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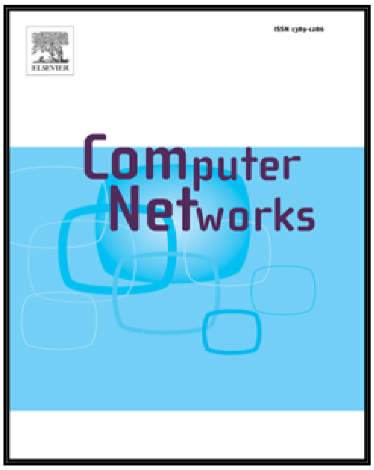

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On Minimizing Energy Consumption Cost in Green Heterogeneous Wireless Networks

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Abstract—**Internet of Things has been adopted as an emerging service for future wireless networks, which, however, introduces new challenges for transmission bandwidth and energy guarantees. In this paper, we study the problem of energy cost minimization in heterogenous wireless networks with hybrid energy supplies from the perspective of resource allocation. Owing to the temporal and spatial diversities of user traffic and renewable energy, we propose both centralized and distributed heuristic algorithms to obtain approximate solutions by iteratively addressing the following sub-problems: the total energy minimization problem, green energy allocation problem, user association problem, and green energy reallocation problem. At first, based on the temporal traffic statistics, we obtain estimated average energy consumption profiles for all base stations; Second, we allocate the green energy in the temporal domain for each base station to minimize its energy cost based on its estimated energy consumption profile; Third, in each slot, we perform spatial resource allocation and propose a centralized and a distributed user association algorithm, given the allocated green energy and practical user distribution in each slot. Fourth, after user association and data transmission, we readjust the temporal green energy allocation for each BS to further improve green energy utilization. Simulation results show that compared with two peer algorithms, our proposed solution can significantly reduce the total energy cost.**

Index Terms—**Energy efficiency, renewable energy, heterogeneous wireless network, resource allocation, Internet of Things.**

I. Introduction

The Internet of Things (IoT) has been becoming an important service in wireless networks owning to its wide range of applications in smart cities, environment monitoring and etc [1], [2]. As more and more objects are connected via radio medium, great challenges have been posed on transmission bandwidth and energy consumption. Envisioning the fast development of IoT with the ever-increasing data traffic, wireless networks have been bound to consume huge energy for data transmission. Particularly, *base stations* (BSs) consume more than 50 percent of the energy, as shown in the breakdown of power consumption, in a typical wireless network. Owning to the huge energy consumption, wireless networks already represent around 0.2% of total carbon emissions, and this is expected to increase every year [3]. How to reduce the energy consumption cost of BSs has become a strategic objective for ensuring the success of IoT in wireless communications industry.

An attractive approach for saving energy in wireless networks is to deploy heterogeneous networks consisting of both macro cells and small cells [4]. Adding more low power pico BSs in macro cells to realize the shorter propagation distances between BSs and end users can achieve 60% reduction of the overall energy consumption, compared with the conventional homogeneous deployment [3]. How to deploy and operate heterogeneous wireless networks in an energy efficient way have been studied recently [5]–[8]. However, these works mainly focus on reducing the on-grid energy consumption.

Another innovative solution is to exploit renewable energy to power BSs for wireless data transmissions with less unit energy cost, such as using solar energy, wind energy and so on [9]. German mobile operator E-Plus [10] has launched the first generation of green BSs by using a combination of solar and wind power. To adapt to dynamics of green power and mobile traffic, a new green energy powered BS mode with five energy related components has been proposed in [11]. In [12], Piro et al. have evaluated the great potential of energy cost and CO_2 emission savings for different scenarios in a heterogeneous green network. However, these studies take into consideration the utilization of green energy according to the known network traffic statistics yet without considering the green energy generation profile.

In this paper, we study the problem of minimizing the energy consumption cost in a heterogeneous wireless network with hybrid energy supplies from the perspective of mobile user association and green energy allocation in both the temporal and spatial dimension. In such a network, BSs can be powered by either on-grid energy or green energy. But due to the circuit constraint, a BS cannot be powered by both energies at the same time. It is generally believed that green energy is much cheaper than on-grid energy. Thus, maximizing the green energy utilization could lead to total energy cost minimization. On the one hand, the charging of green energy like solar power is often with temporal dynamics, and mobile traffic also embodies temporal and spatial diversities. All these factors make the energy cost minimization a very challenging issue.

In this paper, we first formulate the cost minimization problem as a constrained optimization problem. As this problem involves both temporal and spatial optimization of resource al-

Bang Wang and Qiang Yang are with the School of Electronic Information and Communications, Huazhong University of science and technology (HUST), Wuhan, China. Email: wangbang@hust.edu.cn.

Laurence T. Yang is with the School of Computer Science and Technology, Huazhong University of Science and Technology (HUST), Wuhan, China. He is also with the Department of Computer Science, St. Francis Xavier University, Antigonish, Canada. Email: ltyang@gmail.com.

Chunsheng Zhu is with the Department of Electrical and Computer Engineering, The University of British Columbia, Canada. Email: chunsheng.tom.zhu@gmail.com.

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location different from previous studies, we then decompose it into four sub-problems: the total energy minimization problem, green energy allocation problem, user association problem, and green energy reallocation problem. Accordingly, our solution consists of four parts each solving one of sub-problems. They are the *energy consumption estimation* (ECE) algorithm, *green energy allocation* (GEA) algorithm, *user association* (UA) algorithm, and *green energy reallocation* (GER) algorithm.

