Energy-Efficient Secondary Traffic Scheduling with MIMO Beamforming

Haichuan Ding[1], Hao Yue[1], Jianqing Liu[1], Pengbo Si[2], and Yuguang Fang[1]

[1]Department of Electrical and Computer Engineering, University of Florida, Gainesville, FL 32611,
Email: dhcbit@gmail.com, {hyue,jianqingliu}@ufl.edu, fang@ece.ufl.edu
[2]College of Electronic Information and Control Engineering, Beijing University of Technology, Beijing 100124, China,
sipengbo@bjut.edu.cn

***Abstract*—When equipped with multiple antennas, secondary users in cognitive radio networks are able to communicate even when neighboring primary users are active by transmitting in the null space of the communication channel occupied by primary users. In this case, the throughput of a secondary link is limited by the transmission power and the dimension of the null space, i.e., the number of active primary users nearby. Since the number of active primary users is time-varying, the required transmission power to support certain data rate changes from time to time. Thus, secondary users could adapt their transmission to the variation of the primary traffic to improve energy efficiency. In view of that, we develop an energy-efficient traffic scheduling scheme for secondary users equipped with multiple antennas. By formulating the traffic scheduling problem as a Markov decision problem, an energy-efficient transmission scheme is derived from linear programming. The analytical results are verified by simulations and the impacts of various parameters are discussed. The superiority of the derived scheme is also shown by comparing with a randomized scheme.**

I. Introduction

Recently, the wide spread of wireless technology has led to the rapid growth of wireless data traffic and spectrum demand. In contrast, a lot of spectrum bands are underutilized due to the static spectrum allocation policy. Cognitive radio (CR) has been introduced as an effective approach to increase spectrum utilization and meet increasing spectrum demand [1]. With CR technology, secondary users are allowed to access the licensed bands as long as the quality of service (QoS) of primary users is guaranteed [2].

Traditionally, the QoS protection for primary users is achieved through an interference power constraint, which limits the available spectrum bands to the secondary users [3], [4]. To allow secondary users to access the licensed spectrum bands more aggressively, a MIMO based scheme was proposed in [8] where beamforming techniques are adopted to allow secondary users to communicate in the null space of the communication channels occupied by primary users. In this case, the throughput of secondary links is limited by the number of active primary users nearby and the transmission power [6]. As primary users' traffic is time-varying, the required transmission power for secondary users to achieve certain throughput varies at different time spots. This indicates the secondary users' energy consumption could be minimized by adapting their transmission to the variation of primary traffic. On the other hand, battery-powered wireless devices are widely used and their battery could be easily drained by the ever growing applications and services. Thus, secondary users would benefit from an energy-efficient transmission scheme [5]. Although the feasibility and the superiority of this MIMO based transmission scheme have been demonstrated in existing works [3], [8], it has not been well addressed from an energy-efficient perspective.

In this paper, a cognitive radio network where secondary users are equipped with multiple antennas is considered. With MIMO beamforming technologies, secondary users could communicate in the null space of the primary channels. Aiming to minimize the secondary user's long-term average energy consumption, the optimal secondary traffic scheduling scheme is investigated under both queue length and overflow constraints. The traffic scheduling problem is formulated as a Markov decision problem. Different from existing works, the number of active primary users nearby has been included in the system state as it directly determines the energy consumption of this MIMO based transmission scheme. Noticing the corresponding Markov decision process has a unichain structure, the optimal steady state probability is derived through linear programming and the optimal transmission scheme is obtained accordingly. The analytical results are validated by simulations, and the impacts of queue length and overflow probability on the average energy consumption are investigated. Then the relation between queue length and overflow probability is presented. We also compare the derived transmission scheme with a randomized transmission scheme and the results indicate the derived scheme is more energy-efficient than its randomized counterpart.

The rest of this paper is organized as follows. The MIMO based transmission scheme and traffic models are introduced in Section II. The Markov decision problem is formulated in Section III and the optimal traffic scheduling scheme is derived in the same section. Then simulation results and the impacts of various parameters are presented in Section IV. Finally,

This work was partially supported by the US National Science Foundation under grant CNS-1343356.

978-1-4799-5952-5/15/$31.00 ©2015 IEEE

conclusions are drawn in Section V.

II. System Model

A. Network Model

A slotted cognitive radio network where N_p primary links coexist with N_s secondary links is considered. The transmitter and the receiver of the ith primary link are denoted as PT_i and PR_i ($i = 1, \cdots, N_p$), respectively. The transmitter and the receiver of the jth secondary link are denoted as ST_j and SR_j ($j = 1, \cdots, N_s$), respectively. Each primary user has a single antenna and each secondary user is equipped with n antennas. A secondary service provider (SSP) is adopted to coordinate the transmissions of the secondary links such that they will not interfere with each other [7].

