Admission Control and Channel Allocation for Supporting Real-time Applications in Cognitive Radio Networks

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***Abstract*—Proper admission control in cognitive radio networks is critical in providing QoS guarantees to secondary unlicensed users. In this paper, we study the admission control and channel allocation problem in overlay cognitive radio networks under the maximum cumulative delay constraint. We formulate it as a Markov decision process problem, and then solve it by transforming the original formulation into a stochastic shortest path problem. We further simulate the performance of a class of threshold-based admission control with the largest-delay-first channel allocation policy, and show its advantage over other two benchmark policies.**

I. INTRODUCTION

In order to support the quality of service (QoS) of secondary unlicensed users while limiting interferences to primary licensed users, it is important to carefully design a good admission control mechanism in cognitive radio networks. Compared with the admission control in conventional communication networks, the unique challenge here is to incorporate the impact of primary users on the availability of the communication resources.

There are several previous results on the admission control for cognitive radio networks (*e.g.*, for underlay networks [1]–[3] and overlay networks [9]). In underlay cognitive radio networks, admission control is often jointly pursued with power allocation as the secondary users have to satisfy the interference constraints posed by primary users. In overlay cognitive radio networks, admission control is often jointly pursued with channel allocation as the secondary users can only access the current idle channels not occupied by primary users. There are some results studying the channel allocation for overlay cognitive radio networks [4]–[8]. In [4]–[6], the authors derived optimal and suboptimal decentralized strategies for secondary users' sensing and access decisions for throughput maximization. In [7] and [8], the authors developed opportunistic scheduling policies for cognitive radio networks with static primary users and mobile secondary users under the collision constraints. Admission control also can be jointly considered with other mechanisms, *e.g.*, Kim and Shin [9] devised optimal admission and eviction control for the dynamic spectrum market using semi-Markov decision process and linear programming.

In this paper, we consider the joint admission control and channel allocation problem for overlay cognitive radio networks. We consider a network with multiple primary users and multiple secondary users, and take into account of the maximum cumulative delay constraints of the secondary users.

Our model is motivated but different from the ones in [4]–[9]. We consider an infrastructure based secondary network, where the admission control decision is made by the secondary base station. Such network architecture enables better QoS support to secondary users. Furthermore, we focus on the admission control and resource allocation for real-time applications with maximum delay constraints. This is very different from the throughput maximization of elastic data traffic that has been studied before.

Our key results and contributions are as follows:

- *Problem Formulation*: We formulate the admission control and channel allocation problem with maximum cumulative delay constraints as a Markov decision process (MDP) problem. To the best of our knowledge, this formulation has not been studied in previous literature.
- *MDP Analysis*: We transform the long term average revenue maximization problem into a stochastic shortest path problem. We then prove that the expected cost generated by the iteration of Bellman's equation converges to the optimal cost.
- *Performance Evaluation*: We classify admission control policies into different threshold-based classes, and propose a largest-delay-first channel allocation policy. We show that it is better than the other two benchmark policies through simulations.

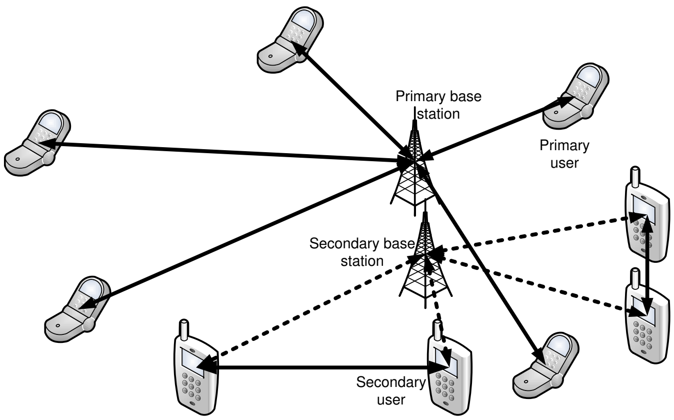

Fig. 1. A cognitive radio network scenario. In the secondary network, the dotted arrows denote the control channels between the secondary base station and the secondary users, and the solid arrows denote the data channels used (either between the primary base station and primary users, or between a secondary transmitter and a secondary receiver).

