Throughput Maximization for Opportunistic Spectrum Access via Transmission Probability Scheduling Scheme

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Abstract—In this paper, we propose a novel transmission probability scheduling scheme for opportunistic spectrum access in cognitive radio networks. With the proposed scheme, the secondary user's throughput over a single channel is maximized while collision probability perceived by the primary user is constrained under a required threshold since the secondary user optimally schedules its transmission probabilities during the primary user's idle period. Moreover, we deeply study the maximum achievable throughput of the secondary user when the idle period of the primary user is different distribution to analyze the performance of the proposed transmission probability scheduling scheme. In a practical communication systems, where primary user's traffic pattern and parameters are unknown and the secondary user's spectrum sensing is imperfect, a novel predictor, which is based on hidden Markov model, is also proposed to predict the future channel states and to enable the transmission probability scheduling for the secondary user. Conducted simulations show that the proposed transmission probability scheduling scheme and predictor are effective and can offer good system performances.

I. INTRODUCTION

Recently, dynamic spectrum access (DSA) has been proposed to improve the utilization efficiency of the licensed spectrum. Among all existing DSA technologies introduced in [1], opportunistic spectrum access (OSA) is one of promising and emphasized techniques, in which spectrum holes are defined as frequency bands allocated to primary (licensed) users. However, a particular time and specific geographical location have not being utilized in the scheme of OSA [2]. To utilize these spectrum holes with required protection for the primary users over the same frequency band, secondary (unlicensed) users have to adopt strict constraints on interference, e.g., for packet-based primary users, OSA schemes usually constrain the probability of collision with the primary user's packet under a predefined threshold [3] - [5], [8], [10], [13]. Therefore, it is indeed needed to study how to maximize the secondary user's throughput under a certain constraint of collision probability for primary user's packets.

Specifically, some effective approaches, which is based on optimal channel selection in multi-channel systems, have been

proposed in the literature. In [3], an optimal channel selection strategy based on the constrained Markov decision process (CMDP) was proposed to maximize the secondary user's throughput under the constraint of collision probability. In [4], an optimal sensing and access strategy based on partially observable Markov decision process (POMDP) was proposed. In [5], a joint design of the PHY layer spectrum sensor and the MAC layer access strategy has been considered. In [6], optimal strategies were proposed to maximize the total expected data rate of the secondary user without *a priori* knowledge of the primary user's channel statistics. In [7], a method to suppress sidelobes of the orthogonal frequency division multiplexing (OFDM) signals was proposed, which enables the OFDM-based secondary users to utilize noncontiguous spectrum holes over multi-channels.

Moreover, the problem of the throughput maximization also has been addressed in single-channel systems. In [8], secondary user's sensing and transmission structure was optimized to maximize the secondary user's throughput under the consideration of sensing overhead. In [9], the achievable throughput for the secondary network was maximized by adopting an optimal sensing time. In [10], an optimal spectrum access policy was derived asymptotically under the assumption that the secondary user's slot length approaches zero. However, the problem is still open for the throughput maximization of the secondary user under the collision probability constraints when the secondary user's slot length is finite. Moreover, one of assumptions in all existing schemes is that the secondary user has *a priori* knowledge of the primary user's idle period distribution, which is not appropriate in practical communication systems [10].

In this paper, we develop a novel access scheme for the secondary user with periodic sensing and slotted structure, which aims at exploiting instantaneous spectrum opportunities over a single channel that is allocated to a packet based primary user. We propose that, in a primary user's idle period that covers a number of the secondary user's slots, the secondary user's transmission probabilities for these idle slots could be optimally scheduled, so that the throughput of the secondary user is maximized while the collision probability with the primary user's packets being constrained under a required threshold. We formulate the maximization problem

as a linear programming problem that is efficient to solve. To better illustrate the proposed access scheme, analysis of maximum achievable throughput for three typical cases with different distributions of primary user's idle period is presented. Numerical results show that the improvement of throughput by adopting the proposed access scheme highly depends on the distribution of primary user's idle period. When the idle period follows hyper-Erlang distribution [13], the throughput improvement is as high as 100%. For practical situations, where the traffic pattern of the primary user and its parameters are unknown, we develop a method, which is based on hidden Markov model (HMM), to predict the future channel states by learning past periodic sensing results. Moreover, the impact of sensing errors on the performance of the proposed scheme is also illustrated.

