

Online Ski Rental for ON/OFF Scheduling of Energy Harvesting Base Stations

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Abstract—The co-existence of small cell base stations (SBSs) with conventional macrocell base station is a promising approach to boost the capacity and coverage of cellular networks. However, densifying the network with a viral deployment of SBSs can significantly increase energy consumption. To reduce the reliance on unsustainable energy sources, one can adopt 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 optimize their ON and OFF schedule. 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 operational costs consisted of energy consumption and transmission delay of a network. For the original problem, we show an algorithm can solve the problem in the illustrative case. Then, to reduce the complexity of the original problem, an approximation is proposed. To solve the approximated problem, a novel approach based on the *ski rental framework*, a powerful online optimization tool, is proposed. Using this approach, each SBS can effectively decide on its ON/OFF schedule autonomously, without any prior information on future energy arrivals. By using competitive analysis, a deterministic online algorithm (DOA) and a randomized online algorithm (ROA) are developed. The ROA is then shown to achieve the optimal competitive ratio in the approximation problem. Simulation results show that, compared to a baseline approach, the ROA can yield performance gains reaching up to 15.6% in terms of reduced total energy consumption of SBSs and up to 20.6% in terms of per-SBS network delay reduction. The results also shed light on the fundamental aspects that impact the ON time of SBSs while demonstrating that the proposed ROA can reduce up to 69.9% the total cost compared to a baseline approach.

Index Terms—Energy Harvesting, Cellular Networks, Optimization, Small Cell Networks, Online Algorithms, Ski Rental Problem.

I. INTRODUCTION

Despite their promising potential for enhancing the capacity and coverage of cellular systems, small cell networks (SCNs) can also increase the overall power consumption of a cellular system since the access network and edge facilities take up to 83% of mobiles' operator power consumption [2]. To this end, enhancing the energy efficiency of dense SCNs has emerged as a major research challenge [3]. In particular, there has been a recent significant interest, not only in minimizing energy consumption, but also in maximizing the use of green energy

by deploying energy harvesting, self-powered base stations (BSs) that rely solely on renewable and clean energy for operation [4]. Thus, deploying self-powered BSs is currently being demonstrated by various network operators. For instance, LG Uplus deploys solar-powered LTE BSs in mountain areas of South Korea [5], and, also, a large solar-powered BS cluster is deployed in Tibet by China Mobile [6]. Clearly, one can realize the vision of truly green cellular networks by deploying self-powered, energy harvesting small cell base stations (SBSs) that rely solely on renewable energy for their operation [7].

Recently, numerous works have focused on the use of energy harvesting techniques in cellular networks [8]–[17]. For instance, the work in [8] overviews key design issues for adopting energy harvesting into cellular networks and propose energy harvesting-aware user association and BS sleep mode optimization problems. With regards to the user association problem in energy harvesting scenarios, the authors in [9] consider a model in which wireless BSs are powered by both grid power and green energy in energy harvesting heterogeneous cellular networks. For this model, the authors propose a user association scheme that minimizes the average traffic delay while maximizing the use of green energy. Furthermore, the authors in [10] propose a probabilistic framework to model energy harvesting and energy consumptions of BSs and investigate a distributed user association problem when BSs are powered by energy harvesting. Also, to study the problem of user association, in [11], the authors considered a network in which the uncertainty of energy harvesting is modeled within a competitive market with the SBSs being the consumers who seek to maximize their utility function.

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. Therefore, several recent works have focused on optimizing energy efficiency in energy harvesting systems by intelligently turning BSs ON and OFF [12]–[17]. For instance, the authors in [12] provide a model to measure the performance of heterogeneous networks with self-powered BSs. In [13], when BSs are powered by both a renewable source and the power grid, the authors propose an algorithm to maximize the utilization of green energy so that the grid power consumption can be minimized. Moreover, the work in [14] develops a number of algorithms to minimize grid power consumption when considering hybrid-powered BSs. For solving a capital expenditure minimization problem, the authors in [15] propose an ON/OFF scheduling method for

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self-powered BSs. The work in [16] investigates the problem of minimizing grid power consumption and blocking probability by using statistical information for traffic and renewable energy. The authors in [17] study the optimal BS sleep policy based on dynamic programming with the statistical energy arrival information.

In this existing body of literature that addresses ON/OFF scheduling in energy harvesting networks [13]–[17], 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 [8], [9], [14], and [16] 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. In [18] and [19] the problem of ON/OFF scheduling of base stations is studied for a heterogeneous network using reinforcement learning. However, these works are focused on classical grid-powered networks and do not take into account the presence of energy harvesting in the system. Also, unlike the work in [12] 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 contributions of this paper is to develop a novel framework for optimizing the ON and OFF schedule of self-powered SBSs in a cellular network in which multiple SBSs coexist with a macrocell base station (MBS). In particular, an optimization problem is formulated that seeks to minimize the operational cost that captures both the power and delay of the system by appropriately determining the SBSs ON and OFF scheduling, *in the presence of complete uncertainty on the energy harvesting process*. We cast the problem as an online optimization and we analyze its properties. We show that, under an illustrative case, an algorithm achieves a competitive ratio, defined as the ratio of an online algorithm's to the optimal cost of an offline algorithm, of 2. Then, to overcome the complexity of the original problem, an approximation is derived and shown to allow the decomposition of the original problem into a set of distributed online optimization problems that are run at each SBS. To solve the resulting per-SBS online optimization problem, a novel approach based on the *ski rental problem*, a powerful online optimization tool [20], is proposed. In particular, we present two schemes to solve the ski rental problem: a deterministic online algorithm (DOA) and a randomized online algorithm (ROA). On the one hand, the DOA is a benchmark scheme designed to turn each SBS OFF at a predetermined time so as to achieve a competitive ratio of 2. On the other hand, the ROA enables the SBSs to make a decision according to a probability distribution, and it can achieve an optimal competitive ratio of $e/(e-1)$ which provides an upper bound for the approximated problem. The proposed algorithms allow the SBSs to effectively decide on their ON/OFF schedule, without knowing any prior

information on future energy arrivals. *To the 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 empirical competitive ratio of using the ROA to solve the original problem is 1.86. This demonstrates that the ROA achieves a reasonable performance gap compared to the ideal, offline optimal solution found by exhaustive search. Also, our results show that the ROA can decrease the total operational cost compared to the DOA and a baseline approach. Moreover, the ROA can reduce total energy consumption of SBSs and per-SBS network delay compared to DOA or a baseline that turns SBSs ON during the same fixed period for all SBS. This performance advantage is shown to reach up to 15.6% and 11.4% in reducing the energy consumption of a network relative to a baseline and the DOA, respectively. The ROA also decreases the delay per SBS up to 20.6% and 8.4% relative to a baseline and the DOA, respectively. In particular, we observe that the ON time of each SBS is affected by various factors including the harvested energy and the power consumption of BSs.

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. In Section IV, we propose online algorithms based on the ski rental framework. In Section V, the performance of the proposed algorithm is demonstrated with using extensive simulations. Finally, conclusions are drawn in Section VI.

II. SYSTEM MODEL

Consider the downlink of a two-tier heterogeneous small cell network in which an MBS is located at the center of a service area. In this network, a set \mathcal{J} of J self-powered SBSs are deployed. Moreover, we define the set of all BSs as $\mathcal{B} = \{0, 1, 2, \dots, J\}$ where the MBS is indexed by 0. We assume that the SBSs and the MBS will use different frequency bands and, therefore, the MBS and the SBSs will not interfere. In contrast, within the SBS tier, frequency bands may be reused and, as such, the SBS will interfere with one another. In this system, when activated, the SBSs can offload traffic from the MBS, thus reducing the overall network congestion. A set \mathcal{I} of I UEs is randomly distributed in the coverage of the MBS where each UE can access either an SBS or MBS. Each UE can be connected with only one of the BSs at a certain time t within a period of T .

An illustration of our system model is shown in Fig. 1. In our considered system, while the MBS is connected to the conventional power grid, SBSs are self-powered and rely exclusively on energy harvesting sources. In such case, the self-powered SBSs will operate as a means to boost capacity and to complement the existing grid powered MBS. 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. Since the characteristics of the harvested energy can be highly dynamic, we do not make any specific assumption on the energy harvesting process. Thus, our model can accommodate any type of energy harvesting mechanism. To enhance the overall

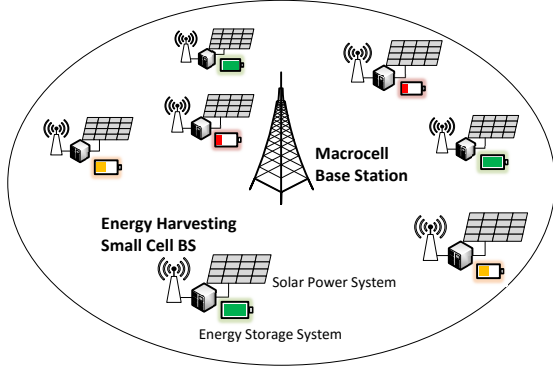


Fig. 1: System model of a heterogeneous deployment with self-powered SBSs.

energy efficiency of the system, we assume that the SBSs can dynamically turn ON or OFF, depending on the network state, energy harvesting state, and other related parameters. To manage the intermittent and uncertain nature of energy harvesting, energy storage systems (ESS) can be used. Energy harvesting is assumed to be done irrespective on whether an SBS is turned ON or OFF. Thus, an SBS will store energy in its ESS when it is turned OFF, and this stored energy can be used when it is turned ON to service users. Also, when it is turned ON, an SBS can store the excess of harvested energy if instantaneous harvested energy is enough to operate an SBS.

