An Energy and Delay Aware Downlink Power Control Strategy for Solar Powered Base Stations

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***Abstract*—Using renewable resources like solar energy to power the base stations (BSs) has emerged as a promising solution for greening cellular networks. One of the key challenges in operating a network of such BSs is to intelligently manage the green energy available to the BSs while ensuring reliable quality of service (QoS). This paper presents a methodology for maximizing the QoS, in terms of the network latency, given the constraints on the energy availability at the solar-powered BSs. In contrast to existing approaches based on user association reconfiguration, our methodology uses a combination of intelligent energy allocation and BS downlink power control. Using a real BS deployment scenario from UK, we show the efficacy of our algorithm and demonstrate its superior performance compared to existing benchmarks.**

***Index Terms*—Green communications, downlink power control, energy efficiency, delay aware, solar energy, base stations.**

I. Introduction

The increasing number of cellular deployments around the globe to extend the coverage and capacity has led to an increased contribution of cellular networks to the worldwide energy consumption (currently 3%) and worldwide carbon emissions (currently 2%). These increased deployments are also reflected in the increasing operating expenditure for the network operators. All these factors have pushed operators, government agencies and researchers to develop "green" cellular networks. One of the major areas of exploration in this direction has been to use renewable resources like solar energy for powering the cellular BSs, which alone comprise around 60% of power consumption in cellular networks. Such solar powered BSs are carefully provisioned with resources like PV panels and batteries, taking into account the trade-off between the CAPEX (capital expenditure) and QoS performance [1]. 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 the bad weather periods. In absence of such energy management, the network can experience critical power outages and degradation in QoS during these times. Reducing the network energy consumption is one option for solving this problem. In related work, [2] proposes a framework for BS switching and transmit power control with the objective of minimizing the energy used in the network. In [3], the authors propose dynamic switching of BSs to minimize the overall energy consumption. An energy-efficient scheme for resource allocation in OFDMA systems with hybrid energy harvesting BSs is proposed in [4]. Further, [5] proposes an algorithm 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. Methodologies which consider the delay performance of the system in addition to the network energy consumption include [6] and [7]. Their approach is to manage the available energy and network latency 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 and demonstrates its performance gains over existing approaches. In addition to downlink power control, our methodology uses a temporal energy allocation algorithm to intelligently manage the green energy available to the BSs. Our methodology considers stand alone BSs and can be easily extended to scenarios with hybrid energy supplies. We show the efficacy of the proposed methodology by simulations using real BS deployment and solar energy traces for London, UK and comparing the results with existing benchmarks.

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II. System model and Problem formulation

A. Traffic model, BS load and Network latency

We consider a cellular network with $\mathcal{B}$ base stations. Let $\mathcal{R}$ be the region served by the BSs. We use $x \in \mathcal{R}$ to denote the user location. For simplicity, this letter primarily focuses on downlink communication (i.e. BSs to MTs). We denote the downlink transmit power of the BSs by a vector P, with cardinality $\mathcal{B}$. The transmit power levels can take discrete values i.e. $P(j) \in \{0, \omega, 2\omega, \cdots, P_{max}\}$ where j is the index of the BS, ω is the granularity of power control, and P_{max} is the maximum transmit power level allowed. We assume file transfer requests arrive following a Poisson point process with arrival rate $\lambda(x)$ per unit area at location x, with average file size of $\frac{1}{\mu(x)}$. The traffic load density at x is then defined as $\gamma(x) = \frac{\lambda(x)}{\mu(x)}$, and $\gamma(x)$ captures the spatial traffic variability. Using Shannon's capacity formula, the rate offered at location x served by a BS j can generally be given 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

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

where σ is the noise power, $\mathcal{I}_j$ is the set of interfering BSs for BS j, and $g_j(x)$ is the channel gain between BS j and the user at location x, which takes into account the path loss and the shadowing loss. We assume perfect information of the channel gain in this paper and this may be estimated given the topological details of the terrain, and drive-through site surveys. We also introduce a function $u_j(x)$ which specifies the BS user association (and is 1 if x is served by BS j, and 0 otherwise). The BS load can now be defined as ρ_j, which denotes the fraction of time BS j is busy serving its traffic requests and is given by [6]

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

The MTs attach to the BS with the strongest signal. Since traffic arrivals are Poisson processes, the sum of traffic arrivals at the BSs is also a Poisson process. As service process at a BS follows a general distribution, the BSs may be modeled as a M/G/1-PS (processor sharing) queue. The average number of flows at BS j can thus be given by by $\frac{\rho_j}{1-\rho_j}$ [7]. From Little's law, the delay experienced by a traffic flow is directly proportional to the average number of flows in the system. Thus we take the total sum of the flows in the network as the network latency indicator, Λ, which is given by [7]

