Access Strategy in Energy Harvesting Super WiFi Network: A POMDP Method

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***Abstract*—The recently announced Super Wi-Fi Network proposal in United States is aiming to enable Internet access in a nation-wide area. As traditional cable-connected power supply system becomes impractical or costly for a wide range wireless network, new infrastructure deployment for Super Wi-Fi is required. The fast developing Energy Harvesting (EH) techniques receive global attentions for their potential of solving the above power supply problem. While one critical issue is that from the user's perspective, how to make network selection and access strategy. Unlike traditional wireless networks, the battery energy state and tendency in EH bases networks have to be taken into account when making network selection and access, which has not been well investigated. In this paper, we propose a practical and efficient framework for multiple base stations access strategy in an EH powered Super Wi-Fi network. We consider the access strategy from the a user's perspective, who exploits downlink transmission opportunities from one base station. To formulate the problem, we used Partially Observable Markov Decision Process (POMDP) to model users' observations on the base stations' battery situation and decisions on the base station selection and access. Simulation results show that our methods are efficacious and significantly outperforms the traditional widely used CSMA method.**

I. Introduction

In order to expand the coverage area of wireless network, many algorithms and implementations have been proposed. Recently, the Federal Communications Commission published the Super Wi-Fi proposal, aiming to make use of lower-frequency white spaces between television channel frequencies and create a nationwide wireless network. However, the ambitious task of building a countrywide network is confronted with many obstacles. An inevitable problem is how to deploy practical backhaul and energy supply system. Apparently, traditional cable-based systems may be not appropriate, considering the cost of deploying and maintaining the network. Despite all the above difficulties, there are solutions and many successful experimental deployments of Super Wi-Fi are accomplished accordingly. Wireless backhual has been proven to be effective [1] as a replacement of cable backhaul. Meanwhile, the fast developing energy harvesting (EH) technology provides an ideal replacement as the power supply problem, which could make use of a wide range of ambient energy including piezoelectric, thermal, solar energy, etc.

As the deployment of EH network is just emerging, new wireless protocols and modification are required, as some preliminary studies pointed out in [2]. Especially, from users' perspective, when confronted with EH powered network, how to make network selection and access strategies is a practical and important problem. Different from traditional networks, a prominent issue in EH powered networks is that the energy state and tendency of one base station (BS) need to be taken into account when making BS selection and access. Previously, the access strategy problem in traditional wireless networks has been studied extensively, among which Markov Decision Process has been widely used, with some challenges and solutions summarized in [3]. Access process among different users is a typical game process, and thus game theory, summarized in [4] and pricing theory used in [5], have been applied respectively. In [6], the access strategy towards multiple base stations with negative externality is considered. More recently, a POMDP MAC layer opportunistic access was proposed in [7], and a learning based approach to access between packet bursts was studied in [8].

However, all the aforementioned studies on users' access strategy did not consider the energy harvesting scenario. In this work, we propose a user access strategy for the fast booming Super Wi-Fi network, focusing on the influence of BS's battery state on users' access strategy. As long time transmission is not guaranteed in EH network, leaving and arriving of users are more frequent. Instead of using a static system model, we consider a model where the number of accessing users and the energy of the BS's battery are dynamic. Meanwhile, a new stochastic process illustrating users' arriving, leaving, and a battery's energy transition based on quasi-static formulation are combined to describe the system state transition. Considering that in EH powered wireless network the full knowledge of the system is unrealistic, we build a Partially Observable Markov Decision Process (POMDP) model to formulate the access strategy problem, i.e., users make the network access strategy by using the partially observed BSs' battery information. It is worth to mention that although our work focuses on solar energy harvesting, the conclusion and the algorithm could be generalized to any access problems in EH powered network.

The rest of this paper is organized as follow. We describe the system model In Section II. In Section III, the POMDP access strategy is presented. We show how we formulate the POMDP states to obtain the optimal access strategy. And a suboptimal strategy is proposed. In Section IV, we evaluate the performance of our proposed approach with several famous traditional algorithms. In Section V we draw the conclusion.