At time t , the ON or OFF state of SBS j is denoted by $\sigma_j(t)$ which is defined as follows:

$$\sigma_j(t) = \begin{cases} 1, & \text{if SBS } j \text{ is turned ON at time } t, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

For the MBS, $\sigma_0(t) = 1$ since the MBS is always turned ON. The set of switched-ON BSs at time t is denoted by $\mathcal{B}^{\text{on}}(t) = \{j | \sigma_j(t) = 1, \forall j \in \mathcal{B}\}$. Similarly, the set of switched-OFF BSs can be shown as $\mathcal{B}^{\text{off}}(t) = \mathcal{B} \setminus \mathcal{B}^{\text{on}}(t)$.

A. Network Performance

We model the network performance between BS and UE. In the downlink, the signal to interference and noise ratio (SINR) between UE i and SBS $j \in \mathcal{J}$ at time t can be shown as

$$\gamma_{ij}(\sigma(t)) = \frac{P_j^{\text{tx}} \sigma_j(t) h_{ij}}{\sum_{j' \in \mathcal{B}^{\text{on}} \setminus \{j\}} P_{j'}^{\text{tx}} \sigma_{j'}(t) h_{ij'} + \rho^2}, \quad (2)$$

where $\sigma(t) = [\sigma_j(t) | \forall j \in \mathcal{J}]$, h_{ij} is the channel gain between UE i and SBS j , P_j^{tx} is the transmit power of the connected SBS j , and ρ^2 is the noise power. If an UE is associated with an SBS, the UE can receive interference from the other SBSs. On the other hand, when a UE is associated with the MBS, the UE does not experience any interference from the SBSs. Therefore, when UE i is associated with the MBS, the signal to noise ratio (SNR) at UE i will be:

$$\gamma_{i0}(\sigma(t)) = \frac{P_0^{\text{tx}} h_{i0} \sigma_0(t)}{\rho^2}, \quad (3)$$

where h_{i0} is the channel gain between UE i and the MBS, and P_0^{tx} is the transmit power of the MBS. The channel gain h_{ij} can be seen as the time-averaged gain.

When $\gamma_{ij}(\sigma(t))$ is given, UE i is associated with the BS $j^*(i, \sigma(t))$ that provides the largest SINR or SNR depending on whether $j^*(i, \sigma(t))$ is an SBS or MBS, respectively. Therefore, the user association can be given by:

$$j^*(i, \sigma(t)) = \operatorname{argmax}_{j \in \mathcal{B}^{\text{on}}(t)} \gamma_{ij}(\sigma(t)). \quad (4)$$

By using the user association rule in (4), the user association of whole network is updated at each time t . Then, the set of UEs associated with the same BS j can be defined by

$$\mathcal{I}_j(\sigma(t)) = \{i | j^*(i, \sigma(t)) = j, \forall i\}. \quad (5)$$

The set $\mathcal{I}_j(\sigma(t))$ changes over time t according to the user association results from (4). If $j \neq 0$, then $\mathcal{I}_j(\sigma(t))$ indicates the set of UEs associated with SBS j . Otherwise, when $j = 0$, then $\mathcal{I}_0(\sigma(t))$ indicates the set of UEs connected to the MBS. Subsequently, the set of all UEs \mathcal{I} can be divided into $J + 1$ subsets at most, each of which is denoted by $\mathcal{I}_j(\sigma(t))$, $j \in \mathcal{J}$. Thus, each UE should be associated with one of BSs at any time $0 \leq t \leq T$ from (4), and, thus, we have $\mathcal{I} = \cup_{j=0}^J \mathcal{I}_j(\sigma(t))$, $0 \leq t \leq T$.

When the user association is determined by (4), the achievable data rate of UE i is given by

$$c_{ij}(\sigma(t)) = \frac{B}{|\mathcal{I}_j(t)|} \log_2(1 + \gamma_{ij}(\sigma(t))), \quad (6)$$

where $|\mathcal{I}_j(t)|$ is the number of UEs associated with SBS j at time t , and B is the bandwidth of an SBS ($B = B_s$) or MBS ($B = B_m$). When the MBS can transmit data to UEs using bandwidth B_m , time slots are scheduled for the $|\mathcal{I}_0(t)|$ UEs using a round robin scheduling. In the considered model, whenever a file of K bits needs to be transmitted to each UE, we can define the total transmission delay between BS j and all UE in $\mathcal{I}_j(t)$ at time t as

$$\phi_j(\sigma(t)) = \sum_{i \in \mathcal{I}_j(\sigma(t))} \frac{K}{c_{ij}(\sigma(t))}. \quad (7)$$

B. Power Consumption

Next, we define the power consumption models for the MBS and SBSs. When modeling the power consumption of BSs, the resource utilization of a BS monotonically increases as the number of UE connections increases. Thus, the power consumption of a BS increase as the utilization become higher. The power consumption model for a BS includes two components: the utilization-proportional power consumption and the fixed power consumption. The utilization-proportional power consumption depends on the signal processing functions and, hence, it varies depending on the number of associated UEs at a BS. Meanwhile, the fixed power components pertain to the power consumed due to components such as the power amplifier or the cooler. Thus, a fixed amount of power is required to operate the BS regardless of the number of the associated UEs. The power consumption of a BS at time t is therefore given by:

$$\psi_j(\sigma(t)) = \frac{|\mathcal{I}_j(\sigma(t))|}{M} (1 - q) P_j^{\text{op}} + q P_j^{\text{op}}, \quad (8)$$

where q is a weighting parameter that captures the tradeoff between the utilization-proportional power consumption and the fixed power, P_j^{op} is the maximum power consumption when the BS is fully utilized, and M is the maximum number of UE connections. If the type of BS j is a MBS, then we set $M = M_m$, and, if BS j indicates an SBS, then $M = M_s$. The MBS can provide service to the larger number of UEs since the MBS has higher computing capability than an SBS;

thus, the different service capabilities can be presented by $M_m \geq M_s$. Also, $P_j^{\text{tx}} = aP_j^{\text{op}}$ where the constant a denotes the fraction of the transmit power P_j^{tx} out of the total the maximum operational power P_j^{op} . For example, if $q = 1$, the BS consumes constant power regardless of the utilization level of the BS. On the other hand, if $q = 0$, the power consumption of the BS is proportional to the utilization, which is a more realistic BS power consumption model. Note that $\psi_j(\sigma(t))$ is the power required to turn ON SBS j at time t , and it depends on the number of UEs associated with SBS j .

As mentioned, SBSs use energy harvesting as a primary energy source, so an ESS can be used to store the excess energy for future use. The available amount of energy at time t is given by

$$E_j(t) = \min \left(\int_0^{t-\epsilon} \Omega_j(\tau) d\tau - \int_0^t \psi_j(\sigma(\tau)) d\tau, E_{\max} \right), \forall j \in \mathcal{J}, \quad (9)$$

where $E_j(t) \geq 0$ is the stored energy of SBS j at time t , $\psi_j(\sigma(t))$ is the consumed power of SBS j , $\Omega_j(t)$ is the amount of energy arrival of SBS j , ϵ is a small number, and E_{\max} is the maximum capacity of ESS. $\Omega_j(t)$ captures the uncertainty of energy harvesting in the time domain. Since an SBS solely relies on the energy harvesting, if $E_j(t)$ becomes zero at a certain time t , SBS j is turned OFF at time t , and the UEs connected to SBS j are handed over to other SBSs or the MBS according to the user association rule (4).

C. Operational Expenditure of Base Stations

Given the defined network delay and power consumption models, we define operational costs incurred when using an SBS or MBS. First, we account for the operational cost of a given SBS per unit time when an SBS is turned ON. In the ON state, UEs associated with SBS j experience the network delay given by $\phi_j(\sigma(t))$. Since higher delay is an unfavorable aspect, the operational cost has to increase with the network delay of UEs. Moreover, while an SBS is turned ON, it will incur a power consumption cost. Thus, to turn SBS j ON at time t , the required cost of using SBS j can be defined by

$$r_j(\sigma(t)) = \alpha_D \phi_j(\sigma(t)) + \alpha_P \psi_j(\sigma(t)), \quad (10)$$

where the constant α_D is the monetary cost per unit transmission delay, and the constant α_P is the monetary cost per unit power consumption. α_D and α_P can be used to change the weighting of delay and power consumption. The delay and energy are combined in (10) so as to balance the tradeoff between the two metrics. The cost $r_j(\sigma(t))$ of a given SBS j can vary over time due to the fact that the user association of UEs can change between two different times t and t' , i.e., $\mathcal{I}_j(\sigma(t)) \neq \mathcal{I}_j(\sigma(t'))$. Thus, different user associations can result in different $\phi_j(\sigma(t))$ and $\psi_j(\sigma(t))$ since the data rate of each UE and the number of connected UEs per SBS are different.

