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Renewable Energy-Aware Video Download in Cellular Networks

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***Abstract* — The use of renewable energy (RE) sources is a promising solution to reduce grid power consumption and carbon dioxide emissions (CO_{2e}) of cellular networks. However, the benefit of utilizing RE is limited by its highly intermittent and unreliable nature leading to mismatch between generation and base station (BS) needs, resulting in low savings in grid power. To address the above challenges, we propose a novel base station time resource allocation technique using data storage at user equipments (UEs) to optimally utilize renewable energy to reduce grid power consumption. The proposed approach transforms the surplus RE (in excess of the BS power requirements) to excess data delivered to the users and stored in UE data storages, to draw from in deficit periods (when RE generation is lesser than BS requirements) to reduce grid power. Though the proposed approach is applicable to any application that utilizes UE data buffer, we formulate the problem for mobile video and propose a algorithm for RE aware BS resource allocation during mobile video download, as the latter will dominate wireless traffic and hence BS power consumption. Our experimental results using sample solar and BS utilization traces demonstrate the ability of the proposed approach to reduce grid power consumption by increasing solar power utilization while satisfying user QoS requirements.**

***Index Terms*— Renewable energy; Base station power consumption; Grid power consumption; Mobile video; UE data buffer**

I. Introduction

The total energy consumption and carbon dioxide equivalent (CO_{2e}) emission of mobile cellular networks globally for 2020 has been estimated to more than 120TWh and 179 million tons (Mt) [1, 2]. According to [3], base stations (BSs) consume 80% of the total power in cellular networks. There has been significant research and deployment of energy efficient BSs, ranging from physical layer approaches involving RF chain switching [4] to network level techniques wherein active BS selection and user association [5] is performed. While the above techniques focus on reducing BS power consumption to mitigate the rising grid power consumption and CO_{2e} emissions, in this work we propose to utilize renewable energy to minimize overall BS grid power consumption. Though the last few years have seen tremendous growth in the use of renewable energy (RE) in the residential, commercial, and industrial sectors, its use for BSs has mostly remained elusive. The primary challenge in utilizing RE energy for BSs is the highly intermittent, unreliable and variable nature of renewable energy availability across time and space [6] which leads to mismatch between RE

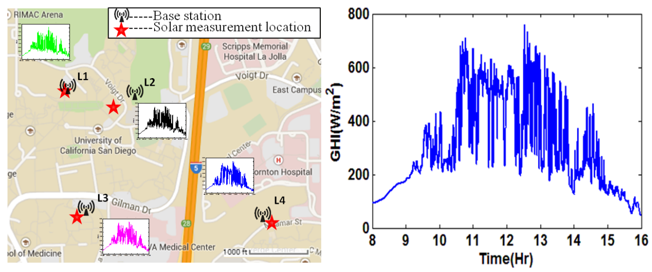

Figure 1. (a) left, Map showing locations of 4 BSs and nearby solar irradiance measurement, (b) right, solar irradiance at L1 on Dec. 11, 2014 between 8AM-4PM

generation and BS needs, resulting in poor utilization of RE and low savings of grid power. One approach to overcome the problem is the use of renewable power systems with high capacity energy storage [7]. However, according to [7], energy storage devices (battery) accounts for 75% of total cost of the RE system, which limits the economic viability and growth of renewable energy powered BSs. To address the above challenges, we propose novel BS resource allocation technique to optimally utilize renewable energy to minimize grid power consumption, **using renewable energy systems which do not need energy storage**. The proposed approach achieves the above by (a) dynamically adapting the time resource allocation when there is surplus renewable energy such that excess data is delivered to the users beyond their throughput requirements and stored in UE data storages, and (b) drawing from the same in deficit periods (when renewable energy generation is lesser than base station requirements) to reduce grid power. It should be noted that the proposed technique aims to minimize grid power consumption by **increasing** BS power consumption to deliver excess data to the users in the RE surplus period and **decreasing** the BS power consumption in the RE deficit period by reducing the user data rates.

