On Optimizing Green Energy Utilization for Cellular Networks with Hybrid Energy Supplies

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***Abstract*—Green communications has received much attention recently. For cellular networks, the base stations (BSs) account for more than 50 percent of the energy consumption of the networks. Therefore, reducing the power consumption of BSs is crucial to achieve green cellular networks. With the development of green energy technologies, BSs are able to be powered by green energy in order to reduce the on-grid energy consumption, thus reducing the CO_2 footprints. In this paper, we envision that the BSs of future cellular networks are powered by both on-grid energy and green energy. We optimize the energy utilization in such networks by maximizing the utilization of green energy, and thus saving on-grid energy. The optimal usage of green energy depends on the characteristics of the energy generation and the mobile traffic, which exhibit both temporal and spatial diversities. We decompose the problem into two sub-problems: the multi-stage energy allocation problem and the multi-BSs energy balancing problem. We propose algorithms to solve these sub-problems, and subsequently solve the green energy optimization problem. Simulation results demonstrate that the proposed solution achieves significant on-grid energy savings.**

***Index Terms*—Green communications, energy efficient networking, renewable energy, cellular networks.**

I. INTRODUCTION

IN wireless cellular networks, energy consumption is mainly drawn from BSs (base stations). According to the power consumption breakdown [1], BSs consume more than 50 percent of the power of a cellular network. In addition, the number of BSs is expected to be doubled by 2012 [2]. Thus, reducing the power consumption of BSs is crucial to green cellular networks. One of the popular techniques improving the energy efficiency of cellular networks is to design and optimize the power saving communication protocols that adjust the transmit power of the transceivers according to the traffic intensity. Radio access networks are dimensioned for peak hour traffic, and thus the utilization of the base stations can be very inefficient during the off-peak hours. The most intuitive idea is to switch off the BSs when the traffic load is below a certain threshold for a certain time period [3]. When some BSs are switched off, radio coverage and service provisioning are taken care of by the devices that remain active. The BS switching problem can be formulated as an optimization problem that minimizes the number of active BSs while meeting the traffic load in the access network. Oh *et al.* [4] discussed the dynamic operation of cellular base stations. They showed that during periods of low traffic, some redundant BSs can be switched off to provide significant energy savings. Zhou *et al.* [5] proposed a centralized greedy algorithm and a decentralized algorithm to solve the problem, and illustrated the relationship between the energy saving and the outage probabilities. Oh *et al.* [6] proposed the threshold based method to switch the BSs on/off, and showed that the energy saving ratio is related to the traffic characteristics and the number of the neighboring BSs. Bhaumik *et al.* [7] proposed a multi-layer cellular architecture that adjusts cell sizes between two fixed values according to the traffic demand. The proposed scheme shows an energy saving of up to 40% as compared to the regular cellular architecture.

These methods are effective when cellular networks experiencing low traffic demand. However, when the traffic demand is intense, few BSs can be switched off, and thus these "sleep mode" based algorithm may not be effective. When traffic demand is intense, heterogeneous radio access networks which utilize a diverse set of base stations achieves higher spectral and energy efficiency per unit area. The network deployment featuring high density deployments of small, low power BSs achieves higher network energy efficiency than the sparse deployment of few high power base stations do. Etoh *et al.* [8] pointed out that heterogeneous network deployment will bring up to 50 percent reduction of the total BS power consumption. Samdanis *et al.* [9] examined the energy efficiency of cellular networks with joint macro and pico coverage, and showed that the joint deployment can reduce the total energy consumption by up to 60% in an urban area.

To reduce the carbon footprint, green energy powered BSs are designed. Ericsson [10] has developed a wind-powered tower for wireless base stations of cellular networks. Nokia Siemens Networks [11] has also developed a green BS which relies on a combination of solar and wind power to avoid using any grid electricity. Green energy such as sustainable biofuels, solar and wind energy are promising options to save the on-grid energy consumed by BSs and reduce the CO_2 footprint. To take advantages of green BSs, Zhou *et al.* [12] proposed the hand over parameter tuning algorithm and the power control algorithm to guide mobile users to access the BSs with green energy supply, thus reducing the grid electricity expense and CO_2 emission. Han and Ansari [13] proposed an energy aware cell size adaptation algorithm named ICE. This algorithm balances the energy consumption among BSs, and enables more users to be served with green energy.

However, owing to the dynamics of green energy generation

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and the limited capacity of energy storage, green energy may not guarantee sufficient power supplies for BSs. Thus, we envision future BSs to be powered by multiple types of energy sources, e.g., the grid, solar energy, and wind energy. In such cellular networks, BSs are powered by green energy if they have enough green energy stored in their batteries; otherwise, the BSs switch to on-grid energy to serve mobile users. It is desirable to know how to optimize the utilization of green energy in order to reduce the on-grid energy consumption of cellular networks. In this paper, we aim to optimize the utilization of green energy during the peak traffic hour. In other words, we leverage the green energy to reduce the on grid energy consumption of cellular network during the peak traffic hour.

We consider solar energy as the green energy source. The solar energy generation depends on many factors such as temperature, sun light intensity, the geolocation of the solar panel, and so on. However, the daily solar energy generation in a given area exhibits temporal dynamics that peaks around noon and bottoms during the night. The BSs' energy consumption depends on the mobile traffic, which shows both temporal and spatial diversities [14]. The temporal traffic diversity indicates that the traffic demands at individual BSs are highly different over time while the spatial traffic diversity means that closely located BSs may experience different traffic intensities at the same time period of a day, and therefore, they experience different energy consumption. Therefore, in order to reduce the on grid energy consumption of cellular networks during the peak traffic hours, the green energy optimization (GEO) problem is to balance the energy consumption among BSs.

The GEO problem involves the optimization in two dimensions: the time dimension and the spatial dimension. We thus decompose the GEO problem into two sub-problems: the multi-stage energy allocation (MEA) problem and the multi-BSs energy balancing (MEB) problem based on the characteristics of the green energy generation and the mobile traffic.

The MEA problem is to optimize the green energy allocation at individual BSs to accommodate the temporal dynamics of both the green energy generation and the mobile traffic. We propose the MEA algorithm to solve the MEA problem. Taking advantages of the spatial diversity of the mobile traffic, the MEB problem is to balance the green energy consumption among BSs so as to reduce the on-grid energy consumption of the cellular network. The energy consumption of BSs is adjusted by adapting the cell size of the BSs.[1] A BS adapts its cell size by varying its pilot signal strength. However, to maintain the coverage, it may not be practical to vary the pilot signal strength arbitrarily. Therefore, the MEB algorithm selects the best pilot signal strengths for individual BSs from a few alternatives. When a BS increases its cell size, the energy efficiency of the BS may decrease [14]. Therefore, the MEB algorithm only increases a BS's cell size when it has a sufficient amount of green energy. In other words, the MEB algorithm may reduce the energy efficiency of the BSs powered by green energy in order to increase the energy efficiency of the BSs powered by on-grid energy. Generally, BSs with a large amount of green energy increase their cell sizes to accommodate more mobile traffic while BSs with a small amount of green energy shrink their cell sizes to offload mobile traffic to their neighboring BSs. By adjusting the energy consumption of individual BSs, the energy consumption among BSs is balanced. As a result, the green energy shortage on BSs is reduced. Therefore, after having applied the energy allocation (EA) algorithm, the number of BSs that can be powered by green energy is increased, and thus the on-grid energy consumption is reduced.

