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Research Article

Energy Cost Minimization in Heterogeneous Cellular Networks with Hybrid Energy Supplies

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The ever increasing data demand has led to the significant increase of energy consumption in cellular mobile networks. Recent advancements in heterogeneous cellular networks and green energy supplied base stations provide promising solutions for cellular communications industry. In this article, we first review the motivations and challenges as well as approaches to address the energy cost minimization problem for such green heterogeneous networks. Owing to the diversities of mobile traffic and renewable energy, the energy cost minimization problem involves both temporal and spatial optimization of resource allocation. We next present a new solution to illustrate how to combine the optimization of the temporal green energy allocation and spatial mobile traffic distribution. The whole optimization problem is decomposed into four subproblems, and correspondingly our proposed solution is divided into four parts: energy consumption estimation, green energy allocation, user association, and green energy reallocation. Simulation results demonstrate that our proposed algorithm can significantly reduce the total energy cost.

1. Introduction

Owing to the ubiquitous usage of smartphones and bandwidth hungry applications, wireless cellular networks have experienced immense growth in traffic load, leading to massive deployment of *base stations* (BSs) as well as huge increase of energy consumption. For example, the number of BS sites operated by China Mobile has increased from 400,000 in 2005 to 1.5 million in 2014. Meanwhile, the total energy consumption of China Mobile significantly increased from 2000 GWh in 2005 to 17110 GWh in 2014 [1]. As reported in [2], BSs consume a significant portion, amounting to about 60%–80%, of energy in a wireless cellular network. Therefore, reducing the energy consumption of BSs has become a strategic target for the mobile communications industry.

Diverse mechanisms to reduce the BSs' energy consumption have been explored in both academia and industry [3–5]. Among them, the heterogeneous cellular network (HetNet) [6], which consists of different types of BSs with different transmission powers and coverage areas, is seen as a promising approach. The HetNet architecture can be characterized by the high density deployment of low power small BSs within a large macro cell. The deployed small BSs are closer to end users, which enables less transmission power for advantageous path loss conditions. It is therefore believed that HetNets with high density deployment of low power small BSs can significantly reduce energy consumption, compared with a low density deployment of high-power macro BSs [7].

It has been reported that the telecommunication industry is responsible for about 2 percent of the total CO_2 emissions worldwide, and the percentage is expected to double in 2020 [8]. To reduce the carbon footprint, recently, integrating some green energy, such as wind and solar power, into the existing cellular networks has became another research priority [9–12]. German mobile operator E-Plus (available: https://nsn.com/news-events/publications/unite-magazine-issue-10/e-plus-launches-germany-s-first-zero-co2-off-grid-base-station) has launched the first generation of green BSs by adopting a combination of solar and wind power only. Without using on-grid electricity, E-Plus can lead to zero CO_2 emissions. This also makes it possible for BSs consisting of both green energy and on-grid energy supplies.

In this article, we focus on the energy cost minimization in a green heterogeneous cellular network with hybrid energy supplies (HCN-HES). An example architecture of such a network is illustrated in Figure 1, where both macro and pico