The rest of the paper is organized as follows. We describe the system model in Section II, and formulate the admission control and channel allocation problem as a Markov decision process problem in Section III. In Section IV, we transform the problem into a stochastic shortest path problem and prove the convergence of the Bellman's equation. Section V provides simulation results of our proposed algorithms. Finally, Section VI concludes the paper.

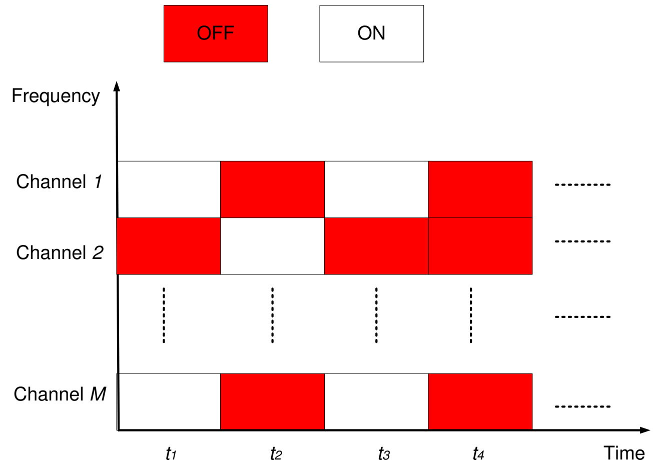

Fig. 2. Channel model of the cognitive radio network.

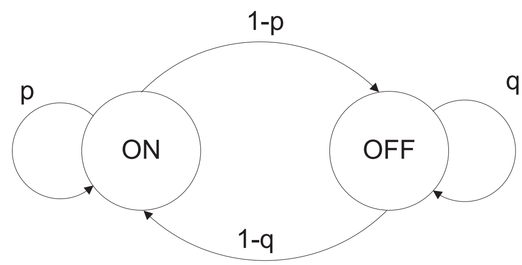

Fig. 3. Markovian ON/OFF model of channel activities.

II. System Model

We study a cognitive radio network with multiple primary users and secondary users as shown in Fig. 1. The network has M primary users, each of which occupies a separate frequency channel and access the channel randomly. Secondary users arrive at the network randomly with random sojourn times. We consider the overlay spectrum sharing, where a secondary user cannot utilize a channel in the presence of an active primary user in that channel. The admitted secondary users will sense the availability of channels and pass the sensing results to the secondary base station. The secondary base station will make the admission control and channel allocation decisions to support the secondary users' QoS.

A. Channel Model

The network has M primary users, and hence M orthogonal frequency channels. When a channel is not used by the corresponding primary user, it can be accessed by one secondary user. Here we assume that no more than one secondary user is allowed to transmit over the same channel. When the primary user is active, no secondary user can access the corresponding channel. For the convenience of analysis, we consider a time slotted channel model as shown in Fig. 2. We assume that the availabilities of all channels follow the same Markovian ON/OFF model as shown in Fig. 3. The state "ON" means that there is no transmission of the primary user, *i.e.*, the channel is idle, while state "OFF" means that the channel is busy. If the state of the channel in time slot t, $S(t)$, is "ON", the state of the next slot $S(t+1)$ is "ON" with probability p and "OFF" with probability $(1-p)$; if $S(t)$ is "OFF", $S(t+1)$ is "OFF" with probability q and "ON" with probability $(1-q)$.

For simplicity, we assume that all secondary users experience the same channel availability independent of their locations. This is reasonable when the communication range of the primary users is large, thus the transmission of each primary user affects all secondary users. Furthermore, we assume that all channels are homogeneous and can provide the same user-independent data rates when they are available. In the future work, we will consider the case where secondary users have location dependent channel availabilities and different channel conditions.

B. Secondary Network Model

In the secondary network, we consider a class of real-time applications such as video streaming and VoIP. Supporting such applications requires relatively steady data rates and needs to satisfy stringent delay constraints. Here we consider the video streaming service as the representative real-time service. One secondary user can consist of one secondary node communicating with the secondary base station, or a secondary transmitter-receiver pair communicating in an ad hoc fashion (the scenario in Fig. 1).

In the cognitive radio network, the number of available channels changes over time because of the activities of the primary users. Our objective is to support as many secondary users as possible while satisfying their QoS requirements. For simplicity, we assume that secondary users are homogeneous. Each secondary user only requires one available channel to satisfy its rate requirement. We consider an infinite backlog system, where there are sufficient secondary users waiting to be served (e.g., many users waiting to use the video streaming services). Once a secondary user is admitted into the secondary network and starts to get service, it will continue to stay in the system with certain probability as long as the cumulative delay is no larger than $D_{\max}$. Once such maximum delay is reached, the user can no longer sustain its QoS requirement (e.g., freezing happens at the receiver), and thus is forced to terminate.