II. System Model

As depicted in Fig. 1, the secondary user exploits spectrum holes while limits the interference perceived by the primary user who works on the same channel in an OSA-based cognitive radio network (CRN). The primary user has the priority to access the channel and it is not responsible for any sort of notification to secondary user for its transmission. Suppose that the primary user's traffic pattern follows an ON/OFF model, in which its state becomes busy ("ON", packet transmission) or idle ("OFF", idle period/spectrum hole) alternatively. The distribution of busy or idle periods is supposed to be general. Thus, the secondary user should target at a temporal utilization of spectrum holes and vacate the channel as quickly as possible when the primary user's state turns from idle to busy.
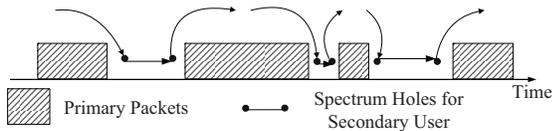
Fig. 1. The OSA-based CRN.

Suppose that the secondary user is equipped with a half-duplex transceiver, i.e., the secondary node is no longer capable of sensing the channel or receiving data during its transmitting data. To periodically schedule sensing and transmission, the secondary user employs a slotted communication protocol as depicted in Fig. 2, in which L denotes the time duration for one secondary user slot. At the beginning of a slot, e.g., the k-th slot (k is a positive integer), there is a sensing duration denoted as the k-th sensing sub-slot for the secondary user to turn off the transmitter and sense the channel, the remaining duration in this slot is denoted as the k-th data sub-slot for data transmission. To protect the primary packets, secondary user is allowed to access the channel only when the current sensing result shows that the state of the primary user is idle.

However, for an OSA-based CRN, strict interference constraint is needed to be imposed on the secondary user to ensure that the interference perceived by the primary user lies
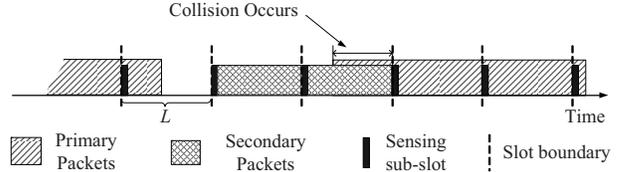
Fig. 2. Slotted structure of the secondary user.

below a required threshold. Due to the fact that the secondary user could not sense the channel during its transmission, collision occurs if the primary user accesses the channel when the secondary user is transmitting, which may result in both primary user's and secondary user's packets loss. For the case of perfect sensing, collisions only occur at the head of a primary user's packets, which are denoted as type-I collisions. For imperfect sensing case, collisions may happen during primary user's transmission process due to the missed detection, which are denoted as type-II collisions. To protect the primary packets from excessive collisions, we define the average ratio of collisions in all primary packets during a certain time duration U as a measure of the interference caused by secondary users from the primary user's perspective, which is denoted as the average packet collision ratio (APCR) as R_{C}, i.e.,

$$R_{\mathrm{C}} = \lim_{U \to +\infty} \frac{N_{\mathrm{C}}}{N_{\mathrm{P}}}, \tag{1}$$

where N_{P} denotes the number of the primary user's packets during U, and N_{C} denotes the number of collision events during U. In this study, we aim at constraining R_{C} under a required threshold R_{TH}. In other words, the primary user could tolerate the interference when $R_{\mathrm{C}} \le R_{\mathrm{TH}}$.

Moreover, we are really concerned about the throughput of the secondary user in CRN, which depends on the utilization efficiency of the spectrum holes. In this paper, we employ an efficiency of spectrum hole utilization as a measure of the secondary user's throughput in the OSA-based CRN. Thus, the normalized secondary user's throughput is defined as

$$T = \lim_{U \to +\infty} \frac{N_{\mathrm{S}}}{N_{\mathrm{IDLE}}}, \tag{2}$$

where N_{S} denotes the number of idle slots successfully utilized by the secondary user during U, and N_{IDLE} denotes the total number of idle slots during U.

