Green Energy and Delay Aware Downlink Power Control and User Association for Off-Grid Solar Powered Base Stations

Vinay Chamola, Bhaskar Krishnamachari and Biplab Sikdar

***Abstract*—Cellular base stations (BSs) powered by renewable energy like solar power have emerged as a promising solution to address the issues of reducing the carbon footprint of the telecom industry as well as the operational cost associated with powering the BSs. This paper considers a network of off-grid solar powered BSs and addresses two key challenges while operating them (a) avoiding energy outages and (b) ensuring reliable quality of service (in terms of the network latency). In order to do so, the problem of minimizing the network latency given the constrained energy availability at the BSs is formulated. Unlike existing literature which have addressed this problem using user-association reconfiguration or BS on/off strategies, we address the problem by proposing an intelligent algorithm for allocating the harvested green energy over time, and green energy and delay aware downlink power control and user association. Using a real BS deployment scenario, we show the efficacy of our methodology and demonstrate its superior performance compared to existing benchmarks.**

***Index Terms*—Green communications, off-grid base station, resource management, solar energy, cellular networks.**

I. Introduction

Using renewable resources like solar energy to power the BSs has emerged as a promising solution for greening cellular networks. According to statistics from Global System Mobile Association (GSMA), at the end of 2014 there were around 43,000 solar powered BSs around the globe [1]. They not only are a green solution for reducing the carbon foot-print of cellular networks, but also provide a means to reduce the operating expenditure. Additionally, many of the growing telecom markets in the world like those in the Asian and African continents lack reliable grid power. In such locations, the telecom operators are forced to use diesel generators as an alternative energy source which has an operational cost 10 times higher as compared to powering the BSs by the grid [2]. There are currently 321,000 off-grid BSs and they are predicted to grow by 22% by the year 2020. Around 80% of these would be installed in African and Asian countries. In such scenarios, networks of solar powered BSs are a promising solution for the telecom operators and there have already been some successful deployments of the same. Examples of these include solar powered BSs deployed by Zong Telecom in Pakistan, Bhutan Telecom Limited in Bhutan, Telkomsel in Indonesia, and Orange in Africa [3]. Some existing works which study off-grid solar powered BSs include [4]-[5]. Among the various choices to power an off-grid BS by renewable energy sources (e.g. solar power, wind energy, natural gas); solar power is one of the most popular choice [6].

Solar powered BSs are carefully provisioned with resources like photo-voltaic (PV) panels and batteries, taking into account the trade-off between the CAPEX (capital expenditure) and quality of service performance [7]-[8]. Due to cost constraints, the BSs cannot be over-provisioned beyond a certain degree and thus they require additional effort for managing the green energy available to them, specifically during bad weather periods. In the absence of such energy management, the network can experience critical power outages during these times. Another key challenge in operating a network of such BSs is to intelligently manage the green energy available to the BSs while ensuring reliable QoS. This paper presents a methodology for maximizing the QoS, in terms of minimizing the network latency, given the constraints on the energy availability at the solar-powered BSs. In contrast to existing approaches based on just user association reconfiguration or BS on/off strategies, our methodology uses a combination of intelligent energy allocation, and green energy and delay aware BS downlink power control and user association. We show the performance gains of the proposed methodology over existing benchmarks (the GALA scheme [9] , the ICE scheme [10] and the SWES scheme [11]) through simulations using a real BS deployment scenario from United Kingdom (UK).

The rest of this paper is organized as follows. Section II presents the literature review. Section III presents the system model. Section IV presents the problem formulation. Section V presents the solution methodology. Section VI presents the numerical results and Section VII concludes the paper.

II. Literature Review

Reducing the network energy consumption is one of the ways of solving the problem of avoiding energy outages at the BSs during bad weather periods [12]. In related work, [13] introduces the concept of energy saving in a network by BS switching (i.e. switching off some of the BSs to reduce network energy consumption). Some basic issues in dynamic BS switching are described in [14], [15] and [16]. A

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framework for BS switching and transmit power control with the objective of minimizing the energy used in the network is proposed in [17]. In [11], the authors propose a scheme (named SWES) for dynamic switching of BSs to minimize the overall energy consumption. This scheme saves energy by turning off BSs and it is a greedy heuristic which seeks to determine the minimum number of BSs required to serve the area, with the desired quality of coverage. The authors in [18] propose cell breathing techniques for bringing down the network energy consumption. Cell breathing refers to BSs reconfiguring the area being served by them. The authors in [18] achieve cell breathing by adjusting the transmit power levels of the BSs. The author in [19] proposes a rate and power control based energy-saving technique for orthogonal frequency division multiple access (OFDMA) systems. An energy-efficient scheme for resource allocation in OFDMA systems with hybrid energy harvesting BSs is proposed in [20] where a dynamic programming approach for power allocation is used to minimize the network energy consumption. Further, [10] proposes an algorithm, named ICE, for green energy aware load balancing to minimize the overall energy consumption, achieved by tuning the beacon levels of the BSs.

The studies above are primarily focused on minimizing the network energy consumption. However, these studies do not consider the impact of the energy minimization on the network delay performance. Studies which address network delay performance include [21] which proposes a distributed user association scheme using a primal-dual formulation for traffic load balancing. Authors in [22] propose an α-optimal user association policy for flow level cell load balancing with the objective of maximising the throughput or minimizing the system delay. However the above-mentioned schemes ([21],[22]) consider BSs powered by the grid and thus do not account for the green energy availability at the BSs.

Methodologies which consider green energy availability in addition to the delay performance include [9] and [23]. The authors in [9] propose the GALA scheme which accounts for the green energy availability at the BS while making user-association decisions. The authors formulate the problem of minimizing the sum of weighted latency ratios of the BSs where the weights are chosen to account for the green energy availability at the BSs. Authors in [23] consider BSs powered by hybrid supplies and formulate the problem of minimizing the weighted sum of the cost of average system latency and the cost of on-grid power consumption. The approach in [9] and [23] to manage the available energy and network latency is by reconfiguring the BS-MT (mobile terminal) user-association. In contrast to such an approach, this paper presents a methodology for energy and latency management based on downlink transmit power control in addition to user association reconfiguration, and demonstrates its performance gains over existing approaches. Also the above-mentioned studies solve the problem of latency management and green energy utilization for a given instant of time and do not deal with the allocation of the available green energy over time. Thus, in addition to downlink power control and user association reconfiguration, our methodology uses a temporal energy allocation algorithm presented in our earlier work [24] to intelligently manage the green energy available to the BSs so as to maximize the benefit derived from it. With this energy allocation in place, this paper presents a comprehensive framework for the operation of an off-grid BS, guiding the energy allocation, power control, as well as user-association which has been missing in existing literature. Note that although [25] uses green energy and delay aware BS power control and user association reconfiguration, the problem scenario and formulation are quite different from the ones addressed in this paper. It considers the scenario where the BSs are connected to the grid and the challenge is to manage the trade-off between grid energy savings and the QoS. However, in the scenario of off-grid solar powered BSs we have different challenges to address like avoiding power outages.

The main contributions of the paper are as follows:

- Unlike existing literature which deals with operational strategies for grid connected BS either with or without hybrid supplies (e.g. [26]), we focus on developing operational strategies for a network of off-grid solar powered BSs. The off-grid scenario brings forth challenges such as energy outages which are not a concern for grid connected BSs.
- Existing literature has primarily used user-association reconfiguration for managing the green energy availability and the network latency performance. But our proposed framework uses BS downlink transmit power control in addition to user association reconfiguration and shows its performance gains over existing schemes. Additionally, we propose a green energy and delay aware user-association scheme for the off-grid scenario.
- We propose a simple temporal energy allocation algorithm which guides the green allocation over time so as to maximize the utilization of the harvested green energy.
- With the above-mentioned aspects, we present a complete framework for guiding the operations of an off-grid network of solar powered BSs which guides the temporal energy allocation, BS downlink power control, as well as the user association policy.

