Optimal Myopic Sensing and Dynamic Spectrum Access in Cognitive Radio Networks with Low-complexity Implementations

Yang Li†, Sudharman K. Jayaweera†, Mario Bkassiny† and Keith A. Avery‡
†Department of Electrical and Computer Engineering, University of New Mexico, Albuquerque, NM, USA
Email: {yangli, jayaweera, bkassiny}@ece.unm.edu
‡Space Vehicles Directorate, Air Force Research Laboratory (AFRL), Kirtland AFB, Albuquerque, NM, USA

***Abstract*—Cognitive radio techniques allow secondary users (SU's) to opportunistically access underutilized primary channels that are licensed to primary users. We consider a group of SU's with limited spectrum sensing capabilities working cooperatively to find primary channel spectrum holes. The objective is to design the optimal sensing and access policies that maximize the total secondary throughput on primary channels accrued over time. Although the problem can be formulated as a Partially Observable Markov Decision Process (POMDP), the optimal solutions are intractable. Instead, we find the optimal sensing policy within the class of *myopic* policies. Compared to other existing approaches, our policy is more realistic because it explicitly assigns SU's to sense specific primary channels by taking into account spatial and temporal variations of primary channels. Contributions: 1) formulation of a centralized spectrum sensing/access architecture that allows exploitation of all available primary spectrum holes; and 2) proposing sub-optimal *myopic* sensing policies with low-complexity implementations and performance close to the myopic policy. We show that our proposed sensing/access policy is close to the optimal POMDP solution and outperforms other proposed strategies. We also propose a Hidden Markov Model based algorithm to estimate the parameters of primary channel Markov models with a *linear* complexity.**

***Index Terms*—Cognitive radios, dynamic spectrum access (DSA), Markov chains, partially observable Markov decision processes (POMDP), Hungarian algorithm, Neyman-Pearson detector, myopic sensing, Hidden Markov Model (HMM).**

I. Introduction

IT IS now widely accepted that a large number of licensed communication channels in a wide range of frequency bands are underutilized [1]. Dynamic spectrum access (DSA) techniques implemented on Cognitive radio (CR) platforms are proposed as a method to improve the utilization of the communication spectrum resources. To achieve this though, CR's must have the ability to measure, to sense, and to learn the channel characteristics and availabilities to adjust their transmission and/or reception parameters in order to communicate efficiently while avoiding interference with licensed and/or unlicensed users [2].

In this paper, we consider a centralized CR network in which multiple cognitive secondary users (SU's) with limited spectrum sensing capabilities cooperatively find and access spectrum white-spaces on multiple primary channels. The objective is to design the combined optimal channel sensing and access policy. This combined optimal policy maximizes the total secondary system throughput accrued over time over all primary channels. This policy is also required to satisfy a constraint on the probability of collisions with licensed transmissions. We assume that the decision-making (both sensing and access) in the CR network is centralized: a central unit, called the *secondary system decision center* (SSDC), gathers all channel sensing results from SU's over a dedicated control channel; the decisions of sensing and access are made at the SSDC and informed to the distributed SU's over the same dedicated control channel. We model each primary channel occupancy dynamics as a two-state (*idle* and *busy*) i.i.d. Markov chain. This Markov model, also known as the Gilbert-Elliot model [3], has been commonly used to abstract physical primary channels with memory (see, for example [4]–[10]). Note that under our formulation, primary channels can easily be generalized to be non-identical in terms of their Markov parameters.

Although this DSA problem can be formulated as a Partially Observable Markov Decision Process (POMDP) problem, as was discussed previously in [4]–[8], the optimal solution to the POMDP is *computationally prohibitive* because of the continuum of the state space. Many schemes presented in literature such as in [4]–[8] have previously proposed and derived the *myopic* channel sensing solutions under certain assumptions and conditions. For example, assuming that the state transition probabilities are partially known, [4], [5], [7] developed a myopic channel sensing strategy and proved that this *myopic* policy is the optimal POMDP solution under the assumption of a certain ordering of the state transition probabilities. However, this *myopic* policy was derived for a single SU without explicitly considering multiple SU's with transmission collisions and their possible cooperations. In [6], as a follow-up work of [4], [5], the proposed myopic policy is extended to any number of primary channels with no limitation on the number of the primary channels the SU can sense at each time, which means that multiple channel selection is considered. However, possible SU cooperations and SU allocation issues are not discussed.

In this paper, on the other hand, we derive the centralized *optimal myopic* channel sensing policy and the access policy that jointly maximize *instantaneous* total secondary system throughput on the primary channels, without considering the

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impact on future expected total secondary system throughput. Note that, by *optimal myopic* policy we refer to the policy that is optimal within the class of myopic policies. The proposed *myopic* channel sensing policy is applicable for any number of primary channels, any number of SU's, and any channel state transition probabilities. To support our solutions, we also propose a Hidden Markov Model (HMM) based algorithm that efficiently estimates the channel transition probabilities when they are assumed unknown, with a *linear* complexity only in the number of primary channels. Moreover, in [4]–[6], the structure of the channel sensing policy was derived based on the unrealistic assumption that sensing errors are negligible. However, under the formulation in our paper, we show that the optimal *myopic* channel sensing policy depends on the probability of white-space detections. Thus, we explicitly characterize the channel access policy based on a Neyman-Pearson (NP) detector, taking into account the interference constraint imposed by the primary users (PU's). Although imperfect sensing was also considered in the myopic sensing policy in [7], it was developed for the case of a single SU scenario without considering cooperation and collisions among multiple SU's. Assuming imperfect sensing and a Bernoulli process model for the primary channel dynamics (with some conditions on the Bernoulli process means), a *decentralized* multi-user channel sensing problem was formulated as a distributed Multi-Armed Bandit (MAB) problem in [11], in which an order-optimal decentralized policy was constructed.

In [8], the authors assumed that the SU spectrum sensing is matched-filter based: In other words, having perfect knowledge about the primary signaling. Clearly, this is not always justifiable and indeed in many situations may not be realistic. In contrast, we consider both extreme cases: 1) secondary system has no knowledge of the primary signaling (energy detection); and 2) secondary system has perfect knowledge of the primary signaling (matched-filter based detection). When partial knowledge about primary signaling is available, other sensing strategies such as waveform based sensing and cyclostationarity based sensing [2] can be expected to perform in between the performance obtained with these two extremes. Also, in [8], it is assumed that the real-valued observations at the secondary radios are directly sent to a SSDC. This is not realistic because limited bandwidth and transmission opportunities are the reasons for dynamic spectrum sharing at the first place. Taking a more realistic approach, we propose that the SU's only send quantized versions of their observations to the SSDC. Moreover, [8] assumed that *all* SU's are to be assigned to sense the *single* primary channel that has the highest belief of being idle at each time. This model is clearly wasteful since only one primary channel can be accessed at each time no matter how many are available. This restriction reduces the total secondary system throughput because the transmission opportunities on other unsensed channels are missed entirely. In our model, we allow different time-varying channel fading coefficients for different SU's in modeling the nature of the wireless channels. As a result, our *myopic* sensing policy exploits the spatial diversity of the wireless links and makes the sensing and access decisions accordingly. Our method is also applicable for primary channels with different bandwidths and/or different signal-to-noise ratios (SNRs), although in the case of a single primary system all channel bandwidths may be identical as assumed, for example, in [8]. Compared with the algorithm of [8], the performance results show that a better system performance in terms of higher secondary system total throughput is achieved with our proposed strategy.

Since finding the optimal solution to our proposed *myopic* sensing problem has an exponential complexity, we also apply the Hungarian algorithm iteratively to obtain a sub-optimal myopic sensing policy in polynomial time. This iterative Hungarian algorithm extends the well-known Hungarian algorithm [12] by allowing more than one vertex to be connected to a single vertex of the other bipartite set. This is equivalent to allowing more than one SU to sense a single primary channel. We also propose a heuristic algorithm that solves the channel assignment problem at a *linear* complexity order. The simulation results show that these proposed low-complexity algorithms can lead to performance that is very close to the optimal myopic policy, yet with a significant reduction in the computation time.

The remainder of the paper is organized as follows: In Section II we introduce the system model. In Section III, the access and sensing decisions are derived. The algorithm with linear complexity that is used to estimate the primary channel state transition probabilities is introduced in Section IV. In Section V we show the simulation results. In Section VI we conclude by summarizing our results.

II. Problem Formulation

A. Primary channel state model

We denote by $k = \{0, 1, 2, \cdots\}$ the indices of a semi-infinite slotted time horizon. We assume a group of N SU's, and a collection of M primary channels. The primary channels are modeled as statistically identical and independent two-state Markov chains. As shown in Fig. 1, the state *busy* (state 1) indicates the channel is occupied by PU's; the state *idle* (state 0) indicates no PU transmissions over that channel and it is available for SU's to access. We denote by $S_m(k) \in \{0, 1\}$

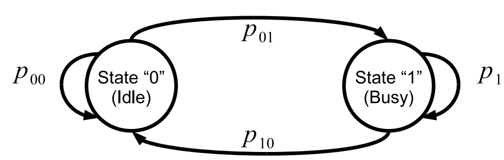


Fig. 1: Model for primary channel state dynamics: Two-state Markov chain

the true state of the m-th primary channel in time slot k. We assume that the state of a primary channel does not change within a single time slot. The stationary transition probability of the Markov model from state i to state j is defined as

$$p_{ij} = \Pr\{S_m(k+1) = j \mid S_m(k) = i\}, \ \ \forall i, j \in \{0, 1\}. \quad (1)$$

The *transition probability matrix* of the Markov model is denoted by $\mathbf{P} = \begin{pmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{pmatrix}$. We denote the vector $\pi =$

$[\pi_0, \pi_1]$ as the stationary distribution vector, such that $\pi = \pi\mathbf{P}$ with π_0 and π_1 being the stationary distribution of idle and busy, respectively. When a SU successfully accesses a primary channel that is *actually free* during a given time slot, the SU is assumed to receive a reward proportional to the bandwidth of that channel. If a SU accesses a primary channel that is in state *busy*, it causes a collision with PU transmission and the SU gets a zero reward. The accumulated total reward of all SU's is used as a measure of the secondary system throughput over the primary channels.

B. Secondary system sensing and access decisions

In order to detect spectrum opportunities, SU's perform spectrum sensing. We assume that each SU is equipped with a single antenna, such that when a SU is performing channel sensing, no simultaneous communication can be performed. Also assume that a single SU can only sense one primary channel at a time, but multiple SU's may simultaneously sense the same primary channel. As shown in Fig. 2, SU's sense primary channels during the designated sensing periods at the beginning of each time slot and we assume that if a PU intends to use its channel during a transmitting period, it starts to transmit from the beginning of that time slot.