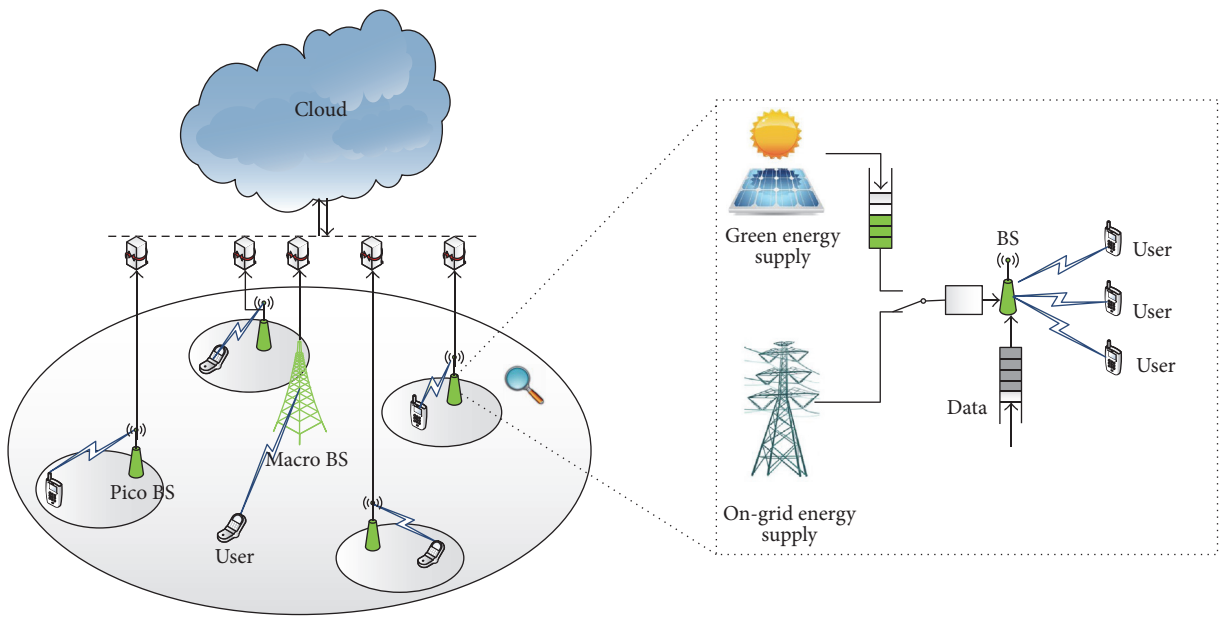


Figure 1: An architecture example of a heterogeneous cellular network with hybrid energy supplies.

BSs are equipped with green energy harvesting equipment as well as on-grid electricity. We first introduce the design issues of HCN-HES in the next section. The unit cost of the green energy is much cheaper than that of the on-grid energy and even free [13]. Therefore, it is not enough to only minimize the total energy consumption without discriminating different energy sources. Furthermore, with cheaper green energy, minimizing total energy cost can be equivalent to minimizing CO_2 emissions.

In a HCN-HES, not only the green energy harvesting, but also the traffic load distribution exhibit both temporal and spatial dynamics. Therefore, the cost minimization problem involves both spatial and temporal optimization for resource allocation. We next discuss the motivations, challenges, and approaches for energy cost minimization in the HCN-HES. Through the comparison of three different strategies for the resource allocation, we can see that the strategy with optimization in both spatial traffic balancing and temporal green energy allocation can obtain the smallest energy cost, compared with the strategy with no optimization or another strategy with optimization only in the spatial traffic balancing. The comparison illustrates that it is feasible to realize the energy cost minimization through a carefully designed resource allocation scheme. Although some existing approaches, such as user association and BS sleeping, can be used to maximize the green energy utilization for spatial traffic balancing, they have not been integrated with green energy allocation in the temporal domain. We then present a novel solution which combines both the temporal green energy allocation and spatial mobile traffic distribution. In simulation, we compare our proposed solution with two peer algorithms, where the one is a strategy without optimization for resource allocation and the other is a method with optimization only in the spatial domain, to illustrate its potential for significant energy cost reduction. Furthermore, its distributed version with slight performance degradation is rather easy to implement for practical network operations.

In summary, the contributions of this article are as follows:

(1) We study the BS powered by hybrid energy supplies and analyze the temporal and spatial diversities of renewable energy and mobile traffic.

(2) We illustrate the feasibility of energy cost minimization and transform the total energy cost saving problem into a constrained optimization problem.

(3) We discuss the challenges for the spatial traffic balancing and temporal green energy allocation to achieve the energy cost minimization and summarize the existing approaches from different optimization perspectives.

(4) We propose a novel solution consisting of four sub-algorithms with the integrated optimization in both the spatial and temporal domain and compare its performance with two peer algorithms.

2. Overview of the HCN-HES

Our system model considers a HetNet with two types of BS: macro BS and pico BS, with macro BSs each covering a larger area and pico BSs within macro cells each covering a smaller area (see Figure 1).

2.1. Hybrid Energy Supplies and Hybrid Powerd BS. Among all the green energy technologies, solar power is deemed the most appropriate due to the wide availability of solar energy as well as high efficiency of commercial photovoltaic (PV) panels. In this article, due to the limited space, we focus on the PV technology as the source of green energy, but we remark

that most of the following discussions apply as well to other energy sources. Due to the structural differences between macro BSs and pico BSs, the power consumption of a pico BS is orders of magnitude smaller than the typical macro BS. Thus, a macro BS needs to be equipped with a larger size of PV panel and a larger volume of storage battery to guarantee its normal functioning.

Generally, green energy generation may possess both temporal and spatial diversities. For example, solar energy generation depends on many factors such as temperature, sunlight intensity, and the geographical location of the solar panel. The energy generation by PV at different locations may be different. Moreover, the daily solar energy generation in a given area exhibits temporal dynamics that peak around noon and bottom during the night. Due to the temporal variation of energy arrivals, it is hard to guarantee the quality of service (QoS) of a communications system solely powered by the harvested solar energy, and services may even be interrupted when the green energy storage is depleted.

Recently, hybrid energy supply, where the energy comes from a power on-grid and a green energy harvester, has emerged as an alternative solution. The hybrid powered BSs (HPBS) are not only connected to power grid but also equipped with stand alone green power generators (see in Figure 1). Green energy can be utilized to reduce the on-grid power consumption, while on-grid energy can serve as a backup power source, whenever the practical power demand exceeds the green energy storage. However, due to the circuit constraint, a HPBS cannot be powered by both on-grid energy and green energy at the same time. Instead, we can switch the use of different powers in different time intervals according to the traffic load and green energy storage. Therefore, switching algorithms should be appropriately designed to favor the utilization of green energy.