In this paper, we will mainly focus on solar power, however, our insights and proposed approach will apply to wind and other RE sources which show similar temporal variations. Solar radiation consists of direct solar radiation and diffuse solar radiation, the latter getting scattered, absorbed, and reflected within the atmosphere, mostly by clouds, but also by particulate matter and gas molecules [8]. The direct and diffuse components together incident on horizontal surface are termed as global horizontal irradiance (GHI) and is measured in W/m^2. To get deeper insight into the nature of variations in solar irradiance, we measured the GHI at 1 second resolution near four BS locations on University of California, San Diego (UCSD) campus, as shown in Fig. 1(a). Fig. 1(b) shows solar irradiance data collected at BS marked L1 in Fig. 1(a) on December 11, 2014 from 8AM-4PM. We observe very rapid temporal variations in GHI ranging approximately from 200W/m^2 to 800W/m^2, with similar observations for other days and also for the other locations shown in Fig. 1(a). Moreover, BS utilization also has large temporal variations during the day [9], which will lead to significant temporal variation of the resulting BS power consumption. Therefore, the focus of the proposed approach will be to adjust BS utilization in a manner that reduces the mismatch between generated solar power and BS needs while ensuring that the QoS requirements of users are satisfied.

A. Related Work

Various relevant recent works that address the use of renewable energy to minimize grid power in wireless cellular communication are briefly discussed below. In [10], the authors focus on a single BS-UE link of a grid-connected BS with RE, and propose an optimal BS resource allocation technique to minimize grid power consumption with QoS constraints. Unlike the above technique which considers only a single user, our approach allocates BS resources to multiple users and utilizes their buffer to minimize grid power consumption. The authors in [11] propose a BS cooperation scheme to minimize the grid power cost by shrinking the cell size of BSs relying on grid power and offload traffic to BSs with excess RE. However, the approach requires frequent inter-cell coordination to adapt cell size while our technique is applicable to a single cell and do not require inter-cell coordination. The authors in [12] propose to increase compression ratio of video traffic or increase delay of data traffic in order to reduce grid power consumption when the RE is in deficit. Unlike the above approach which requires real time adaptation of video compression ratio and may lead to degradation of user QoS, our approach minimizes grid power consumption while ensuring that user QoS is not compromised.

Mobile video traffic will be 72 percent of all consumer Internet traffic in 2019 globally, up from 55 percent in 2014 [13]. Therefore, BS resource utilization and thereby power consumption will largely be due to mobile video download. Hence it is critical to minimize the BS power when satisfying the QoS requirements of users downloading mobile video. Previous works [14, 15] focus on power saving of mobile devices by shaping the traffic transmitted to users and extending the periods of no transmission or idle periods of mobile devices, but do not consider the impact of traffic shaping on BS energy consumption, and more specifically on reducing BS grid power consumption, which is the objective of our work. The authors in [16] propose to utilize the rate predictions for wireless video download and adapt the video bitrate to minimize BS power consumption. While [16] does not consider RE and UE data storage, our proposed approach utilizes RE and UE data storage to minimize grid power consumption during video download.

To the best of our knowledge, this is the first work which dynamically adapts BS time resource allocation and thereby BS power consumption in a RE-aware manner during mobile video download by (a) increasing the transmission rate provided to the users beyond their minimum rate requirements during periods of surplus solar power and storing in UE data storage (b) utilizing the excess data stored in UE data storage to reduce transmission rate or stop transmission during deficit periods to minimize grid power consumption. Note that the increase and decrease in transmission rate provided to the users to optimize the utilization of solar power is done in a manner that satisfies the user QoS requirements and maintains the BS utilization below a certain threshold. We propose a novel approach which transforms the UE data storage to effective "energy" storage to be used in lieu of conventional energy storage during mobile video download.

The rest of the paper is organized as follows. In section II, the system model is described and the problem formulation is presented. We present the proposed solar power-aware BS time resource allocation methodology and algorithm developed in section III. In section IV, the performance of the proposed algorithm is evaluated via simulation. Finally, we conclude the paper in section V.

II. System Model and Problem Formulation

In this section, we will first present the system model comprising of network, channel, traffic demand, and BS power consumption models. Then, we formulate the optimization problem to minimize the total grid power consumption by utilizing solar power with constraints of user QoS and BS utilization.

