Access Strategy in Super WiFi Network Powered by Solar Energy Harvesting, A POMDP Method

Tingwu Wang*, Chunxiao Jiang*, Yan Chen†, Yong Ren*, and K. J. Ray Liu†
* Department of Electronic Engineering, Tsinghua University, Beijing, 100084, P. R. China
†Department of Electrical and Computer Engineering, University of Maryland, College Park, MD 20742, USA
E-mail: wtw12@mails.tsinghua.edu.cn, {jchx, reny}@tsinghua.edu.cn, {yan, kjrliu}@umd.edu

***Abstract*—The recently announced Super Wi-Fi Network proposal 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 needed. The fast developing Energy Harvesting (EH) techniques receive global concerns for their potential of solving the above power supply problem. Many studies have been done on traditional access strategy, but the access strategy in EH wireless network with multiple Base Stations (BS) remains a field with tremendous research potential. Different from traditional wireless network, a Base Station (BS) in EH powered network harvests energy from the ambient environment. And as the energy is limited, the BS will not broadcast its system state to all the users within its range, which provides incomplete information for the users. Thus the access strategy has to be carefully chosen. In this paper, we propose a practical and efficient framework for multiple BSs access strategy in an EH powered Super Wi-Fi network. In our work, we consider the access strategy from the opportunistic user (OU) perspective, who exploits downlink transmission opportunities with the Passive Users (PU). To formulate the problem, we used Partially Observable Markov Decision Process (POMDP) to model the real world uncertainty. 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 revised. And 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 comes across many obstacles. An inevitable problem is how to deploy practical backhaul and energy supply system. Traditional cable-based systems are excessive, considering the cost for deploying and maintaining the network, and sometimes impossible as well as dangerous in complex environment. 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 for cable backhaul. And the fast developing 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 needed, as some preliminary studies pointed out [2]. Previously, the access strategy problem has been a core problem in wireless communications, and many researchers have been doing some brilliant work in the literature. Markov Decision Process have been widely used in wireless network, with some challenges and solutions summarized in [3]. Access process is a typical game process, and therefore game theory, summarized in [4], and pricing theory, used in [5], has been applied respectively. In [6], the access strategy towards multiple BSs with negative externality is considered. More recently, a POMDP MAC layer opportunistic access is proposed by Dr. Zhao in [7]. A learning based approach to access between packet bursts is studied in [8].

However, all the mentioned existing studies on the access strategy did not consider the multiple BSs access strategy under energy harvesting, while, as mentioned above, using EH powered BSs is the best practicable ways of realizing Super Wi-Fi network. In this work, we propose an access strategy that is exercisable in the fast booming Super Wi-Fi network, and consider the corresponding problems that we may encounter during the real world implementation. As long time transmission is not guaranteed in EH network, leaving and arriving of users are more frequent. Instead of using an invariant system state model, We consider a model where the number of accessing users and the battery are dynamic. A revised birth and death process and a battery transition formulation based on quasi-static assumption are combined to describe system state transition. Besides, unlike most of the models where the influence of the OUs on the BSs is neglected, we consider the case where an OU affects system state by making actions. For example, the OU could cause energy exhaust, collision and system low efficiency if it performs short-sighted and selfish strategy, or causing energy waste when it is too conservative. And as in EH wireless network, the full knowledge of the system is unrealistic, the POMDP model is used to formulate the problem. To sum up, we propose an algorithm that is able to overcome the drawbacks in previous models. And although our work focuses on solar energy harvesting, it is clear that the conclusion and the algorithm could be generalize 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. And in Section III, the

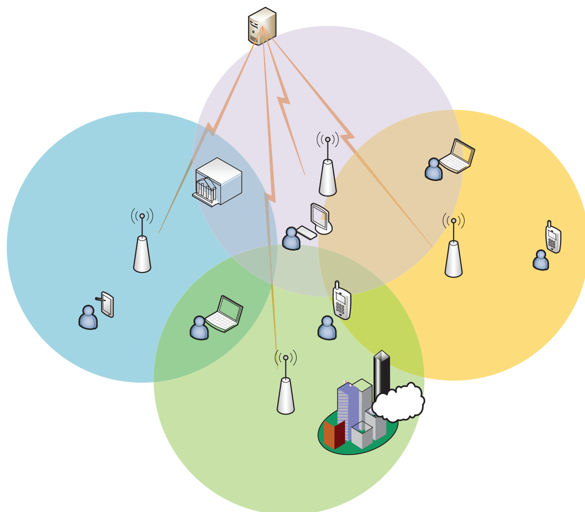


Fig. 1. A schematic map of Super Wi-Fi system.