III. System Model

In this section we describe the traffic model considered in the paper. We also describe the formulation of the BS load and the network latency.

A. *Traffic Model, BS Load and Network Latency*

We consider a network of cellular BSs offering coverage to a geographical region $\mathcal{R}$. We denote the set of the BSs as $\mathcal{B}$ and the user locations are denoted by $x \in \mathcal{R}$. For simplicity, in this paper, we focus only on downlink communication (i.e. BSs to MTs). We denote the downlink transmit power vector of the BSs by P. The BSs can only operate at discrete values of transmit power levels which are denoted by $P(j) \in \{0, \omega, 2\omega, \cdots, P_{max}\}$, where $P(j)$ denotes the power level of the j-th BS, ω is the granularity of power control, and P_{max} is the maximum transmit power level at which the BSs can operate. We assume that file transfer requests at location x arrive following a Poisson point process with arrival rate

$\lambda(x)$ per unit area and an average file size of $\frac{1}{\mu(x)}$. We define the traffic load density at location x as $\gamma(x) = \frac{\lambda(x)}{\mu(x)}$, where $\gamma(x)$ captures the spatial traffic variability. Assuming BS j is serving the users at location x, the rate offered by the BS to the users can be generally given using the Shannon-Heartley theorem [22] as

$$c_j(x) = BW_j \log_2(1 + SINR_j(x)) \tag{1}$$

where BW_j is the total bandwidth offered by the j-th BS and $SINR_j(x)$ is given by

$$SINR_j(x) = \frac{g_j(x)P(j)}{\sigma^2 + \sum_{m \in I_j} g_m(x)P(m)} \tag{2}$$

where $g_j(x)$ denotes the channel gain between BS j and the user at location x and it accounts for the shadowing loss and path loss, σ^2 denotes the noise power level, and I_j is the set of interfering BSs for BS j. This paper assumes perfect information of the channel gain which may be estimated given the topological details of the terrain, and drive-through site surveys. For simplicity, we use the average value of SINR at a given location for calculating the data rate offered by a BS at that location. Next, we introduce a user association indicator function $u_j(x)$ which specifies the user association between the BSs and the MTs. This value is 1 if users at location x are served by BS j and is 0 otherwise. We now define the BS load ρ_j, which denotes the fraction of time BS j is busy serving its traffic requests and is given by [9]

$$\rho_j = \int_{\mathcal{R}} \frac{\gamma(x)}{c_j(x)} u_j(x) dx. \tag{3}$$

Definition 1: The feasible set of the BS loads $\rho = (\rho_1, \cdots, \rho_{|\mathcal{B}|})$ is denoted by $\mathcal{F}$ and can be defined as

$$\mathcal{F} = \Big\{ \boldsymbol{\rho} \ | \ \rho_j = \int_{\mathcal{R}} \frac{\gamma(x)}{c_j(x)} u_j(x) dx, \ \ 0 \leq \rho_j \leq 1 - \epsilon, \ \ \forall j \in \mathcal{B}, \\ u_j(x) \in \{0, 1\}, \sum_{j=1}^{|\mathcal{B}|} u_j(x) = 1, \ \ \forall j \in \mathcal{B}, \ \ \forall x \in \mathcal{R} \Big\},$$

where ϵ is an arbitrarily small positive constant.

The MTs attach to the BS based on the scheme described later in the paper in Section V-C. Since file transfer arrivals are Poisson processes, the sum of transfer requests arriving at the BSs is also a Poisson process. Since the service process at a BS follows a general distribution, the BSs may be modeled as a M/G/1-processor sharing queue. The average number of flows at BS j can thus be given by $\frac{\rho_j}{1-\rho_j}$ [23]. According to Little's law, the delay experienced by a traffic flow is directly proportional to the average number of flows in the system [14]. Thus we take the total number of the flows in the network as the network latency indicator, $\mathcal{D}$, which is given by [23]

$$\mathcal{D} = \sum_{j \in \mathcal{B}} \frac{\rho_j}{1 - \rho_j}. \tag{4}$$

The indicator above has been used in several contemporary studies to quantify the network latency performance (e.g. [11], [22]–[24]).

B. BS Power Consumption

This paper considers a network of macro BSs. The power consumption of BS j is denoted as $L(j)$, and is given as [27]

$$L(j) = P_0(j) + \Delta P(j)\rho_j, \ \ 0 \leq \rho_j \leq 1, 0 \leq P(j) \leq P_{max} \tag{5}$$

where P_0 is the power consumption at no load (zero traffic) and Δ is the slope of the load dependent power consumption.

C. Solar Energy Resource and Batteries

We use statistical weather data provided by National Renewable Energy Laboratory (NREL) [28]. This is fed to NREL's System Advisor Model (SAM) tool which yields the hourly energy generated by a PV panel with a given rating. The BSs are assumed to use lead acid batteries to store the excess energy harvested by the PV panels. These are a popular choice in storage applications on account of their lower cost and being more time tested than other alternatives.

IV. Problem Formulation

Our objective is to maximize the benefit derived from the green energy available to the BS, in terms of improving the system level latency. While doing so, we desire to avoid energy outages at the BSs. Thus, we consider the problem, [P1], as minimizing the total system level latency during the day, given the harvested solar energy available to the BSs. The problem can be formulated as

$$\begin{aligned} \textbf{[P1]} \ \ & \underset{E_t, \ P_t, \ \rho_t}{\text{minimize}} \quad \sum_{t=1}^{24} \mathcal{D}_t \\ & \text{subject to:} \quad \rho \in \mathcal{F}, \qquad \forall t \\ & \qquad \sum_{t=1}^{24} L_t(j) \leq \mathcal{G}(j), \ \ \forall j \in \mathcal{B} \end{aligned}$$

where the network latency for the t-th hour of the day is denoted by $\mathcal{D}_t$, $L_t(j)$ denotes the BS j's power consumption for the t-th hour, and $\mathcal{G}(j)$ denotes the green energy budget available to the j-th BS during the day. Note that the design variables in the above problem are the green energy allocation (denoted by E), the transmit power levels (P) and the BS loads (ρ).

V. Solution Methodology

To solve the problem formulated in Section IV, we propose the Green energy and delay Aware User association and Resource Allocation (GAURA) scheme which consists of three parts: (a) temporal energy allocation (b) BS downlink power control and (c) user association reconfiguration. In Section V-A we propose an algorithm for intelligently allocating the green energy budget over time. Further, given the energy allocation, in Sections V-B and V-C we address the optimization problem by suitably adjusting the downlink transmit power levels of the different BSs and applying user association reconfiguration, respectively.

Algorithm 1 The TEA Algorithm

Initialize: $E_{excess}(j) = 0, \quad \forall j \in \mathcal{B}$
for $j = 1 : \mathcal{B}$ **do**
  $\mathcal{G}(j)$= $S_{ini}(j) - S_{cr}(j) + \sum_{t=1}^{24} \mathcal{H}_t(j)$
  for $t = 1 : 24$ **do**
    $B_t^{exp}(j) = S_{t-1} + H_t(j) - L_t(j);$
    if $B_t^{exp}(j) > S_{cap}(j)$ **then**;
      $E_{excess}(j) = E_{excess}(j) + (B_t^{exp}(j) - S_{cap}(j))$
    end if
  end for
  $\mathcal{G}(j) = \mathcal{G}(j) - E_{excess}(j)$
  for $t = 1 : 24$ **do**
    $E_t(j) = \mathcal{G}(j) \frac{L_t(j)}{\sum_{h=1}^{24} L_h(j)}$
  end for
end for

A. Temporal Energy Provisioning

The energy available to power the BS on a given day comes from two sources: (a) the solar energy harvested by the BS during the day and (b) the charge remaining in the batteries from the previous day. This energy needs to be used intelligently during the day. To determine the green energy provisioning during the different hours of the day, we propose the Temporal Energy Allocation (TEA) algorithm (shown in Algorithm 1) which is described below.