A. Network and Channel Model

Consider downlink communication in a cellular network with a set of BSs B. Without loss of generality, we will consider one BS, $b \epsilon B$ and its I associated users. Time is equally divided into n transmission slots of duration λ. The achievable transmission rate from BS b to user i at n^{th} slot is given by

$$r_{ib}^{n} = BW\log_2\left(1+\frac{g_{ib}^{n}p_{b,tx}^{n}}{\sum_{j\in B\setminus\{b\}} g_{ij}^{n}p_{j,tx}^{n}+N_0BW}\right) \qquad (1)$$

where BW and $p_{b,tx}^{n}$ denote the overall bandwidth and transmit power of BS b at n^{th} slot. g_{ib}^{n} denotes the channel gain from BS b to user i at n^{th} slot, including path loss attenuation, shadowing and other factors if any, and g_{ib}^{n} is assumed to be constant during each slot. N_0 is noise power spectral density. As we will focus on a single BS, henceforth, we will drop the subscript b from the BS related variables.

B. Traffic Demand and BS Utilization

As discussed earlier, we focus on mobile video download. For a given video bitrate, the BS transmission rate should be selected in a manner that the video buffer does not overflow or underflow.

Let us consider the transmission slot n. The transmission rate required by the i^{th} user δ_i^n depends on the bitrate

V_{BR} and the buffer level (amount of buffer data or playback time available). The transmission rate required by the i^{th} user is lower bounded by the minimum required buffer level Buf_i^{Min} to ensure no stalling and upper bounded by the maximum amount of buffer available Buf_i^{Max} to prevent overflow and is given by

$$Buf_i^{Min,n} \leq \lambda\delta_i^n \leq Buf_i^{Max,n} \quad (2)$$

The minimum required buffer level $Buf_i^{Min,n}$ is given by

$$Buf_i^{Min,n} = \begin{cases} Buf_{Stall} - Buf_i^{n-1}, Buf_{Stall} > Buf_i^{n-1} \\ 0, \; Buf_{Stall} \leq Buf_i^{n-1} \end{cases} \quad (3)$$

where Buf_i^{n-1} is the buffer level at the end of the $n-1^{th}$ slot. The buffer level Buf_{Stall} is a pre-defined value and may be set (by the service provider) to reduce the risk of stalling. The maximum amount of buffer available $Buf_i^{Max,n}$ is given by

$$Buf_i^{Max,n} = Buf_{Size,i} - Buf_i^{n-1} \quad (4)$$

where $Buf_{Size,i}$ is the total size of the i^{th} user's buffer. The buffer level at end of slot n is given by the sum of the buffer level in $n-1^{th}$ slot and the data accumulated in the buffer $\lambda t_i^n r_i^n$ by transmitting at r_i^n reduced by the data used for playback λV_{BR}.

$$Buf_i^n = Buf_i^{n-1} + \lambda t_i^n r_i^n - \lambda V_{BR} \quad (5)$$

where t_i^n is the fraction of total time resource allocated by the BS to satisfy the transmission rate requirement of the i^{th} user in transmission slot n. The time resource allocated by the BS to the i^{th} user is given by

$$t_i^n = \delta_i^n / r_i^n \quad (6)$$

The BS utilization is the aggregate of the time resources allocated to all the I users and is given by

$$\rho^n = \sum_{i=1}^{I} t_i^n \quad (7)$$

C. Base Station Power Consumption Model

The power consumption of BS in transmission slot n can be modeled as

$$P^n = (1-q)\rho^n P^{Max} + qP^{Max} \quad (8)$$

where $q \in [0,1]$ denotes the portion of the static power consumption for the BS and P^{Max} is the maximum power consumption when the BS is fully utilized. P^{Max} is a function of the transmit power p_{tx} with nonnegative coefficients a and b and is given by

$$P^{Max} = ap_{tx} + b \quad (9)$$

D. Problem Formulation

If R^n is the solar energy produced in transmission slot n, then the grid power consumption is given by

$$G^n = max[0, P^n - R^n] \quad (10)$$

Since we assume no energy storage, the solar power generated at each transmission slot must be consumed instantaneously or it will dissipate. Given the solar power R^n, channel conditions and buffer availability of each user, our objective is to determine time resource allocation t_i^n at each transmission slot to minimize the total grid power consumption of BS while satisfying the QoS requirements of all users and maintaining the BS utilization below a certain threshold.

