Access Points Selection in Super WiFi Network Powered by Solar Energy Harvesting

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***Abstract*—The announced yet not realized Super Wi-Fi Network is planning to enable Internet access in a nation-wide area. The infrastructure deployment for Super Wi-Fi is a crucial problem. As traditional cable-connected power supply becomes impractical or costful, Energy Harvesting (EH) becomes a promising method. In an EH powered network, previous models studying single access point (AP) access strategy or multi AP selection become invalid, as a result of the drastic changing number of users and battery states in the BS. In this paper, we study the access strategy from the users' perspective and proposed a practical as well as efficient framework for deploying EH powered Super Wi-Fi network. In our work, the Secondary User (SU) tries to connect to different BS with varing number of Primary User (PU) and battery state, exploiting downlink transmission opportunities. In order to formulate the problem, instead of assuming full knowledge of the system, we used Partially Observable Markov Decision Process (POMDP) to incorporate the real world uncertainty. Simulation results show that our method remakably outperforms the random, myopic and the traditionly widely used listen-before-talk algorithm. And in order to reduce the complexity of the POMDP, we proposed an algorithm that is sub-optimal yet able to accommendate to environmental changes.**

I. Introduction

The battle to expand the coverage area of wireless access keeps pushing forward, and the Federal Communications Commission published Super Wi-Fi proposal, aiming to make use of lower-frequency white spaces between television channel frequencies and create a national wide wireless network. While there are a few successful experimental deployments of Super Wi-Fi, the task of building a nation wide network comes across many obstacles. Traditional cable-based backhaul and energy supply system are, first of all, costfull considering the labor for deploying and maintaining the network in various situations, and secondly, sometimes impossible in extreme, complex and even dangerous environments. Despite all the difficulties, there are solutions. The wireless backhual has been proven to be effective [1] as a replacement for cable backhaul. And the fast developing EH technology provides an ideal solution for the power supply problem. EH could support wireless network service with adequate ambient energy, making use of piezoelectric, thermal, solar energy etc.

Clearly, to make use of the ambient energy, new protocols and modification are needed for the current wireless standards, as some preliminary studies pointed out [2]. The access strategy problem has always 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, with some challenges and solutions summarized in [3]. As the access process is a typical game process, the game thoery, summarized in [4], and pricing theory, used in [5], has been applied respectively. More recently, a POMDP MAC layer opportunistic access is proposed by Dr. Zhao in [6], where the opportunistic spectrum access is proposed. A learning based approach to access between packet bursts is studied in [7].

However, all the existing works on the AP selection or single AP access strategy have at least one of the following drawbacks. Firstly, most of them assume a infinite and always sufficient battery supply. As mentioned above, the infinite battery supply is not practical in building the Super Wi-Fi network. In deploying wide range wireless network, AP with limited battery and constantly energy exhaust is unavoidable. Secondly, many of the work do not consider the fact that the number of user and the remaining battery is changing quickly. Learning based algorithm may perform disasterly bad when they are learning parameters determined by system states that are changing rapidly, causing merely oscillating learning parameter results and low performance. Or more often the case, the algorithm suffers because of wrong belief of the states. Thirdly, the influence of the desicion maker, i.e. the SU, is neglected. When SU makes a decision, it inevitebly affects the state transition. The desicion maker could cause energy exhaust if it performs short-sighted strategy, causing the PUs as well as himself starve or too unambitious causing energy waste in finite battery storage. The collision and lower SINR could also be triggered by the desicion maker. Fourthly, the full knowledge of the system is unrealistic. The assumption that the desicion maker has the full knowledge will make the model simple, but will make the implementation in real life irrealizable. In this work, we propose an algorithm that is able to overcome the aformentioned drawbacks. And although our work focuses on solar energy harvesting, it is clear that the conclusion and the algorithm could be generalize to any AP selection problem 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 POMDP formulation is presented, showing how we abstract the continous battery state and user state to controlable POMDP states and draws the optimal desicion. In Section IV, we evaluate the performance of our proposed approach with several famous

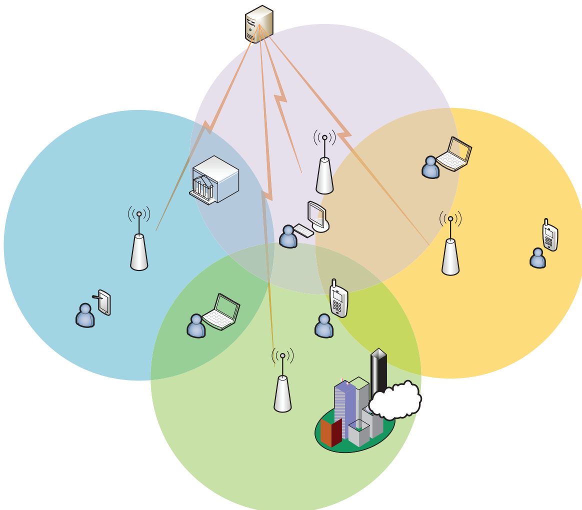


Fig. 1. A schematic map of Super Wi-Fi system.