Next, we model the cost for using the MBS. When self-powered SBSs rely solely on the harvested energy that is highly uncertain and intermittent, they might need to turn OFF if they have no more energy. Therefore, to avoid the risk of such energy depletion, the SBSs can go into an energy-saving OFF state to store additional energy for future use. Due to this energy storage need, the system can end up with a large

number of OFF SBSs which, in turn, will degrade the network performance as it increases congestion at the MBS and the ON SBSs. Thus, to prevent such a network congestion, if SBS j decides to switch OFF, we assume that it will be charged a cost b_j . By setting a flat-rate cost b_j , the network can control how often the SBSs can turn OFF, particularly when they still have a sufficient amount of energy stored. Here, as b_j increases, the penalty of turning a given SBS j OFF becomes larger; thus, the SBSs will have an incentive to maintain the ON state as long as possible. In a dynamic network, the ON and OFF states of the SBSs can change over time thus also changing the user association. In such a dynamic network, finding an exact, flat rate b_j is difficult. Therefore, we propose to derive this cost based on a worst-case assumption. In particular, to define the cost b_j , first we find the maximum cost of using the MBS which is then scaled by a parameter $\alpha_B \in [0, 1]$. The cost b_j is the maximum cost that can be incurred by turning OFF and transferring traffic to the MBS. To find the maximum cost of using the MBS in the worst case, suppose that all UEs can be associated with the MBS so that the network delay and power consumption of the MBS are maximized. Here, when a portion of the maximum cost is incurred to an SBS, the incurred cost can depend on the UEs in the SBS denoted by the set $\mathcal{I}_j(\sigma(0))$. By doing so, the maximum cost of using the MBS can be divided into the per-SBS costs. If UE $i \in \mathcal{I}_j(0)$ is connected to the MBS, the transmission delay of UE i will be $\frac{K}{\frac{B_m}{T} \log_2(1 + \gamma_{i0}(0))}$. By summing over all UEs in $\mathcal{I}_j(0)$, we obtain the network delay corresponding to the UEs in $\mathcal{I}_j(0)$, as shown as

$$\Phi_0^{\mathcal{I}_j(0)} = \sum_{i \in \mathcal{I}_j(0)} \frac{K}{\frac{B_m}{T} \log_2(1 + \gamma_{i0}(0))}. \quad (11)$$

Also, the portion of the power consumption of the MBS that is consumed by the UEs in $\mathcal{I}_j(0)$ will be:

$$\Psi_0^{\mathcal{I}_j(\sigma(0))} = \frac{|\mathcal{I}_j(\sigma(0))|}{M} (1 - q) P_0^{\text{op}} + q P_0^{\text{op}}. \quad (12)$$

Consequently, whenever an SBS j decides to turn OFF, the accompanying cost, due to the handover to the MBS, will be given by:

$$b_j = \alpha_B \left(\alpha_D \Phi_0^{\mathcal{I}_j(\sigma(0))} + \alpha_P \Psi_0^{\mathcal{I}_j(\sigma(0))} \right) T, \quad (13)$$

where $\alpha_B \in [0, 1]$ is the fraction of the maximum cost. For example, when we set $\alpha_B = 0.10$, then 10% of the maximum cost of using the MBS during time period T will be incurred to SBS j . Thus, if the value of b_j is too high, being turned ON becomes an affordable option, so SBS j is turned ON until the whole harvested energy is used. On the other hand, if the value of b_j is low, SBSs tend to be turned OFF to keep the stored harvested energy due to a low penalty in switching SBSs OFF.

III. PROBLEM FORMULATION

Given the operational costs, 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 dynamically changing and very limited. To be able to operate using 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 energy 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. In our problem, information on energy arrival is unknown, so an online optimization approach is suitable. To cope with the inherent uncertainty of energy harvesting while balancing the tradeoff between energy consumption and network delay, we introduce a novel, self-organizing *online optimization framework* for optimizing the ON and OFF schedule of self-powered SBSs.

A. ON/OFF Scheduling as an Online Optimization Problem

We formulate the global ON and OFF scheduling problem with the goal of minimizing the sum of costs that encompass the costs of using an SBS and the MBS in (10) and (13), as follows:

$$\min_{\sigma(t), \mathbf{x}} \sum_{j=1}^J \left(\int_0^{u_j} r_j(\sigma(\tau)) \sigma_j(\tau) d\tau + b_j x_j \right), \quad (14)$$

$$\text{s.t.} \quad \sigma_j(t) + x_j \geq 1, \quad 0 \leq t \leq u_j, \quad \forall j, \quad (15)$$

$$\sigma_j(t) \in \{0, 1\}, \quad 0 \leq t \leq u_j, \quad \forall j, \quad (16)$$

$$x_j \in \{0, 1\}, \quad \forall j, \quad (17)$$

where $\mathbf{x} = [x_j | \forall j \in \mathcal{J}]$, respectively. The ON and OFF states of SBS j at time t is denoted by $\sigma_j(t)$ in (16). Also, x_j in (17) indicates whether SBS j is determined to be turned OFF before SBS j 's stored energy is depleted at time u_j . In (15) and (16), time $t > u_j$ is not considered since SBS j is turned OFF due to energy depletion. Note that u_j is the first moment when energy harvesting constraint (9) is not satisfied. Thus, each SBS can experience energy depletion at a different time u_j since the amount of energy arrival of SBS j denoted by $\Omega_j(t)$ is unknown before time t , and SBS j cannot know the future energy status, as observed in many real-world scenarios [21]. For example, when energy is harvested from the environment, the amount of harvested energy can quickly change due to factors such as weather conditions which can change rapidly during are changing in a short period of time. Not only the sudden weather, long-term seasonal changes also brings uncertainty into energy harvesting. Therefore, the uncertainty of the harvested energy at each moment can be captured by $\Omega_j(t)$, and, thus, the energy depletion time u_j is *unknown* in our problem. In essence, our problem is online where energy harvesting brings in uncertainty about the future event. The period T can be defined in various ways. For example, T can be defined as a short period of time during which the SBS can stay ON using a fully charged battery.

Also, it is required to reduce the network congestion by increasing the use of the harvested energy, so the ON time of each SBS needs to be extended. In problem (14), if an SBS is turned OFF due to energy depletion, the cost of using the MBS is not incurred to the SBS so as to provide incentives for SBSs to maintain a longer ON period. However, if SBS j is turned OFF according to its decision, the cost of using the MBS is incurred to the SBS, as captured by setting $x_j = 1$. Therefore, the ON and OFF scheduling solution given by $\sigma_j(t)$ and x_j

can be determined by SBS j during $1 \leq t \leq u_j$ so that UEs in $\mathcal{I}_j(\sigma(t))$ can be connected to either SBS j ($\sigma_j(t) = 1$) or the MBS ($x_j = 1$) by satisfying constraint (15).

If the problem is offline, then it can be readily solved. For example, in the offline scenario, the optimal solution is either always ON strategy ($\sigma_j(t) = 1, 0 \leq t \leq u_j, x_j = 0$) or OFF strategy ($\sigma_j(t) = 0, 0 \leq t \leq u_j, x_j = 1$). When u_j is known in offline, it is possible to compute the total costs corresponding to a strategy that the SBS uses. Thus, since the SBS can compare the costs of all possible solutions, the optimal solution can be found. However, such offline scenario is not available in real environment due to the uncertainty of energy harvesting as mentioned above. Thus, the problem (14) needs to be considered in an online optimization framework.

To solve (14), one must develop a suitable online algorithm. To assess the effectiveness of such an algorithm, we need to use competitive analysis. Competitive analysis [22] is a method used to compare between the performance of online algorithms and that of an optimal offline algorithm. One key metric in competitive analysis is the so-called competitive ratio, defined next:

Definition 1. The *competitive ratio* of an online algorithm is defined by

$$\kappa = \max_{u_j} \frac{\beta_{\text{ALG}}(u_j)}{\beta_{\text{OPT}}(u_j)}, \quad \forall u_j, \quad (18)$$

where u_j is a random time instant when harvested energy is depleted, $\beta_{\text{ALG}}(u_j)$ is the cost of an online algorithm that corresponds to the total cost of the problem (14), and $\beta_{\text{OPT}}(u_j)$ is the optimal cost achieved by using an offline algorithm that knows all input information.

When we use an online algorithm, our goal is to find an algorithm that minimize the competitive ratio κ . Therefore, in competitive analysis, the competitive ratio is meaningful since it shows the performance of an online algorithm [23]. For this analysis, the competitive ratio of online algorithms is evaluated for a given arbitrary input sequence that corresponds to uncertain energy arrivals. In our model, the arbitrary input sequence is characterized by u_j that is the moment of energy depletion. From the competitive analysis, even though an SBS does not know the input sequence, the use of online algorithms will give a solution that can at least achieve the cost of $\kappa \beta_{\text{OPT}}(u_j)$.

To analyze this problem, first, we consider two special cases in which: a) $r_j(\sigma(t))$ is decreasing over time or b) $r_j(\sigma(t))$ is increasing over time. If an SBS's $r_j(\sigma(t))$ decreases, the SBS can have motivation to extend its ON time since the cost of using SBS becomes inexpensive. Thus, the SBS can simply extend the ON time. On the other hand, if $r_j(\sigma(t))$ increases, the SBS has less motivation of maintaining the ON state. Moreover, in this case, it is possible that the SBS could stay in the OFF state from the beginning if the SBS knew the increasing of $r_j(\sigma(t))$. Therefore, since the SBS cannot change its previous decisions in the case in which $r_j(\sigma(t))$ is increasing, it is difficult to minimize the total cost.