$$min \sum_{n=1}^{N} G^n \quad (11)$$

$$s.t. \quad 0 \leq t_i^n \leq 1, n = 1,2,..,N, \; i = 1,2,..,I \quad (12)$$

$$\sum_{i=1}^{I} t_i^n \leq 1, \; n = 1,2,..,N, \quad (13)$$

$$Buf_i^{Min,n} \leq \lambda t_i^n r_i^n \leq Buf_i^{Max,n}, n = 1,2,..,N, \; i = 1,2,..,I, \quad (14)$$

The first constraint given by (12) states that in every transmission slot, each user should be assigned a non-negative time fraction. The second constraint given by (13) states that the BS time resource utilization should not exceed one (BS utilization limit). The third constraint given by (14) states that the time fraction allocated to the i^{th} user and the resulting transmission rate should ensure that the buffer does not under flow or over flow. In this work, the video bit rate is not adapted; hence the only factor impacting video quality and user experience is the amount of stalling. The bounds on transmission rate in (14) ensure no stalling for all transmission slots and hence ensure that the total video download time does not exceed the video duration. Therefore, we can ensure that the user QoS requirements are satisfied.

In the next section, we will present RE aware BS time resource allocation technique which will modulate the BS power consumption in a manner that achieves the objective in (11) while satisfying the constraints (12)-(14).

III. Solar Power-Aware Resource Allocation (SPAR) Methodology and Algorithm

In this section, we will first describe the proposed solar power-aware resource allocation methodology to minimize grid power consumption. We then propose an online algorithm which determines the time resource allocation and hence the transmission rate provided to users.

A. SPAR Methodology

From (10), we can infer that the principle of minimization of grid power is to modulate the BS power consumption profile to minimize the difference between BS power consumption and solar power. We achieve this as follows: (a) When the solar power generated is more than the minimum BS power required to ensure that minimum transmission rate requirements of all users are satisfied, that is, $R^n > P^n$, we transmit excess data to the users to be stored in their video buffer, while satisfying constraints (12-14). This results in increased BS utilization and thereby increased BS power consumption enabling increased utilization of solar power. Increasing transmission rate increases the buffer level of the user or the video playback time available to more than the minimum required. This can be seen as transforming the surplus RE "watts" to excess "bits" stored in users' video buffers. (b) During deficit periods when $R^n < P^n$, the grid power consumption can be reduced by reducing or stopping video delivery to users who can utilize the video data in the buffer stored in preceding surplus periods. In this manner, we will affect the transmission rate and BS utilization to modulate the BS power consumption to match solar power availability while satisfying the transmission rate requirements of all users and BS utilization is maintained below the threshold.

B. SPAR- Online resource allocation algorithm

We will now present the Solar Power-Aware Resource Allocation Algorithm (SPAR), which is an online algorithm to minimize grid power consumption while satisfying the user QoS and BS utilization constraints. We assume that I users are scheduled in each transmission slot and the channel state information and buffer level information of users are periodically reported to the BS using Channel Quality Indicator (CQI) and Buffer Status Report (BSR) [17]. Based on the above information and the amount of generated solar power, the BS will run SPAR for every transmission slot. The two main steps of the SPAR algorithm are shown in Fig. 2. In Step 1, the BS will serve the users who have insufficient buffer, i.e., whose buffer level $Buf^{n-1} < Buf_{NStall}$. The time resource required to guarantee smooth playback of these users is calculated and the corresponding BS utilization ρ is determined. Using ρ, the BS power consumption P' required to satisfy the minimum rate requirements of users is computed.

