Green Access Point Selection for Wireless Local Area Networks Enhanced by Cognitive Radio

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Green Access Point Selection for Wireless Local Area Networks Enhanced by Cognitive Radio

Wendong Ge · Shanzhi Chen · Hong Ji · Xi Li · Victor C. M. Leung

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Abstract In wireless local area networks (WLANs) made up of Extended Service Sets, access point (AP) selection is a key issue to improve the network performance and balance the traffic load. WLANs operating in the shared Industrial, Scientific and Medical band can benefit from the use of cognitive radio (CR) techniques to enable dynamic access to spectrum holes that are free from interference. In this paper, we propose an optimal Green AP Selection (GAPS) scheme, in which AP selection is optimized to maximize the system throughput while minimizing the energy consumption, for multi-rate WLANs enhanced by CRs. Different from most existing AP selection schemes, GAPS takes into account of the state transition tendency of APs and the influence of Automatic Rate Fallback mechanism in the Distributed Coordination Function. The AP selection problem is formulated as a restless bandit problem and solved by the primal-dual index heuristic algorithm based on first order relaxation to yield the GAPS scheme with the "indexability" property and hence a low complexity. GAPS is further divided into offline computation, which accounts for the bulk of the computations, and online selection, with a low complexity to facilitate implementation. Extensive simulation results illustrate the significant performance improvements of GAPS compared with existing AP selection schemes in different scenarios.

Keywords WLANs · cognitive radio · access point selection · green communication · restless bandits

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1 Introduction

Wireless local area network (WLAN) is an effective and flexible wireless access technology that has been widely deployed in offices, homes and public places to enable stations (STAs) to enjoy high-speed access to the Internet at low cost by associating with selected access points (APs). IEEE 802.11 WLANs share the Industrial, Scientific and Medical (ISM) band with other devices such as microwave ovens, cordless phones, Bluetooth devices and ZigBee devices [1], and need to cope with the coexistence program to achieve an acceptable performance. In a large scale WLAN [2], multiple APs, each forming a Basic Service Set (BSS), are interconnected by a local distribution system to form an Extended Service Set (ESS). When a STA intends to access such a WLAN, the STA needs to select the most appropriate AP in the ESS to associate with, according to various criteria such as the radio signal strength. Accordingly, study of AP selection schemes is of interest.

A lot of work has been done on AP selection in WLANs. In [3], an AP selection strategy for the association procedure in large-scale WLANs is presented, which considers the different node topologies among candidate BSSs, and the effects of hidden terminals due to their significant adverse impact on throughput. In [4], the authors present an AP selection strategy in the office environment covered by a WLAN based on a quality-of-service (QoS) information element that is advertised by APs. On this basis, voice stations are able to select the AP that is associated with the least number of voice stations so as to achieve a lower call blocking probability. In [5], the authors propose an AP selection mechanism, called the High-Rate First Association in order to achieve load balancing and the efficient use of radio resource. Two AP selection algorithms are proposed in [6], which estimates the AP traffic load by observing and estimating the IEEE 802.11 frame delays and uses the results to determine which AP to use. The AP selection scheme in [7] aims to achieve overall load balancing and optimum resource utilization in the network. In [8], the authors address the joint problem of AP selection and channel assignment with the objective to satisfy a given user load vector with the minimum number of channels. Authors of [9] propose decentralized AP selection strategies and show that the proposed strategies can achieve an efficient and fair share of wireless access resources. In [10] the authors evaluate the performance of distributed AP selection algorithms in which terminals are responsible for both AP selection and the necessary measurements, and justify that selfish distributed algorithms can perform as well as centralized ones. The features of the AP selection scheme proposed in [11] are that it considers access contention in the Distributed Coordination Function (DCF) of the IEEE 802.11 medium access control (MAC) layer, and it can be applied to the 802.1le standard to support different access classes. In [12], the authors present an AP selection policy to mitigate the problem of low data-rate STAs interfering with high data rate STAs; the selection metric encapsulates several cell and connection parameters into a single value. [13] studies the joint problem of distributed access point selection and power allocation in cognitive radio networks, but it does not consider the DCF mechanism. In [39], the authors present an efficient solution to determine the user-AP associations for max-min fair bandwidth allocation. In [40], the authors propose an online AP association strategy that not only achieves a minimal throughput (among all clients) that is provably close to the optimum, but also works effectively in practice with a reasonable computational overhead. To sum up, none of these previous studies on AP selection simultaneously takes into account the coexistence problem in the ISM band, reduction of energy consumption, and the influence of Automatic Rate Fallback (ARF) mechanism employed for rate adaptation in IEEE 802.11 WLANs.

Since no mechanism exists for ISM-band devices that are operated independently to negotiate radio frequency (RF) spectrum usage, performance of WLANs tends to be degraded by coexisting ISM-band devices [14]. Cognitive Radio (CR) is a promising technology that can be employed by WLANs to cope with the coexistence problem [15, 18]. As a WLAN incorporating CR can sense the ISM-band interference at each AP, the AP could move the operating channel to one in which interference is minimized, and the WLAN can encourage more STAs to associate with the AP experiencing less interference, in order to improve the network performance and balance the traffic load between different APs [19, 20]. Moreover, 802.11h provides transmission power control in order to prolong the battery life of STAs [21]. As the interference from coexisting ISM-band devices experienced by each AP, and its link quality with a specific STA, are distinct, the STA will be instructed to operate with different transmit power when it selects and associates with a different AP. Furthermore, to maximize data link throughput while minimizing frame errors, ARF is implemented in WLANs to adjust the transmission data rate according to the link condition, which is deduced from the number of retransmissions [22]. Variations of the radio environment might cause a STA transmission to be received with different signal-to-interference-plus-noise ratio (SINR) and correspondingly different bit-error ratio (BER) at different APs, which cause different date rates to be selected when a STA associates with different APs. Thus the impact of ARF ought to be considered in AP selection. Accordingly, in this paper, the AP selection problem in multi-rate WLANs enhanced by cognitive radio is investigated, with the objective of selecting the appropriate AP for each STA so as to maximize the data rate based on DCF and ARF, and minimize the energy consumption of the STA. This problem is formulated as a restless bandit problem, which is solved by the primal-dual index heuristic algorithm based on the first order relaxation. This yields the proposed Green AP Selection (GAPS) scheme. The distinct features of this scheme are as follows.

- The GAPS scheme has an indexability property that dramatically reduces computation complexity and simplifies its implementation. AN STA simply calculates the indices of all the APs offline and selects among the potential APs ones that have the lowest index.

- The GAPS scheme not only considers the effects of traffic load, ISM-band interference and channel condition on the DCF performance at each AP, but also predicts the tendency of ARF state variations according to a Markov model of the wireless channel. One of its objectives is to maximize the throughput based on DCF and ARF.
- The GAPS scheme selects the appropriate APs that can satisfy an STA QoS demand with the lowest transmit power at the STA, according to the ISM-band interference and channel condition, thus reducing the STAs energy consumption and prolonging its battery life.
- The GAPS scheme not only considers the current reward, but also takes long-term reward into account.
- The GAPS scheme works in a distributed manner. There is no need for a centralized WLAN controller to control the AP-selection of all the STAs. Each STA selects its AP independently. Thus the proposed scheme is scalable.

The rest of this paper is organized as follows. Section 2 introduces the system model, including the mechanisms of DCF and ARF. Section 3 describes the AP selection problem in multi-rate WLANs with CR, and formulates this problem as a restless bandit problem, which is solved by the primal-dual index heuristic algorithm based on the first order relaxation in Section 4. Section 5 details the GAPS algorithm and analyzes the computational complexity and communication overhead. Extensive simulation results are provided in Section 6 to compare the performance of GAPS with existing methods, and Section 7 concludes this study.