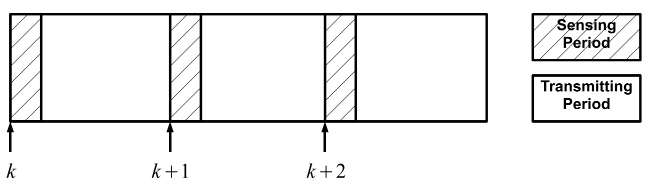


Fig. 2: Slotted time horizon with Sensing Periods and Transmitting Periods.

The SSDC collects all channel sensing results from the SU's over a dedicated control channel to decide whether to access each of the channels and to make decisions on future sensing allocations. This centralized structure may incur some delay due to the need for exchanging sensing reports and decisions. There is a tradeoff between allocating a larger bandwidth for control channels to achieve a smaller delay and the bandwidth available for actual communications. However, this is not addressed in this paper due to space limitations. We use the $M \times N$ matrix $\mathbf{Y}_k$ to denote the sensing reports from SU's at time k with $\mathbf{Y}_k(m,n) = y_{m,n}(k)$, where $y_{m,n}(k)$ denotes the sensing report from n-th SU of the state of m-th primary channel at time k. We use the $M \times N$ matrix $\mathbf{A}_k$ to denote the sensing decision made by the SSDC at time k, where $\mathbf{A}_k(m,n) \in \{0,1\}$, with $\mathbf{A}_k(m,n) = 1$ or 0 representing n-th SU should or should not sense primary channel m at time k respectively. Since we assume that one SU can only sense one channel at a time, we have the constraint $\sum_{m=1}^{M} \mathbf{A}_k(m,n) = 1, \forall n$. We denote by $\mathcal{N}_m(k) = \{n : \mathbf{A}_k(m,n) = 1\}$ the set of indices of SU's that are assigned to sense the m-th channel at time k. We assume that whenever a particular channel is identified as *idle* at the SSDC, one SU is assigned to access that channel. The SSDC is responsible for balancing accessing opportunities among the SU's (fairness), or assigning SU's with any particular priorities. These fairness issues are not addressed in this paper due to space limitations, although they can be integrated into our decision-making framework as an optimization problem with constraints. The sensing and access decisions at the SSDC are further derived in Section III.

C. Secondary user sensing models and local sensing reports

For all (m,n) pairs such that $\mathbf{A}_k(m,n) = 1$, we denote by $\mathbf{r}_{m,n}(k)$ the L-length complex-valued observation vector on the m-th channel, from SU n in time slot k:

$$\mathbf{r}_{m,n}(k) = S_m(k) h_{m,n}(k) \mathbf{x}_m(k) + \mathbf{w}, \tag{2}$$

where $S_m(k) \in \{0,1\}$ is the m-th channel state in time slot k, $\mathbf{x}_m(k) \in \mathbb{C}^L$ is the complex-valued primary signal vector, $\mathbf{w} = [w_1, \cdots, w_L]^T \in \mathbb{C}^L$ is a complex random vector of L zero-mean i.i.d Gaussian random variables with real and imaginary parts, each $\mathcal{N}(0, \sigma_w^2/2)$. Thus, each $w_i \in \mathbf{w}$ is circularly symmetric and denoted by $\mathcal{CN}(0, \sigma_w^2)$. Denote $h_{m,n}(k) = \alpha_{m,n}(k) e^{j\theta_{m,n}(k)}$, the complex channel gain of the primary channel between the primary transmitter on the m-th primary channel and the n-th SU in time slot k, with amplitude $\alpha_{m,n}(k)$ and phase $e^{j\theta_{m,n}(k)}$. We assume that each SU has perfect knowledge of their own channel gain in each time slot for each of the primary channels. In practice, it can be assumed that the primary transmitter, if active, would periodically send training sequences/preambles to primary receivers for the purpose of synchronization and channel estimation [13]. The SU's may overhear and make use of these training sequences to estimate the fading coefficients between the primary transmitters and the secondary receivers. When a primary channel is idle, the secondary system may rely on the database service [14] maintained through learning at the SSDC to obtain the channel knowledge. We consider two models for $\mathbf{x}_m(k)$ which can be considered as two extreme cases: 1) secondary system has *no* knowledge about the primary signaling; 2) secondary system has *perfect* knowledge about the primary signaling.

In the CR context, when communication opportunities are scarce (limited bandwidth and large amount of SU's), it is reasonable to assume that instead of transmitting raw data vector $\mathbf{r}_{m,n}(k)$'s, the SU's can only transmit quantized versions as reports to the SSDC. Without loss of generality, we assume the simplest case: the reports from SU's to the SSDC are compressed/quantized to 0's and 1's which can also be considered as estimates of the state of primary channels. For both aforementioned $\mathbf{x}_m(k)$ models, we use $y_{m,n}(k) \in \{0,1\}$ to denote the report of the m-th primary channel state from the n-th SU to the SSDC, in time slot k. We assume that these $y_{m,n}(k)$'s are received error free at the SSDC. As shown in Fig. 3, the m-th channel true state $S_m(k)$ and the report $y_{m,n}(k)$ can be modeled as the input and output of a *Binary Asymmetric Channel* (BAC), respectively. The two hypotheses on the m-th channel are $\mathcal{H}_1 : S_m(k) = 0$, and $\mathcal{H}_0 : S_m(k) = 1$, respectively. We use $\lambda_{m,n}^1(k)$, and $\lambda_{m,n}^0(k)$ to denote the crossover probabilities under $\mathcal{H}_1$, and $\mathcal{H}_0$, respectively. The *maximum a posteriori probability* (MAP)

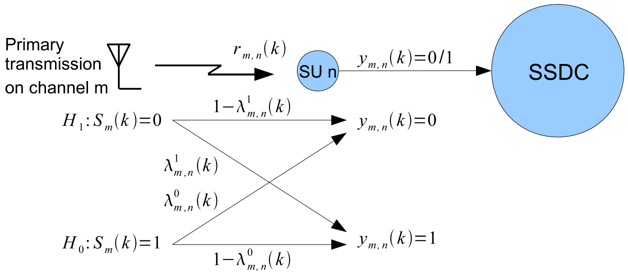


Fig. 3: SU's' reports of observations on primary channels can be modeled as Binary Asymmetric Channels.

decision rule used to determine $y_{m,n}(k)$ is given by

$$y_{m,n}(k) = \arg\max_{i\in\{0,1\}} \Pr\{S_m(k) = i \mid \mathbf{r}_{m,n}(k))\}, \tag{3}$$

which can be shown to be equivalent to the following likelihood ratio test:

$$\mathcal{L}(\mathbf{r}_{m,n}(k)) = \frac{f_{\mathbf{r}|0}(\mathbf{r}_{m,n}(k) \mid S_m(k) = 0)}{f_{\mathbf{r}|1}(\mathbf{r}_{m,n}(k) \mid S_m(k) = 1)} \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta_m(k), \tag{4}$$

where $\eta_m(k) = \frac{\Pr\{S_m(k)=1\}}{\Pr\{S_m(k)=0\}} = \frac{\pi_1}{\pi_0}$ and $f_{\mathbf{r}|s}$ denotes the conditional likelihood function of the complex-valued vector $\mathbf{r}$ given the state s.

1) When the secondary system has no knowledge about the primary signaling: In general, we assume that the elements of $\mathbf{x}_m(k)$ are correlated and having a complex zero-mean Gaussian distribution with an unknown covariance matrix $\mathbf{\Sigma_x}$. We denote: $\mathbf{x}'_m(k) = \left[\Re\{\mathbf{x}^T_m(k)\}\ \Im\{\mathbf{x}^T_m(k)\}\right]^T$ and $\tilde{\mathbf{x}}_{m,n}(k) = \left[\Re\{h_{m,n}(k)\mathbf{x}^T_m(k)\}\ \Im\{h_{m,n}(k)\mathbf{x}^T_m(k)\}\right]^T$, where $\mathbf{x}_m(k) \sim \mathcal{CN}(\mathbf{0}, \mathbf{\Sigma_x})$. It can be shown that $\tilde{\mathbf{x}}_{m,n}(k)$ is Gaussian and thus we denote $\tilde{\mathbf{x}}_{m,n}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma_{\tilde{x}}})$, where $\mathbf{\Sigma_{\tilde{x}}}$ denotes the unknown covariance matrix of $\tilde{\mathbf{x}}_{m,n}(k)$. We also denote $\mathbf{R}_{m,n}(k) = [\Re\{\mathbf{r}^T_{m,n}(k)\}\ \Im\{\mathbf{r}^T_{m,n}(k)\}]^T$, and $\mathbf{W} = [\Re\{\mathbf{w}^T\}\ \Im\{\mathbf{w}^T\}]^T$. Then the complex-valued observation vector model (2) can be written as: $\mathbf{R}_{m,n}(k) = S\tilde{\mathbf{x}}_{m,n}(k) + \mathbf{W}$, where $\mathbf{W} \sim \mathcal{N}\left(\mathbf{0}, \frac{\sigma_w^2}{2}\mathbf{I}\right)$ and $\mathbf{R}_{m,n}(k) \sim \mathcal{N}\left(\mathbf{0}, S\mathbf{\Sigma_{\tilde{x}}} + \frac{\sigma_w^2}{2}\mathbf{I}\right)$. In this case, the MAP rule can be shown [15] to be equivalent to the following decision rule: $y_{m,n}(k) = \begin{cases} 0 & \text{, if } \mathbf{R}^T_{m,n}(k)\mathbf{Q}_{m,n}(k)\mathbf{R}_{m,n}(k) \le \eta^*_{m,n}(k) \\ 1 & \text{, if } \mathbf{R}^T_{m,n}(k)\mathbf{Q}_{m,n}(k)\mathbf{R}_{m,n}(k) > \eta^*_{m,n}(k) \end{cases}$, where $\mathbf{Q}_{m,n}(k) = \frac{2|h_{m,n}(k)|^2\sigma_x^2}{\sigma_w^2(\sigma_w^2+|h_{m,n}(k)|^2\sigma_x^2)}\mathbf{I}$ and $\eta^*_{m,n}(k) = 2\left(\ln\frac{\eta_m(k)(\sigma_w^2+|h_{m,n}(k)|^2\sigma_x^2)^L}{\sigma_w^{2L}}\right)$ in case the elements of $\mathbf{x}_m(k)$ are assumed i.i.d. [1]. Then, we have $\mathbf{R}_{m,n}(k)^T\mathbf{Q}_{m,n}(k)\mathbf{R}_{m,n}(k) = \mathbf{Q}_{m,n}(k)\mathbf{r}^H_{m,n}(k)\mathbf{r}_{m,n}(k)$, where the superscript H denotes the conjugate transpose and $\mathbf{r}_{m,n}(k) \sim \mathcal{CN}\left(\mathbf{0}, \frac{S|h|^2\sigma_x^2+\sigma_w^2}{2}\mathbf{I}\right)$. Then, the MAP rule can be shown to be equivalent to the following decision rule: $y_{m,n}(k) = \begin{cases} 0 & \text{, if } \mathbf{r}^H_{m,n}(k)\mathbf{r}_{m,n}(k) \le \eta'_{m,n}(k) \\ 1 & \text{, if } \mathbf{r}^H_{m,n}(k)\mathbf{r}_{m,n}(k) > \eta'_{m,n}(k) \end{cases}$, where $\eta'_{m,n}(k) = \eta^*_{m,n}(k)\frac{\sigma_w^2(\sigma_w^2+|h_{m,n}(k)|^2\sigma_x^2)}{2|h_{m,n}(k)|^2\sigma_x^2}$. The quantity $\frac{2\mathbf{r}^H_{m,n}(k)\mathbf{r}_{m,n}(k)}{\sigma_w^2}$ (under $\mathcal{H}_1$), and $\frac{2\mathbf{r}^H_{m,n}(k)\mathbf{r}_{m,n}(k)}{\sigma_w^2+|h_{m,n}(k)|^2\sigma_x^2}$ (under $\mathcal{H}_0$) can be shown distributed as χ^2_{2L}, thus the crossover probabilities can be obtained as