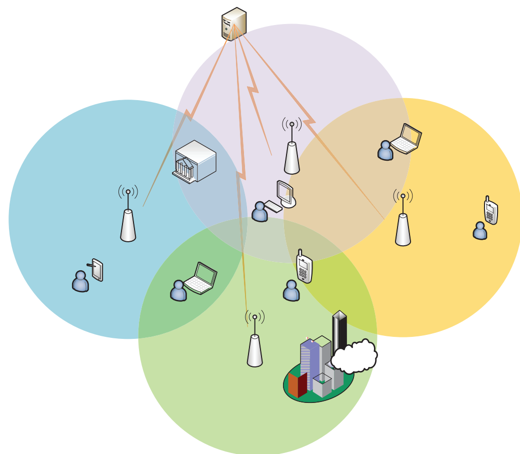

Fig. 1. A schematic map of Super Wi-Fi system.

II. System Model

As shown in Fig. 1, in an EH network with multiple BSs, each BS is supplied by EH devices and connected to the server by wireless backhaul. In each time slot, the BS harvests a certain quantity of solar energy, denoted as E_H, and stores it into its battery. At the same time, to serve the users connected to the BS, energy E_T is consumed for transmission. We denote the battery quantity of the BS as Q_B, which can be any value from 0 to the battery volume B_M. In every times slot, the BSs could serve multiple users, the number of which is denoted as $S_U = i$, $i = 0, 1, \ldots, N_U - 1$, where N_U is the maximum number of users the BS could serve simultaneously due to limited spectrum and coding ability. Note that different BSs in the network could have different battery volume B_M and maximum serving users N_U.

At the start of each time slot, users with new service demand could decide either to access or sense one of the BSs within its range. We denote the action as $\Phi = \Phi_a^i$ for accessing the i^{th} BS, and $\Phi = \Phi_s^i$ for sensing. In the case of sensing, the BS will respond to the user by sending its next-time-slot system state in a short message which requires negligible energy consumption. In the case of accessing, the user sends a request to the chosen BS. When the request is achievable, the BS activates user's transmission immediately. Otherwise, the BS declines the request and inform the user its next-time-slot system state, again with a low energy consuming short message. In the above process, the short message could be used as observation by a user to update his/her belief of the BS state (e.g., battery state, number of users in the system). Therefore, the user's action has to be careful chosen. On one hand, the users are intent to maximize their utility by making enough access attempts. On the other hand, sensing is necessary, as the lack of information will result in useless attempts, causing energy waste and access failures.

From the BSs' perspective, certain protections are needed, as malicious users could keep accessing one BS and use up all the energy. To focus our work on formulation from the users' perspective and not to be distracted by protection details, a simple protection is used in our work. If a BS is currently not serving any users and the battery is low, the BS would reserve the last quantity of energy that could serve a user for one time slot and forbid new users from using it. Meanwhile, in our work, we consider rational users who could observe multiple BSs and chooses an action in every time slot to maximize the number of successful access. The number of the observed BSs by the user is denoted as N_A.

III. POMDP BS Access Strategy

As POMDP could solve decision making problems of different decision horizon lengths under uncertainty, it perfectly depicts the above EH Super Wi-Fi model. In order to formulate the problem, two key components in the system model, user number and battery, are carefully considered.

A. User Model

As in traditional wireless network, the users arrive and leave the BS with certain probability [6]. Between adjacent time slots, new users may arrive and old users may leave or be forced to leave when battery is insufficient. A revised birth and death process that considers forced leaving are proposed as follow,

$$\zeta\left(S_U'|S_U, Q_B, \Phi\right) = \begin{cases} \lambda, & \text{if } Q_B \text{ is enough and } S_U' = S_U + 1, \\ \mu S_U, & \text{if } Q_B \text{ is enough and } S_U' = S_U - 1, \\ I_0\left(S_U'\right), & \text{if } Q_B \text{ is insufficient}, \\ 0, & \text{otherwise}. \end{cases} \quad (1)$$

In the above equation, λ is the arriving rate and the $\mu' = \mu S_U$ is the leaving rate of users. The forced leaving is formulated by the indicator function $I_0\left(S_U'\right)$, which indicates that S_U' next time slot is sure to be 0. Energy depletion happens when $Q_B - E_T \leq 0$.