The rest of the paper is organized as follows. In Section II, we present the green energy generation model and mobile traffic model adopted in this paper. In Section III, we present the formulation of the green energy optimization problem, and analyze the properties of the problem. Section IV presents the proposed solution on the green energy optimization problem. Section V shows the simulation results, and concluding remarks are presented in Section VI.

II. System Model

A. Network Scenario

Consider a cellular network whose BSs can be powered by either on-grid energy or green energy. At a time slot, if a BS's stored green energy is larger than its energy demand, the BS is powered by green energy; otherwise, the BS is powered by on-grid energy.[2] We assume that the cellular network experience high traffic volumes, and our proposed algorithms aim to reduce the main grid energy consumption of the cellular network at such traffic condition. Owing to this assumption, our algorithm will not enable the sleeping mode of BSs which is usually applied to improve the energy efficiency of cellular networks during off-peak traffic hours. The assumption is valid because we consider solar energy as the green energy source, and solar energy can only be generated during day time which is also the time period when the cellular networks usually experience high traffic volumes. We further assume the BSs are able to adapts their coverage area by changing their pilot signal power levels, and the maximum power level of a BS is Q. With a large coverage area, the BS may serve more users, and thus the BS may consume more energy.

B. Green Energy Model

We consider solar panels as the green energy generators. Solar panels generate electrical power by converting solar radiation into direct current electricity using semiconductors that exhibit the photo-voltaic effect. Solar energy generation depends on various factors, such as the temperature, the solar intensity, and the geolocation of the solar panels. However, the hourly solar energy generation can be estimated by using typical annual meteorological weather data for a given geolocation. In this paper, we adopt the System Advisor Model (SAM) [16] and PVWatts model [17] to estimate the hourly solar energy generation. Fig. 1 shows the estimation of the

[1]The basic idea of optimizing cell sizes for energy saving in cellular networks with hybrid energy supplies was first presented at IEEE Globecom 2012 [15].

[2]The case of utilizing multiple energy sources simultaneously complicates the system design (which requires multiple input source converter and controller) and is beyond the scope of this paper.

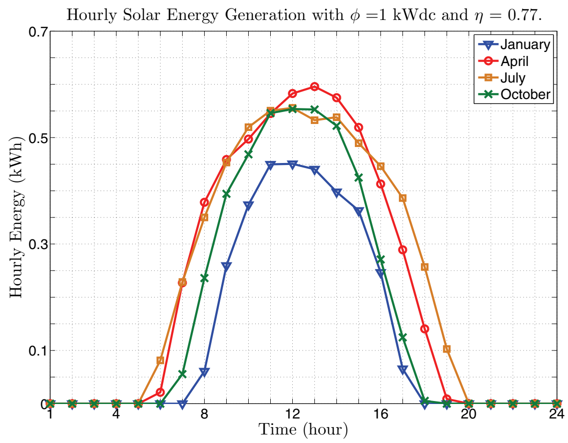

Fig. 1. The hourly solar energy generation.

hourly solar energy generation of four different months in New York City. In this estimation, we set the nameplate capacity, ϕ, and the DC-to-AC derate factor, η, to 1 $kWdc$ and 0.77, respectively. From the estimation, the solar panels start to generate energy from around 6:00 AM. The solar energy generation keeps increasing and peaks at around 1:00 PM, and ends at about 7:00 PM. We divide the time period into time slots, and derive the energy generation rate at the ith time slot, α_i, using the SAM and PVWatts models. Here, we only consider the solar energy generation changes at a time scale of several minutes rather than considering the instantaneous solar energy fluctuations. This because our algorithm optimizes the cell size of BSs at an interval of several minutes, and the instantaneous energy generation changes may not significantly affect the performance of our algorithm. Since the solar energy generation exhibits temporal dynamics, the available solar energy cannot always guarantee the sufficient energy supplies to the BSs. BSs located in the same geographical region are assumed to experience almost the same weather environment including solar intensity and temperature. Thus, in this paper, we assume that the solar panels of all the BSs yield the same green energy generation rate.

C. Energy Consumption Model

According to network measurement studies, the energy consumption of BSs are directly related to the traffic loads on the BSs [18], and linear models have been proposed for expressing the influence of traffic load on the instantaneous energy consumption of the BSs [19]. Therefore, in the paper, we model the energy consumption of BSs by two parts: the static energy consumption which is the energy consumption of the BSs without any traffic loads, and the dynamic energy consumption which is related to the traffic volume of the BSs [20].

D. Network Traffic Model

The mobile traffic volume exhibits both temporal and spatial diversity [14]. On the temporal diversity, traffic volume at individual BSs is highly dynamic over time, and it typically peaks between 10:00 AM and 6:00 PM, and bottoms between 1:00 AM and 5:00 AM. However, the traffic volume is almost stable at the same time of consecutive days. Peng *et al.* [14] showed that the traffic load difference in two consecutive days is less than 20% for 70% BSs in their network measurement studies. Therefore, we assume that the traffic load at individual BSs can be estimated using the historical mobile traffic statistics, and hence the energy consumption of individual BSs can be estimated. On the spatial diversity, traffic load intensity is quite diverse among the closely located BSs, and the diversity is more evident during the peak time [14]. Assuming the BSs always have data transmission to mobile users during each time slot, and the BSs transmit data to all the users with the same data rate. Therefore, the traffic volume at individual BSs is determined by the number of users associated with the BSs. Following the mobile traffic statistics, the total number of mobile users in the system varies at different time slots—the temporal diversity of the mobile traffic. On the other hand, we assume mobile users are randomly distributed in the area. Thus, the number of users on individual BSs are different—the spatial diversity of mobile traffic.

III. Problem Formulation

Consider a cellular networks with N BSs and M mobile users. Assuming the duration of time is divided into L time slots, and the length of each time slot is τ seconds. Let $\vec{P_i^0} = (p_{i,1}^0, p_{i,2}^0, \cdots, p_{i,n}^0)$ be the pilot signal power of BSs at the ith time slot. Then, the user-BS association matrix at the ith time slot, X_i, is determined by $\vec{P_i^0}$. Let $X_i(k,j) = 1$ when user k is associated with BS j; otherwise, $X_i(k,j) = 0$. Assume the BSs always have data transmission to mobile users during the τ seconds. The energy consumption of BS j during the ith interval can be expressed as

$$C_{i,j} = \sum_{k=1}^{M} X_i(k,j) P_{k,j} \tau + P_{i,j}^{fix} \tau. \tag{1}$$

Here, $P_{k,j}$ is the dynamic power consumption of BS j for serving user k, and $P_{i,j}^{fix}$ is the static power consumption when the BS is in the active status. Since we assume the cellular networks experience high traffic volume, $\sum_{k=1}^{M} X_i(k,j) > 0$. Therefore, all the BSs are in the active status.

