Energy Agile Packet Scheduling to Leverage Green Energy for Next Generation Cellular Networks

© 2015 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

This material is presented to ensure timely dissemination of scholarly and technical work. Copyright and all rights therein are retained by authors or by other copyright holders. All persons copying this information are expected to adhere to the terms and constraints invoked by each author's copyright. In most cases, these works may not be reposted without the explicit permission of the copyright holder.

Citation:


URL:
http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6655120
Energy Agile Packet Scheduling to Leverage Green Energy for Next Generation Cellular Networks

Tao Han, Student Member, IEEE, Xueqing Huang, Student Member, IEEE, and Nirwan Ansari, Fellow, IEEE
Advanced Networking Laboratory
Department of Electrical and Computer Engineering
New Jersey Institute of Technology, Newark, NJ, 07102, USA
Email: {th36, xh89, nirwan.ansari}@njit.edu

Abstract—Green communications has received much attention recently. Utilizing green energy in wireless cellular networks is promising to reduce the main grid electricity consumption, and thus to reduce the CO₂ footprint. However, owing to the fluctuating nature of green energy, it is challenging to use green energy in cellular networks. In this paper, we propose an energy agile packet scheduler which maximizes the utilization of green energy by optimizing the packet scheduling. The packet scheduling optimization problem is NP-hard in the strong sense. The energy agile scheduler approximates the optimal packet scheduling solution in two steps. First, the energy agile scheduler balances the BS’s energy consumption in transmitting packets among time slots. Second, within each time slot, the energy agile scheduler optimizes the bandwidth allocations to minimize the BS’s energy consumption. Simulation results demonstrate that the proposed energy agile scheduler achieves significant main grid energy savings.

I. INTRODUCTION

In wireless cellular networks, energy consumption is mainly drawn from base stations (BSs). According to the power consumption breakdown [1], BSs consume more than 50 percent of the power of a cellular network. Thus, reducing the power consumption of BSs is crucial to green cellular networks. Many works [2]–[5] have been done on enhancing the energy efficiency of cellular networks.

Designing off-grid BSs and communication protocols to enable utilization of renewable energy in cellular access networks is promising for reducing the on-grid energy consumption of cellular networks. Renewable energy such as sustainable biofuels, solar and wind energy are promising options to save the main grid electricity consumed by BSs and reduce the CO₂ footprint. Zhou et al. [6] proposed the HO (Hand Over) parameter tuning algorithm for target cell selection, and the power control algorithm for coverage optimization to guide mobile users to access the BSs with green energy supply, thus reducing the on-grid power consumption and CO₂ emission. Han and Ansari [7] proposed an energy aware cell size adaptation algorithm named ICE (Intelligent Cell Recycling), which balances the energy consumption among BSs, enables more users to be served with green energy, and therefore reduces the main grid electricity consumption.

Envisioning future BSs to be powered by multiple types of energy sources, e.g., the grid, solar energy, and wind energy. Han and Ansari [8] also proposed to optimize the utilization of green energy for cellular networks by cell size optimization. The proposed algorithm achieves significant main grid energy savings by scheduling the green energy consumption along the time domain for individual BSs, and balancing the green energy consumption among BSs for the cellular network.

However, owing to the fluctuating nature of the renewable sources, the availability of green energy is not always guaranteed. Therefore, most of the existing systems which are utilizing green energy usually store green energy in batteries, and then draw electricity from the batteries. In these systems, although the energy sources are sustainable, the batteries, during their manufacturing and recycling, may result in more CO₂ emissions than without utilization of green energy at all [9]. In addition, the battery-related costs usually dominate the total costs of green energy systems [10], and limit the penetration of green energy. To augment the utilization of green energy in wireless cellular networks, it is desirable to eliminate batteries from the renewable energy system. If the batteries are eliminated, green energy should be utilized when it is generated; otherwise, it is wasted. To maximize the utilization of green energy, we propose to shape the elastic mobile traffic to match green energy supplies by optimizing the packet scheduling.

