Sleep Control for Base Stations Powered by Heterogeneous Energy Sources

(Invited Paper)

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***Abstract*—This paper considers a cellular network with base stations (BSs) powered by heterogeneous energy sources, i.e., besides conventional BSs connected to the power grid, some BSs are purely powered by the renewable energy. BS sleep is introduced not only to save grid power, but also to store renewable energy for future use when the temporal traffic variation does not match with the energy arrivals. The challenge of the BS sleep control lies in the possible energy outage of those BS powered by the renewable energy, and this will lead to network coverage hole and thus severely affect the service quality. The optimal sleep policy is obtained through dynamic programming, and due to its high complexity, we further propose a simple heuristic algorithm. By simulations, we evaluate and compare the proposed algorithms with a greedy scheme that utilizes renewable energy whenever possible, and show that the greedy scheme can lead to severe energy outage, while our algorithms wisely store harvested energy through BS sleep.**

I. Introduction

To realize sustainable development of wireless technologies while keeping track with the mobile traffic explosion, it is crucial to reduce the CO_2 emissions of wireless communication systems [1]. From the operation point of view, base station (BS) sleep can save energy consumption during the period of low traffic load [1] [2]. Another promising candidate is to exploit renewable energy, e.g. solar energy, wind energy and so on. The technology, termed as “energy harvesting”, was initially used to power small wireless sensors [3], while recently it has been adopted to power larger wireless equipments such as BSs [4]. For example, there are over 10,000 BSs powered by solar or wind energy in China, among which China Mobile has constructed over 9,000[1]. However, the energy harvesting technology for cellular networks is still in its infancy stage, due to two key challenges: First, renewable energy arrival is highly dynamic and uncertain, and thus hinders reliable transmission; Second, the limited battery capacity, together with imperfections of modern battery technologies makes it hard to utilize renewable energy efficiently.

In literature, some efforts have been made to address above challenges. The impact of dynamic energy arrival on the single link throughput has been analyzed in [5], [6], and the optimal power allocation structure, namely *directional water-filling (WF)*, is introduced. The directional WF can only be used in a non-causal manner, i.e., future channel variation and energy arrival are known. There are also causal policies for energy harvesting transmitters [3], [7], using Markov decision process (MDP) approaches [16]. For applications like cellular networks, maintaining coverage is the principle requirement, and thus people start to consider the coexistence of energy harvesting and grid power supplies [8], [9]. In our previous work [13], the average grid power consumption of a single link is minimized through optimizing the ratio of the transmit power from energy harvesting and grid power for each time slot. We further extend the analysis to multicell environment where each BS is powered by both the power grid and renewable energy [14]. In fact, it is more realistic to consider the case where BSs are powered by either grid power or renewable energy, but not both. It is because BSs with renewable energy are often deployed where there is no grid power supply. However, this scenario has barely been considered.

In view of the above issue, in this paper we consider the BS sleep control for a cellular network, where some BSs are powered by renewable energy only, and the rest are conventional BSs connected to power grid. When a BS goes into sleep mode, its traffic can be re-associated to adjacent active BSs [2]. For grid powered BS, the objective of sleep is to save grid energy. For renewable energy powered BSs, they will often face the mismatched temporal traffic variation and energy dynamics, as shown in Fig. 1. A BS will go to sleep when there is no enough harvested energy in the battery, or it can decide to store energy in sleep mode during the low traffic period for future use in case of energy outage. The energy outage occurs when the current energy storage and energy arrivals of an active BS powered by renewable energy cannot support its associated traffic. To avoid the energy outage and save the grid power, it is vital to carefully coordinate the sleep of both kinds of BSs. Based on dynamic programming (DP), optimal BS sleep policy is obtained according to the energy and traffic dynamics. Regarding the high complexity of DP algorithm, we also propose a heuristic algorithm, which decides the number of active BSs with renewable energy proportional to the network traffic, and then uses a localized DP to sleep grid powered BSs. Remark that our work is based on the statistical energy arrival information [10]–[12], as it may not be practical or necessary to track the energy arrival in small time granularity. A recent study [9] has used the energy