2 System model

In this paper, we consider an Extended Service Set (ESS) of a WLAN, which consists of N APs with CR capabilities, i.e., each AP has additional intelligence to collect its own state information about the channels and estimate the state transition probabilities based on historical observations [23]. Every AP selects one channel according to some channel assignment scheme such as one based on graph coloring or the least congested channel search (LCCS) [24]. Obviously, selecting an appropriate channel assignment scheme helps to enhance the performance of AP selection, which is outside of the scope of this work. We denote the set of these N APs and their corresponding N channels as $\mathscr{N} = \{1, 2, \cdots, N\}$. The STAs associating with the same AP share a common channel based on DCF. Besides, each STA adjusts its date rate according to ARF. DCF and ARF are reviewed below (Fig. 1).

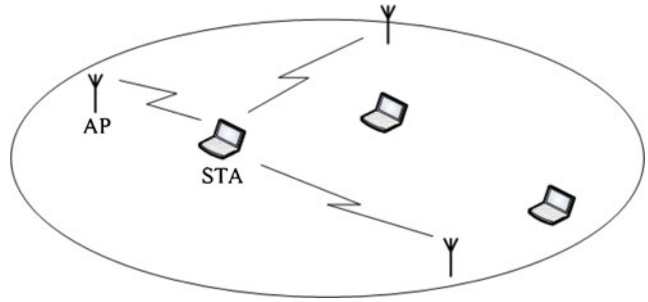


Fig. 1 System model

2.1 Distributed coordination function

DCF based on carrier-sensed multiple access with collision avoidance (CSMA/CA) is the basic access protocol supported by all IEEE 802.11 compliant devices [25]. In DCF, when the channel is detected idle for a period of Distributed Inter-Frame Space (DIFS) by an STA that has a packet to send, the STA initializes a backoff counter to a random integer number selected from the interval $[0, CW-1]$ uniformly, where time is slotted and *CW* is the contention window. The backoff counter decreases every slot when the channel is idle, while it is frozen when the channel is busy. When the backoff counter reaches zero, the STA transmits the packet if the channel is sensed idle for DIFS. If a collision occurs, *CW* is doubled and the STA backs off to retransmit this packet by repeating the above process. If the transmission is successful, *CW* is set to the initial value for a new transmission.

The DCF process is analyzed in [25] using a Markov model to derive the throughput. It is assumed that there are K_n STAs sharing the n-th channel that has been assigned to the n-th AP, where $n \in \mathscr{N}$. In a fully loaded system, the probability τ_n that an STA attempts a transmission in a time slot can be solved numerically from the following equations.

$$\tau_n = \frac{2\left(1-2p_n^{\mathrm{c}}\right)}{\left(1-2p_n^{\mathrm{c}}\right)(W_n+1)+p_n^{\mathrm{c}}W_n\left(1-\left(2p_n^{\mathrm{c}}\right)^{K_n}\right)} \quad (1)$$

and

$$p_n^{\mathrm{c}} = 1-(1-\tau_n)^{K_n-1} \quad (2)$$

where W_n is the minimum contention window and p_n^{c} is the probability of a collision in this channel. Thus the probability of successful transmission per unit time in the n-th channel can be represented as

$$P_n^{\mathrm{tr}}(K_n) = \frac{\tau_n(1-\tau_n)^{K_n-1}}{\sigma P_n^{\mathrm{idle}} + T_n^{\mathrm{s}} P_n^{\mathrm{succ}} + T_n^{\mathrm{c}}\left(1-P_n^{\mathrm{idle}}-P_n^{\mathrm{succ}}\right)} \quad (3)$$

where σ is the idle slot duration, T_n^{s} is the duration of a successful transmission and T_n^{c} is the duration of a collision;

P_n^{idle} and P_n^{succ} can be deduced deduced as $P_n^{\text{idle}} = (1-\tau_n)^{K_n}$ and $P_n^{\text{succ}} = K_n\tau_n(1-\tau_n)^{K_n-1}$. According to [26], T_n^{s} and T_n^{c} can be represented as represented as

$$T_n^{\text{s}} = T_{\text{DIFS}} + T_{\text{SIFS}} + 2\delta + (B_{\text{Head}} + B_{\text{Payload}} + B_{\text{ACK}}) \Big/ \bar{R}_n^{\text{ARF}} \tag{4}$$

and

$$T_n^{\text{c}} = T_{\text{SIFS}} + \delta + T_{\text{Timeout}} + (B_{\text{Head}} + B_{\text{Payload}}) \Big/ \bar{R}_n^{\text{ARF}} \tag{5}$$

where T_{DIFS} and T_{SIFS}, respectively, are the durations of DIFS and the Short Short Inter-Frame Space (SIFS), $\delta = 2\mu$s, T_{Timeout} is duration of the Acknowledgment (ACK) time out, B_{Head}, B_{Payload}, and B_{ACK}, lengths (in bits) of the header, the payload, and the ACK frame, $\bar{R}_n^{\text{ARF}}$ is the average ARF frame, $\bar{R}_n^{\text{ARF}}$ is the average ARF data rate of the n-th channel and can be obtained from this channel can be shown as

$$R_n^{\text{DCF}} = P_n^{\text{tr}}(K_n) \cdot B_{\text{Payload}}. \tag{6}$$

2.2 Automatic rate fallback

ARF is widely used to adjust the data rate in multi-rate WLANs. In ARF, we assume that the data rates are classified into L levels, which are denoted as $\mathscr{R} = \{R_1^{\text{ARF}}, R_2^{\text{ARF}}, \cdots, R_L^{\text{ARF}}\}$. The transmission failure probability of date frames corresponding to the rate $R_i^{\text{ARF}} \in \mathbf{R}$ can be represented as [27]

$$p_i^n = 1 - \left(1 - p_n^{\text{c}}(K_n)\right)\left(1 - p_i^{\text{e}}\right) \tag{7}$$

where $p_n^{\text{c}}(K_n)$ is the transmission failure probability due to collision in DCF, which is a function of K_n and can be obtained from the Eqs. (1) and (2), and p_i^{e} is the transmission failure probability due to the radio environment that is related to the BER p_i^{b}. According to the Physical Layer Convergence Protocol, the relationship between p_i^{e} and p_i^{b} can be shown as [28]

$$p_i^{\text{e}} = 1 - \left(1 - p_1^{\text{b}}\right)^{8\times 24}\left(1 - p_i^{\text{b}}\right)^{8\times(28+B_{\text{Payload}})} \tag{8}$$

assuming that the transmission failure probability of the ACK frame is negligible [28].

ARF utilizes two counters, S and F, to record the consecutive numbers of successful and failed transmissions, respectively. We denote the thresholds to increase and decrease the rate as θ_{s} and θ_{f}. When $S = \theta_{\text{s}}$, the STA tries to transmit with the next higher rate, which is named as "probe state". If the probing is successful, the rate is increased and S is reset, or else the rate is unchanged and S is reset. When $F = \theta_{\text{f}}$, the STA decreases the rate and F is reset.

3 Access point selection problem

3.1 Problem description

When an STA tries to access the ESS initially, according to the received signal strength, it chooses $\bar{N}$ best APs as available APs, which are denoted collectively as $\bar{\mathscr{N}} = \{1, 2, \cdots, \bar{N}\}$. We assume that the STA service duration is divided into T equal-length epochs, which are denoted as $\mathscr{T} = \{1, 2, \cdots, T\}$, and denote the length of each epoch as T_{e}. We assume that T is large enough to be considered as infinite. At the beginning of the each epoch, every available AP sends its state information to this STA through the beacon broadcast. In the residual time of each epoch, according to the received state information, the STA independently selects the most appropriate M APs to transmit the data. If the STA is a conventional one, it can utilize only one channel at any time, i.e., $M = 1$. In the future, a novel STA may be available that has multiple wireless interfaces and can use more than one channels (or APs) simultaneously, and APs can work cooperatively with each other, in which case $M > 1$. Thus the AP selection problem is how the STA selects the M APs from $\bar{\mathscr{N}}$ according to their states in each epoch [7], in order to optimize some given objectives. The states of an AP considered by each STA include

- The number of STAs associated with the AP,
- The interference from other ISM devices experienced by the AP,
- The channel gain from the STA to the AP (measured by signal receiver in the AP and conveyed to the STA via beacon [2]).