B. Primary Traffic

Each primary link has two states, i.e., on and off. The state of each primary link remains unchanged during each time slot and evolves as a two-state Markov chain. Specifically, when a primary link is active in the current slot, it will keep active in the next slot with probability p. When a primary link is inactive currently, it will remain silent in the next slot with probability q [10], [11]. Denote the status of the ith primary link in slot t as ϑ_{it}. Then, $\vartheta_{it} = 1$ and $\vartheta_{it} = 0$ indicate the primary link is active and inactive, respectively. $\mathcal{A}_t = \{i|\vartheta_{it} = 1\}$ is the index set of all the active primary links in slot t. The number of active primary links in slot t, denoted as m_t, equals to $|\mathcal{A}_t|$, the cardinality of $\mathcal{A}_t$.

C. MIMO Based Secondary Transmission Scheme

In traditional cognitive radio networks, secondary users can transmit over a certain spectrum band only when the interference power constraints at the primary users are satisfied, which limits the number of available bands to secondary users. As reported in [8], when secondary users are equipped with multiple antennas, beamforming can be utilized for them to communicate in the null space of the channels occupied by primary users. With this MIMO based transmission scheme, in the considered network, secondary users could access a licensed band for transmission as long as the dimension of the considered null space is positive. Next, a brief introduction on this MIMO based transmission scheme is provided.

When ST_j intends to communicate with SR_j in slot t, it first precodes its signal with a precoding matrix such that the transmitted signal will not interfere with the primary links. Meanwhile, SR_j processes the received signal with a beamforming matrix to nullify the interference from the primary links. For ease of presentation, we assume all primary links are active, i.e., $\mathcal{A}_t = \{1, 2, \cdots, N_p\}$ and $m_t = N_p$. As shown in Fig. 1, the channel vector between ST_j and PR_i is $\mathbf{g}_{ji} \in \mathbb{C}^{1\times n}$ and the channel vector between PT_i and SR_j is $\mathbf{r}_{ij} \in \mathbb{C}^{n\times 1}$. The channel from ST_j to all primary receivers is $\mathbf{G} = \begin{bmatrix} \mathbf{g}_{j1}^T & \mathbf{g}_{j2}^T & \cdots & \mathbf{g}_{jN_p}^T \end{bmatrix}^T \in \mathbb{C}^{N_p\times n}$ and the channel from all the primary transmitters to SR_j is $\mathbf{R} = \begin{bmatrix} \mathbf{r}_{j1} & \mathbf{r}_{j2} & \cdots & \mathbf{r}_{jN_p} \end{bmatrix} \in \mathbb{C}^{n\times N_p}$, where $\mathbf{g}_{j1}^T$ is the transpose of $\mathbf{g}_{j1}$. The singular value decomposition of $\mathbf{G}$ and $\mathbf{R}$ can be expressed as $\mathbf{G} = \mathbf{V}_G \begin{bmatrix} \mathbf{\Lambda}_G & \mathbf{0}_{N_p\times(n-N_p)} \end{bmatrix} \mathbf{U}_G^\dagger$ and $\mathbf{R} = \mathbf{V}_R \begin{bmatrix} \mathbf{\Lambda}_R \\ \mathbf{0}_{(n-N_p)\times N_p} \end{bmatrix} \mathbf{U}_R^\dagger$, respectively, where $\mathbf{\Lambda}_G$ and $\mathbf{\Lambda}_R$ are diagonal matrices of the singular values[1], and $\mathbf{U}_G^\dagger \in \mathbb{C}^{n\times n}$ is the conjugate transpose of $\mathbf{U}_G$. Let $\mathbf{U}_G = \begin{bmatrix} \mathbf{U}_{G1} & \mathbf{U}_{G2} \end{bmatrix}$ and $\mathbf{V}_R = \begin{bmatrix} \mathbf{V}_{R1} & \mathbf{V}_{R2} \end{bmatrix}$, where $\mathbf{U}_{G1} \in \mathbb{C}^{n\times N_p}$ is formed by the vectors corresponding to $\mathbf{\Lambda}_G$, and $\mathbf{V}_{R1} \in \mathbb{C}^{n\times N_p}$ is formed by the vectors corresponding to $\mathbf{\Lambda}_R$. Before transmission, ST_j projects its signal $\mathbf{x}_{sj} \in \mathbb{C}^{n\times 1}$ to the null space of $\mathbf{G}$ such that the received interference power at each primary receiver is zero. After transmission, the received signal at SR_j is

$$\mathbf{y} = \mathbf{H}\tilde{\boldsymbol{x}}_{sj} + \mathbf{R}\boldsymbol{x}_p + \mathbf{n}, \tag{1}$$