Thus, we present an example case where the cost of using an SBS $r_j(\sigma(t))$ decreases as the time t increases. By doing so, we can propose an ON and OFF scheduling algorithm that

achieves a finite competitive ratio. Note that the decreasing of $r_j(\sigma(t))$ can be physically observed when an SBS increases the transmission power so that it can decrease the delay cost of the SBS as shown in our simulations. In such case, we propose an online algorithm in which the SBS is turned OFF at a predetermined time \bar{t} . When the value of $r_j(\sigma(t))$ decreases, each achieved value for $r_j(\sigma(t))$ will be denoted by $r_{(v)}$. These values are then arranged in a descending order where v indicates the order of a given value $r_{(v)}$, as follows:

$$r_{(1)} > r_{(2)} > \dots > r_{(v-1)} > r_{(v)}. \quad (19)$$

Here, we note that, $r_j(\sigma(t))$ changes from $r_{(v-1)}$ to $r_{(v)}$ at time $t_{(v-1)}$, and $r_{(v)}$ stays constant from $t_{(v-1)}$ to $t_{(v)}$ where $t_{(0)} = 0 < t_{(1)} < t_{(2)} < \dots < t_{(v-1)} < t_{(v)}$.

Theorem 1. When $r_j(\sigma(t))$ decreases over time t in the problem (14), the initial SBS's OFF time is given by $\bar{t} = b_j/r_{(1)}$ at time $t_{(0)}$. Also, at time $t_{(v-1)}$, $v \geq 2$, the SBS's OFF time is updated using the following equation:

$$\bar{t} = \frac{b_j}{r_{(v)}} - \frac{1}{r_{(v)}} \sum_{v'=1}^{v-1} t_{(v')} (r_{(v')} - r_{(v'+1)}). \quad (20)$$

Then, the OFF time \bar{t} increases when it is updated by (20). Also, an online OFF time scheduling algorithm that uses \bar{t} can achieve a competitive ratio of 2.

Proof. See the Appendix. \square

In Theorem 1, at the time in which the SBS's cost $r_j(\sigma(t))$ is updated, the SBS update its ON time by setting a larger value for \bar{t} . Thus, the updated \bar{t} effectively optimizes the problem.

To investigate more dynamically changing $r_j(\sigma(t))$ needs to be considered. However, since the value of $r_j(\sigma(t))$ depends on the ON/OFF state of SBSs in a network, the exact value of a future $r_j(\sigma(t))$ cannot be known and expected. For instance, if the neighboring SBSs are turned OFF, the interference at SBS j will be reduced thus increasing the data rate of UEs that are associated with SBS j . This, in turn, results in a smaller delay cost and reduces $r_j(\sigma(t))$. At the same time, UEs associated with other, neighboring SBSs may be handed over to SBS j . Then, the number of UEs served by SBS j increases thus increasing the delay cost. In addition, due to the increase of the number of UEs, the power consumption of SBS j also increases thus yielding a higher $r_j(\sigma(t))$. As seen from these illustrative scenarios, the OFF scheduling of the various SBSs can either increase or decrease $r_j(\sigma(t))$. Therefore, the cost of using a given SBS will not always be monotonically increasing or decreasing thus making it very challenging to find a solution to the optimization problem in (14) by estimating the future variation of $r_j(\sigma(t))$ over time t . Moreover, to solve (14), the ON and OFF states of all SBS must be collected by the network which can generate additional signaling overhead for information exchange. This can also require the use of a centralized controller. Naturally, in a dense SCN, such centralized control may not be possible or scalable.

Consequently, in essence, our goal is to devise a self-organizing approach in which the solution to (14) can be done locally at each SBS. Clearly, solving this problem for a generic, non-monotonically changing $r_j(\sigma(t))$ is challenging

and, therefore, we need to use an approximation. One natural way is to assume that $r_j(\sigma(t))$ is not time-varying, which can simplify the problem because the interference and user association that change over time do not need to be considered, as discussed next.

B. Approximated Problem

To relax the time dependence from $r_j(\sigma(t))$, we assume that the cost will be equal to $r_j = r_j(\sigma(0))$. In other words, the initial cost, which is generally known to the network, will be used as a flat cost of using an SBS. This approximation can help simplify the problem by considering a worst-case assumption for the interference, as follows. As mentioned, the cost $r_j(\sigma(t))$ incurred to an SBS j is affected by interference when other SBSs are randomly turned OFF. However, by approximating $r_j(\sigma(t))$ using a constant value, the scheduling decisions will no longer be dependent and, thus, each SBS can make its own decision without having global knowledge about other SBSs' ON and OFF states. Note that the largest value of the interference is captured in the approximated problem since all SBSs are turned ON at the beginning. Thus, the SBSs can compute the value of r_j even though all SBSs are not actually turned ON. One key advantage of the proposed approach is that an SBS can determine the solution at the beginning of each period T . Thus, distributed optimization can be done by computing locally, and also it reduce network overhead since signaling is not required. Here, the approximated problem can be given by:

$$\begin{aligned} \min_{\sigma(t), x} \quad & \sum_{j=1}^J \left(\int_0^{u_j} r_j \sigma_j(\tau) d\tau + b_j x_j \right), \\ \text{s.t.} \quad & (15), (16), \text{ and } (17). \end{aligned} \quad (21)$$

To solve problem (21), we decompose it into smaller, per SBS subproblems. As shown next, each SBS can solve an individual optimization subproblem, so the approximated problem in (21) can be solved in a distributed way.

Proposition 1. The problem in (21) can be decomposed into $|\mathcal{J}|$ subproblems.

Proof. The objective function of the problem (21) can be shown to be a sum of functions of $\sigma_j(t)$ and x_j as shown as (21). Thus, changing of $\sigma_j(t)$ and x_j does not affect $\sigma_{j'}(t)$ and $x_{j'}$, $j' \neq j$. Therefore, the objective function of (21) can be separated into $|\mathcal{J}|$ functions. Also, each SBS's energy storage is not connected to other SBSs' energy source. Thus, due to the isolated energy harvesting system of each SBS, the amount of stored energy shown as (9) is managed independently by each SBS. Hence, the problem (21) can be decomposed into $|\mathcal{J}|$ subproblems. \square

Now, we have $|\mathcal{J}|$ subproblems derived from the approximated problem in (21). The ON or OFF decision of an SBS does not affect the decision of another SBS, so we can solve $|\mathcal{J}|$ subproblems in parallel. By solving each of the per-SBS problems, we can significantly reduce complexity and overhead while allowing for a self-organizing implementation. Consequently, each SBS will solve its local version of (21) that seeks to minimize its individual cost function given by

$$\begin{aligned} \min_{\sigma_j(t), x_j} \quad & \int_0^{u_j} r_j \sigma_j(\tau) d\tau + b_j x_j, \\ \text{s.t.} \quad & (15), (16), \text{ and } (17). \end{aligned} \quad (22)$$

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, (22) is still formulated as an online optimization problem, for which an online algorithm is needed to make a decision in real time under an uncertain future. Remarkably, the problem in (22) is analogous to the so-called *ski rental problem* [20], an online optimization framework that enables such decision making in face of uncertainty, as discussed next.

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

First, we will 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 [22]. 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 problem in (22) 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 (10) and (13), 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 (21) [24]. An online algorithm can solve the problem at each present time without having whole information about future energy harvesting results.

To solve the BS ON/OFF scheduling problem, one may consider other methods such as Markov decision processes, dynamic programming, reinforcement learning, or convex online optimization. However, those are not suitable frameworks for studying the problem considered in this work since additional assumption or information on energy harvesting process would be required to model the environment.

We use online algorithms to solve the optimization problem, and competitive analysis is used to study the performance of the online algorithms. We first analyze the optimal offline strategy when assuming energy arrival information over the entire period is given. The offline optimal cost can be shown as

$$\beta_{\text{OPT}}(u_j) = \begin{cases} r_j u_j, & 0 \leq u_j \leq \frac{b_j}{r_j}, \\ b_j, & \frac{b_j}{r_j} \leq u_j \leq T. \end{cases} \quad (23)$$

The optimal solution is using the rent option until b_j/r_j if

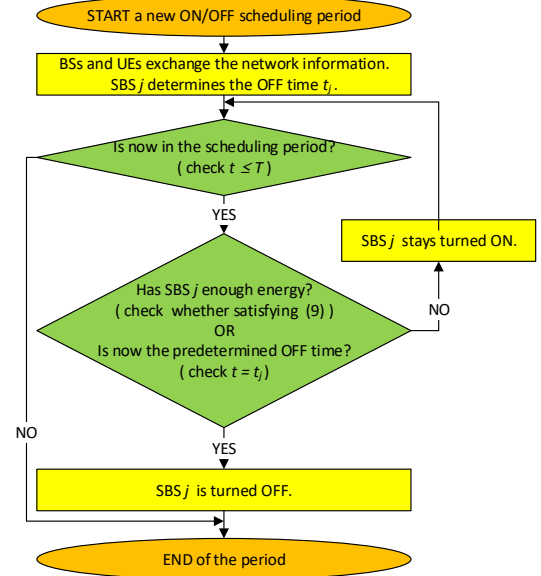


Fig. 2: Flowchart of Algorithm 1.