B. Battery Formulation

The harvested energy E_T is determined by the environmental parameters. Gaussian models have been proved effective in predicting solar intensity [9], [10]. The harvest model assumes that the solar intensity in a long time period are Gaussian distributed, and the solar intensity during one single time slot, the length of which denoted as T_L, remains unchanged. Thus, the solar intensity W_e could be formulated as Gaussian distributed $\mathcal{N}\left(x; \mu_S, \sigma_S\right)$ with average intensity μ_S and variance σ_S^2. In current devices, the harvesting power per reference solar intensity is $E_H = W_e J_{op} V_{op} \Omega_S T_L \eta$, where the J_{op} and V_{op} is the optimal operating point, the Ω_S is the number of solar cells and the η is the efficiency [11].

The transmitting power is set by BSs to provide enough SINR for the receiving users. Current power adjustment algorithms that use feedback are not valid, as the system state are fast changing between time slots. Therefore here a static power management is implemented, where the BS sacrifices some energy to insure a successful transmission every time slot. The power consumption in a BS is determined by the number of accessing users, which is denoted as $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. As wide range telecommunication has negligible between-user interference, we assume the transmission power is proportional to the number of serving users, i.e., $\Upsilon_T(S_U, Q_B, \Phi) = P_T(S_U + \Theta(S_U, Q_B, \Phi_a))$, where P_T is the transmission power for single user. $\Theta(S_U, Q_B, \Phi_a)$ is 1 if the rational user could successfully access, otherwise it is 0. Correspondingly, we assume the battery volume $B_M = \rho P_T T_L$, where ρ is an integer. Note that for the nonlinear transmission power function, our method could still work by setting different battery levels in the below formulation. When the required battery is more than the BS's remaining battery, the BS will provide a best effort service. Users with the higher priority are served. In our case, the rational user has the lowest priority. Given the E_H, E_T, the battery in the next time slot could be calculated as,

$$Q'_B = \min\{Q_B + E_H - E_T, B_M\}. \tag{2}$$

In EH powered BSs, the battery is a continuous value. But in a POMDP, the states have to be discrete. Intuitively, we could use more battery states to approximate continuous value, but this brings much increase in the complexity of the algorithm. Luckily, a certain number of discrete levels could provide enough information during the decision making. We could set battery levels according to the possible energy consumption in each time slot $T_L \Upsilon_T(S_U, Q_B, \Phi)$. In the case of linear power function, the levels are set as $S_B = \lfloor Q_B/(P_T T_L) \rfloor$. And the number of battery states is $N_B = B_M/(P_T T_L) + 1 = \rho + 1$. Thus, by knowing the battery states, the user would know whether the battery is sufficient for transmission.

The prediction of future battery states are base on transition probability between battery states. In order to calculate the transition probability, we assume the fluctuate of discrete battery state is quasi-static. i.e., the residue energy $Q_B - S_B P_T T_L$ is uniformly distributed between $[0, P_T T_L)$. Although errors are brought by this assumption, the quasi-static assumption is proven to be effective after a large number of time slots [10]. We denote the change of battery state between time slot as $\Delta_B = S'_B - S_B$. Event ξ_j represents that the real battery quantity change $E_H - E_T$ is equivalent to more than j but less than $j+1$ battery state change, namely $\xi_j := \{j \le \frac{E_H - E_T}{P_T T_L} \le j+1\}$. Then the probability that the battery state will change by Δ_B given E_H and user action can be computed as follows

$$\begin{aligned} &\Pr(\Delta_B = i|\Phi, E_H, \xi_j) \\ &= \begin{cases} \frac{(E_H - E_T)}{P_T T_L} - j, & i = j+1, \\ (j+1) - \frac{(E_H - E_T)}{P_T T_L}, & i = j, \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{3}$$

