Two-Dimensional Optimization on User Association and Green Energy Allocation for HetNets With Hybrid Energy Sources

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***Abstract*—In green communications, it is imperative to reduce the total on-grid energy consumption as well as minimize the peak on-grid energy consumption, since the large peak on-grid energy consumption will translate into the high operational expenditure (OPEX) for mobile network operators. In this paper, we consider the two-dimensional optimization to lexicographically minimize the on-grid energy consumption in heterogeneous networks (HetNets). All the base stations (BSs) therein are envisioned to be powered by both power grid and renewable energy sources, and the harvested energy can be stored in rechargeable batteries. The lexicographic minimization of on-grid energy consumption involves the optimization in both the space and time dimensions, due to the temporal and spatial dynamics of mobile traffic and green energy generation. The reasonable assumption of time scale separation allows us to decompose the problem into two sub-optimization problems without loss of optimality of the original optimization problem. We first formulate the user association optimization in space dimension via convex optimization to minimize total energy consumption through distributing the traffic across different BSs appropriately in a certain time slot. We then optimize the green energy allocation across different time slots for an individual BS to lexicographically minimize the on-grid energy consumption. To solve the optimization problem, we propose a low complexity optimal offline algorithm with infinite battery capacity by assuming non-causal green energy and traffic information. The proposed optimal offline algorithm serves as performance upper bound for evaluating practical online algorithms. We further develop some heuristic online algorithms with finite battery capacity which require only causal green energy and traffic information. The performance of the proposed optimal offline and online algorithms is evaluated by simulations.**

***Index Terms*—HetNets, hybrid energy sources, user association, green energy allocation, convex optimization.**

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I. Introduction

NOWADAYS, the unprecedented growth in the cellular industry has pushed the limits of energy consumption in wireless networks. The conventional cellular network which consumes 60 billion kWh per year approximately is one of the major issues in green communications. Particularly, 80% of the energy in cellular network is consumed by base stations (BSs), which generate over a hundred million tons of carbon dioxide annually [1].

Heterogeneous networks (HetNets), where various small cells are densely underlaid in a macro-cellular network, is a promising technique to achieve more spectrum-efficient and energy-efficient communications in order to meet the requirements of fifth generation (5G) broadband wireless networks. In contrast with the conventional macro BSs (MBSs), BSs in the "small cells" cover much smaller areas and hence require significantly lower transmit powers, which brings up about 50% reduction in overall energy consumption of all BSs as shown in [2].

A large amount of studies on radio resource allocation in HetNets are based on the assumption that BSs are powered by constant energy sources, such as power grid or diesel generators, see [3]–[6] and references therein. However, in practice, sometimes the direct connection to power grid is not readily available, especially in some undeveloped areas, since the infrastructure expenditure on power grid is prohibitively expensive [7]. In such situation, energy harvesting provides a practical solution where BSs are capable of harvesting green energy from the renewable energy sources, such as solar panels and wind turbines, thereby substantially reducing the operating cost of service providers.

Integrating energy harvesting capability into BSs poses many challenges to resource allocation algorithm design, due to the randomness of energy availability in renewable energy sources. A overview of research challenges for green energy enabled mobile networks was provided in [8]. Authors of [9] developed a traceable model for HetNets where all BSs are assumed solely powered by renewable energy sources, and provided a fundamental characterization of regimes under which the HetNets with renewable energy powered BSs have the same performance as the ones with constant energy sources powered BSs. In [10], adaptive user association was formulated as an optimization problem, which aimed for maximizing the number of supported users and for minimizing the radio resource

consumption in HetNets with renewable energy powered BSs. Yet, although the amount of renewable energy is potentially unlimited, the intermittent nature of the energy from renewable energy sources will result in highly random energy availability in BSs, which requires other complementary stable energy supplies. As the power grid is capable of providing persistent energy supply, the BSs powered by hybrid energy sources, a combination of power grid and renewable energy sources, are preferable to those solely powered by renewable energy sources in order to ensure uninterrupted service [11], [12]. The concept of hybrid energy sources has been accepted by the industry. Huawei has already deployed BSs which draw their energy from both constant energy supplies and renewable energy sources [13].

An earlier line of research studies the coordinated multi-input multi-output (MIMO) systems [14], user association [15], [16], power allocation [17], energy balancing [18] and network planning [19] in the hybrid energy sources powered scenario. Authors of [14] investigated how renewable energy storage size affects the system performance. In [15], an optimal user association algorithm was proposed for traffic delay and on-grid energy consumption tradeoff in HetNets. Extending the solutions of [15], the authors of [16] addressed the backhaul constraint and the uplink-downlink asymmetry in the context of designing the user association algorithm in HetNets relying on hybrid energy sources. Studies in [17]–[19] focused on the total on-grid energy consumption minimization. To this end, offline and heuristic online power allocation algorithms based on the two-stage water filling policy for a single-link wireless communication were proposed in [17], energy allocation and balancing algorithms for conventional cellular networks were developed in [18], and a cellular network planning framework was designed in [19].

Different from the existing research, in this paper we consider the two-dimensional optimization on user association and green energy allocation to optimize the on-grid energy consumption in HetNets with hybrid energy sources. We assume the harvested green energy can be stored in rechargeable batteries. In the hybrid energy powered scenario, on-grid energy is consumed only when the total energy consumption exceeds the allocated green energy. As such, the reduction of on-grid energy consumption relies on the optimization of energy consumption and green energy allocation. However, the renewable energy always exhibits temporal dynamic, such as the daily solar energy generation in a given area peaks around noon, and bottoms during the night. The energy consumption of BSs depends on the mobile traffic load, which also shows both temporal and spatial dynamics [20]. Thus the optimization of on-grid energy consumption involves the optimization in both the time and space dimensions.

Furthermore, in contrast with the existing research which considers the total on-grid energy consumption minimization only, in this paper we aim to minimize both total and peak on-grid energy consumptions. This can be justified by the fact that in real networks, the high peak on-grid energy consumption will translate into high operational expenditure (OPEX) for mobile network operators, as electric systems need to maintain sufficient capacity of on-grid energy generation to meet the expected peak on-grid energy consumption plus a reserve margin [21]. In addition, the extra costs of high-capacity equipments are usually covered by industrial consumers, such as mobile network operators, thereby resulting in the increasing OPEX for mobile network operators. In this sense, it is not sufficient to only reduce the total on-grid energy consumption. The minimization of peak on-grid energy consumption is also imperative.

The main contributions of the paper are presented as follows.

- Distinct with the existing research which focuses on the minimization of total on-grid energy consumption only, we formulate the two-dimensional optimization problem to lexicographically minimize the on-grid energy consumption in HetNets with hybrid energy sources, thereby reducing both total and peak on-grid energy consumptions.
- Taking advantage of the time scale separation assumption, we decompose the problem into two sub-optimization problems without loss of optimality of the original optimization problem. We first formulate the user association optimization in space dimension via convex optimization to minimize total energy consumption through distributing the traffic appropriately across different BSs in a certain time slot. We then optimize the green energy allocation across different time slots for an individual BS to lexicographically minimize the on-grid energy consumption, based on the traffic load determined by the first sub-optimization problem.
- To solve the two-dimensional optimization problem, a low complexity optimal offline algorithm with infinite battery capacity is proposed by assuming the non-causal green energy and traffic knowledge, that amounts to the harvested green energy and traffic of all time slots known as priori. We theoretically prove the optimality of the proposed optimal offline algorithm, and demonstrate its effect by simulations.
- In practice, the amounts of harvested green energy and traffic are random in nature and cannot be predicted precisely in advance. In this case, online algorithms relying on the information of previous and current time slots are required. The proposed optimal offline algorithm provides useful performance upper bound for the more practical online algorithms, and sheds light on the design of online algorithms. Thus inspired by the proposed optimal offline algorithm, we develop some heuristic online algorithms with finite battery capacity by utilizing causal green energy and traffic information, and evaluate their performance via simulations.

The remainder of the paper is organized as follows. Section II presents the system model. The two-dimensional optimization problem is formulated in Section III. Sections IV and V elaborate the optimal offline algorithm and heuristic online algorithms, respectively. In Section VI, the performance of the proposed optimal offline and heuristic online algorithms is evaluated by simulations. Section VII concludes the paper.

II. System Model

We consider the 2-tier downlink HetNets where tier 1 is modeled as macrocell and tier 2 as picocell. MBSs provide basic coverage, whereas Pico BSs (PBSs) are deployed in the coverage area of each MBS to enhance capacity. In our model, a macrocell geographical area $\mathcal{L} \subset \mathbb{R}^2$ is served by a set of BSs $\mathcal{B}$ including one MBS and several PBSs, where all BSs are assumed to share the same frequency band. Let $x \in \mathcal{L}$ denote a location and $i \in \mathcal{B}$ index i-th BS, where $i = 1$ indicates the MBS and the others are PBSs. Assuming the duration of time is divided into $|\mathcal{T}|$ time slots, the length of each time slot is τ seconds and $t \in \mathcal{T}$ denotes the t-th time slot. All BSs in our model are powered by both power grid and renewable energy sources. In order to provide a general model, we do not assume a particular type of renewable energy source. The proposed algorithm is carried out within a macrocell geographical area $\mathcal{L}$ and across all time slots $\mathcal{T}$ in order to optimize the on-grid energy consumption.