[1] http://labs.chinamobile.com/news/73010

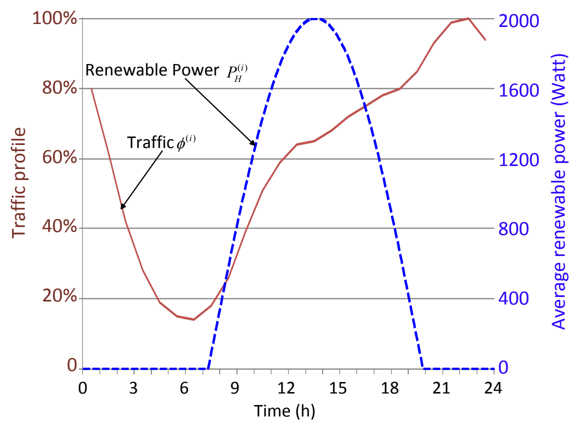

Fig. 1. Daily traffic (solid line) [17] and renewable energy profile (dashed line) [18].

profile for BS planning, and our work [14] also exploits the statistical energy arrival information to control BS sleep.

The paper is organized as follows. In Section II, the system model is introduced. The grid power minimization problem is formulated in Section III. Both the optimal DP algorithm and the low complexity heuristic algorithm are described in Section IV, which are evaluated through simulations in Section V. We conclude the paper in Section VI.

II. System Model

We consider a wireless cellular system with totally M BSs denoted as $\mathcal{M} = \{1, 2, \ldots, M\}$. Part of the BSs, denoted by $\mathcal{M}_{\mathcal{H}} = \{m_1, m_2, \ldots, m_K\}(K \leq M)$, are merely powered by renewable energy. And the rest, denoted by $\mathcal{M}_{\mathcal{G}} = \mathcal{M} \setminus \mathcal{M}_{\mathcal{H}}$, are conventional BSs powered by the power grid. Both kinds of BSs can go to sleep mode.

The time period of interest (for example, 24 hours) is divided into T time intervals. The traffic arrival in cell m in time interval i is a Poisson process with intensity $\lambda_m^{(i)}$. The traffic is assumed uniformly distributed in each cell, but asymmetric among cells. Assume that the system have the statistical traffic information, i.e., the average arrival rate profile $\boldsymbol{\lambda} = \{\lambda_m^{(i)}\}_{m=1,\ldots,M}^{i=1,\ldots T}$, which is periodic with T. All users arrive randomly and then remain stationary until the transmission is finished. The transmission duration of each user follows exponential distribution with mean $1/\mu$.

Assume that each BS $m \in \mathcal{M}$ can work in two modes: *active* mode (denoted as $s_m^{(i)} = 1$) and *sleep* mode (denoted as $s_m^{(i)} = 0$). In each time interval $i = 1, \ldots, T$, the system works in the fixed state $\boldsymbol{s}^{(i)} = \{s_m^{(i)}\}_{m=1}^M$. The state space is

$$\mathcal{S} = S_1 \times S_2 \times \ldots \times S_M, \tag{1}$$

where $S_m = \{0, 1\}, m \in \mathcal{M}$. The power consumption model of a BS is

$$P_{BS,m}^{(i)} = \begin{cases} P_0 + \Delta_P P_T, & \text{if } s_m^{(i)} = 1 \\ P_S, & \text{if } s_m^{(i)} = 0, \end{cases} \tag{2}$$

where P_0 is the constant power including the baseband processor, the converter, the cooling system, and etc., Δ_P is the inverse of power amplifier efficiency factor, and P_T is the transmit power. Here we assume P_T is fixed.