2.2. Green Energy Models: Generation and Consumption. Although the solar power generation process is dependent on the PV panel locations and weather conditions, some prediction models can be obtained from practical measurements, which can be used to direct the HPBS operations [14]. In this article, we use the PVWatts model (available: http://pvwatts.nrel.gov/) to predict the hourly solar energy generation in Beijing City. Based on the measured data for a typical day, the average green energy generation profile is plotted in Figure 2, where the energy harvesting rates are sampled every 10 minutes. We see that the solar energy generation starts from around 7:00 AM, keeps increasing and peaks at around 1:00 PM, and ends at about 6:00 PM after sunset. Notice that the weather conditions would impact the charging rate, but the overall charging trend is similar in different days.

To quantify the energy consumption of each BS, an energy consumption model has been proposed in the European project ERATH [15]. The transmission power for data transmission of user j from its associated BS i is

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

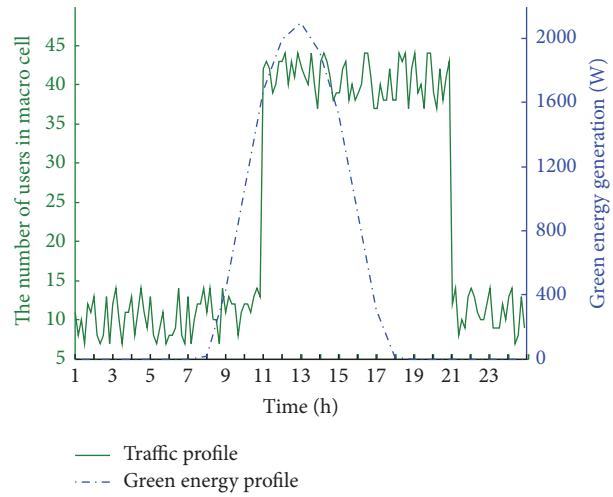


Figure 2: Solar energy harvesting and mobile traffic profiles in one typical day.

where R_0 is the downlink transmission data rate of user j and $g_{i,j}$ is the channel gain between user j and BS i. N_0 denotes the noise power level. And $W_{i,j}$ is the bandwidth of user j allocated by its associated BS i.

The total power consumption P_i of the BS i can be calculated by

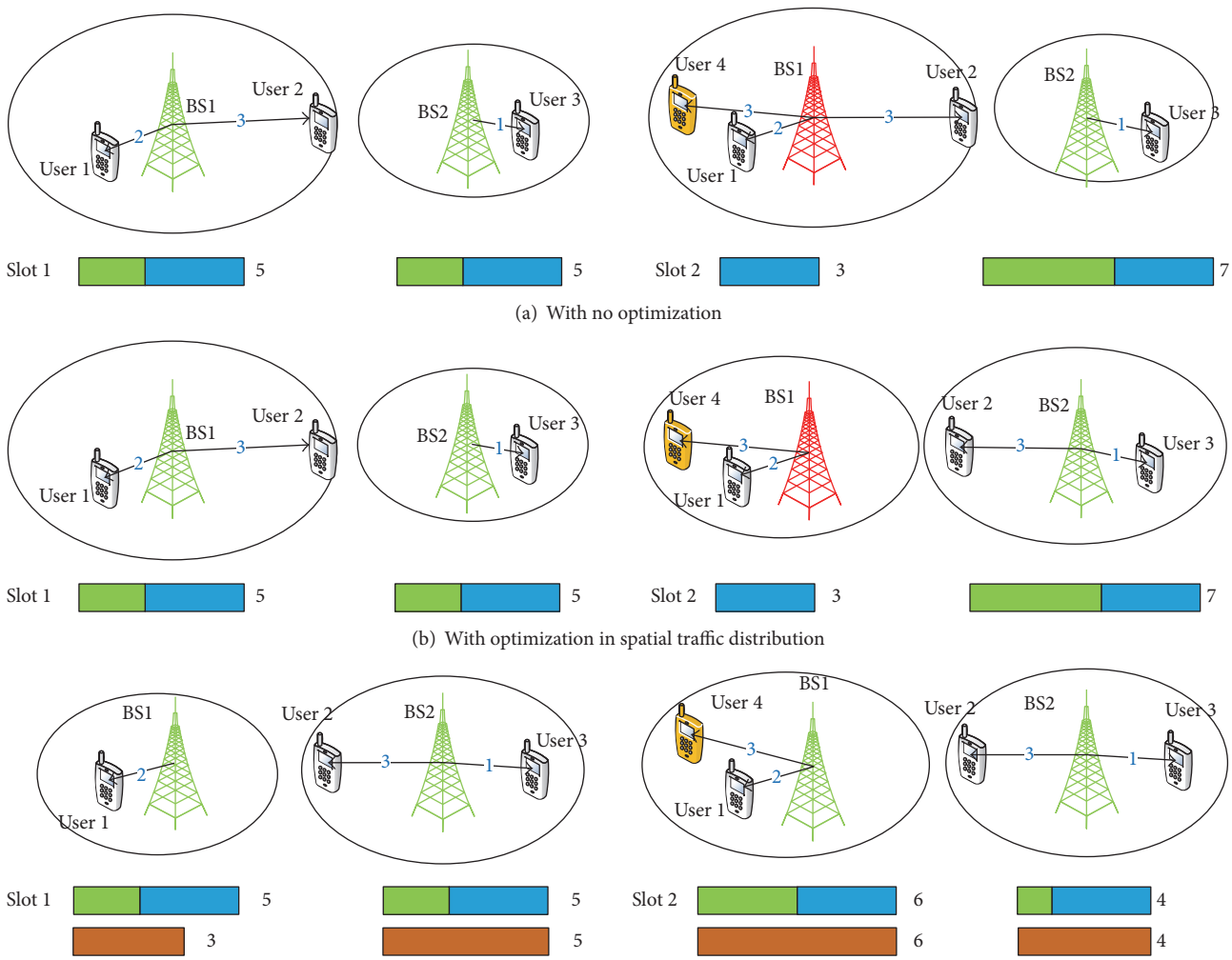
$$P_i = \begin{cases} \sum_j X(i,j) P_{i,j} + P_0, & \text{in active mode,} \\ P_{\text{sleep}}, & \text{in sleep mode,} \end{cases} \quad (2)$$

