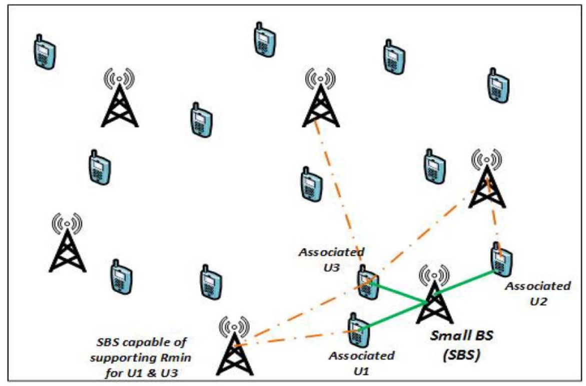

Fig. 2. The evaluation of BSC through the calculation of ν_f and ϕ_f.

IV. User Association and Dynamic Sleeping Using Centrality Analysis

This section introduces a new approach to choose which SBS is to deactivate and offload its users to neighboring SBSs. This approach exploits the centrality analysis that is used in graph theory to indicate the most important vertices within a graph [15]. In this section, base station centrality (BSC) analysis is presented to mark the SBSs that have the most potential to be deactivated without affecting the users' QoS. The basic idea of BSC is to introduce a metric that shows the fitness of every individual SBS to be deactivated. The fitness of every SBS is evaluated according to its ability to offload its users to neighboring SBSs. In other words, a SBS that is able to offload its users to more neighboring SBSs will have more potential to deactivate without interrupting the service of the associated users. Thus, BSC provides intuition for choosing which SBSs to deactivate instead of a random approach.

We introduce two parameters to calculate the BSC, ν_f, ϕ_f. ν_f indicates wether all users associated with the SBS f can be offloaded or not, while ϕ_f denotes the total number of SBSs that SBS f can offload its associated users to. User can be offloaded to any SBS that can support QoS, i.e., R_{min}. Thus, we define the BSC of a SBS in the network as follows:

$$BSC_f = \nu_f \phi_f \quad \forall f \tag{28}$$

Eq. (28) captures the effect of the number of SBSs that its associated users can be offloaded on the BSC of SBS f. Hence, BSC works as an indicator on how every SBS is centered within the network, which means that as the BSC increases the SBS f is placed close to many other SBSs. Therefore, the higher the BSC is, the SBS is more likely to be deactivated and its users offloaded to other SBSs.

Fig. 2 illustrates how to evaluate the BSC of SBS f on a topology with dense SBSs network. In Fig. 2 users $U1$, $U2$ and $U3$ are associated with SBS $f=1$ according to the best SINR. However, those users who are associated with this SBS can also be associated with other SBSs that can support their QoS (i.e., R_{min}). Fore example, U3 can be associated with three other SBSs, while each of the other two users can be associated with one SBSs. In this example ϕ_1 will be equal to five since the associated users can be offloaded to five SBSs in total, and ν_1 will be equal to one since all associated users

Algorithm 2 Dynamic Sleeping Using BSC

1: Input: $h^{c}_{fu}[n]; hr_f[n]; R_{min}; P_{max}; \omega N_0$
2: Initialize: $p^{c}_{fu}[n]^{[0]}; y^{[0]}_{f} = 1; k = 0$
3: **while** True **do**
4: Calculate SINR $\forall u, \forall f$, and associate users with BSs according to the highest SINR.
5: **if** $z_{uf} = 0 \quad \forall u \in U$ **then**
6: $y_f := 0 \quad \forall f \in F$
7: **end if**
8: **for** `<f=1 : |Active SBSs|>` **do**
9: Calculate ν_f, ϕ_f
10: $BSC_f = \nu_f \phi_f$
11: **end for**
12: $y^{[k]}_{f'} \leftarrow 0$, BS f' is the BS with the highest *BSC*, and associates its users with the neighboring BS $\bar{x}^{c[k]}_{fu}$.
13: Solve problem [$\mathcal{L}$] and let the solution be: $\bar{\mathbb{T}}^{[k]} = [\bar{p}^{c}_{uf}[n]^{(k)}, \bar{\lambda}_f[n]^{(k)}, \bar{\mu}_f[n]^{(k)}]$
14: **if** $\mathbb{S}^{[k]} \leq \mathbb{S}^{[k-1]}$ **then**
15: $\mathbb{T}^* := \bar{\mathbb{T}}^{[k]}$
16: $x^{*c}_{fu} := \bar{x}^{c[k]}_{fu}$
17: $y^*_f := \bar{y}^{[k]}_f$
18: **else if** problem [$\mathcal{L}$] is infeasible **then**
19: $\nu_f := 0$
20: **end if**
21: k:= k+1
22: **if** $\nu_f = 0 \ \ \forall f \in F$ **then**
23: Break
24: **else**
25: Go to step 4
26: **end if**
27: **end while**
28: Output: $\mathbb{T}^*, y^*_f, x^{*c}_{fu}$