In wireless cellular networks, the packet schedulers are designed to maximize system throughput while meeting the users’ QoS requirements. Such packet schedulers usually estimate the channel quality perceived by the users, and schedule the users with favorable channel conditions. However, without considering green energy supplies, the existing packet scheduler may not fully take advantage of green energy. To optimize the utilization of green energy, we propose the energy agile (EA) packet scheduler to maximize the utilization of green energy. The intuitive idea is that, in order to maximize the utilization of green energy, the EA packet scheduler balances the BS’s energy consumption among time slots by optimizing the packet scheduling. As a result, the transmissions of some packets will be delayed for energy savings. Therefore, the EA packet scheduler trades the packet delay for main grid electricity savings. The effectiveness of the EA packet
schedules in reducing the main grid electricity consumption is determined by the diversities of the users’ data traffic in terms of the packet arrivals, packet intervals and packet sizes [11]. A larger diversity may indicate a larger variation on BS’s energy consumption in individual time slots. Thus, by balancing the energy consumption among time slots, the EA packet scheduler may achieve more main grid electricity savings. In addition, as a result of the balancing, the bandwidth in individual time slots may not be fully utilized, and the residual bandwidth can thus be utilized to further reduce the BS’s energy consumption.

II. System Model

In this paper, we consider a mobile system with a single BS with $M$ active mobile users under the coverage of the BS, and focus on the downlink packet transmission for elastic flows. We assume that the time domain is divided into multiple time slots. In each time slot, multiple packets can be scheduled and transmitted. Within a time slot, the total bandwidth is divided into a series of non-overlapping frequency channels. Packets from different users are transmitted using different channels. Because the BS’s power consumption can be well approximated by a linear function of the transmission power [12], reducing the BS’s transmit power is equivalent to reducing the BS’s power consumption. Therefore, we consider the transmit power as the BS’s power consumption in the problem formulation. We consider a BS with hybrid power supplies: main grid electricity and green energy. We consider solar panels as the green energy generators. Solar panels generate electrical power by converting solar radiation into direct current electricity using semiconductors that exhibit the photovoltaic effect. Because of disadvantages of banking green energy in batteries or on the grid (net metering), we do not assume the green energy can be stored. In other words, if the green energy is not consumed when it is generated, the green energy is wasted. Therefore, to maximize the utilization of green energy, we optimize the packet scheduling by matching the BS’s energy demand to the green energy supplies.

We propose the EA packet scheduler as shown in Fig. 1. The EA packet scheduler schedules packets in two steps. In the first step, the EA packet scheduler takes packets from users’ data buffers according to the PF packet scheduling algorithm $^1$. Instead of transmitting the scheduled packets immediately, the EA packet scheduler store the packets in the its buffer, i.e., the EA packet scheduler schedules and stores packets for $h$ time slots. Since the EA packet scheduler exploits the diversity of users’ traffic demands to balance the BS’s energy consumption among time slots, the parameter $h$ should be properly selected according to the characteristics of the users’ traffic. A small $h$ may not allow any diversity in term of users’ traffic demands. However, a larger $h$ does not always guarantee a higher diversity. Besides, since the EA packet scheduler stores the packets for $h$ time slots before transmitting them, the packet delay is up to $2h$ time slots. Therefore, the larger the $h$, the longer the packet delay experienced by the users. In the second step, all the packets are fed into the energy saving (ES) packet scheduler for packet transmission optimization. The ES packet scheduler schedules and transmits the stored packets within $\lfloor (1+\alpha)h \rfloor$ time slots. Here, $\alpha \geq 0$ is the packet delay coefficient. By adapting $\alpha$, the EA packet scheduler can adjust the BS’s energy consumption in individual time slots, and changes the additional packet delay experienced by the users. A larger $\alpha$ allows more time slots to be used to transmit the packets. Given the number of packets, a larger the $\alpha$ allows less number of the packet to be transmitted in one time slot. Therefore, the BS’s energy consumption in individual time slots is reduced. Thus, by adapting $\alpha$, the BS’s energy consumption can be adjusted to match the green energy supplies. On the other hand, with a larger $\alpha$, the users experience a longer packet delay. Hence, the selection of $\alpha$ also reflects the trade off between the BS’s energy consumption in individual time slots and the users’ packet delay.