where $X(i,j) \in \{0,1\}$ stands for the connection relationship between user j and BS i. We note that a BS needs to be in active status when at least one user is associated with it. P_0 is the static power consumption for the BS when the BS is in the active status, incurred by signal processing, active circuit blocks, and so forth. And P_{sleep} is the power consumption in the sleep mode, in which no user is associated with the BS.

2.3. Traffic Model. The mobile traffic also exhibits both temporal and spatial diversity [16]. In the spatial domain, mobile users can be simply modelled as evenly distributed in the network. In the temporal domain, the traffic load can be estimated using the historical statistics, and the traffic load does not change much at the same time of consecutive days. For example, a commonly used peak and off-peak model is as follows. The temporal characteristics of mobile traffic are divided into two periods: the peak period and off-pear period. The peak period spans from 10 AM to 6 PM, and off-peak periods are from 1 AM to 5 AM. In one period, the number of users can be modelled as a uniform distribution with the mean value obtained from historical statistics. Figure 2 plots such a mobile traffic profile.

3. Energy Cost Minimization in HCN-HES

In this section, we first introduce the motivations for energy cost minimization with an illustrative example and then



(a) With no optimization

(b) With optimization in spatial traffic distribution

(c) With optimization in both spatial traffic distribution and temporal green energy allocation

Figure 3: An illustration of the feasibility of energy cost minimization. The line between a BS and a user indicates the user associated with the BS, and the number on the line is its energy consumption. The green, blue, and brown rectangles represent the residual green energy from previous slots, green energy generated at the current slot, and the assigned green energy at the current slot, respectively.

discuss the challenges and review the approaches to solve this minimization problem.

3.1. Motivations for Energy Cost Minimization. As discussed before, the operational expenditure (OPEX) of a cellular mobile network is mostly determined by the energy consumption cost of BSs. With the deployment of HetNet, a user can be simultaneously within the coverage areas of multiple BSs. This introduces some degree of freedom for a user to choose a BS with a smaller transmission power without compromising its service requirement. However, only minimizing the total power consumption is not enough in HCN-HCS, as sometimes consuming more green energy is more favorable for its lower cost and lower carbon footprint. On the other hand, consuming as much stored green energy as possible in the current slot may not be a good strategy, as the newly generated green energy may not be enough to support the traffic demand in the next slot.

For the purpose of illustrating the feasibility of energy cost minimization, we consider a simple network scenario of two neighboring BSs, BS1 and BS2, and two consecutive slots, slot1 and slot2. The initial green energy storage is set the same for the two BSs as 5 units at the beginning of slot1. The green energy generation rate is also set the same for the two BSs as 3 units per slot. In slot1, there are three users, namely, user1, user2, and user3, in the network, while in slot2, besides the existing three users, a new user, user4, joins the network. For simplicity, we set the unit cost for on-grid energy as 1 and 0 for green energy.

Figure 3(a) illustrates the "with no optimization" strategy. In slot1, user1 and user2 are associated with BS1 and consume 2 units and 3 units of energy from BS1, respectively. And user3 is associated with BS2 and consumes 1 unit of energy. Obviously, in slot1, BS1 and BS2 both could be powered by green energy. After slot1, the green energy storage for BS1 and BS2 becomes 3 units and 7 units, respectively. In slot2, the new

user4 is associated with BS1 and consumes 3 units energy. The total energy consumption of BS1 increases to 8 units, larger than the 3 units' green energy storage of BS1. Thus, BS1 has to be powered by on-grid energy and consumes 8 units on-grid energy. Therefore, the total energy cost of the two slots can be calculated as 8 units.