A. Traffic Model

In this subsection, we ignore the time slot index t for simplicity. We assume that the traffic requests arrive according to a inhomogeneous Poisson point process with the arrival rate per unit area $\lambda(x)$, and the traffic size is independently distributed with mean $\mu(x)$. Here, $\lambda(x)\mu(x)$ captures the spatial traffic variability, where a hot spot can be characterized by a higher arrival rate or a larger traffic size.

Assuming a mobile user at location x is associated with BS i, the transmission rate to this user $r_i(x)$ can be generally expressed according to Shannon Hartley theorem [22], with W denoted as the operating bandwidth,

$$r_i(x) = W \log_2 \left(1 + \mathrm{SINR}_i(x)\right), \tag{1}$$

where

$$\mathrm{SINR}_i(x) = \frac{p_i g_i(x)}{\sum_{k \in \mathcal{B}, k \neq i} p_k g_k(x) + \sigma^2}, \tag{2}$$

here σ^2 is the noise power level and p_i is the transmission power of BS i, which is constant in our work. The channel power gain $g_i(x)$ between BS i and the user at location x includes pathloss and shadowing. Note that fast fading is not considered here since the time scale of user association is much larger than the time scale of fast fading. As such, $r_i(x)$ can be considered as a time-averaged transmission rate [23].

In order to guarantee the quality of service (QoS) of users in a sense that all users are served with the required traffic amount, the fraction of resource blocks allocated by BS i to the user at location x is derived as

$$\varrho_i(x) = \frac{\lambda(x)\mu(x) y_i(x)}{r_i(x)}, \tag{3}$$

where $y_i(x)$ is the user association indicator, if user at location x is associated with BS i, $y_i(x) = 1$, otherwise $y_i(x) = 0$. We assume at each time one user can only associate with a single BS, and thus we have $\sum_{i \in \mathcal{B}} y_i(x) = 1$. The average traffic load density of BS i is denoted as $\varrho_i(x)$.

Based on the traffic load density, the set $\mathcal{F}$ of the feasible loads of BSs $\boldsymbol{\rho} = (\rho_1, \ldots, \rho_{|\mathcal{B}|})$ is given by

$$\mathcal{F} = \Big\{ \boldsymbol{\rho} | \rho_i = \int_{\mathcal{L}} \varrho_i dx,\ 0 \le \rho_i \le 1 - \varepsilon, \\ \sum\nolimits_{i \in \mathcal{B}} y_i(x) = 1,\ y_i(x) \in \{0, 1\},\ \forall x, \forall i \Big\}, \tag{4}$$

where ε is an arbitrarily small positive constant to ensure $\rho_i < 1$.

B. Energy Consumption Model

We assume both MBSs and PBSs in the HetNets are powered by hybrid energy sources: power grid and renewable energy sources. Each BS is capable of harvesting green energy from renewable energy sources. We assume each BS is equipped with a rechargeable battery with maximum capacity as B_i^{max} to store the harvested and residual energy. According to [24], rechargeable battery can be modeled by an ideal linear model, where the changes in the energy stored are linearly related to the amounts of energy harvest or spent, provided that the maximum battery capacity is not exceeded. Note that small BSs such as PBSs may have smaller energy harvesting rates and battery capabilities than those of MBSs. We also assume there is no energy transfer among BSs. Each BS will allocate green energy harvested by itself in each time slot. If the allocated green energy is not sufficient to support traffic demand, the BS will consume the energy from the power grid.

Generally, BSs consist of two types of energy consumptions: static energy consumption and adaptive energy consumption. Adaptive energy consumption is related to the transmission powers of BSs and is typically linear to the loads of BSs [25]. Static energy consumption is the energy consumption when BS is idle without any traffic load. Here we adopt the linear approximation of BS energy consumption model in [25], with $E_i(t)$ denoted as the energy consumption of BS i at t-th time slot,

$$E_i(t) = \Delta_i p_i \rho_i(t) \tau + E_i^s, \tag{5}$$

where Δ_i is the slop of load-dependent energy consumption of BS i, p_i is transmission power of BS i, τ is the length of each time slot, $\rho_i(t)$ is the traffic load of BS i at t-th time slot, and E_i^s is the static energy consumption of BS i in each time slot. It is worthwhile mentioning that the small BSs such as PBSs and femto BSs generally have smaller static energy consumptions than those of MBSs since they have neither big power amplifiers nor cooling equipments.

Then we denote $G_i(t)$ as the green energy allocation of BS i at t-th time slot, and the on-grid energy consumption of BS i at t-th time slot is expressed as

$$E_i^{grid}(t) = \max\left(E_i(t) - G_i(t), 0\right). \tag{6}$$

III. Problem Formulation

Due to the disadvantages of high peak on-grid energy consumption, we aim to not only reduce the total on-grid energy consumption but also achieve the time-fair on-grid energy consumption, that is, to make the on-grid energy consumption evenly distributed with respect to time as much as possible. We achieve this by using lexicographic minimization which is defined as below.

Definition 1: Let $\mathbf{A_1}$ and $\mathbf{A_2}$ be two resource allocations. A resource vector $\mathbf{L^A}$ is a sorted resource vector of a resource allocation, if $\mathbf{L^A}$ is the result of sorting $\mathbf{A}$ in non-increasing order, and L_i^A is the i-th element in $\mathbf{L^A}$. We say $\mathbf{A_1} = \mathbf{A_2}$ if $\mathbf{L^{A_1}} = \mathbf{L^{A_2}}$, $\mathbf{A_1} < \mathbf{A_2}$ if there exists an i such that $L_i^{A_1} < L_i^{A_2}$ and $L_j^{A_1} = L_j^{A_2}$, $\forall j < i$, and $\mathbf{A_1} > \mathbf{A_2}$ otherwise. $\mathbf{A}^*$ is the optimal lexicographic minimization resource allocation if there is no other resource allocation $\mathbf{A}' < \mathbf{A}^*$.

Note that lexicographic optimization is a well-established method for radio resource allocation control in wireless networks, see [26], [27] and references therein.

We denote $\boldsymbol{G} = \{G_i(t) | \forall i, \ \forall t\}$ and $\boldsymbol{\rho} = \{\rho_i(t) | \forall i, \ \forall t\}$. Thus, in this paper our problem is to find optimal loads of BSs $\boldsymbol{\rho}$ and optimal green energy allocation $\boldsymbol{G}$ in order to lexicographically minimize the on-grid energy consumption, which is given by

$$\mathbf{P1}: \quad \underset{\boldsymbol{\rho}, \boldsymbol{G}}{\text{Lexicographically minimize}}$$

$$\left\{ \sum_{i \in \mathcal{B}} E_i^{grid}(1), \cdots, \sum_{i \in \mathcal{B}} E_i^{grid}(t), \cdots, \sum_{i \in \mathcal{B}} E_i^{grid}(|\mathcal{T}|) \right\}, \quad (7)$$

$$\text{s.t.}: \ R_i(1) = B_i^0, \ \forall i \quad (8)$$

$$R_i(t) = R_i(t-1) + Q_i(t-1) - G_i(t-1), \ \forall i, t \geq 2 \quad (9)$$

$$G_i(t) \leq R_i(t) + Q_i(t), \ \forall i, \ \forall t \quad (10)$$

$$R_i(t) + Q_i(t) \leq B_i^{\max}, \ \forall i, \ \forall t \quad (11)$$

$$\boldsymbol{\rho} \in \mathcal{F}, \ \forall t, \quad (12)$$

where $Q_i(t)$ is the amount of green energy harvested by BS i at t-th time slot. $R_i(t)$ is the residual energy left from the previous time slots, and it is available at t-th time slot. $B_i^{\max}$ is the maximum battery capacity of BS i. $G_i(t)$ is the green energy allocation of BS i at t-th time slot. We assume the harvested green energy $Q_i(t)$ arrives at the beginning of t-th time slot, and the initial energy stored in the battery is B_i^0. (9) represents the 'storage evolution' dynamics. (10) is the energy causality constraint, that is BS cannot consume more green energy than it has stored. (11) means excessive energy cannot be stored in the rechargeable battery.