The ECE and GEA algorithms are offline algorithms based on the historical mobile traffic distribution and green energy generation statistics. The ECE algorithm is to obtain an estimated average energy consumption profile for each BS based on the mobile traffic temporal and spatial statistics. The GEA algorithm is to optimize the green energy allocation across different time slots to minimize the energy cost for each BS over all slots. The UA and GER algorithms are online algorithms to be executed in each slot based on the practical mobile traffic distribution. We first propose a centralized user association algorithm (CUA) to decide the user-BS association in each slot based on the allocated green energy and the practical user distribution in this slot. However, it is usually difficult to collect all information of the whole network and to coordinate among different BSs. We then propose a distributed user association algorithm (DUA) without coordination among different BSs and with low complexity. Based on the practical user-BS association scheme in each slot, the GER algorithm adjusts green energy allocation again for each BS to further improve green energy utilization. We conduct simulations for a typical heterogeneous network and compare the proposed solution with recent peer algorithms. Simulation results demonstrate that our proposed solution can significantly reduce the total energy cost.

The rest of the paper is organized as follows. Section II reviews some related work on energy efficiency in wireless networks. Section III presents the system model, and the problem formulation is provided in Section IV. The proposed solution is presented in Section V and evaluated in Section VI. Finally, the paper is concluded in Section VII.

II. Related Work

Energy efficiency has become a severe problem for wireless networks. Many methods have been proposed to improve the power efficiency of wireless networks [13]–[17]. However, they mainly focus on the homogeneous network scenario. For instance, Suarez et al. [13] propose a novel distributed green cell breathing algorithm based on the synchronized BS clusters to avoid the drawbacks of centralized approaches. In [14], a polynomial-time algorithm with joint BS activation and power control has been proposed to minimize the total power consumption of the whole network while maintaining the network coverage. Moon et al. [15] study the energy-efficient user association problem from a population game-theoretic perspective and propose a distributed association algorithm through appropriate association pricing. In [16], the authors aim to minimize the total power consumption for cellular systems by jointly considering BS deployment and power allocation, while providing user transmission rate and quality of experience guarantees.

Considering the ever-increasing demand for higher data rates, one promising shift on the network deployment is to use heterogeneous networks consisting of macro, micro, pico and femto cells. For such a heterogeneous network architecture, many energy saving strategies have been proposed [18]–[25]. For example, Wang and Rangapillai [18] consider a cooperative clustering model and propose a BS cooperation scheme to improve the energy efficiency of heterogeneous networks. In [20], the authors propose an energy efficient user association algorithm in cognitive heterogeneous networks, exploiting the available context-aware information, such as users' channel measurements and throughput requirements, and the available spectrum resources of each BS, to associate the users in an energy efficient way while maintaining high spectrum efficiency. In [21], given the coverage constraints, a feasible focusing searching algorithm has been proposed to find the optimal number of small BSs to be placed so as to maximize the network energy efficiency. Zhu et al. [23] propose an energy efficient user association scheme based on small cell sleeping in heterogeneous networks. However, all above studies assume that each BS is equipped with only on-grid energy sources, and have not considered the usage of green energy with lower cost. In [25], the authors provide a taxonomy for the existing user association algorithms in various heterogeneous networks, as well as some design guidelines and potential solutions for user association in the upcoming fifth generation mobile networks.

There are also some studies considering the wireless networks with hybrid energy supplies [26]–[33]. Liu et al. [26] propose an adaptive user association in green heterogeneous networks, where all BSs are assumed solely powered by the harvested renewable energy, to achieve a good tradeoff between the number of accepted user equipments and the radio resource consumption. In [27], a two-stage dynamic programming algorithm has been proposed to minimize the average on-grid power consumption while satisfying the user blocking probability requirement by adapting BSs' on-off states, active resource blocks as well as renewable energy allocation. Wang et al. [30] propose to reassign users originally associated with on-grid energy powered BSs to green pico BSs powered by renewable energy in green heterogeneous networks, so to make the best of green energy. Han and Ansari [32] propose energy allocation and balancing algorithms in the temporal and spatial domains, in order to reduce the on-grid energy consumption in wireless homogeneous networks powered by hybrid energy supplies. However, these works do not take into consideration the temporal and spatial variations of green energy generation and/or mobile data traffic.

The work by Liu et al. [34] is the most related our work, which has studied the on-grid energy minimization in green heterogeneous networks, considering the temporal and spatial dynamics of mobile traffic and green energy generation. However, their algorithms to lexicographically minimize the on-grid energy consumption have not considered the difference between the predicted and realistic mobile traffic. In this paper, we not only consider the historical statistics of green energy charging model and mobile data traffic, but also propose online algorithms to adapt to the practical traffic distribution, so as to minimize the total energy consumption cost.

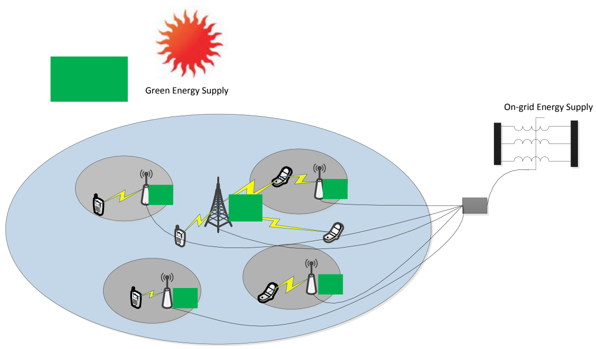

Fig. 1. An example green heterogeneous wireless network architecture.

III. System Model

A. Network Model

In this paper, we consider a heterogeneous wireless 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 slot is τ seconds and $k \in \mathcal{K}$ denotes the k-th slot.

B. Traffic Model

The mobile traffic shows both temporal and spatial diversities [35]. 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.

