Power Management of Cache-enabled Cooperative Base Stations Towards Zero Grid Energy

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***Abstract*—With the increasing demand of high speed mobile data transmission, densely deployed small cell base stations capable of caching popular contents have recently emerged as a promising technique to improve the quality of service for mobile users. In this paper, we investigate the cooperative transmission and power management problem for a set of "off-grid" base stations in a cellular network hierarchy that are powered solely by on-site renewable energy sources. The network throughput maximization problem is mathematically formulated as a mixed-integer non-linear programming problem. In the proposed formulation, a base station can adjust its transmission power in a coordinated multipoint communication scheme and/or switch to a "sleep mode" for energy saving. Based on the Lyapunov optimization theory, an efficient near-optimal solution method is proposed with provable bound of the optimality gap. Experimental results on a realistic setup show that the proposed algorithm can achieve up to 2.96x download throughput per user compared to some baseline algorithms.**

I. Introduction

With the rapid proliferation of smart devices and fast changing communication patterns towards high speed multimedia communications, the global annual mobile data traffic is predicted to reach 587 exabytes by 2021, which is 122 times more than that in 2011 [1]. As a result, mobile device users, especially those on the edge of base stations in a traditional cellular network layout may suffer from poor quality of service (QoS). Furthermore, in highly populated urban areas and/or during peak hours, the ever increasing mobile data traffic can pose a burden to the existing backhaul links and the core network. To address these issues, the next generation wireless network, i.e. 5G, introduces the concept of *network densification* in which a large number of cache enabled small base stations (sBSs) are deployed as a complement to conventional macro base stations (MBSs) in previous cellular networks. The dense deployment of sBSs naturally helps improve the QoS by reducing the average distance from a mobile user to the nearest base station while synergizing well with other 5G techniques such as massive multiple-input multiple-output (MIMO) and millimeter wave transmissions. To further address the congestion problem in backhaul links, caching popular contents in base stations is proposed as one of the most promising solutions [2], [3]. Equipped with local storage entities caching requested contents, base stations are capable of directly transmitting contents to users, thus alleviating the need to download the requested content from the core network.

While network densification helps improve the QoS, it is associated with a significant power consumption overhead because of the large number of deployed sBSs. According to data in references [2], [4], there can be 100 times more sBSs than MBSs in a cellular network in practice, resulting in twice as much the total peak power consumption. In terms of environmental impacts, it has been reported that information and communication technology (ICT) already contributes around 2% of the global carbon dioxide emission and is expected to increase rapidly in the future. Moreover, 10% of the world's electric energy is consumed by the ICT infrastructure and base stations contribute to around 60% of the power consumption in cellular networks.

From the perspective of energy efficiency, base stations need to be self-organizing, energy-efficient, and environmental-friendly. One promising solution, as already adopted by many telecom operators around the world [5], is to use *off-grid* base stations that are powered solely by renewable energy generated from energy harvesting systems (e.g. photovoltaic cells) [6].

On the other hand, power management policies can be designed to switch a base station into a "sleep mode" in order to save energy when there is no user to be serviced. Generally speaking, power management for an off-grid base station is a non-trivial problem because of the sporadic and intermittent nature of commonly used renewable energy source and the limited energy storage capacity in a base station. Without a reliable prediction of energy generation and user request profile, over-conservatively reducing the transmission power of base stations can significantly affect the network throughput, while activating base stations too often will quickly drain the energy storage and may cause failure in service later on.

Another potential issue with dense sBS deployment is the inter-cell interference, which is usually addressed using cooperative transmission schemes such as coordinated multipoint (CoMP) communication [7], [8]. CoMP allows a user equipment (UE) to establish connections with several base stations at the same time while the involved base stations can be viewed as a virtual MIMO array that schedule and process the transmitted signals in a coordinated manner [9].