$$\lambda^1_{m,n}(k) = 1 - \frac{1}{\Gamma(L)}\gamma\left(L, \frac{\eta'_{m,n}(k)}{\sigma_w^2}\right), \tag{5}$$

$$\lambda^0_{m,n}(k) = \frac{1}{\Gamma(L)}\gamma\left(L, \frac{\eta'_{m,n}(k)}{\sigma_w^2 + |h_{m,n}(k)|^2\sigma_x^2}\right), \tag{6}$$

where the gamma function $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$ and the lower incomplete gamma function $\gamma(s,x) = \int_0^x t^{s-1}e^{-t}dt$. We assume that the threshold $\eta_m(k) = \frac{\pi_1}{\pi_0}$ is informed from the SSDC.

2) When the secondary system has perfect knowledge about the primary signaling: It is assumed that $\mathbf{x}_m(k) = \mathbf{x}$ is known and the matched-filter [15] based sensing is employed. The optimal MAP rule (3) can then be derived as [15] $y_{m,n}(k) = \begin{cases} 0 & \text{, if } \Re(\mathbf{r}_{m,n}(k)\mathbf{x}'^H_{m,n}(k)) \le \frac{\mathbf{x}'_{m,n}(k)\mathbf{x}'^H_{m,n}(k) - \sigma_w^2\ln(\eta_m(k))}{2} \\ 1 & \text{, if } \Re(\mathbf{r}_{m,n}(k)\mathbf{x}'^H_{m,n}(k)) > \frac{\mathbf{x}'_{m,n}(k)\mathbf{x}'^H_{m,n}(k) - \sigma_w^2\ln(\eta_m(k))}{2} \end{cases}$, where $\Re(\cdot)$ denotes the real part operation, and $\mathbf{x}'_{m,n}(k) = h_{m,n}(k)\mathbf{x}$. Now, given $S_m(k) = 0$, $\frac{\Re(\mathbf{r}_{m,n}(k)\mathbf{x}'^H_{m,n}(k))}{\sqrt{\mathbf{x}'_{m,n}(k)\mathbf{x}'^H_{m,n}(k)}} \sim \mathcal{N}(0, \sigma_w^2/2)$; whereas given $S_m(k) = 1$, $\frac{\Re(\mathbf{r}_{m,n}(k)\mathbf{x}'^H_{m,n}(k))}{\sqrt{\mathbf{x}'_{m,n}(k)\mathbf{x}'^H_{m,n}(k)}} \sim \mathcal{N}\left(\sqrt{\mathbf{x}'_{m,n}(k)\mathbf{x}'^H_{m,n}(k)}, \sigma_w^2/2\right)$. Thus, the resulting crossover probabilities are given as

$$\lambda^1_{m,n}(k) = Q\left(\frac{|h_{m,n}(k)|^2\mathbf{x}^H\mathbf{x} - \sigma_w^2\ln(\eta_m(k))}{\sqrt{2}|h_{m,n}(k)|\sigma_w\sqrt{\mathbf{x}^H\mathbf{x}}}\right), \tag{7}$$

$$\lambda^0_{m,n}(k) = Q\left(\frac{|h_{m,n}(k)|^2\mathbf{x}^H\mathbf{x} + \sigma_w^2\ln(\eta_m(k))}{\sqrt{2}|h_{m,n}(k)|\sigma_w\sqrt{\mathbf{x}^H\mathbf{x}}}\right), \tag{8}$$

where function $Q(\cdot)$ is the tail probability of the standard normal distribution and the superscript H denotes the conjugate transpose.

III. Channel Access and Sensing Decisions at the SSDC

A. Channel access decisions at the SSDC

To meet the constraint of collision probability with PU's on *every* channel, the optimal access decisions at the SSDC must be based on a classical NP detector [15]. Note that we refer to the '*access decision*' as the decision at the SSDC about whether a primary channel is idle or not, whereas the decision on which SU should access which primary channel is called the '*access assigning decision*'. Let the variable length vector $\mathbf{y}_k(m,:) = \{y_{m,n}(k) : \forall n \in \mathcal{N}_m(k)\}$ denote all channel sensing reports corresponding to the m-th channel at time k and the variable length vector $\mathbf{y}_{0:k}(m,:) = \{\mathbf{y}_0(m,:), \cdots, \mathbf{y}_k(m,:)\}$ denote the sensing history on the m-th primary channel, from time 0 to k. Let $\mathbf{S}^m_{0:k}$ denote the historic state of m-th channel from time 0 to k. The set of all possible historic channel state vectors is denoted by $\mathcal{S}_c = \{0,1\}^{k+1}$.

[1]Note that the assumption of the components of $\mathbf{x}_m(k)$ being i.i.d. is shown to be optimal for detecting zero-mean constellation signals when there is no knowledge about the primary signal [16]. In this case, the matrix $\mathbf{Q}_{m,n}(k)$ is found to be a scalar and the sufficient test statistic $\mathbf{R}_{m,n}(k)^T\mathbf{R}_{m,n}(k)$ can be considered as a measure of the primary signal energy, also known as the energy detection [15].

$$\mathcal{L}(\mathbf{y}_k(m,:)) = \frac{P_{m,1}(\mathbf{y}_k(m,:))}{P_{m,0}(\mathbf{y}_k(m,:))} = \prod_{n\in\mathcal{N}_m(k)} \left(\frac{\lambda^1_{m,n}(k)}{1-\lambda^0_{m,n}(k)}\right)^{y_{m,n}(k)} \left(\frac{1-\lambda^1_{m,n}(k)}{\lambda^0_{m,n}(k)}\right)^{1-y_{m,n}(k)}. \tag{9}$$

At time k, for the m-th primary channel, the SSDC chooses one of the two possible hypotheses based on $\mathbf{y}_{0:k}(m,:)$: $\mathcal{H}_1$(channel *idle*, $\mathbf{y}_{0:k}(m,:) \sim P_{m,1}$) and $\mathcal{H}_0$(channel *busy*, $\mathbf{y}_{0:k}(m,:) \sim P_{m,0}$), where $P_{m,1}$, and $P_{m,0}$ denote the conditional distributions of $\mathbf{y}_{0:k}(m,:)$ given $S_m(k) = 0$, and $S_m(k) = 1$, respectively. The likelihood ratio for the m-th channel is given by $\mathcal{L}(\mathbf{y}_{0:k}(m,:)) = \frac{P_{m,1}(\mathbf{y}_{0:k}(m,:))}{P_{m,0}(\mathbf{y}_{0:k}(m,:))}$, which is generally difficult to obtain as a useful closed-form expression due to the fact that at each time k, the number of SU's on m-th channel changes and thus as time evolves, the complexity increases. To simplify the access decision structure, we assume that the access decisions regarding the m-th channel are based only on the current observations $\mathbf{y}_k(m,:)$. The likelihood ratio at the SSDC is then given by (9). Note that in order to obtain the knowledge of $\lambda^0_{m,n}(k)$ and $\lambda^1_{m,n}(k)$ at the SSDC, the SU's are required to send the quantity $|h_{m,n}(k)|$ to the SSDC in each time slot. Along with the sensing report $y_{m,n}(k)$, a total number of $2N$ messages are needed at the SSDC in each time slot k, where N is the number of SU's in the secondary system. The log-likelihood ratio can be found as $\mathcal{LLR}(\mathbf{y}_k(m,:)) = \sum_{n\in\mathcal{N}_m(k)} y_{m,n}(k)c_{m,n}(k) + d_m(k)$, where $c_{m,n}(k) = \ln\left(\frac{\lambda^1_{m,n}(k)}{1-\lambda^0_{m,n}(k)}\cdot\frac{\lambda^0_{m,n}(k)}{1-\lambda^1_{m,n}(k)}\right)$, and $d_m(k) = \sum_{n\in\mathcal{N}_m(k)} \ln\left(\frac{1-\lambda^1_{m,n}(k)}{\lambda^0_{m,n}(k)}\right)$. The sufficient statistic for access decision at the SSDC regarding the m-th channel is then given by $\mathcal{T}_m(k) = \sum_{n\in\mathcal{N}_m(k)} y_{m,n}(k)c_{m,n}(k)$, and the test is equivalent to

$$\mathcal{T}_m(k) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \tau_m(k) - d_m(k) = \tau'_m(k), \tag{10}$$

where $\tau_m(k)$ and $\tau'_m(k)$ are the thresholds for the log-likelihood ratio test and the test of the sufficient statistic $\mathcal{T}_m(k)$, respectively. Let $f^i_{m,k}$ and $F^i_{m,k}$ denote the conditional probability mass function (pmf) and the conditional cumulative distribution function (cdf) of the random variable $\mathcal{T}_m(k)$ under hypothesis $\mathcal{H}_i$, respectively. We denote the variable set $\mathcal{C}_m(k)$ as the set of discrete values that $\mathcal{T}_m(k)$ takes at time k. The optimal access-decision regarding the m-th channel is then given by the randomized decision rule:

$$\tilde{\delta}_{NP}(\mathbf{y}_k(m,:)) = \begin{cases} 1, & \text{if } \mathcal{T}_m(k) > \tau'_m(k) \\ \gamma_m(k), & \text{if } \mathcal{T}_m(k) = \tau'_m(k) \\ 0, & \text{if } \mathcal{T}_m(k) < \tau'_m(k) \end{cases}. \tag{11}$$