can be offloaded to other SBSs. Thus, the BSC of SBS $f = 1$ equals 5.

Algorithm 2 calculates the BSC values of all the active SBSs. First, In steps (1,2) we provide the algorithm with the parameters and set some initial values. Then, for every iteration SBS (f): First, in step (4) the algorithm will associate the users with the SBS that provides the best SINR. Second, in steps (5-7) all SBSs that have no associated users are deactivated. Third, in steps (8-11) the BSC is evaluated for every SBS by calculating ν_f and ϕ_f. Then, in steps (12, 13), the algorithm will deactivate the SBS with the highest BSC and offload its associates to neighbouring SBSs that can support QoS requirements. After the association, the algorithm will solve the optimization problem ($\mathcal{L}$) and produce a candidate solution for the continuous variables $\bar{\mathbb{T}}^{[k]} = [\bar{p}^{c}_{uf}[n]^{(k)}, \bar{\lambda}_f[n]^{(k)}, \bar{\mu}_f[n]^{(k)}]$. Fourth, in steps (14-20), if the optimization problem returned to be infeasible, then we set ν_f to be zero to indicate that SBS f cannot be deactivated, and else if, objective function value for problem ($\mathcal{L}$) at iteration (k) is less than its value at iteration ($k - 1$), then the candidate solution is set as the best solution. Finally, in steps (22-26), if $\nu_f = 0$ for all SBSs then the algorithm break with $\mathbb{T}^*, y^*_f, x^{*c}_{fu}$ is the final solution. Otherwise, go back to step (4) and recalculate the BSC for the remaining active SBSs.

Algorithm 2 is dominated by two loops that affect its complexity. First, **while** loop with a number of iterations equals the number of active SBSs in the network which in the worst-case scenario equal F. Therefore, **while** loop has a linear complexity of $\mathcal{O}(F)$. On the second loop, **for** has two parts: a maximum number of iterations of F to evaluate the BSC for all active SBSs, and the evaluation of optimization problem $\mathcal{L}$. Problem $\mathcal{L}$ is a monotone convex optimization problem that according to [19] has at most $\mathcal{O}(\sqrt{n}\log 1/(\epsilon))$ iterations, where n is the number of variables and ϵ is the solution accuracy. Therefore, the complexity of **for** loop is $\mathcal{O}(F + \sqrt{n}\log 1/(\epsilon))$. As a result Algorithm 2 has a total complexity of $\mathcal{O}(F(F + \sqrt{n}\log 1/(\epsilon)))$. However, since n is much larger than F, Algorithm 2 complexity is $\mathcal{O}(F\sqrt{n}\log 1/(\epsilon))$.

TABLE II
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
P_{max}	2 W	R_{max}	4 Mbps
N_0	-174 dBm/Hz	ω	5 MHz
B_{max}	6 J	τ	100 ms
η	0.9	E_b	4 W
β_0	0.01	α	2

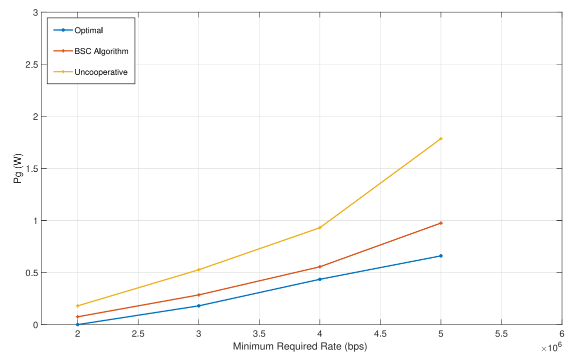

Fig. 3. The optimal results compared to BSC algorithm and the uncooperative as the R_{min} increases.