For the renewable powered BSs $m \in \mathcal{M}_{\mathcal{H}}$, denote the available energy stored in the battery by $E_m^{(i)}$. If $L^{(i)}(P_0 + \Delta_P P_T) \leq E_m^{(i)}$, where $L^{(i)}$ is the length of interval i, i.e., the renewable energy is enough for BS m to be active, we have $S_m = \{0, 1\}$. Otherwise, $S_m = \{0\}$, i.e., the BS m must turn to sleep mode to wait for new energy arrival. We could also turn a BS into sleep mode eventhough the energy stored in the battery is enough when the current traffic load is low, and the energy stored can be used in the future.

At the beginning of each time interval, the BSs take the action $\boldsymbol{u}^{(i)} = \{u_m^{(i)}\}_{m=1}^M$. The action space is

$$\mathcal{U} = U_1 \times U_2 \times \ldots \times U_M, \tag{3}$$

where $U_m = \{0, 1\}, m \in \mathcal{M}$. Denote $u_m^{(i)} = 1$ as the action that BS m switches its working mode and $u_m^{(i)} = 0$ otherwise, as that BS m maintains its working mode. Accordingly the states of BSs are updated by the following function

$$s_m^{(i+1)} = |s_m^{(i)} - u_m^{(i)}|. \tag{4}$$

Note for $m \in \mathcal{M}_{\mathcal{H}}$, if $L^{(i)}(P_0 + \Delta_P P_T) \leq E_m^{(i+1)}$, we have $U_m = \{0, 1\}$. Otherwise, $U_m = \{0\}$ if $s_m^{(i)} = 0$, and $U_m = \{1\}$ if $s_m^{(i)} = 1$, which means the BS m must turn to sleep mode.

We ignore small-scale fast fading, and use pathloss channel model. The received SINR of user u in cell m is

$$\text{SINR}_u = \frac{P_T \beta (d_{mu})^{-\alpha}}{\sigma^2 + \sum_{m': S^{(m')}=1, m' \neq m} P_T \beta (d_{m'u})^{-\alpha}}, \tag{5}$$

where β is the pathloss constant, α is the pathloss exponent, d_{mu} is the distance between BS m and user u, P_T is the transmit power, and σ^2 is the noise power. The transmission rate is

$$r_u = W_u \log_2(1 + \text{SINR}_u), \tag{6}$$

where W_u denotes the radio resource allocated to user u. A BS allocates its bandwidth to associated users to satisfy the rate requirement r_0, i.e., $W_u = r_0 / \log_2(1 + \text{SINR}_u)$. A newly arrived user u' will first associate to the BS with the largest SINR, if the required bandwidth exceeds the available bandwidth in the BS, it will try the adjacent BSs. If the user fails to find a BS to provide service, it will be blocked. With the mentioned association scheme, the users in the coverage of a sleep BS can associate to adjacent active BSs. The blocking probability of cell m with a BS supported by power grid in time interval i is

$$p_{\text{blk},m}^{(i)} = \bar{p}_{\text{blk},m}^{(i)} \triangleq \left[\Pr\left(W_{u'} + \sum_u W_u > W_{\max} \right) \right]^{|\mathcal{A}(m)|}, \tag{7}$$

where $W_{\max}$ is the total bandwidth of a BS, and $\mathcal{A}(m)$ denotes the area including cell m and its adjacent cells. The detailed derivation for $\bar{p}_{\text{blk},m}^{(i)}$ can be found in our previous work [2]. For renewable energy powered BSs, a blocking event can be caused by energy depletion, of which the probability is calculated by

$$\hat{p}_{\text{blk},m}^{(i)} = \max\{0, \frac{P_{BS} - P_m^{(i)}}{P_{BS} - P_S}\}, \quad (8)$$

where $P_m^{(i)}$ is the average renewable energy arrival in cell m during time interval i. Hence, the blocking probability for renewable powered BSs is $p_{\text{blk},m}^{(i)} = \hat{p}_{\text{blk},m}^{(i)} + (1-\hat{p}_{\text{blk},m}^{(i)})\bar{p}_{\text{blk},m}^{(i)}$.