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

B. BS Power Consumption

In this letter we consider macro BSs, where the power consumption for BS j, denoted by $L(j)$, is modeled as [1]

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

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

This letter uses statistical weather data provided by National Renewable Energy Laboratory (NREL) [8] which is fed to NREL's System Advisor Model (SAM) tool to yield the hourly energy generated by a PV panel of a given rating. We assume that the BSs use lead acid batteries to store the excess energy harvested by the PV panels. Lead acid batteries are a popular choice in storage applications because they are a time tested option, and are also much cheaper than other technologies.

D. Problem Formulation

We consider the problem of minimizing the total system level latency, given the harvested solar energy available to the BSs. We can formulate the problem as

$$\begin{aligned} \underset{P}{\text{minimize}} \quad & \sum_{i=1}^{24} \Lambda_i \\ \text{subject to:} \quad & 0 \le \rho_{ij} \le 1 \\ & \sum_{i=1}^{24} L_i(j) \le G_{available}(j). \end{aligned}$$

Algorithm 1 Temporal Energy Allocation

```
1: for j = 1 : B do
2:     G_available(j) = B_ini(j) − B_cr(j) + Σ_{i=1}^{24} HE_i(j);
3:     for i = 1 : 24 do
4:         E_i(j) = G_available(j) L_i(j) / Σ_{h=1}^{24} L_h(j);
5:     end for
6: end for
```

where Λ_i denotes the network latency indicator for the i-th hour, ρ_{ij} denotes the delay for BS j in the i-th hour, and $L_i(j)$ denotes the BS j's load (power consumption) for the i-th hour, and $G_{available}(j)$ denotes the energy budget available to BS j during the day, respectively.

In Section III-A we propose a scheme for intelligently allocating the green energy budget over time. Further, given the energy allocation, in Section III-B we address the optimization problem by suitably adjusting the downlink transmit power levels of the different BSs. The problem of power level control of set of BSs is a non-convex optimization problem. Thus to find the global minima of the optimization problem one has to search over the whole search space of possible power levels which is computationally very complex. The order of computations increases with the number of BS's as $O(G^{\mathcal{B}K})$ where G is the number of power levels a BS can use and K is the number of hours under consideration. In this paper we propose a computationally simpler greedy algorithm for downlink power control.

III. Proposed Framework

A. Temporal Energy Provisioning

Everyday the BS harvests a random amount of solar energy during the day and may also have some charge remaining in the batteries from the previous day. This overall budget of available energy should be used intelligently during the day. Our framework ensures that at the end of the day, the battery level does not go below a certain critical level B_{cr} (which is to guarantee power availability to run the BSs in the early morning hours on the next day). Also, to avoid battery degradation we assume that batteries are disconnected from the BS when the battery level goes below a certain threshold depth of discharge (DoD), ν, corresponding to the battery level B_c. The proposed energy provisioning strategy is shown in Algorithm 1 which allocates the energy available ($G_{available}$) in proportion to the BS load in a given hour. B_{ini} denotes the initial battery level while HE_i and E_i denotes the energy harvested by the BS and energy allocated to the BS for a given hour i, respectively. We assume that we have the information of the harvested energy in advance, which can be done through weather forecast. Further, we assume that information of the traffic profile from previous weeks is available, which is used to generate the predicted BS load (L) for the initial energy allocation. Note that this allocation is an initialization step and is later updated (as shown in section III-B). We assume that a central server does these operations at the beginning of the day and the decisions made by it guide the power control operations of the BSs during the day. We assume that the central server has complete network information.

B. Downlink Transmission Power Control

The transmission power of a BS affects the traffic served by the BS, the BS load and the BS power consumption. We define *sufficiency ratio* of BS j during hour i, $\varphi_i(j)$, (which indicates if a BS is energy constrained or not) as

$$\varphi_i(j) = \frac{E_i(j)}{L_i(j)}. \tag{6}$$

A BS has to address two challenges in its operations: (a) Traffic overload ($\rho > 1$) and (b) Energy deficiency ($\varphi < 1$). To address these two issues simultaneously, we introduce a term *strain index* denoted by Ψ which captures the intensity of these problems faced by the BS. Ψ is defined as