POMDP formulation is presented, showing how we abstract the continuous battery state and user state to POMDP states and draws the optimal decision. And a suboptimal strategy is proposed. In Section IV, we evaluate the performance of our proposed approach with several famous traditional algorithm. Finally, Section V draws the conclusion.

II. System Model

In this section, before we illustrate the proposed POMDP algorithm, we describe the system model of the Super Wi-Fi network. As shown in Fig1., like in other wireless network, the OU could observe multiple BSs, the number of which is denoted as N_A. In the network, users that only access one certain BS due to limitations like geographical distribution is called Passive User (PU). For each BS, there is a maximum number of users that it could serve simultaneously due to limited spectrum, as BS could not maintain the SINR for overcrowded users. We use the notation N_U to represent the maximum number of users. Thus, the user state in each BS could be denoted as $S_U = i, i = 0, 1, ..., N_U$. Different from the discrete user state, the battery could be any continuous value between 0 and the maximum battery value B_M. Note that in our work, The B_M and N_U for different BS could be different and our method still works.

A. Access and Observation Model

During each time slot, a certain quantity of energy, denoted as E_H is harvested, and energy E_T is consumed during transmission. Between adjacent time slots, new PUs may arrive and old PUs may leave after finishing their service or the battery is not adequate for every service. And thus a revised birth and death process is used to describe the process of user behaviors. The transition probability of number of PUs is calculated as,

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

In the above equation, λ is the arriving rate and the $\mu' = \mu S_U$ is the leaving rate of the process. Note that when the battery is exhausted, all the users are dropped, which is represented by the indication function $I_0\left(S_U'\right)$, i.e., $S_U' = 0$ if battery is not enough. Whether the Q_B is adequate or not is shown in the next subsection. At the start of each time slot, the OU could either decide to access or sense one of the BSs within its range. When the OU decide to access the i^{th} BS, namely $\Phi = \Phi_a^i$, it sends a request signal to the chosen BS. And if the BS has the requested battery for serving this extra requrest, it will activate OU's transmission in this time slot. But there is also risk that the request fails because of low power and collision. In this case, the BS will reject the request. Whether the transmission is successful or not, the BS will feedback the user its system state with a short costless signal. When collision happens, the energy is wasted due to low SINR. In order save time and energy, a more conservative idea is to sense the BS, i.e. Φ_s^i. When the BS receives a sense signal, it only transmits its system state to the user with neglectable energy consumption.

B. Physical Battery Model

The harvested energy E_T is determined by the environmental parameters, which, in our case, is the sun light intensity. Gaussian model has been proved effective in predicting sun light intensity [9], [10]. In a small time slot, denoted as T_L, the average solar intensity remains unchanged. In our work, the solar intensity W_e is assumed to be Gaussian distributed with average intensity μ_S and variation σ_S, $\mathcal{N}\left(x; \mu_S, \sigma_S\right)$. The harvested energy is given as $E_H = W_e J_{op} V_{op} \Omega_S T_L \eta$, where the J_{op} and V_{op} is the optimal operating point of the existing harvesting devices [11], the Ω_S is the number of solar cells and the η is the harvesting efficiency. The transmitting energy is adjusted to make sure transmission with certain SINR. It is important to note that, current feedback-based power adjustment algorithm like Inner Loop Power Management is not valid as the system state changes during the time slots. Here a static power management is implemented. The power consumption in a BS is determined by number of PUs and the OU's action, which is $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. In most cases, the access of OU could be regarded as an extra PU for the BS, i.e., for BS i, $\Upsilon_T(S_U, Q_B, \Phi = \Phi_a^i) = \Upsilon_T(S_U + 1, Q_B, \Phi \neq \Phi_a^i)$. When the required battery is more than the BS's remaining battery, the users with the higher priority is served. In our case, the OU has the lowest priority. Now we could define the event that Q_B is adequate as $Q_B - \Upsilon_T(S_U, Q_B, \Phi) \leq 0$. Thus the battery in the next time slot could be expressed as follow,

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

To protect PUs from OU that uses up all the energy, the OU will not be served by BS in shortage of energy, for example, BS with energy for only serving one user in one time slot.

III. POMDP AP SELECTION

In Section II we describe the system model, it is clear that decision has to be carefully chosen. There are several factors to be considered: the tradeoff between immediate reward and the long term reward and the uncertainty of system state during decision making. POMDP, which is recently developing as a strong tool to deal with decision making under uncertainty, come as a perfect solution to this system. However, before we could formulate our proposed algorithm, it is important to define our system state.