In the temporal domain, 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 $\mathbf{X} = \{\mathbf{X_1}, \mathbf{X_2}, ..., \mathbf{X_K}\}$ denote the user-BS association matrix. We use $\mathbf{X_k}$ to denote the user-BS association relationship at the k-th slot. The element $X_k(i,j)$ stands for the connection relationship between user j and BS i at the k-th slot, i.e.,

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

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

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 $L_i = \sum_{j\in\mathcal{M}} X_k(i,j)$ to denote the number of users served by the BS i. So the bandwidth allocated for a user j associated with BS i is 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 due to their different traffic demands. By letting $R_j = R_0$, we can obtain the transmission power for data transmission of user j from its associated BS i as:

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

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

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

The total power consumption of BS i is calculated by [36]:

$$P_{i,k}^{total} = P_{i,k} + P_0. \tag{5}$$

Considering a short single 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 slot is given by

$$C_{i,k} = P_{i,k}^{total}\tau. \tag{6}$$

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

IV. Problem Formulation

At the beginning of the k-th slot, the stored green energy at BS i is denoted by $E_{i,k}$, which is determined by the green energy consumption and generation of the previous slot. For each BS i, $E_{i,k}$ evolves from slot k to slot $k+1$ 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 harvested green energy power of BS i in the k-th slot, which can be predicted based on the historical renewable energy statistics [37]. $E_{i,1}$ is the initial green energy stored at BS i. We assume that a BS has the sufficiently large battery capacity, so we do not consider battery overflow. We assume that each BS is powered by just one kind of energy at any one slot. Denote $\overrightarrow{A}=(A_1,A_2,\cdots,A_i,\cdots,A_N)$ as the green energy allocation scheme for all BSs, where A_i is the green energy allocation vector for the BS i during all slots. Besides, we use its element $A_{i,k}$ to denote the green energy allocation of BS i at the k-th slot, and $A_{i,k}\le E_{i,k}+P_{i,k}^{h}\tau$. Let $\alpha_{i,k}$ be the indicator function of using which energy source:

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

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

Different kinds of energy have different unit costs. Let λ and μ 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 $\lambda>\mu\ge 0$ [38]*[ref]*. The energy cost of BS i at the k-th 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 III, we can obtain that the energy consumption of each BS is dependent on its associated users, i.e., the user-BS association $X_k(i,j)$. 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 consumption 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:

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

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 in the current 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 spatial 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 four 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 to minimize the total energy cost in each slot according to the practical user distribution. The fourth sub-problem is to further improve green energy utilization in the future slots based on the realized user-BS association scheme in the current slot.

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 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 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 slots. The green energy allocation for one BS can be expressed as the following problem:

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

subject to: (c4), (c6). By optimizing green energy allocation for each BS across all 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 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 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), (c6).

D. Green Energy Reallocation Problem

Although a realized user-BS association scheme in a slot is obtained based on the allocated green energy and practical user distribution, it is possible that we cannot utilize all the allocated green energy exactly in the current slot. So we may need to adjust green energy allocation again for each BS in future slots. The green energy reallocation problem can be formulated as follows:

$$\min_{\overrightarrow{A}} \sum_{k=1}^{K} \sum_{i=1}^{N} J_{i,k}. \tag{14}$$

subject to: (c4), (c6).

V. The Proposed Solution

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

A. Energy Consumption Estimation Algorithm

The proposed ECE algorithm aims to obtain an estimated energy consumption profile for each BS. Considering the near-term stability of mobile traffic, we can estimate the total energy consumption based on the historical mobile traffic statistics. 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 slot. Let $C^e_{i,k}$ indicate the estimated energy consumption of BS i at the k-th slot. For each 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 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 for each BS over all time slots. However, the green energy generated in one slot cannot be used in its previous slot. In addition, the total available green energy in one slot depends on the green energy generated at the current slot and the residual green energy from previous slots. In order to reduce the energy cost of the current slot, we need to change the green energy allocation in the previous 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 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:

$$A_{i,k} = \begin{cases} E_{i,1} + P^h_{i,1}\tau, & k = 1, \\ P^h_{i,k}\tau, & k > 1, \end{cases} \tag{15}$$

and optimize the green energy allocation of each time slot according to the time sequence. The GEA algorithm calculates the energy cost of first time slot, and then adds next time slot into green energy allocation optimization, iteratively. If the energy cost of the newly added time slot is larger than that of the previous time slot, this proposed algorithm will reduce the green energy allocation in previous time slots, so allocate the saved green energy to the current time slot.

Theorem 1: The proposed GEA algorithm achieves the optimal solution for the green energy allocation problem.

Proof: Since the amount of available green energy at one time slot depends both on the green energy generated at this time slot and on the residual green energy from its previous time slots, the energy cost at one time slot can be reduced only by optimizing the green energy allocation in the previous time slots. For each BS $i \in \mathcal{N}$, if its energy cost at one time slot is larger than that in the previous slot, i.e., $J^e_{i,m} > J^e_{i,m-1}$, then the GEA algorithm reduces the green energy allocation of the time slots previous to the m-th time slot, so it can allocate more green energy to the m-th time slot to ensure $J^e_{i,m} \le J^e_{i,m-1}$. When decreasing $J^e_{i,m}$, we find the n-th slot from the 1st to $(m-1)$-th slot, such that $J^e_{i,n} < \bar{J}^e$. Here, $\bar{J}^e$ is the average energy cost for BS i from the n-th slot to

Algorithm 2 The GEA Algorithm

Input: $C^a_{i,k}$, $E_{i,1}$, $P^h_{i,k}$, $\forall i \in \mathcal{N}$, $\forall k \in \mathcal{K}$, τ;
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 $m = 2$; $m \le K$; $m++$; **do**
    if $J^e_{i,m} > J^e_{i,m-1}$ **then**
      for $n = 1$; $n \le m-1$; $n++$; **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 $n = t$; $n \le m$; $n++$; **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 CUA phase one