The lexicographic minimization of on-grid energy consumption **P1** aims to find the optimal green energy allocation $\boldsymbol{G}$, as well as determine which BS each user should associate with, or equivalently, to find the optimal loads of BSs $\boldsymbol{\rho}$, in order to minimize both total and peak on-grid energy consumptions. The on-grid energy is consumed only when the total energy consumption exceeds the green energy allocated in each time slot. As such, the reduction of on-grid energy consumption depends on the optimization of both the energy consumption and green energy allocation. According to equation (5), the energy consumption of BS is decided by the traffic load of BS, which exhibits temporal and spacial dynamics. In this sense, in order to reduce the total energy consumption throughout the whole network, user association decision should be made to distribute the traffic load appropriately among all BSs, thereby minimizing the energy consumption. The renewable energy also shows temporal dynamic, such as the daily solar energy generation in a given area peaks around noon, and bottoms during the night. As such to minimize both the total and peak on-grid energy consumptions, the green energy allocation should be optimized among all time slots $\mathcal{T}$. In other words, the lexicographic minimization of on-grid energy consumption **P1** involves optimization in both time and space dimensions. In the space dimension, traffic load among BSs should be distributed appropriately within the whole network. In the time dimension, the green energy allocation across different time slots should be optimized.

Hence, solving **P1** is very challenging as the highly complex coupling of user association and green energy allocation. For analysis tractability, we shall make an assumption on the time-scale separation that traffic request arrival and departure process and the corresponding user association process are much faster than the period on which the green energy allocation across different time slots is determined. From statistics in real networks [20], [28], the traffic pattern, e.g., traffic distribution, and green energy generation rate vary over time, but could be assumed almost constant during a certain period, e.g., one hour. Since the time scale for determining green energy allocation is similar to the order of traffic pattern and green energy generation rate changing, it is definitely much larger than that of traffic request arrival and departure process, e.g., typically less than several minutes [23].

With this in mind, we can assume both the traffic pattern and green energy generation rate are stationary during one time slot. Furthermore, shown in (6), $E_i^{grid}(t)$ reduces with decreasing $E_i(t)$, where $E_i(t)$ is determined by ρ_i, the traffic load of BS i. Furthermore, the value of $E_i(t)$ is independent with the value of green energy allocation $G_i(t)$. Therefore we decompose the optimization problem into two sub-optimization problems. In space dimension, the traffic load is distributed appropriately across different BSs $\mathcal{B}$ in a certain time slot to minimize the total energy consumption $\sum_{i \in \mathcal{B}} E_i(t)$. While in time dimension, the green energy allocation $\boldsymbol{G}$ is optimized across different time slots $\mathcal{T}$ in order to lexicographically minimize the on-grid energy consumption, based on the traffic load derived from the optimization in space dimension. Note that the solutions for these two decomposed sub-optimization problems are also optimal for the original problem **P1**, which will be made clear in the proof of **Theorem 4**.

A. Space Dimension: User Association Optimization

The user association optimization in space dimension is to determine which BS each user should associate with, or equivalently, to find the optimal traffic load $\boldsymbol{\rho}$ for any given time slot. It aims to minimize the total energy consumption of all BSs

during one time slot, while guaranteeing QoS requirements for all users in a sense that all users are served with the required traffic amount, which is given by

$$\begin{aligned} &\min_{\boldsymbol{\rho}} \quad \sum\nolimits_{i\in\mathcal{B}} [E_i(t)] \\ &\text{s.t.}: \ (12) \end{aligned} . \tag{13}$$

Since $y_i(x) \in \{0, 1\}$, $\mathcal{F}$ in (12) is not a convex set. In order to facilitate the convex optimization problem formulation, we relax $y_i(x) \in \{0, 1\}$ to $0 \le y_i(x) \le 1$, where $y_i(x)$ specifies the probability that the user at location x is associated with BS i. The time slot index t is omitted here for simplicity, and then the updated set $\tilde{\mathcal{F}}$ of the feasible loads of BSs $\boldsymbol{\rho} = (\rho_1, \ldots, \rho_{|\mathcal{B}|})$ is

$$\tilde{\mathcal{F}} = \left\{ \boldsymbol{\rho} | \rho_i = \int_{\mathcal{L}} \varrho_i dx, \ 0 \le \rho_i \le 1 - \varepsilon, \right. \\ \left. \sum\nolimits_{i\in\mathcal{B}} y_i(x) = 1, \ 0 \le y_i(x) \le 1, \ \forall x, \ \forall i \right\}. \tag{14}$$

The authors in [22] have proved that the set $\tilde{\mathcal{F}}$ is convex.

Then we introduce a penalty function $L_i(\rho_i(t))$ to the original sub-optimization problem (13), and formulate the user association optimization in space dimension as a convex optimization given by

$$\begin{aligned} &\textbf{P1.1}: \quad \min_{\boldsymbol{\rho}} \quad \sum\nolimits_{i\in\mathcal{B}} [E_i(t) + L_i(\rho_i(t))] \\ &\text{s.t.}: \ \boldsymbol{\rho} \in \tilde{\mathcal{F}}, \forall t, \end{aligned} \tag{15}$$

By adding penalty $L_i(\rho_i(t))$ into the objective, the traffic could be balanced among BSs, which avoids cells getting too congested. Furthermore, such load balancing benefits the QoS provision by reducing the average traffic delay. Although there may be other methods to design the penalty function, in this paper we define the penalty as following:

$$L_i(\rho_i(t)) = \omega_i \log\left(\frac{1}{1 - \rho_i(t)}\right), \tag{16}$$

where ω_i is the weight to adjust the significance of the penalty of BS i. Larger value of traffic load $\rho_i(t)$ will lead to higher penalty value. Due to the low transmission power and limited capacity of picocells, picocells have higher chance to become the early capacity bottleneck. Thus the weight of picocell always has higher value than that of macrocell. In general, the value of weight can be selected as a composite tradeoff among signal quality, spectrum efficiency and load balancing needs, and it can also be adapted in real time to address the dynamic changes in the network. We will demonstrate the effect of different values of ω_i in the simulation section. It is worthwhile mentioning that as the value of ω_i goes to zero, the objective function of the modified sub-optimization problem given in (15) is asymptotically equivalent to the objective function of the original sub-optimization problem without penalty function given in (13).

Remark 1: Although we formulate the sub-optimization problem **P1.1** via probabilistic user association $\tilde{\mathcal{F}}$, the proposed user association algorithm in Section VI determines the optimal deterministic user association. This will be made clear in the proof of **Theorem 1** and **Theorem 2**.

B. Time Dimension: Green Energy Allocation Optimization

Based on the traffic load derived from the user association optimization in space dimension, the green energy allocation in time dimension is to optimize the green energy allocation across different time slots to lexicographically minimize the on-grid energy consumption. As there is no energy transfer among BSs in our model, the lexicographical minimization of on-grid energy consumption of the whole network can be achieved by lexicographically minimizing the on-grid energy consumption of every individual BS separately, which is formulated as

$$\begin{aligned} &\textbf{P1.2}: \quad \underset{\mathbf{G}}{\text{Lexicographically minimize}} \\ &\left\{ E_i^{grid}(1), \cdots, E_i^{grid}(t), \cdots, E_i^{grid}(|\mathcal{T}|) \right\}. \\ &\text{s.t.}: (8), (9), (10), (11) \end{aligned} \tag{17}$$

IV. Proposed Optimal Offline Algorithm

In this section, we study the two-dimensional optimization in offline setup with non-causal information, where both the amounts of harvested green energy and traffic of all time slots are known in advance. We propose optimal offline algorithm to solve the lexicographic minimization of on-grid energy consumption **P1** with low computational complexity when the battery capacity is infinite ($B_i^{\max} = \infty$). Since original optimization problem **P1** is decomposed into two sub-optimization problems, we resolve **P1** by solving the two sub-optimization problems. The solution of the user association optimization in space dimension estimates the traffic load, thereby calculating the energy consumption of all BSs in each time slot according to equation (5). Based on this solution, optimal green energy allocation across different time slots is achieved by solving optimization problem in time dimension. Hence the proposed optimal offline algorithm consists of the user association algorithm in space dimension and the green energy allocation algorithm in time dimension. User association algorithm is implemented in all BSs $\mathcal{B}$ and users at an individual time slot to determine the optimal traffic load of BSs in order to minimize total energy consumption throughout the whole network. Then based on the optimal traffic load in every time slot, green energy allocation algorithm is implemented in an individual BS to determine the green energy allocation across different time slots $\mathcal{T}$, aiming to lexicographically minimize the on-grid energy consumption.

A. User Association Algorithm in Space Dimension

In this subsection, we propose the user association algorithm which achieves the global optimum in minimizing the total energy consumption of all BSs in a certain time slot. Since the user association focuses the optimization of space dimension in a snapshot regardless of the time dimension, we omit time slot index t in the presentation of the proposed user association

algorithm for simplicity. The proposed user association algorithm is implemented in an iterative manner: BSs periodically measure and advertise their loads, and then users make user association decisions based on the advertised information to minimize $f(\boldsymbol{\rho}) = \sum_{i\in\mathcal{B}} [E_i + L_i(\rho_i)]$. The BS and user sides update iteratively until convergence.

In order to guarantee convergence, we assume the user arrival and departure process is faster relative to the period in which BSs advertise their loads. Particularly, once BSs advertise their loads, users are able to make user association decisions based on the advertised BS loads, prior to the next BS advertising load update.

In the following, we will elaborate the explicit procedures of the proposed user association algorithm.