A. Battery Transition

In the implementation of EH powered BSs, the battery is a continuous value. And in a POMDP, the states have to discrete. Intuitively, we could use more battery states to represent the same battery volume, but this brings much increase in the complexity of POMDP. In our work, we convert the continuous battery quantity into N_B discrete battery states $S_B = \lfloor Q_B N_B / B_M \rfloor$. S_B could take values from level 0, 1, ..., $N_B - 1$. In order to calculate the transition probability between adjacent battery states, we assume the fluctuate of discrete battery state is quasi-static. Under the assumption, for a given discrete battery state S_B, the residue energy $Q_B - B_M S_B / N_B$ is uniformly distributed between $[0, B_M/N_B]$. Clearly errors are brought by this assumption, but the quasi-static assumption is proven to be effective and works well after many time slots [10]. We denote the battery state changing between time slot as $\Delta_B = S_{B,'} - S_B$. We define a event ξ_j to denote that the real battery quantity change is more than j but less than $j+1$ levels. $\xi_j := \{j \leq N_B \frac{E_H - E_T}{B_M} \leq j+1\}$ Then the probability could be computed as follow,

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

In the equation, as mentioned in previous section, $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. The situation where the $E_H - E_T \leq 0$ is simply doing the mirror computation of the above equation. When we consider the Gaussian distributed light density, the actual battery transition is then,

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

In the equation, the mean and variance of the Gaussian distribution are scaled accordingly after mutiplication.

B. System Transition Probability

When the user transition probability and battery transition probability is computable, we could focus on the formulation of POMDP. Note that the POMDP state is the system state, which contains state information of all BS. To make the following math more readable and flexible, two equivalent notation of system state is used simultaneously, i.e. the centralized form of system state S and the decentralized form of system state $S_D = \{S_B^1, S_U^1, ..., S_B^{N_A}, S_U^{N_A}\}$. $S = 1, 2, ... N_S$, where $N_S = (N_B N_U)^{N_A}$ is the number of system state. For the transition probability for a single BS, the probability of S_U' and S_B' in the next slot are conditionally independent given the current S_U, S_B and Φ.

$$\mathrm{P}\left(S_U', S_B' | S_U, S_B, \Phi\right) = \zeta\left(S_U' | S_U, S_B, \Phi\right) \delta\left(S_B' | S_U, S_B, \Phi\right) \tag{5}$$

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

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

In the case of battery overflow, $S_B' = N_B - 1$, all the extra battery is abondoned. We truncate the probability above Δ_B^{Max} as they are as small as zero by 4 decimals. The overall transition is computed as,

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

C. POMDP Optimal Algorithm

In POMDP formulation, the OU only has the partial knowledge of the system. At the end of each slot, the OU could get the BS's system state S_B^O and S_U^O, which we use $\mathcal{O}$ to denote. The observation probability function is given as follow.

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

$S_B^{t,'}$ and $S_U^{t,'}$ are the system state of the target BS next time slot. The indicator function is either 1 or 0. The reward is define as $R = 1$ if the access succeeds, else $R = 0$. Then the value function of a single state is,

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

where π denotes the optimal action in that state. As no full knowledge is held for the OU, we use a belief vector to denote the system belief $\beta = [\beta\left(S=1\right), \beta\left(S=2\right), ..., \beta\left(S=N_S\right)]$. Then the particular policy tree with a certain belief β is given as

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

For simplicity, if we already know all the value function of at the time $t-1$ during iterations, a value vector $\alpha_t^{\Phi} = [\alpha_t^{\Phi}(S=1), \alpha_t^{\Phi}(S=2), ..., \alpha_t^{\Phi}(S=N_S)]$ could be used to simplify the value function as, $V_t^{\Phi}(\beta) = \sum \beta(S)\alpha_t^{\Phi}(S)$. Note that for the same Φ and t, there are multiple possible α vectors. and the optimal action is

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

The corresponding value function could be calculated under action $\pi(\beta)$. However, the corresponding optimal policy is not as easy as it seems to be, as the β has a continous value. But fortunately, note that the V_t could be regarded as the function value of β in a hyper coordinate, the axis of which is 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 into several α-vector-dominated hyperplanes. The partition of belief space in time t could be calculated given all the dominating α_{t-1}. The details of algorithm for solving the partition could be find in a well written tutorial [12]. At the end of the time slot, the OU will update its belief vector according to its observation.