Algorithm 1 Deterministic Online Algorithm (DOA)

- 1: Initialization: SBS $j \in \mathcal{J}$ has a predetermined value $t_j = b_j/r_j$.
 - 2: **while** $t \leq T$
 - 3: Update $t \leftarrow t + \epsilon$.
 - 4: **If** ((9) is unsatisfied) or $(t = t_j)$,
 - 5: **then** SBS j is turned OFF.
 - 6: **else** SBS j maintains its ON state.
 - 7: **end while**
 - 8: At $t = T$, update $P_j^{\text{op}}, P_j^{\text{tx}}, \forall j \in \mathcal{J}$, and user association.
-

energy is depleted earlier than b_j/r_j . Otherwise, the buy option should be chosen with one time payment b_j at time 0.

A. Deterministic Online Algorithm

To design an online algorithm that can achieve a close performance to optimal, we first investigate how close performance a deterministic online algorithm can yield. A deterministic approach is mainly operated by a predetermined parameter when making decision of ON/OFF scheduling. In a deterministic online algorithm (DOA), SBS j is turned OFF at a predetermined time t_j , $0 \leq t_j \leq T$. This flowchart in Fig. 2 shows the structure of Algorithm 1 where the OFF time is determined at the beginning of the period. From time 0 to t_j , the rent option is used, and the cost increases along with the rental cost r_j per time. Then, at time t_j , the buy option is purchased for the one time cost b_j . DOA can be shown as Algorithm 1. The competitive ratio κ of DOA is given by

$$\frac{\beta_{\text{DOA}}(u_j)}{\beta_{\text{OPT}}(u_j)} = \begin{cases} \frac{r_j u_j}{\min\{r_j u_j, b_j\}}, & 0 \leq u_j \leq t_j, \\ \frac{r_j t_j + b_j}{\min\{r_j u_j, b_j\}}, & t_j \leq u_j \leq T, \end{cases} \quad (24)$$

where β_{DOA} is the cost of DOA.

We want to minimize κ subject to $\beta_{\text{DOA}}(u_j) \leq \kappa \beta_{\text{OPT}}(u_j)$ for every u_j from 0 to T . Therefore, when $u_j = t_j = b_j/r_j$, the competitive ratio becomes 2 known as the best possible competitive ratio of a deterministic, online algorithm [20].

B. Randomized Online Algorithm

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. For instance, it is known that, when a randomized approach is used to address a ski rental problem, it is possible to achieve a lower competitive ratio of $\frac{e}{e-1}$ [20], [25], while DOA achieves the competitive ratio of 2.

To develop an ROA for our problem, a competitive analysis analogous to the one done in [20] will be followed. For an arbitrary input, 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 $\mathbb{E}[F_j(t_j)] < \kappa\beta_{\text{OPT}}(u_j)$ where $\mathbb{E}[F_j(t_j)]$ is the expected cost of the problem (22) redefined by $F_j(t_j) = \begin{cases} r_j u_j, & \text{if } u_j < t_j, \\ r_j t_j + b_j, & \text{if } u_j \geq t_j, \end{cases}$ provided that unknown time of energy depletion is given by u_j . This will be adequate for our problem in that the input sequence is the unknown and uncertain energy arrivals at a given SBS. 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 $\kappa\beta_{\text{OPT}}$.

In this section, when the rental price r_j and the buying price b_j are values related to the cost of using an SBS and the MBS, respectively, we will compute the expected cost of ROA. 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

$$\mathbb{E}[F_j(t_j)] = \int_0^{u_j} (r_j t_j + b_j) p_j^{\text{off}}(t_j) dt_j + \int_{u_j}^T r_j u_j p_j^{\text{off}}(t_j) dt_j, \quad (25)$$

where $p_j^{\text{off}}(t_j)$ is the first-order 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 an upper bound on $F_j(t_j)$, 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 if new energy arrives suddenly at that moment. 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

Algorithm 2 Randomized Online Algorithm (ROA)

- 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** $t \leq T$
 - 4: Update $t \leftarrow t + \epsilon$.
 - 5: **If** ((9) is unsatisfied) or $(t = t_j)$,
 - 6: **then** SBS j is turned OFF.
 - 7: **else** SBS j maintains its ON state.
 - 8: **end while**
 - 9: At $t = T$, update $P_j^{\text{op}}, P_j^{\text{ix}}, \forall j \in \mathcal{J}$, and user association.
-

SBS 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:

$$p_j^{\text{on}}(t_j) = c e^{\frac{r_j}{b_j} t_j} + \kappa, \quad (26)$$

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 $b_j/r_j < u_j$ 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 $\kappa = \frac{e}{e-1}$. Therefore, we have

the ON probability $p_j^{\text{on}}(t_j) = \frac{e - e^{\frac{r_j}{b_j} t_j}}{e-1}$.

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

$$p_j^{\text{off}}(t_j) = \begin{cases} \frac{e^{\frac{r_j}{b_j} t_j} - 1}{e-1}, & 0 \leq t_j \leq \frac{b_j}{r_j}, \\ 1, & \frac{b_j}{r_j} \leq t_j \leq T. \end{cases} \quad (27)$$

The proposed online ski rental algorithm is summarized in Algorithm 2. From (27), we observe the tradeoff between rent and buy. As mentioned, the rental price is a cost related to using an SBS while the buying price reflects the cost of using the MBS. For example, the rental price is reduced if using an SBS yields lower delay cost, or the power consumption of an SBS is reduced. Also, the buying price increases if the delay from using the MBS increases, or the power consumption of the MBS increases. Therefore, if r_j is low and b_j is high, then it implies that using SBS will reap benefits in terms of delay cost or power consumption, so the rent time becomes longer. In contrast, 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. Each SBS will now run Algorithm 2 and decide at time $t = 0$ when to turn OFF, without knowing any information on energy arrivals, by using the distribution in (27). From (27), we can observe that the OFF time can be adjusted by changing the value of T . For example, if b_j/r_j increases by having a longer period of T , the ON time can be extended, so it can prevent the frequent ON/OFF switching. Also, it can be helpful to reduce the frequent handovers.

When using the Algorithm 2, we can verify that the expected competitive ratio of ROA is $\frac{e}{e-1}$ if $r_j T \geq b_j$ is satisfied. When the rental option is chosen during the whole period T , the total cost is $r_j T$. If the total cost is smaller than selecting the buy option such that $r_j T < b_j$, then this leads to a special case. For such a case, since the optimal solution is always choosing the rental option, the SBS is not turned OFF until the energy is exhausted. Therefore, to find a solution of our interest, we should consider the case in which $r_j T \geq b_j$.

Then, to show the expected competitive ratio, we calculate the expected cost of ROA. First, let us consider when $0 \leq u_j < b_j/r_j$ and $b_j/r_j < T$. By using (25), the expected cost is

$$\mathbb{E}[F_j(t_j)] = \int_0^{u_j} (r_j t_j + b_j) p_j^{\text{off}}(t_j) dt_j + \int_{u_j}^{b_j/r_j} r_j u_j p_j^{\text{off}}(t_j) dt_j + \int_{b_j/r_j}^T r_j u_j p_j^{\text{off}}(t_j) dt_j = \frac{r_j u_j e}{e-1}, \quad (28)$$

where $p_j^{\text{off}}(t_j) = \begin{cases} \frac{r_j}{b_j} \frac{e^{r_j t_j}}{e-1}, & 0 \leq t_j \leq b_j/r_j, \\ 0, & b_j/r_j \leq t_j \leq T. \end{cases}$ The third

integration in (28) becomes zero since $p_j^{\text{off}}(t_j) = 0$ in $b_j/r_j \leq t_j \leq T$. Second, by letting $b_j/r_j \leq u_j < T$, we have the expected cost shown as

$$\mathbb{E}[F_j(t_j)] = \int_0^{b_j/r_j} (r_j t_j + b_j) p_j^{\text{off}}(t_j) dt_j + \int_{b_j/r_j}^{u_j} r_j u_j p_j^{\text{off}}(t_j) dt_j + \int_{u_j}^T r_j u_j p_j^{\text{off}}(t_j) dt_j = \frac{b_j e}{e-1}. \quad (29)$$

The second and third terms in (29) become zero since $p_j^{\text{off}}(t_j) = 0$ in $b_j/r_j \leq t_j \leq T$. By using Definition 1 and the optimal cost given by (23), the expected competitive ratio of ROA is $\kappa = e/(e-1)$. As a result, for an arbitrary energy arrival, an ROA provides the OFF time of SBS that can have the expected cost of $e/(e-1)$ times of the minimum cost of the problem (22). Also, while the ROA has the optimal competitive ratio, the solutions found by the online algorithms are suboptimal as shown in the definition of competitive ratio [24], [25]. In fact, given uncertainty of energy harvesting, it is challenging to find the optimal solution of problems.

Then, we can derive the average OFF time period of each SBS when the ROA is used to solve problem (21) in the worst case that yields the optimal competitive ratio.