In the equation, as mentioned in previous section, $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. When $E_H - E_T \le 0$, the probability could be calculated the same way. The battery transition can be written as

$$\begin{aligned} &\Pr(\Delta_B = i|\Phi) = \\ &\int_{i\epsilon_T + E_T}^{(i+1)\epsilon_T + E_T} \Pr(\Delta_B = i|\Phi, E_H, \xi_i)\, \mathcal{N}(E_H; \bar{\mu_S}, \bar{\sigma_S})\, dE_H + \\ &\int_{(i-1)\epsilon_T + E_T}^{i\epsilon_T + E_T} \Pr(\Delta_B = i|\Phi, E_H, \xi_{i-1})\, \mathcal{N}(E_H; \bar{\mu_S}, \bar{\sigma_S})\, dE_H. \end{aligned} \tag{4}$$

In the equation, $\epsilon_T = P_T T_L$ and $\bar{\mu_S}$, $\bar{\sigma_S}$ are scaled from μ_S, σ_S after the multiplication with harvesting device coefficients.

C. System Transition Probability

The POMDP state is the overall system state, which combines all the BSs' system state. To make the following math more readable and flexible, the system state S and $S_D = \{S_B^1, S_U^1, \ldots, S_B^{N_A}, S_U^{N_A}\}$ are equivalent and used simultaneously. We have $S = 1, 2, \ldots N_S$, where $N_S = (N_B N_U)^{N_A}$. We first calculate the transition probability for a single BS. From conditionally independence we have

$$\mathrm{P}(S'_U, S'_B|S_U, S_B, \Phi) = \zeta(S'_U|S_U, S_B, \Phi)\, \delta(S'_B|S_U, S_B, \Phi). \tag{5}$$

The $\zeta(S'_U|S_U, S_B, \Phi)$ is given in equation (1). And the battery transition is calculated based on the equation (4) as follows

$$\begin{aligned} &\delta(S'_B|S_U, S_B, \Phi) \\ &= \begin{cases} \Pr(\Delta_B = S'_B - S_B|\Phi), & \text{if } S'_B \le N_B - 1, \\ \sum_{\Delta_B = S'_B - S_B}^{\Delta_B = \Delta_B^{Max}} \Pr(\Delta_B|\Phi), & \text{if } S'_B = N_B - 1. \end{cases} \end{aligned} \tag{6}$$

When the battery is fully charged, $S'_B = N_B - 1$, all the extra harvested battery is abandoned. Note that we truncate the probability for $\Delta_B > \Delta_B^{Max}$ as they are as small as zero by 4 decimals. Thus the POMDP state transition is computed as

$$T(S'|S, \Phi) = \prod_{i=1}^{i=N_A} \mathrm{P}\left(S_B^{i,'}, S_U^{i,'}|S_U^i, S_B^i, \Phi\right). \tag{7}$$

D. Observation Function and POMDP Iteration Algorithm

In POMDP formulation, the user only has the partial knowledge of the system. As mentioned above, the user could get the target BS's next-time-slot system state S_B^O and S_U^O at the end of each time slot. We use observation O to represent S_B^O, S_U^O. The observation probability function given the system state in the next time slot is

$$Z(O|S', \Phi) = \Pr\left(O \middle| S_U^{t,'}, S_B^{t,'}\right) = I_{S_U^{t,'}, S_B^{t,'}}\left(S_U^O, S_B^O\right). \tag{8}$$

$S_B^{t,'}$ and $S_U^{t,'}$ are the system state of the target BS next time slot. The indicator function is 1 when $S_U^{t,'} = S_U^O$, $S_B^{t,'} = S_B^O$ or 0 otherwise.

The reward is define as $R = 1$ if the access succeeds, else $R = 0$. Then the value function of a single state is

$$V_t^{\Phi}(S) = R(S, \Phi) + \gamma \sum_{S'} T(S'|S, \Phi)\, V_{t-1}^{\pi}(S'), \tag{9}$$

where π denotes the optimal action in that state. As no full knowledge is held for the user, we use a belief vector to denote the user's system state belief $\beta = [\beta(S=1), \beta(S=2), \ldots, \beta(S=N_S)]$. Then the particular value function with a certain belief β is given by

$$V_t^{\Phi}(\beta) = \sum_S R(S,\Phi)\,\beta(S) + \gamma \sum_S \sum_{S'} \beta(S)\,T(S'|S,\Phi)\,V_{t-1}^{\pi}(S'). \tag{10}$$