In Step 2, solar power generated R^n is compared with P'. If $R^n \leq P'$, it is a deficit period and BS will not further allocate time resource to other users. On the other hand, if $R^n > P'$, then it is surplus period and BS utilization and power consumption can be increased without consuming grid power. The BS utilization is increased by increasing the transmission rate provided to users in the range between minimum rate requirement and maximum possible rate (constraint (14)). For every user, the ratio of achievable transmission rate to the video bitrate $r_i^n/V_{BR,i}$ is determined and the users are sorted in the descending order of the ratio. Subsequently, users are selected sequentially from the list and the time resource allocated is given by

$$t_i^n = t_i^n + \frac{Buf_{Size,i^*} - Buf_{i^*}^{n-1}}{\lambda r_i^n} \tag{15}$$

This step is repeated till either the available BS time resource is exhausted or buffers of all users are full or BS power consumption exceeds R^n.

We will now discuss the rationale behind using $r_i^n/V_{BR,i}$ to sort users. At each slot, our objective is to allocate time resource to enable greatest transmission rate reduction during future deficit periods to reduce grid power consumption. If we consider the available buffer of each user as an item and the available BS time resource as the knapsack, then the time allocation problem can be seen as the knapsack problem. Accordingly, we define the weight and value of the item as follows. The weight of each item is the required time resource to completely fill the buffer of i^{th} user and is defined as $(Buf_{Size,i^*} - Buf_{i^*}^{n-1})/r_i^n$. The value of each item is the duration the BS can pause transmission to i^{th} user in subsequent deficit periods and is defined as $(Buf_{Size,i^*} - Buf_{i^*}^{n-1})/V_{BR,i}$. Further, since the time resource or the knapsack is divisible, the problem can be treated as the fractional knapsack problem. The optimal solution to the fractional knapsack problem is obtained when the items are chosen in a greedy manner, i.e., in descending order of the ratio of value of the item to the weight of the item [18]. Taking the ratio of value to the weight, we get $r_i^n/V_{BR,i}$ which is the metric used to sort the users in Step 2. Hence we can conclude that, given the channel conditions and buffer levels of the users and the solar power output, the time resource allocation performed in Step 2 is optimal for the transmission slot *n*. Sorting of items requires $O(|I|\, log|I|)$ time, so the complexity of SPAR is $O(|I|\, log|I| + 2|I|)$ is then bounded by $O(|I|\, log|I|)$, where $|I|$ is the cardinality of the set of users *I*.

Solar Power-Aware Resource (SPAR) Allocation Algorithm

Input: R^n, $\boldsymbol{I}$, $\{CSI_i | i = 1,2,..,I\}$, Buf_{NStall}, $\{(Buf_{Size,i}, Buf_i^{n-1}) \mid i = 1,2,..,I\}$, $V_{BR,i}$

Output: $\{t_i^n | i = 1,2,..,I\}$, ρ^n

Initialize $t_i^n \leftarrow 0\ \forall i$; $i \leftarrow 0$; $\rho^n = 0$

Step 1: Allocate minimum required time resources to users whose buffer level is lower than the minimum required

while ($i \leq I$)
  if $Buf_i^{n-1} < Buf_{NStall,i}$
    $t_i^n = \frac{Buf_{NStall,i} - Buf_i^{n-1}}{\lambda r_i^n}$
    $\rho^n = \rho^n + t_i^n$
  end if
  $i \leftarrow i+1$;
end while

$P' = (1-q)\,\rho^n P^{Max} + qP^{Max}$

Step 2: Allocate additional time resources if it is a surplus period

while ($I \neq \emptyset$ and $(R^n - P') > 0$ and $\rho^n \leq 1$)
  $i^* = \mathbf{max}_{1<i<I}\ \frac{r_i^n}{V_{BR,i}}$
  $t_{i^*} = t_{i^*} + \frac{Buf_{Size,i^*} - Buf_{i^*}^{n-1}}{\lambda\, r_{i^*}}$
  $\rho^n = \rho^n + t_{i^*}$
  $P' = (1-q)\,\rho^n P_{max} + qP_{max}$

Figure 2. SPAR Algorithm.

IV. Simulation Framework and Results

In this section, we discuss the simulation framework developed and results obtained by using the proposed SPAR algorithm, and compare the results obtained by using conventional non-RE aware BS time resource allocation scheme during mobile video download.