III. Problem Formulation

The following optimization problem is considered: Given the traffic profile $\boldsymbol{\lambda} = \{\lambda_m^{(i)}\}_{m=1,\ldots,M}^{i=1,\ldots T}$ and the renewable energy profile $\boldsymbol{P} = \{P_m^{(i)}\}_{m=1,\ldots,M}^{i=1,\ldots T}$, where $P_m^{(i)}$ is the average renewable energy harvesting power in cell m during time interval i, we aim to minimize the average grid power consumption while satisfying the blocking probability requirement, through adjusting the BS working state $\boldsymbol{s} = \{s_m^{(i)}\}_{m=1,\ldots,M}^{i=1,\ldots T}$, . The problem is thus formulated as

$$\min_{\boldsymbol{s}} \ \frac{\sum_{i=1}^{T}\sum_{m\in\mathcal{M}_\mathcal{G}} L^{(i)} P_{G,m}^{(i)}}{\sum_{i=1}^{T} L^{(i)}} \quad (9)$$

$$\text{s.t.} \quad \sum_{i=1}^{T}\sum_{m=1}^{M} \omega_m^{(i)} p_{\text{blk},m}^{(i)} \leq p_{\text{target}}, \quad (10)$$

where $L^{(i)}$ denotes the length of time interval i, $P_{G,m}^{(i)}$ is the grid power input for $m \in \mathcal{M}_\mathcal{G}$, $p_{\text{blk},m}^{(i)}$ is the blocking probability of cell m in time interval i. The weighting factor $\omega_m^{(i)}$, which satisfies $\sum_{i=1}^{T}\sum_{m=1}^{M}\omega_m^{(i)} = 1$, reflects the system sensitivity to the blocking probability in each time interval. For instance, if $\omega_m^{(i)}$ is set to

$$\omega_m^{(i)} = \frac{\lambda_m^{(i)}}{\sum_{t=1}^{T}\sum_{k=1}^{M} L_t \lambda_k^{(t)}}, \quad (11)$$

the constraint (10) is to guarantee the average blocking probability.

IV. BS Sleep Algorithms

A. Dynamic Programming Algorithm

The optimal solution for problem (9) can be found by solving the following unconstrained optimization problem with a weighted combination of the power consumption and the blocking probability

$$\min_{\boldsymbol{s}} \frac{\sum_{i=1}^{T} L^{(i)} \sum_{m\in\mathcal{M}_\mathcal{G}} P_{G,m}^{(i)}}{\sum_{i=1}^{T} L^{(i)}} + \beta \sum_{i=1}^{T}\sum_{m=1}^{M} \omega_m^{(i)} p_{\text{blk},m}^{(i)}, \quad (12)$$

where the factor $\beta > 0$ acts like a Lagrangian multiplier and indicates the relative importance of the weighted blocking probability with respect to the average grid power consumption. Denote the minimum objective value of problem (12) for a given β as $P_{\text{Gave},\beta}^* + \beta p_{\text{blk},\beta}^*$, where $P_{\text{Gave},\beta}^*$ and $p_{\text{blk},\beta}^*$ represent the average grid power and the weighted blocking probability, respectively. As the objective (12) is minimized, $P_{\text{Gave},\beta}^*$ must be the minimum average grid power to guarantee that the weighted blocking probability is no more than $p_{\text{blk},\beta}^*$. Hence, the solution for (12) is also the one for (9) where $p_{\text{target}} = p_{\text{blk},\beta}^*$. By adjusting the value of β and solving the corresponding problem (12), we can find a set of optimal points $(P_{\text{Gave},\beta}^*, p_{\text{blk},\beta}^*)$. For a given p_{target}, if a corresponding point can be found by setting appropriate value of β, the optimal solution for the original problem is found. Otherwise, we get a suboptimal result by adopting the point with the largest weighted blocking probability less than p_{target}.