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

D. 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 PUs, changes quickly. The POMDP formulation tries to maximize success access ration $\eta_A = N_S/N_T$, where N_S is number of success access and N_T is the number of all 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,

$$\max_{\Phi_t, t=0,...,N_T} \sum_{t=1}^{N_T} \mathrm{E}[\mathrm{H}(\beta^T, \Phi_t)], \tag{13}$$

where the $\mathrm{H}(S^T, \Phi_T) = \sum \min(E_H, E_T + B_M - Q_B)$ is the overall harvesting energy of all the BSs combined. Now a suboptimal could be proposed by maximizing the system's next-time-slot harvested energy.

$$\Phi_t(\beta) = \arg\max \mathrm{E}[\mathrm{H}(\beta^{t+1}, \Phi_t)], \tag{14}$$

When sense is the best action, the OU 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 PUs will be forced to leave the BS earlier because of OU. And in most cases, the transmitting power $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. Thus the reward will increase linearly with the harvested energy. Second, the EB method is a unselfish method, which would sacrifice some reward, but will protect the PUs and overall utility. Third, the EB method could implement learning algorithm and adjust to quick changes of the environmental parameters, which will be show in the journal version of this work.

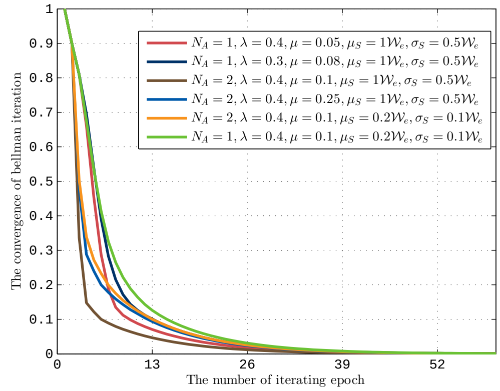


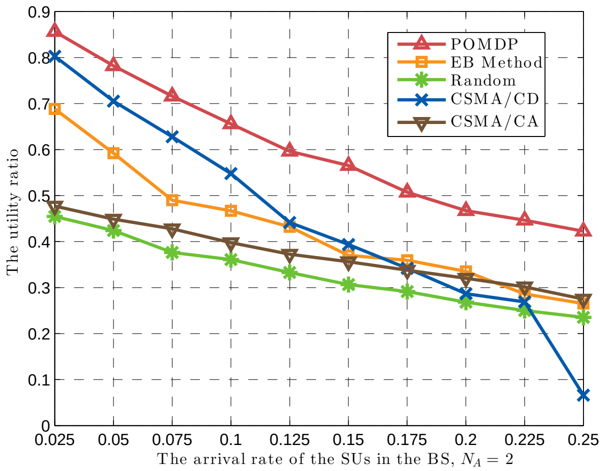
Fig. 2. Illustration of the convergence of the POMDP iteration algorithm

IV. Simulation Results

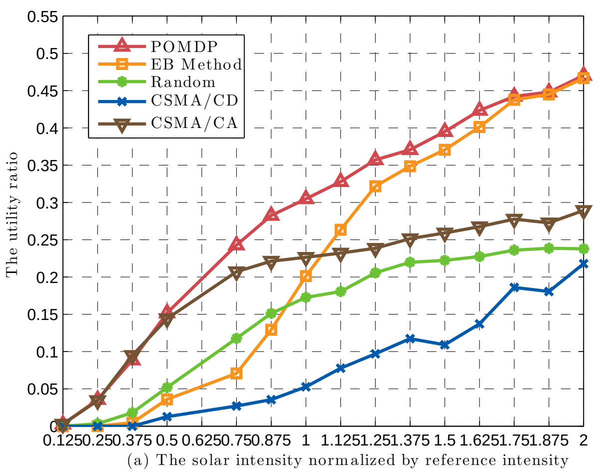
In this section, the convergence and effectiveness of the algorithm is illustrated. In Fig.2, the convergence of the POMDP iteration algorithm is shown, where discount factor $\gamma = 0.9$. A bellman stoping criteria is used to determine the iteration stop. In the figure the α vector error shows the convergence of the iteration algorithm. The POMDP simulation tool is provided by [12]. As is clear in the fig, the algorithm converges exponentially.

The effectiveness of the algorithm is calculated by comparing the η_A during the overall time slots $N_T = 10000$. In the simulation, we use the parameters as follow. The reference benchmark solar intensity is given as $\mathcal{W}_e = 1\mathrm{kW}/m^2$, which is the average intensity on the surface of Earth [13]. We use the work from [14], where the optimal power per benchmark solar intensity $\mathcal{W}_e$ is $P_H = J_{op}V_{op} = 1.32\mathrm{mW}/\mathcal{W}_e$, with a efficiency $\eta = 75\%$. And there are $\Omega_S = 40$ cells in one harvesting device. The time slot length is $T_L = 200\mathrm{ms}$. And as there is no corresponding industry implementation, we assume a transmission power strategy $E_T = \Upsilon_T(S_U, Q_B, \Phi)$ that is proportional to the number of serving users, which is rational considering a wide range wireless network with negligible between-user interference. Transmission power for each user is $P_T = 40\mathrm{mW}$.