User Side: At the beginning of k-th iteration, users get the traffic loads $\boldsymbol{\rho}^{(k)}$ of all BSs via broadcast. And then the user at location x chooses the optimal BS by

$$j^{(k)}(x) = \arg\max_{i\in\mathcal{B}} r_i(x)\Big(\Delta_i p_i \tau + L_i'\left(\rho_i^{(k)}\right)\Big)^{-1}. \tag{18}$$

where $L_i'(\rho_i^{(k)}) = \partial L_i(\rho_i^{(k)})/\partial\rho_i^{(k)}$.

Then the user association indicator is updated by

$$y_i^{(k)}(x) = \begin{cases} 1, & \text{if } i = j^{(k)}(x) \\ 0, & \text{otherwise,} \end{cases} \tag{19}$$

where $y_i^{(k)}(x)$ is broadcasted to all BSs.

BS Side: The updated user association indicators from the user side will change the loads of BSs, and thus during the k-th iteration, the new traffic load of BS i is given by

$$T_i\left(\rho_i^{(k)}\right) = \min\left(\int_{\mathcal{L}} \frac{\lambda(x)\mu(x)y_i^{(k)}(x)}{r_i(x)}dx,\ 1-\varepsilon\right). \tag{20}$$

Based on the derived $T_i(\rho_i^{(k)})$, BS i updates the next advertising traffic load as [22]

$$\rho_i^{(k+1)} = \theta\rho_i^{(k)} + (1-\theta)T_i\left(\rho_i^{(k)}\right), \quad \forall i \in \mathcal{B}, \tag{21}$$

where $0 \le \theta < 1$ is an exponential averaging parameter.

The following provides proof on optimality and convergence of the proposed user association algorithm in space dimension.

Lemma 1: A unique optimal $\boldsymbol{\rho}*$ exists to minimize $f(\boldsymbol{\rho}) = \sum_{i\in\mathcal{B}} [E_i + L_i(\rho_i)]$, when $\boldsymbol{\rho}$ is defined on $\tilde{\mathcal{F}}$.

Proof: The objective function $f(\boldsymbol{\rho}) = \sum_{i\in\mathcal{B}} [E_i + L_i(\rho_i)]$ is a convex function of $\boldsymbol{\rho}$ when $\boldsymbol{\rho}$ is defined on $\tilde{\mathcal{F}}$, since $\nabla^2 f(\boldsymbol{\rho}) > 0$ when $\boldsymbol{\rho} \in \tilde{\mathcal{F}}$. As such, there exists a unique optimal $\boldsymbol{\rho}*$ that minimizes $f(\boldsymbol{\rho})$. □

We denote $\boldsymbol{\rho}^{(k)} = (\rho_1^{(k)}, \cdots, \rho_{|\mathcal{B}|}{}^{(k)})$ and $\mathbf{T}(\boldsymbol{\rho}^{(k)}) = (T_1(\rho_1^{(k)}), \cdots, T_{|\mathcal{B}|}(\rho_{|\mathcal{B}|}{}^{(k)}))$.

Lemma 2: When $\boldsymbol{\rho}^{(k)} \neq \boldsymbol{\rho}*$, $\mathbf{T}(\boldsymbol{\rho}^{(k)}) - \boldsymbol{\rho}^{(k)}$ is a descent direction of $f(\boldsymbol{\rho}^{(k)})$.

Proof: This lemma can be proved by deriving $\langle \nabla f(\boldsymbol{\rho}^{(k)}), \mathbf{T}(\boldsymbol{\rho}^{(k)}) - \boldsymbol{\rho}^{(k)}\rangle \le 0$, where $\langle , \rangle$ is the symbol of inner product. Let $y_i(x)$ and $y_i^T(x)$ be the user association indicators of BS i that result in the traffic load $\rho_i^{(k)}$ and $T_i(\rho_i^{(k)})$, respectively.

$$\begin{aligned}
&\left\langle \nabla f\left(\boldsymbol{\rho}^{(k)}\right), \mathbf{T}\left(\boldsymbol{\rho}^{(k)}\right) - \boldsymbol{\rho}^{(k)}\right\rangle \\
&= \sum_{i\in\mathcal{B}} \left(\Delta_i p_i \tau + L_i'\left(\rho_i^{(k)}\right)\right)\left(T_i\left(\rho_i^{(k)}\right) - \rho_i^{(k)}\right) \\
&= \sum_{i\in\mathcal{B}} \left(\Delta_i p_i \tau + L_i'\left(\rho_i^{(k)}\right)\right)\int_{\mathcal{L}} \frac{\lambda(x)\mu(x)\left(y_i^T(x) - y_i(x)\right)}{r_i(x)}dx \\
&= \int_{\mathcal{L}} \lambda(x)\mu(x)\sum_{i\in\mathcal{B}} \frac{\left(\Delta_i p_i \tau + L_i'\left(\rho_i^{(k)}\right)\right)\left(y_i^T(x) - y_i(x)\right)}{r_i(x)}dx.
\end{aligned} \tag{22}$$

Note that

$$\sum_{i\in\mathcal{B}} \frac{\left(\Delta_i p_i \tau + L_i'\left(\rho_i^{(k)}\right)\right)\left(y_i^T(x) - y_i(x)\right)}{r_i(x)} \le 0 \tag{23}$$

holds, since $y_i^T(x)$ derived from equation (18) (19) maximizes the value of $r_i(x)(\Delta_i p_i \tau + L_i'(\rho_i^{(k)}))^{-1}$. Therefore we have $\langle \nabla f(\boldsymbol{\rho}^{(k)}), \mathbf{T}(\boldsymbol{\rho}^{(k)}) - \boldsymbol{\rho}^{(k)}\rangle \le 0$. □

Theorem 1 (Convergence): The traffic load $\boldsymbol{\rho}$ converges to $\boldsymbol{\rho}* \in \mathcal{F}$.

Proof: Since $\rho_i^{(k+1)} - \rho_i^{(k)} = \theta\rho_i^{(k)} + (1-\theta)T_i(\rho_i^{(k)}) - \rho_i^{(k)} = (1-\theta)(T_i(\rho_i^{(k)}) - \rho_i^{(k)})$, and $0 \le \theta < 1$, $\boldsymbol{\rho}^{(k+1)} - \boldsymbol{\rho}^{(k)}$ is also a descent direction of $f(\boldsymbol{\rho}^{(k)})$ according to Lemma 2. Then based on Lemma 1 where $f(\boldsymbol{\rho}^{(k)})$ is a convex function and is lower bounded by 0, we conclude that $f(\boldsymbol{\rho}^{(k)})$ converges. Suppose $f(\boldsymbol{\rho}^{(k)})$ converges to some point other than $f(\boldsymbol{\rho}*)$, then $\boldsymbol{\rho}^{(k+1)}$ produces a descent direction again, which means $f(\boldsymbol{\rho}^{(k)})$ can further decrease in the next iteration. This contradicts the convergence assumption, and hence $\boldsymbol{\rho}^{(k)}$ converges to $\boldsymbol{\rho}*$. Since $\boldsymbol{\rho}^{(k)}$ is derived based on (18), (19), (20), (21), where $y_i^{(k)}(x) \in \{0, 1\}$, $\boldsymbol{\rho}*$ is in the feasible set $\mathcal{F}$. □

Remark 2: The computational complexity of the user association algorithm for an individual user is $\mathcal{O}(|\mathcal{B}|)$ for each iteration. According to [22], although the convergence speed depends on the value of θ, fixed θ close to 1 generally works well for the convergence. However, how to optimize θ is beyond the scope of this paper. In our simulation, we set $\theta = 0.98$, simulation results have shown our proposed user association algorithm converges quickly to the optimum, within 60 iterations.

Theorem 2: Suppose the feasible set $\mathcal{F}$ is not empty[1] and the traffic load $\boldsymbol{\rho}$ converges to $\boldsymbol{\rho}*$, the user association corresponding to $\boldsymbol{\rho}*$ minimizes $f(\boldsymbol{\rho})$, which is the optimum of **P1.1**.

[1]Up till now, we consider the condition where the **P1.1** is feasible, that is the feasible set $\mathcal{F}$ is not empty with $\rho_i \le 1-\varepsilon, \forall i \in \mathcal{B}$. However in the circumstance when the **P1.1** is not feasible due to high traffic load, the admission control is required. In this case, the admission control with the objective to minimize the sum of energy consumption and cost of blocking traffic can be formulated with the similar approach in our previous work [29], where a threshold is used to determine whether a particular user should be blocked or not, and the user association algorithm stays intact as the algorithm presented above in this section.

Proof: Denote $\boldsymbol{y}* = \{y_i*(x)|y_i*(x) \in \{0, 1\},\ \forall i,\ \forall x\}$ and $\boldsymbol{y} = \{y_i(x)|y_i(x) \in \{0, 1\},\ \forall i,\ \forall x\}$ as the user association corresponding to $\boldsymbol{\rho}*$ and $\boldsymbol{\rho} \in \mathcal{F}$, respectively.

