# Energy Cost Minimization via Intelligent Temporal and Spatial Resource Allocation in Green Heterogeneous Cellular Networks

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***Abstract*—The ever increasing data demand has led to the significant increase of energy consumption in cellular networks. In this paper, we study the problem of energy cost saving in heterogenous cellular networks with hybrid energy supplies. Owing to the diversities of mobile traffic and renewable energy, the energy cost saving problem involves both temporal and spatial dimensional optimization. We decompose the whole problem into three sub-problems and correspondingly our proposed solution is divided into three parts: First, we obtain average estimated energy consumption profiles for all base stations; Second, we allocate the green energy for each base station to minimize its energy cost based on its estimated energy consumption profile; Third, given the allocated green energy in the current slot, we perform the user association to minimize the total energy cost of the network. Simulation results demonstrate that our proposed algorithm can significantly reduce the total energy cost.**

## I. Introduction

With the ever-increasing of data traffic, wireless cellular networks have been bound to produce huge energy consumption [1], [2]. Particularly, *base stations* (BSs) consume more than 50 percent of the energy, as shown in the breakdown of power consumption in a typical cellular network [3]. The rising energy costs have made more and more researchers and engineers focus on the solutions to address the energy efficiency in wireless communications.

An attractive approach is to deploy heterogeneous networks, in which macro BSs provide large coverage generally, and one or more low power pico BSs cover a small area with dense traffic [4]. Such joint deployment of macro cells and pico cells can achieve 60% reduction of the overall energy consumption, compared with the conventional homogeneous deployment [3]. Based on the heterogeneous network architecture, many energy saving strategies have been proposed [5]–[9]. For example, the authors [9] sought an optimal macro/micro BS density for energy-efficient heterogeneous cellular networks. It provides theoretic analysis for energy efficient cellular network planning and dynamic operation control. Besides, authors in [8] investigated an energy-efficient dynamic network selection for users, balancing the data rate and power consumption.

Another emerging solution is the green cellular network powered by renewable energy sources, such as wind and solar [10]–[16]. In [17], Piro et al. demonstrated that a heterogeneous network with renewable energy could be an effective and sustainable solution, through evaluations of energy costs and $CO_2$ emissions savings for different scenarios. Liu et al. [13] proposed an adaptive user association in the green heterogeneous networks, maintaining a good tradeoff between the number of accepted user equipments and the radio resource consumption. Han and Ansari [11] proposed energy allocation and balancing algorithms in order to reduce the on-grid energy consumption in homogeneous networks powered by hybrid energy supplies. In [10], a two-stage dynamic programming algorithm has been proposed to minimize the average grid power consumption while satisfying the users' blocking probability requirements, adapting BSs' on-off states, active resource blocks as well as renewable energy allocation. Kong and Wang [14] proposed to reassign users originally associated with on-grid energy powered BSs to green pico BSs powered by renewable energy or macro BSs in green heterogeneous networks, so to make the best of green energy for energy cost saving. However, these works do not take into consideration the optimal utilization of green energy according to the green energy generation profile and the network traffic statistics. In [18] the authors proposed a joint user association and green energy allocation algorithm to lexicographically minimize the on-grid energy consumption in an offline manner without considering the difference between predicted and realistic mobile traffic.

In this paper, we aim to achieve the efficient utilization of green energy for the total energy cost minimization in a green heterogeneous network, where BSs can be powered by either on-grid energy or green energy. Owing to the temporal and spatial diversities of mobile traffic and renewable energy, we decompose this problem into three sub-problems: the total energy minimization problem, green energy allocation problem, and user association problem. Our solution consists of three algorithms to solve the three sub-problems accordingly. They are the *energy consumption estimation* (ECE) algorithm, *green energy allocation* (GEA) algorithm, and *user association* (UAC) algorithm. In the ECE algorithm, we obtain a minimum estimated energy consumption profile for each BS based on the mobile traffic statistics. Given the estimated energy consumption profile, the GEA algorithm optimizes the

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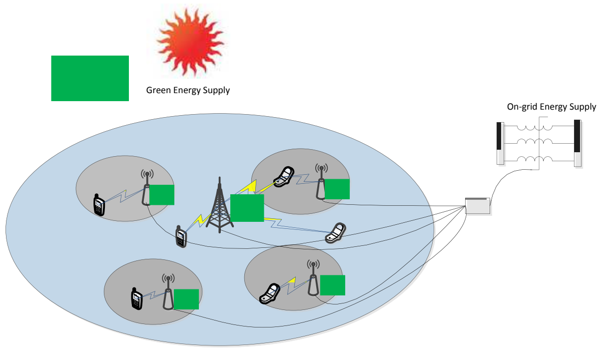


Fig. 1. An example green heterogeneous cellular network architecture.

green energy allocation across different time slots to minimize the energy cost for each BS overall time slots. The ECE and GEA algorithms are offline algorithms based on the historical mobile traffic and green energy generation statistics. The UAC algorithm is an online algorithm to decide the user-BS association in each time slot based on the allocated green energy and the practical user distribution. We conduct simulations for a seven-cell heterogeneous network and compare the proposed solution with the recent peer algorithms. Simulation results demonstrate that our proposed one can significantly reduce the total energy cost.

The rest of the paper is organized as follows: Section II presents the system model, and the problem formulation is provided in Section III. The proposed solution is presented in Section IV and evaluated in Section V. Finally, the paper is concluded in Section VI.