This randomized decision rule says: 1) access the m-th channel if $\mathcal{T}_m(k) > \tau'_m(k)$; 2) do not access the m-th channel if $\mathcal{T}_m(k) < \tau'_m(k)$; and 3) access the m-th channel with probability $\gamma_m(k)$ if $\mathcal{T}_m(k) = \tau'_m(k)$. We denote by ζ the collision probability constraint on each individual primary channel. It can be shown that the threshold $\tau'_m(k)$ must be chosen such that $\Pr\{\mathcal{T}_m(k) > \tau'_m(k) \mid \mathcal{H}_0\} \le \zeta < \Pr\{\mathcal{T}_m(k) > \tau'^{-}_m(k) \mid \mathcal{H}_0\}$, where we denote by $\Pr\{\mathcal{T}_m(k) > \tau'_m(k) \mid \mathcal{H}_0\}$ the probability of colliding with primary user on the m-th channel at time k. The quantity $\tau'^{-}_m(k) = \max\{\tau : \tau \in \mathcal{C}_m(k), \tau < \tau'_m(k)\}$ is defined to be the maximum value in $\mathcal{C}_m(k)$ that is less than $\tau'_m(k)$. The choice of $\tau'_m(k)$ is illustrated in Fig. 4 where it can be seen that $\tau'_m(k)$ is unique, given the monotonicity of the complementary cdf $\Pr\{\mathcal{T}_m(k) > \tau \mid \mathcal{H}_0\}$. We can see that this is equivalent to choosing $\tau'_m(k)$ such that $1 - F^0_{m,k}(\tau'_m(k)) \le \zeta < 1 - F^0_{m,k}(\tau'^{-}_m(k))$ (note that $\Pr\{\mathcal{T}_m(k) > \tau \mid \mathcal{H}_0\} = 1 - F^0_{m,k}(\tau)$). The randomization variable $\gamma_m(k)$ is then given by $\gamma_m(k) = \frac{\zeta - \left(1-F^0_{m,k}(\tau'_m(k))\right)}{F^0_{m,k}(\tau'_m(k)) - F^0_{m,k}(\tau'^{-}_m(k))}$. Note that, the structure

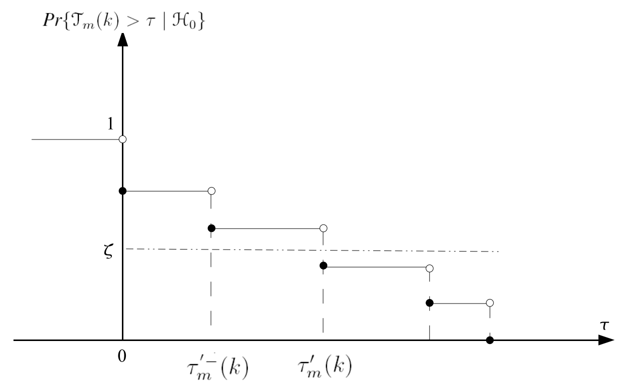


Fig. 4: The choice of of the threshold $\tau'_m(k)$, given a false alarm probability ζ.

of the optimal access decision at the SSDC is independent of what type of local sensing rules were used at the distributed SU's. In turn, the above access decision rule at the SSDC is valid for any assumptions on the knowledge of primary signals by the SU's, including the considered two extreme cases, since as long as the local sensing decisions are quantized as 0 or 1 before transmitting to the SSDC, all that matters are the crossover probabilities $\lambda^1_{m,n}(k)$ and $\lambda^0_{m,n}(k)$ in terms of the access decision-making at the SSDC. The probability of detection of white-spaces is then given in (12), which is used in the sensing decision-making (for) at the SSDC as described next.

$$\begin{aligned} & P_{D,m}(k, \mathbf{A}_k) \\ = \; & \Pr\{\mathcal{T}_m(k) > \tau'_m(k) \mid \mathcal{H}_1\} \\ & \qquad + \gamma_m(k)\Pr\{\mathcal{T}_m(k) = \tau'_m(k) \mid \mathcal{H}_1\} \\ = \; & 1 - F^1_{m,k}(\tau'_m(k)) + \gamma_m(k)\cdot f^1_{m,k}(\tau'_m(k)). \end{aligned} \tag{12}$$

B. Optimal and sub-optimal myopic sensing decisions at the SSDC

The sensing decision at the SSDC determines which primary channel each SU should sense at each time. We define

$b_0(m,k) = \Pr\{S_m(k) = 0 \mid \mathbf{y}_{0:k-1}(m,:)\}$ and $b_1(m,k) = 1 - b_0(m,k)$ as the belief of the m-th channel being *idle* and *busy* at time k respectively. We denote the belief vectors as $\mathbf{b}_0(k) = [b_0(1,k), \cdots, b_0(M,k)]^T$ and $\mathbf{b}_1(k) = [b_1(1,k), \cdots, b_1(M,k)]^T$.

Assuming the sensing observations of SU's at time k are mutually independent, the belief that the m-th channel being *idle* in next time slot $k+1$ is updated at the SSDC using the Bayes' formula:

$$b_0(m,k+1) = \frac{\sum_{i\in\{0,1\}} p_{i0}\left[\prod_{n\in\mathcal{N}_m(k)} f_i(y_{m,n}(k))\right] b_i(m,k)}{\sum_{i\in\{0,1\}}\left[\prod_{n\in\mathcal{N}_m(k)} f_i(y_{m,n}(k))\right] b_i(m,k)}, \tag{13}$$

where $f_i(y_{m,n}(k)) = \Pr\{Y_{m,n}(k) = y_{m,n}(k) \mid S_m(k) = i\}, \forall i \in \{0,1\}$ is the conditional pmf of the local decisions from the n-th SU and $Y_{m,n}(k)$ is a random variable denoting the report from the n-th SU about the m-th channel at time k (note that $y_{m,n}(k)$ is a realization of the random variable $Y_{m,n}(k)$). For those primary channels that were not sensed by any SU, the belief is updated simply based on the Markovian evolution of primary channels: $[b_0(m,k+1), b_1(m,k+1)] = [b_0(m,k), b_1(m,k)]\mathbf{P}$, where $\mathbf{P}$ is the state transition probability matrix. The belief vectors $\mathbf{b}_0(1)$, and $\mathbf{b}_1(1)$ are initialized with the stationary distribution $\pi = [\pi_0\,,\pi_1]$ of the Markov model.

We denote by the random vector $\hat{\mathbf{S}}(k) = \left[\tilde{\delta}_{NP}(1,k), \cdots, \tilde{\delta}_{NP}(M,k)\right]^T$ the vector of NP detector outcomes at the SSDC at time k. Given a sensing assignment $\mathbf{A}_k$, the probability of $\hat{\mathbf{S}}(k) = \mathbf{s} \in \{0,1\}^M$ can be found as $\Pr\{\hat{\mathbf{S}}(k) = \mathbf{s}\} = \prod_{m=1}^{M} \frac{\{b_0(m,k)P_{D,m}(k,\mathbf{A}_k)+(1-b_0(m,k))\zeta\}^{\mathcal{I}\{\mathbf{s}(m)=0\}}}{\{b_0(m,k)(1-P_{D,m}(k,\mathbf{A}_k))+(1-b_0(m,k))(1-\zeta)\}^{-\mathcal{I}\{\mathbf{s}(m)=1\}}}$, where $\mathcal{I}_E$ is the indicator function of event E and ζ is the predefined collision probability. We define the M by N matrix $\mathbf{H}'_k$ such that $\mathbf{H}'_k(m,n) = h'_{m,n}(k)$, $\forall\ m,n$, where $h'_{m,n}(k)$ denotes the channel coefficient of the channel between the n-th SU and its desired receiver on channel m. Note that the optimal secondary access assigning decisions can be obtained by an integer programming problem which can be solved using a graph matching algorithms[2], as suggested in [17]. Due to space limitations, we omit details of the algorithm. Let us denote by $n_m(\mathbf{s}, \mathbf{A_k}, \mathbf{H}'_k)$ the index of the SU that is assigned to access the m-th channel, after sensing in time slot k, according to this optimal secondary access assigning decisions. We denote by $h'_m(\mathbf{s}, \mathbf{A}_k, \mathbf{H}'_k) \triangleq h'_{m,n_m(\mathbf{s},\mathbf{A_k},\mathbf{H}'_k)}(k)$ the channel coefficient on the m-th channel from the SU that is assigned to access that channel. Let $r_m(k, \hat{\mathbf{S}}(k), \mathbf{A}_k, \mathbf{H}'_k)$ be the secondary transmission rate on the m-th channel which can be written as: $r_m(k, \hat{\mathbf{S}}(k), \mathbf{A}_k, \mathbf{H}'_k) = B_m \log_2\left(1 + \frac{P_{n_m(\hat{\mathbf{S}}(k),\mathbf{A_k},\mathbf{H}'_k)}|h'_m(\hat{\mathbf{S}}(k),\mathbf{A}_k,\mathbf{H}'_k)|^2}{N_0 B_m}\right)$, if $\sum_n \mathbf{A}_k(m,n) \geq 1$, $S_m(k) = 0$, and $\tilde{\delta}_{NP}(m,k) = 1$, and $r_m(k, \hat{\mathbf{S}}(k), \mathbf{A}_k, \mathbf{H}'_k) = 0$ otherwise, with B_m being the bandwidth of the m-th primary channel, P_n being the transmit power of the n-th SU and N_0 is the single-sided power spectrum density of the secondary receiver noise. The expected total transmission rate/reward on all the primary channels in time slot k is then found in (14), where $\mathbb{E}_{\hat{\mathbf{S}}(k)}$ denotes the expectation with respect to the vector $\hat{\mathbf{S}}(k)$ and the expectation is given in (15).

[2]A graph matching problem finds the optimal *one-to-one* matching between the elements of two bipartite sets such that it optimizes the sum-weights of the connecting edges.