A large body of prior literature aims at solving some aspects of the aforementioned problems of ultra-dense sBSs. In work [10], Chiang *et al.* consider a cache-enabled base station switch-off scheme for saving energy under the cooperation transmission powered by solar energy. A centralized local search is implemented to reduce the total energy consumption. In work [11], Cili *et al.* study the combination of CoMP transmission and cell switch-off technique to achieve more energy efficiency. Chamola *et al.* [12] investigate a downlink power management policy for cellular base stations with hybrid power supplies. The network delay is considered for the energy minimization problem. However, there is no prior research on

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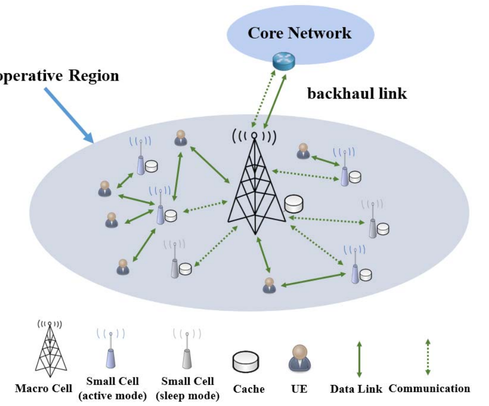

Fig. 1. Graphical illustration of a two-tier cache-enabled HetNet.

a complete solution to the power management of cooperative off-grid base stations. Besides, algorithms proposed by prior work usually have high complexity and become intractable when the problem size is large.

In this paper, we propose an online power management framework for a cellular network consisting of cooperative off-grid base stations powered by energy harvesting modules. Rechargeable battery packs are deployed in base stations to deal with the intermittent energy supply so that harvested energy can be used at a later time. Each base station is equipped with a content cache to directly transmit cached contents to requested users without downloading them from the core network. Based on Lyapunov optimization theory, the network throughput maximization problem with power and energy constraints is formulated as a mixed-integer non-linear programming problem. To develop an efficient algorithm, the original problem is decomposed into a number of subproblems, each of which can be solved using standard convex optimization techniques with a provable optimality gap. The effectiveness of the proposed control framework in practice is demonstrated by experimental results based on realistic user request traces.

The rest of this paper is structured as follows. In Section II, the system model of a cache-enabled two-tier cellular network is introduced. In Section III and Section IV, we propose the problem formulation and solution method. Experimental results are presented in Section V. Section VI concludes the paper.

II. System Model

We consider a two-tier cache-enabled cooperative HetNet as shown in Fig. 1, where a tier-1 MBS covers a set of UEs $\mathcal{M} = \{1, \cdots, j, \cdots, M\}$ and is associated with a number of tier-2 sBSs $\mathcal{N}_S = \{1, \cdots, i, \cdots, N\}$. We use $\mathcal{N} = \mathcal{N}_S \cup \{0\}$ to represent the MBS and all its associated sBSs. In addition, the MBS is also connected to a hub in the core network via a backhaul link to access contents on the Internet. We consider the case in which sBSs are deployed to enhance capacity in locations with high demand under the coverage of MBSs and a UE is in the coverage of at least one MBS. A CoMP communication scheme is used in which an MBS and its associated sBSs are capable of forming a cooperative region and jointly transmitting data to a UE, thus increasing the effective downloading throughput. Coordinated transmission between multiple MBSs is not considered and a UE will only connect to the MBS with the highest signal strength if it is in multiple MBS's coverage. As a result, without loss of generality, we can focus on one cooperative region consisting of one MBS (which will be referred to as "the MBS") and its associated sBSs and connected UEs.

All MBSs and sBSs are considered to be off-grid, i.e. the only power source of a base station is its energy harvesting module. Rechargeable batteries are used to store excessive harvested energy for later use. A base station can choose to either operate in an "active mode" in which it can perform data transmission or enter a "sleep mode" in which it does not monitor user requests or transmit data for energy saving purpose.