## II. System Model

### A. Network Model

In this paper, we consider a heterogeneous cellular network consisting of both macro BSs and pico BSs. Each macro BS covers a larger area, and each pico BS within a macro cell covers a smaller area. Mobile users are assumed to be evenly distributed in the network. For energy supply, all the BSs in our model are powered by both on-grid energy and renewable energy sources. We consider to use solar panels as the source of green energy. Fig. 1 illustrates an example green heterogeneous network with hybrid energy supplies.

Let $\mathcal{N}_1$, $\mathcal{N}_2$, and $\mathcal{M}$ denote the set of macro BSs, pico BSs and mobile users, respectively. $|\mathcal{N}_1| = N_1$, $|\mathcal{N}_2| = N_2$, and $|\mathcal{M}| = M$. We use $\mathcal{N} = \{1, 2, \cdots, N\}$ to denote the set of all BSs in the network, i.e., $\mathcal{N}$ =$\mathcal{N}_1 \cup \mathcal{N}_2$, and $N = N_1 + N_2$. We use the subscript $i \in \mathcal{N}$ to denote the $i$-th BS [1], and $j \in \mathcal{M}$ index the $j$-th user. The operational time of our algorithm is divided into $K = |\mathcal{K}|$ time slots, the length of each time slot is $\tau$ seconds and k $\in \mathcal{K}$ denotes the $k$-th time slot.

### B. Traffic Model

The mobile traffic shows both temporal and spatial diversities [19]. In the temporal domain, individual BS exhibits high traffic dynamics over time. We can find that the peak hour spans from 10 AM to 6 PM, and off peak hours are from 1 AM to 5 AM. However, the traffic volume has near-term stability. It is almost constant over a short term like several minutes of the same time in consecutive days. Thus, we can predict the average traffic load across several time slots based on the historical mobile traffic statistics. Here, we assume that each user has the same data rate yet maybe with different service durations. So the traffic volume at an BS can be equivalent to the number of users served by this BS.

According to the temporal and spatial traffic dynamics, we use a peak and off-peak temporal traffic model for mobile users. The mean number of users in the peak period is much larger than that in the off-peak period. In each period, the number of users is uniformly distributed around the mean value. In the spatial domain, we assume that mobile users are randomly distributed in the area.

### C. Data Transmission Model

In this paper, we focus on the downlink data transmission as the main energy consumption of all BSs. Let $\mathbf{X} = \{\mathbf{X_1}, \mathbf{X_2}, ..., \mathbf{X_K}\}$ be the user-BS association matrix. We use $\mathbf{X_k}$ to denote the user-BS association relationship at the $k$-th time slot. And the element $X_k(i, j)$ stands for the connection relationship between user $j$ and BS $i$ at the $k$-th time slot, i.e.,

$$X_k\left(i, j\right) = \begin{cases} 1, & \text{user } j \text{ is served by BS } i, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Note that a user in the system can be associated with only one BS, either a macro BS or a pico BS. That is, $\sum_{i \in \mathcal{N}} X_k\left(i, j\right) = 1, \forall j \in \mathcal{M}, \forall k \in \mathcal{K}$.

For simplicity, we ignore the time slot index $k$ in this subsection below. During the connection period, according to the Shannon Theorem, we can obtain the downlink transmission data rate of user $j$:

$$R_j = W_{i,j} \log_2(1 + \frac{g_{i,j} P_{i,j}}{N_0 W_{i,j}}), \tag{2}$$

where $P_{i,j}$ is the transmission power of BS $i$ for user $j$ data transmission, and $g_{i,j}$ is the channel gain between user $j$ and BS $i$, which in general includes path loss, shadowing and antenna gain. $N_0$ denotes the noise power level. And $W_{i,j}$ is the bandwidth of user $j$ allocated by its associated BS $i$. To reduce the computational complexity, we adopt a simple *equal share strategy* to allocate the available bandwidth of each BS to its associated users. We use $L_i = \sum\limits_{j \in \mathcal{M}} X_k\left(i, j\right)$ to denote the number of users served by the BS $i$. So the bandwidth allocated for any user $j$ of its associated users can be computed by $W_{i,j} = \frac{W_i}{L_i}$, where $W_i$ is the available bandwidth of BS $i$.

### D. Energy Consumption Model

In this paper, we assume that each user has the same data rate requirement $R_0$ when admitted to the network. But different users may have different service time because of their different traffic demands. Then by letting $R_j = R_0$, we can

[1]Without specifically stated, a BS can be either a macro BS, or a pico BS.

obtain the transmission power for data transmission of user $j$ from its associated BS $i$:

$$P_{i,j} = \frac{N_0 W_{i,j}(2^{R_0/W_{i,j}} - 1)}{g_{i,j}}. \quad (3)$$

The total transmission power of BS $i$ at the $k$-th time slot is:

$$P_{i,k} = \sum_{j \in \mathcal{M}} X_k\,(i,j) P_{i,j}. \quad (4)$$

The total power consumption of BS $i$ is calculated by

$$P_{i,k}^{total} = P_{i,k} + P_0. \quad (5)$$

Considering a short single time slot, we assume that BS $i$ is in the active status all the time. And $P_0$ is the fixed circuit power consumption for the BS $i$. The energy consumption of BS $i$ at the $k$-th time slot is given by

$$C_{i,k} = P_{i,k}^{total} \tau. \quad (6)$$

## III. Problem Formulation

At the beginning of the $k$-th time slot, the stored green energy at BS $i$ is denoted by $E_{i,k}$, which is determined by the energy consumption and generation of the previous time slot. For each BS $i$, $E_{i,k}$ evolves to time period $k+1$ as

$$E_{i,k+1} = E_{i,k} + P_{i,k}^h \tau - \alpha_{i,k} C_{i,k}, \forall k \in \{1, ..., K-1\}. \quad (7)$$