III. Problem Formulation and Analysis

Denote $W$ as the total bandwidth, and $w_{k,i}$ as the bandwidth allocated to the $k$th mobile user in the $i$th time slot. Assuming the mobile users are experiencing the frequency flat fading. Let $l_k$ be the number of packets from the $k$th user scheduled by the PF packet scheduler within $(1+\alpha)h$ time slots. Denote $S_{k,m}$ as the size of the $m$th packet fed into the scheduler from the $k$th mobile user. Denote $\tau$ as the interval of one time slot, and assume the channel state information does not change within $h$ time slots. Therefore, if the $k$th user is scheduled in the $i$th time slot on one channel, then the data rate is

$$R_{k,i} = w_{k,i} \log(1 + \frac{P_{k,i}G_{k,i}}{N_0w_{k,i}}).$$

(1)

Here, $P_{k,i}$ is the BS’s transmit power, and $G_{k,i}$ is the channel gain from the BS to the $k$th user in the $i$th time slot. $N_0$ is the downlink noise power spectral density. Then, the BS’s transmit power toward the $k$th mobile user is derived as:

$$P_{k,i} = \frac{N_0w_{k,i}}{G_{k,i}}(2\tau R_{k,i}/w_{k,i} - 1).$$

(2)

The BS’s total transmit power in the $i$th time slot is

$$P_i = \sum_{k=1}^{M} P_{k,i}.$$  

(3)

$^1$Here, we assume packet by packet transmission. In other words, the packets are not segmented to transmit in multiple time slots.
Denote \( P^g \) as the amount of green energy generated in the \( i \)th time slot; then, the main grid power consumption in the \( i \)th time slot is

\[
P^m_i = \max(P^t_i - P^g_i, 0).
\]

To ensure the QoS of the mobile users, the packets fed into the scheduler should be delivered within \( [(1 + \alpha)h] \) time slots. We aim to minimize the main grid power consumption by optimizing the packet scheduling. Therefore, the packet scheduling optimization (PSO) problem can be formulated as follows:

\[
\begin{align*}
\min & \quad \sum_{i=1}^{h} P^m_i \\
\text{subject to} & \quad \sum_{k=1}^{M} P_{k,i} \leq P^{\max}, \\
& \quad \sum_{k=1}^{M} w_{k,i} \leq W, \forall i \\
& \quad \sum_{i=1}^{[(1+\alpha)h]} R_{k,i} = \sum_{m=1}^{l_k} S_{k,m}, \forall k.
\end{align*}
\]

Here, \( P^{\max} \) is the BS’s maximum transmit power. During each time slot, packets from different users may be scheduled to be transmitted. Since 1) users are experiencing different channel fading, and 2) the users’ traffic demands are different, the BS usually consumes different amount of transmit power in different time slots. Given the amount of green energy, to solve the PSO problem, we first balance the energy consumption among \( [(1 + \alpha)h] \) time slots to ensure the green energy is fully utilized in each time slot. To balance the energy consumption, the transmission of some packets may be deferred. For example, a packet, which is originally scheduled to be transmitted in the first time slot according to the PF scheduling algorithm, may be rescheduled to be transmitted in the second time slot for main grid power savings. Therefore, balancing the energy consumption among time slots is actually trading packet transmission delay for main grid power savings. However, since the users’ traffic is elastic, and we enforce all the packet fed into the scheduler to be transmitted within \( [(1 + \alpha)h] \) time slots. Thus, the users’ QoS can be adjusted by properly selecting \( \alpha \).