1: **for** $k = 1$; $k \le K$; $k++$; **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** $P_{i,k} > P_i^{\max}$ **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** $P_{n,k} \le P_n^{\max}$ **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 $P_{i,k}$, $\mathcal{L}_{i,k}$, $\forall i \in \mathcal{N}$, $\forall k \in \mathcal{K}$.

the m-th slot. In this way, from the n-th to the m-th slot, we decrease for $J^e_{i,k} < \bar{J}^e$ (or increase for $J^e_{i,k} \ge \bar{J}^e$) 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 $\bar{J}^e$. After the GEA algorithm, we can see $J^e_{i,m} \le J^e_{i,k}$, $\forall k \in \{1, 2, ..., m-1\}$. Assuming $J^e_{i,m}$ is the m-th largest energy cost among all time slots, it is impossible to reduce the $J^e_{i,m}$ without further increasing the largest to the $(m-1)$-th largest energy cost. Therefore, the proposed GEA algorithm achieves the optimal green energy allocation.

Note that the GEA algorithm can be done by each BS itself. For one BS, the computational complexity of the GEA algorithm is $O(K^2)$ in the worst case, where K is the total number of the time slots. Since the GEA algorithm is an offline algorithm based on the the historical mobile traffic and green energy generation statistics, such computational complexity is acceptable even when the whole duration of the time is very large.

C. Centralized 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 practical user distribution. We next propose an online centralized user association (CUA) algorithm, which consists of two 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 CUA 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., $P_{i,k} > P_i^{\max}$, 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 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., $C_{i,k} \le A_{i,k}$ (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., $C_{i,k} \le A_{i,k}$, 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

Algorithm 4 The CUA 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 $J_{i,k}$, $\mathcal{L}_{i,k}$, $\forall i \in \mathcal{N}, \forall k \in \mathcal{K}$.

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 $J_{n,k}$ 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 the second phase of the CUA algorithm.

The CUA algorithm is executed in each slot for all BSs. In one slot, the computational complexity of the CUA algorithm is $O(NM^2)$, which is dominated by the additional association in Algorithm 4 that green BSs deprive on-grid BSs of one or more users to make the most of the allocated green energy.

D. Distributed User Association Algorithm

In a heterogeneous network, it is usually difficult to collect global information of the whole network and to coordinate among different BSs. Thus, we next propose a distributed user association (DUA) algorithm to solve the UA problem with low complexity.

The conventional MCG algorithm can lead to a balanced load distribution, in which each user j measures the channel gains between itself and its hearable BSs and connects to the BS i^* with the maximum gain, i.e.,

$$i^* = \arg\max_{i \in \mathcal{N}} g_{i,j}. \tag{16}$$

Although this distributed MCG algorithm can obtain a minimum total energy consumption, it did not consider the green energy consumption of each BS. To make the best use of allocated green energy, we assign a multiplicative channel gain biasing factor $b_{i,k}$ to each BS i for the k-th slot, as if the allocated green energy of one BS is sufficient, more users can be offloaded to this BS. So each user j measures the channel gain $g_{i,j}$ and biasing factor $b_{i,k}$, then associates itself with the BS i^* that has the largest biased channel gain, i.e.,

$$i^* = \arg\max_{i \in \mathcal{N}} (b_{i,k} * g_{i,j}). \tag{17}$$

Denote $\xi_{i,k} = \frac{C_{i,k}}{A_{i,k}}$ as the *energy drain ratio* (EDR) for the i-th BS in the beginning of the k-th slot. If $\xi_{i,k} > 1$, the allocated green energy is not sufficient to support the energy demand, and the BS i has to be powered by on-grid energy. So the BS i should throw out one or more its associated users, until its allocated green energy is enough to meet its energy consumption demand. Besides, the larger the value of $\xi_{i,k}$, the more traffic should be offloaded from the BS i. According to Eq. (17), the BS i should be assigned to a biasing factor $b_{i,k} < 1$ to offload its traffic load.

If $0 < \xi_{i,k} \leq 1$, the BS i can be powered by green energy with sufficient green energy allocation. And the smaller the $\xi_{i,k}$, the larger the gap between the allocated green energy and energy demand. To achieve a more efficient utilization of its allocated green energy, the $\xi_{i,k}$ should close to 1 such that more users can be served by the BS i while keeping $\xi_{i,k} \leq 1$. Based on Eq. (17), we should set $b_{i,k} > 1$. Besides, the smaller the value of $\xi_{i,k}$, the larger the value of $b_{i,k}$. In this way, each BS i should be assigned to a biasing factor $b_{i,k}$ adaptively updated based on the estimated EDR $\xi_{i,k}$.

According to the above analysis, we propose the following biasing factor function:

$$b_{i,k} = \begin{cases} 1 + \log_\gamma(\xi_{i,k}), & 0 < \xi_{i,k} \leq 1, \\ \gamma^{(\xi_{i,k}-1)}, & \xi_{i,k} > 1, \end{cases} \tag{18}$$

where $0 < \gamma < 1$, and it is a positive parameter chosen based on the number of users in the macro cell. Notice that $b_{i,k}$ is an increasing function of γ for a given $\xi_{i,k}$: the larger the γ, the larger the $b_{i,k}$. If $b_{i,k}$ is too big, it is likely that the BS i would attract more users, leading to the energy consumption $C_{i,k}$ larger than $A_{i,k}$ and more energy cost. In our simulations

