Online Ski Rental for Scheduling Self-Powered, Energy Harvesting Small Base Stations

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Abstract—The viral and dense deployment of small cell base stations (SBSs) will lie at the heart of 5G cellular networks. However, such dense networks can consume a significant amount of energy. In order to reduce the network's reliance on un-sustainable energy sources, one can deploy self-powered SBSs that rely solely on energy harvesting. Due to the uncertainty of energy arrival and the finite capacity of energy storage systems, self-powered SBSs must smartly schedule their ON and OFF operation. In this paper, the problem of ON/OFF scheduling of self-powered SBSs is studied in the presence of energy harvesting uncertainty with the goal of minimizing the tradeoff between power consumption and flow-level delay. To solve this problem, a novel approach based on the *ski rental framework*, a powerful online optimization tool, is proposed. To find the desired solution of the ski rental problem, a randomized online algorithm is developed to enable each SBS to autonomously decide on its ON/OFF schedule, without knowing any prior information on future energy arrivals. Simulation results show that the proposed algorithm can reduce power consumption and delay over a given time period compared to a baseline that turns SBSs ON by using an energy threshold. The results show that this performance gain can reach up to 12.7% reduction of the total cost. The results also show that the proposed algorithm can eliminate up to 72.5% of the ON/OFF switching overhead compared to the baseline approach.

I. INTRODUCTION

To support 24.3 Exabytes of mobile traffic in 2019, new cellular networking architectures are needed. One promising solution is by deploying dense, heterogeneous small cell networks (SCNs), which can increase the capacity up to 100 times [1]. However, dense small cell networks can also increase the overall power consumption of a cellular system. The power consumption from the access network and edge facilities account for up to 83% of mobiles' operator power consumption. To this end, enhancing the energy efficiency of dense SCNs has emerged as a major research challenge [2]. In particular, the grid power consumption can be significantly reduced by deploying energy harvesting, self-powered small cell base stations (SBSs) that rely solely on renewable and clean energy for operation [3]. However, reaping the benefits of self-powered SBSs mandates effective and self-organizing ways to optimize the ON and OFF schedules of such SBSs, depending on uncertain and intermittent energy arrivals, which are often uncertain and intermittent.

Recently, numerous research works have focused on the use of energy harvesting techniques in cellular networks [4]–[9]. For instance, the authors in [4] provide a model to measure the performance of heterogeneous networks with self-powered SBSs. Also, the work in [5] overviews key design issues for adopting energy harvesting into cellular networks. Along with energy harvesting, base station (BS) ON/OFF scheduling has been actively studied to enhance energy efficiency. In [6], the authors propose algorithms to minimize grid-power consumption when considering hybrid-powered BSs. For solving a capital expenditure minimization problem, the authors in [7] propose an ON/OFF scheduling method for self-powered BSs. The work in [8] investigates the problem of minimizing grid power consumption and blocking probability by using statistical information for traffic and renewable energy. The authors in [9] study the optimal BS sleep policy based on dynamic programming with the statistical energy arrival information.

In the existing body of literature that addresses ON/OFF scheduling in energy harvesting networks [6]–[9], it is generally assumed that statistical or complete information about the amount and arrival time of energy is perfectly known. However, in practice, energy arrivals are largely intermittent and uncertain since they can stem from multiple sources. Moreover, turning SBSs ON and OFF based on every single energy arrival instance can lead to significant handovers and network stoppage times. Further, the existing works [5], [6], and [8] on energy harvesting networks often assume the presence of both smart grid and energy harvesting sources at every SBS. In contrast, here, we focus on cellular networks in which SBSs are completely self-powered and reliant on energy harvesting. Unlike [4] which focuses on the global performance analysis of self-powered SBSs, our goal is to develop self-organizing and online algorithms for optimizing the ON/OFF schedule of self-powered SBSs.

The main contribution of this paper is to develop a novel framework that enables self-powered SBSs to autonomously find their optimal ON and OFF schedule, in the presence of *energy harvesting uncertainty*. In particular, we formulate an optimization problem that seeks to minimize delay and power consumption by properly turning off SBSs. To solve this problem, a novel approach based on the ski rental problem, a powerful online optimization framework [10], is proposed. We solve the proposed ON/OFF ski rental problem using a distributed randomized algorithm that enables each SBS to smartly make a decision on its ON and OFF time without having any prior information on future energy arrivals. *To the*
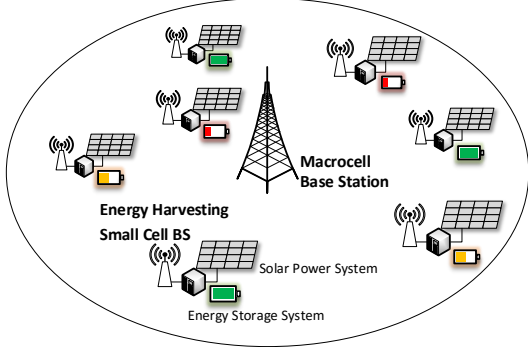
Fig. 1: System model of a heterogeneous deployment with self-powered SBSs.

best of our knowledge, this is the first work that exploits the online ski rental problem for managing energy uncertainty in cellular systems with self-powered SBSs. Simulation results show that the proposed algorithm can reduce power consumption and delay over a given time period compared with a baseline that turns SBSs ON based on a pre-determined energy threshold.