We first note that the BSs require some charge in the batteries to power them during the early morning hours of the next day, as the solar energy is only available after sunrise. Therefore it is required that the battery level does not go below a certain level at the end of the day, which we denote by S_{cr}. Thus the energy budget which is actually available to the j-th BS for use is given by $\mathcal{G}(j)$= $S_{ini}(j) - S_{cr}(j) + \sum_{t=1}^{24} \mathcal{H}_t(j)$ where $S_{ini}(j)$ denotes the battery level of the j-th BS at the beginning of the day, and $\mathcal{H}_t(j)$ denotes the solar energy harvested by BS j in the t-th hour of the day. Additionally, the battery level at any time cannot exceed the battery capacity. To accomodate this constraint, before doing the energy allocation, the expected battery level at the end of each hour, B_t^{exp}, is noted. If this estimated battery level exceeds the battery capacity (S_{cap}), the excess energy (tracked through the variable E_{excess}) is discarded. The overall available energy budget is now allocated to the different hours of the day in proportion to the estimated BS power consumption during that hour. The energy allocated to BS j in the t-th hour is denoted by $E_t(j)$.

The proposed algorithm requires the information of the solar energy expected to be harvested during the day. There exist many methodologies to predict the solar energy generation, usually days and hours in advance. These could be integrated with weather forecasts to give a more accurate prediction. Some models for the prediction of solar energy include [29] and [30]. Additionally, with the increasing adoption of renewable energy for various applications, there exist many companies which specialize in solar energy prediction for such applications (e.g. [31]). Note that the proposed framework only needs an hourly estimate of the solar energy generation which makes the task even simpler. We also assume that the information of traffic profile from previous weeks is available, which is used to generate the predicted BS power consumption (L) for the initial energy allocation. Note that this energy allocation is only an initialization step and is later updated as shown in Section V-B. We assume that there is a central server which does these operations at the beginning of the day and the decisions made by it guide the temporal energy allocation during the day.

B. Green Energy and Delay Aware Transmission Power Control

We begin this section by with the following proposition that affects downlink power control.

Proposition 1. *The network latency ($\mathcal{D}$) is a non-convex function of the BS power levels.*

We use simulations to show that the network delay ($\mathcal{D}$) is a non-convex function of the BS power levels. We consider a network of BSs as shown in Figure 3, and the simulation settings are as described in Section VI. We consider the BSs operating at 3 p.m. in the afternoon and with BSs 2, 4, 5 and 6 operating at transmit power level 20 W. Next, we vary the power levels of BS 1 and BS 3 and study the effect of doing so on the network latency. Figure 1 shows the network latency for different values of power levels for BS 1 and BS 3. From the figure we can easily conclude that the network latency is a non-convex function of BS power levels.

The problem of power level control of a set of BSs to address the objective function in [P1] is thus a non-convex optimization problem with respect to the BS power levels. Finding the global minima of the optimization problem requires a search over the whole search space of possible power levels, which has very high computational complexity. For $\mathcal{B}$ BS's, the computational complexity is given by $O(Q^{|\mathcal{B}|\mathcal{T}})$ where Q denotes the number of power levels a BS can operate at and $\mathcal{T}$ denotes the number of hours under consideration. Thus to address the power control problem, next we propose a greedy heuristic with very low computational complexity.

We assume that a central server does the power control operations at the beginning of the day and the decisions made by it guide the power levels of the BSs during the day. The power control decisions are made for a time granularity of a hour. To facilitate the power control operations, we assume that the central server has the information of the average hourly traffic profile at a given location which is used for evaluating the underlying user association based on the user association policy proposed in Section V-C. In existing literature, there exist many papers which study, model and predict traffic in cellular networks (e.g. [32], [33] and [34]). These models can be used for the real time implementation of the proposed power control algorithm. Note that such an assumption is not uncommon and has been considered in many contemporary works like [35] and [36].

The BS load, BS power consumption and the traffic served by a BS are affected by its transmit power level. For the transmit power level control operations, it is important to capture the information whether a BS is energy constrained or not. In order to do so, we define *deficiency ratio* of BS j during hour t, $\Theta_i(j)$, as

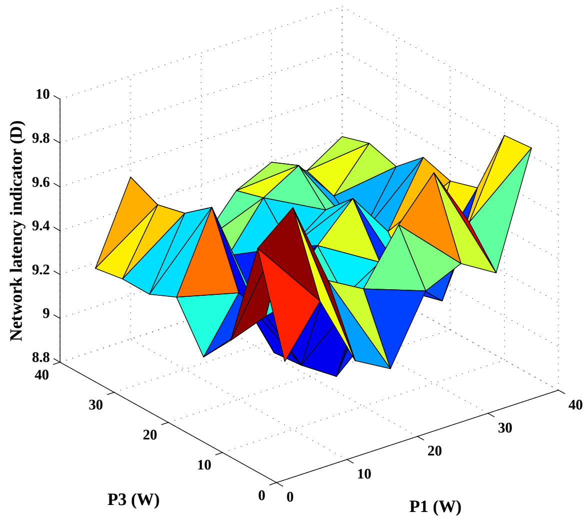

Fig. 1. Latency variation with power control operations on BS 1 and BS 3.

$$\Theta_t(j) = L_t(j)/E_t(j). \tag{6}$$

Note that the case when $L_t(j) > E_t(j)$ corresponds to a situation where the power consumption of the j-th BS in the t-th hour is more than the green energy allocated for that given hour, which indicates that the BS is energy constrained. While determining power levels for the BSs, two concerns regarding the operations of the BSs need to be accounted for which are to avoid energy deficiency (i.e. $\Theta(j) > 1$) and to avoid traffic overload at a BS (i.e. $\rho_j > 1$). To capture the intensity of these problems faced by a BS, we define a term *strain index* which is given by

$$\Psi(j) = \max(0, \Theta(j) - 1) + \max(0, \rho_j - 1). \tag{7}$$

Next, we propose the green energy and delay aware power control algorithm (Algorithm 2) which is aimed at eliminating the strain index and improving the network latency performance. The operation of Algorithm 2 can be explained as follows. The proposed algorithm is sequentially carried out for each hour of the day. For a given hour, the BS power control begins by trying to eliminate the strain index (Ψ) for the BSs. To achieve this, the BS with the largest value of strain index is identified at every step (using $\max(\Psi)$) and its transmit power level is reduced by ω (line 6 in Algorithm 2). This reduction in transmit power level contributes to relieving the strain of the BS in terms of energy deficiency as well as traffic overload. The reason for this is as follows. When the transmit power level of a BS is reduced, some of its users are offloaded to nearby BSs which reduces the BS load (ρ). Further, as the BS load is reduced, the power consumption of the BS which is dependent on the BS load (as shown in (5)) is also reduced. After all the BSs have zero strain index, the power control operations are done so as to minimize the overall system latency. For this, one by one the BSs reduce their transmit power by ω and the system latency with the new set of power levels is stored in the vector Γ_{pc} (lines 10-19 in Algorithm 2). The BS for which the reduction of power level leads to the largest reduction in the system latency, while allowing all BSs to have $\Theta > 1$ (which is tracked by the vector $Poss$), updates its transmit power level. This process is continued until there is no further improvement in the system latency by powering down any of the BS (lines 20-26 in Algorithm 2). The latency improvement is checked through the status variable $Latency\_reduction$ which is true when the latency reduces by power control operation, and it is set false otherwise. Note that the latency improvement brought by the power control operations is because of the load balancing effect and interference management.