Algorithm 5 The GER Algorithm

```
1:  for each BS i ∈ N do
2:      for k = 1; k ≤ K; k++; do
3:          if C_{i,k} ≤ A_{i,k} then
4:              A_{i,l} = A_{i,l}(1 + (A_{i,k} − C_{i,k}) / Σ_{l=k+1}^{K} A_{i,l}), l ∈ {k+1, ..., K};
5:          end if
6:          if A_{i,k} < C_{i,k} ≤ E_{i,k} + P^h_{i,k} τ then
7:              α_{i,k} = 1;
8:              A_{i,l} = A_{i,l}(1 − (C_{i,k} − A_{i,k}) / Σ_{l=k+1}^{K} A_{i,l}), l ∈ {k+1, ..., K};
9:          end if
10:         if C_{i,k} > E_{i,k} + P^h_{i,k} τ then
11:             A_{i,l} = A_{i,l}(1 + A_{i,k} / Σ_{l=k+1}^{K} A_{i,l}), l ∈ {k+1, ..., K};
12:         end if
13:     end for
14: end for
15: Return A_{i,k}, α_{i,k}, ∀i ∈ N, ∀k ∈ K.
```

we choose empirical value of $\gamma = 0.6$ and $\gamma = 0.4$ in peak and off-peak period, respectively.

Our proposed DUA algorithm consists of the user-side algorithm and the BS-side algorithm. First, each user j measures the channel gain $g_{i,j}$ from its hearable BSs and reports to its selected serving BS i^* with the largest channel gain. This step can be done at the beginning of the current slot or the end of last slot. Then, each BS i estimates its energy consumption based on its traffic load and obtains the estimated EDR $\xi_{i,k}$. According to Eq. (18), each BS i calculates the biasing factor $b_{i,k}$ and announces it to the network. Finally, on the user-side algorithm, each user j selects the appropriate BS i^* with the largest biased channel gain.

The user side algorithm:

1) Each user j measures the channel gain $g_{i,j}$ and receives the biasing factor $b_{i,k}$ from its hearable BS $i \in \mathcal{N}$. If it cannot receive any $b_{i,k}$, we set $b_{i,k} = 1$ as the initial state of the system.

2) Each user j selects the optimum BS i^* with the largest value of the biased channel gain, satisfying the formula $i^* = \arg\max_{i \in \mathcal{N}} (b_{i,k} * g_{i,j})$.

3) Each user j feedbacks the user-BS association $X_k(i^*, j) = 1$ to BS i^*.

The BS side algorithm:

1) Each BS i receives the user-BS association information $X_k(i,j) = 1$ [2], and let $\mathcal{L}_{i,k} = \mathcal{L}_{i,k} \cup \{j\}$.

2) Each BS i calculates its total energy consumption $C_{i,k}$ according to Eqs. (3)-(6).

3) Each BS i calculates its estimated EDR $\xi_{i,k}$ based on the $C_{i,k}$ and the allocated green energy $A_{i,k}$.

4) Each BS i calculates its channel gain biasing factor $b_{i,k}$ according to Eq. (18), and announces the biasing factor.

E. Green Energy Reallocation Algorithm

Note that the actually consumed green energy may not be exactly the same as the allocated one in each slot. So after having obtained the practical user-BS association in the current slot, we need to adjust green energy allocation again for each BS in its future slots. The green energy reallocation algorithm is presented in **Algorithm 5**.

Recall that after the GEA algorithm, if a BS has enough allocated green energy in one slot, it can associate one or more users previously associated with other BSs powered by on-grid energy. However, the proposed CUA algorithm ensures that such an additional association will not make this green BS use green energy more than its allocated volume. So, for each BS $i \in \mathcal{N}$ in the current k-th slot, if it has sufficient allocated green energy, the unused green energy $(A_{i,k} - C_{i,k})$ is allocated in the following slots (line 1 to 5 in Algorithm 5).

Also after the CUA algorithm, although a previously on-grid powered BS can disassociate one or more users to other green BSs, it may still happen that its allocated green energy in one slot is not enough to support its energy consumption. In this case, we may have two options: One is to *borrow* some stored green energy from the future slots, if it has such; The other is to stick to the current green energy allocation *without borrowing*, and hence this BS can only use on-grid energy. We adopt the first approach in Algorithm 5. Indeed, our simulation results in the next section will show that such a borrowing strategy performs much better than the strategy without borrowing.

If $A_{i,k} < C_{i,k} \leq E_{i,k} + P^h_{i,k}\tau$, which means its allocated green energy in this slot is not enough but it has enough stored green energy, 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 slots. If $C_{i,k} > E_{i,k} + P^h_{i,k}\tau$, the BS i can only be powered by on-grid energy, and the allocated green energy in this slot has to be allocated to the following slots (line 10 to 12 in Algorithm 5). And the energy increments (decrements) in the following time slots above are proportional to the amount of allocated green energy in each slot.

Note that the GER algorithm is executed by each BS itself. For one BS, the computational complexity of the GER algorithm is $O(K^2)$ in the worst case.

VI. 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 are set as 46dBm and 30dBm, respectively, and the value of fixed power expenditure are 23dBm and 20dBm, respectively. The path loss models are set according to [39]: $L(d) = 128.1 + 37.6\log(d)$ and $L(d) = 130.7 + 36.7\log(d)$ for 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.

[2]This initial association in the current decision epoch can be obtained in the end of last slot

Fig. 2. Mobile traffic and green energy charging profiles versus different slots in one typical day.