Theorem 2. *The expected OFF time period of the SBS is $T - \frac{1}{e-1} \frac{b_j}{r_j}$.*

Proof. SBS j is turned OFF at time t_j , so the OFF time period becomes $T - t_j$. Therefore, the expected OFF time period within period T is given by $\int_0^T (T - t_j) p_j^{\text{off}}(t_j) dt_j = \int_0^{b_j/r_j} (T - t_j) \frac{r_j}{b_j} \frac{e^{(r_j/b_j)t_j}}{e-1} dt_j = T - \frac{1}{e-1} \frac{b_j}{r_j}$. \square

In the classical ski-rental problem, the skiing period is not determined by T ; thus, the average buying time period cannot be derived. However, in our problem, by using a given period T , the average OFF time period can be derived. The result shows how b_j and r_j affect the OFF time period. From the result, if the cost of using the MBS, b_j , becomes inexpensive, the OFF time period is longer. Also, if the cost of using SBS, r_j , is decreasing, then the OFF time is reduced, and the SBSs can be turned ON for a longer time.

Next, we discuss the case that the ROA solves the original problem (14). Due to the difficulty of theoretical analysis in

TABLE I: Simulation parameters

Notation	Value
$P_0^{\text{op}}, P_j^{\text{op}}$	20 W, 10 W
$P_0^{\text{tx}}, P_j^{\text{tx}}$	33 dBm, 23 dBm
B_s, B_m	10 MHz, 10 MHz
M_s, M_m	10 users, 50 users
ρ^2	-104 dBm
carrier frequencies	2.1 GHz bands

problem (14), we numerically evaluate the empirical competitive ratio of the ROA with respect to the problem (14) throughout simulations. Furthermore, we carry out simulations to evaluate the OFF time when the ROA is used to solve problem (14) in Section V.

V. SIMULATION RESULTS AND ANALYSIS

For our simulations, the SBSs and UEs are randomly distributed in a 0.5×0.5 km² area with one MBS located at the center of the area as shown in Fig 3. Statistical results are averaged over a large number of independent simulation runs during time period $2T$ with the parameters in Table 1. Simulations during $2T$ allow a clear observation of the impact of the unused energy in the first period which can be exploited in the next period. In the simulation, all values are updated with the time resolution of $\epsilon = 0.1$ sec. Without loss of generality, during $T=10$ sec, we assume that energy arrivals per second follow a Poisson process in which energy arrival rate is 20, and each arrived energy is 0.2 J; for example, it can model a 4 W solar panel or wind generation having power density of 4 W/m² [26]. Also it is assumed that initially stored energy of SBS j is set to $E_j(0) = 60$ J where the maximum capacity of ESS is $E_{\text{max}} = 100$ J. We use $q = 0.9$ and $K = 10^5$ bits. We compare our online ski rental approach ROA and DOA to the *baseline* approach that turns all SBSs OFF at a certain, pre-determined time t_j .

Fig. 3 shows a snapshot example for 15 SBSs, and 30 UEs at $t = 2$ when ROA is used. In Fig. 3, 9 SBSs are turned ON while 6 SBSs are turned OFF. Here, user association is shown as dotted lines between ON SBSs and UEs. From the beginning, four OFF SBSs out of the 6 OFF SBSs initially stay in the OFF state since they do not have any associated UE as shown in Fig. 3. We can observe that the other two SBSs are turned OFF by the ROA scheduling since the UEs of two OFF SBSs are located near the MBS. In contrast, most of the ON SBSs are located far from the MBS. In Fig. 3, as UEs in $\mathcal{I}_j(0)$ are located closer to the MBS, the delay cost of using the MBS, ϕ_0 , decreases. Therefore, the buy price in (13) becomes lower. Thus, as the use of the MBS becomes inexpensive, the SBS tends to buy the MBS resource earlier. Also, as the UEs are located farther from any given SBS j , the delay cost of using this SBS, $\phi_j(0)$, will increase. Thus, the rental price in (10) becomes higher. Since the use of the SBS becomes more expensive, the SBS will buy the MBS resource earlier.

Fig. 4 shows, jointly, the total energy consumption of SBSs and the average network delay per SBS, for various numbers of SBSs with 15 UEs, $E_j(0) = 30$ J, $\alpha_D = 0.05$, $\alpha_P = 0.0001$, and $\alpha_B = 0.05$. From Fig. 4, we can see that, for all algorithms, as the network size increases, the delay per SBS will decrease, but the total energy consumption will increase.

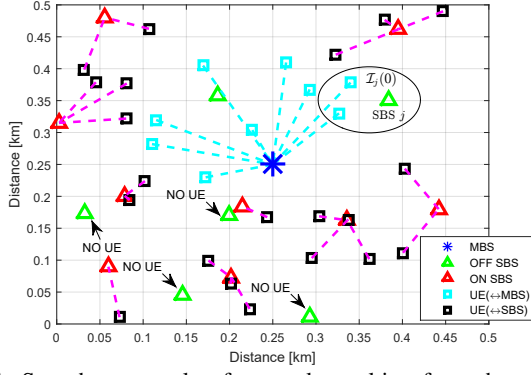


Fig. 3: Snapshot example of network resulting from the proposed ROA approach.

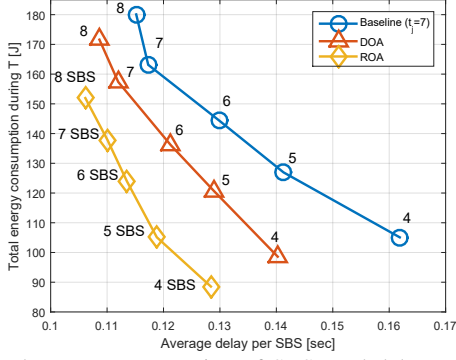


Fig. 4: Total energy consumption of SBSs and delay cost per SBS for the ROA, DOA, and baselines.

This is due to the fact that having more SBSs turned ON will enable the network to service users more efficiently, however, this comes with an increase in energy consumption. From Fig. 4, we can clearly see that ROA reduces both the delay and the energy consumption as compared to the baseline. It is because ROA results the different turned-OFF time of SBSs while all SBSs are turned OFF at the same designated time in the baseline. Thus, it is possible to mitigate interference and enhance network performance when ROA is used. This performance advantage, reaches up to 20.6% reduction in the delay relative to the baseline $t_j = 7$ for a network with 4 SBSs and 15.6% reduction in energy consumption relative to the baseline for a network with 8 SBSs. Finally, compared to the DOA scheme, Fig. 4 shows that ROA will reduce the delay of up to 8.4% (for 4 SBSs) and the energy by up to 11.4% (for 8 SBSs).

In Fig. 5, we show the total cost of the network as the network size varies for 30 UEs, $\alpha_D = 0.05$, $\alpha_P = 0.05$, and $\alpha_B = 0.05$. From Fig. 5, we can first see that the overall cost of the network given by (14) will increase as the number of SBSs increases. This is mainly due to the fact that increasing the number of SBSs will increase the overall power consumption of the network. Also, the sum of delay of SBSs increases along with the number of SBSs in the network. Fig. 5 shows that the cost increase of the proposed ROA is much slower than the increase of the DOA and the baseline approach. This demonstrates the effectiveness of the proposed approach in maintaining a low network cost. In particular, Fig. 5 shows that, at all network sizes, the proposed online ski rental approach yields reduction in the overall cost of the

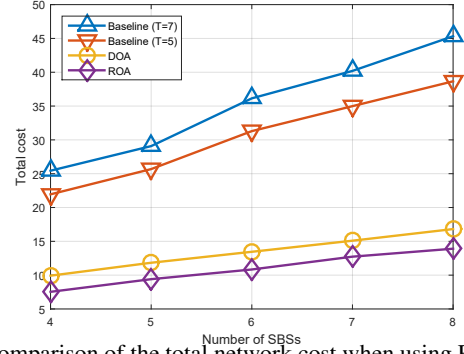


Fig. 5: Comparison of the total network cost when using ROA, DOA, and a baseline.

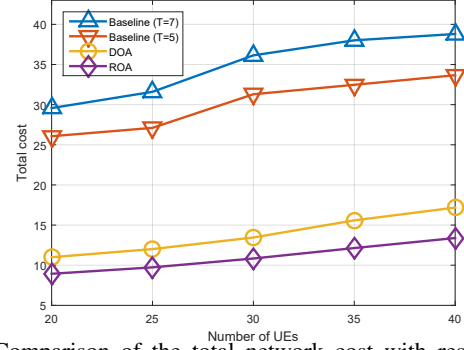


Fig. 6: Comparison of the total network cost with respect to the number of UEs.

network. This performance advantage of ROA reaches up to 69.9% reduction of the average cost for 8 SBSs compared to the baseline with $t_j = 7$.

In Fig. 6, the total cost of the network is shown when the number of UEs varies for a network with 6 SBSs, $\alpha_D = 0.05$, $\alpha_P = 0.05$, and $\alpha_B = 0.05$. Fig. 6 shows that the total cost of the network increases along with the number of UEs. This is because of the fact that increasing the number of UEs will naturally lead to a higher network delay. Nonetheless, we can clearly see that the cost increase of the proposed ROA is slower than that of the DOA and the baseline approach. This shows that the increase of the overall cost is limited by using the proposed ROA. Fig. 6 shows that the performance advantage of ROA can yield a reduction of up to 65.4% of the average cost for 40 UEs compared to the baseline $t_j = 7$.