For a given hour, for the transmit power levels determined by the proposed algorithm, the BSs may not be using all of the energy allocated to them for that hour. We denote the leftover energy by $\mathcal{U}$ in the algorithm and this energy is distributed to the subsequent hours in proportion to their

Algorithm 2 Green Energy and Delay Aware Power Control Algorithm

1: Initialize: $P_t(j) = P_{max}, \quad \forall j \in \mathcal{B}$
2: Compute Ψ for all BSs
3: $\Psi(j) = max(0, \Theta(j) - 1) + max(0, \rho_j - 1)$
4: **while** $max(\Psi) > 0$ **do**
5:     a. $g : \arg\max_{j \in \mathcal{B}} \Psi$
6:     b. $P_t(g) = max(0, P_t(g) - \omega)$;
7: **end while**
8: $Latency\_reduction = True$;
9: **while** $Latency\_reduction = True$ **do**
10:     Γ_{old}= network latency with power vector P.
11:     **for** $j = 1 : |\mathcal{B}|$ **do**
12:         $P_{curr} = P_t$
13:         $P_{curr}(j) = max(0, P_t(j) - \omega)$
14:         Compute network latency for power vector P_{curr} and store in $\Gamma_{pc}(j)$
15:         **if** $\max(\Theta) > 1$ **then**
16:             $Poss(j)$= $False$
17:         **else** $Poss(j)$= $True$
18:         **end if**
19:     **end for**
20:     a. h : index of BS having $Poss = True$ for which power control leads to minimum network latency (Γ_{pc})
21:     b. Set Γ_{new} = $\Gamma_{pc}(h)$
22:     **if** $\Gamma_{new} < \Gamma_{old}$ **then**
23:         $P_t(h) = max(0, P_t(h) - \omega)$;
24:     **else**
25:         Set $Latency\_Improvement = False$
26:     **end if**
27: **end while**
28: **for** $j = 1 : |\mathcal{B}|$ **do**
29:     $L_t(j) = P_0(j) + \Delta P_t(j)\rho_j$
30:     $\mathcal{U}_t(j) = E_t(j) - L_t(j)$
31:     **for** $h = t + 1 : 24$ **do**
32:         $E_h(j) = E_h(j) + \mathcal{U}_t(j) \frac{L_h(j)}{\sum_{m=t+1}^{24} L_m(j)}$
33:     **end for**
34: **end for**

respective traffic loads (lines 28-34 in Algorithm 2). Note that with each iteration of the power control operations, the load levels at each BS change. Thus after each iteration (consisting of Algorithm 1 followed by Algorithm 2) we use the new load levels at each BS as the input to Algorithm 1 for the next iteration. After a few iterations (typically 3-4), solution for transmit power levels converges. The worst case computational complexity of the proposed algorithm is given by $O(\mathcal{Q}|\mathcal{B}|^2)$.

Remarks: The power control operations begin with addressing the energy outage and the traffic overload issue. Once that is addressed, power level control is done to bring down the network latency. As the problem of minimizing the network latency by power control operations is a non-convex optimization problem, the proposed algorithm obtains a local optimal solution. The proposed algorithm has the rationale of a greedy descent approach where the BS whose power level decrement leads to the largest reduction in the delay is powered down. Thus the power levels at any subsequent iteration of power control operation has delay performance better than that before it. Further, when decrementing the power level of none of the BSs leads to a reduction in the delay, we return that set of power levels as the solution of the power level values for that hour.

C. Green Energy and Delay Aware User Association Policy

The user-association policy determines the MT-BS association at any point of time. In this section we propose a green energy and delay aware user association policy. For any given value of power levels and green energy allocation at a given time, the proposed user association policy contributes to achieving the global optimal of value of the objective function (for that set of power levels). The user association policy operates in an iterative way. The BSs periodically measure their traffic loads and use it to determine their coalition factors (defined later in this subsection) which are advertised to the MTs. These coalition factors are used by the MTs to associate with the BSs so as to minimize the objective function. The BSs and MTs update their association until convergence. Note that this can be easily implemented in a distributed manner where the BSs have to just periodically broadcast their coalition factors which can be embedded in the beacon signals of the BSs [14].

For the user-association problem we consider the transformed problem [P2.1], with an intentionally added barrier function in the problem [P1] to have delay and energy aware user association. User association is a continuous phenomenon where the set of active users in the network keeps changing and the users associate with the BSs based on the proposed user-association policy. The proposed user-association policy is applicable at all times and thus we omit the time index t in this subsection. Additionally, we use $D(\rho_j)$ to denote the delay indicator for the j-th BS (i.e. $D(\rho_j) = \frac{\rho_j}{1-\rho_j}$). Note that the constraint corresponding to the energy availability at the BS has been indirectly incorporated in the transformed objective problem through the barrier function $e^{\Theta(\rho_j)}$. The

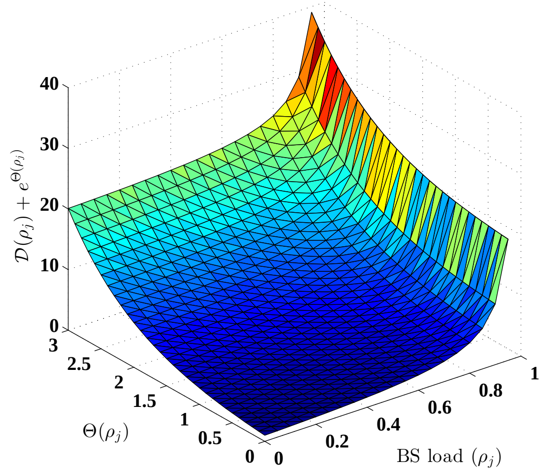

Fig. 2. Variation of components in the objective problem [P2.1] with their respective parameters.

problem [P2.1] is defined as follows

$$\textbf{[P2.1]} \ \underset{\rho}{\text{minimize}} \quad X(\rho) = \sum_{j \in \mathcal{B}} \Big(\mathcal{D}(\rho_j) + e^{\Theta(\rho_j)} \Big)$$
$$\text{subject to:} \quad \rho \in \mathcal{F}$$

and its solution involves finding the optimal BS loads (ρ) which minimizes the value of $X(\rho)$. Note that the value of Θ for BS j is a function of ρ_j, as $\Theta(j) = \frac{L(j)}{E(j)} = \frac{P_0 + \Delta P(j)\rho_j}{E(j)}$. Thus in this subsection, for notational clarity we denote it by $\Theta(\rho_j)$. The intuition behind choosing the particular barrier function (i.e. $e^{\Theta(\rho_j)}$) is as follows. While deciding the user association policy, we not only want the user association policy to bring about delay improvement in the network, but also want it to account for the green energy available at the BS. $\Theta(\rho_j)$, has been defined previously as $\frac{L(j)}{E(j)}$. When a BS is running low on energy, the value $\Theta(\rho_j)$ grows large and thus the users will be discouraged to join that BS (as it increases the value of the objective function sharply). Further, the barrier function is exponential with respect to the value of $\Theta(j)$. Thus after a certain point when the BS starts running very low on energy, its contribution to the objective function increases sharply. Figure 2 shows how the contribution of a given BS j in the objective function in problem [P2.1] varies with its load and Θ values.