At the ith time slot, the stored green energy at BS j is $E_{i,j}$. The amount of stored green energy depends on the energy consumption and generation of the previous time slots. Therefore, $E_{i,j}$ equals to

$$E_{i,j} = \begin{cases} E_{0,j} + \alpha_i \tau, & i = 1; \\ E_{i-1,j} - \beta_{i-1,j} C_{i-1,j} + \alpha_i \tau, & i \geq 2. \end{cases} \tag{2}$$

Here, $E_{0,j}$ is the initial green energy stored at BS j. We assume that the capacity of the battery is sufficiently large to store green energy at individual BSs. Therefore, we do not consider the energy overflow. $\beta_{i,j}$ is the energy source indicator function. Let $E_{i,j}^A$ be the amount of allocated green energy at the ith time slot in BS j, and $E_{i,j}^A \leq E_{i,j}$. If $E_{i,j}^A \geq C_{i,j}$, then BS j is powered by green energy at the ith time slots, and then $\beta_{i,j}$ equals to 1; otherwise $\beta_{i,j}$ equals to zero. The on-grid energy consumed by BS j during the ith interval is

$$G_{i,j} = (1 - \beta_{i,j}) C_{i,j}. \tag{3}$$

The GEO (green energy optimization) problem can be formulated as

$$\min_{(\vec{P_1^0},\vec{P_2^0},\cdots,\vec{P_i^0},\cdots,\vec{P_L^0})} \quad \sum_{i=1}^{L}\sum_{j=1}^{N} G_{i,j} \tag{4}$$

$$\begin{aligned} subject\ to: \quad & \lambda_{k,i} \geq \gamma, \\ & k \in (1,2,\cdots,M). \end{aligned} \tag{5}$$

Here, γ is the minimum SINR (signal interference noise ratio) requirement. We assume all users have the same SINR requirement. $\lambda_{k,i}$ is the receiving SINR of user k at the ith time slots, and it can be expressed as

$$\lambda_{k,i} = \frac{P_{k,j}\Theta_{k,j}}{\mathcal{N}_0 w_k + \sum_{m\in(1,2,\cdots,N),m\neq j} P_{m,j}\Theta_{m,j}} \tag{6}$$

Here, $\Theta_{k,j}$ is the channel fading between BS j and user k, $\mathcal{N}$ is the noise density, and w_k is the bandwidth allocated to user k.

The GEO problem is to find the optimal pilot signal power of BSs which determines the coverage area of the BSs. Given the user distribution and the coverage area of the BSs, the energy consumption of the BSs can be calculated according to Eqs. 1 and 6. In order to minimize the overall on-grid energy consumption of the cellular networks, the BSs' optimal pilot signal power depends on the BSs' green energy generation and energy consumption. When $\beta_{i,j} = 1, \forall i \in (1,2,\cdots,L), \forall j \in (1,2,\cdots,N)$, the on-grid energy consumption is zero. To reduce the on grid energy consumption, the green energy utilization is to be optimized among L time slots and among N BSs to make $\beta_{i,j} = 1, \forall i \in (1,2,\cdots,L), \forall j \in (1,2,\cdots,N)$. In other words, for individual BSs, the green energy allocation at each time slot should be optimized; for the network, the energy consumption among BSs should be balanced —the BSs with a larger amount of green energy should increase their coverage areas to absorb traffic from the BSs with less green energy. However, owing to the dynamics of green energy and mobile traffics, the energy consumption in the BSs exhibit temporal and spatial dynamics. Therefore, it is difficult to optimize the green energy utilization because the optimization involves two dimensions: the time dimension and the space dimension.

Therefore, the GEO problem is decomposed into two sub-problems. The first sub-problem is the MEA problem, which aims to optimize the green energy usages at different time slots to accommodate the temporal dynamics of the green energy generation and the mobile traffic. The second sub-problem is the MEB problem, which accommodates the spatial dynamics of the mobile traffic and seeks to maximize the utilization of green energy by balancing the green energy consumption among BSs.

A. MEA Problem

Denote $\delta_{i,j} = \frac{C_{i,j}}{E_{i,j}^A}$ as the energy drain ratio (EDR) which is derived by dividing the energy consumption by the allocated green energy. If $\delta_{i,j} > 1$, the allocated green energy is not sufficient to meet the energy demands. The larger the $\delta_{i,j}$, the larger the gap between energy demands and the allocated green energy. If $\delta_{i,j} \leq 1$, the gap is zero. It is desirable to optimize the green energy allocation to let $\delta_{i,j} \leq 1, \forall i \in (1,2,\cdots,L), \forall j \in (1,2,\cdots,N)$, which leads to zero on-grid energy consumption. On individual BSs, the available green energy and the energy consumption vary at different time slots. As a result, the energy gap varies at different time slot. The MEA problem aims to optimize the green energy allocation over time slots to reduce the energy gap.

The MEA problem can be expressed as

$$\min_{(E_{1,j}^A,\cdots,E_{i,j}^A,\cdots,E_{L,j}^A)} \quad (\delta_{1,j},\delta_{2,j},\cdots,\delta_{i,j},\cdots,\delta_{L,j}) \tag{7}$$

$$\begin{aligned} subject\ to: \quad & E_{i,j}^S = E_{i-1,j}^S + \alpha_{i-1}\tau - E_{i-1,j}^A, \\ & E_{i,j}^A \leq E_{i,j}^S + \alpha_i \tau. \end{aligned} \tag{8}$$

Here, $E_{i,j}^S$ is the amount of residual green energy at the beginning of the ith time slot on BS j, and $E_{0,j}^S = E_{0,j}$. Sort $\delta_{i,j}, \forall i \in (1,2,\cdots,L)$ from the largest to the smallest, and denote $\vec{Y_j} = (\delta_j^1, \delta_j^2, \cdots, \delta_j^L)$ as the sorted energy ratio vector for BS j. $(\delta_{1,j},\delta_{2,j},\cdots,\delta_{i,j},\cdots,\delta_{L,j})$ is minimized if its corresponding sorted energy ratio vector $\vec{Y_j}$ has the lowest lexicographical value. By minimizing $(\delta_{1,j},\delta_{2,j},\cdots,\delta_{i,j},\cdots,\delta_{L,j})$, the MEA problem is to balance the green energy utilization among time slots. Solving the MEA problem has two benefits on minimizing the on-grid energy consumption. The first one is that solving the MEA problem may reduce the number of energy gaps on individual BSs. The second one is that solving the MEA problem narrows the energy gaps at individual time slots. With a narrowed energy gap, the probability of filling the gap by solving the MEB problem increase. Therefore, the probability of consuming on-grid energy is reduced.

B. MEB Problem

Owing to the spatial diversity of the mobile traffic, the energy consumption of closely located BSs may exhibit a great difference. The unbalanced energy utilization may result in an under utilization of green energy. To maximize the utilization of green energy, the green energy consumption is balanced among BSs via adapting their cell sizes. The optimal cell sizes are chosen according to the amount of green energy and mobile traffic demands. In general, BSs with larger amount of green energy are enforced to have larger cell sizes. BSs adapt their cell sizes by changing the power of their pilot signals. Mobile users select BSs based on the strength of pilot signals from BSs. Therefore, if a BS increases its cell size by increasing its pilot signal strength, the number of mobile users associated with the BS may increase, and thus the energy consumption of the BS may increase. In this way, the energy consumption among BSs is balanced. The solution to the MEB problem is to optimize BSs' cell sizes at individual time slots, and thus to balance energy consumption among the BSs.