The rest of this paper is organized as follows. In Section II, the system model is presented. In Section III, we present the problem formulation, and we propose an online algorithm that is based on the ski rental framework. In Section IV, the performance of the proposed algorithm is demonstrated with using extensive simulations. Finally, conclusions are drawn in Section V.

II. SYSTEM MODEL

Consider a two-tier heterogeneous small cell network in which a macrocell base station (MBS) is located at the center of a service area. In this network, a set $\mathcal{J}$ of J self-powered SBSs are deployed randomly. Hereinafter, the MBS is indexed by m. Consequently, we define the set of all BSs as $\mathcal{B} = \{m, 1, 2, \cdots, J\}$. In this system, SBSs can offload traffic from the MBS thus reducing the overall network congestion.

An illustration of our system model is shown in Fig. 1. While the MBS is connected to the conventional power grid, SBSs are self-powered and rely exclusively on energy harvesting sources. For example, SBSs can be equipped with solar panels to procure energy for their operation, or alternatively, they can use wireless power transfer from MBS transmissions. To manage the intermittent and uncertain nature of energy harvesting, energy storage systems (ESSs) can be used. An SBS will store energy in its ESS when it is turned OFF and it consumes this stored energy when it is turned ON to service users.

A. Flow-level Model

The performance of our system is modeled by using flow-level dynamics. In the total area $\mathcal{A} \subset \mathbb{R}^2$ served by the BSs in $\mathcal{B}$, we consider that best effort flows arrive at location $x \in \mathcal{A}$ following a Poisson point process. The average arrival rate of the flows at location x is $\lambda(x)$, and the average file size of the flows is $1/\mu(x)$. Then, the traffic load density is defined as $\lambda(x)/\mu(x)$. We assume that the MBS does not interfere with the SBSs; however, SBSs experience mutual interference.

We let $\gamma_m(x) = P_m^{\text{tx}} h_m(x)/N_0$ be the signal to noise ratio. Here, P_m^{tx} is the transmit power of the MBS, $h_m(x)$ is the

channel gain from the MBS to any user at location x, and N_0 is the Gaussian noise. Meanwhile, if the flow at location x is associated with SBS j, $\gamma_j(x) = \frac{P_j^{\text{tx}} h_j(x)}{\sum_{\forall j' \in \mathcal{J}} P_{j'}^{\text{tx}} h_{j'}(x) + N_0}$ is the signal to interference plus noise ratio (SINR) of SBS j with P_j^{tx} being the transmit power of SBS j, and $h_j(x)$ the channel gain from SBS j to any user at location x. When a user at location x is associated with any BS $i \in \mathcal{B}$, the data rate is $c_i(x) = \log_2(1 + \gamma_i(x))$. The system load density of BS i is $\varrho_i(x) = \frac{\lambda(x)}{\mu(x)c_i(x)}$, which represents the fraction of time needed to serve the traffic in a unit area with $c_i(x)$.

We consider a time slotted system in which each operation slot period is T. Within period T, time is further divided into N slots indexed by n which is an integer between 0 and T. At the beginning of each operation slot, without loss of generality, we assume that user association for all users in $\mathcal{A}$ is done by minimizing (4) using known approaches such as those in [11]. Subsequently, the total area $\mathcal{A}$ can be represented by the sum of each non-overlapping area $\mathcal{A}_i$, as follows:

$$\mathcal{A} = \cup_{i \in \mathcal{B}} \mathcal{A}_i = (\cup_{j=1}^{J} \mathcal{A}_j) \cup \mathcal{A}_m, \tag{1}$$