Since $u_j(x) \in \{0, 1\}$, the set $\mathcal{F}$ is not convex. To formulate our problem [P2.1] as a convex optimization problem, we begin with relaxing the user-association indicator function to $0 \le u_j(x) \le 1$, where u_j can be interpreted as the probability that a user at location x associates with BS j. We denote the relaxed set of BS loads as $\tilde{\mathcal{F}}$ and it is given as

$$\tilde{\mathcal{F}} = \Big\{ \boldsymbol{\rho} \ | \ \rho_j = \int_{\mathcal{R}} \frac{\gamma(x)}{c_j(x)} u_j(x) dx, \ \ 0 \le \rho_j \le 1 - \epsilon, \ \ \forall j \in \mathcal{B},$$
$$0 \le u_j(x) \le 1, \sum_{j=1}^{|\mathcal{B}|} u_j(x) = 1, \ \ \forall j \in \mathcal{B}, \ \ \forall x \in \mathcal{R} \Big\},$$

The feasible set $\tilde{\mathcal{F}}$ is convex. The convexity of $\tilde{\mathcal{F}}$ has been proved by the authors in [22]. The problem **[P2.2]** with the relaxation condition is given by

$$\textbf{[P2.2]} \quad \underset{\rho}{\text{minimize}} \quad X(\rho) = \sum_{j\in\mathcal{B}} \left(\mathcal{D}(\rho_j) + e^{\Theta(\rho_j)}\right)$$
$$\text{subject to:} \quad \rho \in \tilde{\mathcal{F}}.$$

Remarks: Note that although we formulate the optimization problem [P2.2] using $\tilde{\mathcal{F}}$, the user association algorithm which we propose in this paper determines the deterministic user association (belonging to $\mathcal{F}$). This is shown in Theorems 1 and 2, later in this section.

Next we describe the working of the proposed user association algorithm. The proposed user association algorithm is a distributed MT-BS association scheme. To guarantee the convergence of the scheme, we assume that traffic arrival and departure processes occur at a faster time scale as compared to that at which the BSs broadcast their coalition factors. Thus, after the BSs broadcast their coalition factors, the users are able to make their association decisions based on the broadcast indicators before the next set of BS coalition factors are broadcast. We also assume that the BSs are synchronized and the coalition factors are broadcast at the same time. We begin with describing the user side and the BS side algorithms for carrying out the proposed user association.

1) **User side algorithm**: The time between two successive BS coalition factor updates is defined as the time slot in our algorithm. At the start of k-th time-slot the BSs send their coalition factors to the users through a broadcast signal. The users at location x in turn choose the BS they associate with based on these coalition factors and the rate offered by the BSs at their location. We use superscript k to denote the value of a particular variable at the beginning of the k-th time slot. The coalition factor, ϕ_j^k broadcast by BS j at the beginning of the k-th time slot is defined as

$$\begin{aligned}\phi_j^k &= \frac{\partial X^k(\rho)}{\partial \rho_j^k} \\ &= \frac{\partial\left(\sum_{j\in\mathcal{B}}\left(\frac{\rho_j^k}{1-\rho_j^k} + e^{\frac{L(j)}{E(j)}}\right)\right)}{\partial \rho_j^k} \\ &= \frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(j)}. \end{aligned} \tag{8}$$

The MTs associate with a BS based on the following rule

$$w^k(x) = \arg\max_{j\in\mathcal{B}} \frac{c_j(x)}{\phi_j^k}, \tag{9}$$

where $w^k(x)$ is the index of the BS with largest value of $\frac{c_j(x)}{\phi^k(j)}$ and $c_j(x)$ is the rate offered by BS j at location x. The optimality of the proposed user association rule in terms of minimizing the objective function has been proved in the subsequent part of this section. The users update their association functions as

$$u_j^k(x) = \begin{cases} 1 & \text{if } j = w^k(x) \\ 0 & \text{otherwise} \end{cases}. \tag{10}$$

For an individual user, the computational complexity of the proposed user side algorithm is $O(|\mathcal{B}|)$.

2) **BS side algorithm:** The BSs measure their load levels at the end of the k-th time slot which we denote by $T_j(\rho_j^k)$ and it can be given as

$$T_j(\rho_j^k) = \min\left(\int_{\mathcal{R}} \frac{\gamma(x)}{c_j(x)} u_j^k(x)dx, 1-\epsilon\right). \tag{11}$$

After measuring this traffic load, the BS updates its traffic load to be used in evaluating the next coalition factor to be broadcast for time slot $k+1$ as [22]

$$\rho_j^{k+1} = \theta\rho_j^k + (1-\theta)T_j(\rho_j^k) \tag{12}$$

with $0 < \theta < 1$ being an averaging exponential factor.

Next, we present the proofs to show the optimality and convergence of the proposed user association algorithm.

Lemma 1. *The objective function* $X(\rho) = \sum_{j\in\mathcal{B}}\left(\mathcal{D}(\rho_j) + e^{\Theta(\rho_j)}\right)$ *is convex in* ρ *when* ρ *is defined on* $\tilde{\mathcal{F}}$.

Proof. To prove this we show that $\nabla^2 X(\rho) > 0$. This can be shown as follows. We consider the value of our objective function as

$$\begin{aligned} X(\rho) &= \sum_{j\in\mathcal{B}}\left(\mathcal{D}(\rho_j) + e^{\Theta(\rho_j)}\right) \\ &= \sum_{j\in\mathcal{B}}\left(\frac{\rho_j}{1-\rho_j} + e^{\frac{P_0+\Delta P(j)\rho_j}{E(j)}}\right). \end{aligned} \tag{13}$$

The first and second order derivatives of the objective function with respect to ρ are given by

$$\nabla X(\rho) = \sum_{j\in\mathcal{B}}\left(\frac{1}{(1-\rho_j)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta(\rho_j)}\right) \tag{14}$$

$$\nabla^2 X(\rho) = \sum_{j\in\mathcal{B}}\left(\frac{2}{(1-\rho_j)^3} + \left(\frac{\Delta P(j)}{E(j)}\right)^2 e^{\frac{P_0+\Delta P(j)\rho_j}{E(j)}}\right). \tag{15}$$

Note that the term $\nabla^2 X(\rho)$ above is always positive as it is sum of terms which are all non-negative and the term $\frac{2}{(1-\rho_j)^3}$ is positive for all the BSs. This proves that the objective function $X(\rho)$ is convex with respect to ρ. ■

Remarks: The proof above is based on the fact that we are considering steady state analysis of the system and thus we can assume the following [10], [22], [23]:

$$\frac{\partial f(\rho_j)}{\partial \rho_g} = 0 \;, \; j \neq g \tag{16}$$

where $f(\rho_j)$ is purely a function of ρ_j and does not depend on ρ_g $(g \neq j)$.

Lemma 2. *A unique optimal user association* $\rho^* \in \tilde{\mathcal{F}}$ *exists which minimizes* $X(\rho) = \sum_{j\in\mathcal{B}}\left(\mathcal{D}(\rho_j) + e^{\Theta(\rho_j)}\right)$.

Proof. This follows from the fact that the objective function $X(\rho)$ is a convex function of ρ when $\rho \in \tilde{\mathcal{F}}$ (as shown in Lemma 1). ■

Lemma 3: *When* $\rho^k \neq \rho^*$, *then* $T(\rho^k)$ *provides a descent direction for* $X(\rho^k)$ *at* ρ^k.