III. Problem Formulation

In this section, we formulate the admission control and channel allocation problem in cognitive radio networks as a Markov decision process (MDP) [10]. In an infinite horizon MDP with a set of finite states $\mathcal{S}$, the state evolves through time according to a transition probability matrix $\{P_{\theta\theta'}\}$, which depends on both the current state and the control decision from a set $\mathcal{U}$. If the network is in state $x_k = \theta$ after the k-th transition and decision $u(x_k) \in \mathcal{U}(\theta)$ is selected, then during the $(k+1)$-th transition, the network moves to state $x_{k+1} = \theta'$ with given probability $P_{\theta\theta'}(u(x_k))$. During the k-th time slot, we obtain a revenue $g(x_k, u(x_k))$, where g is the revenue function. The goal is to maximize the average revenue over all possible decisions at each time slot (stage), which is defined as follows:

$$\lim_{T\to\infty} E\left\{\frac{1}{T}\sum_{k=0}^{T-1} g(x_k, u(x_k))\right\}. \quad (1)$$

A. The State Space

The state consists of the following two components:

- A channel state component, $m = \boldsymbol{n}^T \cdot \boldsymbol{n}$, describes the number of available channels in the current secondary network. Recall that we have M orthogonal channels. The channel availability vector can be characterized by $\boldsymbol{n} = (n_1, n_2, \cdots, n_M)^T$, where

$$n_i = \begin{cases} 1, & \text{channel } i \text{ is available,} \\ 0, & \text{channel } i \text{ is not available.} \end{cases}$$

- A user state component, $\boldsymbol{\omega} = \boldsymbol{\omega_e}$, describes the number of secondary users with different existing delays. Here $\boldsymbol{\omega_e} = (\omega_{e,0}, \omega_{e,1}, \cdots, \omega_{e,D_{\max}})$, where $\omega_{e,i} = j$ for $i = 0, \cdots, D_{\max}$ means that there are j secondary users whose cumulative link delay is i.

We let $\mathcal{N}$ denote the feasible set of the channel state component, and Ω denote the feasible set of the user state component. The state space $\mathcal{S}$ is given by

$$\mathcal{S} = \{\theta = (m, \boldsymbol{\omega}) | m \in \mathcal{N}, \boldsymbol{\omega} \in \Omega\}.$$

State θ is said to be *accessible* from state η if and only if, starting in η, it is possible that the process will ever enter state θ, *i.e.*, $P\{ever\ enter\ \theta | start\ in\ \eta\} > 0$ [12]. Two states that are accessible to each other are said to *communicate*. In our formulation, we define all the states that are accessible from state **0** as the state space $\mathcal{S}$. It is possible that there are no available channels in several consecutive finite time slots. Therefore, state **0** is accessible from any state in the state space. Hence, all the states communicate with each other, and they are *irreducible*. Furthermore, the state space is finite in our formulation, so all the states are *positive recurrent* [12].

B. The Control Space

For each state $\theta = (m, \boldsymbol{\omega}) \in \mathcal{S}$, the set of available control choices $\mathcal{U}(\theta)$ depends on the relationship between the channel state and the user state. The control vector $\boldsymbol{u} = \{u_a, \boldsymbol{u_e}\}$ consists of two parts: u_a denotes the number of admitted new users, and vector $\boldsymbol{u_e} = \{u_{e,i}, \forall i \in [0, D_{\max}]\}$ denotes the numbers of users who are allocated channels in the current time slot and have cumulative delays of $0 \le i \le D_{\max}$ at the beginning of the current time slot. The control vector needs to satisfy the following relationships:

$$\begin{cases} 0 \le u_a, \\ 0 \le u_{e,0} \le \omega_{e,0} + u_a, \\ 0 \le u_{e,i} \le \omega_{e,i}, \quad \forall i \in [1, D_{\max}], \\ 0 \le \displaystyle\sum_{i=0}^{D_{\max}} u_{e,i} \le m. \end{cases} \quad (2)$$

Since $m \le M$ where M is the total number of channels (available and occupied) in the network, the cardinality of the control space $\mathcal{U}$ is $M^{D_{\max}+2}$.