Since $f(\boldsymbol{\rho})$ is a convex function over $\boldsymbol{\rho}$, proving the theorem is equivalent to prove

$$\left\langle \nabla f(\boldsymbol{\rho}*)|_{\boldsymbol{\rho}=\boldsymbol{\rho}*}, \boldsymbol{\rho} - \boldsymbol{\rho}* \right\rangle \geq 0. \tag{24}$$

$$\begin{aligned}
&\left\langle \nabla f(\boldsymbol{\rho}*)|_{\boldsymbol{\rho}=\boldsymbol{\rho}*}, \boldsymbol{\rho} - \boldsymbol{\rho}* \right\rangle \\
&= \sum_{i\in\mathcal{B}} \left(\Delta_i p_i \tau + L_i'(\rho_i*)\right)(\rho_i - \rho_i*) \\
&= \sum_{i\in\mathcal{B}} \left(\Delta_i p_i \tau + L_i'(\rho_i*)\right) \int_{\mathcal{L}} \frac{\lambda(x)\mu(x)\,(y_i(x) - y_i*(x))}{r_i(x)} dx \\
&= \int_{\mathcal{L}} \lambda(x)\mu(x) \sum_{i\in\mathcal{B}} \frac{\left(\Delta_i p_i \tau + L_i'(\rho_i*)\right)(y_i(x) - y_i*(x))}{r_i(x)} dx.
\end{aligned} \tag{25}$$

Since the optimal user association indicator is determined by

$$y_i*(x) = \begin{cases} 1, & \text{if } i = \arg\max\limits_{i\in\mathcal{B}} r_i(x)\left(\Delta_i p_i \tau + L_i'(\rho_i*)\right)^{-1} \\ 0, & \text{otherwise} \end{cases}, \tag{26}$$

we have

$$\sum_{i\in\mathcal{B}} \frac{\left(\Delta_i p_i \tau + L_i'(\rho_i*)\right) y_i(x)}{r_i(x)} \geq \sum_{i\in\mathcal{B}} \frac{\left(\Delta_i p_i \tau + L_i'(\rho_i*)\right) y_i*(x)}{r_i(x)}. \tag{27}$$

Hence $\langle \nabla f(\boldsymbol{\rho}*)|_{\boldsymbol{\rho}=\boldsymbol{\rho}*}, \boldsymbol{\rho} - \boldsymbol{\rho}* \rangle \geq 0$. □

It is worthwhile mentioning that the proposed user association algorithm does not restrict the timely response for two reasons. First, the proposed user association algorithm is totally distributed. Although the interaction between users and BSs may incur overhead on control information exchange, the proposed algorithm does not require any centralized computation, and there is no high algorithmic complexity issue here. Second, the duration of one time slot depends on the dynamics of green energy generation and mobile traffic. As for green energy generation, taking solar energy as an example, the granularity for solar energy generation is usually an hour [28]. For the mobile traffic, the hourly mobile traffic profile can well represent the traffic characteristic for guiding the BS operations [20]. Thus, the time slot duration could be tens of minutes, which is long enough to execute the proposed user association algorithm. As a result, we can conclude that the proposed user association algorithm is able to be implemented whenever a new traffic request arrives and attempts the network access. Additionally, due to the constant traffic pattern during one time slot, the total energy consumption will remain the same during one time slot, regardless of the arrival and departure of the specific traffic flow.

B. Green Energy Allocation Algorithm in Time Dimension

Based on the non-causal traffic information, the user association algorithm in space dimension can estimate traffic load, thereby calculating the energy consumption of all BSs in each time slot according to equation (5). With the knowledge of energy consumption of all BSs, we propose the green energy allocation algorithm for the green energy allocation optimization in time dimension to lexicographically minimize the on-grid energy consumption in an offline manner, with the aid of non-causal green energy information. The green energy allocation optimization is quite complicated, due to the fact that green energy harvested at one time slot cannot be used at its previous time slots, and the available amount of green energy during a certain time slot depends both on the green energy harvested at the current time slot and on the residual green energy harvested from previous time slots. Inspired by the energy allocation algorithm in [18], we propose a green energy allocation algorithm as shown in Algorithm I.

Algorithm I: Green Energy Allocation Algorithm

Input: $E_i(t)$, $Q_i(t)$, $\forall t$, B_i^0;
Initialize $G_i(t)$, $\forall t$, and calculate $E_i^{grid}(t)$, $\forall t$;
for $m = 2$; $m \leq |\mathcal{T}|$; $m++$; **do**
  if $E_i^{grid}(m) > E_i^{grid}(m-1)$ **then**
    for $n = 1$; $n \leq m-1$; $n++$; **do**
      calculate $\bar{g} = \sum_{t=n}^{m} E_i^{grid}(t)/(m-n+1)$;
      if $E_i^{grid}(n) < \bar{g}$ **then**
        $k = n$, and break;
      end if
    end for
    for $n = k$; $n \leq m$; $n++$; **do**
      if $E_i^{grid}(n) < \bar{g}$ **then**
        Decrease $G_i(n)$ to make $E_i^{grid}(n) = \bar{g}$;
      else
        Increase $G_i(n)$ to make $E_i^{grid}(n) = \bar{g}$;
      end if
    end for
  end if
end for
Return $G_i(t)$, $\forall t$.

In the proposed green energy allocation algorithm, we first initialize the green energy allocation as

$$G_i(t) = \begin{cases} B_i^0 + Q_i(t), & t = 1 \\ Q_i(t), & t > 1, \end{cases} \tag{28}$$

where BS consumes all the available green energy in each time slot. Since the green energy cannot be consumed until it is harvested, the proposed green energy allocation algorithm optimizes the green energy allocation of each time slot according to the time sequence. The proposed algorithm computes the on-grid energy consumption of first time slot, and then adds next time slot into green energy allocation optimization iteratively. If the on-grid energy consumption of the newly added time slot is larger than that of the prior time slot, the green energy allocation in previous time slots will be reduced, and the saved energy will be allocated to the current time slot.

Theorem 3: The proposed green energy allocation algorithm achieves the optimal solution for **P1.2** with $B_i^{\max} = \infty$.

Proof: Since the green energy harvested at one time slot cannot be used in the previous time slots, the on-grid energy consumption at one time slot can be reduced only by changing the green energy allocation in the previous time slots. If $E_i^{grid}(m) > E_i^{grid}(m-1)$, the green energy allocations in the time slots previous to m-th time slot are reduced, and more green energy is allocated in m-th time slot, thereby ensuring $E_i^{grid}(m) \leq E_i^{grid}(m-1)$. Specifically, we find the n-th time slot such that $E_i^{grid}(n) < \sum_{t=n}^{m} E_i^{grid}(t)/(m-n+1)$, and then let $\bar{g} = \sum_{t=n}^{m} E_i^{grid}(t)/(m-n+1)$. We will reduce the green energy allocation from n-th to $(m-1)$-th time slot, and increase the green energy allocation in m-th slot, making sure $E_i^{grid}(t) = \bar{g}, t \in \{n, \cdots, m\}$. Assuming $E_i^{grid}(m)$ is the m-th largest on-grid energy consumption among all slots, any attempt to reduce $E_i^{grid}(m)$ will result in further increase of the largest to the $(m-1)$-th largest on-grid energy consumption. Therefore, the proposed green energy allocation achieves the min-max fair. According to [26], the min-max fair vector is the unique optimal solution for the lexicographic minimization problem, which is also Pareto optimal. □

The computational complexity of proposed green energy allocation algorithm is $\mathcal{O}(|\mathcal{T}|^2)$ in the worst case. Such computational complexity is acceptable, since the proposed green energy allocation algorithm optimizes the green energy allocation in an offline manner. If we take one day as the whole duration of the time, the proposed green energy allocation algorithm executes only once a day.

C. Proof of Optimality

In this subsection, we prove the following theorem on the optimality of the proposed optimal offline algorithm.

Theorem 4: The proposed optimal offline algorithm achieves the optimum of the original optimization problem **P1** with $B_i^{\max} = \infty$ and $\omega_i \to 0$.