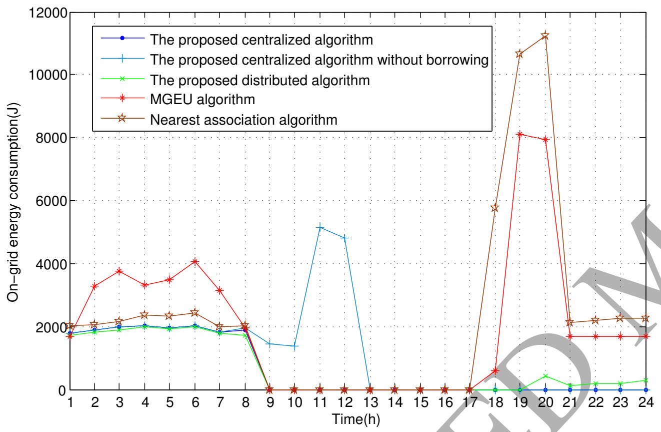

Fig. 3. Comparison of on-grid energy consumption against slots in one day.

For the solar charging model, we use the PVWatts model [37] to predict the hourly solar energy generation in Beijing City. From the measurement report in [35], the temporal characteristics of mobile traffic can be modeled as two different periods: the peak period and off-peak 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. 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 algorithms with each time slot equal to $\tau = 600s$. We compare our proposed solution with the typical nearest association [40], and the *maximum green energy utilization* (MGEU) algorithm [30], in which each green BS serves 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 slot.

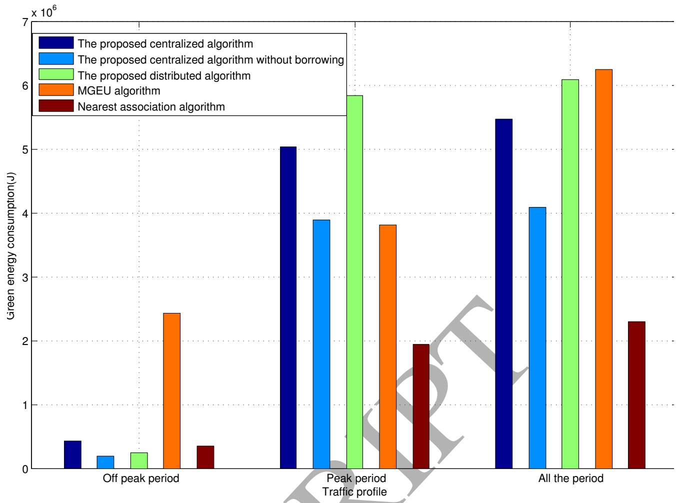

Fig. 4. Comparison of the green energy consumption in different traffic periods of one day.

A. Comparison of Energy Consumption

Fig. 3 compares the on-grid energy consumption against the time slots in one day for the five algorithms. It can be seen that the on-grid energy consumption of our proposed centralized algorithm and distributed algorithm are smaller than that of the MGEU and nearest association algorithm, and their on-grid energy are consumed in a much smoother way in the whole day. This is because we perform an optimized green energy allocation for individual BSs across different time slots. So they can use green energy in a planned and efficient manner in the temporal domain. However, in the MGEU 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 slots. Owing to the lower mobile traffic volume after 21:00, the on-grid energy consumption goes down sharply. Finally, we can find that the on-grid energy consumption of the distributed algorithm is very close to that of the centralized algorithm in the traffic peak period.

In addition, we can observe that the on-grid energy of our proposed centralized algorithm with green energy borrowing is smaller than the one without borrowing. Recall that after the CUA algorithm, an on-grid BS can borrow some green energy previously allocated for the future slots. The GEA algorithm is based on the estimated average energy consumption profile. But due to the randomness of practical user distribution in one slot, the allocated green energy may be smaller than the energy consumption demand. Borrowing some green energy quota from future slots help to minimize the on-grid energy consumption in the current slot. On the other hand, if in some slots, the allocated green energy is larger than the energy consumption demand, the unused green energy will be prorated into the future slots. Therefore, the GER algorithm with borrowing strategy help to smooth out the practical user distribution randomness in different slots, leading to much reduced on-grid energy consumption.

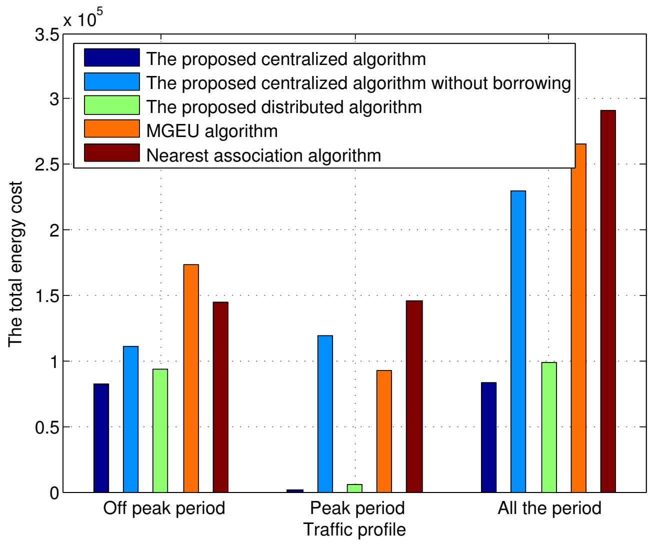

Fig. 5. Comparison of the total energy cost in different traffic periods of one day. $\lambda = 1$, $\mu = 0$.