C. The State Transition

Current state $\theta = \{m, \boldsymbol{\omega}\} \in \mathcal{S}$ together with the control $\boldsymbol{u} \in \mathcal{U}(\theta)$ determines the probability of reaching the next state $\theta' = \{m', \boldsymbol{\omega'}\}$.

First, the transition from m to m' depends on the underlying primary user activity model. We can divide m' available channels into two groups: one group contains m'_1 channels which are available in the last time slot, the other group contains m'_2 channels which are not available in the last time slot. Let us define the set

$$\mathcal{Z} = \{(m'_1, m'_2) | m' = m'_1 + m'_2, 0 \le m'_1 \le m, 0 \le m'_2 \le M - m.\}.$$

Then we can calculate the probability based on the *i.i.d.* ON/OFF model in Section II:

$$P_{mm'} = \sum_{(m'_1, m'_2) \in \mathcal{Z}} C_m^{m'_1} p^{m'_1} (1-p)^{m-m'_1} C_{M-m}^{m'_2} (1-q)^{m'_2} q^{M-m-m'_2}. \quad (3)$$

This enables us to define the channel transition function

$$f_s(m) = m', \text{ with probability } P_{mm'}, \forall m' \in [0, M]. \quad (4)$$

Let us define ω_c as the number of secondary users who complete their connections (not due to delay violation) in the last time slot. For example, a user may voluntarily terminate a video streaming session after the intended content has been watched, or terminate a VoIP session when the conversation is over. If we assume that all users have the same completion probability P_f when they are actively served, then the event of having j out of l users completing their connections, which is denoted as $f_c(l) = j$, happens with probability $C_l^j P_f^j (1-P_f)^{l-j}$.

Finally, define ω_q as the number of secondary users who are forced to terminate their connections during the last time slot. The state transition can be written as

$$\begin{cases} m' = f_s(m), \\ \omega_c = (\omega_{c,0}, \omega_{c,1}, \cdots, \omega_{c,D_{\max}}) = f_c(\boldsymbol{u_e}), \\ \omega_q = \omega_{e,D_{\max}} - u_{e,D_{\max}}, \\ \omega'_{e,i} = u_{e,i} + (\omega_{e,i-1} - u_{e,i-1}) - \omega_{c,i}, \forall i \in [1, D_{\max}], \\ \omega'_{e,0} = u_{e,0} + u_a - \omega_{c,0}. \end{cases} \quad (5)$$

D. The Objective Function

Our objective is to choose the optimal control decision for each possible state to maximize the expected average revenue per time slot (also called stage), *i.e.*,

$$\max \lim_{T\to\infty} E\left\{ \frac{1}{T} \sum_{k=0}^{T-1} g(x_k, u(x_k)) \right\}. \quad (6)$$

Here the revenue function is computed at the end of each time slot k as follows:

$$g(x_k, u(x_k)) = R_c \sum_{i=0}^{D_{\max}} \omega_{c,i}(k) + R_t \sum_{i=0}^{D_{\max}} \omega_{e,i}(k) - C_q \omega_q(k), \quad (7)$$

where $R_c \geq 0$ is the reward of completing the connection of a secondary user (without violating the maximum delay constraint), $R_t \geq 0$ is the reward of maintaining the connection of a secondary user, and $C_q \geq 0$ is the penalty of forcing to terminate the connection of a secondary user.

IV. Analysis of the MDP Problem

We define a sequence of control actions as a policy, $\mu = \{\mu_0(x_0), \mu_1(x_1), \cdots\}$, where $\mu_i(x_i) \in \mathcal{U}(\theta)$ for all i. Let $V_\mu(\theta)$ be the expected revenue in state θ under policy μ. Our objective is to find the best policy μ to optimize the average revenue per stage starting from an initial state θ, *i.e.*,

$$V_\mu(\theta) = \lim_{T\to\infty} \frac{1}{T} E\left\{ \sum_{k=0}^{T-1} g(x_k, \mu_k(x_k)) | x_0 = \theta \right\}. \quad (8)$$

We have the following proposition.

Proposition 1: For any stationary policy[1], the average revenue per stage is independent of the initial state.