Here, $P_{i,k}^h$ is the energy harvesting power of BS $i$ at the $k$-th time slot, which can be predicted based on the historical renewable energy statistics [20]. $E_{i,1}$ is the initial green energy stored at BS $i$. Note that a BS has the sufficiently large battery capacity, and we do not consider battery overflow. We assume that each BS is powered by just one kind of energy at any one time slot. Denote $\overrightarrow{A} = (A_1, A_2, \cdots, A_i, \cdots, A_N)$ as the green energy allocation vector. And $A_i$ is the green energy allocation vector for the BS $i$ during all time slots. Besides, we use its element $A_{i,k}$ to denote the energy allocation of BS $i$ at the $k$-th time slot, and $A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau$. Let $\alpha_{i,k}$ be the indicator function of using which energy source:

$$\alpha_{i,k} = \begin{cases} 1, & \mathrm{A_{i,k} \geq C_{i,k}}, \\ 0, & \mathrm{A_{i,k} < C_{i,k}}. \end{cases} \quad (8)$$

If $\alpha_{i,k} = 1$, BS $i$ is powered by green energy at the $k$-th time slot; Otherwise, this BS is powered by on-grid energy.

Different kinds of energy have different unit costs. Let $\lambda$ and $\mu$ denote the unit energy consumption cost for on-grid energy and green energy, respectively. In general, the unit cost of green energy is much cheaper than that of the on-grid energy, and $\lambda > \mu \geq 0$. The energy cost of BS $i$ at the $k$-th time slot can be computed by

$$J_{i,k} = \lambda(1 - \alpha_{i,k}) C_{i,k} + \mu \alpha_{i,k} C_{i,k}. \quad (9)$$

According to the analysis in Section II, we can obtain that the energy consumption of each BS is dependent on its associated users, i.e., user-BS association matrix $X_k(i,j)$. As the unit cost of green energy is cheaper than that of the on-grid energy, if the BSs which have sufficient green energy could serve more users, the total energy cost of the whole network could be much saved. So the green energy allocation vector $\overrightarrow{A}$ is also a key factor which affects the total energy cost. Thus, our objective is to find one user-BS association matrix $\mathbf{X}$ and a green energy allocation vector $\overrightarrow{A}$ with the least energy cost, yet satisfying the network QoS requirements. We formulate the total *energy cost saving* (ECS) problem as a constrained optimization problem as follows:

$$\min_{\mathbf{X}, \overrightarrow{A}} J = \min_{\mathbf{X}, \overrightarrow{A}} \sum_{k=1}^{K} \sum_{i=1}^{N} J_{i,k}. \quad (10)$$

subject to:

$$\begin{array}{lll} (\mathrm{c1}) & P_{i,k} \leq P_i^{\max}, & \forall i \in \mathcal{N}, \forall k \in \mathcal{K} \\ (\mathrm{c2}) & \sum_{i \in \mathcal{N}} X_k\,(i,j) = 1, & \forall j \in \mathcal{M}, \forall k \in \mathcal{K} \\ (\mathrm{c3}) & X_k\,(i,j) \in \{0,1\}, & \forall j \in \mathcal{M}, \forall i \in \mathcal{N}, \forall k \in \mathcal{K} \\ (\mathrm{c4}) & A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau, & \forall i \in \mathcal{N}, \forall k \in \mathcal{K} \\ (\mathrm{c5}) & R_j = R_0, & \forall j \in \mathcal{M} \\ (\mathrm{c6}) & \lambda > \mu \geq 0. & \end{array}$$

The constraint (c1) is the maximum transmission power budget for each BS. The constraints (c2) and (c3) ensure that each user should be associated with one and only one BS. The constraint (c4) states that the green energy allocation of each BS cannot exceed the sum of its stored green energy and the amount of energy generated at the current time slot. The constraint (c5) is the data rate requirement for each user.

However, due to the dynamics of renewable energy and mobile traffic, the above minimization problem involves both spatial and temporal optimization. On the one hand, we have to balance mobile traffic among BSs within the whole system in the space dimension in each time slot. On the other hand, the green energy allocation across different time slots also have to be optimized. To approach this temporal-spatial optimization, we decompose the ECS problem into three subproblems: The first sub-problem aims to minimize the total energy consumption in the spatial domain by load balancing. The second sub-problem is to optimize green energy allocation for each BS in the temporal domain. The third sub-problem performs user association, with the given allocated green energy in the current slot, to minimize the total energy cost.

### A. Total Energy Minimization Problem

At first, we consider to minimize the total energy consumption by ignoring the energy costs of different energy sources. The unbalanced user association in a time slot may result in an increased total energy consumption. To minimize the total energy consumption, we need to balance the mobile traffic among different BSs. By doing so, we can obtain the estimated energy consumption profiles for all BSs in all time slots based on the mobile traffic statistics. This problem can be formulated as follows:

$$\min_{\mathbf{X}} \sum_{k=1}^{K} \sum_{i=1}^{N} C_{i,k}. \quad (11)$$

subject to: (c1), (c2), (c3), (c5).

### B. Green Energy Allocation Problem

For one BS, we can optimize its green energy allocation across different time slots based on its estimated energy consumption profile, so as to minimize its total energy cost over all time slots. The green energy allocation for one BS can be expressed as the following problem:

$$\min_{A_i}(J_{i,1}, ..., J_{i,k}, ...J_{i,K}), \forall i \in \mathcal{N}. \tag{12}$$

subject to: (c4), (c6). By optimizing green energy allocation for each BS across all time slots, the total energy cost $\sum_{k=1}^{K}\sum_{i=1}^{N} J_{i,k}$ of the whole network during the operational time can also be minimized.