Figure 3(b) illustrates the "with optimization in spatial traffic balancing" strategy. The network operation in slot1 is the same as the above. In slot2, the green energy storage of BS1 is not sufficient to support three users of user1, user2, and user4, but user1 and user4 can only be served by BS1 as they are too far away from BS2. So BS1 reduces its coverage area and offloads user2 to BS2 to optimize the spatial traffic balancing. After the offloading, the energy consumption of BS1 is 5 units, which is still larger than the green energy storage of 3 units in BS1. As a result, BS1 is powered by on-grid energy and consumes 5 units on-grid energy. And the BS2 has sufficient green energy to service both user2 and user3. The total energy cost of the two time slots is 5 units, which is smaller than that of the "with no optimization" strategy.

Figure 3(c) illustrates the "with optimization in both spatial traffic balancing and temporal green energy allocation" strategy. Suppose that we can estimate the traffic increase of BS1 in the next slot. We can first make some green energy allocation for the two slots and reserve more green energy for BS1's energy demand in slot2. Suppose that in slot1 we allocate 3 units of green energy for BS1 and 5 units of green energy for BS2. Thus, in slot1, to only use its allocated green energy, BS1 reduces its coverage area and offloads user2 to BS2. Since the available green energy of BS2 is sufficient to support both user2 and user3, both BSs can be powered by green energy. In slot2, we allocate 6 units and 4 units of green energy for BS1 and BS2, respectively. User2 is still associated with BS2, to balance the spatial traffic distribution. Thus, BS1 and BS2 both can still be powered by green energy, and the total energy cost of two time slots is 0. Compared with the above two strategies, we can see that, through a carefully designed resource allocation scheme, not only the traffic distribution can be balanced, but also the green energy utilization can be optimized, which would further lead to the energy cost reduction.

3.2. Problem Description. Based on the above illustrative example, we can obtain that the energy cost of each BS is dependent not only on its associated users but also on its allocated green energy. Thus, our objective is to find one user-BS association matrix and a green energy allocation vector for the energy cost minimization, yet satisfying the network QoS requirements. Let $\mathbf{X} = \{X_1, X_2, \ldots, X_k\}$ be the user-BS association matrix. We use X_k to denote the user-BS association relationship at the kth time slot. And the element $X_k(i, j)$ represents the connection relationship between user j and BS i at the kth time slot. Denote $\vec{\mathbf{A}} = (A_1, A_2, \ldots, A_i, \ldots, A_N)$ 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 kth time slot, and $A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau$. Here, $E_{i,k}$ is the stored green energy of BS i at the beginning of the kth time slot, and τ is the length of each time slot. $P_{i,k}^h$ is the energy harvesting power of BS i at the kth time slot.

Let $\alpha_{i,k}$ be the indicator function of using which energy source:

$$\alpha_{i,k} = \begin{cases} 1, & A_{i,k} \geq P_{i,k}^{\text{total}} \tau, \\ 0, & A_{i,k} < P_{i,k}^{\text{total}} \tau, \end{cases} \tag{3}$$

where $P_{i,k}^{\text{total}}$ is the total power consumption of BS i at the kth slot. If $\alpha_{i,k} = 1$, BS i is powered by green energy at the kth time slot. Otherwise, this BS is powered by the 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. The energy cost of BS i at the kth time slot can be computed by

$$J_{i,k} = \lambda \left(1 - \alpha_{i,k}\right) P_{i,k}^{\text{total}} \tau + \mu \alpha_{i,k} P_{i,k}^{\text{total}} \tau. \tag{4}$$

Thus, the total *energy cost saving* (ECS) problem can be formulated as a constrained optimization problem as follows:

$$\begin{aligned} \min_{\mathbf{X}, \vec{\mathbf{A}}} \quad & J = \min_{\mathbf{X}, \vec{\mathbf{A}}} \sum_k \sum_i J_{i,k} \\ \text{subject to} \quad & \text{(c1)} \ P_{i,k} \leq P_i^{\max} \\ & \text{(c2)} \ \sum_i X_k(i, j) = 1 \\ & \text{(c3)} \ X_k(i, j) \in \{0, 1\} \\ & \text{(c4)} \ A_{i,k} \leq E_{i,k} + P_{i,k}^h \tau \\ & \text{(c5)} \ \lambda > \mu \geq 0. \end{aligned} \tag{5}$$

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) shows that the unit cost of green energy is much cheaper than that of the on-grid energy.

3.3. Challenges. From the illustrative example in Section 3.1, we can see that the total energy cost is dependent on the energy consumption of each BS, as well as the energy source used in each time slot. In one slot, how to distribute traffic load among different BSs determines the power consumption of each BS. As for the energy source, it is dependent on both the energy consumption and green energy storage of each BS. On the other hand, the green energy storage is also related to the temporal charging process of individual BS. Therefore, the energy cost minimization problem poses great challenges for integrated optimization in both the spatial and temporal domain.