Proof: Since the revenue $g(x_k, \mu_k(x_k)) < \infty$ for all x_k and μ_k, we have

$$\lim_{T\to\infty} \frac{1}{T} E\left\{ \sum_{k=0}^{K} g(x_k, \mu_k(x_k)) \right\} = 0 \quad (9)$$

[1]A policy is a stationary policy if whenever the state is θ, the policy μ chooses the same decision, $\mu(\theta)$, independent of the period.

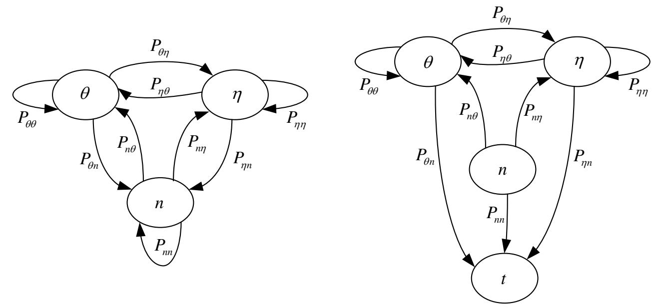

Fig. 4. Transition probability of the shortest path problem.

for any finite value of K. Consider a stationary policy μ whose control decision only depends on the state of the system. According to the MDP formulation, all the states are positive recurrent. So starting in state θ, the process will visit state η infinitely often; and the expected time that the process visits state η from state θ is finite [12]. Thus, any state in the state space can be visited from any other state within enough stages (finite) under the stationary policy. Therefore, we assume, under the policy μ, the state $\eta \in \mathcal{S}$ is visited from the state $\theta \in \mathcal{S}$. Let $K_{\theta\eta}(\mu)$ be the number of time slots that the system first passes state η from state θ under policy μ, then the average revenue per stage corresponding to initial condition $x_0 = \theta$ can be expressed as

$$V_\mu(\theta) = \lim_{T\to\infty} \frac{1}{T} E\left\{ \sum_{k=0}^{K_{\theta\eta}(\mu)-1} g(x_k, \mu(x_k)) \right\} + \lim_{T\to\infty} \frac{1}{T} E\left\{ \sum_{k=K_{\theta\eta}(\mu)}^{T-1} g(x_k, \mu(x_k)) \right\}. \quad (10)$$

The first term in (10) is zero according to (9), while the second limit is equal to $V_\mu(\eta)$. So with $E\{K_{\theta\eta}(\mu)\} < \infty$,

$$V_\mu(\theta) = V_\mu(\eta) = V_\mu, \quad (11)$$

for any two states θ and η. ■

A. Stochastic Shortest Path Problem

According to the MDP formulation in Section III, the state space and the control space are finite, and the control policy only depends on the system states. The states of available channels are ergodic in the time domain. Thus we know that any state $n \in \mathcal{S}$ will be visited within the first m stages (with a proper choice of $m > 0$) at least once under all initial states and all stationary policies. This can be proved using contradition. This allows us to divide our infinite dimension decision problem into infinitely many pieces of finite segments, and then to make an important connection of the average revenue maximization problem with a stochastic shortest path problem [13] [14].

Let us consider a sequence of states generated by the MDP. We divide it into "independent" cycles marked by successive visits to the state n. The first cycle includes the transition from the initial state to the first visit of state n, and the k-th cycle ($k = 2, 3, \cdots$) includes the transition from the $(k-1)$-th visit to the k-th visit of state n. Under a control policy ϕ, we assume that the transition probabilities are $\{P_{\theta\eta}(\phi)\}$. Let us define an artificial termination state t, to which each state i moves with probability $P_{\theta t}(\phi) = P_{\theta n}(\phi)$ as show in Fig. 4. In this way, we transform the average revenue problem into the stochastic shortest path problem, whose state trajectories repeat the state trajectories of a single cycle of the average revenue problem.

Under any stationary policy, there will be infinitely many cycles marked by successive visits to state n. Then the average revenue problem in this paper is equivalent to a maximum cycle revenue problem. The objective is to find a stationary policy ϕ that maximizes the average cycle revenue $\frac{R_{nn}(\phi)}{N_{nn}(\phi)}$, where $R_{nn}(\phi)$ is the expected revenue and $N_{nn}(\phi)$ is the expected number of stages starting from state n up to the first return to state n under policy ϕ. Therefore, the ratio $\frac{R_{nn}(\phi)}{N_{nn}(\phi)}$ is equal to the average revenue of the policy ϕ, and we have

$$R_{nn}(\phi) - N_{nn}(\phi)A^* \leq 0, \forall\phi, \quad (12)$$

where A^* is the optimal average revenue starting from the state n to the terminal state t in the stochastic shortest path problem under any stationary policy.