where $\tilde{\boldsymbol{x}}_{sj} = \mathbf{U}_{G2}\mathbf{x}_{sj} \in \mathbb{C}^{n\times 1}$ is the transmitted signal of ST_j after projection. $\boldsymbol{x}_p = \begin{bmatrix} x_{p1} & x_{p2} & \cdots & x_{pN_p} \end{bmatrix}^T \in \mathbb{C}^{N_p\times 1}$, where $x_{p1} \in \mathbb{C}$ is the transmitted signals from PT_1. $\mathbf{n} \sim \mathcal{N}\left(0, \sigma^2\mathbf{I}_n\right)$ is the white Gaussian noise. At the receiving side, SR_j projects the received signal $\mathbf{y}$ to the null space of $\mathbf{R}$ with the projection matrix $\mathbf{V}_{R2}$, i.e.,

$$\tilde{\mathbf{y}} = \mathbf{V}_{R2}^\dagger\mathbf{y} = \mathbf{V}_{R2}^\dagger\mathbf{H}\tilde{\boldsymbol{x}}_{sj} + \mathbf{V}_{R2}^\dagger\mathbf{n} = \tilde{\mathbf{H}}\mathbf{x}_{sj} + \mathbf{V}_{R2}^\dagger\mathbf{n}, \tag{2}$$

where $\tilde{\mathbf{H}} = \mathbf{V}_{R2}^\dagger\mathbf{H}\mathbf{U}_{G2}$ and $\mathbf{V}_{R2}^\dagger\mathbf{n} \sim \mathcal{N}\left(0, \sigma^2\mathbf{I}_{n-N_p}\right)$. From [6], the throughput of the secondary link is

$$\mathcal{T} = \max_{\mathbf{S}_{sj}} \mathrm{E}_{\tilde{\mathbf{H}}}\left[\log_2\left(\left|\mathbf{I} + \frac{1}{\sigma^2}\tilde{\mathbf{H}}\mathbf{S}_{sj}\tilde{\mathbf{H}}^\dagger\right|\right)\right], Tr(\mathbf{S}_{sj}) \le P. \tag{3}$$

where $\mathbf{S}_{sj}$ is the autocorrelation matrix of $\mathbf{x}_{sj}$, $Tr(\mathbf{S}_{sj})$ is the trace of $\mathbf{S}_{sj}$, and P is the transmission power constraint. Noticing $\mathbf{I} + \frac{1}{\sigma^2}\tilde{\mathbf{H}}\mathbf{S}_{sj}\tilde{\mathbf{H}}^\dagger$ is a nonnegative definite matrix, it follows

$$\mathcal{T} = \max_{\omega_l} \sum_{l=1}^{n-N_p} \mathrm{E}_{\eta_l}\left[\log_2\left(1 + \frac{1}{\sigma^2}\omega_l\eta_l\right)\right], \sum_{l=1}^{n-N_p} \omega_l \le P, \tag{4}$$

where η_l is the eigenvalues of $\tilde{\mathbf{H}}$ [9]. Since $N_p = m_t$, $\mathcal{T}$ is just a function of $n - m_t$ and P.

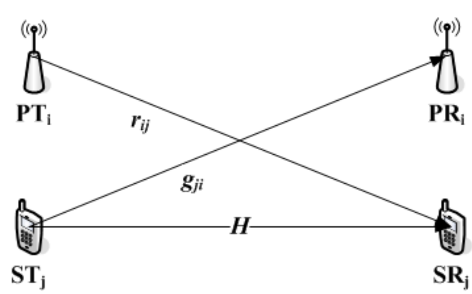

Fig. 1. Interference Channel.

[1] In this paper, all channel matrices are assumed to be full rank.

D. Secondary Traffic

It is assumed that ST_j has a finite buffer of size B and its queue length at the beginning of slot t is b_t. At the start of slot t, ST_j selects to transmit u_t packets according to a decision rule μ_t, where $u_t \in \mathcal{U}_{b_t} = \{0, 1, 2, \cdots, b_t\}$. The number of arrived packets during slot t is a_t and a_t's are assumed to be independently identically distributed (i.i.d.). Similar to [12], the maximum number of arrivals during each slot is required to be no more than B. When the incoming traffic is Poisson distributed, the probability of k arrivals during slot t is [12]

$$\mathrm{P}\left(a_t = k\right) = \left\{ \begin{array}{cc} \frac{\lambda^k}{k!} e^{-\lambda} & 0 \le k \le B-1 \\ 1 - \sum\limits_{l=0}^{B-1} \frac{\lambda^l}{l!} e^{-\lambda} & k = B \end{array} \right. , \quad (5)$$

where λ is the average number of arrivals during each slot. Then, we have

$$b_{t+1} = \min\left\{b_t - u_t + a_t, B\right\}, \quad (6)$$

Without loss of generality, we assume both the duration of each slot and the secondary packet length are fixed. Then, the minimum secondary link throughput $\mathcal{T}$ to support the transmission of u_t packets in slot t is a function of u_t, i.e., $\mathcal{T} = \mathcal{T}(u_t)$. From above discussion, $\mathcal{T}$ is also a function of $n - m_t$ and P, we have