The objectives are

- To maximize the throughput of the STA based on DCF and ARF,
- To minimize energy consumption of the STA.

In this AP selection problem, each STA independently selects its APs not only considering the current states of the APs, but also taking into account the state transition probabilities (obtained by the history information [31]). Thus the problem is suitable to be formulated as a restless bandit problem that will be introduced in the next subsection.

3.2 Restless bandit formulation

The restless bandit problem was first investigated by Whittle [29] in 1988, which provides a powerful modeling framework in clinical trials, aircraft surveillance, worker scheduling and so on. In this problem, there are N parallel projects, each of which can be in one of a finite number of states. In each discrete epoch, M projects are selected and set active, where $M < N$. The active projects can contribute active reward and change its state in a Markovian fashion, according to an active transition probability matrix, while non-active projects can achieve passive reward and evolve with a passive transition probability matrix. The rewards are time discounted by a discount factor. According to the states and transition probability and reward of each project, M projects are selected from N projects in every epoch under some policy. The problem is to find the optimal policy in order to maximize the total discounted rewards.

In the following, we formulate the AP selection problem as a restless bandit problem.

3.3 Action of each station

In the restless bandit process, let $a_n(t)$ be the action of an STA regarding the n-th AP in the t-th epoch, where $n \in \bar{\mathscr{N}}$, $t \in \mathscr{T}$ and $a_n(t) \in \mathscr{A} = \{0, 1\}$ such that $a_n(t) = 1$ if the n-th AP is selected in the t-th epoch, while $a_n(t) = 0$ if it is not selected. Thus the STAs actions regarding the APs need to satisfy the following equation

$$\sum_{n=1}^{N} a_n(t) = M. \tag{9}$$

3.4 State and transition probabilities

The states of the n-th AP with respect to a specific STA include the number of associated STAs, ISM interference at the AP and channel gain between the AP and the STA. The state variables are defined below and the state transition probabilities are presented.

During the t-th epoch, the number of STAs associated with the n-th AP is defined as $\xi_n(t) \in \mathscr{C}_n = \{0, 1, \cdots, C^n_{\max}\}$, where $C^n_{\max}$ is the maximum number of STAs that an AP can accommodate. Thus, $\xi_n(t)$ is modeled as a stochastic variable, evolving according to a finite-state Markov chain. The state transition probability matrix with action a can be represented as $\mathrm{O}^a_n(t) = \left[o^a_{g_n h_n}(t)\right]_{C^n_{\max}\times C^n_{\max}}$, where

$$o^a_{g_n h_n}(t) = \Pr\{\xi_n(t+1) = h_n \,|\, \xi_n(t) = g_n, a_n(t) = a\} \tag{10}$$

and $g_n, h_n \in \mathscr{C}_n$, $a \in \mathscr{A}$. $\mathrm{O}^a_n(t)$ can be obtained from historical historical data collected at the AP. If the arrival process $\Lambda_n(t)$ and departure process $\mathrm{M}_n(t)$ of the traffic in the n-th AP are modeled as Poisson processes with arrival rate λ_n and departure rate μ_n, considering the AP in the hot spot [30], $\mathrm{O}^a_n(t)$ can also be follows. When $h_n \geq g_n$,

$$\begin{aligned} o^a_{g_n h_n}(t) &= \sum_{k=1}^{g_n}\{\Pr\{\mathrm{M}_n(t+T_\mathrm{e}) - \mathrm{M}_n(t) = k\} \\ &\quad \times \Pr\{\Lambda_n(t+T_\mathrm{e}) - \Lambda_n(t) = k + h_n - g_n - a\}\} \\ &= \sum_{k=1}^{g_n} \frac{(\mu_n T_\mathrm{e})^k}{k!} \mathrm{e}^{-\mu_n T_\mathrm{e}} \cdot \frac{(\lambda_n T_\mathrm{e})^{k+h_n-g_n-a}}{(k+j_n-i_n-a)!} \mathrm{e}^{-\lambda_n T_\mathrm{e}} \\ &= \sum_{k=1}^{g_n} \frac{(\mu_n)^k(\lambda_n)^{k+h_n-g_n-a}(T_\mathrm{e})^{2k+h_n-g_n-a}}{k!(k+h_n-g_n-a)!} \\ &\quad \times \mathrm{e}^{-(\mu_n+\lambda_n)T_\mathrm{e}} \end{aligned} \tag{11}$$

When $h_n < g_n$,

$$\begin{aligned} o^a_{g_n h_n}(t) &= \sum_{k=g_n-h_n+a}^{g_n} \{\Pr\{\mathrm{M}_n(t+T_\mathrm{e}) - \mathrm{M}_n(t) = k\} \\ &\quad \times \Pr\{\Lambda_n(t+T_\mathrm{e}) - \Lambda_n(t) = k + j_n - i_n - a\}\} \\ &= \sum_{k=g_n-h_n+a}^{g_n} \frac{(\mu_n)^k(\lambda_n)^{k+h_n-g_n-a}(T_\mathrm{e})^{2k+h_n-g_n-a}}{k!(k+h_n-g_n-a)!} \\ &\quad \times \mathrm{e}^{-(\mu_n+\lambda_n)T_\mathrm{e}} \end{aligned} \tag{12}$$

The interference from other ISM-band devices to the AP can be modeled as a Markov chain by dividing the continuous interference power into discrete levels for simplification [31]. We assume the interference seen by the n-th AP in the t-th epoch to be a stochastic variable $\eta_n(t)$ evolving according to a finite-state Markov chain, which is characterized by a set of states $\mathscr{D}_n = \{d_1, d_2, \cdots, d_D\}$, where D is the number of discrete interference levels. There is a trade-off in the choice of D: a small value reduces the complexity of the problem, whereas a larger value enhances the accuracy of the solution. The transition probability matrix of the state with action a can be represented as $\Psi^a_n(t) = [\psi^a_{x_n y_n}(t)]_{D\times D}$, where

$$\psi^a_{x_n y_n}(t) = \Pr\{\eta_n(t+1) = y_n \,|\, \eta_n(t) = x_n, a_n(t) = a\} \tag{13}$$

and $x_n, y_n \in \mathscr{D}_n$, $a \in \mathscr{A}$. The interference state transition probability matrix can be determined from historical data collected by the CR sensing capability of the AP.

We consider block fading channels between STAs and APs [33], which may also be modeled by Markov chains by dividing the continuous channel gain into discrete levels for simplification. We denote the channel gain as $\varsigma_n(t)$, where the states are assumed to be $\mathscr{E}_n = \{e_1, e_2, \cdots, e_E\}$. Thus, the transition probability matrix can be represented as $\Phi_n(t) = [\phi_{u_n v_n}(t)]_{E\times E}$, where

$$\phi_{u_n v_n}(t) = \Pr\{\varsigma_n(t+1) = v_n | \varsigma_n(t) = u_n\} \tag{14}$$

and $u_n, v_n \in \mathscr{E}_n$. For Rayleigh fading channels, $\phi_{u_n v_n}(t)$ can be approximated as follow [33]. If $u_n = v_n + 1$ and $1 \le v_n \le E-1$,

$$\phi_{u_n v_n}(t) \approx \frac{\sqrt{\frac{2\pi\Gamma_{u_n}}{\bar{\Gamma}}}\mathrm{e}^{\left(-\frac{\Gamma_{u_n}}{\bar{\Gamma}}\right)}T_P}{\mathrm{e}^{\left(-\frac{\Gamma_{v_n}}{\bar{\Gamma}}\right)} - \mathrm{e}^{\left(-\frac{\Gamma_{u_n}}{\bar{\Gamma}}\right)}}. \tag{15}$$

If $u_n = v_n - 1$ and $2 \le v_n \le E$,

$$\phi_{u_n v_n}(t) \approx \frac{\sqrt{\frac{2\pi\Gamma_{v_n}}{\bar{\Gamma}}}\mathrm{e}^{\left(-\frac{\Gamma_{v_n}}{\bar{\Gamma}}\right)}T_P}{\mathrm{e}^{\left(-\frac{\Gamma_{u_n}}{\bar{\Gamma}}\right)} - \mathrm{e}^{\left(-\frac{\Gamma_{v_n}}{\bar{\Gamma}}\right)}}. \tag{16}$$

where Γ_{u_n} and Γ_{v_n} are the SINRs corresponding to the states u_n and v_n, respectively, $\bar{\Gamma}$ is the expected SINR and T_P is the packet duration.