The MEB problem can be formulated as

$$\min_{\vec{P_i^0}} \quad (\delta_{i,1},\delta_{i,2},\cdots,\delta_{i,j},\cdots,\delta_{i,N}) \tag{9}$$

$$\begin{aligned} subject\ to.: \quad & \lambda_{k,i} \geq \gamma, \\ & \beta_{i,j} C_{i,j} \leq E_{i,j}^A, \\ & k \in (1,2,\cdots,M). \end{aligned} \tag{10}$$

Sort $\delta_{i,j}, \forall j \in (1,2,\cdots,N)$ from the largest to the smallest, and denote $\vec{X_i} = (\delta_i^1, \delta_i^2, \cdots, \delta_i^N)$ as the sorted energy ratio

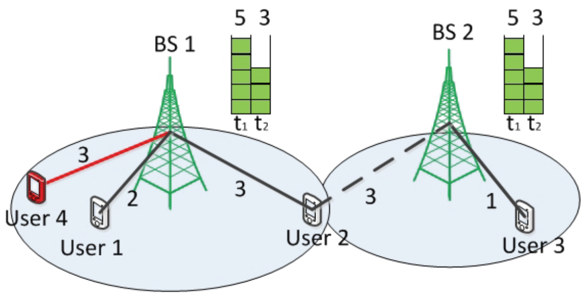

Fig. 2. The rational of the decomposition.

vector for in the ith time slot. $(\delta_{i,1}, \delta_{i,2}, \cdots, \delta_{i,j}, \cdots, \delta_{i,N})$ is minimized if its corresponding sorted energy ratio vector $\vec{X}_i$ has the lowest lexicographical value.

Theorem 1. *The MEB problem is NP-hard.*

Proof: The theorem can be proved by reducing any instance of the partition problem [21] to the MEB problem. For the sake of brevity, we omit the detailed proof. ■

C. The Rational of the Decomposition

The GEO problem involves the optimization in two dimensions: the time dimension and the space dimension. The optimization in the time dimension, the MEA problem, is to optimize the green energy utilization at each time slot for individual BSs while the optimization in the space dimension, the MEB problem, is to balance the energy consumption among BSs. For illustrative purposes, consider the network scenario shown in Fig. 2. BS 1 and BS 2 are neighboring BSs but experience different traffic demands, and thus they consume different amounts of energy. The green energy generation is the same in both BSs, which is 5 units in the first time slot and 3 units in the second time slot. In the first time slot, there are three users in the network: user 1, user 2, and user 3. User 1 and user 2 are associated with BS 1, and consume 2 units and 3 units of energy from BS 1, respectively. User 3 is associated with BS 2, and consumes 1 unit of energy. In the second time slot, there are four users in the network, and the new user, user 4, is associated with BS 1, and consumes 3 units of energy. We compare three network operation strategies: 1) with no optimization, 2) with only the optimization in space dimension, and 3) with the optimization in both time and space dimensions. For the first network operation strategy, BS 1 consumes zero unit on-grid energy in the first time slot. In the second time slot, three users are associated with BS1 and the total energy consumption is 8 units. Since BS 1 only has 3 units of green energy, which are less than the energy consumption, BS 1 is powered by on-grid energy and consumes 8 units on-grid energy. BS 2 consumes zero unit on-grid energy in both time slots. For the second operation strategy, BS 1 consumes zero unit on grid energy in the first time slot. In the second time, since BS 1 does not have sufficient green energy, it reduces the coverage area and offloads user 2 to BS 2. After the offloading, the energy consumption on BS 1 is 5 units, which are larger than the amount of green energy in BS 1. As a result, BS 1 is powered by on-grid energy and consumes 5 units on-grid energy in the second time slot. Since BS 2 only consumes 1 unit green energy in the first time slot, the available green energy in BS 2 in the second time slot is 7 units. Therefore, BS 2 has sufficient green energy to provide service to both user 2 and user 3, and thus BS 2 consumes zero unit on-grid energy in both time slots. For the third operation strategy, BS 1 optimizes the green energy utilization in the time dimension. As a result, BS 1 allocates 3 units of green energy in the first time slot, and allocate 5 units of green energy in the second time slot. Then, in the first time slot, BS 1 reduces its coverage area and offloads user 2 to BS 2. The energy consumption of BS 1 becomes 2 units, which are less than the green energy allocation. Thus, BS 2 is powered by green energy, and consumes zero units on-grid energy. In the second time slot, user 2 is still associated with BS 2. The available green energy and the energy consumption in BS 1 are 6 units and 5 units, respectively. Therefore, BS 1 can be powered by green energy. Thus, by optimizing green energy utilization in both time dimension and space dimension, BS 1 consumes zero unit on-grid energy in both time slots. Although user 2 is offloaded to BS 2, BS 2 has sufficient green energy to provide service to both user 2 and user 3. Therefore, the network consumes zero unit on grid energy. Hence, optimizing green energy utilization in both the time dimension and the space dimension reduces the on grid energy consumption. Therefore, we decompose the GEO problem into the MEA problem and the MEB problem.

IV. The GEO Algorithm

In this section, we propose the GEO algorithm to solve the GEO problem with low computational complexity. Since the GEO problem is decomposed into two sub-problems: the MEA problem and the MEB problems, we tackle the GEO problem by solving the sub-problems. The solution of the MEA problem estimates the amount of green energy allocated at individual BSs during each time slot. Based on this solution, optimal cell size adaptation is achieved by solving the MEB problem. Given the cell sizes, individual BSs apply the energy allocation (EA) algorithm to re-calculate their green energy usage, and determine whether to consume on-grid energy at the current time slot. Therefore, the GEO algorithm consists of the MEA algorithm, the MEB algorithm, and the EA algorithm. As shown in Fig. 3, the MEA algorithm and the EA algorithm are implemented in individual BSs, and the MEB algorithm is implemented in the network controller which coordinates the BSs in the network. Individual BSs apply the MEA algorithm to optimize the green energy allocation at individual time slots based on the estimation of the mobile traffic and the green energy generation, and feedback the green energy allocation to the network controller. The network controller balances the green energy usage among the BSs by applying the MEB algorithm, and determines the BSs' cell sizes. Based on the cell sizes, individual BSs calculate their energy consumption and apply the EA algorithm to calculate the green energy allocation, and determine whether to utilize green energy at the current time slot.

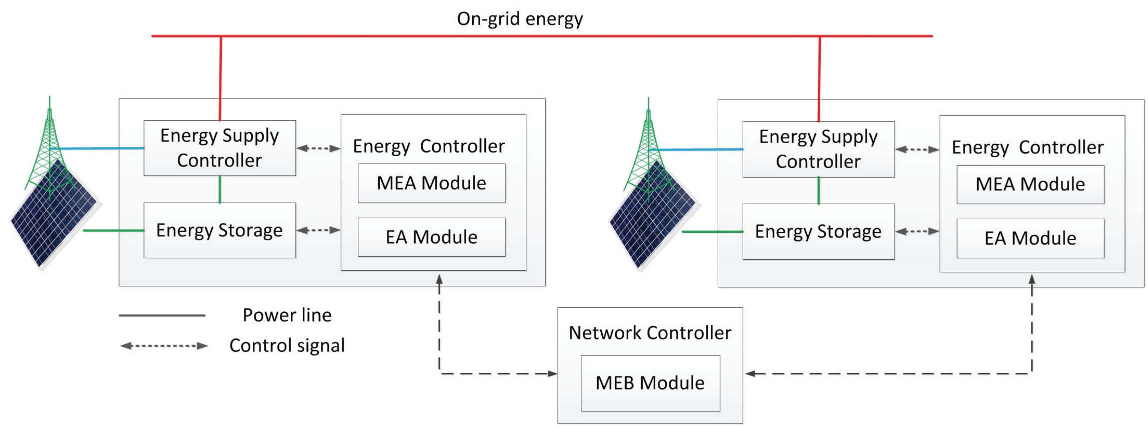

Fig. 3. The illustration of the GEO algorithm.