### C. User Association Problem

The green energy allocation vector obtained above is based on the estimated energy consumption profile from mobile traffic statistics. But in practice, the user distribution in each time slot may have some variation. Therefore, with the guideline of the green energy allocation vector, we need to perform user association based on practical user distribution in each time slot, so as to further minimize the total energy cost. The user association problem can be formulated as follows:

$$\min_{\mathbf{X}} \sum_{k=1}^{K}\sum_{i=1}^{N} J_{i,k}. \tag{13}$$

subject to: (c1), (c2), (c3), (c5).

## IV. The Proposed Solution

Corresponding to the above three sub-problems, the proposed solution is divided into three parts, namely, the energy consumption estimation (ECE) algorithm, green energy allocation (GEA) algorithm and user association (UAC) algorithm.

### A. Energy Consumption Estimation Algorithm

Considering the near-term stability of mobile traffic, we can estimate the total energy consumption based on the historical mobile traffic statistics. In the proposed ECE algorithm, we aim to obtain the estimated energy consumption profile for each BS. Here, given one instance of user distribution, we use the nearest association scheme and calculate the total energy consumption. In this way, each individual user is associated with its nearest BS, so we can obtain a minimum total energy consumption. **Algorithm 1** provides the pseudo-codes for the ECE algorithm.

Denote $\mathcal{L}_{i,k}$ as the associated user set of BS $i$ at the $k$-th time slot. Let $C^e_{i,k}$ indicate the estimated energy consumption of BS $i$ at the $k$-th time slot. For each time slot $k, \forall k \in \mathcal{K}$, each user $j \in \mathcal{M}$ is associated with the BS $i^*$ with the maximum channel gain (MCG) (line 2 to 7 in Algorithm 1). Therefore, each user is served with the minimum energy consumption. Then we calculate the energy consumption $C^e_{i,k}$ for each BS at each time slot (line 8 to 12 in Algorithm 1). Note that this algorithm should be executed many times to obtain the average estimated energy consumption profile $C^a_{i,k}$ for each BS at each time slot.

**Algorithm 1** The ECE Algorithm

1: Generate an instance of user distribution;
2: **for** $k = 1$; $k \le K$; $k++$; **do**
3: Initialize $\mathcal{L}_{i,k} = \emptyset$, $\forall i \in \mathcal{N}$;
4: **for** each user $j \in \mathcal{M}$ **do**
5: $i^* = \arg\max_{i \in \mathcal{N}} g_{i,j}$, $\mathcal{L}_{i^*,k} = \mathcal{L}_{i^*,k} \cup \{j\}$;
6: **end for**
7: **end for**
8: **for** $k = 1$; $k \le K$; $k++$; **do**
9: **for** each BS $i \in \mathcal{N}$ **do**
10: Calculate $C^e_{i,k}$;
11: **end for**
12: **end for**
13: Return $C^e_{i,k}$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$.

### B. Green Energy Allocation Algorithm

Based on the green energy generation model and the average estimated energy consumption profile, we need to obtain the green energy allocation vector to minimize the energy cost of each BS over all time slots. However, the green energy generated at one time slot cannot be used at its previous time slot. In addition, the total available green energy in one time slot depends on the green energy generated at the current time slot and the residual green energy from previous time slots. In order to reduce the energy cost of the current time slot, we need to change the green energy allocation in the previous time slots. Our proposed GEA algorithm is provided in **Algorithm 2**.

Let $J^e_{i,k}$ be the estimated energy cost of BS $i$ at the $k$-th time slot. Here, to reduce the operational complexity, the energy cost mode can be simplified as $J^e_{i,k} = C^a_{i,k} - A_{i,k}$. Then we initialize the green energy allocation as follows:

$$A_{i,k} = \begin{cases} E_{i,1} + P^h_{i,1}\tau, & \text{k} = 1, \\ P^h_{i,k}\tau, & \text{k} > 1, \end{cases} \tag{14}$$

and calculate $J^e_{i,k}$ (line 1 in Algorithm 2). For each BS $i \in \mathcal{N}$, if its energy cost at one time slot is larger than that at the previous time slot, i.e., $J^e_{i,m} > J^e_{i,m-1}$, then we find the $n$-th time slot from the 1st to $(m-1)$-th time slot, such that $J^e_{i,n} < \bar{J}^e$ (line 5 to 10 in Algorithm 2). Here, $\bar{J}^e$ is the average energy cost for BS $i$ from the $n$-th time slot to the $m$-th time slot. When $J^e_{i,n} > \bar{J}^e$, we find such $n$-th time slot to prevent green energy from being allocated to the initial $n$-th time slot for the 'equal sharing' of total energy cost across different time slots. In this way, from the $n$-th to the $m$-th time slot, we decrease for $J^e_{i,n} < \bar{J}^e$ (or increase for $J^e_{i,n} \ge \bar{J}^e$) the green energy allocation $A_{i,k}$ with an amount of $|A_{i,k} - C^a_{i,k} + \bar{J}^e|$ to make $J^e_{i,k}$ equal to $\bar{J}^e$ (line 11 to 17 in Algorithm 2). After the GEA algorithm, we can see $J^e_{i,m} \le J^e_{i,k}$, $\forall k \in \{1, 2, ..., m-1\}$.