The problem (12) can be solved by DP approach [16], which divides the whole problem into simple per-stage sub-problems. The per-stage cost is the weighted combination of the average grid power and the blocking probability, denoted as a function of the current action and state

$$c^{(i)}(\boldsymbol{s}^{(i)}, \boldsymbol{E}_C^{(i)}) = \frac{L^{(i)}\sum_{m\in\mathcal{M}_\mathcal{G}} P_{G,m}^{(i)}}{\sum_{i=1}^{T} L^{(i)}} + \beta \sum_{m=1}^{M} \omega_m^{(i)} p_{\text{blk},m}^{(i)}, \quad (13)$$

where $\boldsymbol{E}_C^{(i)} = \{E_{C,m}^{(i)}\}_{m=1,\ldots,M}$ and $\boldsymbol{s}^{(i)} = \{s_m^{(i)}\}_{i=1,\ldots,M}$. The DP algorithm breaks the original problem down into subproblems with respect to the stage, where the objective is to minimize the cost of each time slot plus that of the following slots. The per-slot sub-problems are solved recursively. The *cost-to-go* function is defined recursively as

$$J^{(i)}(\boldsymbol{E}_C^{(i)}) = \begin{cases} \min\limits_{\boldsymbol{s}^{(i)}} c^{(i)}(\boldsymbol{s}^{(i)}, \boldsymbol{E}_C^{(i)}), & i=T \\ \min\limits_{\boldsymbol{s}^{(i)}} \Big\{ c^{(i)}(\boldsymbol{s}^{(i)}, \boldsymbol{E}_C^{(i)}) + J^{(i+1)}(\boldsymbol{E}_C^{(i+1)}) \Big\}, & i<T \end{cases} \quad (14)$$

which denotes the minimum cost of the sub-problem with slot i as its initial stage. Performing a backward induction of the cost-to-go functions (14) from time slot T to slot 1, we can obtain the minimum cost equal to $J_1(\mathbf{0})$.

B. Heuristic Algorithm

Assume the number of the battery states for a renewable energy power BS is N_B. The total number of states of the network is $N_B^K 2^M$, where K denotes the number of renewable energy powered BSs, and the states will exponentially grow with the network size. Due to the *curse of dimensionality* [16], the DP algorithm will result in an overwhelming computational complexity if the network size is large. As a consequence, the proposed optimal DP algorithm is difficult to implement in large systems. Here we consider a low complexity heuristic algorithm for large-scale applications as follows:

- Activate the renewable energy powered BSs proportional to the average network traffic intensity. The BSs are randomly selected as long as their harvested energy is enough to carry the associated traffic in current time interval. For instance, the number of active renewable energy powered BSs are calculated as

$$N_H^{(i)} = \frac{\sum_{m=1}^{M}\lambda_m^{(i)}}{\sum_{i=1}^{T}\sum_{m=1}^{M}\lambda_m^{(i)}} N_H^{\max}, \quad (15)$$

where $N_H^{\max}$ is set so that the required active number $N_H^{(i)}$ can be guaranteed.

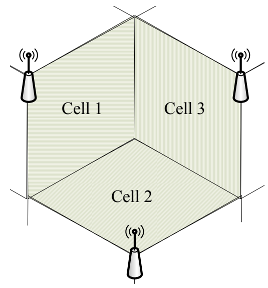

Fig. 2. A Network consisting of three sectorized BSs.

- Given the states of renewable energy powered BSs, optimize the states of each power grid powered BS locally, and iteratively find the BS on-off policy. Specifically, in each iteration, for each BS $m \in \mathcal{M}_G$, we look at a cluster composed of cell m and its first tier neighbors, and find the optimal sleep policy of the cluster. We can use a simplified version of DP for this cluster with much lower complexity [2]. Then we update the overall policy by replace the states of BSs in the cluster. The iteration terminates when the overall cost does not decrease any more.

The heuristic algorithm greatly reduces the number of states to $KN_B + 2^{|\mathcal{A}|}$, as we only need to check the energy of each BS powered by renewable energy to see if it is enough, and the size of the cluster $|\mathcal{A}|$ for local DP does not increase with the network size.