Proof: The proposed optimal offline algorithm consists of two sequential algorithms: the user association algorithm in space dimension and the green energy allocation algorithm in time dimension. User association is first implemented to minimize the total energy consumption $\sum_{i\in\mathcal{B}} E_i(t)$ in every time slot, and let $E^*(t) = \sum_{i\in\mathcal{B}} E_i(t)$ be the resulting minimum total energy consumption in t-th time slot. Then the green energy is allocated across different time slots to lexicographically minimize the on-grid energy consumption $\{E_i^{grid}(1), \cdots, E_i^{grid}(t), \cdots, E_i^{grid}(|\mathcal{T}|)\}$ for any individual BS, and we denote the resulting optimal on-grid energy consumption as $\mathbf{E}^{*grid} = \{E_i^{*grid}(t) | \forall i, \ \forall t\}$. According to Algorithm I, $\mathbf{E}^{*grid}$ has the property of $E_i^{*grid}(t) \leq E_i^{*grid}(t-1), \ \forall t > 1$, and achieves the min-max fair in on-grid energy consumption. We assume that in the t-th time slot, another user association pattern with the resulting total energy consumption $\ddot{E}(t)$ is adopted, and the user association pattern in the other time slots is the same as that in the proposed optimal offline algorithm. It is obvious that $\ddot{E}(t) > E^*(t)$. If the case with $\ddot{E}(t)$ wants to achieve the same on-grid energy consumption in t-th time slot as the case in the proposed optimal offline algorithm, more green energy need to be allocated in t-th time slot. In doing so, more green energy need to be transferred from the previous time slots, which may increase the on-grid energy consumption in the previous time slots. If we denote $\ddot{\mathbf{E}}^{grid} = \{\ddot{E}_i^{grid}(t) | \forall i, \ \forall t\}$ as the resulting on-grid energy consumption in the case with $\ddot{E}(t)$, we can conclude that $\ddot{\mathbf{E}}^{grid}$ is lexicographically larger than $\mathbf{E}^{*grid}$. Therefore the proposed optimal offline algorithm, in which user association is determined to minimize the total energy consumption, and then green energy is allocated to lexicographically minimize the on-grid energy consumption, achieves the optimum of the original optimization problem P1. □

Note that the proposed optimal offline algorithm provides the optimal solution based on the assumption that the traffic pattern and green energy generation are constant during one time slot. However, in real networks, the network condition may be more complicated and dynamic: the traffic pattern and green energy generation may present slight fluctuation even within a time slot. In this context, our proposed algorithm asymptotically approaches the optimal solution.

In summary, in the scenario with infinite battery capacity, the optimal offline algorithm is executed in two stages. First, user association is determined to minimize the total energy consumption in every time slot. Then green energy is allocated across different time slots to lexicographically minimize the on-grid energy consumption. However, in the general case, if the battery capacity is finite, we cannot arbitrarily save the green energy for future use due to limited battery capacity. The structure of optimal green energy allocation cannot be presented in a simple and clear way as in Algorithm I. Intuitively, in contrast with the case of infinite battery capacity where green energy is conservatively used to achieve optimality, in the case of finite battery capacity the green energy should be allocated first to minimize the energy overflow. We will propose some heuristic online algorithms based on this intuition, and the proposed optimal offline algorithm in the infinite battery capacity can be treated as the performance upper bound of the online algorithms in finite battery capacity.

V. Heuristic Online Algorithms

In this section, we consider the formulated two-dimensional optimization problem **P1** in online setup with causal information, where only the amounts of harvested green energy and traffic of the current and previous time slots are known. Furthermore, the historical green energy and mobile traffic statistics are available to estimate the harvested green energy and traffic across different time slots [28], [30].

The user association optimization in the proposed optimal offline algorithm in Section IV decides the user association in a certain time slot to minimize the total energy consumption. As mentioned in Section IV, the proposed user association algorithm is capable of timely response and only requires the traffic information of the current time slot. In this sense, it can already be implemented in the online manner. The green energy allocation in the proposed optimal offline algorithm in Section IV requires the non-causal green energy and traffic knowledge, which is not practical. But its structure sheds light on the design of online algorithms. As such, in this section,

heuristic online green energy allocation algorithms are proposed with online setup. More specifically, the online green energy allocation will update in each time slot according to the amount of energy consumption and available green energy, as well as the battery capacity.

A. Constant On-Grid Energy Consumption Level Algorithm

Motivated by the green energy allocation in the proposed optimal offline algorithm which tries to achieve uniform on-grid energy consumption as much as possible, we propose a constant on-grid energy consumption level algorithm. The constant on-grid energy consumption level is defined as

$$\tilde{g}_i = \left(\sum_{t \in \mathcal{T}} \tilde{E}_i(t) - \sum_{t \in \mathcal{T}} \tilde{Q}_i(t) - B_i^0 \right) \Big/ |\mathcal{T}|, \tag{29}$$

where $\tilde{E}_i(t)$ is the statistics on total energy consumption of BS i at t-th time slot, which can be calculated based on the historical traffic statistics and the proposed user association algorithm. $\tilde{Q}_i(t)$ is the historical statistics on harvested green energy of BS i at t-th time slot. Then the intended green energy allocation of BS i at t-th time slot is

$$\tilde{G}_i(t) = \max\{E_i(t) - \tilde{g}_i, 0\}. \tag{30}$$

However, the allocated green energy cannot be larger than the maximum available green energy of BS i at t-th time slot, which is given by

$$G_i^{\max}(t) = R_i(t) + Q_i(t). \tag{31}$$

Thus the green energy allocation of BS i at t-th time slot is calculated as

$$G_i(t) = \min\left\{\tilde{G}_i(t), G_i^{\max}(t)\right\}. \tag{32}$$

As such, the on-grid energy consumption of BS i at t-th time slot is

$$E_i^{grid}(t) = \max\{E_i(t) - G_i(t), 0\}. \tag{33}$$

Due to the limit on battery capacity and the randomness of green energy arrival, green energy overflow in the online setup may exist. Hence in addition, we bring in the *green energy overflow prevention*. If the expected stored energy exceeds the battery capacity $B_i^{\max}$, the minimum green energy allocation is

$$G_i^{\min}(t) = R_i(t) + Q_i(t) - B_i^{\max}. \tag{34}$$

As such, the green energy allocation of BS i at time slot t is determined as

$$G_i(t) = \min\left\{\max\left\{\tilde{G}_i(t), G_i^{\min}(t)\right\}, G_i^{\max}(t)\right\}. \tag{35}$$

The green energy overflow prevention well meets the battery capacity constraint from the average point of view, and is expected to improve the performance, although the green energy overflow can not be completely avoided.

B. Adaptive On-Grid Energy Consumption Level Algorithm

For finite time transmissions, the constant on-grid energy consumption level algorithm is apparently not optimal due to the variation of traffic load and available green energy across different time slots. We thus propose the adaptive on-grid energy consumption level algorithm to improve the performance. The on-grid energy consumption level is updated for each time slot, which is given by

$$\tilde{g}_i(t) = \frac{E_i(t) + \sum_{m=t+1}^{|\mathcal{T}|} \tilde{E}_i(m) - \left(R_i(t) + Q_i(t) + \sum_{m=t+1}^{|\mathcal{T}|} \tilde{Q}_i(m) \right)}{|\mathcal{T}| - t + 1}. \tag{36}$$

In this case, the intended green energy allocation of BS i at t-th time slot is

$$\tilde{G}_i(t) = \max\{E_i(t) - \tilde{g}_i(t), 0\}. \tag{37}$$

Then the green energy allocation in the adaptive on-grid energy consumption level algorithm without and with *green energy overflow prevention* are presented as same as (32) and (35), respectively.

VI. Simulation Results

To evaluate the performance of the proposed algorithms, we simulate a 2-tier downlink HetNet. The theoretical analysis throughout paper is independent with the spatial distribution of BSs. In the simulation, we model the locations of all BSs to be fixed. The simulated HetNet is composed of 19 macrocells. In each macrocell, 3 PBSs are symmetrically located along a circle with radius 200m and MBS in the center. As for the traffic model, similar to our previous work [31], we simulate the file transfer requests following a homogenous Poisson point process where $\lambda(x) = \lambda$ for the sake of simplicity, but note that our model can still be applied to the scenario with heterogeneous traffic distributions. Each request is assumed to have exactly one file with mean file size μ as 100 Kbits.

As mentioned, the proposed user association algorithm is able to be executed within one time slot. Note that the theoretical analysis throughout paper is independent with the exact duration of one time slot, and also not restricted to a particular type of renewable energy source. To evaluate the effectiveness of the proposed algorithms in accommodating the temporal dynamic of mobile traffic and green energy generation, we use the statistics in [28] which provides hourly solar energy generation in June around London gatwick airport, and [30] which estimates the typical daily traffic variation in European areas as shown in Fig. 1. The daily traffic variation is plotted relative to the peak traffic demand. In our simulation, we assume all BSs are in the same weather environment and bear the same traffic variation trend. We evaluate the performance of the proposed algorithms during the time scale of 24 hours.