**Algorithm 2** The GEA Algorithm

**Input:** $C^a_{i,k}$**,** $E_{i,1}$**,** $P^h_{i,k}$**,** $\forall i \in \mathcal{N}$**,** $\forall k \in \mathcal{K}$**,** $\tau$**;**
**Output:** $A_{i,k}$**,** $\forall i \in \mathcal{N}$**,** $\forall k \in \mathcal{K}$**;**

Initialize $A_{i,k}$, and calculate $J^e_{i,k}$;
**for** each BS $i \in \mathcal{N}$ **do**
  **for** $m = 2$; $m \leq K$; $m++$; **do**
    **if** $J^e_{i,m} > J^e_{i,m-1}$ **then**
      **for** $n = 1$; $n \leq m-1$; $n++$; **do**
        Calculate $\bar{J}^e = \frac{\sum_{k=n}^{m} J^e_{i,k}}{m-n+1}$;
        **if** $J^e_{i,n} < \bar{J}^e$ **then**
          t=n; **Break**;
        **end if**
      **end for**
      **for** $n = t$; $n \leq m$; $n++$; **do**
        **if** $J^e_{i,n} < \bar{J}^e$ **then**
          Decrease $A_{i,n}$ to let $J^e_{i,n} = \bar{J}^e$;
        **else**
          Increase $A_{i,n}$ to let $J^e_{i,n} = \bar{J}^e$;
        **end if**
      **end for**
    **end if**
  **end for**
**end for**

**Algorithm 3** The UAC phase one

1: **for** $k = 1$; $k \leq K$; $k++$; **do**
2:   Initialize $\mathcal{L}_{i,k} = \emptyset$, $\forall i \in \mathcal{N}$;
3:   **for** each user $j \in \mathcal{M}$ **do**
4:     $i^* = \arg\max_{i \in \mathcal{N}} g_{i,j}$, $\mathcal{L}_{i^*,k} = \mathcal{L}_{i^*,k} \cup \{j\}$;
5:   **end for**
6:   **for** each BS $i \in \mathcal{N}$ **do**
7:     Calculate $P_{i,k}$;
8:     **while** $P_{i,k} > P^{\max}_i$ **do**
9:       $j^* = \arg\min\{g_{i,j} - g_{n,j} | g_{i,j} > g_{n,j}, j \in \mathcal{L}_{i,k}, n \in \mathcal{N} \backslash \{i\}\}$, and $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \backslash \{j^*\}$, $\mathcal{L}_{n,k} = \mathcal{L}_{n,k} \cup \{j^*\}$;
10:       Calculate $P_{i,k}$ and $P_{n,k}$;
11:       **if** $P_{n,k} \leq P^{\max}_n$ **then**
12:         Update $\mathcal{L}_{i,k}$ and $\mathcal{L}_{n,k}$;
13:       **else**
14:         $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \cup \{j^*\}$, $\mathcal{L}_{n,k} = \mathcal{L}_{n,k} \backslash \{j^*\}$ and set $g_{i,j^*} - g_{n,j^*} = +\infty$;
15:       **end if**
16:       Recalculate $P_{i,k}$ and $P_{n,k}$;
17:     **end while**
18:   **end for**
19: **end for**
20: Return $P_{i,k}$, $\mathcal{L}_{i,k}$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$.

### C. User Association Algorithm

The ECE and GEA are offline algorithms in order to obtain the estimated energy consumption profiles and green energy allocation vectors, respectively. Owing to the difference between predicted and realistic mobile traffic, we need to execute user association at each time slot based on the current user distribution. We next propose an online user association algorithm, which consists of three phases.

**Phase one:** In this phase, we first obtain an initial user-BS association scheme by letting each user to be associated with its nearest BS without violating the constraint (c1). **Algorithm 3** provides the pseudo-codes for the first phase of the UAC algorithm. For each time slot $k, \forall k \in \mathcal{K}$, each user $j$ is served by the BS $i^*$ with the maximum channel gain (line 3 to 5 in Algorithm 3). Then, we calculate the total transmission power $P_{i,k}$ for each BS $i$. When it violates the maximum transmission power budget, i.e., $P_{i,k} > P^{\max}_i$, we throw out the user $j^* \in \mathcal{L}_{i,k}$ to the BS $n \in \mathcal{N} \backslash \{i\}$ iteratively, until the power budget constraint can be satisfied (line 8 to 17 in Algorithm 3). Here, user $j^*$ has the minimum channel gain difference $g_{i,j} - g_{n,j}$, that is, among available user $j \in \mathcal{L}_{i,k}$, user $j^*$ is the closest to one of its neighbor BS $n \in \mathcal{N} \backslash \{i\}$ (line 9 in Algorithm 3). We calculate the $P_{n,k}$. If the BS $n$ does not violate the power budget constraint, we associate $j^*$ to BS $n$; Otherwise, we do not consider user $j^*$, and set $g_{i,j^*} - g_{n,j^*} = +\infty$ to prevent it being selected again (line 11 to 15 in Algorithm 3).

**Phase two:** After the first phase, we can obtain an initial user association scheme. However, it does not consider the green energy allocation for each BS. To make the best of the green energy, it is possible to make BSs with sufficient allocated green energy to serve more users. Meanwhile, considering the larger energy consumption of macro BS, we first take measure to guarantee macro BSs powered by green energy.