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 a wireless time-slotted access process in details As shown in Fig1., like in other wireless network, the decision maker could observe mutiple BSs, the number of which is denoted as N_A. For each BS, there is a maximum number of users that it could serve simultaneously due to limited spectrum, as overcrouded user could not maintain its receiving SINR. 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 continous value between 0 and the maximum battery value B_M. The B_M and N_U for different BS could be different.

A. Access and Observation Model

During each time slot, a certain quantity of energy, denoted as E_H is harvested, and a certain number of energy E_T is consumed during transmission of wireless signals. Between adjacent time slots, the number of PUs is changed after their service request is fullfilled or the battery exhausts or shortage. And thus a revised birth and death process is used to describe the process of user behavior. 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 birth rate and the $\mu' = \mu S_U$ is the death rate of the process. Note that when the battery is exhausted, all the users are droped, which is represented by a indication function $I_0\left(S'_U\right)$. The user number in next time slot is zero. Whether the Q_B is adequate or not is determined by S_U, Q_B as well as the SU's decision, Φ. And it is illustrated in the coming physical battery subsection. At the start of each time slot, the SU could either decide to access or sense one of the BSs within its range. When the SU decide to access the i^{th} BS, the action is Φ_a^i. It sends a request signal to the chosen BS. And if the BS has the requested battery, it will activate SU's transmission in this time slot. At the end of the transmission, the BS would attach the system state of this BS to the PU. But there is also risk that the SU fails because of low power or waste energy because of collision. In this case, the BS will reject the request and send back a short message informing the BS of the BS's system state. So in order to save time and energy, a more conservative idea is to sense the BS, i.e. Φ_s^i. When the BS receives a hello sense signal, it also transmits short 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 density, and the battery volume. Gaussian model has been proved effective in predicting sun light intensity [8], [9]. In a small time slot, denoted as T_L, the average light density remains unchanged. In our work, the light intensity W_e is assumed to be Gaussian distributed with average intensity μ_S and variation σ, $\mathcal{N}\left(x;\mu_S,\sigma\right)$. The harvested energy 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 of the existing harvesting devices [10], the Ω_S is the number of solar cells and the η is the harvesting efficiency. The consumed energy is adjusted to make sure transmission with certain SINR. It is important to note that from the BS perspective, current feedback-based iteration algorithm that evolves several time slots 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 users, which is $E_T = \Upsilon_T(S_U, Q_B, \Phi)$. In most cases, the access of SU 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 under the best effort principle. In our case, the SU has the lowest priority. Now we could define that 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,

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

III. POMDP AP selection

In Section II we describe the system model, it is clear that decision has to carefully chosed. There are several factors to be consider: 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 desicion 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, and, before that, discretize the battery state.

A. Battery Transition

In the implementation of EH powered BS, the battery is a continous value. And in a POMDP, the states have to discrete. Intutively, we could use more battery states to represent the same battery volume, but this bring much increase in the complexity of POMDP. In our work, we convert the continous 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 there is error in the assumption, as the battery residue is not uniformly distributed, but the quasi-static assumption is proven to be effective and have small error after many time slots [9]. We denote the discrete battery state changing between time slot as Δ_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.

$$\xi_j := \left\{ j \le N_B \frac{E_H - E_T}{B_M} \le j+1 \right\} \tag{3}$$

Then the probability could be computed as follow,

$$\begin{aligned} &\Pr\left(\Delta_B = i | \Phi, E_H, \xi_j\right) \\ &= \begin{cases} N_B \frac{(E_H - E_T)}{B_M} - j, & i = j+1 \\ (j+1) - N_B \frac{(E_H - E_T)}{B_M}, & i = j \\ 0, & \text{otherwise.} \end{cases} \end{aligned} \tag{4}$$