Other simulation parameters are shown in Table I. Figs. 2–6 evaluate the performance of the proposed optimal offline algorithm in the scenario with infinite battery capacity. Figs. 7 and 8 demonstrate the performance of the proposed online algorithms

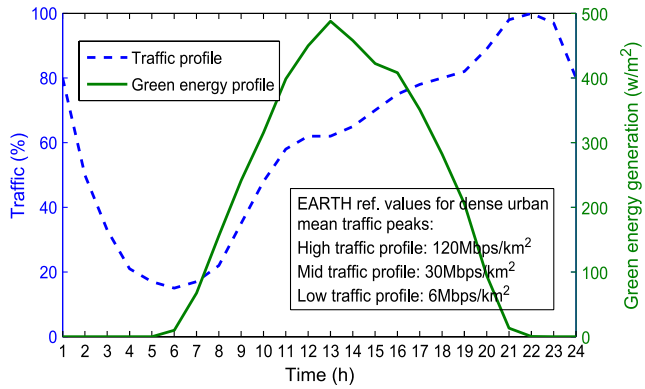

Fig. 1. Traffic and green energy profiles versus different time slots.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Bandwidth	10 MHz
Inter site distance	500 m
Transmission power of MBS	46 dBm
Transmission power of PBS	30 dBm
Noise power	-174 dBm/Hz
Pathloss between MBS and user	$128.1 + 37.6\log_{10} d\,(km)$ [32]
Pathloss between PBS and user	$140.7 + 36.7\log_{10} d\,(km)$ [32]
Log-normal shadowing fading	10 dB [32]
Static power consumption of MBS	780 W [25]
Static power consumption of PBS	13.6 W [25]
Slop of MBS load-dependent energy	4.7 [25]
Slop of PBS load-dependent energy	4.0 [25]
Initial energy stored in MBS	2 kWh
Initial energy stored in PBS	0.002 kWh

with finite battery capacity. Here we set the battery capacity of macrocell[2] as S times of the average harvested green energy in one time slot, where S is the relative battery capacity. The proposed optimal offline algorithm in the infinite battery capacity can be treated as the performance upper bound for the online algorithms in finite battery capacity.

A. Behavior of the Proposed Optimal Offline Algorithm

In Figs. 2 and 3, we focus on the snapshot of the time slot with peak traffic demand in the mid traffic profile condition, and verify the effectiveness of the user association algorithm in space dimension in the proposed optimal offline algorithm. Fig. 2 compares the snapshot of the resulting user association pattern in one macrocell area with and without the optimization/penalty function in space dimension. In the user association without optimization, users will associate with the BS from which they receive the strongest downlink reference signal received power (RSRP). Due to the power disparity of the high power MBS and low power PBS, Fig. 2 demonstrates that in the user association without optimization most users associate with MBS, which will overload the marcocell and make the PBS deployment ineffective. On the contrary, in the user association with optimization in space dimension without penalty function, where user association is determined by minimizing $\sum_{i\in\mathcal{B}}[E_i(t)]$, we observe that many users associate with the PBSs. Although it effectively offloads the traffic from the congested macrocell to picocells, due to the limited capacity of picocells, excessive offloaded users may congest the picocells. The proposed user association with optimization and penalty function in space dimension compromises the above two schemes, where users are well-balanced and the probability of congestion is further reduced. Such traffic balancing achieves a good tradeoff between energy saving and average traffic delay reduction which is demonstrated in Fig. 3.

The overall load balancing achieved by adding the penalty function comes at the cost of slight increase in the total energy consumption. Here, we quantize the load balancing benefits via the average traffic delay. We assume users associated with the same BS are served on the round robin fashion. When we consider the system as M/GI/1 multi-class processor sharing system as in [33], $\rho_i/(1-\rho_i)$ is equal to the average number of flows at BS i, and $\sum_{i\in\mathcal{B}}\frac{\rho_i}{1-\rho_i}$ is the total number of flows in the system [22]. According to the Little's law, the average number of flows is mathematically related to the average delay experienced by a typical traffic flow. Fig. 3 calculates average traffic delay and total energy consumption with different weights of macrocell ω_m. The less average traffic delay means the less congestion and more effective load balancing. As shown in Fig. 3, the increment of total energy consumption is marginal compared with the average traffic delay reduction. For example, in the case of $\omega_m = 10^0$ and $\omega_p/\omega_m = 3$, where ω_p denotes the weights of picocell, there is 90% reduction in average traffic delay with 0.22% increase in total energy consumption compared with the case without penalty function ($\omega_m \to 0$). We can also notice the performance of $\omega_p/\omega_m = 3$ is better than that of $\omega_p/\omega_m = 1$. Taking $\omega_m = 10^0$ as an example, compared with the case of $\omega_p/\omega_m = 1$, the case of $\omega_p/\omega_m = 3$ can get 11.2% more reduction in the average traffic delay, but only increases the total energy consumption by 0.17%. This verifies the effectiveness of our design in making $\omega_p/\omega_m > 1$ for HetNets to avoid the early capacity bottleneck of picocells. Note that such tradeoff graph may also be used to choose the value of ω_m and ω_p/ω_m in practice based on the maximum tolerable traffic delay. In the following simulation of this section, we set $\omega_m = 10^0$ and $\omega_p/\omega_m = 3$.

Fig. 4 testifies the effectiveness of the green energy allocation algorithm in time dimension in the proposed optimal offline algorithm. Fig. 4 shows the green energy allocation and on-grid energy consumption versus different time slots with and without optimization in time dimension. In the case without optimization, BSs consume the green energy as long as they harvest it from the renewable energy sources. Fig. 4 illustrates that the proposed green energy allocation algorithm in time dimension optimizes the green energy allocation over time slots. As a result, on-grid energy is consumed in a more uniform way with respect to time, which mitigates the high peak on-grid energy consumption problem. However, in the case without optimization, due to the high green energy generation rate during 10:00 and 16:00 as shown in Fig. 1, the on-grid energy consumption goes down dramatically, but rapidly escalates

[2]In the simulation, we assume both the energy harvesting rate and battery capacity of picocell are 2.5% of those of marcocell. This assumed ratio is reasonable, since the transmission power ratio of picocell and marcocell is 2.5% defined in the 3GPP standard.

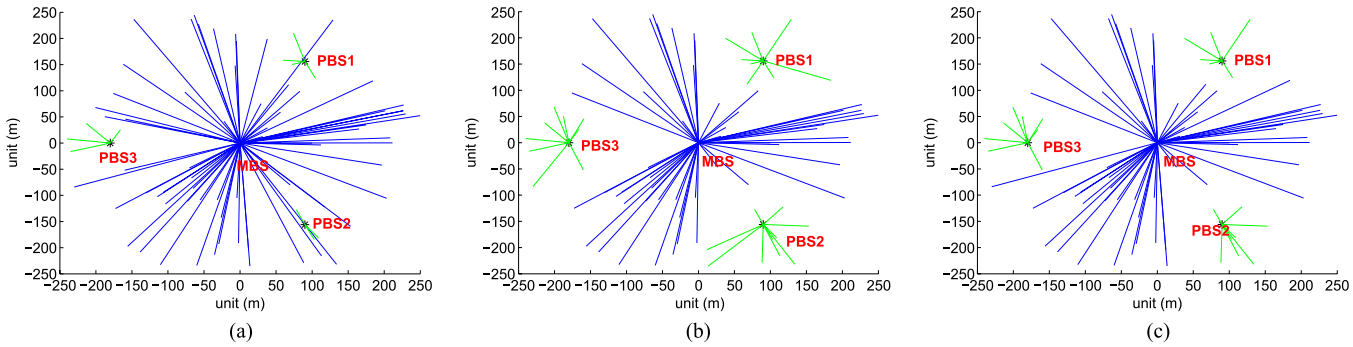

Fig. 2. Snapshot of user association pattern. (a) Without optimization in space dimension. (b) With optimization but no penalty function in space dimension. (c) With optimization and penalty function in space dimension.

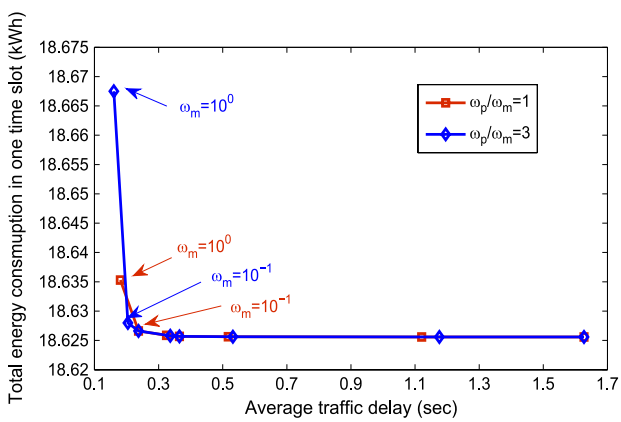

Fig. 3. Tradeoff between average traffic delay and total energy consumption by varying the weight of macrocell from 10^0 to 10^{-20}.

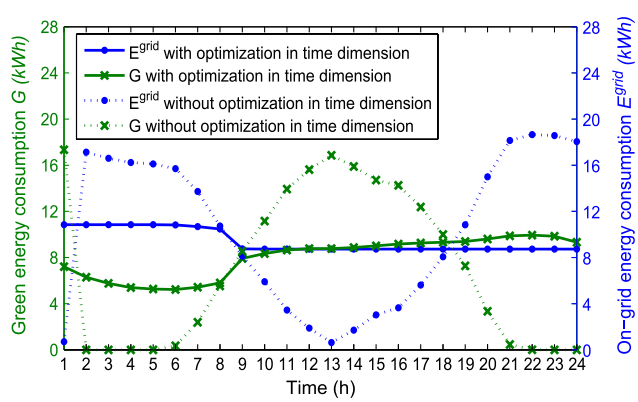

Fig. 4. Green energy allocation and on-grid energy consumption versus different time slots o/w optimization in time dimension.