For simplicity, if we already know all the value function of at the time $t-1$ during iterations, an alpha value vector $\alpha_t^{\Phi} = [\alpha_t^{\Phi}(S=1), \alpha_t^{\Phi}(S=2), \ldots, \alpha_t^{\Phi}(S=N_S)]$ could be used to simplify the value function as $V_t^{\Phi}(\beta) = \sum \beta(S)\,\alpha_t^{\Phi}(S)$. Thus, the optimal action can be give by

$$\pi(\beta) = \arg\max_{\alpha_t^{\Phi}} \sum_S \beta(S)\,\alpha_t^{\Phi}. \tag{11}$$

The corresponding value function $V_t^{\Phi}(\beta)$ could be calculated using action $\pi(\beta)$. However, the corresponding optimal policy is not as easy as it seems to be, as the β has a continuous value, and even for the same Φ and t, there are still multiple possible α vectors during iterations. But fortunately, the V_t could be regarded as the function value of β in a hyper coordinate system, the axes of which are the components of β. As each set of α_t vector could be regarded as a set of parameters of a hyper linear function, there is a dominated hyperplane structure in the model. The continuous belief space is divided by several α-vector-dominated hyperplanes into several partitions. The partitions of belief space in time t could be calculated given all the dominating α_{t-1}. The details of algorithm for solving the partitions could be find in a well written tutorial [12].

After obtaining the optimal action, the user could act accordingly, and update its belief vector after receiving the observation by using the following formula.

$$\beta'(S'|\Phi,O) = \frac{\sum_O Z(O|S',\Phi)\sum_S T(S'|S,\Phi)\,\beta(S)}{\sum_{S'}\sum_O Z(O|S',\Phi)\sum_S T(S'|S,\Phi)\,\beta(S)}. \tag{12}$$

E. Suboptimal Access Policy

The optimal POMDP solution could be calculated off-line within seconds when the number of states is small. However, the use of POMDP method is limited when N_A is massive, and when the environment parameters, like solar coefficients μ_S, σ, the birth rate λ and death rate μ of users, change quickly. The POMDP formulation will maximize success access ratio $\eta_A = N_S/N_T$, where N_S is number of success access and N_T is the number of the time slots. We propose a dual perspective of solving the problem by focusing on the harvested energy. We name it Energy Based (EB) Method. The problem is reformulated as,

$$\max_{\Phi_t, t=0,\ldots,N_T-1} \sum_{t=1}^{N_T} \mathrm{E}\big[\mathrm{H}\left(\beta^t, \Phi_t\right)\big], \tag{13}$$

where the expectation function $\mathrm{E}[\cdot]$ considers the probability of receiving different observations and thus having different

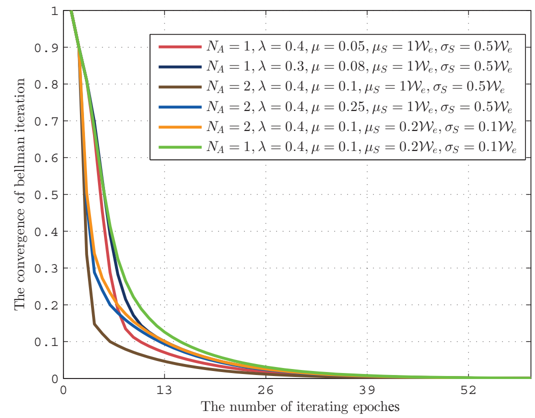

Fig. 2. Illustration of the convergence of the POMDP iteration algorithm

belief vector β^t, and $\mathrm{H}(\beta^t, \Phi_t)$ is the overall harvesting energy in all the BSs as follows

$$\mathrm{H}\left(\beta^t, \Phi_T\right) = \sum \beta^t(S) \sum_{i=1}^{N_A} \min\left(E_H^i,\, E_T^i + B_M - Q_B^i\right) \tag{14}$$