V. Simulation Evaluations

In the simulations, we use the BS power consumption model from the EARTH project [17], and the channel model from LTE standard [19]. We set $P_0 = 712.2$W, $\Delta_P = 15.96$, $P_T = 40$W, and the cell radius $R = 1000$m. The bandwidth is $W_0 = 10$MHz. The path-loss is $\mathrm{PL}^{\mathrm{dB}} = 34.5 + 35\log_{10}(d_{mu})$, and the noise power is -174dBm/Hz.

Firstly, we consider a cluster of 3 sectorized cells as depicted in Fig. 2 to test the DP algorithm. We assume $r_0 = 2\text{Mbps}, \mu = 1\text{s}^{-1}$. The traffic follows the profile illustrated in Fig. 1. Assume that the user arrival rate of sector m in slot i is $\lambda_m^{(i)} = \psi_m \phi^{(i)} \lambda_{\max}$, where $\lambda_{\max} = 7.5\text{s}^{-1}, 0 < \phi^{(i)} \leq 1, \psi_1 : \psi_2 : \psi_3 = 3 : 2 : 1, \sum_m \psi_{(m)} = 1$, and the traffic is uniformly distributed in each sector. The same energy profile depicted in Fig. 1 is adopted for all renewable energy powered BSs, because in reality the energy arrival intensity (e.g. solar power) will be almost the same in a local area.

Assuming there are only one BS powered by the power grid, and the rest two are powered by solar energy, we get the energy-blocking tradeoff results as shown in Fig. 3. For the case that the cell with highest traffic load (cell 1) is powered by power grid, the grid power consumption is the highest when the blocking probability requirement is loose. However, when the blocking probability requirement is stringent, it consumes least grid power compared with other two cases. The reason is that, for the high target blocking probability, the harvested

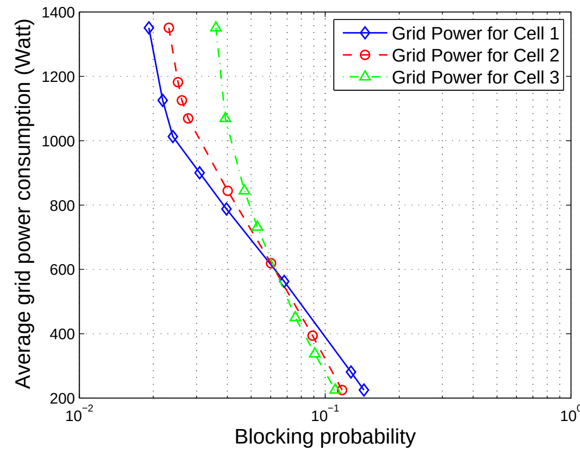

Fig. 3. Tradeoff between blocking probability and grid power consumption.

energy is almost enough. Hence, equipping a energy harvesting device in the high traffic load BS can use the harvested power more efficiently. On the other hand, for the stringent target blocking probability case, it is more preferable to use stable grid power for the cell with high traffic load.

Next we study the performance of the proposed low-complexity algorithm in a larger network. We consider a 10 by 10 hexagonal network as shown in Fig. 4. The time-varying and asymmetric traffic distribution is configured as follows:

- Average arrival rate (or traffic intensity) of the whole network $\lambda(t) = \sum_{m=1}^{M} \lambda_m(t)$ varies along time domain with period of $T = 24$h according to Fig. 1.
- N_h *hotspots* are generated and move along some directions every 24 hours a cycle. Assume each hotspot covers 2-tiers cells.
- Set the arrival rates of the hotspot center cells as $\lambda_m(t) = \lambda_h(t)$. Then the arrival rates of the lst-tier of hotspot center cells are $\lambda_m(t) = \alpha_l \lambda_h(t), l = 1, 2$, and the others are $\lambda_m(t) = \alpha_3 \lambda_h(t)$, where $0 \leq \alpha_3 \leq \alpha_2 \leq \alpha_1 \leq 1$.