Thus, the state of the n-th AP can be modelled as $s_n(t) = [\xi_n(t), \eta_n(t), \varsigma_n(t)]$, where $s_n(t) \in \mathscr{S}$. And its transition probability matrix can be shown as

$$\begin{aligned}\Pi_n^a(t) &= \left[\pi^a_{i_n j_n}(t)\right]_{H_n\times H_n}\\ &= \left[\left(o^a_{g_n h_n}(t), \psi^a_{x_n y_n}(t), \phi_{u_n v_n}(t)\right)\right]_{H_n\times H_n}\end{aligned} \tag{17}$$

where $H_n = C^n_{\max} \times D \times E$. Each AP can obtain $o^a_{g_n h_n}(t)$ and $\psi^a_{x_n y_n}(t)$ according to its historical data, and get $\phi_{u_n v_n}(t)$ according to the beacon received from the n-th AP. (we assume that channel gains in uplinks and downlinks are symmetrical). Since the AP selection problem in this paper is a discrete optimization problem, trivial deviation of the local condition from the state transition statistics might hardly affect the selection of AP.

3.5 System reward

In this AP problem, the optimization objectives are the throughput based on DCF and ARF and the energy consumption of the STA. Thus we first deduce the formulation of these two parameters with respect to each AP.

We assume that the transmit power of each STA $P_n^{\mathrm{tr}}(t)$ is quantized into B levels, denoted as $P_n(t) \in \mathbf{P} = \{P_1, P_2, \cdots, P_B\}$. If the n-th AP is selected in the t-th epoch, the SINR at the receiver must be over the threshold for proper reception; i.e.,

$$\gamma_n(t) = \frac{\varsigma_n(t)P_n^{\mathrm{tr}}(t)}{\eta_n(t)+N_0} \ge \gamma_{\mathrm{th}} \tag{18}$$

where γ_{th} is the SINR threshold and N_0 is the power spectrum density of additive white Gaussian noise (AWGN). Thus, the minimum feasible transmit power can be represented as

$$P_n^{\mathrm{tr}}(t) = \left\{\min\{P_i\} \,\middle|\, P_i \in \mathbf{P}, P_i \ge \frac{\gamma_{\mathrm{th}}(\eta_n(t)+N_0)}{\varsigma_n(t)}\right\} \tag{19}$$

If the maximum power could not satisfy the SINR threshold demand, the transmit power will select the maximum one.

According to the modulation and coding method used in $R_i^{\mathrm{ARF}} \in \mathscr{R}$ such as QPSK or 16QAM, the the relationship table between SINR and BER can be obtained, where the BER $p^{\mathrm{b}}_{i,n}(t)$ with the n-th in the t-th epoch can be looked up. Thus $p_i^n(t)$ corresponding to $R_i^{\mathrm{ARF}} \in \mathscr{R}$ can be calculated with Eqs. (7) and (8). If we define the state of ARF as the data rate, its process can be modeled as a discrete-time Markov chain (DTMC), which is illustrated in Fig. 2 [28]. We suppose that the period of AP selection is much longer than the packet transmission time; i.e., numerous data frames are transmitted in each epoch. Thus the stationary probability of the state with the n-th AP in the t-th epoch is meaningful and can be represented as [28]

$$\bar{\Pi}_1^n(t) = \left[1 + q^n_{1,2'}(t) + \sum_{i=2}^{L-1}\left(1+q^n_{i,(i+1)'}(t)\right)\prod_{j=2}^{i}\frac{\left(1-p_j^n(t)\right)q^n_{j-1,j'}(t)}{q^n_{j,j-1}(t)} + \prod_{j=2}^{M}\frac{\left(1-p_j^n(t)\right)q^n_{j-1,j'}(t)}{q^n_{j,j-1}(t)}\right]^{-1} \tag{20}$$

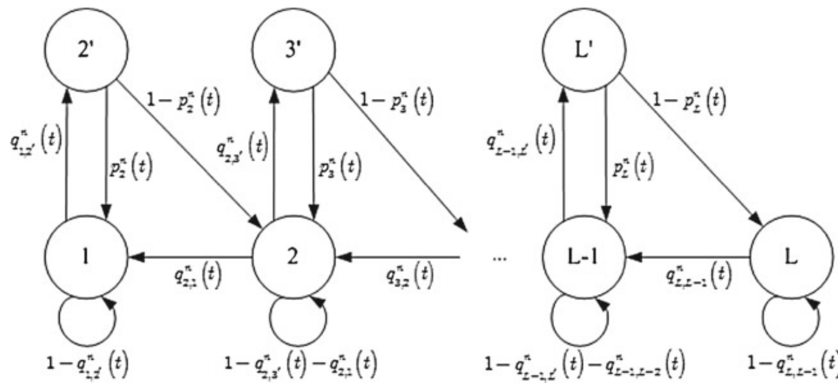
and

$$\bar{\Pi}_i^n(t) = \bar{\Pi}_1^n(t)\prod_{j=2}^{i}\frac{\left(1-p_j^n(t)\right)q^n_{j-1,j'}(t)}{q^n_{j,j-1}(t)} \quad (2 \le i \le L) \tag{21}$$

where

$$q^n_{i,(i+1)'}(t) = \frac{p_i^n(t)\left(1-p_i^n(t)\right)^{\theta_s}}{1-\left(1-p_i^n(t)\right)^{\theta_s}} \quad 1 \le i \le L-1 \tag{22}$$

Fig. 2 DTMC for ARF



and

$$q_{i,i-1}^{n}(t)=\begin{cases}\frac{(1-p_i^n(t))(p_i^n(t))^{\theta_{\mathrm{f}}}}{1-(p_i^n(t))^{\theta_{\mathrm{f}}}} & \text{if}\, p_i^n(t)\neq 1\\ 1/\theta_{\mathrm{f}} & \text{if}\, p_i^n(t)=1\end{cases}\quad 2\leq i\leq L \tag{23}$$

Thus, when the n-th AP is selected in the t-th epoch, the average throughput based on ARF can be shown as

$$\bar{R}_n^{\mathrm{ARF}}(t)=\sum_{i=1}^{L}\bar{\Pi}_i^n(t)R_i^{\mathrm{ARF}}(t) \tag{24}$$

According to Eq. (6), the average throughput based on DCF and ARF can be represented as

$$R_n^{\mathrm{DA}}(t)=P_n^{\mathrm{tr}}(\xi_n(t))\cdot\bar{R}_n^{\mathrm{ARF}}(t)\cdot T_{\mathrm{s}} \tag{25}$$

Additionally, when the n-th AP is selected, the energy consumption in the t-th epoch can be shown as

$$W_n^{\mathrm{e}}(t)=P_n^{\mathrm{tr}}(t)T_{\mathrm{e}} \tag{26}$$

Therefore, the system reward can be represented by

$$\begin{cases}R_{s_n}^1=\kappa_1 R_n^{\mathrm{DA}}(t)-\kappa_2 W_n^{\mathrm{e}}(t)\\ R_{s_n}^0=0\end{cases} \tag{27}$$

where κ_1 and κ_2 are the weights of throughput and energy consumption, and $\kappa_1+\kappa_2=1$.