In such a case, a suboptimal could be proposed by maximizing the system's next-time-slot harvested energy, i.e.,

$$\Phi\left(\beta^t\right) = \arg\max \mathrm{E}\big[\mathrm{H}(\beta^{t+1}, \Phi_t)\big], \tag{15}$$

When BS sensing is the optimal action, the user will choose to sense the BS that is not sensed for the longest time. Due to the limited space, some key rationality of the EB method is summarized. First of all, when the solar intensity is strong, we could assume few users will be forced to leave because of resource competitions and depletion, and thus the energy consumed by them are stable. As the transmission power is proportional to number of users, we could deduce that the more energy the system harvests, the more utility the rational user could achieve. Besides, the EB method is an unselfish method, which would sacrifice some reward, but tends to protect overall utility. And EB method could use learning algorithm to adjust to quick environmental changes.

IV. Simulation Results

In this section, the convergence and effectiveness of the algorithm are illustrated. Fig. 2 shows the convergence of the POMDP iteration algorithm, where the y-axis means a user's value difference between two adjacent iterations and the discount factor is $\gamma = 0.9$. A Bellman stoping criteria is used to determine the stop of iteration. In the figure, the α vector error shows the convergence of the iteration algorithm. The POMDP simulation tool is provided by [12]. As we can see from the results, our proposed POMDP algorithm converges exponentially under various parameter settings.

The effectiveness of the algorithms is validated by comparing the η_A under the overall time slots $N_T = 10000$. In the simulation, parameters are used as follow. The reference

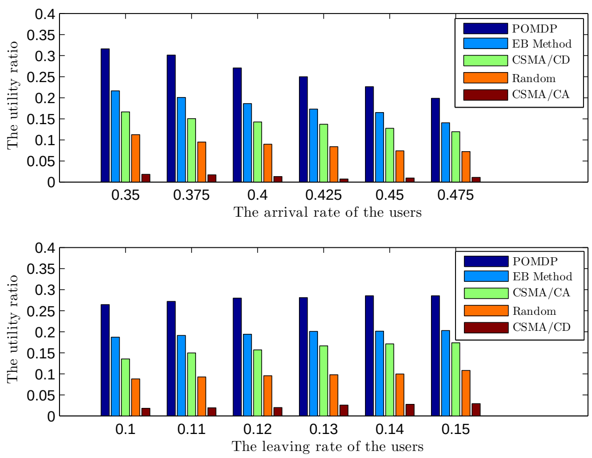

Fig. 3. The utility ratio in two BSs with different user arriving rate and leaving rate