We assume that the expected stage "cost" incurred at state θ to be $A^* - g(\theta, \mu)$, whose optimal average value is zero under the optimal control policy[2]. Then the associated stochastic shortest path problem is essentially equivalent to the original average revenue per stage problem. Let $h^*(\theta)$ denote the optimal cost of the stochastic shortest path starting at state $\theta \in \mathcal{S}$, then we get the corresponding Bellman's equation in the following form [10]:

$$h(\theta) = \min_{\phi \in \mathcal{U}(\theta)} [A^* - g(\theta, \phi) + \sum_{\eta \in \mathcal{S}} p_{\theta\eta}(\phi) h(\eta)], \ \theta \in \mathcal{S}. \quad (13)$$

If ϕ^* is a stationary policy that maximizes the cycle revenue, we have the following equations:

$$h^*(\theta) = A^* - g(\theta, \phi^*) + \sum_{\eta \in \mathcal{S}} p_{\theta\eta}(\phi^*) h^*(\eta), \ \theta \in \mathcal{S}, \quad (14)$$

and

$$R_{nn}(\phi^*) - N_{nn}(\phi^*)A^* = 0. \quad (15)$$

B. Optimal Admission Control and Channel Allocation

In this section, we show that the optimal admission control problem can be solved by solving the Bellman's equation (16) in the stochastic shortest path problem.

Proposition 2: For the stochastic shortest path problem, given any initial conditions $h_0(\theta), \ \forall\theta \in \mathcal{S}$, the sequence $h_k(\theta)$ generated by the iteration

$$h_{k+1}(\theta) = \min_{\phi \in \mathcal{U}(\theta)} [A^* - g(\theta, \phi) + \sum_{\eta \in \mathcal{S}} P_{\theta\eta}(\phi) h_k(\eta)] \quad (16)$$

converges to the optimal cost $h^*(\theta)$ for each state θ.

[2]If we assume that the expected stage "cost" incurred at state θ to be $-g(\theta, \mu)$, the optimal average "cost" is $-A^*$ under the optimal control policy.

Owing to space constraints, the proof of Proposition 2 is provided in the online technical report [11]. Proposition 2 shows that the optimal differential cost h^* for the admission control and channel allocation problem satisfies the Bellman's equation. Then given the optimal average revenue A^* and the optimal differential cost h^*, the optimal decision at state θ, $\phi^*(\theta)$, minimizes the immediate differential cost of the current stage plus the remaining expected differential cost, *i.e.*,

$$\phi^*(\theta) = \arg \min_{\phi \in \mathcal{U}(\theta)} [A^* - g(\theta, \phi) + \sum_{\eta \in \mathcal{S}} p_{\theta\eta}(\phi) h^*(\eta)] \quad (17)$$

for each state θ.

V. Simulation Results

There are a number of methods to solve the Bellman's equation to obtain the values of A^* and h^*. Most of these are variations of the value iteration or the policy iteration algorithms. A comprehensive treatment can be found in [13] and [14]. Once we obtain the optimal values, the optimal decision at each time slot (stage) can be determined by (17). However, since the control space is generally very large, the computation overhead for obtaining the optimal solution is very large. In this paper, we will restrict the simulation studies to a class of policies. More detailed discussions of various policies including the optimal one will be provided in [11].

As we know, the control decision involves both admission control (u_a) and channel allocation ($\boldsymbol{u_e}$). We will restrict ourselves to a special class of *threshold-based* policies for admission control. For a policy with a threshold T_h, a new user will be admitted if and only if the total number of admitted users is no larger than T_h. We group all policies with the same threshold T_h into one class. Since there are many ways of performing channel allocation after admission control, there are still many policies in the same class. For example, consider a network with a total $M = 5$ channels and a maximum delay constraint $D_{\max} = 5$. In a given time slot, if the threshold $T_h = 4$, the number of available channels $m = 3$, and there are two admitted users with $\boldsymbol{\omega_e} = (0, 0, 1, 0, 1, 0)$, then the control decision can be either $\boldsymbol{u} = \{u_a, \boldsymbol{u_e}\} = (2, \ [1, 0, 1, 0, 1, 0])$ or $\boldsymbol{u} = \{u_a, \boldsymbol{u_e}\} = (2, \ [2, 0, 1, 0, 0, 0])$ or several other possiblities.