Spatial Traffic Balancing. In a HetNet with the seamless deployment of pico BSs within the coverage of macro BSs, due to the much higher transmission power of macro BSs than

the pico BSs, an unbalanced traffic load distribution is usually obtained without some appropriate traffic balancing scheme in the spatial dimension. Meanwhile, in order to optimize the energy utilization in a HCN-HES, not only the power consumption of each BS but also its available green energy should be taken into consideration. In a typical time slot, the available green energy among different BSs may exhibit spatial diversity. Thus, in each slot, to make the best of the green energy, the power consumption among different BSs should be optimized according to the allocated green energy of each HPBS. The BSs that have more allocated green energy are reserved to service more users, yet without exceeding their capacities.

Temporal Green Energy Allocation. For each individual HPBS, on one hand, the green energy generated in one time slot could not be used in its previous slots. On the other hand, since the available green energy in one time slot depends on the green energy generated in the current time slot and the residual green energy from previous slots, the excessive usage of green energy in the current slot will result in a shortage of green energy supply in the future. Therefore, for each HPBS, in order to optimize its performance in the long run, its green energy allocation across different time slots has to be balanced. As discussed above, mobile traffic shows temporal dynamics and the green energy generation varies along the time horizon, but both of them can be estimated using the historical statistic data. To solve the temporal green energy balancing problem, elements such as the current green energy generation and power consumption, and estimations of future green energy harvesting and power consumption should be considered. Moreover, the result of the temporal green energy allocation of each HPBS is also related to the spatial traffic balancing among different BSs in each time slot. Owing to the difference between the predicted and realistic energy demand in one slot, some adjustment of green energy allocation for future time slots may be needed.

3.4. Approaches. Some algorithms have been proposed to approach the cost minimization problem from different perspectives, including green energy aware user association [10, 11], BS sleeping [17], and integrated green energy allocation and spatial traffic balancing algorithms [18, 19].

Green Energy Aware User Association. In [10, 11], we have proposed green energy aware user association schemes to minimize the total energy cost, while guaranteing the users' data rate requirements for a HCN-HES. It includes two optimization phases: The first is to minimize the total power consumption for all BSs, which is to obtain an initial user association scheme such that no more user reassociation can further reduce the total power consumption; As the power demand may not exactly match the green energy storage for each BS, the second phase is to adjust some user-BS associations to make full utilization of green energy storage across BSs. In particular, the BSs with more remaining green energy need to serve more users who are previously connected to the BSs powered by on-grid energy, as along as they still can be powered by green energy. However, these schemes focus on the energy cost minimization only in one slot and ignore the user traffic and green energy charging dynamics in the time domain.

Green Energy Aware BS Sleeping. In [17], Gong et al. have studied the joint optimization problem of BS sleeping and resource allocation in a cellular network, where each BS is powered by hybrid green energy and on-grid electricity. A two-stage dynamic programming algorithm has been proposed to minimize the average on-grid power consumption, while satisfying the user blocking probability requirements. In the first stage, the authors only consider the BSs' on-off state and proposed a standard dynamic programming algorithm to solve the minimum average on-grid power consumption. In the second stage, given the BSs' working states, they propose an iterative resource allocation algorithm, which updates the per-BS resource allocation based on the allocation results of the other BSs, and the process is repeated until the resource allocation solution does not change between two consecutive iterations. However, this joint BS sleeping and resource allocation scheme is only studied in the homogeneous networks with hybrid energy supplies.

Energy Consumption Aware Green Energy Allocation. In [18], a green energy allocation scheme has been proposed to lexicographically minimize the on-grid energy consumption in a HCN-HES. Based on the optimal traffic balancing among BSs, it optimizes the green energy allocation in the time domain. It computes the on-grid energy consumption of the first time slot and then adds next time slot into green energy allocation optimization iteratively. Thus, it can save the green energy from previous time slots to the current time slot, if the on-grid energy consumption of the newly added time slot is larger than that of the prior time slot. However, this scheme to lexicographically minimize the on-grid energy consumption only focuses on the exact mobile traffic model and dose not consider the difference between the predicted and realistic traffic distribution.

4. Performance Study

4.1. The Proposed Scheme. As discussed above, owing to the diversities of traffic distribution and charging process, the energy cost minimization problem in a HCN-HES involves both temporal and spatial optimization of resource allocation. Furthermore, the optimization in one domain is also interleaved with the optimization in the other domain, which makes this problem hard to solve. On one hand, we can use some estimation model to predict traffic and energy arrival process based on historical statistics. As long as such predictions are correct, we can obtain optimal solutions as if all uncertainties are removed. On the other hand, such predictions may not exactly match the practical traffic and energy distributions. Therefore, we may need to make some adjustment for resource allocation according to the practical situation. With these considerations, our proposed solution consists of both offline algorithms and online algorithms.