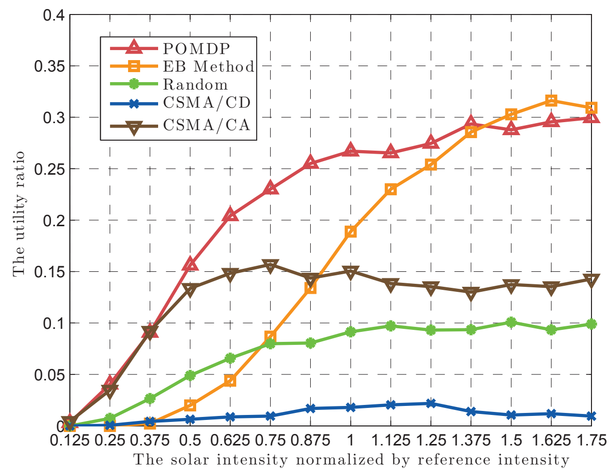

Fig. 4. The utility ratio in two BSs with $N_U = 2$, $N_B = 3$

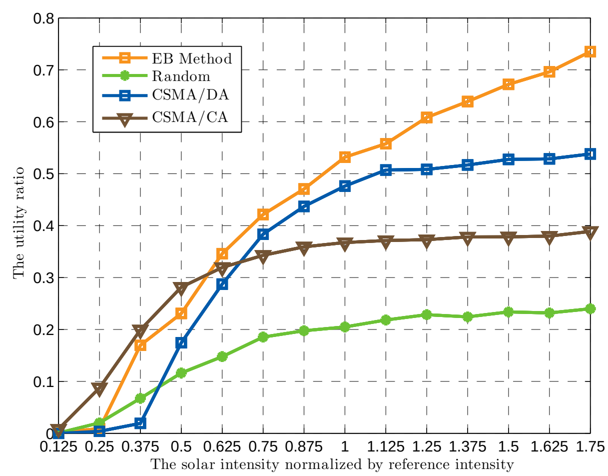

Fig. 5. The utility ratio in three BSs with $N_U = 4$, $N_B = 8$

benchmark solar intensity is given as $\mathcal{W}_e = 1\text{kW}/m^2$, which is the average intensity on the surface of Earth [13]. We use the date from work [14], where the optimal power per benchmark solar intensity $\mathcal{W}_e$ is $P_H = J_{op}V_{op} = 1.32\text{mW}/\mathcal{W}_e$, with a efficiency $\eta = 75\%$. And there are $\Omega_S = 40$ cells in one harvesting device. The time slot length is $T_L = 200\text{ms}$. Transmission power for serving one user is $P_T = 40\text{mW}$.

In order to show the efficiency, several algorithms are implemented as comparisons. including Carrier Sensing Multiple Access/Collision Avoidance, Collision Detection (CSMA/CA and CSMA/CD). Note that here the "carrier sensing" means that one user senses the BSs, i.e., receives the short message from one BS, instead of the physical carrier. The CSMA/CD method stops new request when detecting a failure, and then an exponential back-off algorithm is used. After c failures, a random number of sleeping time slot between 0 and $2^c - 1$ is chosen. The CSMA/CD method would access the BS after the user senses the BS in the last time slot and knew that a successful service is available. In random access algorithm, the user simply chooses action with equal probability.

In Fig. 3, the effectiveness of our algorithms are shown. We consider double BSs with possible number of users $N_U = 2$, $N_B = 3$. In the simulation, the $\mu_S = 1$ and $\sigma_S = 0.5$. In Fig. 3-(a), the leaving rate is $\mu = 0.1$, while in Fig. 3-(b), the arrival rate $\lambda = 0.4$. As shown in the figure, the performance of proposed POMDP is significantly higher, with the EM method's overall performance following at the second place, which validates the efficiency of our algorithms. In the figure, we also find that when the number of possible serving positions is limited, the crowded system makes the CSMA/CD method almost useless.

In Fig. 4, the utility of the algorithms under different solar intensity is studied. In the simulation, we consider two BSs with $N_U = 2$, $N_B = 3$, and the leaving rate $\mu = 0.1$, arriving rate $\lambda = 0.4$. Again the proposed POMDP has the best performance. In the figure, one prominent point is that when the solar intensity is strong, the utilities of the traditional algorithms' are saturated, failing to further enhance users' utility, due to the reason that those algorithms are not able to make use of the EH information of the system. The CSMA/CD algorithm even has lower performance when the intensity is stronger. A simple analysis could be given. When the solar intensity is small, the utility of CSMA/CD increases with intensity due to more available sources. But when the solar intensity is strong, as the more users are staying in the BS, the user has less chances of being served in the crowded system, and thus the utility decreases. Another worth mentioning point is that, as we predicted, when the solar intensity is strong, the suboptimal EB method will approach and even outperform the proposed POMDP method, which can decrease the complexity to a large extent. The outperformance is mainly brought by the approximations in the POMDP formulation, such as the quasi-static approximation. At the same time, when the solar intensity is weak, the EB method has a relatively ordinary performance, which could be analysed as follow. When the energy is inadequate, the assumption of the EB method that, few users will be forced to leave the BSs because of the new user, is violated, as there is a strong between-user resource competition. Thus, due to the unselfish nature of the EB algorithm, the EB user will execute less accesses to avoid energy waste, and have lower utility ratio meanwhile.

In Fig. 5, we consider the senario where the system states are too massive for the POMDP strategy to be computed within a short time. In the network, we consider three BSs with $N_U = 4$, $N_B = 8$, and the leaving rate $\mu = 0.1$, arriving rate $\lambda = 0.4$. Besides that the CSMA/CD method has a good performance as the serving positions are redundant, the performance of each algorithm is similar to what is shown in Fig. 4. Traditional algorithms are saturated when the solar intensity is strong. And what is important in the figure is that, for systems with massive system states, the EB method still works and has good performance. Thus the suboptimal EB method could be used to decrease the complexity of the POMDP method and maintain a high utility ratio at the same time.