In the next section, we thoroughly study how to maximize the throughput of the secondary user while the APCR is below a required threshold.

III. Throughput Maximization with The Proposed Transmission Probability Scheduling Scheme

In this section, we propose a transmission probability scheduling (TPS) scheme for the OSA-base CRN, in which secondary user optimally schedules its transmission probabilities for the data sub-slots during the idle period of the primary user. With the proposed TPS scheme, the throughput of the

secondary user is maximized while the APCR perceived by the primary user is constrained under a required threshold.

Obviously, it is needed to know the sensing results for the secondary user to identify a spectrum hole, in which the sensing result is binary for every sensing sub-slot, i.e., either busy or idle. We first assume that the sensing results are perfect, which makes sense in high signal-to-noise ratio (SNR) environment. The sensing result $X(k)$ for the k-th (k is a positive integer) sensing sub-slot is written as,

$$X(k) = \begin{cases} 1, & \text{if busy} \\ 0, & \text{if idle.} \end{cases} \quad (3)$$

As depicted in Fig. 3, an idle period, i.e., new spectrum opportunity, is identified by the secondary user at the k-th sensing sub-slot if the current sensing result $X(k)$ is idle and the previous sensing result $X(k-1)$ is busy. Then, the secondary user predicts the primary user states in the following N sensing sub-slots. N is the number of prediction steps and ideally $N \rightarrow +\infty$. Based on the prediction, the secondary user schedules its transmission probabilities in the following N data sub-slots. If the k-th to the $(k+i)$-th sensing sub-slot are all idle, the secondary user transmits its packet in the $(k+i)$-th data sub-slot with the probability $P_k^{\text{T}}(i)$, $i = 0, 1, ..., N-1$. Otherwise, the secondary user stops its transmission and waits for the next spectrum opportunity.
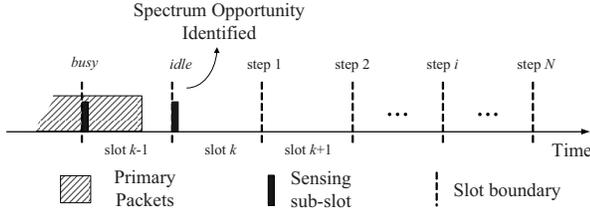
Fig. 3. Spectrum opportunity identification.

In the following, we present how to obtain the optimal transmission probabilities that achieves throughput maximization for the secondary user under the APCR constraint.
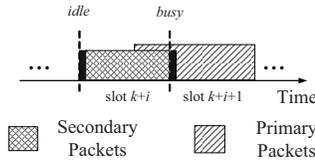
Fig. 4. Collision between the primary users and secondary users.

Firstly, we derive the collision probability P_k^{C} for the coming primary packet. As shown in Fig. 4, secondary user transmits during the $(k+i)$-th data sub-slot, if $X(k+i+1) = 1$, it is reasonable to consider that the primary user accesses the channel again during the $(k+i)$-th data sub-slot and a collision occurs; otherwise, the secondary user transmission during the $(k+i)$-th data sub-slot is successful. With the transmission

probabilities $P_k^{\text{T}}(i)$, we have

$$P_k^{\text{C}} = \sum_{i=0}^{N-1} B_k(i) \cdot P_k^{\text{T}}(i), \quad (4)$$

where $B_k(i)$ is the probability that the primary user keeps idle during the k-th to the $(k+i-1)$-th data sub-slot and accesses the channel during the $(k+i)$-th data sub-slot, we have

$$B_k(i) = \begin{cases} \Pr(X(k+i+1) = 1), & i = 0 \\ \\ \Pr(X(k+1) = 0, ..., X(k+i) = 0, X(k+i+1) = 1), \\ 0 < i \le N-1 \end{cases}$$
$$(5)$$

$$\lim_{N \to \infty} \sum_{i=0}^{N-1} B_k(i) = 1. \quad (6)$$

For large enough N, $\sum_{i=0}^{N-1} B_k(i) \approx 1$ and $\sum_{i=N}^{+\infty} B_k(i)$ is negligible.