A. Service Model

In this paper, a slotted time model is adopted in which each time slot has a duration of τ. Each UE may request for at most one file (e.g. videos, texts, images, etc.) in each time slot, which is considered to be known at the beginning of the time slot. Please note that this model can be easily extended to the case where a UE requests multiple files at the same time by creating "dummy" UEs at the same location. In addition, since caching benefits smaller files such as news or weather information much more than large files such as movies [13], we focus on small files that can be transmitted within the same time slot that they are requested.

Both MBSs and sBSs are equipped with content caches capable of storing files that may be requested by UEs. Due to the complex dynamics of the user request pattern and the finite cache space, one cannot guarantee that all requested files can be found in the cache of an sBS or MBS. As a result, files that are missing in the base stations' caches have to be downloaded from the core network. A file request from a UE will be sent to the MBS and all associated sBSs that are in active mode. If an sBS has the requested file in its cache, it can choose to join the CoMP scheme with a specific transmission power. On the other hand, the MBS can choose to join the CoMP scheme by either transmitting the requested file from its cache or relaying the requested file from the core network. Please note that since the design of caching policy in base stations is not the focus of this paper, we assume that a base station is aware of the applied caching policy and knows its cached content.

A set of binary variables $F_{ij}[t]$'s are used to represent the caching status of requested files. $F_{ij}[t]$ is set to 1 if the file requested by UE j in time slot t is present in the cache of base station of i and set to 0 otherwise. The size of the file requested by UE j in time slot t is denoted by $O_j[t]$. In the case that UE j does not request any file in time slot t, one can simply set $O_j[t]$ to 0.

B. Channel Model

When downloading files in a CoMP scheme, the signal-to-interference-plus-noise ratio (SINR) for UE $j \in \mathcal{M}$, denoted by $SINR_j$, is defined as

$$SINR_j[t] = \frac{\sum_{i \in \mathcal{N}} P_{ij}^{tx}[t] g_{ij}}{P_j^{int} + \sigma^2} \qquad (1)$$

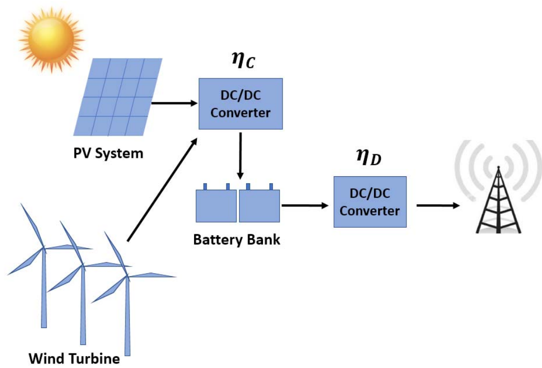

Fig. 2. Energy flow in an off-grid base station.

where $P_{ij}^{tx}[t]$ is the transmission power that base station i assigns to UE j. P_j^{int} is the aggregate interference seen by UE j from outside the cooperative region, g_{ij} is the channel gain from base station i to UE j, and σ^2 is the noise spectral density. The channel gain, g_{ij}, can be further expanded as

$$g_{ij} = h_{ij} \cdot L(d_{ij}) \tag{2}$$

where d_{ij} is the distance between base station i and UE j, $L(\cdot)$ is the log-distance path loss function, and h_{ij} accounts for the channel fading. Furthermore, according to Shannon-Hartley theorem, the data transmission rate achieved at UE j can be calculated as

$$R_j^{ue}[t] = BW \cdot \log_2(1 + SINR_j[t]) \tag{3}$$

where BW is the effective bandwidth of the channel.

C. Energy Consumption Model

The block diagram of the power flow within an off-grid base station is shown in Fig. 2.