where $\mathcal{A}_i$ is the area covered by BS $i \in \mathcal{B}$. Note that the initial user association can be changed when an SBS is turned OFF. Suppose that SBS j is turned OFF at time $t_j, \forall j \in \mathcal{J}$. We let $\mathcal{L}_{i,n}$ be the area served by BS i at time n. When $\mathcal{L}_{i,n}$ is the coverage area of BS i at time n, a user at location $x \in \mathcal{L}_{i,n}$ is associated with BS i. Due to the SBSs' ON/OFF operations, $\mathcal{L}_{i,n}$ can change at different n. For example, if SBS j is ON ($n < t_j$), $\mathcal{L}_{j,n} = \mathcal{A}_i$. However, if SBS j is turned OFF ($n \geq t_j$), $\mathcal{L}_{j,n} = \varnothing$, and $\mathcal{L}_{m,n} = \mathcal{A}_i \cup \mathcal{A}_m$, which means that the users served by SBS j are handed over to the MBS. The ON or OFF state of SBS j is denoted by σ_j^n that is given by

$$\sigma_j^n = \begin{cases} 1, & \text{if SBS } j \text{ is turned ON at time } n, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

Then, the utilization of BS $i \in \mathcal{B}$ needed to serve an area $\mathcal{L}_{i,n}$ at time n is:

$$\rho_i^{\mathcal{L}_{i,n}} = \int_{x \in \mathcal{L}_{i,n}} \varrho_i(x) dx. \tag{3}$$

From (3), the total delay needed to serve the total area $\mathcal{A}$ at time n is captured via the following cost function:

$$\Phi_n = \sum_{i \in \mathcal{B}} \phi_i^{\mathcal{L}_{i,n}} = \sum_{i \in \mathcal{B}} \frac{\rho_i^{\mathcal{L}_{i,n}}}{1 - \rho_i^{\mathcal{L}_{i,n}}}, \tag{4}$$

where $\phi_i^{\mathcal{L}_{i,n}}$ is a delay cost of BS i to serve $\mathcal{L}_{i,n}$ at time n.

B. Power Consumption Model

Next, we define the power consumption models for the MBS and SBSs. When modeling the power consumption of the MBS, the hardware system of the MBS includes complex components such as RF transmission, signal processing, battery backup, power supply, and cooling. Thus, the power consumption model for the MBS includes two components: the utilization-proportional power consumption and the fixed power consumption. The power consumption of MBS m at time n is therefore given by:

$$\psi_m^{\mathcal{L}_{m,n}} = (1-q)\rho_m^{\mathcal{L}_{m,n}} P_m^{\text{op}} + q P_m^{\text{op}}, \tag{5}$$

where q is a weighting parameter between the utilization-proportional power consumption and the fixed power, and P_m^{op} is the maximum power consumption when the MBS is fully utilized. Also, $P_m^{\text{tx}} = aP_m^{\text{op}}$ where the constant a denotes the fraction of the transmit power P_m^{tx} out of the total the maximum operational power P_m^{op}. For example, if $q = 1$, the MBS consumes constant power regardless of the utilization level of the MBS. On the other hands, if $q = 0$, the power consumption of the MBS is proportional to the utilization, which is an ideal BS power consumption model. For the SBSs, a constant power consumption model is used since SBS hardware has lower complexity than the MBS. If SBS j is turned ON, it consumes the operational power P_j^{op} that includes the transmit power P_j^{tx}.[1] An SBS consumes power when it is ON, so the power consumption of SBS j at time n is

$$\psi_{j,n} = P_j^{\text{op}} \sigma_j^n. \qquad (6)$$

Since SBSs use energy harvesting as a primary energy source, ESS can be used to store excessive energy for future use. Thus the available amount of energy at time n is given by

$$E_j^n = \min(E_j^{n-1} - \psi_j^{n-1} + \Omega_j^n, \ E_{\max}), \quad \forall j \in \mathcal{J}, \qquad (7)$$

where $E_j^n \geq 0$ is the stored energy of SBS j at n, Ω_j^n is the amount of energy arrival of SBS j at n, and $E_{\max}$ is the maximum capacity of ESS. Then, the total power consumption needed to serve the total network-wide area $\mathcal{A}$ at time n is:

$$\Psi_n = \sum_{j=1}^{J} \psi_j^n + \psi_m^{\mathcal{L}_{m,n}}. \qquad (8)$$

III. ON/OFF SCHEDULING AS AN ONLINE SKI RENTAL PROBLEM

Given the defined delay cost, power cost, and energy state, our goal is to analyze the optimal ON and OFF scheduling problem for the SBSs. In cellular networks consisting of self-powered SBSs, the amount of available energy is very limited. To enable energy harvesting as a primary energy source of SBSs, self-powered SBSs should intelligently manage their ON and OFF states considering delay, power, and energy state. Moreover, since future energy arrivals can be highly unpredictable, optimizing the ON and OFF schedule of SBSs is a very challenging problem. By properly scheduling its OFF duration, an SBS can reduce its the power consumption while also storing more energy for future use. However, at the same time, the SBS must turn ON for a sufficient period of time to service users and offload MBS traffic. To cope with the inherent uncertainty of energy harvesting while balancing the tradeoff between power consumption and cost, we introduce a novel, self-organizing online optimization framework for optimizing the ON and OFF schedule of self-powered SBSs.