**Theorem 1.** The PSO problem is NP-hard in the strong sense when \( [(1 + \alpha)h] \geq 3 \).

**Proof:** The theorem can be proved by reducing any instance of the 3-Partition problem to a simple case of the PSO problem. Thus, the PSO problem is NP-hard in the strong sense. For sake of the brevity, we omit the detailed proof.

IV. THE APPROXIMATION ALGORITHM

Since the PSO problem is NP-hard in the strong sense, it does not admit a pseudo polynomial algorithm unless \( P = NP \). In this section, we propose a heuristic algorithm to approximate the optimal solution of the PSO problem with low computational complexity, and implement the heuristic algorithm in the ES packet scheduler. The heuristic algorithm solves the PSO problem in two steps. In the first step, the algorithm partitions all the packets among \( [(1 + \alpha)h] \) time slots in order to balance the energy consumption among the time slots. In the second step, the algorithm optimizes the bandwidth allocation to minimize the energy consumption in individual time slots.

**A. Partition the packets**

Since the duration of \( [(1 + \alpha)h] \) time slots is very short, we assume the users’ channel gain and the green energy generation do not change. As analyzed in the previous section, in order to minimize the main grid power consumption, the energy consumption should be balanced among \( [(1 + \alpha)h] \) time slots. Therefore, the proposed algorithm partitions the packets into \( [(1 + \alpha)h] \) time slots to achieve similar power consumption in each time slot. When the packets are scheduled by the PF packet scheduler, the bandwidth and transmit power are calculated and allocated for transmitting individual packets. We sort the packets according to their allocated transmit power from the largest to the smallest. Let \( \lambda \) be the total number of packets and \( P_{k,m} \) be the transmit power allocated to the \( m \)th packets of the \( k \)th user. Then, we propose the largest fit (LF) algorithm which starts with the smallest index, and iteratively schedules the packets into the time slot at which the BS’s current total transmit power is the smallest. Denote \( P^t_i \) as the temporary transmit power in each time slot and \( P^s_i \) as the transmit power of the packet indexed as the \( i \)th packet. The pseudo code of the proposed algorithm is shown in Algorithm 1.

**B. Optimize the bandwidth allocation**

Applying the LF algorithm, the packets are partitioned among \( [(1 + \alpha)h] \) time slots. Based on the packets partition, for each time slot, we can derive the data rate requirements of users whose packets are scheduled. After balancing the packets among time slots, in individual time slots, the bandwidth may no be fully utilized. Therefore, the BS’s power consumption can be further reduced by optimizing the bandwidth allocation in individual time slots. Hence, we optimize the bandwidth allocation in each time slot to minimize the energy consumption and at the same time meet the users’ data rate constraints. Assume the number of users whose packets are scheduled in the \( i \)th time slot is \( \gamma \), and the number of scheduled packets from the \( k \)th user is \( n_k \), then the bandwidth optimization (BO) problem can be expressed as:

\[
\begin{align*}
\min & \quad \sum_{k=1}^{\gamma} P_{k,i} \\
\text{subject to} & \quad P^t_i \leq P^{\max}, \\
& \quad \sum_{k=1}^{\gamma} w_{k,i} \leq W, \forall i \\
& \quad R_{k,i} \geq \sum_{m=1}^{n_k} \frac{S_{k,m}}{\tau}.
\end{align*}
\]
When, \( w_{k,i} > 0 \), \( \frac{d^2 P_{k,i}}{d^2 w_{k,i}} > 0 \). Thus, \( P_{k,i} \) is a convex function of \( w_{k,i} \). Hence, the objective function is convex. The constraints of the BO problem satisfy the Slater’s conditions, and hence the Karush-Kuhn-Tucker (KKT) conditions provide necessary and sufficient conditions for the optimality of the BO problem. Therefore, we derive the optimal bandwidth allocation by solving the KKT conditions of the BO problem.