Fig. 7 shows the empirical competitive ratio for a network consisting of 3 SBSs and 15 UEs with $\alpha_D = 0.05$, $\alpha_P = 0.05$, and $\alpha_B = 0.05$. To compute empirical competitive ratio, the total cost of the solution resulting from the ROA is divided by the total cost of the offline optimal solution. The optimal cost of each network realization is found by running exhaustive search where all possible OFF times of SBSs are computed. Since the time complexity of the exhaustive search is $\mathcal{O}\left((T/\epsilon)^J\right)$, we reduce the time resolution to $\epsilon = 0.2$ sec and run the simulation for one period T . We can see that, in 50% of all iterations, the ROA can yield a total cost that is 1.36 times that of the offline optimal cost. Also, over a total of 800 simulation runs, the empirical competitive ratio in the worst case is shown to be of 1.86. Thus, the results show that ROA can effectively choose the OFF time in an online manner.

In Fig. 8, the average ON time per SBS within time period T

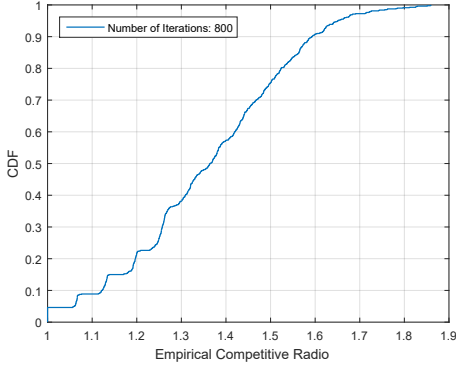


Fig. 7: Empirical competitive ratio between the total cost of the ROA and the optimal cost.

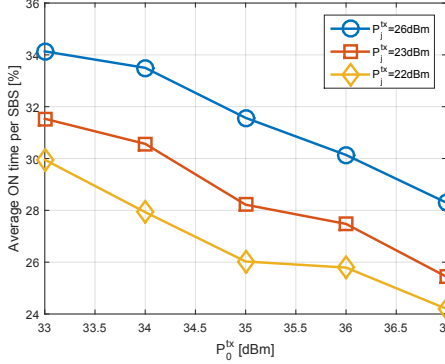


Fig. 8: Average ON time per SBS with respect to the transmit power of an SBS and the MBS during period T .

is shown for different transmit powers of an SBS and the MBS with 6 SBSs, 16 UEs, $\alpha_D = 0.05$, $\alpha_P = 0$, and $\alpha_B = 0.05$. We compare three different values for the transmit power of an SBS, P_j^{tx} : 22, 23, and 26 dBm. If an SBS uses a high P_j^{tx} , then the rent price becomes smaller. As the use of the SBS resource becomes less expensive, the SBS tends to maintain the ON state. This, in turn, results in a longer ON time as shown in Fig. 8. For example, the average ON time increase by 16.9% if P_j^{tx} increases from 22 dBm to 26 dBm when the MBS uses the transmit power of 37 dBm. Moreover, if the MBS uses a high P_0^{tx} , then the buy price becomes smaller. As the cost of using the MBS becomes lower, the SBS tends to use the MBS resource. For example, the average ON time per SBS is reduced by 19.2% if P_0^{tx} increases from 33 dBm to 37 dBm when the transmit power of 22 dBm is used by an SBS in a network.

In Fig. 9, we show the total number of ON/OFF operations within time period T for 16 UEs, $\alpha_D = 0.05$, $\alpha_P = 0.05$, and $\alpha_B = 0.05$. Here, we consider another *baseline* approach that turns an SBS ON if and only if the percentage of charged energy in storage is greater than a threshold K . For example, we set $K = 40$ or 50 such that an SBS maintains its ESS half-charged. We first present two baselines in which an SBS is turned ON if $K = 40$ and $K = 50$, respectively. The ROA and DOA clearly yield a lower number of SBS ON/OFF switchings whereas the baseline ($K = 40$ or 50) turns SBSs ON and OFF more frequently. This is mainly due to the fact that the algorithm based on the stored energy will turn ON SBSs that have more than a certain predetermined level of energy. However, the ROA and DOA switch SBSs OFF

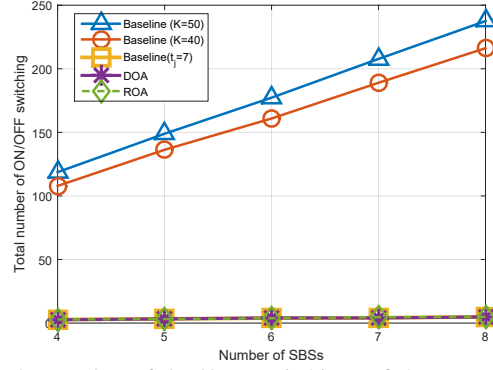


Fig. 9: The number of ON/OFF switchings of the network during one period T .

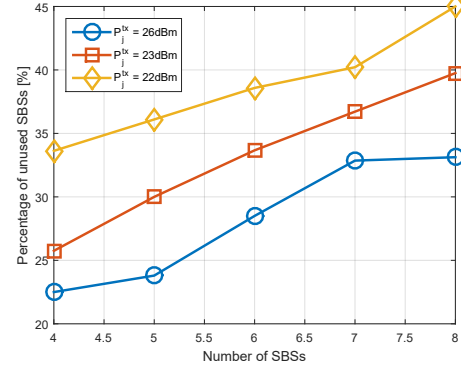


Fig. 10: Fraction of unused SBSs in the network for the different transmit power.

only once in period T . The baseline ($t_j = 7$) also shows the similar number of ON/OFF switchings compared to DOA. Hence, Fig. 9 shows that the performance advantage of ROA reaches up to 97.9% of reduction in the number of ON/OFF switchings when compared to the baseline ($K = 50$) in the network consisted of 8 SBSs.

In Fig. 10, we show the percentage of unused SBSs for different network sizes. We compare three different values for P_j^{tx} : 22, 23, and 26 dBm for 16 UEs, $\alpha_D = 0.05$, and $\alpha_B = 0.05$ while the transmission power of the MBS is fixed to 33 dBm. We set $\alpha_P = 0$ to observe the changes related to network performance. In Fig. 10, the percentage of unused SBS decreases as the transmission power of an SBS increases in the network. When the transmission power of an SBS become higher, UEs can receive higher SINR value in (2) than SNR from the MBS in (3). Thus, larger number of UEs is connected to SBSs, so it can reduce the number of unused SBSs. For example, Fig. 10 shows that the percentage of unused SBSs is reduced by 33% if the transmission power of an SBS increases from 22 dBm to 26 dBm. Also, as the number of SBSs increases, we observe that a higher fraction of SBSs is not used in the network. This is because, as the number of SBSs increases, higher interference will occur thus reducing the SINR at the UEs. In essence, it leads to more UEs that associate with the MBS thus increasing the number of unused SBSs. Indeed, in Fig. 10, we can see that the percentage of unused SBSs increases by 47.2% if the number of SBSs changes from 4 to 8 in the network.

Figs. 11 and 12 show the average ON time per SBS for the different operational power of an SBS P_j^{op} and the MBS

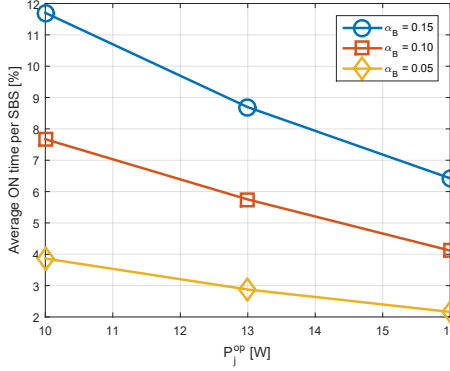


Fig. 11: Average ON time per SBS for different operational power of an SBS

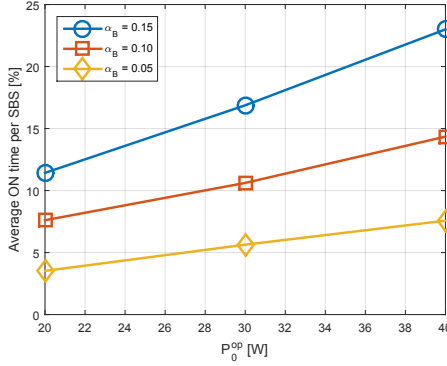


Fig. 12: Average ON time per SBS for different operational power of the MBS

P_0^{op} , respectively, with 6 SBSs, 16 UEs, and $\alpha_P = 0.05$. We set $\alpha_D = 0$ to observe the effects from different power consumptions. In Fig. 11, we observe that the ON time per SBS becomes shorter if an SBS consumes a higher operational power. This is due to the fact that the cost of using an SBS increases with the power consumption of an SBS. As a result, the rent price becomes higher. This means that choosing the rent option becomes less affordable, thus resulting in a shorter average ON time per SBS. From Fig. 11, the average ON time per SBS is shortened by 45 % when the operational power of an SBS is changed from 10 W to 16 W when the MBS uses 20 W. Also, in Fig. 12, we observe that the ON time per SBS can be prolonged if the MBS consumes high P_0^{op} . This can be explained as follows: if P_0^{op} is high, then the buying price (13) becomes higher, so the ON time per SBS becomes longer. The simulation result shows that the average ON time increases 2 times if P_0^{op} increases from 20 W to 40 W when an SBS consumes 10 W.