$$\mathcal{T}\left(u_t\right) = f\left(n - m_t, P\right). \quad (7)$$

Clearly from (7), the transmission power in slot t is a function of m_t and u_t, i.e., $P_t = \tilde{f}\left(m_t, u_t\right)$. For simplicity, we assume each slot has unit duration and thus the energy consumption in slot t is of the same value as P_t, i.e., $\tilde{f}\left(m_t, u_t\right)$, a function of m_t and u_t. Given m_t varies from slot to slot, μ_t should be carefully designed such that the optimal u_t can be selected to minimize the energy consumption. A policy $\pi = \{\mu_1, \mu_2, \cdots\}$ is the collection of the decision rules at different time slots. When all the time slots adopt the same decision rule, π is called a stationary policy. We will derive π^*, which is a collection of the optimal decision rules at different time slots, in the next section.

III. Optimal Transmission Strategy

In this section, the optimal policy π^* will be found to minimize the long term average energy consumption under queue length and overflow constraints. Specifically, the optimization problem can be formulated as

$$\underset{\pi}{\text{minimize}} \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[\tilde{f}\left(m_t, u_t\right)\right] \quad (8)$$

$$s.t. \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[b_t\right] \le \mathrm{D} \quad (9)$$

$$\lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[\mathrm{P}_t^o\right] \le \varepsilon, \quad (10)$$

where β is the initial distribution, P_t^o is the buffer overflow probability at slot t. (9) is the average queue length constraint and (10) is the overflow probability constraint. The optimization problem above will be formulated as a Markov decision problem in the next subsection.

A. Markov Decision Problem Formulation

The system state at slot t is composed of current queue length and the number of active primary links, i.e., $S_t = (b_t, m_t) \in \mathcal{S}$ and $\mathcal{S} = \left\{ (l, \varpi) \middle| \begin{array}{c} l = 0, 1, \cdots, B \\ \varpi = 0, 1, \cdots, N_p \end{array} \right\}$. Based on the fact that the activity of each primary link ϑ_{it} has the Markov property, we will prove m_t satisfies the Markov property in the following Lemma.

Lemma 1 *m_t satisfies the Markov property, i.e., given m_t, the distribution of m_{t+1} is independent of $\{m_i | i = 0, 1, \cdots, t-1\}$.*

Proof: See Appendix. ∎

According to (6), b_{t+1} only depends on a_t, b_t and u_t. Since a_t's are i.i.d, b_{t+1} is independent with $\{b_{t-1}, \cdots, b_1, b_0\}$ and $\{u_{t-1}, \cdots, u_1\}$ given b_t and u_t, where b_0 is the initial queue length. Thus we conclude that the system state $S_t = (b_t, m_t)$'s form a Markov chain in the sense that S_{t+1} is independent with $\{S_{t-1}, \cdots, S_0\}$ and $\{u_{t-1}, \cdots, u_1\}$ given S_t and u_t, where S_0 is the initial state. Then the system state transition probability can be formulated as

$$\begin{aligned} &\mathrm{P}\left(S_{t+1} = s_i \middle| S_t = s_j, u_t = \nu_i\right) \\ =&\mathrm{P}\left(b_{t+1} = \ell_{s_i}, m_{t+1} = \varpi_{s_i} \middle| b_t = \ell_{s_j}, m_t = \varpi_{s_j}, u_t = \nu_i\right) \\ =&\mathrm{P}\left(b_{t+1} = \ell_{s_i} \middle| b_t = \ell_{s_j}, u_t = \nu_i\right) \\ &\times \mathrm{P}\left(m_{t+1} = \varpi_{s_i} \middle| m_t = \varpi_{s_j}\right), \end{aligned} \quad (11)$$

where the last equation in (11) is obtained based on the fact that b_t and m_t are independent with each other. From (5) and (6), it follows

$$\begin{aligned} &\mathrm{P}\left(b_{t+1} = \ell_{s_i} \middle| b_t = \ell_{s_j}, u_t = \nu_i\right) = \\ &\left\{ \begin{array}{cc} \frac{\lambda^{\ell_{s_i} - \ell_{s_j} + \nu_i}}{(\ell_{s_i} - \ell_{s_j} + \nu_i)!} e^{-\lambda} & \ell_{s_j} - \nu_i \le \ell_{s_i} \le B-1 \\ 1 - \sum\limits_{l=0}^{B - \ell_{s_j} + \nu_i - 1} \frac{\lambda^l}{l!} e^{-\lambda} & \ell_{s_i} = B \end{array} \right. \end{aligned} \quad (12)$$

Plug (12) and (30) into (11), the transition probability can be derived. Clearly, the transmission probability $\mathrm{P}\left(S_{t+1} = s_i \middle| S_t = s_j, u_t = \nu_i\right)$ does not depend on t. That is, when the system is in state s_i and takes action ν_i, it will reach state s_j with a fixed probability, which is denoted as $\mathcal{P}_{s_i \nu_i s_j}$.