Half of the BSs are powered by renewable energy, and the energy arrival profile is also from Fig. 1. Recall that the active renewable energy powered BSs are selected from BSs with enough energy storage. For comparison, we compare the *greedy algorithm*, which activates the renewable energy powered BSs as long as their energy is enough to carry traffic for the current time interval. Fig. 5 shows that the proposed algorithm can efficiently utilize the renewable energy to maintain the blocking probability. However for the greedy algorithm, the blocking probability will increase dramatically when the renewable energy arrival does not match with the traffic load, e.g., when the energy arrival rate starts to drop around the time interval 15, the traffic load still keeps increasing as shown in Fig. 1. In this case, some BSs encounter energy outage and are no longer able to provide service, while the rest grid powered BSs cannot afford the network traffic due to coverage limitations. The result indicates that it is important to match the renewable energy with the traffic dynamics by

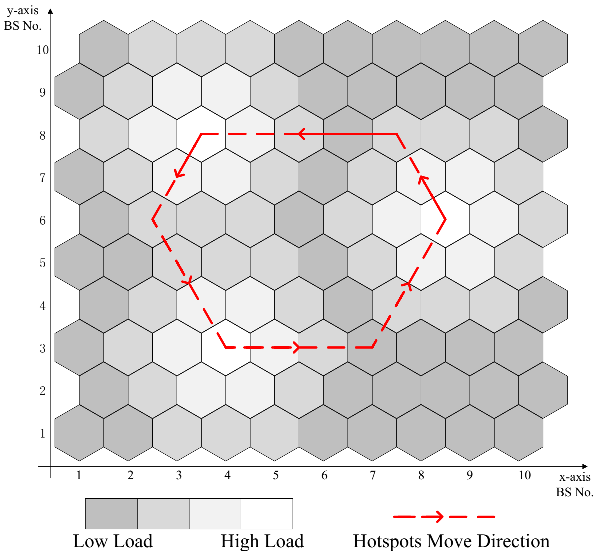

Fig. 4. Simulation layout and a traffic distribution example. $N_h = 3$ hotspots are formed and move along the red-dashed line anticlockwise every 24 hours a cycle. The highest load is $\lambda_h(t)$, and the others are $\alpha_l \lambda_h(t), l = 1, 2, 3, 0 \leq \alpha_3 \leq \alpha_2 \leq \alpha_1 \leq 1$, respectively.

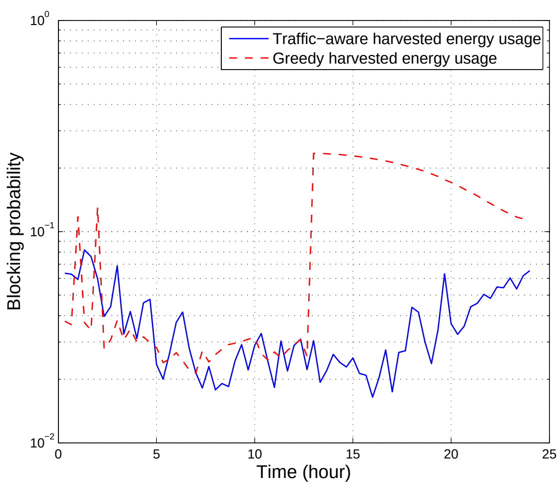

Fig. 5. Performance comparison of heuristic harvested energy usage algorithms.

wisely storing and allocating the harvested energy.

VI. Conclusion

In this paper, we have considered the energy-harvesting-aware sleep control for cellular systems with the mixed deployment of renewable energy and power grid powered BSs. The DP based optimal sleep policy is obtained, and we also propose a low complexity heuristic algorithm for large-scale network applications. Due to the temporal mismatch of network traffic arrival and renewable energy arrival, the greedy way of using the harvested energy can lead to severe energy outage, and thus causes service quality degradation. The proposed algorithms efficiently utilize the renewable energy, and thus save the grid power consumption, while at the same time guarantee user service. Future work will include transit power adaptation, and energy transfer among communication nodes [15].

Acknowledgement

This work is sponsored in part by the National Basic Research Program of China (2012CB316001), the Nature Science Foundation of China (61201191, 60925002), and Hitachi Ltd.

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