A. Simulation Framework

We have developed a Matlab based simulation framework which consists of solar photovoltaic (PV) model, BS power consumption model, user distribution and traffic demand model. The framework allows us to implement different video download techniques and evaluate the grid power consumption for temporally varying solar power generation profiles under varying user distribution and traffic and channel conditions. We will briefly describe the above mentioned models below and the related simulation parameters listed in Table 1.

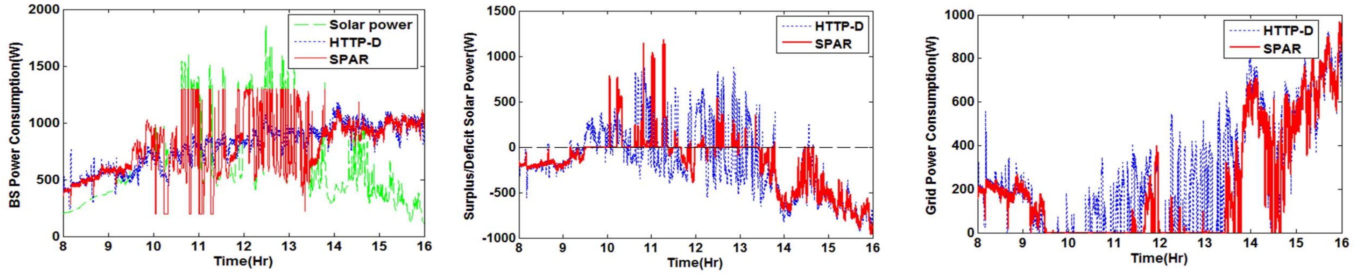

Figure 3. (a) left, solar power and BS power consumption for HTTP-D and SPAR (b) center, surplus/deficit solar power due to HTTP-D and SPAR (c) right, grid power consumption for HTTP-D and SPAR

We assume the solar module associated with the BS uses typical crystalline solar cells with 15% conversion efficiency, and eighteen 110W units, the total area of which is approximately $15\,\text{m}^2$. We use the solar irradiance data measured near the BS located at L1 on UCSD campus, as shown in Fig. 1(b). The linear BS power consumption model elaborated in section IIC is used with the parameters obtained from [19]. The cell radius, system bandwidth and BS power model parameters are listed in Table 1.

We assume users are randomly distributed in the cell. For the channel model, we employ the outdoor macro BS path loss model recommended in Long Term Evolution (LTE) specifications [17]. The number of active users is based on the sample daily BS utilization trace obtained from an anonymous operator [9]. Different users download videos of different bitrates. We assume user buffer size of 1.8 GB. The path loss model, number of users, user buffer size and video characteristics in terms of the video bitrates and duration of the video are specified in Table 1.

We compare the performance of our proposed approach with YouTube Hypertext Transfer Protocol (HTTP) based download technique (termed as HTTP-D) [20]. For HTTP-D, the BS transmits at maximum transmission rate possible given the channel conditions and buffer level in the initial burst phase (the first 40 seconds). Subsequently, in the throttle phase, the video is transmitted at 1.25 times the video bitrate till the video download is complete. As the BS only allocates the minimum required resources (determined by the download mechanism) to the users, HTTP-D can be considered as a representative of non-RE aware BS power minimization technique.

Table 1. Simulation Parameters

Cell radius	1km
Path loss(dB)	$128.1+37.6\log_{10}(R)$, R is the distance between user and BS and is in kilometers
Bandwidth BW	5MHz
Max transmit power P_{Tx}^{Max}	40W
Maximum BS power	1300W
Static BS power	200W
Maximum number of users	60
Video bitrates	{0.5, 0.75,1}Mbps
Video length	30 minutes
UE Buffer size	1.8GB
Simulation time	8 hours

B. *Simulation Results*

Next we present the simulation results obtained by downloading video using the proposed SPAR algorithm and non-RE aware HTTP-D scheme. The measurement of the solar power profile used for the experiments is from 8AM to 4PM. This time period was chosen because solar power generated at the measurement location (UCSD Campus, San Diego) in December before 8AM and after 4PM is negligible compared to the BS needs.