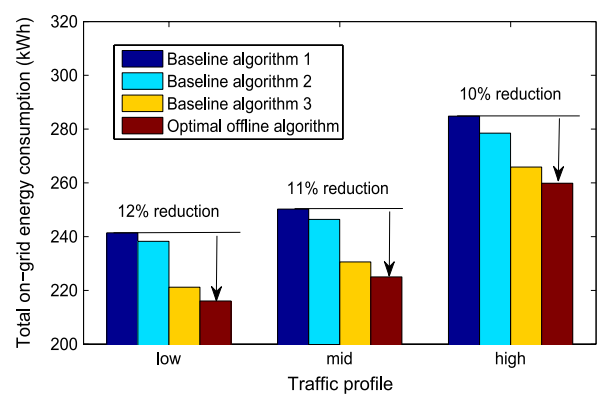

Fig. 5. Total on-grid energy consumption in different traffic profiles. Only offline algorithms are considered.

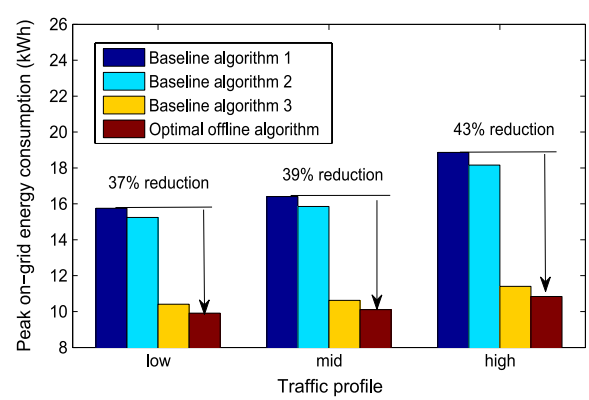

Fig. 6. Peak on-grid energy consumption in different traffic profiles. Only offline algorithms are considered.

after 19:00, since the green energy generation rate experiences rapid decline after then.

B. Comparison of the Proposed Optimal Offline Algorithm With the Baseline Algorithms

For comparison, we consider three baseline algorithms for the proposed optimal offline algorithm. In baseline algorithm 1, there is no optimization in neither space nor time dimension. Baseline algorithm 2 and 3 only have optimization in space and time dimension, respectively. Fig. 5 presents the total on-grid energy consumption within the whole HetNets area and across all time slots in different traffic profiles. Compared with the baseline algorithm 1, the baseline algorithm 2 and 3 can reduce the total on-grid energy consumption. The superiority of baseline algorithm 2 over baseline algorithm 1 demonstrates that the load balancing achieved in our proposed user association algorithm effectively benefits the total energy consumption minimization. Our proposed optimal offline algorithm with optimization in both time and space dimensions achieves the most on-grid energy saving among these four algorithms. The total on-grid energy saving is no less than 10% in all the considered traffic profile conditions, benchmarked by the baseline algorithm 1.

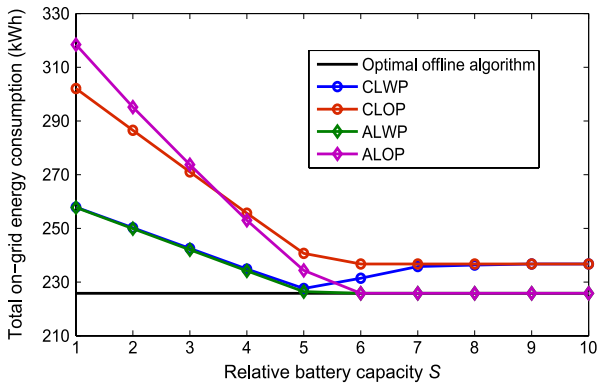

Fig. 7. Total on-grid energy consumption versus different battery capacities.

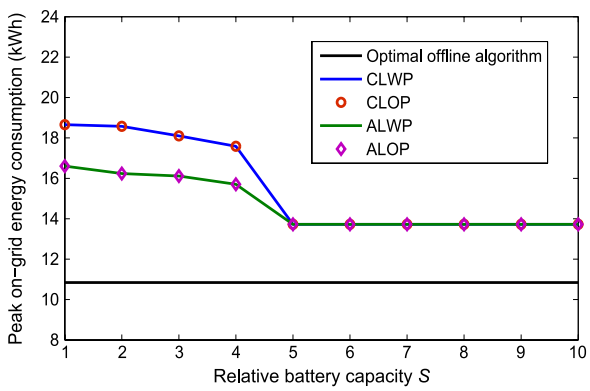

Fig. 8. Peak on-grid energy consumption versus different battery capacities.

Fig. 6 evaluates the peak on-grid energy consumption in different traffic profiles. The peak on-grid energy consumption plotted here is the sum peak on-grid energy consumption of all BSs in one macrocell area. Fig. 6 reveals that compared with the baseline algorithms, our proposed optimal offline algorithm with optimization in both time and space dimensions is able to substantially reduce the peak on-grid energy consumption, with about 40% reduction in all the considered traffic profile conditions. It indisputably addresses the challenge of rising peak on-grid energy consumption, thereby reducing OPEX and maintaining profitability for mobile network operators.

Figs. 5 and 6 demonstrate the design rationale of the proposed optimal offline algorithm which involves the optimization in both time and space dimensions, since it is more effective than the algorithm with optimization in time or space dimension only.

C. Comparison of the Proposed Online and Optimal Offline Algorithms

Fig. 7 shows the total on-grid energy consumption of different online algorithms versus different battery capacities. They are benchmarked by the proposed optimal offline algorithm with infinite battery capacity, which is the performance upper bound for all online algorithms. To facilitate the subsequent explanation, we denote the proposed constant on-grid energy consumption level algorithm without and with green energy overflow prevention as CLOP and CLWP, respectively. We also denote the proposed adaptive on-grid energy consumption level algorithm without and with green energy overflow prevention as ALOP and ALWP, respectively. As shown in Fig. 7, in the low battery capacity regime, say $S < 3$ in our simulation, the CLOP outperforms the ALOP. This can be explained by the fact that ALOP updates the on-grid energy consumption level periodically, and foresees the low green energy generation rate and high traffic load during late night, so more green energy is intended to be saved for the late night. However since there is no green energy overflow prevention, there is a higher chance that the conserved energy will exceed the low battery capacity, resulting in energy overflow. Fig. 7 also reveals that in CLWP, with the growing battery capacity, the total on-grid energy consumption first decreases and then increases. This is because with the increase of battery capacity, more green energy may be saved for the subsequent time slots, which benefits the on-grid energy saving. However when the relative battery capacity exceeds certain value, say $S > 5$ in our simulation, consuming all the conserved green energy may result in the on-grid energy consumption in the subsequent time slots smaller than the predefined constant on-grid energy consumption level. Due to the fact that the on-grid energy consumption in CLWP cannot be smaller than the predefined constant level, the excessive conserved green energy may be wasted, giving rise to the total on-grid energy consumption increase. In addition, we can conclude from Fig. 7 that the green energy overflow prevention is efficient in total on-grid energy saving. It substantially reduces the green energy overflow at low battery capacity regime, and the gain shrinks as battery capacity increases. We can also obverse the performance of ALOP and ALWP approaches that of the optimal offline algorithm with increasing battery capacity.

Fig. 8 demonstrates the effect of battery capacity on the peak on-grid energy consumption in different online algorithms. It shows that as battery capacity increases, the peak on-grid energy consumption of online algorithms reduces, and the gap between online algorithms and optimal offline algorithm decreases. We can also observe that ALOP and ALWP outperform CLOP and CLWP, since ALOP and ALWP are able to update the on-grid energy consumption level adaptively, thereby better utilizing the harvested green energy. Based on Figs. 7 and 8, we conclude that ALWP is superior to the other proposed online algorithms no matter what the size of battery capacity, considering both total and peak on-grid energy consumption reductions.

VII. Conclusion

In this paper, we studied the two-dimensional optimization on user association and green energy allocation to lexicographically minimize the on-grid energy consumption in HetNets with hybrid energy sources, where all BSs are assumed to be powered by both power grid and renewable energy sources. We decomposed the optimization problem into two sub-optimization problems: the user association optimization in space dimension and the green energy allocation optimization in time dimension. We developed the low complexity optimal offline algorithm with infinite battery capacity by assuming non-causal green energy and traffic information, which can serve as performance upper bound for evaluating practical online algorithms.

Simulation results indicate the proposed optimal offline algorithm substantially saves on-grid energy as well as reduces peak on-grid energy consumption. In addition, motivated by the optimal offline algorithm, some heuristic online algorithms with finite battery capacity, utilizing causal green energy and traffic information only, were also proposed and evaluated by simulations. Simulation results demonstrate that the adaptive on-grid energy consumption level algorithm with green energy overflow prevention outperforms the other proposed heuristic online algorithms in terms of both total and peak on-grid energy consumption reductions.

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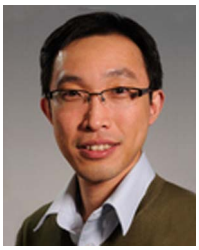

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