Let $\alpha_{i,k}$ indicate whether a BS $i$ is powered by green energy. If $\alpha_{i,k} = 1$, then it is powered by green energy, or called a green BS; Otherwise, it is not, or called an on-grid BS. Denote $\mathcal{S}$ as the green BS set, in which all BSs are powered by green energy. In the second phase, for each time slot $k \in \mathcal{K}$, if the energy consumption of macro BS $i \in \mathcal{N}_1$ is larger than its green energy allocation, we will throw out some appropriate user $j^* \in \mathcal{L}_{i,k}$ as the same way in the first phase, until it can be powered by green energy, i.e., $C_{i,k} \leq A_{i,k}$ (line 4 to 7 in Algorithm 4). We next check which BS can be powered by green energy, and put green BS into the set $\mathcal{S}$ (line 8 to 11 in Algorithm 4). For each BS $i \in \mathcal{N}$, if it has sufficient allocated green energy, i.e., $C_{i,k} \leq A_{i,k}$, it will 'deprive' other BSs of a user $j^*$ iteratively, until its allocated green energy becomes zero (line 12 to 34 in Algorithm 4). If one user $j$ is served by green BS, we will set $g_{i,j} = 0$ (line 14 to 18 in Algorithm 4) in advance. Here, we select the user $j^*$ with the maximum channel gain among all $g_{i,j}$, $\forall j \in \mathcal{M}$, and find the BS $n$ with which it is associated. Before the user $j^*$ is deprived, we calculate $J_{i,k}$ and $J_{n,k}$, and let $J^b_{i,k} = J_{i,k}$ and $J^b_{n,k} = J_{n,k}$ record their energy costs before the deprivation, respectively (line 19 to 20 in Algorithm 4). Assuming that the user $j^*$ is associated to BS $j$, we calculate $C_{i,k}$, $C_{n,k}$, $J_{i,k}$ and $J_{n,k}$

**Algorithm 4** The UAC phase two

1: **for** $k = 1$; $k \leq K$; $k++$; **do**
2: Initialize $\mathcal{S} = \emptyset$;
3: Calculate $C_{i,k}$, $\forall i \in \mathcal{N}$;
4: **while** $C_{i,k} > A_{i,k}, \forall i \in \mathcal{N}_1$ **do**
5: Find appropriate user $j^*$ and BS $n$, $j^* = \arg\min\{g_{i,j} - g_{n,j} | g_{i,j} > g_{n,j}, j \in \mathcal{L}_{n,k}, n \in \mathcal{N} \backslash \{i\}\}$;
6: Set $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \backslash \{j^*\}$, $\mathcal{L}_{n,k} = \mathcal{L}_{n,k} \cup \{j^*\}$;
7: **end while**
8: **for** each BS $i \in \mathcal{N}$ **do**
9: Calculate $C_{i,k}$, and check whether it can be powered by green energy;
10: Put green BS into set $\mathcal{S}$, $\mathcal{S} = \mathcal{S} \cup \{i\}$;
11: **end for**
12: **for** each BS $i \in \mathcal{N}$ **do**
13: **while** $C_{i,k} \leq A_{i,k}$ **do**
14: **for** each user $j \in \mathcal{M}$ **do**
15: **if** the user $j$ is served by BS $m \in \mathcal{S}$ **then**
16: set $g_{i,j} = 0$;
17: **end if**
18: **end for**
19: $j^* = \arg\max\{g_{i,j} | j \in \mathcal{M}\}$;
20: Find the BS $n$ which the user $j^*$ is associated with, calculate $J_{i,k}$ and $J_{n,k}$, and make $J^b_{i,k}$ = $J_{i,k}$, $J^b_{n,k}$ = $J_{n,k}$;
21: Set $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \cup \{j^*\}$, $\mathcal{L}_{n,k} = \mathcal{L}_{n,k} \backslash \{j^*\}$;
22: **if** $\alpha_{n,k} == 0$ **then**
23: Calculate $C_{i,k}$, $C_{n,k}$, $J_{i,k}$ and $J_{n,k}$;
24: **if** $C_{i,k} \leq A_{i,k}$ && $J_{i,k} + J_{n,k} \leq J^b_{i,k} + J^b_{n,k}$ **then**
25: Update $\mathcal{L}_{i,k}$ and $\mathcal{L}_{n,k}$;
26: **if** $C_{n,k} \leq A_{n,k}$ **then**
27: $\alpha_{n,k} = 1$, and $\mathcal{S} = \mathcal{S} \cup \{n\}$;
28: **end if**
29: **else**
30: $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \backslash \{j^*\}$, $\mathcal{L}_{n,k} = \mathcal{L}_{n,k} \cup \{j^*\}$, and **break**;
31: **end if**
32: **end if**
33: **end while**
34: **end for**
35: **end for**
36: Return $J_{i,k}$, $\mathcal{L}_{i,k}$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$.

when the BS $n$ is an on-grid BS. If the energy consumption of BS $i$ is less than its allocated green energy and now the total energy cost of BS $i$ and BS $n$ is decreasing, i.e., $C_{i,k} \leq A_{i,k}$ and $J_{i,k} + J_{n,k} \leq J^b_{i,k} + J^b_{n,k}$, we associate the user $j^*$ to the BS $i$ and check whether the BS $n$ can be powered by green energy; Otherwise, we abandon the association of the user $j^*$ with the BS $i$, and break (line 24 to 31 in Algorithm 4). **Algorithm 4** provides the pseudo-codes for second phase of the UAC algorithm.

**Algorithm 5** The UAC phase three

1: **for** each BS $i \in \mathcal{N}$ **do**
2: **for** $k = 1$; $k \leq K$; $k++$; **do**
3: **if** $C_{i,k} \leq A_{i,k}$ **then**
4: $A_{i,l} = A_{i,l}(1 + \frac{A_{i,k} - C_{i,k}}{\sum_{l=k+1}^{K} A_{i,l}}), l \in \{k+1, ..., K\}$;
5: **end if**
6: **if** $A_{i,k} < C_{i,k} \leq E_{i,k} + P^h_{i,k}\tau$ **then**
7: $\alpha_{i,k} = 1$;
8: $A_{i,l} = A_{i,l}(1 - \frac{C_{i,k} - A_{i,k}}{\sum_{l=k+1}^{K} A_{i,l}}), l \in \{k+1, ..., K\}$;
9: **end if**
10: **if** $C_{i,k} > E_{i,k} + P^h_{i,k}\tau$ **then**
11: $A_{i,l} = A_{i,l}(1 + \frac{A_{i,k}}{\sum_{l=k+1}^{K} A_{i,l}}), l \in \{k+1, ..., K\}$;
12: **end if**
13: **end for**
14: **end for**
15: Return $A_{i,k}$, $\alpha_{i,k}$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$.