A. The MEA Algorithm

Since the mobile traffic volume is almost stable at the same time of two consecutive days [14], the energy consumption can be estimated based on the historical mobile traffic statistics. Given the same weather condition, the solar energy generation at an individual BS in two consecutive days is also stable. Therefore, we solve the MEA problem based on the estimated energy generation and energy consumption. The solution of the MEA problem provides a good estimation of the optimal energy usage at individual BSs during each time slot. Therefore, the idea of the GEO algorithm is to derive an initial energy allocation by solving the MEA problem based on the estimated energy generation and energy demands, and then solve the MEB problem based on the solution of the MEA problem. Solving the MEA problem is to balance the green energy usages among time slots. There are two major difficulties in solving the MEA problem. The first one is that the amount of available green energy at one time slot depends not only on the amount of energy generated at the current time slot but also on the residual green energy from previous time slots. This couples the energy usages at individual time slots, implying that changing the green energy usage at one time slot will affect the green energy allocations of the afterward time slots. The proposed MEA algorithm decouples the dependency of the energy allocations at individual time slots by simply distinguishing the green energy into the green energy generated at the current time slot and the residual green energy from the previous time slots. At the beginning of the algorithm, we allocate the green energy at each time slot according to Eq. (11):

$$E_{i,j}^A = \begin{cases} E_{0,j}^S + \alpha_{i,j}\tau, & i = 1\ ; \\ \alpha_{i,j}\tau, & i > 1. \end{cases} \tag{11}$$

When the MEA algorithm reduces the green energy allocation at one time slot, the saved green energy is stored as the residual energy. If there are sufficient residual energy from previous time slots, the MEA algorithm is allowed to increase the green energy allocation at the current time slot. In this way, changing the green energy allocation at one time slot will not immediately affect the green energy allocation at other time slots. The other difficulty is the constraint that the energy generated at one time slot cannot be used at its previous time slots. To accommodate this constraint, the MEA algorithm optimizes the green energy allocation of individual time slots according to the time sequence. The MEA algorithm calculates the energy allocation of the first time slot, and then iteratively adds the next time slot into the energy allocation optimization. If the EDR of the newly added time slot is larger than that of the previous time slot, the MEA algorithm reduces the green energy allocation in the previous time slots, and allocates the saved energy to the current time slot. The pseudo codes of the MEA algorithm is illustrated in Algorithm 1.

Algorithm 1 The MEA Algorithm

Input: $\hat{C}_{i,j}$, $E_{0,j}^S$, α_i $i \in (1, 2, \cdots, L)$;
Initialize $E_{i,j}^A$ and calculate $\hat{\delta}_{i,j} = \frac{\hat{C}_{i,j}}{E_{i,j}^A}$
for $i = 2$ *to* L **do**
  if $\hat{\delta}_{i,j} > \hat{\delta}_{i-1,j}$ **then**
    for $m = 1$ *to* $i - 1$ **do**
      Calculate $\bar{\delta} = \frac{\sum_{k=m}^{i} \hat{C}_{k,j}}{\sum_{k=m}^{i} E_{i,j}^A}$;
      if $\hat{\delta}_{m,j} < \bar{\delta}$ **then**
        $h = m$, and break;
      end if
    end for
    for $k = h$ *to* $i - 1$ **do**
      if $\hat{\delta}_{k,j} < \bar{\delta}$ **then**
        Reduce $E_{k,j}^A$ to let $\hat{\delta}_{k,j} = \bar{\delta}$;
      end if
    end for
    for $k = h$ *to* i **do**
      if $\hat{\delta}_{k,j} > \bar{\delta}$ **then**
        Increase $E_{k,j}^A$ to let $\hat{\delta}_{k,j} = \bar{\delta}$;
      end if
    end for
  end if
end for
Return $E_{i,j}^A, i \in (1, 2, \cdots, L)$.

Theorem 2. *The proposed MEA algorithm achieves the optimal solution for the MEA problem.*

Proof: Since the green energy cannot be utilized until it is generated, the BS's energy ratio at one time slot can be adjusted only by changing the green energy allocation of the previous time slots. For example, if we want to decrease the energy ratio of the ith time slot, we have to increase $E_{i,j}^S$ by reducing the energy allocation at the previous time slots. If $\hat{\delta}_{i,j} > \hat{\delta}_{i-1,j}$, the proposed MEA algorithm decreases the energy allocations of the time slots prior to the ith time slot, and thus increases the green energy allocation at the ith time slot to assure $\hat{\delta}_{i,j} \leq \hat{\delta}_{i-1,j}$. As a result, $\delta_{i,j}^* \leq \delta_{i-1,j}^*, \forall i \in (2, 3, \cdots, L)$. Here, $\delta_{i,j}^*$ is the solution achieved by the MEA algorithm. When minimizing $\hat{\delta}_{i,j}$, the MEA algorithm, from the previous time slots, finds the hth time slot such that $\hat{\delta}_{h,j} < \frac{\sum_{k=h}^{i} \hat{C}_{k,j}}{\sum_{k=h}^{i} E_{i,j}^A}$. Then, the MEA algorithm reduces the energy allocation of the hth to the $(i-1)$th time slot, and to let $\hat{\delta}_{m,j} = \frac{\sum_{k=h}^{i} \hat{C}_{k,j}}{\sum_{k=h}^{i} E_{i,j}^A}$, $m \in (h, h+1, \cdots, i)$. Assume $\hat{\delta}_{i,j}$ is the nth largest energy ratio among the time slots till the ith time slot. Since $\hat{\delta}_{i,j} \leq \hat{\delta}_{m,j}, m \in (1, 2, \cdots, i-1)$, $\hat{\delta}_{i,j}$ cannot be further decreased without increasing the largest to the $(n-1)$th largest energy ratio. Therefore, the proposed MEA algorithm achieves an optimal solution for the MEA problem. ■

The computational complexity of the MEA algorithm is $O(n^2)$ in the worst case, where n is the total number of the time slots. The MEA algorithm is to optimize green energy allocation based on the estimations of green energy generation and consumption. Therefore, the MEA algorithm optimizes the energy allocation offline, and only executes once during a day. Thus, the computational complexity of $O(n^2)$ is acceptable even when the number of time slots is very large.