In time slot t, if the amount of harvested energy and the energy consumption of base station $i \in \mathcal{N}$ are denoted by $h_i[t]$ and $e_i[t]$, respectively, then the amount of available energy stored in the battery pack at the beginning of time slot t, denoted by $E_i[t]$ will be updated as

$$E_i[t+1] = E_i[t] - \frac{1}{\eta_D} e_i[t] + \eta_C h_i[t] \tag{4}$$

where η_C and η_D are the charging and discharging efficiency of the battery pack, respectively. If the energy capacity of the battery pack in base station i is denoted by C_i^{max}, then the dynamics of $E_i[t]$ should satisfy

$$0 \le E_i[t] - \frac{1}{\eta_D} e_i[t] + \eta_C h_i[t] \le C_i^{max} \tag{5}$$

Generally speaking, the total power consumption of a base station is comprised of a static component (independent of the workload) and a dynamic component (dependent on the workload) [14]. It has been proved that the total power consumption can be approximated as a linear function of its data transmission power output [4].

We adopt a similar power model as in work [15], in which the total energy consumption of a base station $i \in \mathcal{N}$ in time slot t, $e_i[t]$, is given by

$$e_i[t] = \sum_{j \in M} \Delta_p P_{ij}^{tx}[t]\tau + (1 - y_i[t])\, P_i^{slp}\tau + y_i[t] P_i^{act}\tau \tag{6}$$

where Δ_p is the slope of the load-dependent power consumption, P_i^{act} and P_i^{slp} are the static power consumption of base station i in the active mode and sleep mode, respectively, and $y_i(t)$ is a binary variable indicating whether BS is operating in the active mode ($= 1$) or in the sleep mode ($= 0$) in time slot t. According to the data in reference [16], the energy consumption of cache read and downloading via backhaul is usually much lower than the energy consumption of data transmission. Therefore, we choose not to introduce these terms in the energy consumption model.

III. Problem Formulation

In this section, we present the formulation of the base station cooperative control (BSCC) problem. In the BSCC problem, the goal is to maximize the average download throughput of all user requests by selecting the operation mode and setting transmission power of each base station. Since all base stations are off-grid, the control policy should judiciously balance the energy generation and the energy consumption to prevent frequent service outages.

Based on the modeling of system components as in Section II, the BSCC problem can be formally defined as follows

Given: cache information $F_{ij}[t]$ and channel information $g_{ij}[t]$.

Find: the optimal transmission power $P_{ij}^{tx}[t]$ and the operation mode $y_i[t]$.

Maximize:

$$\lim_{T\to\infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{j \in \mathcal{M}} R_j^{ue}[t] \tag{7}$$

Subject to:

$$0 \le P_{ij}^{tx}[t] \le y_i[t] F_{ij}[t] P_i^{max} \qquad \forall i > 0, \forall j \tag{8}$$

$$0 \le P_{0j}^{tx}[t] \le y_0[t] P_0^{max} \qquad \forall j \tag{9}$$

$$\sum_{j \in \mathcal{M}} P_{ij}^{tx}[t] \le P_i^{tot} \qquad \forall i \tag{10}$$

$$\mathbb{E}\left[SINR_j[t]\right] \ge \gamma_{th} \qquad \forall j \tag{11}$$

$$0 \le E_i[t] - \frac{1}{\eta_D} e_i[t] + \eta_C h_i[t] \le C_i^{max} \qquad \forall i \tag{12}$$

$$y_i[t] \in \{0, 1\} \qquad \forall i \tag{13}$$

where $R_j^{ue}[t]$ is the download throughput of UE j in time slot t as defined in Eqn. (1) – (3), P_i^{max} is the maximum transmission power output of base station i, C_i^{max} is the energy capacity of the battery pack in base station i, and the amount of energy storage in base station i, denoted by $E_i[t]$, is updated according to Eqn. (4). Constraint (8) states that an sBS can only help transmit data to UE j when it is in the active mode and the requested file is in the base station's cache. Similarly, constraint (9) ensures that the MBS will transmit data only when it is in the active mode. Constraint (10) sets the limit of total transmission power to P_i^{tot} for each base station i. As a QoS requirement, constraint (11) sets the time-average minimum acceptable SINR for each UE to a threshold value γ_{th}. Constraint (12) guarantees that a battery pack's state of charge is always valid. Constraint (13) sets the domain of decision variables.