Let $\mathbf{S}(k) = [S_1(k), \cdots, S_M(k)] \in \mathcal{S} = \{0,1\}^M$ denote the state of the system at time k. Then the value of state $\mathbf{s} \in \mathcal{S}$ at time 0 is

$$V^{\mathbf{A}_{0:\infty}}(\mathbf{s}) = \mathbb{E}\left\{\sum_{k=0}^{\infty}\sum_{m=1}^{M} \gamma^k r_m(k, \hat{\mathbf{S}}(k), \mathbf{A}_k, \mathbf{H}'_k) \mid \mathbf{S}(0) = \mathbf{s}\right\}$$

which can also be expressed as

$$\begin{aligned} V^{\mathbf{A}_{0:\infty}}(\mathbf{s}) &= \mathbb{E}\left\{\sum_{m=1}^{M} r_m(0, \hat{\mathbf{S}}(0), \mathbf{A}_0, \mathbf{H}'_0) \mid \mathbf{S}(0) = \mathbf{s}\right\} \\ &+ \gamma \sum_{\mathbf{s}'\in\mathcal{S}} P(\mathbf{s},\mathbf{s}') V^{\mathbf{A}_{0:\infty}}(\mathbf{s}'), \end{aligned}$$

where $\mathbf{A}_{0:\infty}$ denotes the SSDC sensing decisions from time $k=0$ to ∞, $\gamma \in (0,1)$ is a discount factor and $P(\mathbf{s},\mathbf{s}')$ is the probability of state transition from $\mathbf{s}$ to $\mathbf{s}'$. Note that, the value function is the expected discounted reward over all primary channels. When the SU's do not have perfect knowledge of the states of the primary channels, the resultant problem is a Partially Observable Markov Decision Process (POMDP) for which the effective state of the system can be taken as the belief vector. An algorithm to obtain optimal decisions for a POMDP problem was derived in [18]. However, unless the number of primary channels is very small, the algorithm leads to very high computational complexity rendering it impractical [5]. As an alternative, an optimal channel sensing decision within the class of *myopic* policies can be obtained by maximizing the total secondary transmission rate/reward over all primary channels at each time step: i.e. making the channel sensing decisions to obtain the instantaneous highest reward, rather than attempting to optimize the average reward accrued over all times. This *optimal myopic* sensing decision $\mathbf{A}^*_k$ can be expressed as:

$$\mathbf{A}^*_k = \underset{\sum_{m=1}^{M}\mathbf{A}_k(m,n)=1}{\arg\max} \sum_{m=1}^{M} \mathbb{E}\left\{r_m(k, \hat{\mathbf{S}}(k), \mathbf{A}_k, \mathbf{H}'_k)\right\}. \tag{16}$$

This optimal sensing decision is designed to jointly maximize the expected secondary system throughput taking into account the impact from the access assigning decision-making. Note that this problem can be cast as a *constrained nonlinear 0-1 programming* problem [19]. Since the objective function in (16) is non-separable, the solution is generally hard to find. The direct search solution has an exponential complexity of M^N.

On the other hand, in order to perform this joint optimization at the SSDC, it is required that the SSDC has perfect knowledge of the channel coefficients $h'_{m,n}(k)$'s between the secondary transmitters and receivers. However, unlike the channel coefficients from the primary radios to the SU's, it might not be realistic to assume that the SSDC has the knowledge of these secondary sender-receiver channel coefficients,

$$\mathbb{E}\left\{\sum_{m=1}^{M} r_m(k,\hat{\mathbf{S}}(k),\mathbf{A}_k,\mathbf{H}'_k)\right\} \sum_{m=1}^{M} B_m \mathbb{E}_{\hat{\mathbf{S}}(k)}\left\{\log_2\left(1+\frac{P_{n_m(\hat{\mathbf{S}}(k),\mathbf{A_k},\mathbf{H}'_k)}|h'_m(\hat{\mathbf{S}}(k),\mathbf{A}_k,\mathbf{H}'_k)|^2}{N_0 B_m}\right)\right\} P_{D,m}(k,\mathbf{A}_k)b_0(m,k), \tag{14}$$

$$\mathbb{E}_{\hat{\mathbf{S}}(k)}\left\{\log_2\left(1+\frac{P_{n_m(\hat{\mathbf{S}}(k),\mathbf{A_k},\mathbf{H}'_k)}|h'_m(\hat{\mathbf{S}}(k),\mathbf{A}_k,\mathbf{H}'_k)|^2}{N_0 B_m}\right)\right\} = \sum_{\mathbf{s}} \log_2\left(1+\frac{P_{n_m(\mathbf{s},\mathbf{A_k},\mathbf{H}'_k)}|h'_m(\mathbf{s},\mathbf{A}_k,\mathbf{H}'_k)|^2}{N_0 B_m}\right) \Pr\{\hat{\mathbf{S}}(k)=\mathbf{s}\}. \tag{15}$$

since it is assumed that the SU's are sensing primary signals, but not SU signals. This makes it reasonable to instead focus on finding an optimal myopic sensing policy in the sense of maximizing the secondary system transmission opportunities on the primary channels, other than the transmission throughput, similar to [8]. The optimal myopic sensing decisions in terms of maximizing the secondary transmission opportunities can be found as

$$\begin{aligned}\mathbf{A}_k^* &= \underset{\sum_{m=1}^{M}\mathbf{A}_k(m,n)=1}{\arg\max} \sum_{m=1}^{M} \mathbb{E}\{r_m(k,\mathbf{A}_k)\} \\ &= \underset{\sum_{m=1}^{M}\mathbf{A}_k(m,n)=1}{\arg\max} \sum_{m=1}^{M} B_m b_0(m,k) P_{D,m}(k,\mathbf{A}_k).\end{aligned} \tag{17}$$

In Section V we will show that the maximization in (16) gives only a marginal performance improvement compared to the performance obtained with the objective function in (17), especially when the number of SU's is large compared to the number of primary channels.

As an alternative with much lower computational complexity, we propose a sub-optimal algorithm for solving (17) based on an iterative Hungarian algorithm [12]. For simplicity, we drop the time indices from the algorithm description and let $B_m = 1$. We assume that the crossover probabilities of the BAC are known. We define the $M \times N$ matrix $\Delta^{(m,n)}$ such that $\Delta^{(m,n)}(m',n') = 1$ if $(m',n') = (m,n)$, and $\Delta^{(m,n)}(m',n') = 0$ otherwise. We use Algorithm 1 below to find the channel sensing assignment $\mathbf{A}$, which provides a sub-optimal solution to (17). In contrast with the Hungarian algorithm solution which forms the optimal one-to-one matching between two bipartite sets, our sensing policy allows multiple SU's to sense a single channel at a time. Thus, an intuitive solution would be to apply the Hungarian algorithm repeatedly among the primary channels with the available SU's that have not yet been assigned. In this algorithm, we set a weighting matrix $\Delta\mathbf{P}$ between the set of SU's and the primary channels. Each weight or element $\Delta\mathbf{P}(m,n)$ of this matrix is defined as the increase in the detection probability on a particular channel m if an additional SU n senses that channel. This is reflected in:

$$\Delta\mathbf{P}(m,n) = \left[P_{D,m}(\mathbf{A}+\Delta^{(m,n)}) - P_{D,m}(\mathbf{A})\right] b_0(m)\ ,$$

where $\mathbf{A}+\Delta^{(m,n)}$ is the new sensing assignment if an available SU n is assigned to sense the m-th channel, given the current sensing assignment $\mathbf{A}$. Therefore, if there are more than $M-1$ unassigned SU's at an iteration, the proposed algorithm assigns exactly M SU's to sense the primary channels. At each iteration, the Hungarian algorithm assigns the SU's such that it maximizes the sum of $\Delta\mathbf{P}(m,n)$ over all $m = 1,\cdots,M$. Note that, at each iteration, the SU's are assigned in a one-to-one mapping. Note that the above sensing decision making procedure applies to both optimization problems in (16) and (17), except when using (16), the extra term in (15) needs to be computed firstly.

The complexity of the Hungarian algorithm is $(\max\{M,N\})^3$ for an $M \times N$ bipartite graph, whereas the complexity of the proposed iterative Hungarian algorithm is in the order of $\lceil \frac{N}{M} \rceil (\max\{M,N\})^3$ since the Hungarian algorithm is used iteratively $\lceil \frac{N}{M} \rceil$ times. In brief, the proposed algorithm solves the channel sensing assignment problem with roughly an order 4 polynomial complexity. Note that, in particular, if $N \leq M$, Algorithm 1 is equivalent to the Hungarian algorithm. Next, we propose a heuristic algorithm that reduces the above complexity to be linear in number of secondary users N. This algorithm, as detailed in Algorithm 2, picks randomly a secondary user n and assigns it to the m-th channel for which it has the highest detection probability. Also, we allow at most $\lceil \frac{N}{M} \rceil$ SU's to sense each channel so that the SU's sense evenly all channels and keep information about the belief of the state of every channel.

Algorithm 1 Iterative Hungarian Algorithm

$\mathbf{A} = 0_{M\times N}$ and $\bar{\mathcal{N}} = \{1,\cdots,N\}$
while $\bar{\mathcal{N}} \neq \emptyset$ **do**
  $\Delta\mathbf{P} = 0_{M\times N}$
  for $m \in \{1,\cdots,M\}$ and $n \in \bar{\mathcal{N}}$ **do**
    $\Delta\mathbf{P}(m,n) = \left[P_{D,m}\left(\mathbf{A}+\Delta^{(m,n)}\right) - P_{D,m}\left(\mathbf{A}\right)\right] b_0(m)$
  end for
  Run the *Hungarian algorithm* for the $M \times N$ bipartite graph whose edge weights are given in $\Delta\mathbf{P}$ to obtain the maximum sum matching.
  Remove the assigned vertices from the set $\bar{\mathcal{N}}$.
  Append the new assignments to matrix $\mathbf{A}$.
end while

Algorithm 2 Heuristic Sensing Assignment

$\mathbf{A} = 0_{M\times N}$ and $\bar{\mathcal{N}} = \{1,\cdots,N\}$.
while $\bar{\mathcal{N}} \neq \emptyset$ **do**
  Pick randomly $n \in \bar{\mathcal{N}}$.
  $m^* = \arg\max_{m\in\{1,\cdots,M\}} B_m b_0(m) P_{D,m}(\Delta^{(m,n)})$
    s.t. $\sum_{n\in\{1,\cdots,N\}} \mathbf{A}(m,n) \leq \lceil \frac{N}{M} \rceil$
  $\mathbf{A} \leftarrow \mathbf{A} + \Delta^{(m^*,n)}$
  $\bar{\mathcal{N}} \leftarrow \bar{\mathcal{N}} \backslash n$
end while

IV. Estimations of primary channel Markov model parameters

The classical algorithm used to estimate the Markov model parameters was provided in [20], which deals with the case of fixed number of observations, but not the case when the number of observations increases with time as in our problem. This classical algorithm has a linear computational complexity in $M \times T$, i.e. the product of the number of channels and the time length. This leads to a high computational complexity as T increases, since all the variables have to be re-initialized and flushed every time for new observations. As a result, in this section, we propose an algorithm to estimate the primary channel Markov model dynamically as time evolves, with a linear computational complexity only in M.