A. Problem Formulation

As a first step, we formulate the global ON and OFF scheduling problem whose goal is to minimize the sum of the delay cost function and the power cost function, as follows:

$$\min_{\rho} \quad \sum_{n=1}^{N}(\Phi_n + \eta\Psi_n), \qquad (9)$$

$$\text{s.t.} \quad \rho = \{\rho_i^{\mathcal{L}_{i,n}} \mid \quad 0 < \rho_i^{\mathcal{L}_{i,n}} < 1, \qquad (10)$$
$$\forall i \in \mathcal{B}_n^{\text{on}}, \ 0 < n \leq T, \ \forall n \in \{1, 2, \cdots, N\}\}$$
$$\mathcal{L}_{j,t} = \mathcal{A}_j, \text{ if } \forall j \in \mathcal{B}_n^{\text{on}}, \qquad (11)$$
$$\mathcal{L}_{m,t} = (\cup_{j \in \mathcal{B} \setminus \mathcal{B}_n^{\text{on}}} \mathcal{A}_j) \cup \mathcal{A}_m, \qquad (12)$$
$$\mathcal{A} = \cup_{i \in \mathcal{B}_n^{\text{on}}} \mathcal{L}_{i,t}, \qquad (13)$$
$$\mathcal{L}_{i,t} \cap \mathcal{L}_{i',t} = \varnothing, \ \forall i, i' \in \mathcal{B}_n^{\text{on}}, \qquad (14)$$
$$E_j^n = \min(E_j^{n-1} - \psi_j^{n-1} + \Omega_j^n, E_{\max}), \forall j \in \mathcal{J}, \quad (15)$$

where η is a weighting parameter that captures the power-delay tradeoff between the delay cost function and the power cost function, and $\mathcal{B}_n^{\text{on}}$ is the set of ON BSs at time n. The problem in (9) is generally difficult to solve. First, the complexity of solving (9) is high since it is a combinatorial problem having an exponentially increasing number of cases along with the number of SBSs. Second, in (9), we want to minimize the total cost over time period T, however, the network may not know the uncertain future energy arrival information. If information about energy arrival is given, an offline algorithm can be used to find a solution for the problem. However, to solve this problem in a dynamically changing environment with uncertain energy arrivals, an online algorithm is more appropriate.

Therefore, to overcome these challenges, we propose a self-organizing approach in which the solution to (9) is done locally at each SBS. In particular, each SBS will solve an online version of the problem in (9) which will be to minimize a local cost that is given by (9) when $J = 1$. We use the fact that the value of the local cost at n is changed only when an ON/OFF state transition occurs. Then, the local cost is modified into an online problem of finding the optimal, per SBS OFF time. Thus, we derive the power and delay costs in the ON or OFF state. For each SBS j, we let t_j be OFF time n where each SBS determines its t_j. When $n < t_j$, SBS j is in ON state, and the costs are fixed as $\Phi_n = \phi_j^{\mathcal{A}_j} + \phi_m^{\mathcal{A}_m}$, and $\Psi_n = P_j^{\text{op}} + \psi_m^{\mathcal{A}_m}$. Similarly when $n \geq t_j, \forall n$, SBS is in OFF state, and the costs are fixed as $\Phi_n = \phi_m^{\mathcal{A}_m \cup \mathcal{A}_j}$, and $\Psi_n = \psi_m^{\mathcal{A}_m \cup \mathcal{A}_j}$. By doing so, $\mathcal{L}_{i,n}$ in Φ_n and Ψ_n is substituted by the coverage of an SBS or the MBS, and the constraints in (11)-(14) can be relaxed. Thus, the local cost that is given by (9) when $J = 1$ becomes

$$t_j(\phi_j^{\mathcal{A}_j} + \phi_m^{\mathcal{A}_m}) + (T - t_j)\phi_m^{\mathcal{A}_m \cup \mathcal{A}_j}$$
$$+ \eta(t_j(P_j^{\text{op}} + \psi_m^{\mathcal{A}_m}) + (T - t_j)\psi_m^{\mathcal{A}_m \cup \mathcal{A}_j}). \quad (16)$$