Proof. As the function $X(\rho)$ is a convex function of ρ when ρ is defined on $\tilde{\mathcal{F}}$, this lemma can be easily proved by showing $< \nabla X(\rho^k), T(\rho^k)) - \rho^k > \leq 0$ (where $< a, b >$ denotes the inner product of vectors a and b). Let $u_j(x)$ and $u_j^T(x)$ be user association indicators which result in BS traffic ρ_j^k and $T_j(\rho_j^k)$, respectively. Then the inner product is given by

$$
\begin{aligned}
&< \nabla X(\rho^k), T(\rho^k) - \rho^k > \\
&= \sum_{j\in\mathcal{B}} \left(\frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(\rho_j)} \right) \left(T_j(\rho^k) - \rho_j^k\right) \\
&= \sum_{j\in\mathcal{B}} \left(\frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(\rho_j)} \right) \\
&\quad \times \left(\int_{\mathcal{R}} \frac{\gamma(x)(u_j^T(x) - u_j(x))}{c_j(x)} dx \right) \\
&= \int_{\mathcal{R}} \gamma(x) \sum_{j\in\mathcal{B}} \frac{\left(\frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(\rho_j)} \right) (u_j^T(x) - u_j(x))}{c_j(x)} dx.
\end{aligned}
$$

Note that

$$
\sum_{j\in\mathcal{B}} \frac{\left(\frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(\rho_j)} \right) (u_j^T(x) - u_j(x))}{c_j(x)} \leq 0
$$

holds because $u_j^T(x)$ from (9) and (10) maximizes the value of $\frac{c_j(x)}{\left(\frac{1}{(1-\rho_j^k)^2} + \frac{\Delta P(j)}{E(j)} e^{\Theta^k(\rho_j)} \right)}$. Thus as a result we can claim that $< \nabla X(\rho^k), T(\rho^k) - \rho^k > \leq 0$ which proves the lemma. ■

In Theorems 2 and 3, we prove the convergence and optimality of the proposed user association scheme, respectively.

Theorem 1: *The traffic load ρ converges to the traffic load $\rho^* \in \mathcal{F}$.*

Proof. To prove this, we show that $\rho^{k+1} - \rho^k$ is also a descent direction of $X(\rho^k)$. Considering the following expression we have

$$
\begin{aligned}
\rho_j^{k+1} - \rho_j^k &= \theta\rho_j^k + (1-\theta)T_j(\rho_j^k) - \rho_j^k \\
&= (1-\theta)(T(\rho_j^k) - \rho_j^k). \qquad (17)
\end{aligned}
$$

Now, based on Lemma 3, we have already shown that $(T(\rho^k) - \rho^k)$ is the descent direction of $X(\rho^k)$, and additionally we have $(1-\theta) > 0$ as $0 < \theta < 1$. Thus even $\rho^{k+1} - \rho^k$ gives the descent direction of $X(\rho^k)$. Further, as $X(\rho^k)$ is a convex function we can easily state that $X(\rho^k)$ converges to the user association vector ρ^*. Suppose $X(\rho^k)$ converges to any point other than $X(\rho^*)$. Then ρ^{k+1} again gives a descent direction so as to decrease $X(\rho^k)$, which is contradiction to the assumption of convergence. Additionally, as ρ^k is derived based on (9) and (10) where $u_j(x) \in \{0,1\}$, ρ^* is in the feasible set $\mathcal{F}$. ■

Theorem 2: *If the set $\mathcal{F}$ is non-empty and the traffic load ρ converges to ρ^*, the user association corresponding to ρ^* minimizes $X(\rho)$.*

Proof. Let $u^* = \{u_j^*(x) | u_j^*(x) \in \{0,1\}, \forall j \in \mathcal{B}, \forall x \in \mathcal{R}\}$ and $u = \{u_j(x) | u_j(x) \in \{0,1\}, \forall j \in \mathcal{B}, \forall x \in \mathcal{R}\}$ be the user association corresponding to ρ^* and ρ, where ρ is some traffic load vector satisfying $\rho \in \mathcal{F}$. Let $\Delta\rho^* = \rho - \rho^*$. As X($\rho$) is a convex function over ρ, the theorem can be proved by showing $< \nabla X(\rho^*), \Delta\rho^* > \geq 0$. In the proof below, we substitute $\frac{\partial X(\rho^*)}{\partial \rho_j^*}$ as $\phi_j(\rho_j^*)$ for notational clarity (these expressions are identical as shown in the derivation leading to (8).

$$
\begin{aligned}
< \nabla X(\rho^*), \Delta\rho^* > &= \sum_{j\in\mathcal{B}} \phi_j(\rho_j^*) (\rho - \rho^*) \\
&= \sum_{j\in\mathcal{B}} \left(\int_{\mathcal{R}} \frac{\gamma(x)(u_j(x) - u_j^*(x))}{c_j(x)\phi_j^{-1}(\rho_j^*)} dx \right) \\
&= \int_{\mathcal{R}} \gamma(x) \sum_{j\in\mathcal{B}} \frac{(u_j(x) - u_j^*(x))}{c_j(x)\phi_j^{-1}(\rho_j^*)} dx.
\end{aligned}
$$

But as optimal user association is determined by the following rule

$$
u_j^*(x) = \begin{cases} 1, & \text{if } j = \arg\max\limits_{j\in\mathcal{B}} \frac{c_j(x)}{\phi_j(\rho_j^*)}, \\ 0, & \text{otherwise.} \end{cases} ,
$$

we thus have,

$$
\sum_{j\in\mathcal{B}} \frac{u_j^*(x)}{c_j(x)\phi_j^{-1}(\rho_j^*)} \leq \sum_{j\in\mathcal{B}} \frac{u_j(x)}{c_j(x)\phi_j^{-1}(\rho_j^*)}. \qquad (18)
$$

Hence, $< \nabla X(\rho^*), \Delta\rho^* > \geq 0$ which proves the theorem. ■

We note that the proposed scheme does not achieve the global optimal solution. The proposed scheme uses power contol operations and user association reconfiguration to manage the network delay and green energy usage. Due to non-convexity of the delay with respect to the power control operations, the proposed scheme does not obtain a global optimal solution but a locally optimal solution (as explained in Section V-B). However, for BSs operating at any given power levels (such as those obtained by our power control mechanism), the user-association mechanism obtain the globally optimal solutions for the relaxed optimization problem as discussed in Section V-C.

The overall worst case complexity of the proposed GAURA scheme for the centralized server is $O(\mathcal{Q}|\mathcal{B}|^2)$ which results from the operations required to determine the power levels of the BSs during the different hours for the day (Section V-B). For the MTs, the complexity is $O(|\mathcal{B}|)$ whereas for the BSs it is $O(1)$ which come from the user-association algorithm.

VI. Numerical Results

To validate the performance of the proposed scheme, we consider a 3G BS deployment by network provider Vodafone near Southwark, London, UK in an area of 1 km^2 with 6 BSs as shown in Figure 3. We assume that 12 V, 205 Ah flooded lead acid batteries are used by the BSs. Each BS is assumed to be equipped with PV panel of 6 kW DC rating and 10 batteries. We consider a carrier frequency of 2.5 GHz and 10 MHz bandwidth with full frequency reuse. We take the noise

Fig. 3. 3G BS deployment near Southwark (London).

power to be -174 dBm/Hz. We assume log normal shadowing with standard deviation 8 dB with the correlation distance for shadowing taken as 50 m [37]. The path loss, denoted by PL has been modeled as [37]

$$PL(dB) = 40(1 - 4 \times 10^{-3} h_{BS}) log_{10}(R) - 18 log_{10}(h_{BS}) + 21 log_{10}(f) + 80 \quad (19)$$

where R is the distance between the BS and the MT, h_{BS} is the BS antenna height above rooftop and f is the carrier frequency in MHz. Based on the suggestions from the baseline test scenario mentioned in the IEEE 802.16 evaluation methodology document [37], we take h_{BS} as 15 metres and the carrier frequency is 2.5 GHz. Thus, the path loss is calculated as

$$PL(dB) = 130.19 + 37.6 \log(R). \quad (20)$$

A homogeneous Poisson point process is used to generate the file transfer requests. The rate of the Poisson process depends on the hour of the day, with the smallest number of file transfer requests in the morning (2-5 a.m.) with an average of 20 requests (equivalently, 20 active users) per unit area (km^2) and the largest number of requests in the evening (5-7 p.m.) with an average of 200 requests per unit area. To model temporal traffic dynamics, a new spatial profile of file transfer requests is generated after every 2 minutes. Each file transfer request is assumed to request 50 KB of data traffic to be served. The entire area (of 1 km^2) is divided into 1600 locations with each location representing a 25 m x 25 m area.