3.6 Problem formulation

The set of admissible policies is denote as $\mathscr{Z}$. The scheduling policy $\zeta\in\mathscr{Z}$ is $[a_n(t)]_{T\times\bar{N}}$, where the element $a_n(t)$ represents the action taken to select the n-th AP in the t-th epoch. The time discount factor for the rewards is set to be β, where $0<\beta<1$. Accordingly, the AP selection problem is to find an optimal scheduling policy that maximizes the total expected discount reward over an infinite horizon, which can be represented as

$$\max_{\zeta\in\mathscr{Z}} E_{\zeta}\left[\sum_{t=1}^{T}\left(\sum_{n=1}^{\bar{N}}R_{i_n}^{a_n(t)}(t)\right)\beta^t\right],$$

s.t.

$$\sum_{n=1}^{\bar{N}}a_n(t)=M,$$

$$\pi_{i_n j_n}^{a}(t)=\Pr\{s_n(t+1)=j_n\,|\,s_n(t)=i_n,a_n(t)=a\} \tag{28}$$

where $i_n,j_n\in\mathscr{S}$. This problem is a typical restless bandit problem, which will be solved in the following section.

4 The primal-dual index heuristic algorithm

There are many approaches to solve the restless bandit problem [34]. Whittle introduced a relaxed version of the problem, which can be solved optimally in polynomial time [29]. Based on this solution he proposed a priority-index heuristic policy, which reduces to the optimal Gittins index policy in the special case of the multi-armed bandit problem [35]. Weber and Weiss investigated the asymptotic optimality, conjectured by Whittle, of his heuristic, as M and N grow to ∞, with M/N fixed [36]. Papadimitriou and Tsitsiklis established that the restless bandit problem is PSPACE-hard, even in the special case of deterministic transition rules and $M=1$. Berstimas and Mora proposed a hierarchy of increasingly stronger LP relaxations based on the result of LP formulations of Markov decision chains. They also introduced a heuristic scheme for the restless-bandit problem that uses the information contained in optimal primal and dual solutions to the first-order relaxation, which has been demonstrated to have less complexity and very close performance compared to the optimal one [37]. Thus in this paper, we utilize this the primal-dual index heuristic algorithm based on the first order relaxation.

We first introduce the first-order relaxation of this restless bandit problem. The total expected discounted time that the n-th AP is in state i_n and active under the scheduling policy $\zeta \in \mathscr{Z}$ can be represented as

$$\chi_{i_n}^{1}(\zeta) = \mathrm{E}_{\zeta}\left[\sum_{t=1}^{T}\theta_{i_n}^{1}(t)\beta^{t}\right] \tag{29}$$

where

$$\theta_{i_n}^{1}(t) = \begin{cases} 1, \text{if the } n\text{−th AP is in state } i_n \text{ and active} \\ \quad \text{at the } t\text{−th time slot,} \\ 0, \text{otherwise.} \end{cases} \tag{30}$$

Similarly, the total expected discounted time that the n-th AP is in state i_n and passive under the scheduling policy $\zeta \in \mathscr{Z}$ can be defined as $\chi_{i_n}^{0}(\zeta)$. We denote that

$$\mathrm{X} = \left\{\left[\chi_{i_n}^{a_n}(\zeta)\right]_{i_n\in\mathscr{S},\, a_n\in\mathscr{A},\, n\in\bar{\mathscr{N}}}\middle|\, \zeta \in \mathscr{Z}\right\} \tag{31}$$

Whittle introduced a relaxed version of the restless bandit problem which can be solved in polynomial time [37]. In this section we reformulate Whittle's relaxation as a polynomial-size linear program. The projection of restless bandit polytope over the space of the variable $\chi_{i_n}^{a_n}$ for the n-th AP is another polytope, which can be represented as

$$\sum_{a_n\in\mathscr{A}}\chi_{j_n}^{a_n} = P_{j_n}+\beta\sum_{i_n\in\mathscr{S}}\sum_{a_n\in\mathscr{A}}\pi_{i_n j_n}^{a_n}\chi_{i_n}^{a_n} \quad \left(n\in\bar{\mathscr{N}},\, j_n\in\mathscr{S}\right) \tag{32}$$

where P_{j_n} is the probability that the initial state of the n-th AP is $j_n \in \mathscr{S}$.

Additionally, when $T \to \infty$, we can also deduce the equation as follows.

$$\begin{aligned}\sum_{n\in\bar{\mathscr{N}}}\sum_{i_n\in\mathscr{S}}\chi_{i_n}^{1}(\zeta) &= \lim_{T\to\infty}\sum_{n\in\bar{\mathscr{N}}}\sum_{i_n\in\mathscr{S}}\mathrm{E}_{\zeta}\left[\sum_{t=1}^{T}\theta_{i_n}^{1}(t)\beta^{t}\right] \\ &= \lim_{T\to\infty}\sum_{t=1}^{T}\mathrm{E}_{\zeta}\left[\sum_{n\in\bar{\mathscr{N}}}\sum_{i_n\in\mathscr{S}}\theta_{i_n}^{1}(t)\right]\beta^{t} \\ &= \lim_{T\to\infty}\sum_{t=1}^{T}M\beta^{t} = \frac{M}{1-\beta}.\end{aligned} \tag{33}$$

Thus the first-order relaxation can be represented as

$$\max_{\mathrm{X}}\sum_{n\in\bar{\mathscr{N}}}\sum_{i_n\in\mathscr{S}}\sum_{a_n\in\mathscr{A}}R_{i_n}^{a_n}\chi_{i_n}^{a_n},$$

s.t.

$$\begin{aligned}&\sum_{a_n\in\mathscr{A}}\chi_{j_n}^{a_n} = P_{j_n}+\beta\sum_{i_n\in\mathscr{S}}\sum_{a_n\in\mathscr{A}}\pi_{i_n j_n}^{a_n}\chi_{i_n}^{a_n} \quad \left(n\in\bar{\mathscr{N}},\, i_n\in\mathscr{S}\right),\\ &\sum_{n\in\bar{\mathscr{N}}}\sum_{i_n\in\mathscr{S}}\chi_{i_n}^{1}(\zeta) = \frac{M}{1-\beta}.\end{aligned} \tag{34}$$

This is a linear programming problem. The dual problem of this primal problem can be shown as

$$\min_{\lambda_{j_n},\lambda}\sum_{n\in\bar{\mathscr{N}}}\sum_{j_n\in\mathscr{S}}P_{j_n}\lambda_{j_n} + \frac{M}{1-\beta}\lambda,$$

s.t.

$$\begin{aligned}&\lambda_{i_n} - \beta\sum_{j_n\in\mathscr{S}}\pi_{i_n j_n}^{0}\lambda_{j_n} \geq R_{i_n}^{0} \quad \left(n\in\bar{\mathscr{N}},\, i_n\in\mathscr{S}\right),\\ &\lambda_{i_n} - \beta\sum_{j_n\in\mathscr{S}}\pi_{i_n j_n}^{1}\lambda_{j_n} + \lambda \geq R_{i_n}^{1} \quad \left(n\in\bar{\mathscr{N}},\, i_n\in\mathscr{S}\right),\\ &\lambda \geq 0.\end{aligned} \tag{35}$$

The dual problem is also a linear programming problem. Thus the problem given by Eqs. (34) and (35) can be solved by the classical algorithm for the linear programming problem such as simplex search method. We denote $\left\{\bar{\chi}_{i_n}^{a_n}\right\}$ and $\left\{\bar{\lambda}_{i_n}, \bar{\lambda}\right\}$ as the optimal solutions of primal problem (34) and dual problem (35). Therefore, the corresponding optimal reduced cost coefficients can be represented as

$$\bar{\gamma}_{i_n}^{0} = \bar{\lambda}_{i_n} - \beta\sum_{j_n\in\Omega}\pi_{i_n j_n}^{0}\bar{\lambda}_{j_n} - R_{i_n}^{0}, \tag{36}$$

$$\bar{\gamma}_{i_n}^{1} = \bar{\lambda}_{i_n} - \beta\sum_{j_n\in\Omega}\pi_{i_n j_n}^{1}\bar{\lambda}_{j_n} + \bar{\lambda} - R_{i_n}^{1}, \tag{37}$$

where $\bar{\gamma}_{i_n}^{0}, \bar{\gamma}_{i_n}^{1} \geq 0$. $\bar{\gamma}_{i_n}^{0}$ and $\bar{\gamma}_{i_n}^{1}$ represent the rates of decrease in the objective value of the primal problem per unit increase in the values of the variables $\chi_{i_n}^{0}$ and $\chi_{i_n}^{1}$, respectively. Here we define δ_{i_n} as the index for the n-th AP when it is in state $i_n \in \mathscr{S}$, which is shown as

$$\delta_{i_n} = \bar{\gamma}_{i_n}^{1} - \bar{\gamma}_{i_n}^{0} \tag{38}$$

Accordingly, in each epoch, the STA calculates the indices of all the APs according to their states. And the M APs that have the smallest indices are selected. The process of the GAPS scheme will be explained in the next section.