According to Section II.D, the possible actions at slot t are limited by b_t and thus the state S_t. Let $\mathcal{U} = \{0, 1, 2, \cdots B\}$ be the finite action space, then $u_t \in \mathcal{U}_{S_t}$ and $\mathcal{U}_{S_t} = \mathcal{U}_{b_t} \subset \mathcal{U}$. Moreover, $\tilde{f}\left(m_t, u_t\right)$ depends on m_t and thus S_t. Then, $\tilde{f}\left(m_t, u_t\right)$ is a function of S_t and can be redefined as $\tilde{f}\left(m_t, u_t\right) = \bar{f}\left(S_t, u_t\right)$. b_t in (9) can be defined as a projection function $\phi\left(S_t, u_t\right) = b_t$. Since the buffer will overflow when

$b_t - u_t + a_t > B$, P_t^o can be formulated as

$$\mathrm{P}_t^o = \mathrm{P}\left(b_t - u_t + a_t > B\right) = 1 - \sum_{l=0}^{B-b_t+u_t} \frac{\lambda^l}{l!} e^{-\lambda}. \quad (13)$$

(13) indicates P_t^o only depends on b_t and u_t. Hence, it can be rewritten as a function of S_t and u_t, i.e., $\mathrm{P}_t^o = \theta\left(S_t, u_t\right)$. Following [13], the tuple $\left\{\mathcal{S}, \mathcal{U}, \mathcal{P}_{s_i \nu_i s_j}, \bar{f}, \phi, \theta\right\}$ defines a constrained Markov decision process (MDP). Then, the optimization problem defined by (8-10) can be reformulated as a constrained Markov decision problem as follows

$$\underset{\pi}{\text{minimize}} \lim_{N \to \infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[\bar{f}\left(S_t, u_t\right)\right], \quad (14)$$

$$s.t. \lim_{N \to \infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[\phi\left(S_t, u_t\right)\right] \le D, \quad (15)$$

$$\lim_{N \to \infty} \frac{1}{N} \sum_{t=1}^{N} \mathrm{E}_\beta^\pi \left[\theta\left(S_t, u_t\right)\right] \le \varepsilon. \quad (16)$$

B. Optimal Transmission Scheme

Noticing the MDP defined in (14)-(16) has a unichain structure, there is a randomized stationary Markov policy $\pi^* = \{\mu^*, \mu^*, \cdots\}$ to be optimal [13]. Under π^*, the system will reach a steady state. Let $\rho\left(s_i, \nu_i\right)$ be the steady state probability that the system is in state s_i and action ν_i is applied. Then, $\rho\left(s_i, \nu_i\right)$ can be derived from the following linear programming

$$\underset{\rho(s_i,\nu_i)}{\text{minimize}} \sum_{s_i \in \mathcal{S}} \sum_{\nu_i \in \mathcal{U}_{s_i}} \bar{f}\left(s_i, \nu_i\right) \rho\left(s_i, \nu_i\right) \quad (17)$$

$$s.t. \sum_{s_i \in \mathcal{S}} \sum_{\nu_i \in \mathcal{U}_{s_i}} \phi\left(s_i, \nu_i\right) \rho\left(s_i, \nu_i\right) \le D \quad (18)$$

$$\sum_{s_i \in \mathcal{S}} \sum_{\nu_i \in \mathcal{U}_{s_i}} \theta\left(s_i, \nu_i\right) \rho\left(s_i, \nu_i\right) \le \varepsilon \quad (19)$$

$$\sum_{s_i \in \mathcal{S}} \sum_{\nu_i \in \mathcal{U}_{s_i}} \rho\left(s_i, \nu_i\right) = 1 \quad (20)$$

$$\sum_{\nu_j \in \mathcal{U}_{s_j}} \rho\left(s_j, \nu_j\right) = \sum_{s_i \in \mathcal{S}} \sum_{\nu_i \in \mathcal{U}_{s_i}} \rho\left(s_i, \nu_i\right) P_{s_i \nu_i s_j} \quad (21)$$

$$\rho\left(s_i, \nu_i\right) \ge 0, \forall s_i \in \mathcal{S}, \forall \nu_i \in \mathcal{U}_{s_i}. \quad (22)$$

This linear programming problem could easily be solved by the simplex or the dual simplex method [14]. When $\rho\left(s_i, \nu_i\right)$ is solved, the optimal decision rule μ^* corresponding to π^* can be derived accordingly. Specifically, when in state s_i, the decision rule μ^* choose action ν_i with probability $\frac{\rho(s_i,\nu_i)}{\sum_{\nu_i \in U_{s_i}} \rho(s_i,\nu_i)}$ [13].