For performance analysis we consider solar insolation on 12th January of typical meteorological year (TMY) data for London from the NREL database [28]. The total energy harvested on this day by a PV panel with 6 kW DC rating is 8.67 kW. P_0, P_{max} and Δ for the BSs are taken as 412.4 W, 40 W and 22.6 respectively [27]. S_{cr} is taken as the energy required to power the BS to operate for at least 5 hours. To avoid battery degradation, we assume that the batteries are disconnected from the BS if the battery level goes below a certain threshold state of charge, $S_c = \nu S_{cap}$, at any point of time. Here S_{cap} is the battery capacity and ν is the threshold which decides the charge level below which the battery is not allowed to discharge. ν, is taken as 0.7. B_{ini} has been randomly chosen for different BSs. ω, the granularity of power control has been taken as 5 W. We assume that a BS is turned off when its transmit power level is 0 W. The averaging factor for the BS side algorithm θ, has been taken as 0.95.

As a benchmark for comparison, we consider a Best-Effort scheme where all BSs operate with transmit power 20 W and a MT associates with the BS that has the strongest signal strength at the MT's location. We also consider ICE [10] and GALA [9] schemes with BSs operating at transmit power 20 W, and SWES [11] which is a BS on-off scheme with BSs operating at 40 W when they are switched on. The ICE, GALA and SWES schemes have been discussed in Section II.

A. Green Energy Performance

Figure 4 shows the battery discharging-charging profiles for the various benchmarks and the proposed algorithm. For clarity, battery levels have been normalized with respect to the maximum battery capacity. It can be seen that the Best-Effort scheme can lead to some of the BSs to run very low on energy at the end of the day. Additionally, one of the BS (BS 4) faces around 6 hours of energy outage during the day. The ICE scheme does better than the Best-Effort scheme by trying to equalize the available green energy. However even in the ICE scheme some of the BSs run low on battery levels at the end of the day and BS 4 still faces 6 hours of energy outage during the day. The performance of the GALA scheme in terms of the battery level profile for the BSs is similar to that of the Best-Effort scheme and BS 4 faces energy outage for around 5 hours during the day. Note that the Best-Effort, ICE and GALA schemes lead to some of the BSs ending up below the critical battery level (S_{cr}) at the end of the day which indicates that there would be energy outages in the early morning hours on the next day. The SWES scheme leads to an un-even discharge of battery levels (as BSs turn on/off so as to maximize the number of BSs to be switched off). Although with this scheme there is no energy outage for any BS during the day, some of the BSs run very low on energy and face energy outage at the end of the day. Note that the proposed GAURA scheme provides a greater capability to avoid uneven discharging. Additionally, it ensures that the battery level of none of the BSs goes below the critical level, S_{cr}, at the end of the day.

Figure 5 shows the average values of battery levels for the BSs for the various schemes, normalized with respect to the battery capacity. Note that the Best-Effort, ICE and GALA schemes can lead to very low values of average battery level at the end of the day. SWES achieves a higher average battery level since some of the BSs have higher battery levels. Additionally, as discussed earlier, due to un-even discharging some of the BSs can run very low on energy in the SWES scheme. The average values of battery levels for the proposed GAURA scheme is greater than the Best-Effort, ICE and GALA scheme but lower than that of the SWES scheme. However as discussed earlier, the GAURA scheme has a more even discharging profile for the various BSs. Table I summarizes some key parameters quantifying the battery level variations, energy outage probability and the delay performance of the BSs for the benchmarks and the

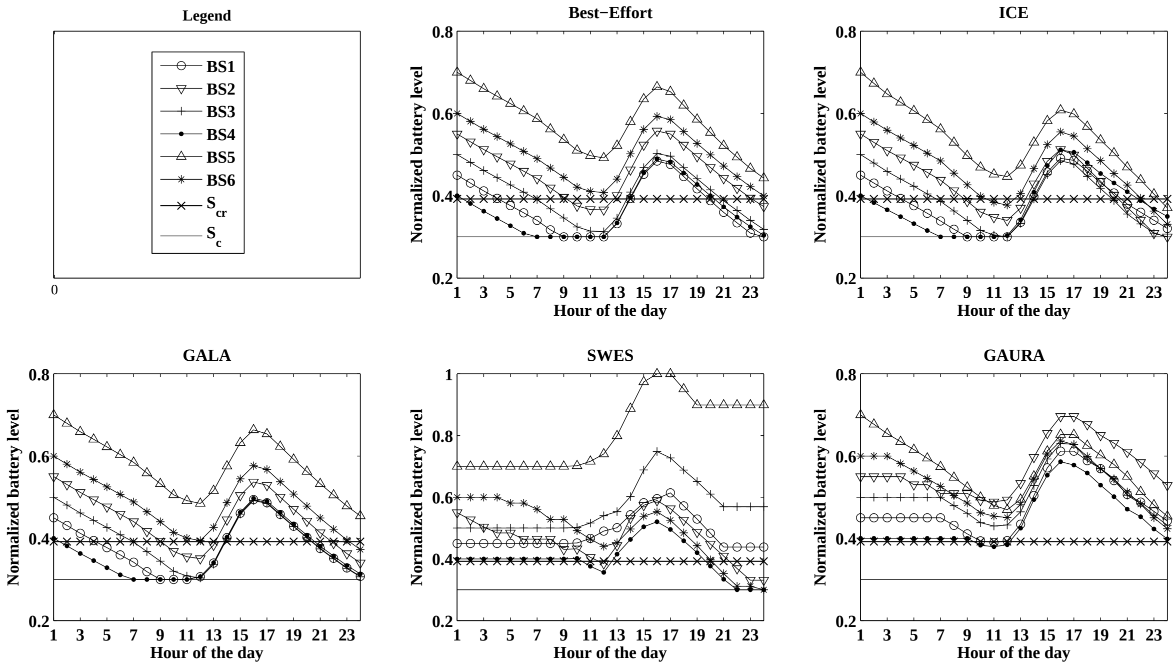

Fig. 4. Battery discharging-charging profiles for the different algorithms.