By subtracting a constant value $(\phi_m^{\mathcal{A}_m} + \eta\psi_m^{\mathcal{A}_m})T$ from (16), we have

$$t_j\phi_j^{\mathcal{A}_j} + (T - t_j)\Delta\phi_m^{\mathcal{A}_j} + \eta(t_j P_j^{\text{op}} + (T - t_j)\Delta\psi_m^{\mathcal{A}_j}), \quad (17)$$

where $\Delta\phi_m^{\mathcal{A}_j} = \phi_m^{\mathcal{A}_m \cup \mathcal{A}_j} - \phi_m^{\mathcal{A}_m}$, and $\Delta\psi_m^{\mathcal{A}_j} = \psi_m^{\mathcal{A}_m \cup \mathcal{A}_j} - \psi_m^{\mathcal{A}_m}$. Then, if an SBS j takes it own decision to turn OFF at t_j, the individual cost per SBS, $F_j(t_j)$ is essentially defined as (17) that can be presented by $r_j t_j + b_j$ where

$$r_j = \phi_j^{\mathcal{A}_j} - \Delta\phi_m^{\mathcal{A}_j} + \eta(P_j^{\text{op}} - \Delta\psi_m^{\mathcal{A}_j}), \qquad (18)$$
$$b_j = (\Delta\phi_m^{\mathcal{A}_j} + \eta\Delta\psi_m^{\mathcal{A}_j})T. \qquad (19)$$

r_j is the difference between the costs yielded by the ON or OFF state of SBS j, and b_j is the delay and power cost when the MBS services the area that was associated with SBS j. Thus, while SBS j is turned ON, the individual cost increases with the rate r_j during the ON period. Also, if the turn OFF time is t_j, a flat cost b_j is additionally imposed to the individual cost. In contrast, if SBS j has to be turned OFF due to energy depletion at a certain time u_j before t_j where u_j is the first time that the energy harvesting constraint (15) is not satisfied, we assume that the SBS can be OFF without incurring any additional cost. In that case, the individual cost $F_j(t_j)$ will be equal to $r_j u_j$. Hence, the per SBS problem is now to minimize the individual cost function when there is uncertainty of energy depletion. Due to the uncertainty of energy harvesting, SBS j does not have any knowledge about future energy arrivals; however, it has to make a decision for how long to turn ON. Since SBS j does not know the whole input sequence (e.g., uncertain energy arrivals), the SBS cannot know the optimal schedule of ON and OFF before time elapses. Thus, the per SBS problem becomes an online optimization problem, for which an online algorithm is needed to make a decision in real time under an uncertain future. Remarkably, the per SBS problem is analogous to the so-called *ski rental problem* [10], an online optimization framework that enables such decision making in face of uncertainty, as discussed next.

B. Randomized Online Algorithm

Here, first, we explicitly define the analogy between ski rental and self-powered BS scheduling. In the classical online ski rental problem, an individual is going skiing for an unknown number of days [12]. The uncertainty on the skiing period is due to factors such as nature or whether this individual will enjoy skiing or not. Here, the individual must decide on whether to rent skis over a short period of time or, alternatively, buy them for a long period of time, depending on the costs of renting and buying, the number of days that he/she will end up skiing, and on whether the skiing activity will be enjoyable. The online ski rental framework provides online optimization techniques that allows one to understand how an individual will make a "rent" or "buy" decision in such a scenario while facing uncertainty due to nature and while accounting for the tradeoff between the costs of rental and purchase and the benefits of skiing.

In this regard, our per SBS problem is similar to the ski rental decision making process. In our model, each SBS is an individual that must *rent* its resources (turn ON) to the network under the uncertainty of energy harvesting or alternatively *buy* more reliable MBS resources (and turn OFF). From (18) and (19), we can see that r_j and b_j will represent the prices for rent and buy, respectively. Thus, the decision of an SBS on how long to turn ON is essentially a decision on how long to rent its resources which require paying r_j per unit time. Once the SBS turns OFF, the network must buy the more expensive but more reliable MBS resources at a price b_j. Given this analogy, we can develop efficient online algorithms to solve the per SBS problem [10]. An *online algorithm* can solve the problem for each present time without having whole information about future energy harvesting results. In particular, to handle uncertainty, a rent or buy decision will be made by using a randomized online algorithm (ROA) by means of a probability distribution for ON/OFF scheduling designed to solve our cost-minimization problem.

To develop an ROA, a competitive analysis must be used. Competitive analysis [12] is a method used to compare between the performance of online algorithms and an performance of the optimal offline algorithm. For this analysis, we assume that an arbitrary input sequence, which corresponds to uncertain energy arrivals, is used to evaluate the performance of ROA. For an arbitrary input, the ROA computes an output (i.e., the turn OFF time, t_j) based on a probability distribution. We want to design an ROA that satisfies $\mathbb{E}[F_j(t_j)] < \kappa\beta_{\text{OPT}}$ where $F_j(t_j)$ is the individual cost per SBS for a value of t_j, and κ is a constant known as a *competitive ratio*, $\mathbb{E}[F_j(t_j)]$ is the expected cost of the online problem, and β_{OPT} is the optimal cost that can be achieved by using an offline algorithm that knows all input information. This is suitable for our problem since the input sequence is the energy arrivals at a given SBS, which are unknown and uncertain. Even though an SBS does not know the input sequence, the use of an ROA will give a solution that can at least achieve the expected cost of $\kappa\beta_{\text{OPT}}$.