IV. SIMULATIONS

In this section, we conduct extensive simulations and evaluate the performance of our scheme. The parameters are set as follows. Buffer size $B = 10$, the number of antennas on each secondary user $n = 3$, the number of primary links $N_p = 2$, the probability for a primary user to keep in the active state $p = 0.3$, the probability for a primary user to remain in the inactive state is $q = 0.6$. The channels are i.i.d. Rayleigh, i.e., each entry in the channel matrices **H**, **G** and **R** follows a circular symmetry normal distribution with mean 0 and variance 1. Then, the energy consumption to transmit u_t packet when there are m_t active primary users can be found in Table I [6][2].

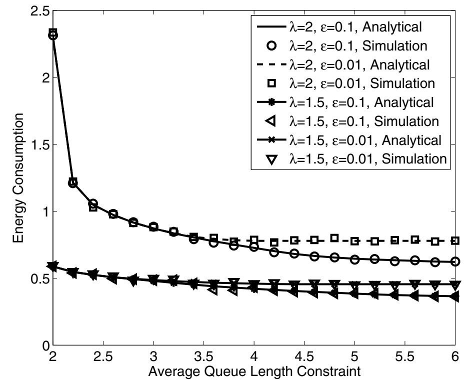

Fig. 2. Average Energy consumption v.s. average queue length constraint.

In Fig. 2, we investigate the impact of the average queue length constraint D on the optimal average energy consumption. The simulation results match well with the analytical results, which verifies previous analysis and the MDP formulation. As shown in Fig. 2, the optimal energy consumption first decreases as D decreases. Intuitively, when D is small, the average queue length constraint is stringent and secondary users tend to transmit packets once they obtain the opportunity. As D increases, the average queue length constraint becomes less stringent and the packets can be stored longer in the buffer for a better opportunity to be transmitted. Thus, the average energy consumption decreases with D. However, when D exceeds a certain threshold, the overflow constraint ϵ begins to take effect and this is why the average energy consumption stops decreasing in Fig. 2. This effect of ϵ can also be seen from the fact that the average energy consumption can be further decreased when ϵ becomes larger. For a fixed D, secondary users will transmit more packets to maintain the average buffer length D when the secondary traffic intensity λ is large. Therefore, the average energy consumption will increase with λ and this is verified in Fig. 2.

The relation between average queue length constraint and the overflow constraint is clearly shown in Fig. 3, where $\lambda = 2$. The perfect match between the analytical and the simulation results validates our analysis again. Obviously, when D reaches a certain value, the overflow probability achieves its maximum value and stops increasing. This again demonstrates the results in Fig. 2.

[2]For simplicity, the noise power σ^2 is set as 1 for simplicity. This simplicity will not affect the proportional relation between power consumptions.

TABLE I
POWER CONSUMPTION

m_t \ u_t	0	1	2	3	4	5	6	7	8	9	10
0	0	0.15	0.45	0.95	1.6	2.6	3.95	5.85	8.35	11.65	15.95
1	0	0.3	0.9	2.05	3.9	6.85	11.2	17.6	26.9	40.25	59.4
2	0	1.36	4.64	10.6	23.6	50.4	107	220	440	890	1800

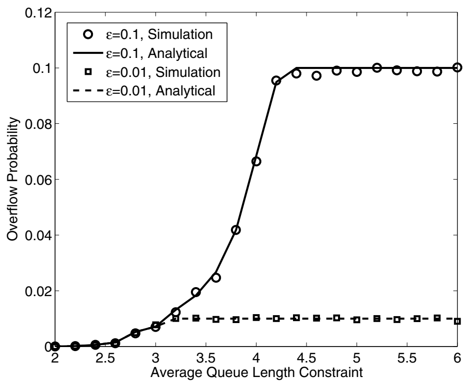

Fig. 3. Overflow probability v.s. average queue length constraint.

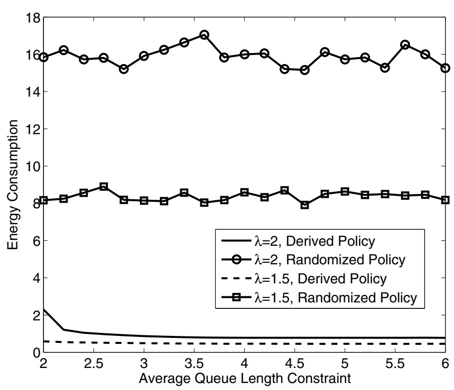

Fig. 4. Energy efficiency comparison.

Since the considered scheduling problem has not been investigated previously, the energy efficient transmission scheme derived in this paper is compared with a randomized transmission scheme. When the randomized transmission scheme is adopted, the secondary user transmits all the packets in its buffer with probability 0.5. In Fig. 4, the overflow probability constraint is set as $\epsilon = 0.01$. It can be observed from Fig. 3 that the derived optimal transmission scheme is more energy efficient than the randomized transmission scheme.