We firstly familiarize the readers with the following concepts introduced in [20]. We denote $\hat{\mathbf{P}}(m,t) = \begin{pmatrix} \hat{p}_{00}(m,t) & \hat{p}_{01}(m,t) \\ \hat{p}_{10}(m,t) & \hat{p}_{11}(m,t) \end{pmatrix}$ as the estimated Markov model transition matrix of the m-th primary channel at time t. The estimated stationary state distribution vector is denoted by $\hat{\pi}(m,t) = [\hat{\pi}_0(m,t)\, \hat{\pi}_1(m,t)]^T$ with $\hat{\pi}(m,t) = \hat{\mathbf{P}}(m,t)\hat{\pi}(m,t)$. For convenience, we use the compact notation $\hat{\lambda}(m,t) = (\hat{\mathbf{P}}(m,t), \hat{\pi}(m,t))$ to indicate the estimated parameter set. We denote $p_{m,n}(j,i,k) = \Pr\{y_{m,n}(k) = j | S_m(k) = i\}, \forall i,j \in \{0,1\}$ as the n-th SU observation symbol probability distributions of the m-th channel at time k. Note that $p_{m,n}(j,i,k) = \lambda^i_{m,n}(k)$, $\forall j \neq i$. At each time t, for the m-th channel, consider the forward variable $\alpha_{m,i}(k,t)$ and the backward variable $\beta_{m,i}(k,t)$ defined as

$$\begin{aligned} \alpha_{m,i}(k,t) &= \Pr\{\mathbf{y}_{0:k}(m,:), S_m(k) = i \mid \hat{\lambda}(m,t-1)\}, \\ &\qquad \forall k \in \{1,\cdots,t\}, \qquad (18) \\ \beta_{m,i}(k,t) &= \Pr\{\mathbf{y}_{k+1:t}(m,:) \mid S_m(k) = i, \hat{\lambda}(m,t-1)\}, \\ &\qquad \forall k \in \{1,\cdots,t-1\}. \qquad (19) \end{aligned}$$

The forward variable $\alpha_{m,i}(k,t), \forall\, m \in \{1,...,M\}$ is evaluated inductively, as follows [20]: 1) Initialization: $\alpha_{m,i}(0,t) = \hat{\pi}_i(t-1)p_m(\mathbf{y}_0(m,:),i,0), \forall i \in \{0,1\}$; 2) Induction:

$$\begin{aligned} &\alpha_{m,j}(k,t) \\ &= \left[\sum_{i\in\{0,1\}} \alpha_{m,i}(k-1,t)\hat{p}_{ij}(m,t-1)\right] p_m(\mathbf{y}_k(m,:),j,k), \\ &\qquad \forall k \in \{1,\cdots,t\},\ j \in \{0,1\}, \qquad (20) \end{aligned}$$

where $p_m(\mathbf{y}_k(m,:),j,k)$ is defined as $p_m(\mathbf{y}_k(m,:),j,k) = \Pr\{\mathbf{y}_k(m,:) \mid S_m(k) = j\}$. The backward variable $\beta_{m,i}(k,t)$,$\forall\, m \in \{1,...,M\}$ is also evaluated inductively, as follows [20]: 1) Initialization: $\beta_{m,i}(t,t) = 1$; 2) Induction: $\beta_{m,i}(k,t) = \sum_{j\in\{0,1\}} \hat{p}_{ij}(m,t-1)p_m(\mathbf{y}_{k+1}(m,:),j,k+1)\beta_{m,j}(k+1,t)$, $\forall k \in \{1,\cdots,t-1\}$, $i \in \{0,1\}$.

After the SSDC gets the observation $\mathbf{y}_t(m,:)$ of channel m at time $t \geq 1$, we define $\xi_{m,i,j}(k,t)$, $\forall k \in \{0,...,t-1\}$ as the probability of channel m being in state i at time k, and in state j at time $k+1$ given the estimated model $\hat{\lambda}(m,t-1)$ and the observation sequence $\mathbf{y}_{0:t}(m,:)$, i.e.: $\xi_{m,i,j}(k,t) = \Pr\{S_m(k) = i, S_m(k+1) = j \mid \mathbf{y}_{0:t}(m,:), \hat{\lambda}(m,t-1)\}$. Thus, $\xi_{m,i,j}(k,t) = \frac{\alpha_{m,i}(k,t)\hat{p}_{ij}(t-1)p_m(\mathbf{y}_{k+1}(m,:),j,k+1)\beta_{m,j}(k+1,t)}{\Pr\{\mathbf{y}_{0:t}(m,:)|\hat{\lambda}(m,t-1)\}}$, where $\Pr\{\mathbf{y}_{0:t}(m,:) \mid \hat{\lambda}(m,t-1)\}$ is given in (21). The summation of $\xi_{m,i,j}(k,t)$ over k can be interpreted as an estimate (at time t) of the expected number of transitions from state i to state j: $\sum_{k=0}^{t-1}\xi_{m,i,j}(k,t) = \mathbb{E}\{\text{number of transitions from } i \text{ to } j\}$. Let $\gamma_{m,i}(k,t)$ denote the probability of channel in state i at time k given the model $\hat{\lambda}(m,t-1)$ and the observation sequence $\mathbf{y}_{0:t}(m,:)$, for $k \in \{0,...,t-1\}$: $\gamma_{m,i}(k,t) = \Pr\{S_m(k) = i \mid \mathbf{y}_{0:t}(m,:), \hat{\lambda}(m,t-1)\} = \frac{\alpha_{m,i}(k,t)\beta_{m,i}(k,t)}{\sum_{i\in\{0,1\}}\alpha_{m,i}(k,t)\beta_{m,i}(k,t)}$. The summation of $\gamma_{m,i}(k,t)$ over $k \in \{0,...,t-1\}$ can be interpreted as an estimate (at time t) of the expected number of times that state i was visited, or equivalently, the expected number of transitions made from state i, so that $\sum_{k=0}^{t-1}\gamma_{m,i}(k,t) = \mathbb{E}\{\text{number of transitions from } i\}$. Thus, a set of re-estimated transition probabilities $\hat{p}_{ij}(m,t) = \frac{\sum_{k=0}^{t-1}\xi_{m,i,j}(k,t)}{\sum_{k=0}^{t-1}\gamma_{m,i}(k,t)}, \forall i,j$ and the stationary state distribution vector $\hat{\pi}(m,t)$ are obtained, resulting in the new parameter set $\hat{\lambda}(m,t) = (\hat{\mathbf{P}}(m,t), \hat{\pi}(m,t))$. For each time t, it has been proven in [21], [22] that either 1) the model $\hat{\lambda}(m,t-1)$ defines a critical point of the likelihood function, in which case $\hat{\lambda}(m,t) = \hat{\lambda}(m,t-1)$; or 2) model $\hat{\lambda}(m,t)$ is more likely than model $\hat{\lambda}(m,t-1)$ in the sense that $\Pr\{\mathbf{y}_{0:t}(m,:) \mid \hat{\lambda}(m,t)\} > \Pr\{\mathbf{y}_{0:t}(m,:) \mid \hat{\lambda}(m,t-1)\}$. Thus, at every time step t, if we iteratively use $\hat{\lambda}(m,t)$ in place of $\hat{\lambda}(m,t-1)$ and repeat the estimation process, then we improve the probability of $\mathbf{y}_{0:t}(m,:)$ being observed from the model until a limiting point is reached [20]. Due to the high complexity of the method (linear in $M \times T$), we propose Algorithm 3 that has a linear complexity only in M. Algorithm 3 drops the backward variable and does not re-initialize $\alpha_{m,i}(0,t)$ at each time $t > 0$ and use $\alpha_{m,i}(t-1,t) = \alpha_{m,i}(t-1,t-1)$ for further induction of the forward variable. The variables $\xi_{m,i,j}$ and $\gamma_{m,i}$ are then computed only for the pair $(t-1,t)$ at each time t. Then the updated estimation $\hat{\lambda}(m,t) = (\hat{\mathbf{P}}(m,t), \hat{\pi}(m,t))$ is obtained as shown in Algorithm 3. The performance of this algorithm is simulated in Section V.

Algorithm 3 Estimation of primary channel Markov model

Initialization: Pick $\hat{\lambda}(m,0)$ **randomly** $\forall m = \{1,\cdots,M\}$**, compute** $\alpha_{m,i}(0,0)$ **with** $\hat{\pi}(m,0)$**.**
while $t \geq 1$ **do**
  for $m = 1:M$ **do**
    $\alpha_{m,i}(t-1,t) \leftarrow \alpha_{m,i}(t-1,t-1), \forall i \in \{0,1\}$
    $\alpha_{m,j}(t,t) \leftarrow \left[\sum_{i\in\{0,1\}}\alpha_{m,i}(t-1,t)\hat{p}_{ij}(m,t-1)\right] \times p_m(\mathbf{y}_t(m,:),j,t), \forall j \in \{0,1\}$
    Compute $\xi_{m,i,j}(t-1,t) = \frac{\alpha_{m,i}(t-1,t)\hat{p}_{ij}(m,t-1)p_m(\mathbf{y}_t(m,:),j,t)}{\Pr\{\mathbf{y}_{0:t}(m,:)|\hat{\lambda}(m,t-1)\}}, \forall i,j \in \{0,1\}$
    Compute $\gamma_{m,i}(t-1,t) = \frac{\alpha_{m,i}(t-1,t)}{\sum_{i\in\{0,1\}}\alpha_{m,i}(t-1,t)}, \forall i \in \{0,1\}$
    Update $\hat{\lambda}(m,t) = (\hat{\mathbf{P}}(m,t), \hat{\pi}(m,t))$ with $\hat{p}_{ij}(m,t) = \frac{\sum_{k=1}^{t}\xi_{m,i,j}(k-1,k)}{\sum_{k=1}^{t}\gamma_{m,i}(k-1,k)}, \forall i,j \in \{0,1\}$
  end for
end while

V. Simulation Results and Discussions

In this section, we first show the performance of our proposed sensing/access strategies including comparison to those

$$\Pr\{\mathbf{y}_{0:t}(m,:) \mid \hat{\lambda}(m,t-1)\} = \sum_{i\in\{0,1\}} \sum_{j\in\{0,1\}} \alpha_{m,i}(k,t)\hat{p}_{ij}(t-1)p_m(\mathbf{y}_{k+1}(m,:),j,k+1)\beta_{m,j}(k+1,t). \tag{21}$$

proposed in [8]: in each time slot, all SU's sense the *single* primary channel with the highest belief of being *idle*. Next, we show the performance of the primary channel Markov model parameter estimation when they are assumed unknown.