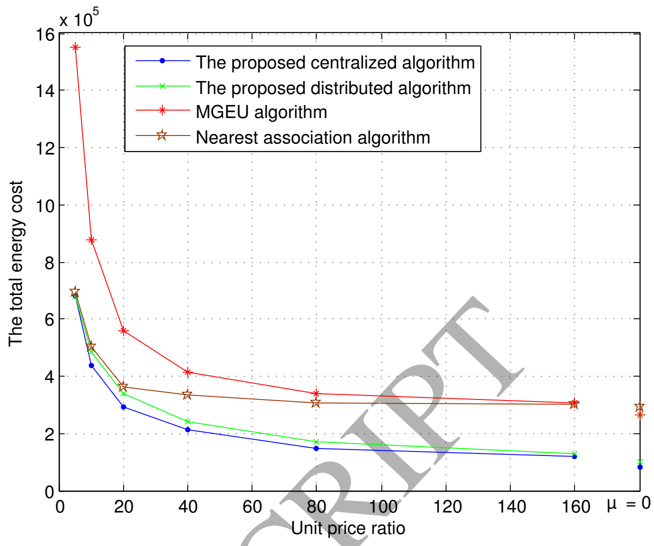

Fig. 6. The total cost with different ratio of unit price of energy.

Fig. 4 compares the green energy consumption in different traffic periods. It is observed that the green energy consumption of our proposed three algorithms and the MGEU algorithm are larger than that of the nearest association algorithm. This is due to that the four algorithms take green energy into consideration in user association, while the nearest association algorithm does not. It is worth of noting that although the MGEU algorithm makes the most utilization of green energy in one day, its total energy cost is larger than that of our proposed algorithms, as to be discussed in the next subsection. This is because that the MGEU does not consider to optimize the green energy utilization across different time slots. In other word, it is a kind of myopic solution of maximizing the green energy utilization for only the current slot, regardless the traffic and charging dynamics in the time domain. It is also observed that the green energy consumption of our proposed centralized algorithm without borrowing is smaller than that of the centralized algorithm. This is due to that the former dose not borrow green energy from the future slots in the current slot. Thus more green energy will be accumulated in the following slots and cannot be utilized sufficiently.

B. Comparison of Total Energy Cost

Fig. 5 compares the total energy cost in different traffic periods. 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 three algorithms cause much smaller energy cost than the other two algorithms. This is because the proposed GEA algorithm performs the green energy allocation optimization in the temporal domain according to statistical green energy charging and mobile traffic profiles; while the others do not. Furthermore, we can further maximize the green energy utilization in each slot by the proposed UA algorithm according to the practical user distribution. Besides, the total energy cost of the centralized algorithm without borrowing is much larger than that of the centralized algorithm. This and the simulation results shown in previous figures indicate that our proposed centralized algorithm has a better performance than the one without borrowing. Note that the MGEU algorithm uses much more on-grid energy in the peak period than that of our proposed centralized and distributed algorithm. Since the MGEU algorithm is a kind of myopic solution to make most utilization of green energy in the current slot, it does not consider to make some green energy reservation generated in off peak period for more traffic requirement in the peak period, hence causing more on-grid energy consumption in the peak period. Finally, among the five algorithms, our proposed centralized algorithm always achieves the minimum energy cost, but our distributed algorithm comes second. This is due to that our DUA algorithm cannot utilize the allocated green energy accurately by simply adopting a biasing factor for each BS, compared with the centralized one with iterative association optimization in each slot.

Fig. 6 plots the total energy cost for different unit price ratios, i.e., λ/μ. As seen from the figure, compared with the MGEU algorithm and nearest association algorithm, the proposed two algorithms achieve 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 energy cost improvement of the centralized algorithm and distributed algorithm are 71.24% and 65.72%, respectively, compared with the nearest association algorithm.

C. Long Term Results

Fig. 7 compares the total energy cost in a long operational time of ten days. It is not unexpected that the total energy costs of the four algorithms increase with the increase of the operational time. Also both the proposed centralized and

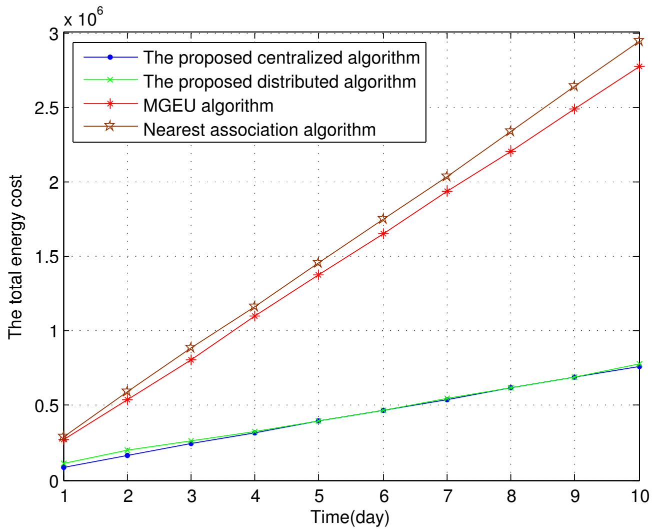

Fig. 7. Comparison of the total energy cost in a long operational term of ten days.

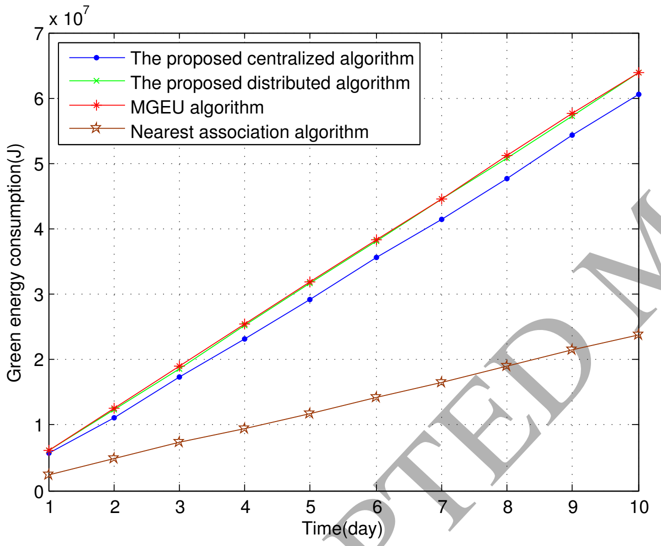

Fig. 8. Comparison of the green energy consumption in a long operational term of ten days.

distributed algorithms outperform the other two algorithms. This is due to that our proposed two algorithms can allocate and utilize green energy in the time and space domain to realize a smaller energy cost every day. In particular, the total energy cost of our distributed algorithm is almost the same as that of the centralized algorithm after four days. This is because that more green energy accumulated from previous days can be allocated for the distributed algorithm.