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

We propose our GD-IDPC (Green energy and Delay aware Intelligent Downlink Power Control) algorithm (Algorithm 2) to eliminate the strain and to improve delay performance. The first step in the BS power control mechanism involves trying to eliminate the strain index for the BSs. For this, at every step, the BS with the maximum value of strain index is identified and its transmit power level is reduced by ω. Such a reduction in the transmit power level reduces the impact of both the traffic overload and energy deficiency on the BS. This is because reducing the transmit power offloads some of the users to other BSs (thus reducing ρ) and also brings further reduction in power consumption due to the term $P(j)$ in Eqn. 5 becoming smaller. Once all the BSs have zero strain index, the next step is to try to minimize the overall system latency. For this, the BSs greedily try to reduce their transmit power by ω and the BS for which reduction of power level leads to the maximum latency reduction (while allowing all BSs to have $\varphi > 1$) updates its transmit power level. This is done until no further latency improvement can be realized. The algorithm is carried out sequentially for each hour of the day. The latency improvement from power control operations is due to its interference management and load balancing effect. Note that with the transmit power levels determined as above, the BSs may not be using all of the energy allocated to them for that hour. The leftover energy (denoted by UE in the algorithm) is distributed to the subsequent hours in proportion to their respective traffic loads. The worst case computational complexity of the algorithm for each hour is $O((G-1)\mathcal{B}^2)$. Note that the load levels at each BS change with each iteration due to the power control operations. 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, thus giving an overall worst case computational complexity as $O(K(G-1)\mathcal{B}^2)$.

IV. Simulation Results

To validate the proposed model, 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 Fig. 1. We assume that 12 V, 205 Ah flooded lead acid

Algorithm 2 The GD-IDPC Algorithm

Initialization
Set $P(j) = P_{max}$ for all $j \in \mathcal{B}$
Compute Ψ for all BSs
$\Psi(j) = max(0, 1 - \varphi(j)) + max(0, \rho_j - 1)$
while $max(\Psi) > 0$ **do**
  a. g : index of BS with maximum Ψ
  b. $P(g) = max(0, P(g) - \omega)$;
end while
$Delay\_Improvement = TRUE$;
while $Delay\_Improvement = TRUE$ **do**
  $\mathcal{D}_{old}$= network latency with power vector P.
  for $j = 1 : \mathcal{B}$ **do**
    $P_{curr} = P$
    $P_{curr}(j) = max(0, P(j) - \omega)$
    Compute network latency for power vector P_{curr} and store in $\mathcal{D}_{pc}(j)$
    if $\min(\varphi) < 1$ **then**
      $FES(j)$= $FALSE$
    else $FES(j)$= $TRUE$
    end if
  end for
  a. h : index of BS having $FES = TRUE$ for which power control leads to minimum network latency ($\mathcal{D}_{pc}$)
  b. Set $\mathcal{D}_{new}$ = $\mathcal{D}_{pc}(h)$
  if $\mathcal{D}_{new} < \mathcal{D}_{old}$ **then**
    $P(h) = max(0, P(h) - \omega)$;
  else
    Set $Delay\_Improvement = FALSE$
  end if
end while
for $j = 1 : \mathcal{B}$ **do**
  $L_i(j) = P_0(j) + \Delta P(j)\rho_j$
  $UE(j) = E_i(j) - L_i(j)$
  for $i = hour + 1 : 24$ **do**
    $E_i(j) = E_i(j) + UE(j)\frac{L_i(BS)}{\sum_{m=hour+1}^{24} L_m(j)}$
  end for
end for

Fig. 1. 3G BS Deployment near Southwark (London)

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 assume log normal shadowing with standard deviation 8 dB and path loss given by $130.19 + 37.6\log(R)$ dB where R is the distance between BS and MT. Other parameters for simulation follow the sug-

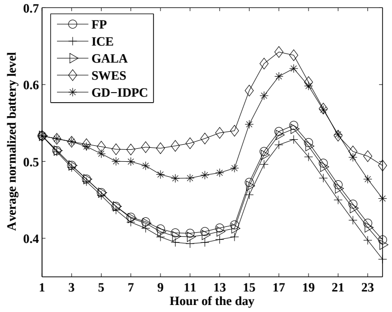

Fig. 2. Average normalised battery charge for the different schemes.

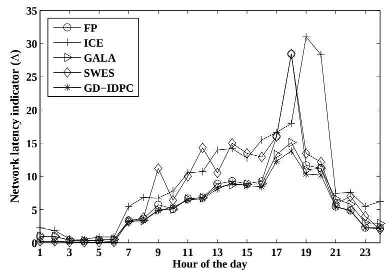

Fig. 3. Delay performance for the different schemes.