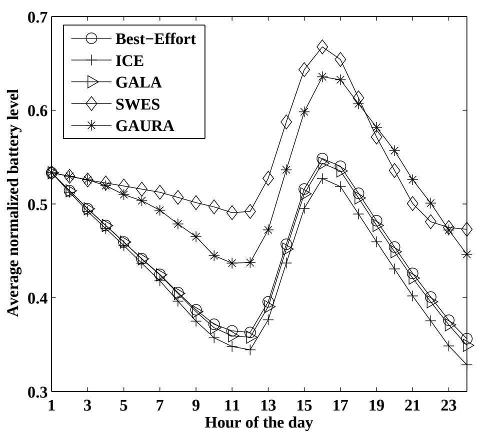

Fig. 5. Average normalized battery charge for the different schemes.

proposed scheme. To quantify the evenness of battery charge levels in the different BSs, we calculate the variance $Var(B)$ which denotes the sum of the variances of the normalized battery levels of the BSs over the day. $Var(B)$ is calculated as

$$Var(B) = \sum_{t=1}^{24} \sum_{j=1}^{\mathcal{B}} \left(\frac{S_t(j) - \tilde{S}_t}{S_{cap}} \right)^2 \tag{21}$$

where $S_t(j)$ is the battery level of j-th BS at the end of the t-th hour and $\tilde{S}_t$ is the average value of battery levels of the different BSs at the end of t-th hour. Note that for the SWES scheme this parameter is highest as battery charge profiles of different BSs are very un-even. For the proposed GAURA scheme it is the lowest indicating most even discharging among the batteries. $\tilde{O}$ denotes the energy outage probability and is calculated as

$$\tilde{O} = \frac{H_{out}}{24\mathcal{B}} \tag{22}$$

TABLE I
COMPARISON OF AVERAGED METRICS FOR DIFFERENT SCHEMES

Scheme	$Var(B)$	$\tilde{O}$	$P_{avg}(W)$	B_{avg}	D_{avg}
Best-Effot	0.86	7.66	544	0.36	6.72
ICE	0.60	7.66	610	0.33	12.73
GALA	0.82	5.55	562	0.34	5.6
SWES	3	2.78	400	0.47	6.85
GAURA	0.43	0	475	0.44	4.96

where H_{out} denotes the number of outage events in the network during the day (i.e. 24 hours of operation). Note that the energy outage probability for the proposed GAURA scheme is 0 whereas for all other schemes there are some energy outage events during the day. Further P_{avg} denotes the average BS power consumption during the day. Note that the average BS power consumption for the Best-Effort, ICE and the GALA schemes are significantly higher than the SWES and GAURA scheme which lead to lower average battery level at the end of the day which is denoted by B_{avg} in the table.

B. Delay Performance

Figure 6 shows the delay performance for the schemes during the different hours of the day. It can be observed from the figure that GALA has good latency performance as compared to the Best-Effort scheme. However, as discussed earlier, GALA is unable to avoid energy outages in some of the BSs and from some of the BSs running very low on energy at the end of the day. Note that in these schemes the delay increases for the hours when there is an outage event. The performance of the ICE and SWES schemes is worse than the performance of the Best-Effort scheme in terms of the delay performance. Note that as compared to the Best-Effort scheme, the benefit of more even discharging of batteries in the ICE scheme and the benefit of higher average battery levels

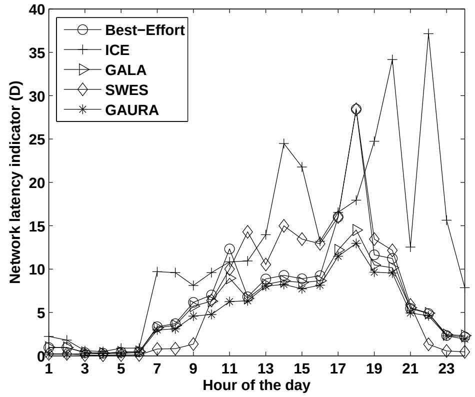

Fig. 6. Delay performance for the different schemes.

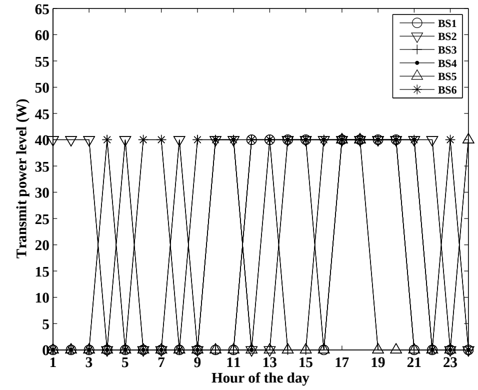

Fig. 7. Transmit power levels for various BSs during the day (SWES).

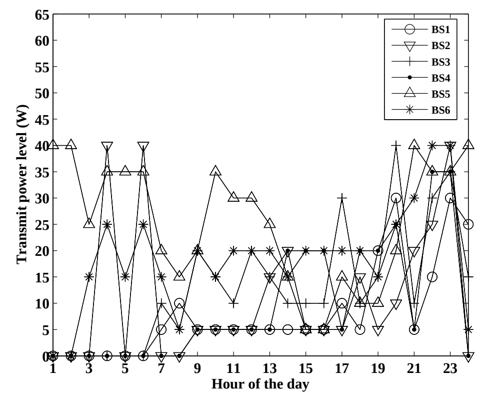

Fig. 8. Transmit power levels for various BSs during the day (GAURA).

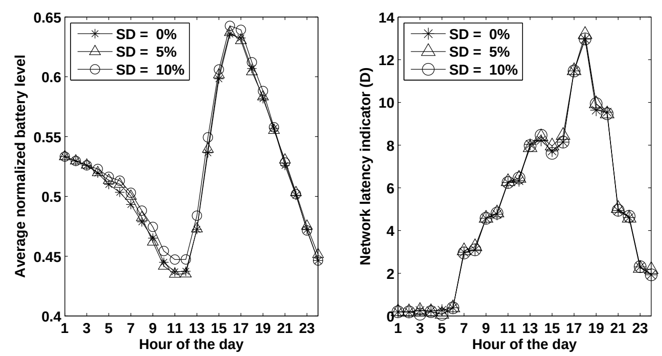

Fig. 9. a. Average normalized battery level for GAURA with prediction error b. Delay performance for GAURA with prediction error.

in the SWES scheme are at the cost of increased delay. In contrast, the proposed GAURA scheme reduces the system latency while simultaneously ensuring that the battery levels do not become very low. The last column in Table I lists the average delay value denoted by D_{avg} for the different schemes. Note that the proposed GAURA scheme gives the lowest average delay followed by GALA, Best-Effort and the SWES scheme, and the value is largest for the ICE scheme.

C. Transmit Power Levels

Figures 7 and 8 show the transmit power levels at which the BSs operate during the different hours of the day for the SWES and the proposed GAURA scheme, respectively. The BSs in Best-Effort, ICE and GALA schemes operate at a fixed transmit power level of 20 W. Note that although SWES can reduce the energy consumption during morning hours by completely switching off most of the BSs, the battery levels fall quickly during afternoon and evening hours on account of most of the BSs being switched on and operating at full transmit power. While GAURA also switches off most of the BSs during morning hours, it avoids a quick decrease in the battery levels during the afternoon and evening hours by adapting the transmit power levels of the BSs to lower values, and the adjustments are done in such a way that the system latency is improved. BSs with very low energy shut down during the early morning hours, and further even during other hours the BSs prefer to operate at lower power levels to save energy.

Remarks: Note that the proposed model assumes perfect knowledge of solar energy and network traffic by the central server. Additional simulations conducted by us show that the performance degradation is not significant even in the presence of 5-10% error in the predicted values of solar energy and network traffic. Figure 9 shows these results. The simulation results correspond to scenarios where the errors in the harvested energy and traffic load follow independent Gaussian distributions with zero mean and standard deviation (SD) of 5% and 10% of the actual value. Note that a SD of 0% represents no prediction error. As can be seen, the presence of errors does not have much of an impact.

VII. Conclusion

This paper proposed a framework for avoiding energy outages and improving the quality of service performance for a network of off-grid solar powered BSs. We formulated the problem of minimizing the system latency given the constraints on the green energy availability at the BSs. We first proposed a methodology for intelligently allocating the green energy available to the BSs over time. Next, with the given energy allocation, we addressed the problem of avoiding energy outages and improving the QoS using the proposed green energy and delay aware power control and user association algorithm. The proposed framework was evaluated using real BS deployment data and solar energy traces, and it outperforms existing benchmarks in terms of reducing energy outages while ensuring good delay performance.

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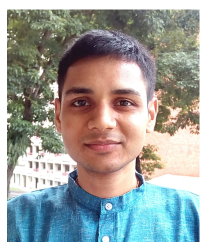

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