In order to show the efficiency, several algorithms are implemented as comparisons. CSMA/CA and CSMA/CD methods are used. Slightly different to the standard CSMA, the OU senses the BSs instead of carrier. And the algorithm tries to avoid collision and energy exhaust. The CD method will stop request when failure detected. A exponential back-off algorithm is used. After c failure, a random number of sleeping time slot between 0 and $2^c - 1$ is chosen. The CA method will only access after the user sense the BS and know that

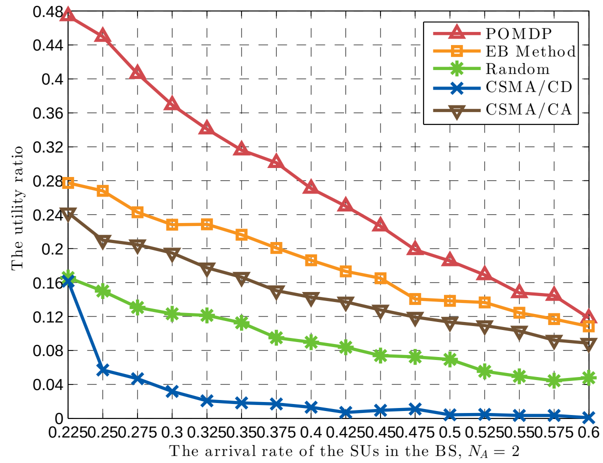


(a) The utility ratio with arrival rate in single BS

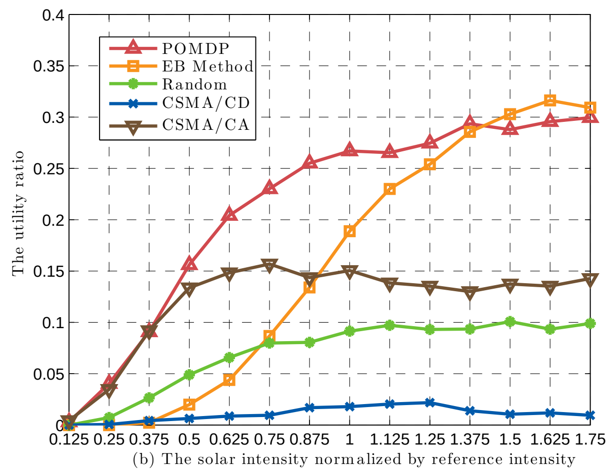


(b) The utility ratio with solar intensity in single BS

Fig. 3. Single BS with $S_U = 0, 1, 2, 3$, $N_B = 8$



(a) The utility ratio with arrival rate in two BS



(b) The utility ratio with solar intensity in two BS

Fig. 4. Two BS with $U_N = 0, 1$, $N_B = 3$

a successful service is available. In random access algorithm, the OU simply chooses action with equal possibility.

In Fig. 3, we consider single BS with possible number of user from 0, 1, 2, 3, $N_B = 8$, $B_M = N_B P_T T_L$, and the leaving rate $\mu = 0.05$. In Fig. 3 (a), the $\mu_S = 1$ and $\sigma_S = 0.5$, and 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. From (a), the CSMA/CD method could have a good performance when the system is not busy, but decreases quickly with the increasing arrival rate of PUs. From (b), it is also clear that even when the solar intensity is strong, the traditional algorithms' ability to increase utility is still obviously limited. As they are not able to make use of the EH information of the system. It is also worth noting that, as we predicted, when the solar intensity is strong, the suboptimal EB method will approach the proposed POMDP method.

In Fig. 4, multiple BSs are considered, with possible number of user from 0, 1,, $N_B = 3$, $B_M = N_B P_T T_L$, and the leaving rate $\mu = 0.05$. Besides what we find in Fig. 3, we also find in Fig. 4 that when the possible serving positions is limited, the crowded system make the CSMA/CD method almost useless. In (b), 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 big, the more solar intensity, the more OUs are staying in the BS, and thus the CSMA/CD has less chances of being served. Also, in (b), the suboptimal EB method could overperform POMDP method when the intensity is big, which is mainly brought by the errors caused in the POMDP formulation, like using the quasi-static assumption.

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. A suboptimal EB method is proposed as well. The affect of solar intensity, PU arriving rate, leaving rate and many other features are considered, proving our work reliable and effective. And the future work of this paper focuses on the adjustment and prediction of system parameters.

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