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

$$\begin{aligned} &\Pr\left(\Delta_B = i | \Phi\right) = \\ &\int_{\frac{iB_M}{N_B} + E_T}^{\frac{(i+1)B_M}{N_B} + E_T} \Pr\left(\Delta_B = i | \Phi, E_H, \xi_i\right) \mathcal{N}\left(E_H; \bar{\mu_S}, \bar{\sigma}\right) dE_H + \\ &\int_{\frac{(i-1)B_M}{N_B} + E_T}^{\frac{iB_M}{N_B} + E_T} \Pr\left(\Delta_B = i | \Phi, E_H, \xi_{i-1}\right) \mathcal{N}\left(E_H; \bar{\mu_S}, \bar{\sigma}\right) dE_H . \end{aligned} \tag{5}$$

In the equation, the mean and variance of the Gaussian distribution are scaled accordingly after mutiplication. After defining the battery change probability, we could compute the system transition probability.

B. System Transition Probability

When the user transition probability and battery transtion 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 system state S and the decentralized 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.

$$\mathrm{P}\left(S_U', S_B' | S_U, S_B, \Phi\right) = \zeta\left(S_U' | S_U, S_B, \Phi\right) \delta\left(S_B' | S_U, S_B, \Phi\right) \tag{6}$$

The user transition $\zeta\left(S_U' | S_U, S_B, \Phi\right)$ is given in equation (1). And the battery transtion is calculated based on the equation (5), which is shown as followed.

$$\begin{aligned} &\delta\left(S_B' | S_U, S_B, \Phi\right) \\ &= \begin{cases} \Pr\left(\Delta_B = S_B' - S_B | \Phi\right) & \text{if } S_B' \le N_B - 1, \\ \sum_{\Delta_B = S_B' - S_B}^{\Delta_B = \Delta_B^{Max}} \Pr\left(\Delta_B | \Phi\right), & \text{if } S_B' = N_B - 1. \end{cases} \end{aligned} \tag{7}$$

In the case of $S_B' = N_B - 1$, the battery is full, meaning that the battery overflows. As the volume of the battery is limited, all the extra battery is abondoned. The notation Δ_B^{Max} is used to simplify our calculation, as the $\Pr\left(\Delta_B | \Phi\right)$ decreases with the Δ_B, and usually when the Δ_B reaches the 5 or 6, the probability reaches zero by 4 decimals in the numerical results. The overall transition is computed by multiply the transition probability of all the BSs.

$$T\left(S' | S, \Phi\right) = \prod_{i=1}^{i=N_A} \mathrm{P}\left(S_B^{i,'}, S_U^{i,'} | S_U^i, S_B^i, \Phi\right) \tag{8}$$

C. POMDP Optimal Algorithm

In POMDP formulation, the SU only has the partial knowledge of the system. At the end of each slot, the SU could get the BS's system state, for the S_B^O and S_U^O which we use $\mathcal{O}$ to denote. The observation probability function given the actual BS state in the next time slot is denoted as follow, $S_B^{t,'}$ and $S_U^{t,'}$ are the system state of the BS t the SU senses or tries to access.

$$\psi\left(O | S_U^{t,'}, S_B^{t,'}\right) = \begin{cases} 1 & \text{if } S_B^O = S_B^{t,'}, S_U^O = S_U^{t,'}, \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

Then the observation function of the whole system could be denoted as,

$$Z\left(O | S', \Phi\right) = \psi\left(O | S_U^{t,'}, S_B^{t,'}\right) \tag{10}$$

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

$$V_t^{\Phi}(S) = R(S, \Phi) + \gamma \sum_{S'} T\left(S' | S, \Phi\right) V_{t-1}^{\pi}\left(S'\right), \tag{11}$$

where π denotes the optimal action in that state. As no full knowledge is held for the SU, we use a belief vector to denote the system belief β,

$$\beta = [\beta (S = 1), \beta (S = 2), ..., \beta (S = N_S)] \tag{12}$$

Then the particular policy tree with a certain belief β is given as

$$\begin{aligned} V_t^{\Phi} (\beta) = & \sum_S R (S, \Phi) \beta (S) + \\ & \gamma \sum_S \sum_{S'} \beta (S) T (S'|S, \Phi) V_{t-1}^{\pi} (S), \end{aligned} \tag{13}$$

For simplicity, if we already know all the value function of at the time $t-1$ during iterations, a value vector α_t^{Φ} that correspond with each state could be computed and used.