We decompose the energy cost minimization problem into four subproblems: 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 the subproblems. 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 UA and GER algorithms are online algorithms to be executed in each slot based on the practical mobile traffic and green energy distributions.

The ECE algorithm is to obtain an estimated average energy consumption profile for each BS based on the mobile traffic temporal and spatial statistics. Given one instance of user distribution, we use the nearest association scheme to obtain a minimum total energy consumption, in which each individual user is associated with its nearest BS. The ECE algorithm should be executed many times to obtain the average estimated energy consumption profile for each BS in each slot.

The GEA algorithm is to obtain the green energy allocation vector to minimize the energy cost for each BS over all time slots, based on the green energy generation model and the average estimated energy consumption profile. We first calculate the energy cost of the first time slot and then iteratively add the next slot into the allocation optimization. The basic idea is to ensure the energy cost of the current slot is not larger than that of its previous slot. If this is not the case, the GEA algorithm will reduce the allocation in previous time slots, so as to allocate the required green energy to the current time slot.

The UA algorithm is to decide the user-BS association based on the allocated green energy and the practical user distribution in each slot. The centralized UA algorithm consists of two phases. In the first phase, we use a modified nearest association to obtain an initial scheme in order to minimize the total power consumption; After this phase, some BSs are powered by green energy, while others are powered by on-grid energy. In the second stage, we make BSs with sufficient allocated green energy to serve more users, without violating their allocated green energy quota, by iteratively depriving one or more appropriate users associated with neighboring BSs powered by on-grid energy.

In a HCN-HES, it is usually difficult to collect all information of the whole network and to coordinate among different BSs. We then propose a distributed UA algorithm with low complexity, which assigns a multiplicative channel gain biasing factor b_i to each BS i in each lot, such that more users can be offloaded to the BS with sufficient allocated green energy:

$$b_i = \begin{cases} 1 + \log_\gamma(\xi_i), & 0 < \xi_i \leq 1, \\ \gamma^{(\xi_i - 1)}, & \xi_i > 1, \end{cases} \tag{6}$$

where ξ_i is the *energy drain ratio* (EDR), defined by the estimated energy demand divided by the allocated green energy, and γ $(0 < \gamma < 1)$ is a positive parameter based on the average traffic load.

Table 1: Network parameters and values.

Parameter	Value
Macro cell radius	600 m
Available bandwidth in each cell	20 MHz
Maximum transmit power	
Macro BS	46 dBm
Pico BS	30 dBm
Static power P_0	
Macro BS	130.0 W
Pico BS	13.6 W
Power in sleep P_{sleep}	
Macro BS	75.0 W
Pico BS	4.3 W
Slope of dynamic power α	
Macro BS	4.7
Pico BS	4.0
Path loss (d in Km)	
Macro cell to users	$128.1 + 37.6\log(d)$
Pico cell to users	$130.7 + 36.7\log(d)$
Thermal noise power level	−174 dBm/Hz
Data rate requirement of each user	10 Mbps
Time interval τ	600 s

The GER algorithm is to adjust green energy allocation vector based on the practical user-BS association and green energy consumption in each slot. Note that the actually consumed green energy may not be exactly the same as the allocated one in each slot. The GER algorithm reallocates the excessive green energy into the following slots proportional to the quota of previously green energy allocation for each future slot.

4.2. Results and Discussions. We consider a 2-tier heterogeneous cellular network consisting of 7 macro cells and 4 pico cells are evenly distributed in each macro cell. All BSs are powered by both on-grid energy and green energy, with different green energy harvesting rates. Table 1 lists the network parameters and values. For the solar energy charging model, we use the PVWatts model to predict the hourly solar energy generation in Beijing City. From the measurement report in [16], the temporal characteristics of mobile traffic can be modelled 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. Figure 2 illustrates an example of the green energy generation profile and mobile traffic profile. We compare our proposed solutions with the typical nearest association algorithm and the maximum green energy utilization (MGEU) algorithm [11].

Figure 4(a) compares the total energy cost in one day. The unit price of the on-grid energy and green energy are set as $\lambda = 1$ and $\mu = 0$, respectively. It can be seen