A. Performance of the proposed myopic spectrum sensing

In order to directly compare the performance of our proposed myopic sensing solution with the results of [8], we first simulate the discounted secondary system reward under the same assumptions as in [8]: 1) perfect knowledge about the primary signaling; 2) the SNR at the n-th SU when sensing the m-th channel at each time k: $SNR = \frac{1}{\sigma_w^2}$; 3) the discount factor is 0.999 for time horizon from 0 to 10000; 4) the SU's sensing reports to the SSDC are directly the observations $r_{m,n}(k)$'s (i.e. no quantizations at local nodes); 5) all channel coefficients $h_{m,n}(k)$'s are set to 1's for all time (i.e. no fading); 6) unit bandwidth for all primary channels; 7) allowed probability of collisions with PU's is $\zeta = 0.1$; and 8) primary channels have i.i.d. Markovian evolutions with the transition matrix: $\mathbf{P} = \begin{pmatrix} 0.9 & 0.1 \\ 0.8 & 0.2 \end{pmatrix}$. In Fig. 5, we show the discounted reward in two cases: 1) 2 primary channels and 1 SU; 2) 2 primary channels and 2 SU's. The performance of the approach in [8] is exactly regenerated in this figure (2 primary channels, 1 SU). When there is only a single SU, the two competing strategies are equivalent and have the same results. However, when there are 2 SU's (the rest of the assumptions staying the same), we see that our proposed approach leads to a higher discounted reward. This is because when all SU's are allocated to sense a single channel, as suggested in [8], SU's lose access opportunities on the other channel.

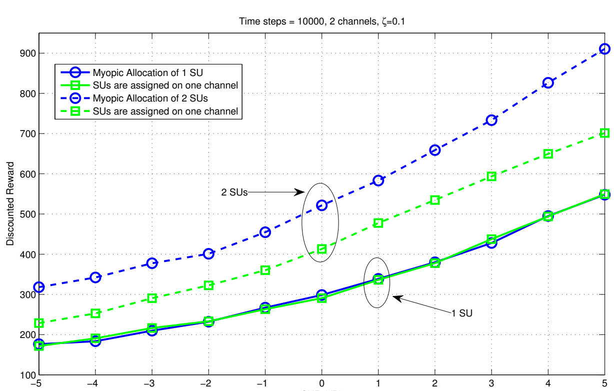


Fig. 5: Discounted reward comparison between our proposed method and the method proposed by [8]

Next, we compare the resulting *percentage of primary channel usage* of our proposed sensing/access strategy to the one proposed in [8]. We define the *percentage of primary channel usage* as:

$$U = \frac{\sum_{m=1}^{M}\sum_{k=1}^{T}(1-\hat{s}_m(k))(1-S_m(k))}{\sum_{m=1}^{M}\sum_{k=1}^{T}(1-S_m(k))}\,, \tag{22}$$

where T is the simulation time. The primary SNR at the n-th SU when sensing the m-th channel is: $SNR = \frac{\sigma_x^2}{\sigma_w^2}$ for the energy detection case, and $SNR = \frac{\pi_1\pi_0}{\sigma_w^2}$ matched filter detection case. Other assumptions are: 1) no discount factor (i.e. $\gamma = 1$); 2) channel coefficients are standard Gaussian distributed: $h_{m,n}(k) \sim \mathcal{N}(0,1)$ and known at each time; 3) unit bandwidth for all primary channels; 4) allowed probability of collisions with PU's is $\zeta = 0.1$; and 5) the primary channels have the same Markov model: $\mathbf{P} = \begin{pmatrix} 0.9 & 0.1 \\ 0.8 & 0.2 \end{pmatrix}$. Fig. 6 shows the *percentage of primary channel usage* for both cases: 1) Energy-detector based sensing; 2) matched-filter based sensing. As expected, when perfect knowledge about the primary signaling is assumed, higher *percentage of primary channel usage* is achieved. We also see that, under both cases, our proposed myopic channel sensing strategy outperforms the strategy of [8]. In the case of perfect knowledge about the primary signaling, the two resulting *percentage of primary channel usage* deviate significantly after -5 dB. Again, this is because the strategy used in [8] constraints all the SU's on a *single* primary channel with the highest believe of being *idle* to sense and access at each time. As the received primary SNR becomes higher, fewer SU's on a single primary channel are needed to achieve an "accurate enough" estimation of the state of that primary channel. As a result, if all the SU's are allocated to a single primary channel at each time, the opportunities on the other channel are lost entirely. When a sufficient number of SU's are available, the more opportunities are lost using the strategy in [8]. In the case of no prior knowledge about the primary signaling, similar performance results are observed for higher primary SNR regions. From Fig. 6, we can also see that the the sub-optimal algorithms (iterative Hungarian algorithm with polynomial complexity and the heuristic algorithm with linear complexity) give sub-optimal (very close to the optimal myopic solution) performance at much lower computational complexities. Similar results for the case of 10 channels and 10 SU's are obtained and shown in Fig. 7.

To address the problem of the performance gap of the optimal myopic sensing solution and the optimal solution to the POMDP, an upperbound is obtained by assuming that SU's perform the proposed optimal myopic sensing, but after obtaining the sensing and access decisions in the current time slot, the current true states of all the channels are revealed to the secondary system in order to obtain the most accurate belief update for next time slot, and this procedure repeats. Note that the true state information in any time slot is not used to make the sensing and assess decision in that time slot, but only for the purpose of belief update for the next time slot. This process yields an upperbound for the optimal POMDP

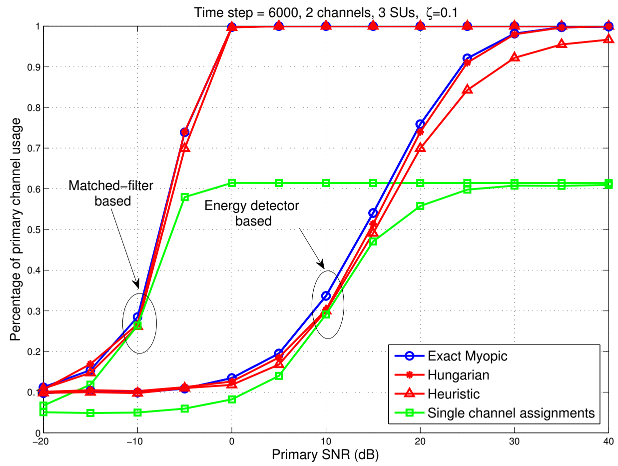


Fig. 6: Comparisons of percentage of primary channel usage with 2 primary channels and 3 SU's.

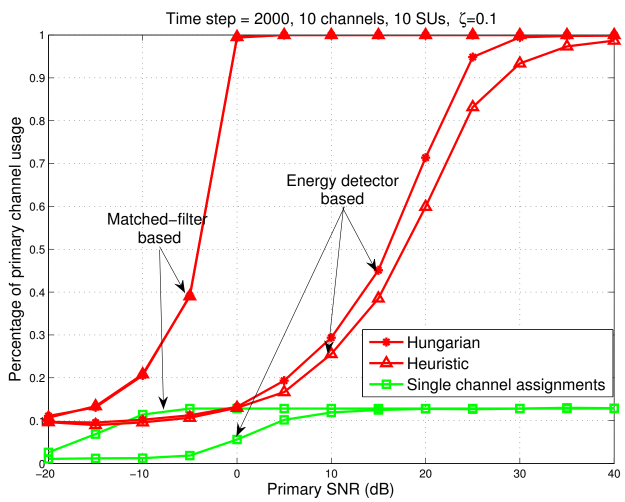


Fig. 7: Comparisons of percentage of primary channel usage with 10 primary channels and 10 SU's.

solution because the optimal myopic policy guarantees the maximum possible reward in each current time slot given the information obtained from the past, whereas revealing the current true states of all channels gives the most accurate belief update, such that no other sensing policy gives better performance than this combined procedure. Fig. 8 and 9 show the performance comparison between the optimal myopic solution and the obtained upperbound (both using the energy based detection): 1) in the first simulation set, as shown in Fig. 8, we set $p_{00} = 0.1$, $p_{01} = 0.9$, $p_{10} = 0.2$, $p_{11} = 0.8$ and simulated 4 channels with 1, 2, 3, and 4 SU's respectively. We see that the performance gap is quite tight. We also plotted the ratio of the myopic performance to the upper bound, which increases with SNR and is bounded below by roughly 0.88; 2) in the second simulation set, as shown in Fig. 9, we set $p_{00} = 0.9$, $p_{01} = 0.1$, $p_{10} = 0.02$, $p_{11} = 0.98$, and the gap is larger compared to the first simulation set, this is due to the *extreme* choices of the state transition probabilities. Note that

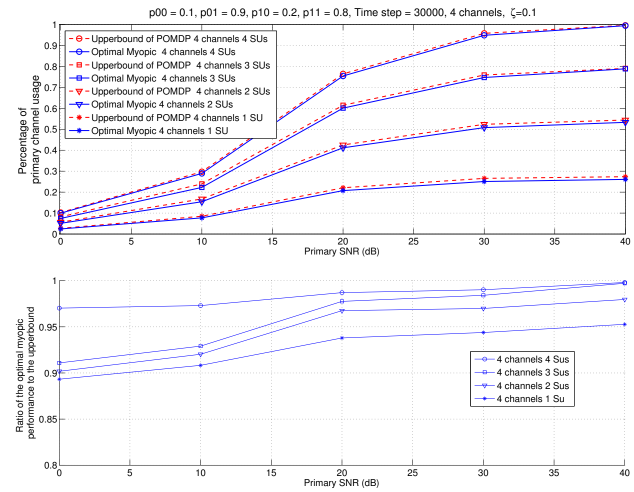


Fig. 8: Comparisons of performance gap between the proposed optimal myopic sensing policy and the upperbound of the optimal POMDP sensing policy, for the case of the following transition probabilities: $p_{00} = 0.1$, $p_{01} = 0.9$, $p_{10} = 0.2$, and $p_{11} = 0.8$. To illustrate clearly in the plot, this simulation is based on the energy based detection. Other sensing techniques give similar results.