In order to constrain the interference towards the primary user, threshold R_{TH} is set as a constraint on APCR. If we set R_{TH} as the threshold of P_k^{C}, i.e., $P_k^{\text{C}} \le R_{\text{TH}}$ for every primary packet, then $R_{\text{C}} \le R_{\text{TH}}$ is satisfied.

Secondly, we derive the expected normalized throughput T_k of the secondary user in the idle period starting from the k-th sensing sub-slot. During the $(k+i)$-th data sub-slot, if the secondary user transmits and no collision occurs, the data sub-slot is considered to be successfully utilized. $I_k(i)$ is the probability that the primary user would not access the channel from the k-th to the $(k+i)$-th data sub-slot, we have

$$I_k(i) = \begin{cases} \Pr(X(k+i+1) = 0), & i = 0 \\ \\ \Pr(X(k+1) = 0, ..., X(k+i) = 0, X(k+i+1) = 0), \\ 0 < i \le N-1 \end{cases}$$
$$(7)$$

$$T_k = \frac{\sum_{i=0}^{N-1} I_k(i) \cdot P_k^{\text{T}}(i)}{\sum_{i=0}^{N-1} I_k(i)}, \quad (8)$$

where $\sum_{i=0}^{N-1} I_k(i)$ is the expectation of the idle period duration. Obviously, if T_k in every idle period is maximized, the secondary user's normalized throughput T is also maximized.

Then, the optimal transmission probabilities that maximize the secondary user's throughput is formulated as follows:

$$\begin{aligned} \text{Max.} \quad & T_k \\ \text{s.t.} \quad & P_k^{\text{C}} \le R_{\text{TH}} \\ & 0 \le P_k^{\text{T}}(i) \le 1, i = 0, ..., N-1, \end{aligned} \quad (9)$$

It is obvious that (9) is a typical linear programming problem [14]. To solve the linear program in (9), $B_k(i)$ and $I_k(i)$ are required. The method of predicting the value of $B_k(i)$ and $I_k(i)$ without *a priori* knowledge of the primary user's idle period distribution is presented in Section IV.

IV. Throughput Maximization with Different Distributions of The Primary User's Idle Period

In this section, three cases with different distributions of the primary user's idle period is discussed respectively for throughput maximization.

A. Unknown distribution

In this subsection, we consider the case when the distribution knowledge of the primary user's idle period is unavailable. In this case, a baseline scheme is employed, in which transmission probability $P_k^{\mathrm{T}}(i)$ is set to R_{TH} for all slots with idle sensing outcome. Thus the resulted APCR of the baseline scheme is equal to R_{TH} according to (4) and (6). The normalized throughput in the idle period starting from the k-th sensing sub-slot is

$$T_k = \frac{\sum\limits_{i=0}^{N-1} I_k(i) \cdot R_{\mathrm{TH}}}{\sum\limits_{i=0}^{N-1} I_k(i)} = R_{\mathrm{TH}}. \tag{10}$$

B. Exponential distribution

Poisson arrival traffic model has been widely used in the literatures [3] - [5], [8]. In this model, the durations of idle period and busy period are assumed to be exponential distributed with parameters λ (idle) and μ (busy), respectively. The channel occupancy of the primary user for this case could be modeled by a two-state continuous time Markov chain with Q-matrix

$$\mathbf{Q} = \begin{bmatrix} -\lambda^{-1} & \lambda^{-1} \\ \mu^{-1} & -\mu^{-1} \end{bmatrix} \tag{11}$$

Through periodic sensing, the sampled states of the primary user form a discrete-time Markov chain with 2×2 transition matrix. Thus, we obtain that

$$\mathbf{A} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} = e^{\mathbf{Q}L}$$
$$= \begin{bmatrix} \mu_0 + \lambda_0 e^{-(\lambda^{-1}+\mu^{-1})L} & \lambda_0\left[1 - e^{-(\lambda^{-1}+\mu^{-1})L}\right] \\ \mu_0\left[1 - e^{-(\lambda^{-1}+\mu^{-1})L}\right] & \lambda_0 + \mu_0 e^{-(\lambda^{-1}+\mu^{-1})L} \end{bmatrix} \tag{12}$$

where L is the slot length, $\lambda_0 = \frac{\lambda^{-1}}{\lambda^{-1}+\mu^{-1}}, \mu_0 = \frac{\mu^{-1}}{\lambda^{-1}+\mu^{-1}}$.