B. The MEB Algorithm

Starting with the initial energy allocation derived from the MEA algorithm, we tackle the MEB problem to balance the energy consumption among BSs. We solve the MEB problem in two steps. First, we design algorithm to minimize the largest EDR among BSs. Then, the MEB algorithm iteratively minimize the mth largest EDR among BSs. Here, $2 \leq m \leq N$. Therefore, the proposed algorithm first finds the BS with the largest EDR, and reduces the cell size of the BS by reducing its pilot signal power in order to reduce its energy demand. While reducing the cell size of a BS, the user-BS associations are changed: users originally associated with the BS may be offloaded to its neighboring BSs. Based on the new user-BS associations, the MEB algorithm re-calculates BSs' energy demands and derives their EDRs. On calculating BSs' EDRs, the MEB algorithm first derives the minimum required transmission power, $P_{k,j}$, to satisfy user k's minimum SINR requirement according to Eq. (6), then calculates the energy demands of BS j according to Eq. (1), and eventually updates BS j's EDR.

While reducing the energy demand of a BS, EDRs of the other BSs may increase beyond or equal to the largest EDR. For example, in Fig. 4, both BSs have 10 units of power storage, and user 2 currently associates with BS 1. The energy demand on BS 1 is 11 which makes the largest EDR to be 1.1. Therefore, BS 1 reduces its pilot power to enable user 2 switch to BS 2. As a result, the EDR of BS 2 will be 1.1 which the largest EDR, and BS 2 will reduce its pilot power.

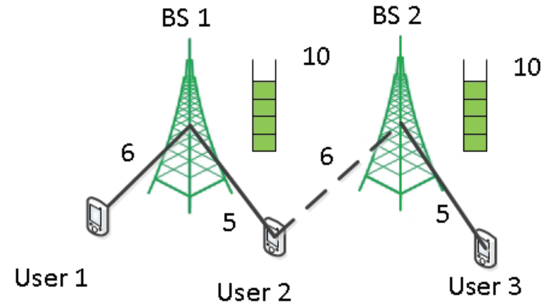

Fig. 4. Illustration of the problem in cell size adaptation.

Then, user 1 will switch back to BS 1. The ping-pong process hardly reaches the optimal solution.

To address this problem, we introduce the concept of the energy dependent set (EDS).

Definition 1. Let $\delta_{i,j}$ be the EDR of BS j at the ith time slot. $\delta_{i,\kappa} = \max_{1 \leq j \leq N} \delta_{i,j}$. Let $\delta'_{i,j}$ be the EDR of BSs j after the pilot power reduction of BS κ. Then, EDS $\mathbf{D} = \{j | \delta'_{i,j} > \delta_{i,\kappa}, j \in (1, 2, \cdots, N)\}$.

In order to minimize the largest EDR, the pilot signal power of the BSs in the EDS should be reduced together to enable the users to be offloaded to the BSs outside the EDS. Denote $\mathbf{A}$ as the set of total BSs. The pseudo code of the proposed largest EDR minimization (LEM) algorithm is listed as Algorithm 2 below.

Algorithm 2 The LEM Algorithm

Initialize $\vec{P_i^0}$ and $E_{i,j}^A, j \in (1, 2, \cdots, N)$;
OPT = FALSE;
while (OPT == FALSE) **do**
  Find the largest EDR, δ_i^{max}.
  Find the set $\mathbf{S}$ that $\delta_{i,j} = \delta_i^{max}, j \in \mathbf{S}$;
  Given $\mathbf{S}$ and δ, update EDS $\mathbf{D}$ and calculate the pilot power reduction, $\vec{w}$;
  if ($\mathbf{D} == \mathbf{A} \parallel \exists j \in \mathbf{D}$ *such that* $w_j \geq p_{i,j}^0$) **then**
    OPT = TRUE;
  else
    Reduce $p_{i,j}^0$ by w_j, $j \in \mathbf{D}$;
  end if
end while
Return $\vec{P_i^0}$ and δ_i^{max};

Lemma 1. *The largest EDR is minimized if either of the following conditions is satisfied:*
1) The energy dependent set $\mathbf{D}$ *equals to the BS set* $\mathbf{A}$*;*
2) $w_j \geq p_{i,j}^0$, $\exists j \in \mathbf{D}$.

Proof: For the first condition, reducing the pilot power level of all BSs does not change the user-BS association. Therefore, the largest EDR cannot be reduced further. The second one corresponds to the scenario that there exists at least one BS in EDS with its pilot power level being less than its pilot power level decrements. For the second condition, there exist BSs in EDS whose pilot power level cannot be further reduced. Reducing the pilot power level of partial BSs result in the EDRs of certain BSs in the $\mathbf{D}$ being larger than the largest EDR, and therefore the largest EDR cannot be reduced further. ■

The LEM algorithm minimizes the largest EDR. While further minimizing the mth largest EDR, we have to avoid increasing the first to the $(m-1)$th largest EDR. Therefore, we introduce the definition of energy distance:

Definition 2. Given two subsets of BSs, $\mathbf{A}, \mathbf{B}$, $\mathbf{A} \cap \mathbf{B} = \emptyset$, $a \in \mathbf{A}$, and $b \in \mathbf{B}$. The energy distance from a to b is $g_{a,b}$ if reducing BS a's pilot power by up to g power levels does not increase the EDR of BS b. The energy distance from $\mathbf{A}$ to $\mathbf{B}$ is $g^s_{\mathbf{A},\mathbf{B}} = \arg\min g_{a,b}, a \in \mathbf{A}, b \in \mathbf{B}$.

Assume the EDS derived from the mth largest EDR is $\mathbf{D^m}$, and the BSs with the 1st to $(m-1)$th largest EDR are in set $\mathbf{D^o}$. From Definition 2, we derive Lemma 2.

Lemma 2. *The mth maximal EDR, $2 \le m \le N$, is minimized if $\exists d^m \in \mathbf{D^m}$, whose pilot power level decrements, w_{b^m}, is larger than $g^s_{\mathbf{D^m},\mathbf{D^o}}$.*

Proof: Lemma 2 can be readily derived by Definition 2. ■

Then, the MEB algorithm balances the green energy consumption among BSs by minimizing the mth maximal EDR until any condition in Lemma 1 or 2 is satisfied. The pseudo code of the MEB algorithm is shown in Algorithm 3.

Algorithm 3 MEB Algorithm

```
Initialize P⃗_i^0, E^A_{i,j}, j ∈ A and D^o = ∅;
[P⃗_i^0, δ] = LEM(P⃗_i^0, E^A_{i,j}, A);
while (D^o ≠ A) do
  Find the set C* such that δ_{i,j} ≥ δ, j ∈ C*;
  D^o = D^o ∪ C*;
  if (D^o ≠ A) then
    OPT = FALSE;
  end if
  while (OPT == FALSE) do
    Find the largest EDR δ = max δ_{i,j}, j ∈ A \ D^o;
    Find the set C such that δ_{i,j} = δ, j ∈ A \ D^o;
    Given C and δ, update EDS, D, and calculate pilot
    power decrements, w⃗;
    if (D == A \ D^o || ∃j ∈ D such that w_j ≥ p^0_{i,j}) then
      OPT = TRUE;
    else if (D^o ∩ D ≠ ∅ || arg max w_j ≥ g^s_{D,D^o}) then
      OPT = TRUE;
    else
      Reduce p^0_{i,j} by w_j, j ∈ D, update δ;
    end if
  end while
end while
Return P⃗_i^0;
```

The computational complexity of MEB in the worst case is $O(QN^5M)$. Here, Q is the number of the pilot signal's power levels. Theoretically, MEB is a pseudo polynomial time algorithm. However, if any upper bound is imposed on the number of the pilot signal's power levels, the MEB algorithm becomes a polynomial time algorithm [21]. Although scaling with N^5, the MEB algorithm does not restrict the real-time responsiveness of the GEO for two reasons. On the one hand, for a given coverage area, the number of BSs is fixed. If the number of power levels is given, the MEB algorithm only scales with M. Since the MEB algorithm is implemented in the network controller, the computational resources required for executing the MEB algorithm with a large N can be pre-located to enable the real time responsiveness. On the other hand, the time interval between two consecutive cell size adaptations (the duration of one time slot) depends on the dynamics of the green energy generation and the mobile traffic intensity. For the green energy generation, the granularity for solar energy generation prediction is usually an hour [22]. For the mobile traffic intensity, the hourly mobile traffic profile can well represent the mobile traffic's characteristics for guiding the operation of the BSs [14]. Therefore, the time slot duration could be tens of minutes, which are long enough for executing the MEB algorithm.