The BSCC problem is hard to solve in general because of the existence of binary decision variables and the infinite horizon. Furthermore, since it is impractical to assume that the amount of harvested energy is known for all future hours, predicted values of $h_i[t]$'s are often used, which makes online solutions that can adaptively update the control policies more desirable than offline solutions.

IV. Solution Method

In order to develop an efficient online solution to the BSCC problem, we apply the Lyapunov optimization framework [17] to decouple the original problem formulated in Section III into a set of independent subproblems, each corresponding to a base station.

In order to capture the QoS requirement as in constraint (11), a virtual queue $Z_j[t]$ is defined for UE j, which is updated at the beginning of time slot $(t+1)$ as follows

$$Z_j[t+1] = [Z_j[t] - SINR_j[t] + \gamma_{th}]^+ \tag{14}$$

On the other hand, to model the state of charge of the battery pack of base station i, another virtual queue $\tilde{E}_i[t] = C_i^{max} - E_i[t]$ is introduced. Deriving from Eqn. (4), $\tilde{E}_i[t]$ is updated as follows

$$\tilde{E}_i[t+1] = \tilde{E}_i[t] + \frac{1}{\eta_D} e_i[t] - \eta_C h_i[t] \tag{15}$$

Since $R_j^{ue}[t]$ as defined in Eqn. (3) is a concave function of $P_{ij}^{tx}[t]$'s, Jensen's inequality can be used to find a lower bound of $R_j^{ue}[t]$ as follows

$$R_j^{ue}[t] \geq \frac{BW}{N+1} \sum_{i \in \mathcal{N}} \log_2(1 + \frac{P_{ij}^{tx}[t] g_{ij}(N+1)}{P_j^{int} + \sigma^2}) \tag{16}$$

For the convenience of discussion, we define a "penalty" function, denoted by $pen(t)$, as the opposite of the lower bound found in Eqn. (16), i.e.

$$pen(t) = -\frac{BW}{N+1} \sum_{j \in \mathcal{M}} \sum_{i \in \mathcal{N}} \log_2(1 + \frac{P_{ij}^{tx}[t] g_{ij}(N+1)}{P_j^{int} + \sigma^2}) \tag{17}$$

A Lyapunov drift, denoted by $\Delta[t]$ can be defined as

$$\begin{aligned} \Delta[t] = &\frac{1}{2} \sum_{j \in \mathcal{M}} \left(Z_j[t+1]^2 - Z_j[t]^2 \right) + \\ &\frac{1}{2} \sum_{i \in \mathcal{N}} \left(\tilde{E}_i[t+1]^2 - \tilde{E}_i[t]^2 \right) \end{aligned} \tag{18}$$

The BSCC problem can be mapped into a Lyapunov drift-plus-penalty minimization problem [17] that aims at minimizing the time average of the weighted sum of the Lyapunov drift and the penalty function, i.e.

$$\lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} (\Delta[t] + V \cdot pen[t]) \tag{19}$$

where V is a positive constant coefficient that determines the relative importance of the penalty function and the average virtual queue length.

Instead of solving the BSCC problem or the Lyapunov drift-plus-penalty problem with infinite horizons, we solve an opportunistic control (OPC) problem at the beginning of each time slot to only make the control decision for the next time slot, which significantly reduces the problem size. The OPC problem is formally defined as follows

Find: $P_{ij}^{tx}[t]$ and $y_i[t]$, $\forall i, j$

Minimize:

$$\begin{aligned} &V \cdot pen[t] + \sum_{j \in \mathcal{M}} Z_j[t](\gamma_{th} - SINR_j[t]) \\ &+ \sum_{i \in \mathcal{N}} \tilde{E}_i[t] \left(\frac{1}{\eta_D} e_i[t] - \eta_C h_i[t] \right) \end{aligned} \tag{20}$$

Subject to: Constraints (8) – (10), (12), and (13)

It can be proved that a near-optimal solution to the BSCC problem can be obtained by solving the OPC problem at the beginning of each time slot.