V. Conclusion

In this paper, we proposed a powerful POMDP algorithm to solve the access problem in EH powered network, which is promising and instructive in building a national range Super Wi-Fi network. The framework given in this paper is adjustable to EH problems other than the Solar EH one. To reduce complexity and adjust to environmental changes, a suboptimal EB method is proposed as well. The affect of solar intensity, user arriving rate, leaving rate and many other features are considered, proving our work reliable and effective. Future work of this paper could focus on the prediction of system parameters and multiuser accessing scenario.

References

[1] P. Monti, S. Tombaz, L. Wosinska, and J. Zander, "Mobile backhaul in heterogeneous network deployments: Technology options and power consumption," in *Transparent Optical Networks (ICTON), 2012 14th International Conference on*, July 2012, pp. 1–7.

[2] T. Todd, A. Sayegh, M. Smadi, and D. Zhao, "The need for access point power saving in solar powered wlan mesh networks," *Network, IEEE*, vol. 22, no. 3, pp. 4–10, May 2008.

[3] Y. Xu, A. Anpalagan, Q. Wu, L. Shen, Z. Gao, and J. Wang, "Decision-theoretic distributed channel selection for opportunistic spectrum access: strategies, challenges and solutions," *Communications Surveys & Tutorials, IEEE*, vol. 15, no. 4, pp. 1689–1713, 2013.

[4] B. Wang, Y. Wu, and K. J. R. Liu, "Game theory for cognitive radio networks: An overview," *Computer networks*, vol. 54, no. 14, pp. 2537–2561, 2010.

[5] D. Niyato and E. Hossain, "A game theoretic analysis of service competition and pricing in heterogeneous wireless access networks," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 12, pp. 5150–5155, December 2008.

[6] Y.-H. Yang, Y. Chen, C. Jiang, C.-Y. Wang, and K. J. R. Liu, "Wireless access network selection game with negative network externality," *Wireless Communications, IEEE Transactions on*, vol. 12, no. 10, pp. 5048–5060, October 2013.

[7] Q. Zhao, L. Tong, A. Swami, and Y. Chen, "Decentralized cognitive mac for opportunistic spectrum access in ad hoc networks: A pomdp framework," *Selected Areas in Communications, IEEE Journal on*, vol. 25, no. 3, pp. 589–600, April 2007.

[8] K. W. Choi and E. Hossain, "Opportunistic access to spectrum holes between packet bursts: A learning-based approach," *Wireless Communications, IEEE Transactions on*, vol. 10, no. 8, pp. 2497–2509, August 2011.

[9] R. Aguiar and M. Collares-Pereira, "Tag: A time-dependent, autoregressive, gaussian model for generating synthetic hourly radiation," *Solar Energy*, vol. 49, no. 3, pp. 167 – 174, 1992.

[10] M.-L. Ku, Y. Chen, and K. J. R. Liu, "Data-driven stochastic models and policies for energy harvesting sensor communications," *Selected Areas in Communications, IEEE Journal on*, vol. PP, no. 99, pp. 1–1, 2015.

[11] V. Raghunathan, A. Kansal, J. Hsu, J. Friedman, and M. Srivastava, "Design considerations for solar energy harvesting wireless embedded systems," in *Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on*, April 2005, pp. 457–462.

[12] A. Cassandra, "Partially observable markov decision processes," http://www.pomdp.org/index.shtml.

[13] M. A. El-Sharkawi, *Electric energy: an introduction*. CRC press, 2012.

[14] M.-H. Chang, J.-Y. Wu, W.-C. Hsieh, S.-Y. Lin, Y.-W. Liang, and H. Wei, "High efficiency power management system for solar energy harvesting applications," in *Circuits and Systems (APCCAS), 2010 IEEE Asia Pacific Conference on*, Dec 2010, pp. 879–882.