5 Process of GAPS scheme

In this section, we first introduce the steps of the GAPS scheme. Communications overhead and computational complexity of this scheme are then analyzed.

5.1 The steps of the GAPS scheme

The steps of this scheme are divided into offline computation and online selection. In the offline stage:

Step 1: When an STA intends to access the ESS, it selects several potential APs from all the APs according to the signal strength, as the set of available APs $\bar{\mathscr{N}}$, and informs these APs its access request.

Step 2: Every AP has the same state space $\mathscr{S}$ and periodically updates the state transition probability matrix Π_n^a according to the historical information from CR sensing. If the n-th AP receives an access request, it broadcasts $\mathscr{S}$ and Π_n^a through the beacon frame.

Step 3: The STA obtains $\mathscr{S}$ and Π_n^a, and calculates the system reward $R_{s_n}^a$ corresponding to the state $s_n \in \mathscr{S}$.

Step 4: The STA offline calculates the indices of all the states according to the algorithm mentioned in the Section 4, and stores them in its index table.

In the online stage:

Step 5: At the beginning of each epoch, every available AP estimates the state of itself and transmits the state information to STA through the beacon broadcast.

Step 6: According to these states, the STA lookups the index table to find out the corresponding index. The M APs that have the smallest indices are selected for this STA.

5.2 Overhead and complexity of GAPS

The communications overhead is the necessary information exchange between AP and STA. In GAPS scheme, the overhead is divided into two parts. One is the information needed to compute indices table in the offline stage, including $\mathscr{S}$ and Π_n^a, which occurs only one time when the STA joins the ESS. The other is the state information of the available APs for the STA in each epoch, which can be encoded into sequence and easily squeezed into a beacon frame [3]. For example, if $H_n = 50$, 6 bits are adequate for encoding the states. Therefore, communications overhead in this scheme is light compared with the data transmission (maybe hundreds of bits in each epoch).

The computation complexity and the storage complexity in this scheme are also not high. The process of selection is divided into offline computation and online selection. The index table can be computed and stored in the offline stage. What the STA needs to do online is just to lookup the table and finding M maximum indices from N indices which causes little burden in computation ($O(N \log 2M)$). Additionally, the index table is only a "$1 \times H_n$" array, which is easily to store for each STA.

6 Simulation results and analysis

In this section, extensive simulation results are illustrated to compare the performance between the GAPS scheme and the existing schemes, where the GAPS scheme is also called Energy-efficient AP Selection (EAPS) scheme in the figures. The effectiveness of CR functions to enable AP selection is also evaluated. Thus, three schemes are used for comparison. In the existing scheme without CR, the STAs select APs according to the current states such as quality of links or DCF mechanism. In the existing scheme with CR, the ISM interference is further considered. In the GAPS scheme without CR, only the number of associated STAs and channel gain are considered as components of state, namely $s_n(t) = [\xi_n(t), \varsigma_n(t)]$, while other details are the same as the GAPS scheme with CR.

The parameters in the simulations as follows are chosen based on the ones widely adopted in the literature [3, 25, 28]. There are 12 APs covering a 200m-by-200m service area, where STAs are uniformly placed. All the wireless channels in the simulations are assumed to be Rayleigh fading without inter symbol interference. The minimum contention window W is 32. We consider the rate set in ARF as $\mathscr{R} = [1, 2, 5.5, 11]$(Mbps). The time thresholds to increase and decrease the rate are 11 and 2. The arrival rate and departure departure rate are set to be 0.083s^{-1} and 0.0083s^{-1}. The transmit power set is assumed to be $\mathscr{P} = [0.1, 0.2, 0.4, 0.8, 1.6, 3.2, 6.4]$(W). The SINR threshold γ_{th} is set to be 7dB. The background noise N_0 is set to be -117dBm. We also set $T_{\text{SIFS}} = 10\mu$s, $T_{\text{DIFS}} = 50\mu$s, $B_{\text{Head}} = 8000$bits, $B_{\text{Payload}} = 416$bits, and $B_{\text{ACK}} = 340$bits.

The model is coded in Matlab and simulations are run in a PC with Intel Core 2 Duo processor and 4GB RAM, using the parameters mention above. According to the record of historical data, most of interferences from ISM-band devices are concentrated in [10dBm, -30dBm] [38]. For simplification, we divide these into five five classes of states, namely $(-\infty, -20\text{dBm}]$, $(-20\text{dBm}, -10\text{dBm}]$, $(-10\text{dBm}, 0\text{dBm}]$, $(0\text{dBm}, 10\text{dBm}]$ and $(10\text{dBm}, +\infty)$.

According to statistics of ISM interferences in 1000 probability matrix of these states can be represented by

$$\Psi_n^0(t) = \begin{bmatrix} 0.7989 & 0.0491 & 0.0532 & 0.0346 & 0.0642 \\ 0.0353 & 0.8729 & 0.0460 & 0.0050 & 0.0408 \\ 0.0293 & 0.0865 & 0.7270 & 0.1222 & 0.0351 \\ 0.0173 & 0.0907 & 0.1002 & 0.7224 & 0.0695 \\ 0.0213 & 0.0513 & 0.0006 & 0.1095 & 0.8172 \end{bmatrix} \tag{39}$$

and

$$\Psi_n^1(t) = \begin{bmatrix} 0.6214 & 0.1521 & 0.0321 & 0.0907 & 0.1037 \\ 0.0009 & 0.7684 & 0.0823 & 0.0847 & 0.0636 \\ 0.0582 & 0.0510 & 0.7892 & 0.0465 & 0.0551 \\ 0.0840 & 0.0692 & 0.0704 & 0.7304 & 0.0461 \\ 0.0912 & 0.0840 & 0.0269 & 0.0450 & 0.7528 \end{bmatrix} \tag{40}$$

$O_n^a(t)$ and $\Phi_n(t)$ can be obtained by Eqs. (11), (12), (15) and (16), thus $\Pi_n^a(t)$ can be calculated according to Eq. (17).

6.1 Improvement of throughput

Figure 3 compares the throughput based on DCF and ARF in different AP selection schemes. Here, we run the simulations for 1600 epoches and set $M = 4$, $\bar{N} = 12$ and $\kappa_1 = \kappa_2 = 0.5$. From this figure, the average throughput of STAs is around 9.2 Mbps and 7.8 Mbps in the existing scheme with CR and without CR, while it is nearly 12.2 Mbps and 10.9 Mbps in GAPS with CR and without CR. Thus, the throughput in the scheme with CR is higher than the corresponding scheme without CR, which could be ascribed to the fact that CR function can sense the ISM interference and let STA select the AP with lower ISM interference, which is beneficial to the throughput. Additionally, the throughput in the GAPS scheme is higher than that of the existing scheme. The GAPS scheme not only considers more factors regarding the throughput than existing scheme such as load, interference in ISM band, radio environment, DCF and ARF mechanism, but also considers state transitions of these factors, while the existing scheme only takes the current state into account. That is why the throughput of the proposed GAPS scheme is higher than the existing one.