Theorem 1. *If each $h_i[t]$ can be viewed as an i.i.d. process over time slots, there exists a finite optimality gap between the solution achieved by the OPC problems and the optimal solution of the BSCC problem as long as the SINRs, $e_i[t]$'s, and $E_i[t]$'s are bounded.*

Proof. To simplify the expression, we introduce the following functions

$$G_0(\mathbf{P}) = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{j \in \mathcal{M}} R_j^{ue}[t] \tag{21}$$

$$G_{LB}(\mathbf{P}) = -\lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} pen[t] \tag{22}$$

where $\mathbf{P} = \left\{ \left\{ P_{ij}^{tx}[t] \right\}_{t=1}^{\infty}, \{ y_i[t] \}_{t=1}^{\infty} \right\}$ is the series of control decisions. Note that $G_0(\mathbf{P})$ is the objective function of the BSCC problem and $G_{LB}(\mathbf{P})$ is the average opposite value of the penalty function of the OPC problem. We denote the optimal control policies that yield the maximum value of $G_0(\mathbf{P})$ and $G_{LB}(\mathbf{P})$ by $\mathbf{P}_1^*$ and $\mathbf{P}_2^*$, respectively. The solution to the OPC problem over all time slots will be denoted by $\mathbf{P}_0$.

From Eqn. (1) – (3) and constraints (8) and (9), it can be derived that

$$G_{LB}(\mathbf{P}) \geq G_0(\mathbf{P}) - c_0, \quad \forall \mathbf{P} \tag{23}$$

where

$$\begin{aligned} c_0 = \max_{0 \leq x \leq SINR_m} &\left[\log_2(1+x) - \frac{\log_2(1 + SINR_m)}{SINR_m} \cdot x \right] \\ &\cdot M \cdot BW \end{aligned} \tag{24}$$

where $SINR_m$ is the upper bound of SINR for any channel. The value of c_0 is found by deriving the convex hull of the $G_{LB}(\mathbf{P})$ curve.

It has been proved in Theorem 4.8 of reference [17] that

$$G_{LB}(\mathbf{P}_0) \geq G_{LB}(\mathbf{P}_2^*) - \frac{B}{V} \tag{25}$$

where B is a constant. Moreover, applying the bound of $\leq G_{LB}(\mathbf{P})$ in Eqn. (23), we have

$$G_{LB}(\mathbf{P}_2^*) \geq G_{LB}(\mathbf{P}_1^*) \geq G_0(\mathbf{P}_1^*) - c_0 \tag{26}$$

Combining Eqn. (25) and Eqn. (26), we can find the optimality gap as follows

$$G_{LB}(\mathbf{P}_0) \geq G_0(\mathbf{P}_1^*) - c_0 - \frac{B}{V} \tag{27}$$

□

Note that even when $h_i[t]$ is not an i.i.d. process, the OPC-based control is still effective in practice, which is demonstrated in the experimental results in Section V.

To further reduce the complexity of the problem, we rewrite the objective function (20) in OPC problem as

$$\sum_{i \in \mathcal{N}} Sub_i[t], \tag{28}$$

where $Sub_i[t]$ is defined as

$$\begin{aligned} Sub_i[t] = &-\frac{BW}{N+1} \sum_{j \in \mathcal{M}} \log_2(1 + \frac{P_{ij}^{tx}[t] g_{ij} (N+1)}{P_j^{int} + \sigma^2}) \\ &- \sum_{j \in \mathcal{M}} Z_j[t] \cdot BW \cdot \log_2(1 + \frac{P_{ij}^{tx}[t] g_{ij}}{P_j^{int} + \sigma^2}) \\ &+ \sum_{j \in \mathcal{M}} Z_j[t] \frac{\gamma_{th}}{N+1} + \tilde{E}_i[t] \left(\frac{1}{\eta_D} e_i[t] - \eta_C h_i[t] \right) \end{aligned} \tag{29}$$