First, we will compute the expected cost of the ROA. Suppose that the desired ON time of SBS j is t_j where t_j is determined by SBS j. Also, u_j is the possible ON time of SBS j since SBS j can be turned ON up to the moment when energy is depleted at time u_j. At time t_j, the state of the SBS can be either ON or OFF with probability distribution $p_j^{\text{on}}(t_j)$ or $p_j^{\text{off}}(t_j) = 1 - p_j^{\text{on}}(t_j)$. When an SBS decides to turn OFF at t_j, we have

$$\mathbb{E}[F_j(t_j)] = \int_0^{u_j} (r_j t_j + b_j) p_j'^{\text{off}}(t_j) dt_j + \int_{u_j}^T r_j u_j p_j'^{\text{off}}(t_j) dt_j,$$

where $p_j'^{\text{off}}(t_j)$ is the derivative of $p_j^{\text{off}}(t_j)$. Then, from $\frac{d}{du_j}\mathbb{E}[F_j(t_j)] = R_j(u_j)$, the rate of increase of the cost will be expressed by $R_j(u_j) = r_j p_j^{\text{on}}(u_j) + r_j u_j p_j'^{\text{on}}(u_j) + (r_j u_j + b_j) p_j'^{\text{off}}(u_j)$ where $p_j'^{\text{on}} = -p_j'^{\text{off}}$. To find the upper bound on F_j, we focus on the case in which the expected cost is at its largest value. Naturally, this is the same as finding the worst case in the online ski rental problem which corresponds to the case in which the individual buys the skis on one day, but is unable to use them in the next day. In our model, this corresponds to the case in which the SBS pays for the MBS resources at a price b_j at u_j due to the uncertainty of energy. However, at $u_j = t_j$, the SBS does not need to turn OFF by itself, since at that moment, the energy depletion will turn that SBS OFF automatically. In this worst case, the cost-increasing rate $R_j(u_j)$ becomes

$$\begin{aligned} R_j(t_j) &= r_j p_j^{\text{on}}(t_j) + r_j t_j p_j'^{\text{on}}(t_j) + (r_j t_j + b_j) p_j'^{\text{off}}(t_j) \\ &= r_j p_j^{\text{on}}(t_j) - b_j p_j'^{\text{on}}(t_j). \end{aligned}$$

By using the relationship $\mathbb{E}[F_j(t_j)] < \kappa\beta_{\text{OPT}}$, the cost-increasing rate of $\mathbb{E}[F_j(t_j)]$ cannot be larger than the cost-increasing rate of $\kappa\beta_{\text{OPT}}$. The cost-increasing rate of β_{OPT} with respect to u_j can be readily derived by choosing the rent or buy option that yields smaller cost. Now, we divide the range of u_j, t_j into two cases.

First, if $0 < u_j < b_j/r_j$ and $0 < t_j < b_j/r_j$, then the optimal cost-increasing rate is r_j which means that an SBS

Algorithm 1 Proposed Online Randomized Algorithm

1: Initialization: SBS $j \in \mathcal{J}$ determines r_j and b_j.
2: Find t_j s.t. $p_j^{\text{off}}(t_j) = \mu_j$, $\mu_j \sim U(0,1), \forall j \in \mathcal{J}$.
3: **while** $n \leq T$
4:     Update $n \leftarrow n + 1$.
5:     **If** ((15) is unsatisfied) or ($n = t_j$),
6:         **then** SBS j is turned OFF.
7:     **else** SBS j maintains its ON state.
8: **end while**
9: At $n = T$,
    update $P_j^{\text{op}}, P_j^{\text{tx}}, \forall j \in \mathcal{J}$, and user association.

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should be turned ON during t_j. Thus, the cost-increasing rate of ROA cannot be lower than κ times the optimal cost-increasing rate, we have $r_j \kappa = r_j p_j^{\text{on}}(t_j) - b_j p_j'^{\text{on}}(t_j)$. Since this is a first-order linear ordinary differential equation, the solution $p_j^{\text{on}}(t_j)$ is given by $p_j^{\text{on}}(t_j) = c e^{r_j t_j / b_j} + \kappa$ where c is a constant that can be found by using two boundary conditions. If an SBS starts with the ON state, then $p_j^{\text{on}}(0) = \kappa + c = 1$, and then $c = 1 - \kappa$.