C. The EA Algorithm

Based on the solution of the MEB algorithm, individual BSs apply the EA algorithm to adjust their green energy allocations. At the ith time slot, if $C_{i,j} \le E^A_{i,j}$, BS j is powered by green energy; the superfluous green energy, which equals to $(E^A_{i,j} - C_{i,j})$, will be evenly allocated at the following time slots. If $E^A_{i,j} < C_{i,j} \le E_{i,j}$, it indicates that the energy demand is larger than the allocated green energy, but less than the actual available green energy in the batteries. In this case, BS j increases $E^A_{i,j}$ to $C_{i,j}$. As a result, the green energy allocation of the following time slots will be decreased. The energy decrements are proportional to the amount of allocated green energy at each time slot. If $C_{i,j} > E_{i,j}$, BS j is unable to be powered by green energy, and the green energy allocated at the ith time slot will be evenly allocated to the following time slots. The pseudo code of the EA algorithm is shown in Algorithm 4.

Algorithm 4 The EA Algorithm

```
Calculate energy cost C_{i,j} based on P⃗_i^0;
if C_{i,j} ≤ E^A_{i,j} then
  β_{i,j} = 1;
  E^A_{k,j} = E^A_{k,j} + (E^A_{i,j} − C_{i,j})/(L−k+1), k ∈ (i+1, ···, L);
else if E^A_{i,j} < C_{i,j} ≤ E_{i,j} then
  β_{i,j} = 1;
  E^A_{k,j} = E^A_{k,j}(1 − (C_{i,j} − E^A_{i,j}) / Σ_{k=i+1}^{L} E^A_{k,j}), k ∈ (i+1, ···, L);
else
  β_{i,j} = 0;
  E^A_{k,j} = E^A_{k,j} + E^A_{i,j}/(L − k + 1), k ∈ (i+1, ···, L);
end if
Return E^A_{k,j}, β_{i,j}, k ∈ (i+1, ···, L);
```

V. Simulation Results

Simulations are set up as follows. A total of 36 BSs are located in a 6 by 6 grid. The distance between two adjacent BSs is 400 meters. The carrier frequency is 2110 MHz, and

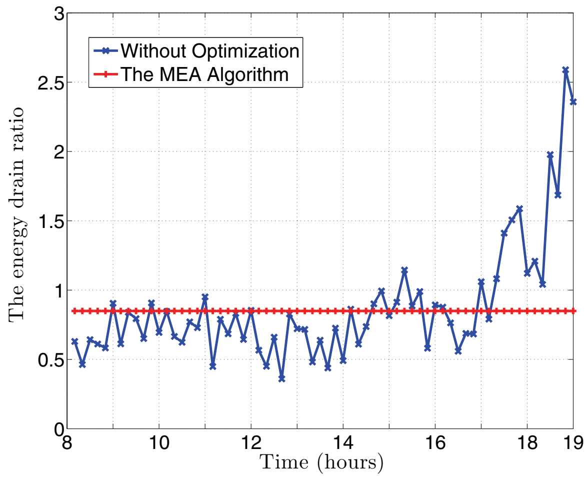

Fig. 5. The energy drain rate of the BS 1.

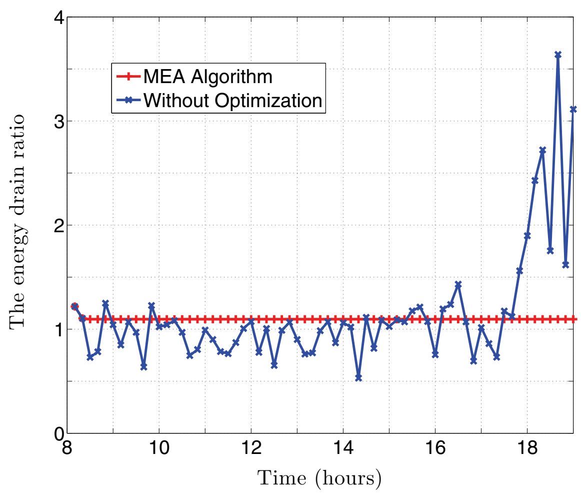

Fig. 6. The energy drain rate of the BS 2.

the bandwidth is 5 MHz. We adopt COST 231 Walfisch-Ikegami [23] as the propagation model with 9 dB Rayleigh fading and 5 dB Shadow fading. For the BS power model, we assume the antenna feeder loss is 3 dB, the transmitter gain is 10 dB, and the power amplifier efficiency is 50%. We adopt the SAM [16] and PVWatts [17] models to estimate the solar energy generation at individual time slots. Since the SAM and PVWatts models only provide hourly energy generation estimations, we apply the linear interpolation method to derive the solar energy generation at each time slot. The solar energy generation profile reflects the solar energy generation at New York City during summer time. To simulate the temporal and spatial diversities of mobile traffic, we assume mobile users are uniformly distributed in the area, and the total number of users in the system peaks between 10 AM and 19 PM, and bottoms between 1 AM and 5 AM. During peak hours, the total number of users is up to 500 while during the off peak hours, the total number of users is up to 20. In order to reflect the mobile traffic characteristic that the traffic volume is almost stable at the same time of two consecutive days, we assume the number of users within BS j's coverage area at the ith time slot of a day is the same as that of the previous day. However, the mobile users are randomly distributed in BS j's coverage area, and thus the energy consumption may vary. The mobile users' data rate is set to 384 $kbps$. For simplicity, we assume BSs have complete knowledge of the users' distances from BSs. We simulate the green energy consumption of the mobile network starting at 8:00 and ending at 19:00. The time slot duration is 600 seconds. In the simulation, we compare the GEO algorithm with the Best-Effort approach, in which the BSs consume green energy as long as the in-stored green energy is larger than the energy demand. The Best-Effort algorithm neither optimizes the energy allocation among time slots nor adapts BSs' cell sizes.

Fig. 5 and Fig. 6 show the performance of the MEA algorithm on two selected BSs. Fig. 5 shows the EDR on BS 1 whose total green energy generation during the simulated time slots is larger than its total energy consumption. The y-axis is the value of EDR, and the x-axis is the time. From the figure, the MEA algorithm optimizes the green energy allocation over time slots. As a result, the EDR of BS 1 is less than 1 for all the time slots, implying that BS 1 can be powered by green energy for all the time slots. Without the MEA algorithm, the EDRs of BS after 17:00 increase dramatically, and they are larger than 1, implying that the BS has to consume on-grid energy.