V. SIMULATION RESULTS

This section provides simulation results that demonstrate the performance of the system model shown in Fig. 1 to minimize the HetNets energy consumption. The parameters in all simulations, unless stated otherwise, are presented on Table II. HE levels are estimated by a truncated normal distribution with a mean equal to 0.2 and standard deviation of 0.07, the truncated normal distribution is set to have values higher than 0.001 [20]. The truncated normal distribution is as follows:

$$f(x) = \begin{cases} \frac{1}{0.07\sqrt{2\pi}} e^{\left(\frac{x-0.2}{0.07}\right)^2}, & \text{if } x \geq 0.001 \\ 0, & \text{otherwise.} \end{cases} \quad (29)$$

For all simulations, we consider an area of 100×100 m^2 where the SBSs and associated users are uniformly distributed over this area. In solving the problem optimally we applied a branch and bound algorithm to solve MINLP. Namely, we used Convex Over and Under ENvelopes for Nonlinear Estimation (Couenne) which aims at finding the global optima of MINLPs by implementing linearization, bound reduction, and branching methods within a branch-and-bound framework [21].

In Fig. 3 we compare the performance of the optimal solution of $\mathcal{F}$ to the BSC algorithm and the uncooperative approach, where the SBSs do not exchange HE. However, $\mathcal{F}$ is very difficult to solve especially for large networks. Therefore,

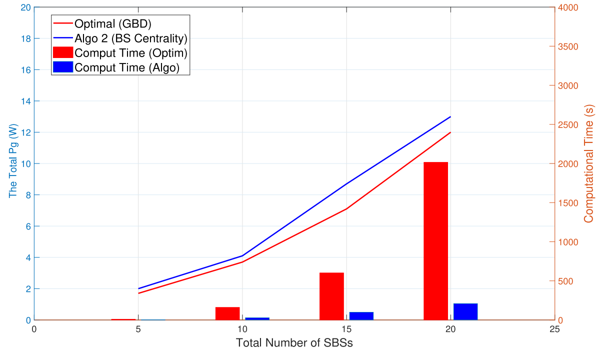

Fig. 4. The optimal results compared to BSC algorithm with respect to the computational time and total p_g consumption.

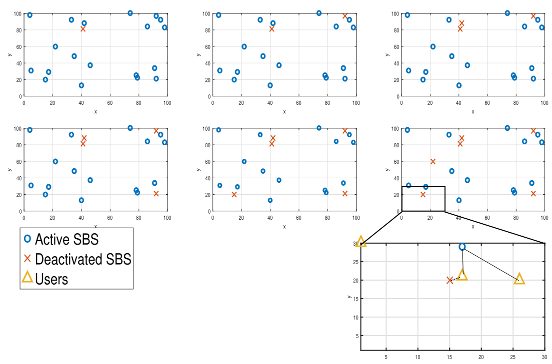

Fig. 5. The behavior of the BSC algorithm for every iteration.

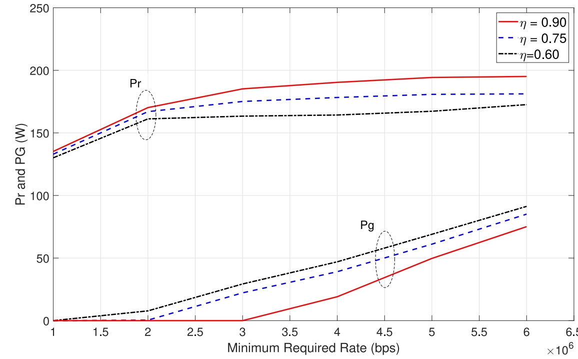

Fig. 6. The Minimum Rate Compared to the Efficiency.