V. CONCLUSIONS

In this paper, we derived an energy-efficient traffic scheduling scheme for secondary users equipped with multiple antennas in cognitive radio networks. Through allowing secondary users to adapt to the variations in primary traffic, the problem was formulated as a constrained Markov decision problem with average queue length constraint and overflow constraint. Having noticed the considered Markov decision problem had a unichain structure, the optimal transmission scheme was derived from a linear programming. Simulation results were provided to validate our analysis and the impacts of various parameters were discussed. Finally, the superiority of the derived transmission scheme was shown by comparing with a randomized transmission scheme.

APPENDIX

By definition of m_t, we have

$$\begin{aligned}
&\mathrm{P}\left(m_{t+1} = \varpi_{t+1} \middle| m_t = \varpi_t, \cdots, m_0 = \varpi_0\right) \\
=&\mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it+1} = \varpi_{t+1} \middle| \sum_{i=1}^{N_p} \vartheta_{it} = \varpi_t, \cdots, m_0 = \varpi_0\right) \\
=&\frac{\mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it+1} = \varpi_{t+1}, \sum_{i=1}^{N_p} \vartheta_{it} = \varpi_t, \cdots, m_0 = \varpi_0\right)}{\mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it} = \varpi_t, \cdots, m_0 = \varpi_0\right)},
\end{aligned} \tag{23}$$

where the first equation follows from $m_t = \sum_{i=1}^{N_p} \vartheta_{it}, \forall t = 0, 1, \cdots$ and the second equation follows from the definition of conditional probability. As we know, the event $\sum_{i=1}^{N_p} \vartheta_{it} = \varpi_t$ is equivalent to $\bigcup_{\{\mathcal{A}_t \| \mathcal{A}_t| = \varpi_t\}} \Omega(\mathcal{A}_t)$, where $\mathcal{A}_t$ is the index set of all active primary links at slot t and $\Omega(\mathcal{A}_t) = \left\{ \begin{array}{c} \vartheta_{it} = 1, \forall i \in \mathcal{A}_t \\ \vartheta_{it} = 0, \forall i \in \{1, \cdots, N_p\}/\mathcal{A}_t \end{array} \right\}$. Then nominator of (23) can be reformulated as

$$\begin{aligned}
&\mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it+1} = \varpi_{t+1}, \sum_{i=1}^{N_p} \vartheta_{it} = \varpi_t, \cdots, m_0 = \varpi_0\right) \\
=& \sum_{\{\mathcal{A}_t \| \mathcal{A}_t| = \varpi_t\}} \mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it+1} = \varpi_{t+1}, \Omega(\mathcal{A}_t), \cdots, m_0 = \varpi_0\right) \\
=& \sum_{\{\mathcal{A}_t \| \mathcal{A}_t| = \varpi_t\}} \Bigg\{ \mathrm{P}\left(\sum_{i=1}^{N_p} \vartheta_{it+1} = \varpi_{t+1} \middle| \Omega(\mathcal{A}_t), \cdots, m_0 = \varpi_0\right) \\
&\times \mathrm{P}\left(\Omega(\mathcal{A}_t), \cdots, m_0 = \varpi_0\right) \Bigg\}.
\end{aligned} \tag{24}$$

From Markov property, (24) can be reformulated as

$$
\begin{aligned}
&\mathrm{P}\left(\sum_{i=1}^{N_p}\vartheta_{it+1}=\varpi_{t+1},\sum_{i=1}^{N_p}\vartheta_{it}=\varpi_t,\cdots,m_0=\varpi_0\right)\\
&=\sum_{\{\mathcal{A}_t||\mathcal{A}_t|=\varpi_t\}}\left\{\mathrm{P}\left(\sum_{i=1}^{N_p}\vartheta_{it+1}=\varpi_{t+1}\middle|\Omega\left(\mathcal{A}_t\right)\right)\right.\\
&\quad\left.\times\,\mathrm{P}\left(\Omega\left(\mathcal{A}_t\right),\cdots,m_0=\varpi_0\right)\right\}. \qquad (25)
\end{aligned}
$$

Based on the definition of $\mathcal{A}_t$, we have

$$
\begin{aligned}
&\mathrm{P}\left(\sum_{i=1}^{N_p}\vartheta_{it+1}=\varpi_{t+1}\middle|\Omega\left(\mathcal{A}_t\right)\right)\\
=&\mathrm{P}\left(\sum_{i\in\mathcal{A}_t}\vartheta_{it+1}+\sum_{i\in\{1,\cdots,N_p\}/A_t}\vartheta_{it+1}=\varpi_{t+1}\middle|\Omega\left(\mathcal{A}_t\right)\right)\\
=&\sum_{k=0}^{\min(\varpi_{t+1},|\mathcal{A}_t|)}\left\{\mathrm{P}\left(\sum_{i\in\{1,\cdots,N_p\}/A_t}\vartheta_{it+1}=\varpi_{t+1}-k\middle|\Omega\left(\mathcal{A}_t\right),\right.\right.\\
&\left.\left.\sum_{i\in\mathcal{A}_t}\vartheta_{it+1}=k\right)\mathrm{P}\left(\sum_{i\in\mathcal{A}_t}\vartheta_{it+1}=k\middle|\Omega\left(\mathcal{A}_t\right)\right)\right\} \qquad (26)
\end{aligned}
$$