Fig. 8 and Fig. 9 plot the green energy consumption and residual green energy, respectively. From Fig 8, we can see that the green energy consumption of the four algorithms are growing linearly with the increase of operational time. However, the nearest association algorithm has a minimum growth rate. This is because that it cannot take full advantage of the green energy generated daily. As seen from Fig. 9,

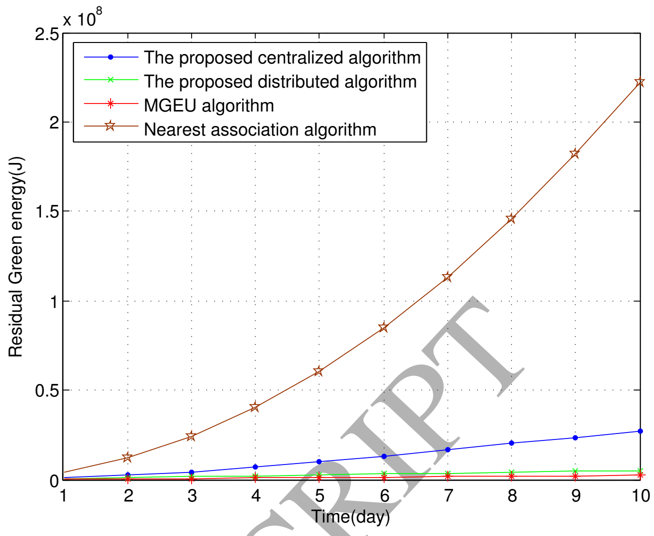

Fig. 9. Comparison of the residual green energy in a long operational term of ten days.

the residual green energy of our proposed two algorithms and MGEU algorithm grow slow, but that of the nearest association algorithm increases rapidly. This is due to that the above three algorithms can almost use up the available green energy every day. And combining Fig. 8 and Fig. 9, we can find that the accumulation rate of green energy is larger than consumption rate for the nearest association algorithm, but they are almost the same for other three algorithms. Actually, the residual green energy of the nearest association algorithm is mainly stored in macro BSs, which, however, cannot be utilized efficiently. Because for the nearest association algorithm, users are mostly served by pico BSs, but the residual green energy cannot be shared across different BSs.

VII. Conclusion

In this paper, we have studied how to reduce the total energy cost in a green heterogeneous wireless network with hybrid energy supplies. We first formulated a total cost minimization problem and decomposed it into four sub-problems. We then proposed our solution to solve these sub-problems, which consists of the ECE algorithm, the GEA algorithm, the UA algorithm, and the GER algorithm. For the UA sub-problem, we have proposed two heuristic algorithms, including a centralized one and a distributed one. Simulation results have demonstrated the effectiveness of the proposed solution in terms of much reduced energy cost compared with the peer algorithms. In addition, the performance of our distributed algorithm is close to the centralized one, but it is with much lower operational complexity.

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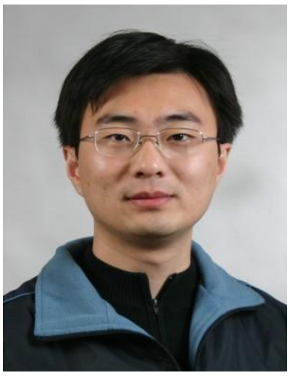

Dr. Bang Wang obtained his B.S. and M.S. from the Department of Electronics and Information Engineering in Huazhong University of Science and Technology (HUST) Wuhan, China in 1996 and 2000, respectively, and his PhD degree in Electrical and Computer Engineering (ECE) Department of National University of Singapore (NUS) in 2004. He is now working as a professor in the School of Electronic Information and Communications, HUST. His research interests include wireless networking issues, recommendation systems and social networks. Dr. Wang had published over 100 technical papers in international conferences and journals.

Qing Yang obtained his B.S. from the Wuhan University of Technology, Wuhan, China in 2014. He is now working toward his Master Degree in in the School of Electronic Information and Communications in Huazhong University of Science and Technology (HUST) Wuhan, China. His research interests include 5G wireless communications and networks, resource management in wireless networks.

Dr. Laurence T. Yang received the BE degree in Computer Science and Technology from Tsinghua University, China and the Ph.D. degree in Computer Science from University of Victoria, Canada. He is a professor in the School of Computer Science and Technology at Huazhong University of Science and Technology, China, and in the Department of Computer Science, St. Francis Xavier University, Canada. His research interests include parallel and distributed computing, embedded and ubiquitous/pervasive computing. His research has been supported by the National Sciences and Engineering Research Council, and the Canada Foundation for Innovation.

Chunsheng Zhu received the B.E. degree in network engineering from the Dalian University of Technology, China, in 2010, the M.Sc. degree in computer science from St. Francis Xavier University, Canada, in 2012, and the Ph.D. degree in electrical and computer engineering from The University of British Columbia, Canada, in 2016. He is currently a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, The University of British

Columbia, Canada. He has authored over 60 papers published or accepted by refereed international journals/magazines and conferences. His current research interests mainly include wireless sensor networks, cloud computing, Internet of Things, social networks, and security.