Based on (5), (7) and (12), we have

$$B_k(i) = p_{00}^i p_{01}, \tag{13}$$

$$I_k(i) = p_{00}^{i+1} = \frac{p_{00}}{p_{01}} \cdot p_{00}^i p_{01} = \frac{p_{00}}{p_{01}} \cdot B_k(i) = \eta B_k(i), \tag{14}$$

where $\eta = \frac{p_{00}}{p_{01}}$ is a constant.

Assume that the number of prediction steps N approaches to infinite, from (6), (4) and (8), the normalized throughput is calculated as

$$T_k = \frac{\lim\limits_{N\to\infty} \sum\limits_{i=0}^{N-1} \eta B_k(i) \cdot P_k^{T}(i)}{\lim\limits_{N\to\infty} \sum\limits_{i=0}^{N-1} \eta B_k(i)} = \frac{P_k^C}{\lim\limits_{N\to\infty} \sum\limits_{i=0}^{N-1} B_k(i)} \leq R_{\mathrm{TH}}. \tag{15}$$

Then, the maximum normalized throughput of the primary user is

$$T_k^{\mathrm{max}} = R_{\mathrm{TH}}. \tag{16}$$

The maximum normalized throughput is the same as that of the baseline scheme. Thus for Poisson arrival traffic model, the transmission probability $P_k^{\mathrm{T}}(i)$ could be set to R_{TH} for all data sub-slots with the idle sensing outcome.

C. Hyper-Erlang distribution and the hidden Markov model based predictor

In wireless networks, the traffic flows are commonly considered to be self-similar. The traditional Poisson arrival traffic model likely becomes invalid to model such kind of traffic. Hyper-Erlang model is a natural choice for self-similar traffic modeling in communications networks with integrated services, which is considered a better fit than the exponential distribution for wireless networks [11] - [13]. Recently, measurements show that the hyper-Erlang distribution is a better fit than the exponential distribution for the white space modeling of the 802.11b-based wireless local area networks (WLAN) [13].

In this subsection, the duration of the primary user's idle period is hyper-Erlang-k-2 distributed (contains two weighted Erlang-k components) according to [12]. We assume that the idle period distribution and its parameters are unknown to the secondary user, then a method to obtain $I_k(i)$ and $B_k(i)$ via hidden Markov model(HMM) based predictor is proposed.

A discrete time HMM with M hidden states and K output symbols is a doubly embedded stochastic process [15] which is denoted by parameters set $\xi = \{\mathbf{P}, \mathbf{B}, \pi\}$, where $\mathbf{P}$ is the M-by-M state transition matrix, which denotes the underlying stochastic process that is not observable. $\mathbf{B}$ is the M-by-K output symbol probability matrix, which stands for the stochastic process that produces the observed output sequence, and the initial state probability vector π gives the probability of being in a particular state at the beginning of the process. In the context of sensing the channel occupancy by the primary user, the output symbol ranges between 0 and 1, where 0 represents an idle sensing output and 1 represents a busy sensing output.