Second, if $b_j / r_j < x$ and $b_j / r_j < t_j$, then using the MBS is the optimal choice. In this case, an SBS should buy the MBS resource before b_j / r_j. Thus, the SBS should remain in the OFF state at b_j / r_j. This fact leads us to find $p_j^{\text{on}}(b_j / r_j) = (1 - \kappa)e + \kappa = 0$, and we find $\kappa = e/(e-1)$. Therefore, we have the ON probability $p_j^{\text{on}}(t_j) = (e - e^{r_j t_j / b_j})(e - 1)$.

Remark 1. *At t_j, SBS j will turn OFF according to the following probability distribution,*

$$p_j^{\text{off}}(t_j) = \frac{e^{r_j t_j / b_j} - 1}{e - 1}. \tag{20}$$

The proposed online ski rental algorithm is summarized in Algorithm 1. From (20), we observe the tradeoff between rent and buy. The rent time becomes shorter if r_j is high and b_j is low. The short rent time means an SBS turns OFF early because buying the MBS resource would be more beneficial than using the SBS resource with the rent price. The proposed algorithm requires a low computational complexity since each SBS makes a decision only based on the probability distribution in (20). To update the distribution in (20) every period T, each SBS needs to obtain a few bits of information from the MBS about its utilization and, thus, Algorithm 1 will require a low signaling overhead. Each SBS will now run Algorithm 1 and can decide at time $t = 0$ when to turn off, without knowing any information on energy arrivals, by using the distribution in (20).

IV. NUMERICAL RESULTS

For our simulations, we assume that the SBSs are randomly distributed in a 2 km $\times$ 2 km area with one MBS located at the center of the area. We use typical parameters from [2]. In particular, the transmit power of an SBS is set to 13 dBm, and the operational power of the SBS is 9 W. Also, the transmit power of the MBS is set to 43 dBm, and the operational power of the MBS is 100 W. We use the modified COST231 path loss model with 2.1 GHz carrier frequency. The total bandwidth is 20 MHz, and the power spectral density of the thermal noise is -174 dBm/Hz. Without loss of generality, we assume that energy arrivals follow a Poisson
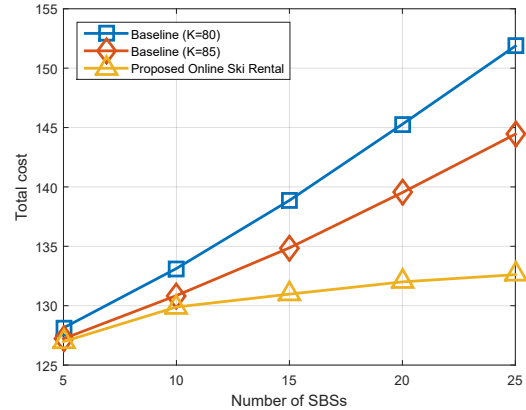

Fig. 2: Comparison of total network cost when using the proposed online ski rental algorithm and a baseline.
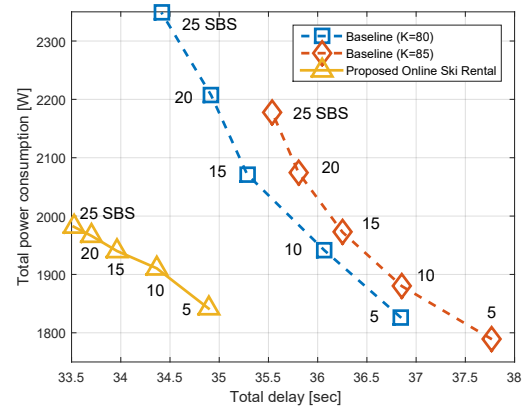

Fig. 3: Total power consumption and delay cost for the proposed algorithm and a baseline.

process in which energy arrival rate is 20, and each arrived energy is 0.2 J during $T = 10$ s, and $E_j^0 = 20$ J. Also, the traffic is assumed to be homogeneous. We use $\eta = 0.05$ and $q = 0.55$. Statistical results are averaged over large number of independent simulation runs during two time periods $2T$. We compare our online ski rental approach to a *baseline approach* that turns an SBS ON if and only if the percentage of charged energy in storage is greater than a threshold K. We set $K = 80$ J or 85 J such that an SBS maintains its ESS half-charged where the maximum capacity of ESS is $E_{\max} = 200$ J.