**Algorithm 1** The Largest Fit Algorithm

```
Calculate \( P_{k,m} \) for all the users;
Sort \( P_{k,m} \) from the largest to the smallest;
Initialize \( \hat{P}_l = 0 \), \( i \in (1, 2, \cdots, h) \);
for \( n = 1 \) to \( \lambda \) do
    \( \beta = \arg \min_{j=1}^{h} \hat{P}_j \);
    Schedule the packet with index \( n \) into the \( \beta \)th time slot;
    \( \hat{P}_\beta = \hat{P}_\beta + P_n \).
end for
```

**V. SIMULATION RESULTS**

In this section, we compare the performance of the proposed EA packet scheduler with the classic PF packet scheduler [13] in term of main grid energy consumption. Simulations are set up as follows. A total of 20 users are randomly distributed within the range of one macro cell. The radius of the macro cell is 250 meters, and the maximum transmit power of the BS is 43 dBm. The carrier frequency, \( f_c \), is 2000 MHz, and the total bandwidth, \( W \), is 10 MHz. We adopt Okumura-Hata path loss model [14]: 128.1 + 37.6log\(_{10}(d/1000)\) + 21log\(_{10}(f_c/2)\), where \( d \) is the distance between the user and the BS. The standard deviation of the shadow fading is 10 dB, the downlink noise density is -174 dBm/MHz, and the antenna gain is 0 dB at both the BS’s and the users’ sides. For simplicity, we assume the users experience frequency flat fading, and BSs have complete knowledge of the users’ channel state information. The duration of a time slot is 1 ms. In each time slot, users generate different types of data traffic including HTTP and FTP traffic according to the traffic model suggested in [15]. We adopt the BS energy model [12] to calculate the BS’s energy consumption based on the BS’s transmit power as follows:

\[
P_{BS} = \frac{P_{RF} + P_{BB}}{(1 - \delta_{DC})(1 - \delta_{MS})(1 - \delta_{cool})}.
\]

Here, \( \eta_{PA} = 0.31 \) is the efficiency of the power amplifier, \( \delta = -3 \text{dB} \) is the antennas’ feeder loss, \( P_{RF} = 12.9 \text{w} \) is the energy consumption of the radio frequency small signal transceiver module [12], and \( P_{BB} = 29.6 \text{w} \) is the energy consumption during the baseband signal processing. \( \delta_{DC} = 0.075 \), \( \delta_{MS} = 0.1 \), and \( \delta_{cool} = 0.9 \) are the energy loss factors incurred by DC-DC power supply, mains supply, and active cooling, respectively [12].

Fig. 2 shows the BS’s energy consumption in individual time slots. In the simulation, \( \alpha = 0 \) and \( h = 5 \). In the figure, EA w/o BO indicates that we only balance the energy consumption among time slots, but do not optimize the bandwidth allocation. As compared with the PF packet scheduler, EA w/o BO balances the BS’s energy consumption within \( h \) time slots. For example, from the eleventh time slot to the fifteenth time slot, the BS’s energy consumption achieved by the PF packet scheduler fluctuates wildly between 220w to 226w. By balancing the energy consumption, EA w/o BO is able to reduce the fluctuation and make the BS’s energy consumption to be around 223w in individual time slots. Since the packets are well partitioned into the \( h \) time slots, the bandwidth in individual time slots may not be fully utilized. Therefore, by applying bandwidth optimization, the EA packet scheduler further reduces the BS’s energy consumption.