**Phase three:** In the third phase, we need to adjust green energy allocation again for each BS to achieve efficient utilization of allocated green energy, based on the user-BS association scheme derived from the second phase. **Algorithm 5** provides the pseudo-codes for this phase of the UAC algorithm. For each BS $i \in \mathcal{N}$, at the $k$-th time slot, if it has sufficient allocated green energy, the residual energy $(A_{i,k} - C_{i,k})$ is allocated at the following time slots (line 1 to 5 in Algorithm 5). If $A_{i,k} < C_{i,k} \leq E_{i,k} + P^h_{i,k}\tau$, we can see that there are enough green energy in the batteries, so we increase $A_{i,k}$ equal to $C_{i,k}$ (line 6 to 9 in Algorithm 5). Thus, the BS $i$ is powered by green energy, but we have to decrease the energy allocation in the following time slots. If $C_{i,k} > E_{i,k} + P^h_{i,k}\tau$, the BS $i$ only can be powered by on-grid energy, and the allocated green energy at this time slot have to be allocated to the following time slots (line 10 to 12 in Algorithm 5). Note that the energy increments (decrements) in the following time slots above are proportional to the amount of allocated green energy at each time slot.

## V. Simulation Results

In our simulations, we consider a 2-tier heterogeneous network consisting of 7 macrocells. There are 4 pico BSs evenly distributed within each macrocell. All BSs are powered by both on-grid energy and renewable energy. The radius of a macrocell is 600m; While the distance between the centers of pico BSs and macro BS is around 0.6 times of the macro cell radius. The required date rate of each user is 10Mbps, and each BS is with 20MHz available bandwidth.

In the simulations, the maximum transmission powers of a macro BS and pico BS is 46dBm and 30dBm, respectively, and the value of fixed power expenditure are 23dBm and 20dBm, respectively. The path loss models are set according to [21]: $L(d) = 128.1 + 37.6\log(d)$ and $L(d) = 130.7 + 36.7\log(d)$ for

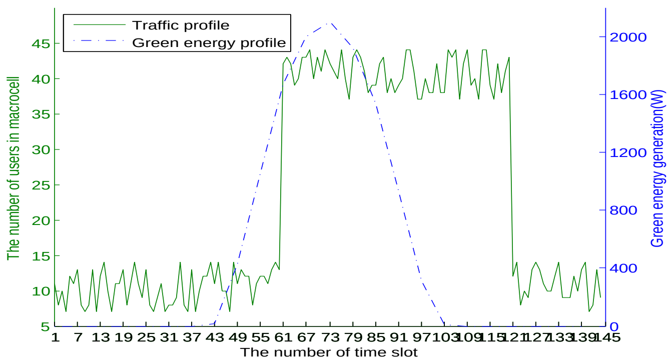


Fig. 2. Traffic and green energy profiles versus different time slots.

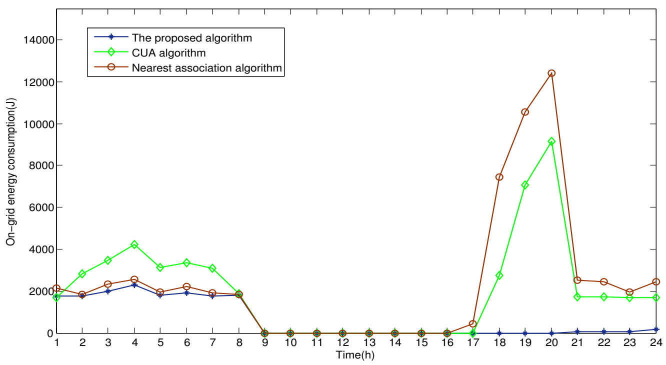


Fig. 3. Comparison of on-grid energy consumption against time slots.

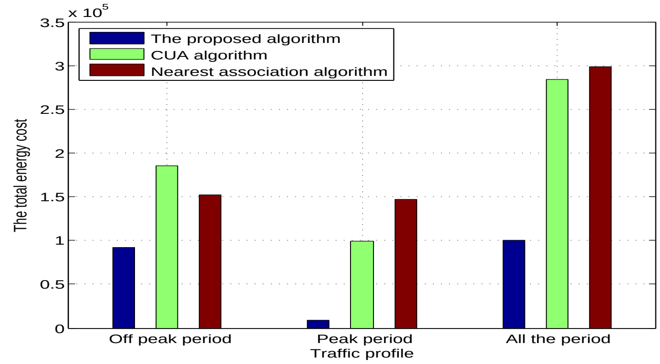


Fig. 4. Comparison of the total energy cost in different traffic profiles. $\lambda = 1$, $\mu = 0$.