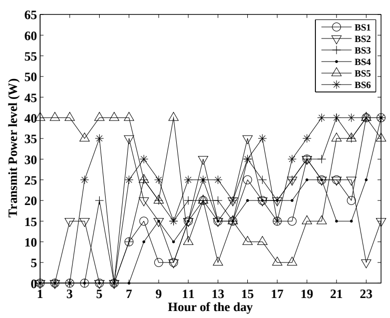

Fig. 4. Transmit power levels for various BSs (GD-IDPC).

gestions in the IEEE 802.16 evaluation methodology document [9]. User request arrivals are generated through a homogeneous Poisson point process whose arrival rate depends on the time of the day, with minimum during early morning (2-5 a.m.) to be around 20 and the maximum number of users in the evening (5-7 p.m.) to be around 200. For simplicity we assume every user arrival requests 50 KB of data traffic to be served. For performance analysis we consider solar insolation on 9th August of typical meteorological year (TMY) data for London from NREL. The total energy harvested on this day by a PV panel with 6 kW DC rating is 10.174 kW. P_0, P_{max} and Δ for the BSs are taken as 412.4 W, 40 W and 22.6 respectively. B_{cr} is taken as the energy required to power the BS to operate for at least 5 hours. ν, the limiting DoD which decides B_c is taken as 0.7. B_{ini} has been randomly chosen for different BSs. ω, the transmit power decrement has been taken as 5 W. We assume that a BS is turned off when its transmit power level is 0 W. As a benchmark for comparison, we consider a fixed power (FP) scheme where all BSs operate with transmit power 20 W. We also consider ICE [5] and GALA [6] schemes with BSs operating at transmit power 20 W, and the SWES [3] which is a BS on-off scheme with BSs operating at 40 W when they are switched on.

Fig. 2 shows the average values of battery levels for the various schemes, normalized with respect to the battery capacity. Note that while FP, ICE and GALA schemes can lead to very low battery levels at the end of the day, SWES achieves higher battery levels but at the cost of increased delay as can be seen in Fig. 3. Further, as can be observed from Fig. 3, GALA has good latency performance, but is unable to bring a reduction in the overall energy consumption and its normalized average battery level is almost same as the FP scheme (as shown in Fig 2). In contrast, the proposed GD-IDPC algorithm reduces the system latency while simultaneously ensuring that the batteries levels do not become low. Note that although SWES can reduce 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 GD-IDPC 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. Fig. 4 shows the transmit power levels at which the BSs operate during the different hours for the proposed GD-IDPC scheme. Note that the proposed model assumes perfect knowledge of solar energy and network traffic by the central server. Additional simulations conducted by us showed 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.

V. Conclusion

This letter proposed a framework for energy allocation and BS downlink transmit power control to achieve intelligent energy management and low system latency for a network of solar powered BSs. The proposed framework was evaluated using real BS deployment data and solar energy traces and it outperforms existing benchmarks, in terms of reducing energy consumption while ensuring good delay performance.

References

[1] V. Chamola and B. Sikdar, "Resource Provisioning and Dimensioning for Solar Powered Cellular Base Stations", *Proc. IEEE GLOBECOM,* Austin, USA, 2014.

[2] L. Bao, "QoS-aware BS switching and cell zooming design for OFDMA green cellular networks," *Proc. IEEE GLOBECOM*, Anaheim, CA, 2012.

[3] E. Oh, K. Son and B. Krishnamachari, "Dynamic base station switching-on/off strategies for green cellular networks," *IEEE Transactions on Wireless Communications,* vol 12, no. 5, pp. 2126-2136, 2013.

[4] D. Ng, E. Lo and R. Schober, "Energy-efficient resource allocation in OFDMA systems with hybrid energy harvesting base station," *IEEE Transactions on Wireless Communications,* vol. 12, no. 7, 2013.

[5] T. Han and N. Ansari, "ICE: Intelligent Cell BrEathing to Optimize the Utilization of Green Energy," *IEEE Communications Letters,* vol. 16, no. 6, pp. 866-869, June 2012.

[6] T. Han et. al., "Green-energy aware and latency aware user associations in heterogeneous cellular networks," *Proc. IEEE GLOBECOM,*, 2013.

[7] D Liu et. al "Distributed delay-energy aware user association in 3-tier HetNets with hybrid energy sources,"*IEEE Globecom Workshops,* 2014.

[8] `http://www.nrel.gov/rredc/solar_data.html`, Last accessed: 10 Sept., 2015.

[9] IEEE 802.16m-08/004r5: IEEE 802.16m Evaluation Methodology Document (EMD), 2009