As mentioned above, the sensing history forms a binary vector $\mathbf{Z}(k)$. Generally speaking, when $\mathbf{Z}(k)$ is given, an optimal ξ to maximize the expectation of $\Pr(\mathbf{Z}(k)|\xi)$ could be trained via the Baum-Welch Algorithm (BWA) [16]. Furthermore, when we get ξ, $\Pr(\mathbf{Z}(k)|\xi)$ could be obtained via the forward-backward procedure [15]. Therefore, based on the trained HMM, the predicted $B_k(i)$ and $I_k(i)$ can be obtained as follows

$$\hat{B}_k(i) = \begin{cases} \dfrac{\Pr(X(k+i+1) = 1, \mathbf{Z}(k)|\xi)}{\Pr(\mathbf{Z}(k)|\xi)}, & i = 0 \\[3mm] \dfrac{\Pr(X(k+1) = 0, ..., X(k+i+1) = 1, \mathbf{Z}(k)|\xi)}{\Pr(\mathbf{Z}(k)|\xi)}, \\[2mm] 0 < i \leq N - 1 \end{cases} \tag{17}$$
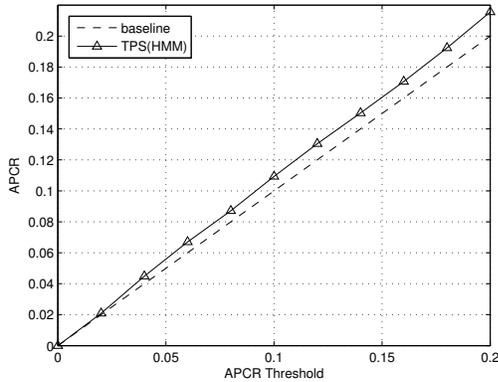
Fig. 5. APCR perceived by the primary user when the idle period of the primary user is exponential distribution.
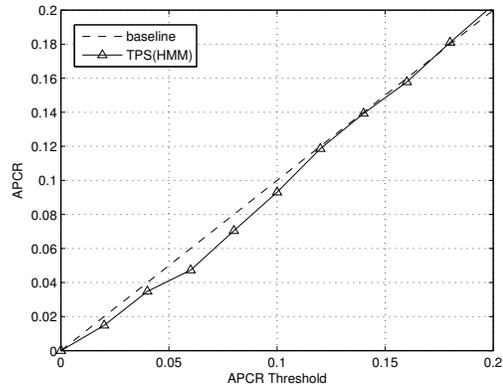
Fig. 6. APCR perceived by the primary user when the idle period of the primary user is hyper-Erlang distribution.

$$
\hat{I}_k(i) =
\begin{cases}
\dfrac{\Pr(X(k+i+1) = 0, \mathbf{Z}(k)|\xi)}{\Pr(\mathbf{Z}(k)|\xi)}, & i = 0 \\[3mm]
\dfrac{\Pr(X(k+1) = 0, ..., X(k+i+1) = 0, \mathbf{Z}(k)|\xi)}{\Pr(\mathbf{Z}(k)|\xi)}, \\[2mm]
\quad 0 < i \le N - 1
\end{cases}
\tag{18}
$$

Simulation results in Section V show that, when the idle period of the primary user follows the hyper-Erlang distribution, the maximum achievable throughput of the secondary user that adopts TPS scheme is beyond that adopts the baseline scheme for nearly 100%.

V. SIMULATION RESULTS

In this section, we present simulation results of the TPS scheme. For the primary user traffic, the primary packet length is fixed to 4 slots, while the duration of the primary user's idle period follows exponential distribution or hyper-Erlang distribution with mean 8 slots. For the TPS scheme, the prediction steps number $N = 40$, the hidden states number for HMM-based predictor is $M = 16$ and the training sequence length is set to 3000. We compare the performance of the TPS scheme with the baseline scheme.

Firstly, we compare the APCR perceived by the primary user when the secondary user adopts different schemes. A group of APCR thresholds $R_{\mathrm{TH}} \in [0, 0.2]$ are given and resulted APCR are measured. We select the low region out of all possible APCR thresholds since over-loose APCR thresholds (e.g. $R_{\mathrm{TH}} > 0.2$) may not constrain secondary users for sufficient protection of the primary user. Then, the APCR versus APCR threshold curves for exponential distribution and hyper-Erlang distribution are plotted in Fig. 5 and Fig. 6, respectively. Apparently, the baseline scheme constrains the APCR perfectly. The TPS scheme using HMM-based predictor achieves a performance that is very closed to that of the baseline scheme.