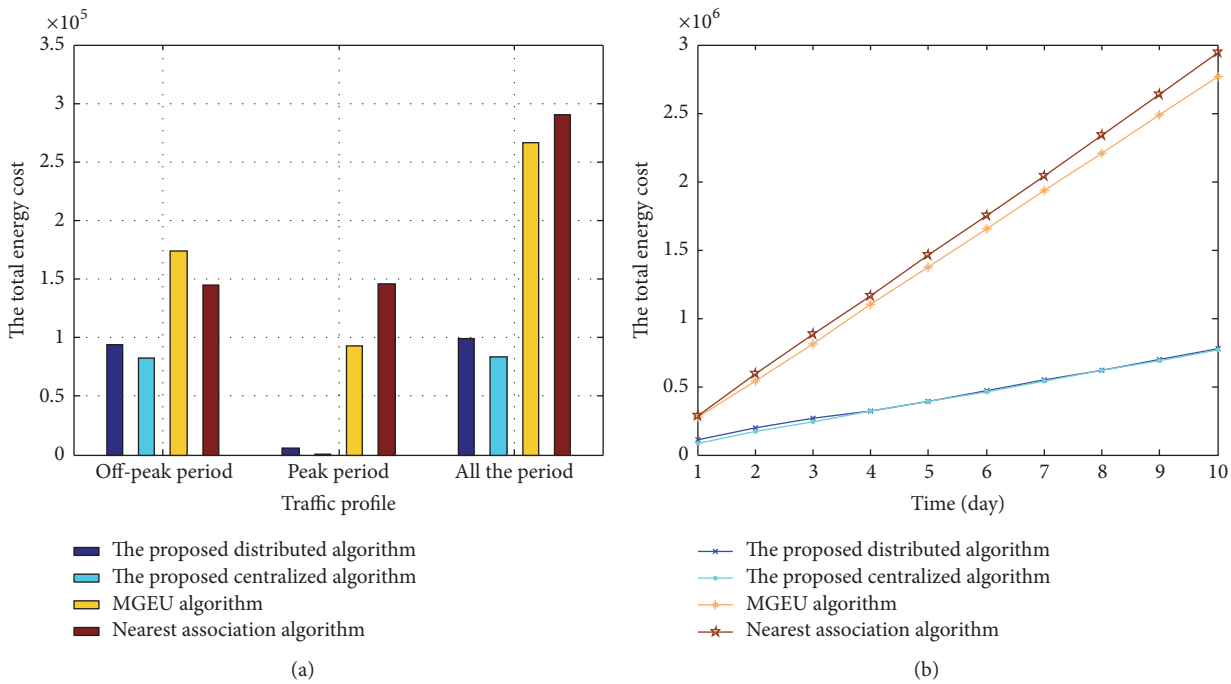


Figure 4: (a) The total energy cost of different traffic periods in one day; (b) the total energy cost in a long operational term of ten days. $\lambda = 1$ and $\mu = 0$.

that our proposed algorithms incur much smaller energy cost than the other two algorithms, especially in the peak period. This is because the proposed algorithms perform 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 also maximize the green energy utilization in each slot by the proposed user association algorithm according to the practical user distribution. The distributed algorithm is slightly worse than the centralized one. This is because it 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. Figure 4(b) 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. 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 more green energy accumulated from previous days can be allocated for the distributed algorithm.

Figure 5 plots the total energy cost against different unit price ratios, that is, λ/μ. Compared with the MGEU algorithm and nearest association algorithm, the proposed 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 the highest energy cost saving. In this case, the energy cost improvements of the distributed algorithm and centralized algorithm are 65.72% and 71.24%, respectively, compared with the nearest association algorithm.

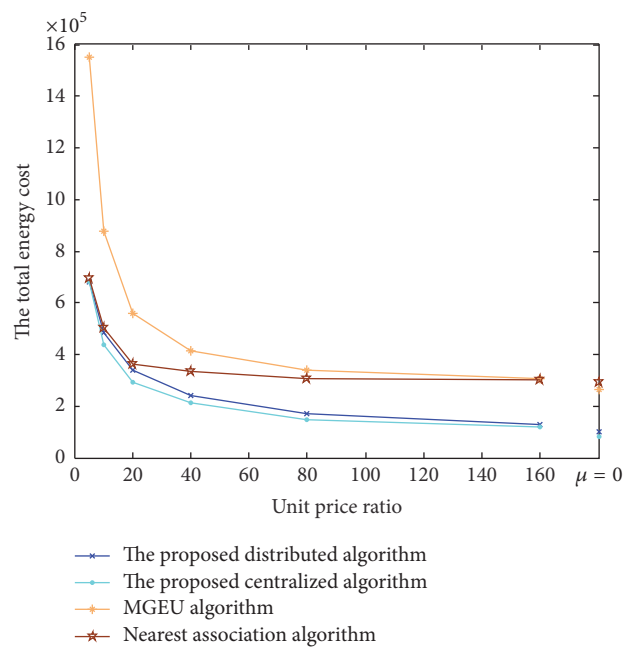


Figure 5: Comparison of the total cost with different ratio of unit price of energy.

5. Conclusion

In this article, we have investigated the energy cost minimization in a future HCN-HES. Since both the mobile traffic and green energy exhibit temporal and spatial dynamics in such a network, new design issues and technical challenges have emerged. Some existing solutions have been discussed, and we have also proposed a new resource allocation scheme to achieve spatial traffic balancing, and temporal green energy balancing. Simulation results have demonstrated the effectiveness of the proposed scheme in terms of significant cost reduction compared with two peer algorithms.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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