Since ϑ_{it}'s are mutually independent Markov chains, it follows

$$
\begin{aligned}
&\mathrm{P}\left(\sum_{i\in\{1,\cdots,N_p\}/A_t}\vartheta_{it+1}=\varpi_{t+1}-k\middle|\Omega\left(\mathcal{A}_t\right),\sum_{i\in\mathcal{A}_t}\vartheta_{it+1}=k\right)\\
&=\binom{N_p-|\mathcal{A}_t|}{\varpi_{t+1}-k}q^{N_p-|\mathcal{A}_t|-\varpi_{t+1}+k}(1-q)^{\varpi_{t+1}-k}, \qquad (27)\\
&\mathrm{P}\left(\sum_{i\in\mathcal{A}_t}\vartheta_{it+1}=k\middle|\Omega\left(\mathcal{A}_t\right)\right)=\binom{|\mathcal{A}_t|}{k}p^k(1-p)^{|\mathcal{A}_t|-k}. \qquad (28)
\end{aligned}
$$

Plug (27) and (28) into (26), it directly follows

$$
\begin{aligned}
&\mathrm{P}\left(\sum_{i=1}^{N_p}\vartheta_{it+1}=\varpi_{t+1}\middle|\Omega\left(\mathcal{A}_t\right)\right)\\
=&\sum_{k=0}^{\min(\varpi_{t+1},|\mathcal{A}_t|)}\left\{\binom{|\mathcal{A}_t|}{k}\binom{N_p-|\mathcal{A}_t|}{\varpi_{t+1}-k}p^k(1-p)^{|\mathcal{A}_t|-k}\right.\\
&\left.\times\,q^{N_p-|\mathcal{A}_t|-\varpi_{t+1}+k}(1-q)^{\varpi_{t+1}-k}\right\}. \qquad (29)
\end{aligned}
$$

Clearly from (29), $\mathrm{P}\left(\sum_{i=1}^{N_p}\vartheta_{it+1}=\varpi_{t+1}\middle|\Omega\left(\mathcal{A}_t\right)\right)$ only depends on the cardinality of $\mathcal{A}_t$, i.e., $|\mathcal{A}_t|$, and is independent with $m_{t-1},\cdots,m_0$. With (25), (29) and $m_t=|\mathcal{A}_t|$, the conditional distribution of m_{t+1} in (23) can be derived as

$$
\begin{aligned}
&\mathrm{P}\left(m_{t+1}=\varpi_{t+1}|\,m_t=\varpi_t,\cdots,m_0=\varpi_0\right)\\
=&\sum_{k=0}^{\min(\varpi_{t+1},\varpi_t)}\left\{\binom{\varpi_t}{k}\binom{N_p-\varpi_t}{\varpi_{t+1}-k}p^k(1-p)^{\varpi_t-k}\right.\\
&\left.\times\,q^{N_p-\varpi_t-\varpi_{t+1}+k}(1-q)^{\varpi_{t+1}-k}\right\}. \qquad (30)
\end{aligned}
$$

By definition of conditional probability

$$
\begin{aligned}
&\mathrm{P}\left(m_{t+1}=\varpi_{t+1}|\,m_t=\varpi_t\right)=\frac{\mathrm{P}\left(m_{t+1}=\varpi_{t+1},m_t=\varpi_t\right)}{\mathrm{P}\left(m_t=\varpi_t\right)}\\
=&\frac{\sum_{\{\mathcal{A}_t||\mathcal{A}_t|=\varpi_t\}}\mathrm{P}\left(m_{t+1}=\varpi_{t+1}|\,\Omega\left(\mathcal{A}_t\right)\right)\mathrm{P}\left(\Omega\left(\mathcal{A}_t\right)\right)}{\mathrm{P}\left(m_t=\varpi_t\right)}. \qquad (31)
\end{aligned}
$$

According to (29), (30) and (31), we have

$$
\begin{aligned}
&\mathrm{P}\left(m_{t+1}=\varpi_{t+1}|\,m_t=\varpi_t,\cdots,m_0=\varpi_0\right)\\
=&\mathrm{P}\left(m_{t+1}=\varpi_{t+1}|\,m_t=\varpi_t\right). \qquad (32)
\end{aligned}
$$

That is, m_t satisfies the Markov property.

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