Furthermore, in Figs. 11 and 12, the average ON time per SBS within time period T is shown for different α_B . As α_B becomes larger, a higher buy price will be incurred when an SBS is turned OFF, so the SBS tends to stay in the ON state without buying the MBS resource. This, in turn, results in a longer ON time as shown in Figs. 11 and 12. Also, the increase in the ON time is proportional to the increase of α_B . For example, in Fig. 11, the average ON time increases three folds if α_B increases from 0.05 to 0.15 when P_j^{op} is 10 W. The same effect can be seen in Fig. 12 where the average ON time is extended three folds if α_B increases from 0.05 to 0.15 when P_0^{op} is 40 W.

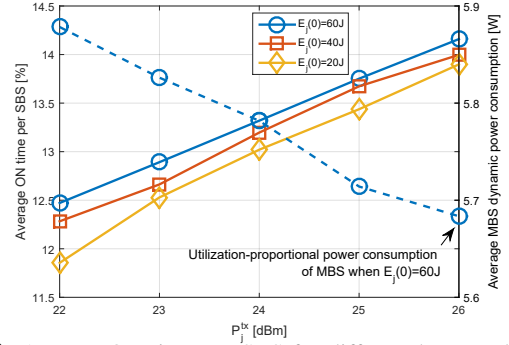


Fig. 13: Average ON time per SBS for different harvested energy.

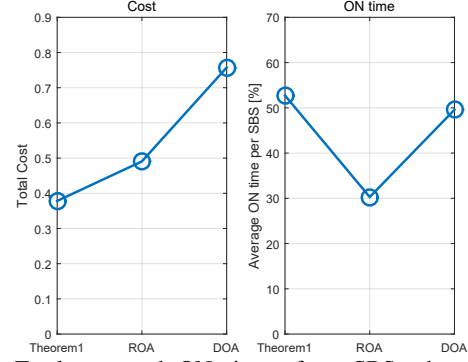


Fig. 14: Total cost and ON time of an SBS when comparing Theorem 1, ROA, and DOA.

In Fig. 13, we show the effect of the initial energy levels on the average ON time for 6 SBSs, 16 UEs, $\alpha_D = 0.05$, $\alpha_P = 0.05$, and $\alpha_B = 0.15$. We compare three different values for $E_j(0)$: 20, 40, and 60 J while other parameters related to energy arrival is given equally. As an SBS has high $E_j(0)$, an increase in the average ON time is observed. The result is due to the fact that a high $E_j(0)$ can help an SBS maintain in ON state for a longer period. For instance, the average ON time per SBS increases by 5.1% if $E_j(0)$ increases from 20 J to 60 J when P_j^{tx} is 22 dBm. Furthermore, we observe that the utilization-proportional power consumption of the MBS is reduced when the ON time per SBS becomes longer. This is because the SBSs will offload UEs from the MBS. Clearly, the use of self-powered SBSs can reduce the power consumption of the MBS as shown in the case of $E_j^{\text{tx}}(0) = 60J$.

In Fig. 14, we investigate the effect of using more information about the dynamics of the rental cost on minimizing the total cost. We compare the update rule (20) in Theorem 1, DOA, and ROA under an illustrative network example in which the rental price is monotonically decreasing over time. The considered network here consists of 1 SBS, 1 MBS, and 10 UEs, for $\alpha_D = 0.05$, $\alpha_P = 0.0001$, and $\alpha_B = 0.05$. To satisfy (19), we set the transmission power P_j^{tx} to 23, 25, 27, and 29 dBm, at the following time instants $t = 0, 1, 3$, and 5, respectively. Therefore, when P_j^{tx} increases at $t = 1, 3$, and 5, the delay cost of the SBS can be reduced; thus, the rental price decreases. In this environment, we can observe that the derived update rule in (20) can reduce the total cost when it is compared to DOA or ROA. This is due to the fact that by using (20), the SBS can use more information on the updated P_j^{tx} to make a better decision as opposed to DOA and ROA which rely solely on only information. The SBS

following (20) can dynamically update its decisions based on the decreasing rental cost, so it is possible to have a longer ON time than the DOA as shown in Fig. 14. For the considered network example, by using (20), SBS will not need to buy the MBS resource whereas the DOA uses the SBS resource and also buy the MBS resource. Thus, Theorem 1 results in the smaller total cost compared to the DOA in the example. Also, ROA can reduce the total cost than the DOA since ROA uses the SBS resource for a short period and chooses to buy the MBS resource earlier. Our example illustrates that the ROA yields a lower cost than the DOA but a higher cost than Theorem 1. However, clearly, by using the ROA, the approximation yields a reasonably good solution, which does not require any full information on the dynamic parameters of the system.

VI. CONCLUSION

In this paper, we have proposed a novel approach to optimize the ON/OFF schedule of self-powered SBSs. We have formulated the problem that minimizing network operational costs during a period. Also, the problem is approximated as an online ski rental problem which enables the network to operate effectively in the presence of energy harvesting uncertainty. To solve this online problem, we have proposed deterministic and randomized online algorithm that is shown to achieve the optimal competitive ratio for the approximated problem. Indeed, we have shown that by using the proposed ROA, 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 ROA can achieve an empirical competitive ratio of 1.86, thus showing that ROA can effectively choose the OFF time in an online manner. The results have also shown that both delay and the ON/OFF switching overhead are significantly reduced when one adopts the online ski rental approach.

APPENDIX

PROOF OF THEOREM 1

Given definitions of $r_{(v)}$ and $t_{(v)}$, we determine \bar{t} such that the accumulated cost up to time \bar{t} equals to the cost of using the MBS b_j ; thus, \bar{t} satisfies

$$r_{(1)}t_{(1)} + r_{(2)}(t_{(2)} - t_{(1)}) + \dots + r_{(v-1)}(t_{(v-1)} - t_{(v-2)}) + r_{(v)}(\bar{t} - t_{(v-1)}) = b_j. \quad (30)$$

At time $t_{(0)}$, the initial SBS's OFF time can be given by $\bar{t} = b_j/r_{(1)}$. At time $t_{(v-1)}$, $v \geq 2$, the SBS's OFF time can be updated by $\bar{t} = \frac{b_j}{r_{(v)}} - \frac{1}{r_{(v)}} \sum_{v'=1}^{v-1} t_{(v')}(r_{(v')} - r_{(v'+1)})$. In the algorithm, an SBS determines the OFF time \bar{t} at the beginning, e.g., $t_{(0)} = 0$. Since the cost is updated from $r_{(v-1)}$ to $r_{(v)}$ at each moment $t_{(v-1)}$, $v \geq 2$, the SBS newly update the OFF time \bar{t} by using (20).

When the previous OFF time \bar{t}_{old} is determined at $t_{(v-2)}$ with $r_{(v-1)}$, \bar{t} is updated at $t_{(v-1)}$ with $r_{(v)}$. Then, \bar{t} is shown as (20), and \bar{t}_{old} is given by $\frac{b_j}{r_{(v-1)}} - \frac{1}{r_{(v-1)}} \sum_{v'=1}^{v-2} t_{(v')}(r_{(v')} - r_{(v'+1)})$. If $\bar{t}_{old} \leq t_{(v-1)}$, the SBS is turned OFF at \bar{t}_{old} . Therefore, $\bar{t}_{old} > t_{(v-1)}$ is required so that an SBS is in the ON state at $t_{(v-1)}$. By using two given conditions, $r_{(v-1)} > r_{(v)}$ and $\bar{t}_{old} > t_{(v-1)}$, the inequality $\bar{t} = \frac{1}{r_{(v)}} (r_{(v-1)}\bar{t}_{old} - t_{(v-1)}(r_{(v-1)} - r_{(v)})) > \bar{t}_{old}$ holds. Hence,

the updated OFF time \bar{t} is later than the previous OFF time \bar{t}_{old} if $r_{(v-1)} > r_{(v)}$.

For an arbitrary $v \geq 2$, the OFF time of SBS j can be determined at time $t_{(v-1)}$ by (20). Also, the energy of the SBS can be depleted at time u where $u \geq t_{(v-1)}$. To derive the competitive ratio, we show the total cost of the algorithm and the optimal cost, respectively. If $t_{(v-1)} \leq u < \bar{t}$, then the total cost of the problem in (14) is given by

$$\beta_{ALG}(u) = \sum_{v'=1}^{v-1} t_{(v')}(r_{(v')} - r_{(v'+1)}) + r_{(v)}u. \quad (31)$$

The optimal cost $\beta_{OPT}(u)$ can be calculated by assuming an offline scenario where energy arrival information over the entire period is given. Thus, the amount of stored energy at each moment becomes known information. In this case, we can find that $\beta_{OPT}(u)$ is the same as (31). Also, if $\bar{t} \leq u$, then the total cost is given by

$$\beta_{ALG}(u) = \sum_{v'=1}^{v-1} t_{(v')}(r_{(v')} - r_{(v'+1)}) + r_{(v)}\bar{t} + b_j.$$

However, the offline optimal cost is given by $\beta_{OPT}(u) = b_j$. Therefore, the worst-case competitive ratio given by (18) becomes 2 in the case of $\bar{t} \leq u$ since $\beta_{ALG}(u)$ can be two times greater than $\beta_{OPT}(u)$ due to (30).

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