Note that $Sub_i[t]$ is independent of $P_{i'j}[t]$'s and $y_{i'}[t]$'s for any $i' \neq i$, and the constraints related to different base stations are also non-overlapping in the OPC problem. Consequently, the optimal solution of the OPC problem can be obtained by solving for optimal $Sub_i[t]$'s for each base station. The subproblem for base station i can be efficiently solved using a loop over the value of $y_i[t]$ (which can be either 0 or 1). In each iteration, the problem of solving for optimal $P_{ij}[t]$'s becomes a standard convex optimization problem and standard solution techniques such as the interior point method [18] can be used. The proposed solution framework is summarized in Algorithm 1.

Algorithm 1: Proposed Online Control Algorithm

for *each time slot* t **do**
    for *each base station* $i \in \mathcal{N}$ **do**
        Observe the virtual queue $Z_j[t]$
        Observe its energy depletion queue $\tilde{E}_i[t]$
        Set $y_i[t] = 1$, solve the $Sub_i[t]$ for active state
        Set $y_i[t] = 0$, solve the $Sub_i[t]$ for sleep state
        Set transmission power $P_{ij}^{tx}[t]$ and operation mode $y_i[t]$ to the set of result achieving smaller $Sub_i[t]$
    end
    for *each* $j \in \mathcal{M}$ **do**
        Compute $Z_j[t+1]$ according to Eqn. (14)
    end
    for *each* $i \in \mathcal{N}$ **do**
        Compute $\tilde{E}_i[t+1]$ according to Eqn. (15)
    end
end

V. Experimental Results

To numerically evaluate our proposed framework, we use the Youtube request trace data from a campus network measurement conducted on the University of Massachusetts' Amherst campus between June 2007 and March 2008[1]. Each data entry in the trace corresponds to a download record of video clip from Youtube server, consisting of a timestamp (in seconds), a client IP address, a requested video ID, and a Youtube server IP address. We parse the data on September 15, 2007 and obtain the information of 19,061 requests from 2,344 unique users. A cooperative region of 1 km^2 is considered which is covered by one MBS and four sBSs. All base stations are assumed to be solely powered using photovoltaic (PV) cells. We extract the solar radiation level from the TMY3 weather dataset on September from National Renewable Energy Laboratory (NREL) at Hawthorne Municipal Airport, Los Angeles[2]. The energy harvested by PV cells is computed using PVWatts calculator[3] with an energy conversion efficiency of 15%. The nominal capacity of batteries C_i^{max} in MBS and sBS is assumed to be 1 KWh and 0.1 KWh, respectively. We set the duration of each time slot to be 10 mins.

To estimate the SINR, the path-loss for an sBS and an MBS are modeled as $30.6 + 36.7 \log_{10}(d)$ and $35.3 + 37.6 \log_{10}(d)$ in dB, respectively [16], where d is the distance specified in kilometers from a UE to a base station. User locations are uniformly generated within the cooperative area. The noise power is set to $\sigma^2 = -95dBm$ [16]. The maximum numbers of cached files in the MBS and sBSs are set to 4,000 and 1,000, respectively. We adopt a least frequently used replacement strategy in caches in sBSs and MBSs which replaces 5% and 2% of entries every two hours. Specifications of other channel- and power- related parameters can be found in Table I. Note that some power-related parameters are set differently for the MBS and the sBSs.

Our proposed algorithm is compared against with two baseline algorithms. The first baseline is referred to as "MBS-only", which only considers the MBS and does not make use of sBSs at all. The second baseline is referred to as "greedy", in which each base station tries to use its maximum transmission power whenever it is possible. When the battery is depleted and there is not enough harvested energy, the base station will simply shut itself down until more energy is available. For the proposed algorithm, we use two different values of V as used in Eqn. (20).