In Fig. 2, we show the total cost of the network as the network size varies. From this figure, we can first see that the overall cost of the network will increase as the number of SBSs increase. This is mainly due to the fact that increasing the number of SBSs will increase the overall power consumption of the network. Fig. 2 shows that the cost increase for the proposed online ski rental approach is much slower than that of the baseline approach. This demonstrates the effectiveness of the proposed approach. In particular, Fig. 2 shows that, at all network sizes, the proposed online ski rental approach yields reduction in the overall cost of the network. This performance advantage reaches up to 12.7% reduction of the average cost for 25 SBSs compared to the baseline with $K = 80$.

Fig. 3 shows, jointly, the power consumption and the total sum of network delay, for various numbers of SBSs.
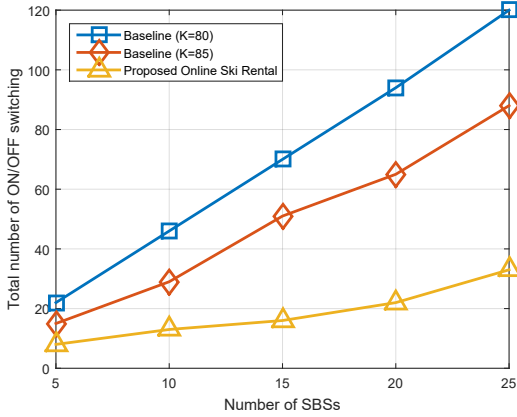
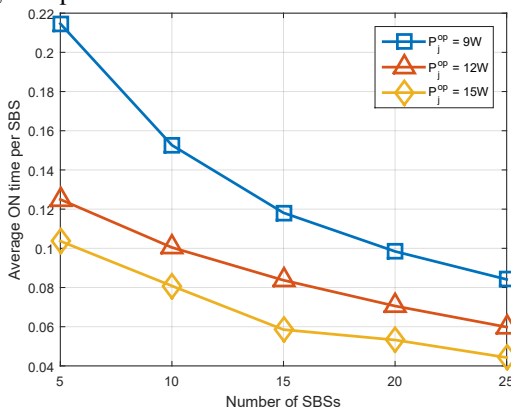Fig. 4: The number of ON/OFF switchings of the network during one period T.

Fig. 5: The average ON time per SBS during period T.

From Fig. 3, we can see that, for both algorithms, as the network size increases, the overall delay will decrease, but the energy consumption will increase. This is due to the fact that having more SBSs will enable the network to service users more efficiently, however, this comes at an increase in power consumption. Nonetheless, the proposed online algorithm is shown to have a much slower increase than the baseline approach. From Fig. 3, we can clearly see that the proposed algorithm significantly reduces both the delay and the energy consumption as compared to the baselines. This performance advantage, reaches up to 7.6% reduction in the delay relative to the baseline $K = 85$ at 5 SBSs and 15.6% reduction in energy consumption relative to the baseline with $K = 80$ at 25 SBSs.

In Fig. 4, we show the total number of ON/OFF operations within period T. The proposed online ski rental approach shows a lower number of SBS ON/OFF switchings whereas the baseline turns SBSs ON and OFF more frequently. This is mainly due to the fact that the baseline ($K = 80$) will turn ON all SBSs that have more than 40% of energy. Thus, in the baseline approach, the ON/OFF operation depends on the on energy arrivals which can be intermittent. However, the proposed approach turns an SBS ON and OFF only once in period T. Also, Fig. 4 shows that the number of switchings for the ski rental approach is less than the number of SBSs. This stems from the fact that, when the rent and buy prices are similar for some SBSs, it could be beneficial to choose the buy option earlier than expected and such SBSs will remain in

an OFF state. Fig. 4 shows that the performance advantage of the online ski rental approach reaches up to 72.5% of reduction in the number of ON/OFF operations for 25 SBSs when compared to the baseline $K = 80$.

Fig. 5 shows the average ON time per SBS within time period T. For the proposed online ski rental approach, we compare three different values for P_j^{op}: 9, 12, and 15 W. If an SBS uses a high P_j^{op}, then the rent price becomes higher. As the use of an SBS becomes more expensive, the SBS tends to buy the MBS resource. This, in turn, results in a shorter ON time as shown in Fig. 5. For instance, the average ON time is reduced by 51.6% if P_j^{op} is increased from 9 W to 15 W for a network with 5 SBSs.

V. CONCLUSION

In this paper, we have proposed a novel approach to optimize the ON/OFF schedule of self-powered small cell base stations. We have formulated the problem as an online ski rental problem which enables the network to operate effectively in the presence of energy harvesting uncertainty. We have shown that by using a randomized online algorithm, each SBS can autonomously decide on its ON time without knowing any prior information on future energy arrivals. Simulation results have shown that the proposed algorithm can reduce power consumption and delay over a given time period compared with a baseline that turns SBSs ON based on an energy threshold. The results show that this performance gain can reach up to 12.7% reduction of the total cost.

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