$$\alpha_t^{\Phi} = [\alpha_t^{\Phi} (S = 1), \alpha_t^{\Phi} (S = 2), ..., \alpha_t^{\Phi} (S = N_S)] \tag{14}$$

Note that for the same Φ and t, there are mutiple α vector. The value function could be re-written as

$$V_t^{\Phi} (\beta) = \sum_S \beta (S) \alpha_t^{\Phi}, \tag{15}$$

and the maximum value function and optimal action is

$$\begin{aligned} V_t^{\pi} (\beta) &= \max_{\alpha_t^{\Phi}} \sum_S \beta (S) \alpha_t^{\Phi}, \\ \pi (\beta) &= \arg\max_{\alpha_t^{\Phi}} \sum_S \beta (S) \alpha_t^{\Phi}, \end{aligned} \tag{16}$$

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 $\beta = [\beta (S = 1), \beta (S = 2), ..., \beta (S = N_S)]$ As the function value V_t is piecewise linear with the β_t, each set of α_t vector could be regarded as a set of parameters of a hyper linear function. So there is a dominanted hyperplane structure in the model, i.e., the continous belief space is divided into several hyperplane, each of them dominanted by one policy. The partition of dominanted hyperplane in time t could be calculated given all the α_{t-1}, the details of algorithm for solving the partition could be find in a well written tutorial [11]. At the end of the time slot, the SU will update its belief vector according to its observation.

$$\beta' (S'|\Phi, O) = \frac{\sum\limits_O Z (O|S', \Phi) \sum\limits_S T (S'|S, \Phi) \beta (S)}{\sum\limits_{S'} \sum\limits_O Z (O|S', \Phi) \sum\limits_S T (S'|S, \Phi) \beta (S)} \tag{17}$$

D. Suboptimal Access Policy

The optimal POMDP solution could be calculated off-line and computed within seconds when the number of states is small. However, the use of POMDP method is limited in two situations: when N_A is massive, and when the environment parameters, like sun light coefficients μ_S, σ, the birth rate λ and death rate μ of PUs, changes drasticly.

The optimal strategy in the original POMDP formulation tries to maximize the reward, which is the number of success

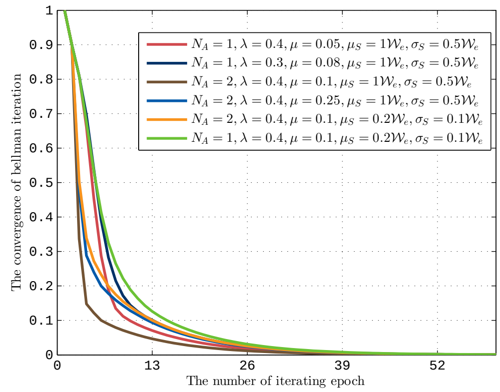


Fig. 2. A schematic map of Super Wi-Fi system.

access during a fix-length time slots N_T. We propose a dual perspective of solving the problem, where we focus on the overall harvested energy. We name it Energy Based (EB) Method. The original problem is reformulated as,

$$\max_{\Phi_t, t=0, ..., N_T} \sum_{t=1}^{N_T} \mathrm{E}[\mathrm{H}\left(S^T, \Phi_t\right)], \tag{18}$$

where the $\mathrm{H}\left(S^T, \Phi_T\right) = \sum \min\left(E_H, E_T + B_M - Q_B\right)$ is the overall harvesting energy of all the BSs combined. Now a suboptimal could be proposed as follow, trying to maximize the system's ability to harvest energy in the next time slot.

$$\Phi_t (S) = \arg\max \mathrm{E}[\mathrm{H}(S^{t,'}, \Phi_t)], \tag{19}$$

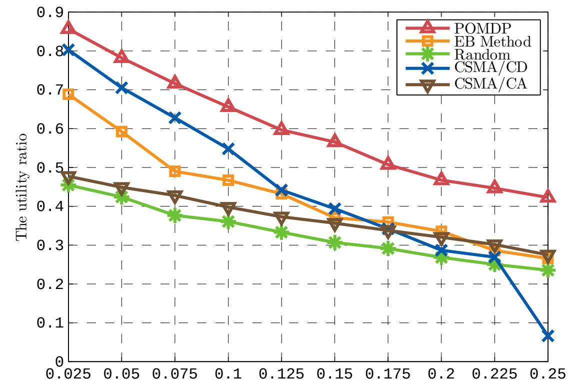
There is good rationality in using an EB perspective. First of all, when the sun density μ_S is strong, we could assume few PU will be forced to leave the BS before its original death time. Second, in most cases, the transmitting power $E_T = \Upsilon_T(S_U, Q_B, \Phi)$ remains quasi linear with the number of user requesting service. Third, the EB method is a unselfish method, which would sacrifice some reward, but will protect the PUs and increase overall utility. Fourth, the EB method could adjust to quick changes of the environmental parameters, which will be show in the journal version of this work.