The average download throughput per user and the state of charge in the battery pack of the MBS in each time slot are shown in Fig. 3 and Fig. 4, respectively. As can be seen from Fig. 3, the proposed algorithm achieves an average throughput of 82.5Mbps when $V = 10^5$ over all time slot and outperforms the two baselines by 2.96x and 1.41x, respectively. From Fig.

[1]http://traces.cs.umass.edu/index.php/Network/Network

[2]http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/

[3]http://pvwatts.nrel.gov/

TABLE I
SIMULATION PARAMETERS.

	Parameter	Value	Parameter	Value
Channel	BW	$10MHz$	γ_{th}	10 dBm
Converter	η_D	0.95	η_C	0.96
MBS [4]	P_0^{max}	$43\ dBm$	Δ_p	4.7
	P_0^{act}	$130\ W$	P_0^{slp}	$75\ W$
sBS [4]	P_i^{max}	$21\ dBm$	Δ_p	4.0
	P_i^{act}	$6.8\ W$	P_i^{slp}	$4.3\ W$

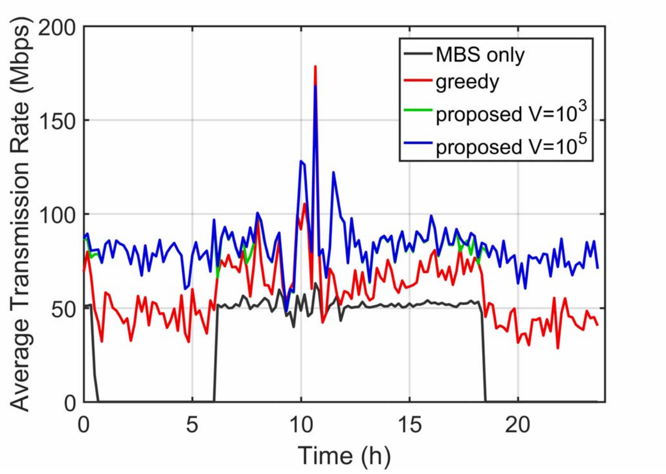

Fig. 3. Comparison of average download throughput per user

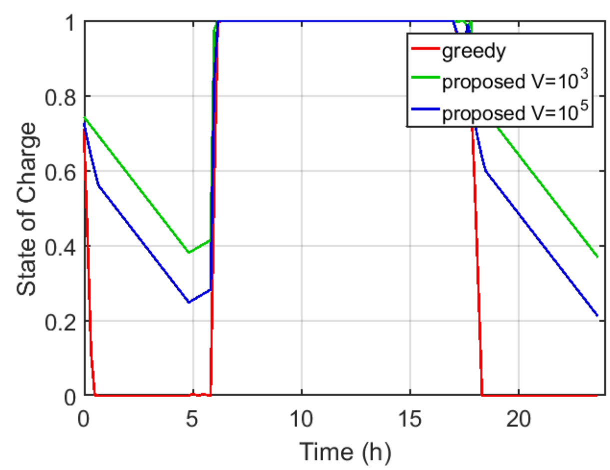

Fig. 4. Trace of state of charge in the MBS

4, one can see that the "greedy" algorithm will quickly drain the battery pack when the energy generation is low while the proposed algorithm can maintain a reasonable state of charge.

When using different values for V, one can observe from the results that there exists a tradeoff between the download throughput and the state of charge in the batteries. When a larger V is used, the download throughput will be higher. However, the battery pack will also be discharged faster, which can potentially increase the risk of battery depletion and service failure.

VI. CONCLUSIONS

In this paper, we investigate cooperative transmission and power management problem for base stations powered solely by renewable energy in a cellular network. We first formulate the data transmission throughput maximization problem into a mixed-integer non-linear programming problem. Then, based on Lyapunov optimization theory, an efficient near-optimal solution method is proposed which is proved to have a bounded optimality gap. Experimental results using realistic setting and data trace show that the proposed algorithm can achieve up to 2.96x average transmission rate compared to some baseline algorithms.

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