In Fig. 4, the effect of number of selected APs on the average throughput is illustrated in different AP selection schemes. In these simulations we set $\bar{N} = 12$, $\kappa_1 = \kappa_2 = 0.5$ and varies M from 1 to 8. Figure 5 indicates that the average throughput based on DCF and ARF in GAPS scheme is higher than that of the existing scheme, regardless of M, and CR function can enhance the throughput, due to the same reason as explained above. Additionally, with the increment of M, the average throughput increases, while the rate of throughput improvement decreases. As each additional AP

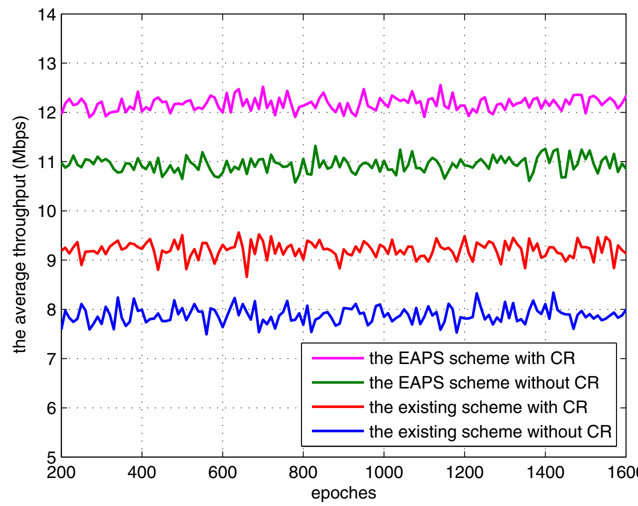


Fig. 3 The throughput performance improvement based on DCF and ARF ($M = 4$ and $\bar{N} = 12$)

can offer more radio resources for packet transmissions, increasing the number of selected APs increases the overall throughput that the STA can obtain. However, according to the AP selection scheme, the STA preferentially selects the AP that can provide the highest throughput first, while additional APs that are selected offer increasingly lower throughput. This causes the rate of throughput improvement to decrease with the number of selected APs.

Figure 5 illustrates the influence of the number of available APs over the throughput based on DCF and ARF in different AP selection schemes. Here we set $M = 2$, $\kappa_1 = \kappa_2 = 0.5$ and vary $\bar{N}$ from 3 to 12. From this figure, we observe that the average throughput increase with the increment of $\bar{N}$. The reason is that large quantity of $\bar{N}$ can provide more and better APs that are beneficial to the throughput based on DCF and ARF. However, when $\bar{N}$ is

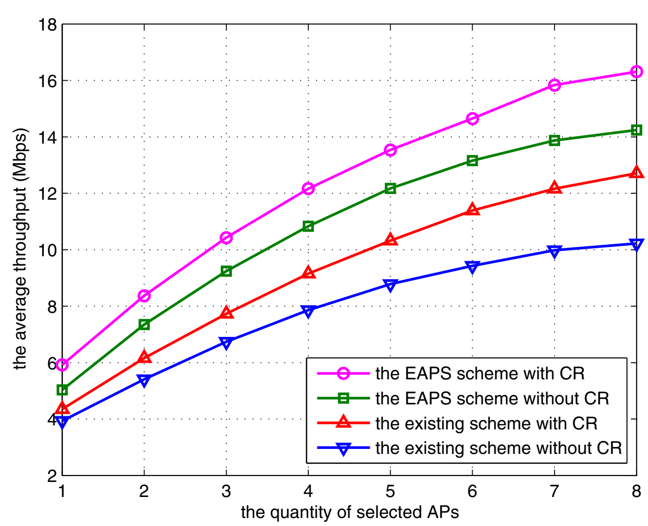


Fig. 4 The average throughput with different selected APs ($\bar{N} = 12$)

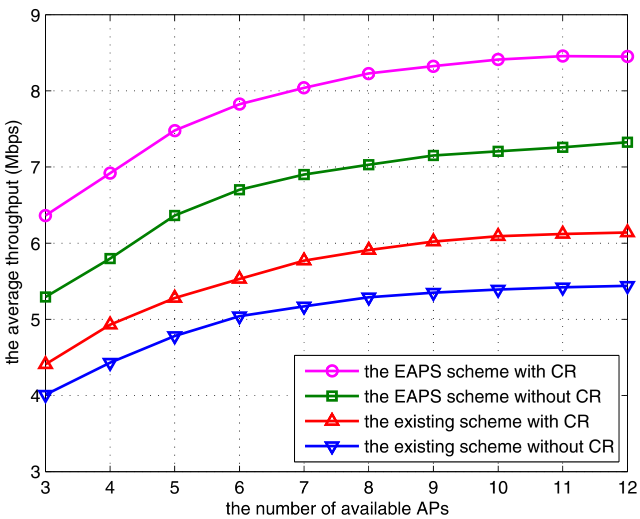


Fig. 5 The average throughput with different available APs ($M = 2$)

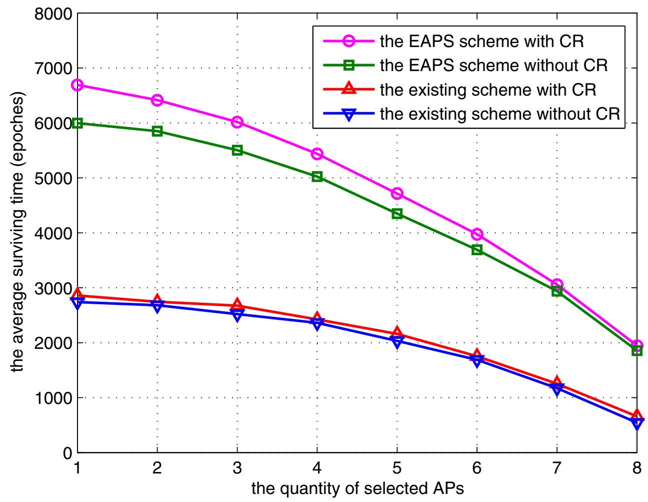


Fig. 7 The average working time with different selected APs ($\bar{N} = 12$)

beyond 8 or 9, the average throughput levels off to an almost zero rate of increase, because the additional APs do not offer acceptable link quality and they do not contribute to providing high throughput based on DCF and ARF. Thus, it is reasonable to set $\bar{N}$ to be below 9, in order to save the radio resource and decrease the load of computation in hardware and software. Besides, the GAPS scheme is superior to the existing one in different $\bar{N}$, due to the same reason as explained above.

6.2 Improvement of Energy Consumption

In Fig. 6, the energy consumption of the different AP selection schemes are compared. In these simulations, we set

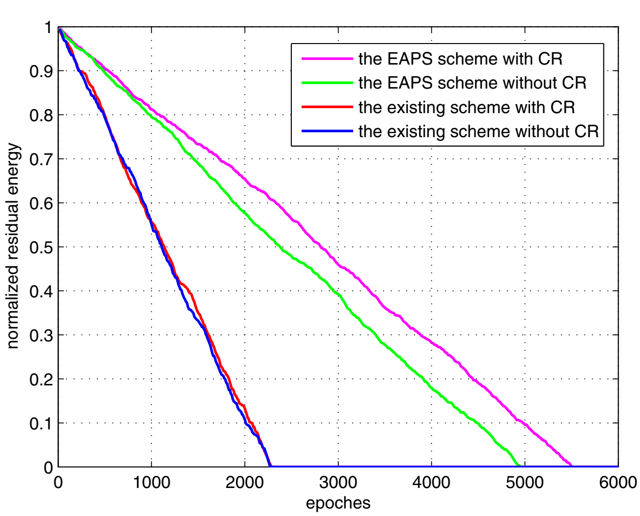


Fig. 6 Energy consumption of different AP selection schemes ($M = 2$ and $\bar{N} = 12$)

$M = 4, \bar{N} = 12, \kappa_1 = \kappa_2 = 0.5$, and use normalized initial energy. According to the results in this figure, the energy of the existing scheme runs out earlier than the proposed scheme. In each epoch, the proposed scheme selects APs that cost less energy according to the states and its variation tendency, while the existing scheme does not consider the energy consumption, which is responsible for this phenomenon. Moreover, in the existing scheme, CR function hardly enhances the surviving time of STA because this scheme has no energy-saving mechanism. In the GAPS scheme, as the ISM interference sensing can enable the estimation of energy consumption to be more exact, the scheme with CR is superior to that without CR in this performance.