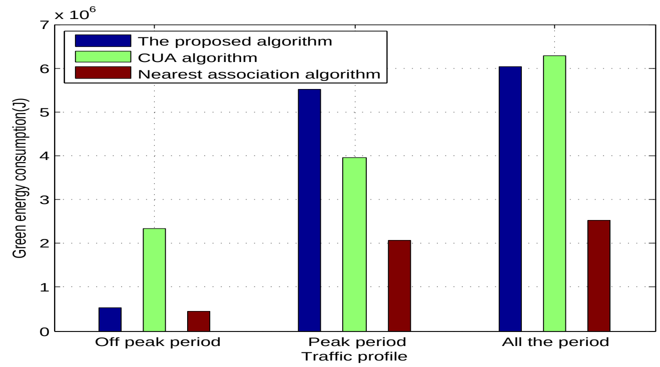


Fig. 5. Green energy consumption in different traffic profiles.

macro BSs and pico BSs, respectively, where $d$ is the distance from a BS to its served user. The noise power level is set to be $N_0 = -174$dBm/Hz.

For the solar charging model, we use the PVWatts model [20] to predict the hourly solar energy generation in Beijing City. From the measurement report in [19], the temporal characteristics of mobile traffic can be modeled as two different periods: the peak period and off-pear period. In the peak period, the number of users is uniformed distributed around the mean value of 40 users; and in the off-peak period, the mean value is 10 users. Furthermore, in the spatial domain, mobile users are evenly distributed in the network. Fig. 2 illustrates an example of the green energy generation profile and mobile traffic profile.

We execute our proposed algorithm for 24 hours, with each time slot equal to $\tau = 600s$. We compare our proposed algorithm with the typical nearest association [22], and the centralized user association (CUA) algorithm [14], in which the BSs serve as many users as possible, as long as they have sufficient green energy, to make the full utilization of the green energy storage in each time slot.

Fig. 3 compares the on-grid energy consumption against the time slots for the three algorithms. It can be seen that the on-grid energy consumption of our proposed algorithm is the smallest, and the on-grid energy is consumed in a more flat way over the whole time duration. This is because we perform an optimized green energy allocation for individual BSs across different time slots. So it can use green energy intelligently. However, in the CUA algorithm and nearest association algorithm, the on-grid energy consumption increases dramatically from 16:00 to 20:00 in the afternoon, since the green energy generation decreases rapidly during this time period, while they don't have enough stored green energy from the previous time slots. Owing to the lower mobile traffic volume after 21:00, the on-grid energy consumption goes down sharply.

Fig. 4 compares the total energy cost in different traffic profiles. The unit price of the on-grid energy and green energy are set as $\lambda = 1$ and $\mu = 0$, respectively. From the simulation results, we can find that our proposed algorithm causes much smaller energy cost than the other two algorithms, especially in the peak period. This is because the proposed GEA algorithm performs the green energy allocation optimization in the time domain; while the others do not. Furthermore, we can further maximize the green energy utilization in each time slot by the proposed UAC algorithm.

Fig. 5 compares the green energy consumption over the time slots in different traffic conditions. It is clearly observed that the green energy consumption of our proposed algorithm and the CUA algorithm are larger than that of the nearest association algorithm. This is due to that the two algorithms can make the best use of the available green energy. Although the CUA algorithm achieves larger utilization of green energy, its

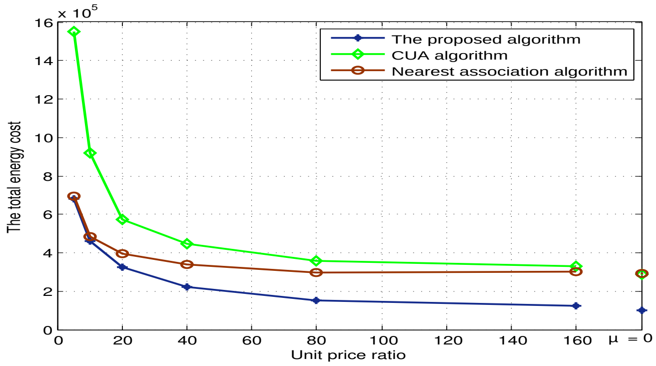


Fig. 6. The total cost with different ratio of unit price of energy.

total energy cost is larger than that of our proposed algorithm. This is because that it does not consider to optimize the green energy utilization across different time slots. In other word, it is a kind of myopic solution of only maximizing the green energy utilization for only the current time slot, regardless the traffic and charging dynamics in the time domain. Recall that in Fig. 4, the CUA algorithm uses much more on-grid energy in the peak period. But our proposed algorithm can use more green energy than other algorithms at peak period. This is due to that the proposed GEA algorithm can make some reservation of green energy generated at off peak period for more traffic requirement in the peak period.

Fig. 6 plots the total energy cost for different unit price ratios, i.e., $\lambda/\mu$. As seen from the figure, compared with the CUA algorithm and nearest association algorithm, the proposed algorithm achieves a much less total energy cost when the unit price ratio is larger than 5. And the total energy cost decreases with the increase of the unit price ratio. In particular, when the unit price of green energy $\mu = 0$, that is, the green energy is free, it reaches to the highest energy cost saving. In this case, the total energy cost of our proposed algorithm, CUA algorithm and nearest association algorithm are $1.01 \times 10^5$, $2.87 \times 10^5$ and $2.92 \times 10^5$, respectively.

## VI. Conclusion

In this paper, we have studied how to reduce the total energy cost in a green heterogeneous cellular network with hybrid energy sources. We first formulated a total cost minimization problem and decomposed it into three sub-problems. We then proposed our solution to solve these sub-problems, which consists of the ECE algorithm, the GEA algorithm, and the UAC algorithm. Simulation results have demonstrated the effectiveness of the proposed algorithm in terms of much reduced energy cost. We notice that the proposed solution is a centralized one. In our next work, we will first design a distributed solution and also take into consideration of potential green energy generation interrupts as well as different traffic QoS requirements.

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