Fig. 3(a) shows the solar power generated (shown as green dot-dash line) and the effect on BS power consumption due to the proposed SPAR algorithm (shown as red solid line) and the non-RE aware HTTP-D (shown as blue dashed line). The BS power consumption for HTTP-D varies depending only on the number of users and their traffic demand. This is evident from the blue plot in Fig. 3(a) which increases with time due to the increased utilization (number of users increasing from 8AM), but does not track the solar power generated. On the other hand, the BS power consumption due to the proposed technique varies depending on not only utilization but also the solar power profile. From Fig. 3(a), we can see that the power consumption of HTTP-D and SPAR are similar between 8AM-9.30AM and 2.30PM-4PM. This is because the solar power generated is lower than the BS requirement and the extended solar deficit period does not allow increasing BS utilization and power consumption. However, the BS power consumption due to SPAR closely tracks the variation in solar power generated between 9.30AM-2.30PM as the BS power consumption increases (decreases) according to high (low) solar power output. This shows the effectiveness of the approach to utilize solar power in the surplus period, and reduce BS power consumption during deficit periods unlike HTTP-D which does not exhibit such variation.

The effectiveness of the techniques in tracking the solar power, i.e., solar power utilization is illustrated in Fig. 3(b). For HTTP-D, we observe large surpluses and deficits which represent unutilized solar power and grid power consumption respectively. In case of SPAR, less surpluses and significantly lower deficits are observed, except during early morning and late afternoon periods when solar power

Table 2. Performance of HTTP-D and SPAR

	Average Unutilized Solar Power	Average Grid Power Consumption
HTTP-D	80.91W	254.77W
SPAR	22.11W	194.12W
Saving	72.7%	23.8%

output is generally lower than the BS power consumption to guarantee smooth playback for all users. The grid power consumption of both techniques is shown in Fig. 3(c). Note that the grid power consumption is computed using (10). We can see that SPAR saves more grid energy than HTTP-D except during long solar deficit periods (8AM-9.30AM and 2.30PM-4PM).

The overall performance of the techniques in terms of savings in grid power consumption and reduction in unutilized solar power is summarized in Table 2. The proposed approach can obtain 72.7% and 23.8% reduction in average unutilized solar power and average grid power consumption respectively compared to HTTP-D. The above results indicate that our proposed technique alleviates the mismatch between intermittent solar generation and BS power consumption and hence can reduce grid power consumption significantly without the aid of energy storage.

Fig. 4 shows the average user buffer level for both techniques. In addition to transmitting additional data to user buffer in surplus period, SPAR maintains at least 1-minute playback time equivalent of buffer level to prevent stalling in the deficit period. The distribution of average buffer for SPAR is similar in trend of the solar power profile, which indicates that the excessive solar power is stored in the form of excess bits in the user buffer. The average buffer level for HTTP-D is flatter since the conventional download mechanism is not aware of solar power.

Though SPAR significantly increases solar power utilization, it cannot translate all the solar power to eliminate grid power consumption during deficit periods. This is because the length of the video sessions and the maximum buffer size limit higher transmission rate that can be allocated to the users. Hence for better utilization of solar power, we can introduce additional low capacity, low cost energy storage at the BS to supplement the data storage used by the proposed technique to store the unutilized solar power as excess bits.

V. Conclusion

In this paper, we propose a novel RE-aware time resource allocation technique which utilizes user data storage to reduce the grid power consumption without the aid of additional energy storage during video download. We propose an online algorithm to determine the BS time resource allocation and hence the transmission rate provided to the user in a RE-aware manner. The simulation results show that our algorithm can significantly reduce grid power consumption compared to conventional non-RE scheme.

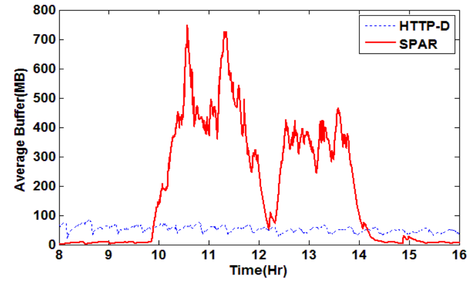

Figure 4. Average user buffer level for HTTP-D and SPAR

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