Figure 7 compares the surviving time of STA with different M in different AP selection schemes. Here we set $\bar{N} = 12, \kappa_1 = \kappa_2 = 0.5$ and vary M from 1 to 8. From this picture, we can find out that the surviving time of STA decreases with the increment of M, which should be attributed to the fact that the STA needs to enhance its transmission power in each epoch when accessing more APs. What is more, with the increment of M, the rate of surviving time decline increases in the GAPS scheme. The reason is that the latter selected APs have worse quality of links and ISM interference, which cost more energy. To sum up, according to Figs. 4 and 7, with the increment of M, the throughput based on DCF and ARF increases, while the surviving time decreases. Thus we need to make a tradeoff between throughput and energy consumption in choosing M. Especially, as small value of M could help to release more channels for other STAs, its value is unreasonable to be set too large.

In Fig. 8, the effect of the number of available APs on the surviving time is illustrated in different AP selection

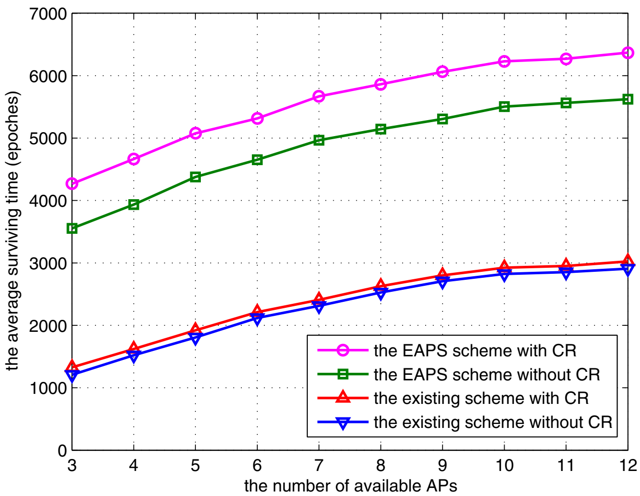


Fig. 8 The average working time with different available APs ($M = 2$)

schemes. In these simulations, we set $M = 2, \kappa_1 = \kappa_2 = 0.5$ and vary $\bar{N}$ from 3 to 12. This figure reveals that the surviving time increases with the increment of $\bar{N}$, which should be ascribed to the fact that in high value $\bar{N}$ it is high probability to exist more APs that cost less energy for STAs. Additionally, when $\bar{N}$ is more than 9 or 10, the rate of surviving time rise is approximate to zero, because the number of better APs for energy consumption is limited. Besides, according to Figs. 5 and 8, the increment of $\bar{N}$ not only increases the throughput based on DCF and ARF, but also prolongs the surviving time of STA. However, it also enlarges the space of selection in GAPS scheme, which is detrimental to the computational complexity. Thus we need to compromise between the performances and complexity of the scheme.

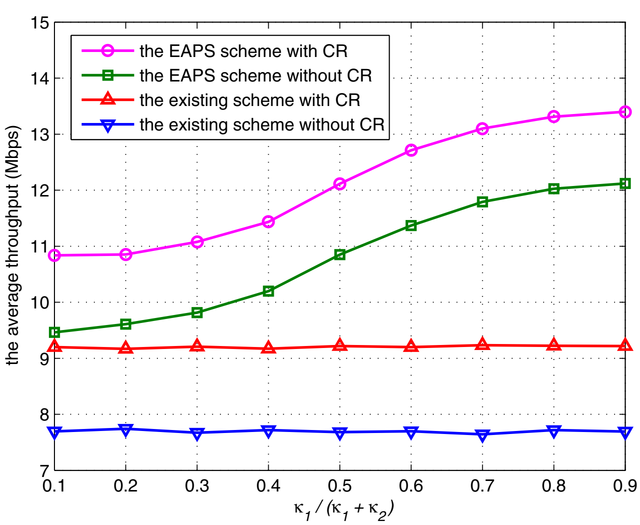


Fig. 9 Effect of weights on the throughput based on DCF and ARF

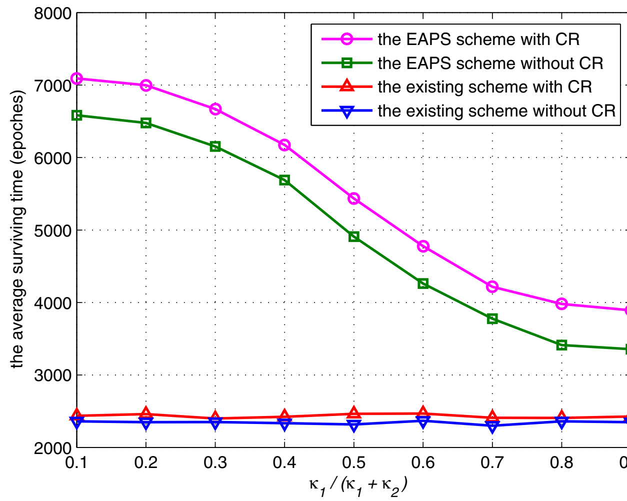


Fig. 10 Influence of weights over the energy consumption

6.3 Effect of weights regarding throughput and energy consumption

Figures 9 and 10 illustrate that by adjusting the respective weights corresponding to the throughput and energy consumption in GAPS, we can trade-off between these two performance metrics. Here, we set $M = 4, \bar{N} = 12$, $\kappa_1 + \kappa_2 = 1$ and vary κ_1 from 0.1 to 0.9. From Figs. 9 and 10, we observe that with the increment of $\kappa_1 / (\kappa_1 + \kappa_2)$ the throughput based on DCF and ARF increases while the surviving time of STA decreases. A relatively higher κ_1 or κ_2 means that STAs select the AP mainly according to the throghput based on DCF and ARF or energy consumption, respectively. Thus, by setting the weights of throughput and energy consumption accordingly, we can achieve the desired trade-off between these two performance metrics. Additionally, when $\kappa_1 / (\kappa_1 + \kappa_2)$ is in relatively higher or lower value, the rates of changes in throughput or surviving time are nearly equal to zero. The reason is that the AP selection problem is a discrete optimization problem. In most epochs, the best APs are selected when the weights are above or below some given thresholds. Thus setting the weights to extreme values is not helpful to improve the performances of energy consumption and throughput based on DCF and ARF.

7 Conclusions

In this paper, we have addressed the AP selection problem for multi-rate WLANs with CR capabilities. Taking the influence of DCF and ARF over the STA throughput into considerations, we have formulated the AP selection problem as a restless bandit problem. The problem formulation not only considers the effects of traffic load, ISM-band interference and channel condition on the STA throughput based on DCF and ARF, but also takes the STAs energy-efficiency into account. We have solved this problem by the primal-dual index heuristic method based on the first order relaxation to yield the GAPS scheme. Especially the proposed scheme is divided into offline computation and online selection, where the complex computation is done offline while the online selection employs a simple table lookup. We have presented extensive simulation results, which illustrate that the GAPS scheme not only achieves higher throughput than the existing scheme, but also costs less energy compared with it. We have also shown that by choosing the corresponding weights and an appropriate number of selected APs, it is possible to trade-off between throughput and energy consumption. Thus how to choose these parameters adaptively is a future work.

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