IV. Simulation Results

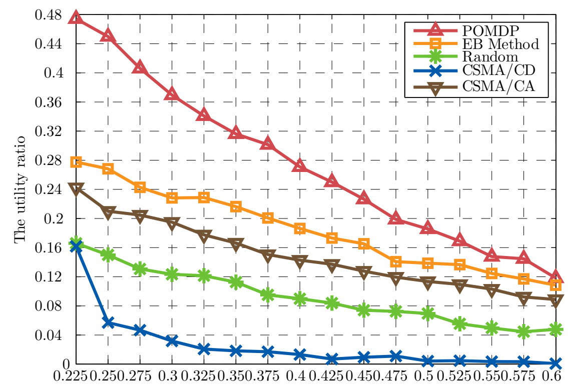
In this section, the convergence and the effectiveness of the algorithm is illustrated. In Fig.2, the convergence of the POMDP iteration algorithm is shown. The discount factor in the iteration is $\gamma = 0.9$. A bellman stoping criteria is used to determined whether or not the iteration has reached the infinite horizon solutions. 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, six different sets of parameters are used, and the algorithm converges exponentially.

The effectiveness of the algorithm is calculated by comparing the ratio of successful access N_S during the overall time slots $N_T = 10000$, namely radio $\eta_A = N_S/N_T$. In the simulation, we use the parameters as follow. The reference benchmark solar intensity is given as $\mathcal{W}_e = 1\text{kW}/m^2$, which is the sunlight on the surface of Earth attenuated by atmosphere in clear conditions when the Sun is near the zenith [13]. We use the work from [14], where the optimal operating output power per benchmark solar intensity $\mathcal{W}_e$ of the harvesting devices 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 $T_L = 200\text{ms}$. And for simplicity, 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 users asking for service, which is rational considering a wide range wireless network with negligible between-user interference. Transmission power for each user is $P_T = 40\text{mW}$.

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 user now sense the BS instead of carrier. And the algorithm tries to avoid collision as well as energy exhaust. The CA sense the BS first, and not ask for transmission until it could be sure. The CD method try to transmit, and sleep



(a) The arrival rate of the SUs in the BS, $N_A = 2$



(b) The arrival rate of the SUs in the BS, $N_A = 2$

Fig. 3. A schematic map of Super Wi-Fi system.

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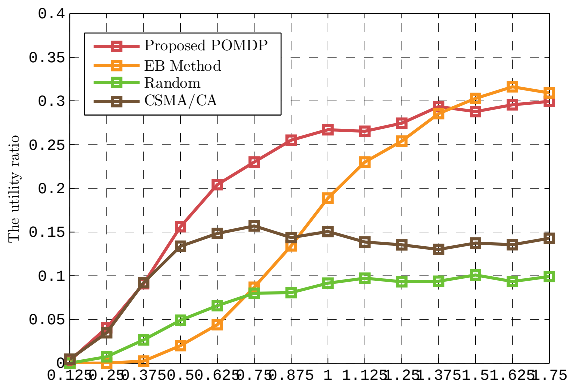
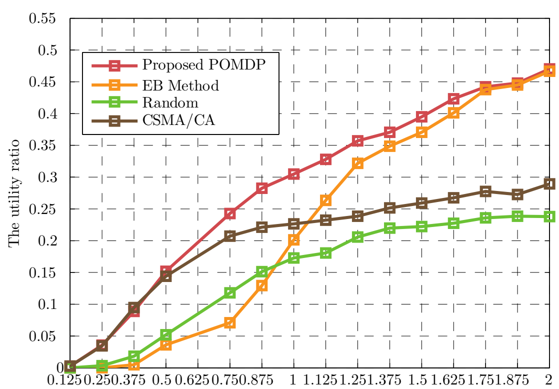


(a) The solar intensity normalized by reference intensity



(b) The solar intensity normalized by reference intensity

Fig. 4. A schematic map of Super Wi-Fi system.