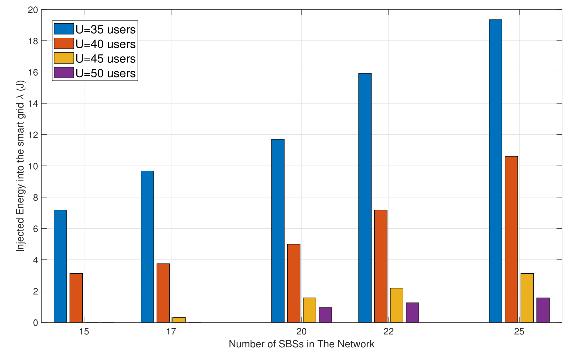

Fig. 7. The relation between the increase of the SBSs in the network and the Injected Energy into the smart grid.

we solve the network for small number of SBSs $F = 5$, and 10 users with increasing the minimum required rate. Fig. 3 shows that using sleeping SBSs to harvest energy and transfer it to other SBSs provides better performance than the noncooperative approach. On the other hand, the BSC algorithm performs close to the optimal solution of $\mathcal{F}$ within a reasonable time.

Fig. 4 compares the performance of the optimal solution of the GBD problem of Algorithm 1 to our proposed approach of BSC in Algorithm 2 in case of the p_g consumption and the computational time. In this scenario, the number of SBSs are [5, 10, 15, 20]; their associated users are [10, 20, 30, 40] respectively, and $N = 4$. Fig. 4 shows that the BSC approach performs close to the optimal solution of the GBD. In fact for small networks the two approaches are very close, while for larger network BSC results in about %10 more energy consumption. On the other hand, the optimal GBD required much longer times for computations than the BSC algorithm, and as the network increases in size, the required computational time increases exponentially (around 2000s for 20 SBSs and 40 users), while BSC achieved a reasonable solution for a much shorter computational time (around 160s).

Fig. 5 shows the behavior of the BSC algorithm on every step. In this scenario we have a topology of 100 × 100m^2 with 20 SBSs and 40 users ($F = 20$ and $U = 40$) with all of the SBSs and associated users uniformly distributed with a minimum rate of 1.5 Mbps. In every step the BSC algorithm chooses the SBS with the highest BSC to deactivate and offload its associated users to other neighboring SBS. The offloaded users are associated with the SBS that provides them with the second highest SINR. The enlarged area in Fig. 5 shows how BSC algorithm deactivated an SBS and associated its users to nearby SBSs.

Fig. 6 investigates the effect of the efficiency parameter (η) and the increase of the QoS requirement, i.e., R_{min} on the amount of power used from both sources (P_g and P_g). In this experiment we used 20 SBSs and 40 users while N = 10. As the results show, for $\eta = 0.9$, the network will rely solely on P_r until the R_{min} reaches 3.00 Mbps then the network will start demanding power from the grid as P_g starts increasing to provide the necessary power to match the increase in user demands. A similar pattern happens in both $\eta = 0.75$ and $\eta = 0.60$, with lower R_{min} required to trigger the demand of the power from the grid (P_g). 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 rates ($R_{min} \leq$ 2Mbps), P_r values for the three scenarios are very close to each other, despite the differences in efficiency. 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. 7 shows the effect of increasing the number of SBSs 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 follows: as the number of users increases, the active SBSs will have no energy left to inject into the network, and only the deactivated SBSs will be injecting energy into the network. However, for larger user population, the algorithm cannot deactivate any SBS because of the high demand. On the other hand, increasing the number of SBSs in the network will result in more HE to be injected into the SG causing less reliance on grid power.

VI. Conclusion

In this paper, energy harvesting in cooperative SBSs HetNets with a 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 to be transferred to other SBSs. Each of the SBSs is equipped with a harvesting device and a finite battery for storing HE. We formulated an optimization problem designed to minimize transmission power driven from the grid under user QoS constraints. Since the formulated problem is MINLP, we proposed a decomposition of the problem into two subproblems, a users association problem and convex optimization problem, and solved them iteratively using GBD. We also introduced a computational efficient algorithm based on network centrality to solve and optimize the user association and energy harvesting of the system model. Finally, performance evaluation was carried out to examine the performance of both the optimal GBD algorithm and the heuristic BSC algorithm on the energy consumption and computational time. As depicted in the results, the BSC algorithm showed superiority on computational time with near optimal results compared to the GBD algorithm which required longer time to reach the optimal solution. Additionally, the results showed the benefit of densifying the network with more SBSs, as the increase of the SBSs numbers will lead to more cooperation in adding more HE to the network.

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