Fig. 6 shows the EDR on BS 2 whose total green energy generation during the simulated time slots is smaller than its total energy consumption. In this case, the MEA algorithm balances the energy allocation among time slots to make the EDRs of the BS at individual time slots slightly larger than 1. However, it does not indicate that the BS consumes on-grid energy at very time slot. Since all the EDRs are slightly larger than 1, the energy gap is likely to be filled by applying the MEB algorithm. Therefore, the overall on-grid energy consumption will be reduced. Without the MEA algorithm, the EDRs of the BS at the end of the data are extremely large, and the energy gap is less likely to be filled by the MEB algorithm.

Fig. 7 shows the effectiveness of the MEB algorithm. In the figure, we sort the EDRs of the BSs from the largest to the smallest, and the x-axis is the BS index while the y-axis is the EDR of the BSs in one time slot. As shown in the figure, the MEB algorithm balances the energy consumption among BSs. In the network, when the EDR of the BS is less than 1, the BS is powered by green energy; otherwise, it consumes on-grid energy. For both Best-Effort approach and the MEB algorithm, the EDRs of the BSs indexed from 16 to 36 are less than 1. It indicates that these BSs are powered by green energy. The EDRs of the BSs indexed from 1 to 15 are larger than 1, implying that these BSs may consume on-grid energy. However, the MEB algorithm reduces the EDRs of these BSs by balancing the energy consumption among the BSs. In other words, the energy gaps are reduced by applying the MEB algorithm. With a reduced energy gap, individual BSs may be more likely to adjust their green energy allocation to fill the energy gap. Therefore, the probability of these BSs powered by green energy is increased. Thus, applying the MEB algorithm balances the energy consumption among BSs,

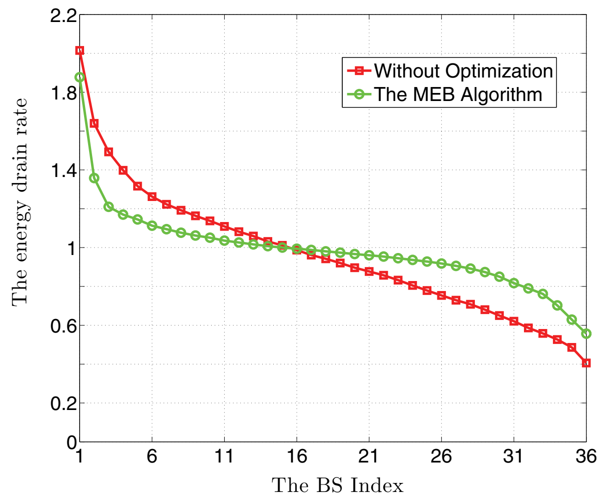

Fig. 7. The performance of the MEB algorithm.

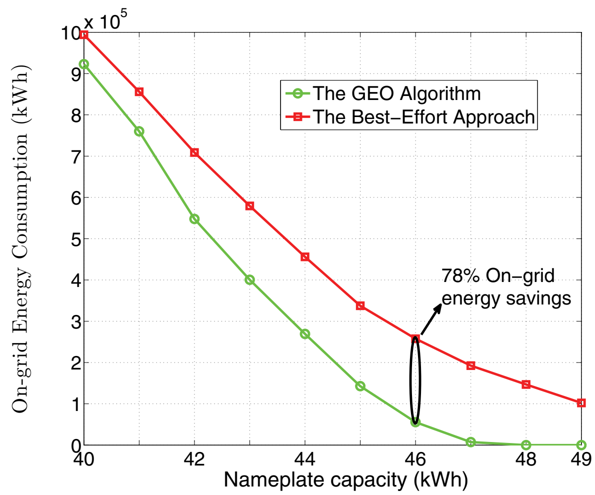

Fig. 8. The on-grid consumption withdifferent generation rate.

and thus reduces the energy gaps of the BSs which are short of green energy. As a result, with reduced energy gaps, the BSs may be enabled to utilize green energy by adjusting the energy allocation using the EA algorithm.

Fig. 8 and Fig. 9 show the mobile network's on-grid energy consumption and green energy consumption at different green energy generation rates, respectively. The nameplate capacity of the solar panel indicates the green energy generation rate. The larger the nameplate capacity, the larger the green energy generation rate. As shown in Fig. 8, as the green energy generation rate increases, the on-grid energy consumption of the mobile network reduces. When the green energy generation rate is larger, more electricity is generated from green energy. Therefore, more BSs can serve mobile users using electricity generated by green energy instead of consuming on-grid energy. When the nameplate capacity of the solar panel is larger than 48 kWh, the GEO algorithm achieves zero on-grid energy consumption while the Best-Effort algorithm still consumes a significant amount of on-grid energy. As compared with the Best-Effort approach, the GEO algorithm can save

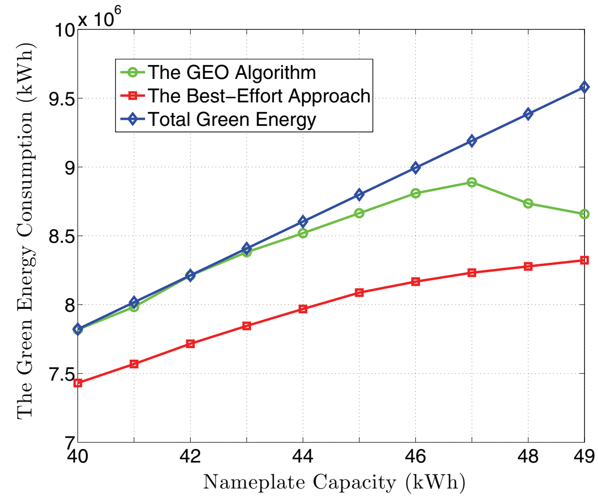

Fig. 9. The green consumption with different generation rate.

upto 78% on-grid energy.

Fig. 9 shows the cellular network's green energy utilization versus different green energy generation rates. As compared with the Best-Effort algorithm, the GEO algorithm enables the BSs to maximize the utilization of green energy. While the green energy generation rate increases, the green energy utilization of the GEO algorithm increases. When the nameplate capacity of the solar panel is larger than 47 kWh, the green energy utilization of the GEO algorithm decreases because the number of BSs which are short of green energy is reduced. In other words, an increasing number of BSs is able to generate sufficient green energy to serve the mobile users under their coverage. Therefore, less BSs are required to increase their cell sizes to cover the area of their neighboring BSs. Hence, the total green energy consumption decreases. As shown in Fig. 8 and Fig. 9, the GEO algorithm is able to maximize the utilization of green energy. As a result, the GEO algorithm requires a smaller green energy generation rate to achieve zero on-grid energy consumption.

VI. Conclusion

In this paper, we have proposed to reduce the on-grid energy consumption of cellular networks with hybrid energy supplies. We formulate the green energy optimization problem, and decompose it into two sub-problems: the multi-stage energy allocation problem and multi-BSs energy balancing problem. We have proposed the MEA algorithm, the MEB algorithm and the EA algorithm to solve these sub-problems, and thus address the GEO problem. The proposed solution has been demonstrated via extensive simulations to be able to save a significant amount of on-grid energy.

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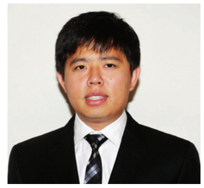

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