We further propose the following *largest-delay-first* channel allocation strategy following the threshold-based admission control: we allocate the available channels to the admitted users with the largest accumulated delay first. For example, our proposed control policy in the last example is $\boldsymbol{u} = \{u_a, \boldsymbol{u_t}\} = (2, \ [1, 0, 1, 0, 1, 0])$.

To demonstrate the performance of the proposed strategy, we define other two channel allocation strategies. First, we study Strategy 1 that allocates available channels to the secondary users with the smallest latency. Then we look at some trade-off strategies between our proposed and the opposite one. One example of them is Strategy 2.

- **Strategy 1:** In the channel allocation step, allocate the available channels to the admitted users with the smallest accumulated delays. If there is a tie, break it randomly.

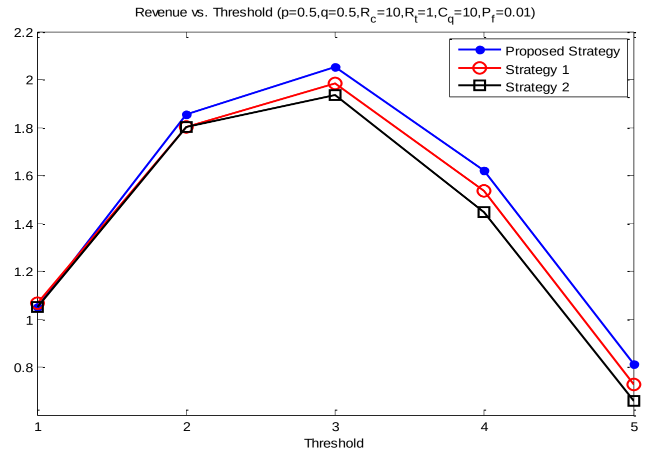

Fig. 5. Revenue versus threshold of three different strategies ($M = 5, D_{\max} = 5$).

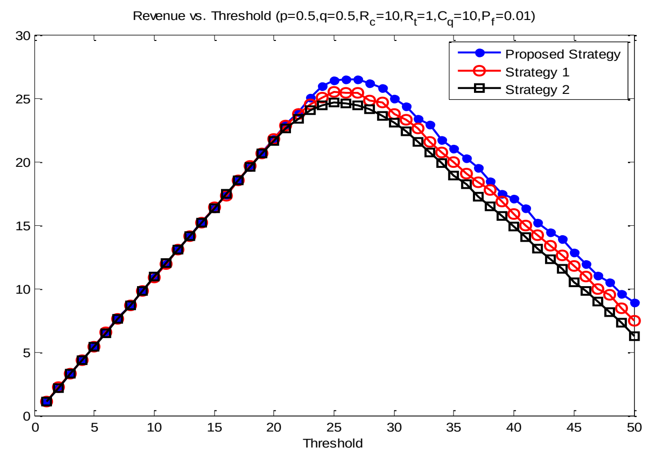

Fig. 6. Revenue versus threshold of three different strategies ($M = 50, D_{\max} = 5$).

- **Strategy 2:** In the channel allocation step, allocate the available channels to the admitted users randomly.

In Fig. 5 and Fig. 6, we show the comparison between the proposed channel allocation policy and the two benchmark policies with $M = 5$ and $M = 50$, respectively. All three policies follow threshold-based admission control policies. From these figures, we observe that the proposed largest-delay-first policy is no worse than the other two under all choices of parameters.

VI. Conclusions

We studied the admission control and channel allocation problem in overlay cognitive radio networks. We considered real-time applications that require constant data rates with stringent delay constraints. Our objective is to support as many secondary users as possible while satisfying their QoS requirements.

In this paper, we formulated the problem as a Markov decision process problem. We first proved that the optimal average revenue was independent of the initial system state. Then we transformed the original problem into a stochastic shortest path problem, and proved that the Bellman's equation converged to the optimal policy. Finally, we simulated the threshold-based admission control plus the largest-delay-first channel allocation policy. In future work, we will further characterize the properties of the optimal policy, and study the performance gap between the optimal one and the one proposed in this paper.

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