Fig. 3 shows the impact of parameter \( h \) on the proposed EA packet scheduler. In the simulation, we set \( \alpha = 0 \). In the figure, the x-axis is the green energy generation rate while the y-axis shows the main grid power consumption. When the green energy generation is less than 158kW, EA w/o BO consumes more main grid energy than the PF packet scheduler. However, when the green energy generation is larger than 158kW, the BS’s power consumption of EA w/o BO is significantly less than that of the PF packet scheduler. This is because by partitioning packets into \( h \) time slots, EA w/o BO is able to reduce the fluctuation of the BS’s power consumption, and makes the BS’s power consumption in most of time slots to be between 153kW and 158kW. Therefore, if the green energy generation is larger than 158kW, with EA w/o BO, the BS can be powered by green energy in most of the time slots, and thus the main grid power consumption is reduced. With bandwidth optimization, the EA packets scheduler further reduces the main grid power consumption. However, the simulation results indicate that a larger \( h \) does not guarantee a better performance in term of main grid power savings. Actually, in the simulation, the EA packet scheduler with larger \( h \) shows worse performance as compared to that with smaller \( h \). However, as shown in Table I, a larger \( h \) does introduce a larger packet delay. Therefore, the parameter \( h \) should be properly selected according to the characteristics of the user traffic.

<table>
<thead>
<tr>
<th>Table I</th>
<th>Packet Delay v.s. Parameter ( h )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h ) value</td>
<td>( h = 5 )</td>
</tr>
<tr>
<td>Packet Delay</td>
<td>5ms</td>
</tr>
</tbody>
</table>

Fig. 4 shows the impact of the parameter \( \alpha \) on the proposed EA packet scheduler. In the simulation, \( h = 5 \). When \( \alpha = 0.2 \), with the EA packet scheduler, the BS’s power consumption in most of the time slots is less than 130kW. Therefore, when the green energy generation rate is larger than 130kW, the main grid power consumption reduces dramatically. When the green energy generation is larger than 135kW, with the EA packet scheduler, the BS consumes zero main grid power. With the PF packet scheduler, only when the green energy generation is larger than 160kW, the BS’s main grid energy...
consumption is reduced to zero. The larger the $\alpha$, the smaller green energy generation rate is required to achieve zero main grid energy consumption. When the green energy generation is less than 90 kW, the EA packet scheduler with $\alpha = 0.6$ consumes the most main grid power. This is because when $\alpha = 0.6$, owing to the energy consumption balancing, the BS’s power consumption in most of the time slots is between 90 kW and 100 kW, and therefore when the green energy generation is less than 90 kW, the EA packet scheduler with $\alpha = 0.6$ consumes the main grid power in most of the time slots. Thus, in this situation, the EA packet scheduler consumes more main grid power. However, when $\alpha = 0.6$, the EA packet scheduler only requires a green energy generation rate of 100 kW to achieve zero main grid power consumption. When $\alpha$ is large, the EA packet scheduler uses additional time slots to transmit the packets. Therefore, it introduces additional packet delay as shown in Table II.

### TABLE II

<table>
<thead>
<tr>
<th>Parameter $\alpha$</th>
<th>Packet Delay (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha = 0.2$</td>
<td>6.52</td>
</tr>
<tr>
<td>$\alpha = 0.4$</td>
<td>7.99</td>
</tr>
<tr>
<td>$\alpha = 0.6$</td>
<td>9.53</td>
</tr>
</tbody>
</table>

From the simulations, we can see that given the green energy generation rate, we can adjust the main grid power consumption by adapting $\alpha$. In other words, the BS’s energy consumption can be matched to the green energy supplies by adjusting $\alpha$. However, a larger $\alpha$ introduces longer packet delay. Therefore, adapting $\alpha$ is actually determining a trade off between main grid energy consumption and the packet delay.

### VI. CONCLUSION

In this paper, we have proposed to reduce the main grid electricity consumption of cellular networks with hybrid energy supplies by optimizing the packets scheduling. We have proposed the EA packet scheduler which trades the packet delay for main grid electricity savings. The proposed EA packet scheduler optimizes the packet scheduling in two steps. In the first step, it balances the BS’s energy consumption among individual time slots. In the second step, it minimizes the BS’s energy consumption by optimizing the bandwidth allocation. The proposed solution has been demonstrated via extensive simulations to be able to maximize the utilization of green energy, and thus save significant amount of main grid energy.

### REFERENCES