Next, the normalized throughput of the secondary user is compared for the two schemes. The secondary user's normal-
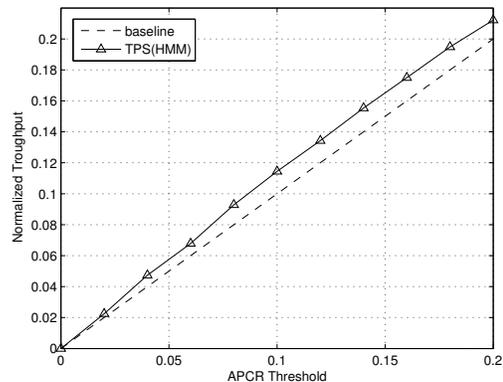
Fig. 7. Normalized throughput of the secondary user when the idle period of the primary user is exponential distribution.

ized throughput versus APCR threshold curves are plotted in Fig. 7 and Fig. 8, respectively. The normalized throughput achieved by the baseline scheme equals to the APCR threshold, which is consistent with (10). It is observed that the TPS scheme using HMM-based predictor outperforms the baseline scheme significantly in hyper-Erlang distribution case, when APCR threshold is set to 0.1, the normalized throughput with the TPS scheme is about 0.2, while the normalized throughput with the baseline scheme is only 0.1. By contrast, the TPS scheme could not achieve higher throughput than the baseline scheme in exponential distribution case, which is consistent with (16). These results verify that, when proper prediction of the primary user state is available, the TPS scheme could increase the secondary user's throughput significantly when the distribution of the primary user's idle period is a hyper-Erlang distribution.

In practical systems, the sensing performance of the secondary user is imperfect. Let set $\{P_f, P_m\}$ denotes the sensing errors, where P_f is the probability of false alarm (recognizing the idle channel as busy) while P_m is the probability of missed detection (recognizing the busy channel as idle). The impact of sensing errors on APCR and secondary user's throughput
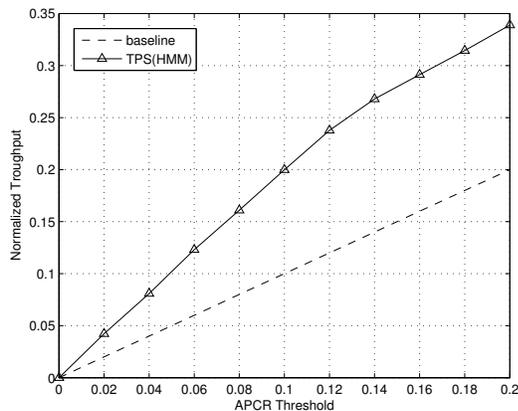
Fig. 8. Normalized throughput of the secondary user when the idle period of the primary user is hyper-Erlang distribution.

Fig. 9. APCR perceived by the primary user with imperfect sensing.

Fig. 10. Normalized throughput of the secondary user with imperfect sensing.

for the TPS scheme are illustrated when the distribution of the primary user's idle period is a hyper-Erlang distribution. For comparison, three groups of sensing error sets $\{P_f, P_m\} = \{0.01, 0.01\}; \{0.03, 0.03\}; \{0.05, 0.05\}$ are simulated.

In Fig. 9 and Fig. 10, in which HMM-based predictor is adopted to predict the primary user's traffic pattern that is unknown to the secondary user, results show that APCR is not increased much even when sensing errors are severe. The reason lies in the capability of the HMM-based predictor that can learn and adapted to the history of sensing results that has been polluted with sensing errors. The secondary user's throughput is more declined as P_f and P_m grow due to the degradation of the predictor's accuracy resulting from sensing errors.

VI. CONCLUSIONS

In this paper, we proposed a transmission probability scheduling scheme to maximize the throughput of the secondary user while constraining the packet collision probability perceived by the primary user under a required threshold in the cognitive radio networks. Simulation results have shown that, for hyper-Erlang distribution of the primary user's idle period, significant throughput improvement was achieved by employing the proposed scheme via the hidden Markov model based predictor.

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