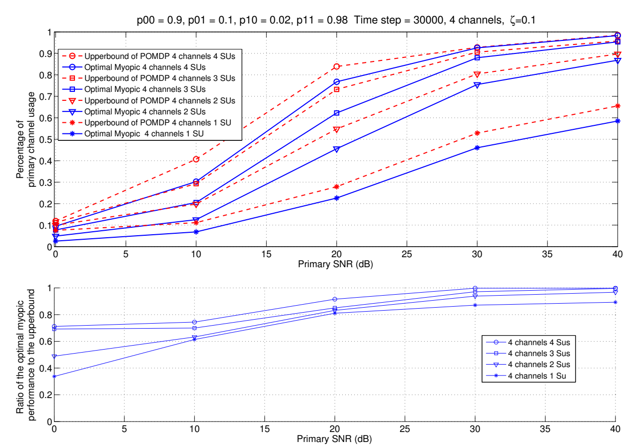


Fig. 9: Comparisons of performance gap between the proposed optimal myopic sensing policy and the upperbound of the optimal POMDP sensing policy, for the case of the following transition probabilities: $p_{00} = 0.9$, $p_{01} = 0.1$, $p_{10} = 0.02$, and $p_{11} = 0.98$. To illustrate clearly in the plot, this simulation is based on the enregy based detection. Other sensing techniques give similar results.

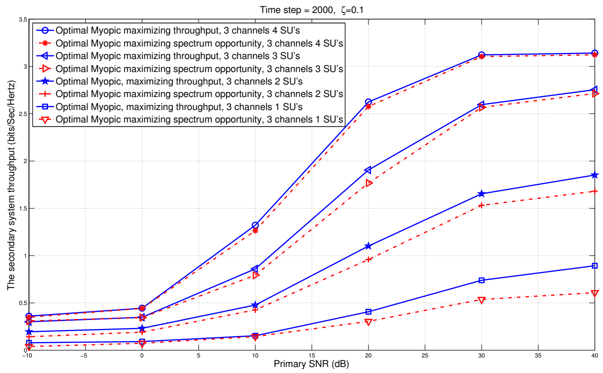


Fig. 10: Acheived secondary system throughput comparison of the energy based detector at the SSDC with two different objective functions: 1) maximizing the secondary sysstem throughput jointly with sensing decision and the access assigning decision, assuming the channel coefficients of the secondary sender-receiver channels are known at the SSDC; 2) maximizing the spectrum opportunities without considering the access assigning decision-making.

the transition probabilities indicate that it is highly probable that channel will stay in either idle or busy for a long period of time and it is not likely to change either from busy to idle or from idle to busy, such that the assumption on the true state revealing at the end of each time slot is significantly more critical than the previous case. Due to this reason, we observe a larger performance gap. We also plotted the ratio of the myopic performance to the uppderbound and found out that the ratio behaves similarly to the previous case and is bounded below by roughly 0.35. Although the performance gap is large at the low SNR when there are only few SUs, we can see that the ratio increases as the number of SU's increases. When there are 4 SU's, the ratio is bounded from below by roughly 0.7. In practical cases, the number of SU's is usually much larger than the number of primary channels, as a result, we conclude that the myopic solution is not far from the upperbound. These results suggest that the proposed optimal myopic solution and its sub-optimal algorithms are practical and efficient.

Fig. 10 justifies the simplification of the objective function in (16) to the one in (17). The secondary system throughput obtained from the objective function in (16) provides only a marginal performance improvement and as the number of SU's increases, the performance gap becomes negligible. Note that practice, the number of SU's is indeed likely to be larger than the number of primary channels which may justify the use of the objective function provided in (17).

B. Estimation of primary channel Markov model parameters

As shown in Fig. 11, we performed Algorithm 3 for the case of one primary channel, one SU and compared it to the algorithm presented in [20] which we denote as method I. We denote Algorithm 3 as method II. In this simulation we assumed the following: 1) the crossover probabilities of the observation BAC channel are: $\lambda_{1,1}^1(k) = \lambda_{1,1}^0(k) = 0.1$; 2) the true values of the channel state transition probabilities are: $p_{00} = 0.9$, $p_{01} = 0.1$, $p_{10} = 0.2$, $p_{11} = 0.8$. From Fig. 11 we see that there is no significant difference between the convergence times of these two methods (method I gives comparatively smoother convergence performance though). Also, both methods converge very close to the correct true values but Method II has a linear complexity only with M (method I has a linear complexity with $M \times T$).

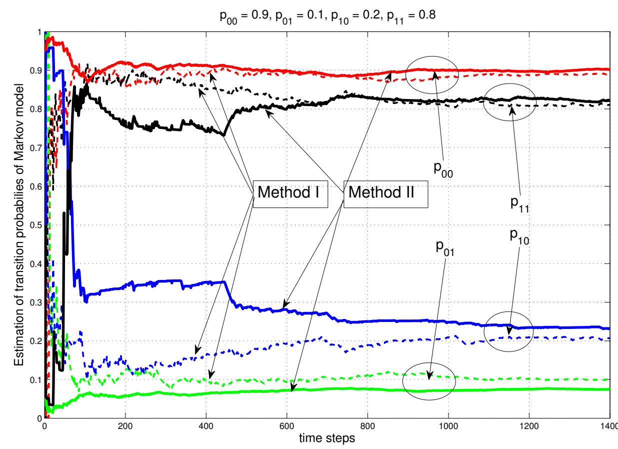


Fig. 11: Estimations of channel Markov model state transition probabilities (Methods I and II).

VI. Conclusions

In this paper, we proposed a *universal myopic* channel sensing and access policy for a centralized CR communication system in which the channel sensing and access decisions are made at a central unit. By using the word *universal*, we mean that our proposed myopic policy is applicable to any number of primary channels, any number of SU's, and any primary channel Markov model parameters, such as the state transition probabilities and stationary distributions. Unlike other existing approaches proposed in literature, our universal *myopic* channel sensing policy is more realistic because our policy explicitly assigns SU's to sense specific primary channels by taking into account the spatial and temporal variations of channel fading coefficients on different primary channels. As alternatives to the high complexity *optimal myopic* channel sensing policy, we proposed two algorithms to obtain sub-optimal policies with low complexities: The first is based on the iterative Hungarian algorithm and it has fourth-order complexity while the second algorithm is based on a heuristic method with a linear complexity. The simulation results showed that the two proposed low-complexity algorithms achieve performance very close to the optimal myopic solution, but with much smaller computational efforts. We also showed that under realistic conditions our approach outperforms previously proposed approaches. To support our *myopic* sensing policy, we also proposed an effective algorithm with linear complexity to estimate unknown channel Markov model.

REFERENCES

[1] "Report of the spectrum efficiency working group." FCC, Tech. Rep., Nov. 2002.

[2] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications," *IEEE Communications Surveys Tutorials*, vol. 11, no. 1, pp. 116 –130, Mar. 2009.

[3] E. N. Gilbert, "Capacity of a burst-noise channel," *Bell System Technical Journal*, vol. 39, pp. 1253–1265, sep 1960.

[4] S. Ahmad, M. Liu, T. Javidi, Q. Zhao, and B. Krishnamachari, "Optimality of Myopic Sensing in Multichannel Opportunistic Access," *Information Theory, IEEE Transactions on*, vol. 55, no. 9, pp. 4040 –4050, sept. 2009.

[5] Q. Zhao, B. Krishnamachari, and K. Liu, "On myopic sensing for multi-channel opportunistic access: Structure, optimality, and performance," *IEEE Transactions on Wireless Communications*, vol. 7, no. 12, pp. 5431 –5440, Dec. 2008.

[6] S. Ahmad and M. Liu, "Multi-channel opportunistic access: A case of restless bandits with multiple plays," in *Communication, Control, and Computing, 2009. Allerton 2009. 47th Annual Allerton Conference on*, 30 2009-oct. 2 2009, pp. 1361 –1368.

[7] K. Liu, Q. Zhao, and B. Krishnamachari, "Dynamic multichannel access with imperfect channel state detection," *Signal Processing, IEEE Transactions on*, vol. 58, no. 5, pp. 2795 –2808, may 2010.

[8] J. Unnikrishnan and V. Veeravalli, "Algorithms for dynamic spectrum access with learning for cognitive radio," *IEEE Transactions on Signal Processing*, vol. 58, no. 2, pp. 750 –760, Feb. 2010.

[9] Y. Chen, Q. Zhao, and A. Swami, "Joint design and separation principle for opportunistic spectrum access in the presence of sensing errors," *IEEE Transactions on Information Theory*, vol. 54, no. 5, pp. 2053 –2071, May 2008.

[10] Q. Zhao, L. Tong, A. Swami, and Y. Chen, "Decentralized cognitive mac for opportunistic spectrum access in ad hoc networks: A pomdp framework," *IEEE Journal on Selected Areas in Communications*, vol. 25, no. 3, pp. 589 –600, Apr. 2007.

[11] K. Liu, Q. Zhao, and B. Krishnamachari, "Distributed learning under imperfect sensing in cognitive radio networks," in *Signals, Systems and Computers (ASILOMAR), 2010 Conference Record of the Forty Fourth Asilomar Conference on*, nov. 2010, pp. 671 –675.

[12] H. W. Kuhn, "The Hungarian method for the assignment problem," *Naval Research Logistics Quarterly*, vol. 2, pp. 83–97, Mar. 1955.

[13] Z. Lu, Y. Ma, and R. Tafazolli, "A first-order cyclostationarity based energy detection approach for non-cooperative spectrum sensing," in *Personal Indoor and Mobile Radio Communications (PIMRC), 2010 IEEE 21st International Symposium on*, sept. 2010, pp. 554 –559.

[14] "IEEE Standard for Information Technology–Telecommunications and information exchange between systems Wireless Regional Area Networks (WRAN)–Specific requirements Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Policies and Procedures for Operation in the TV Bands," *IEEE Std 802.22-2011*, pp. 1 –680, 1 2011.

[15] H. V. Poor, *An Introduction to Signal Detection and Estimation*, 2nd ed. New York, NY, USA: Springer-Verlag, 1994.

[16] A. Sahai, N. Hoven, and R. Tandra, "Some Fundamental Limits on Cognitive Radio," in *in Forty-second Allerton Conference on Communication, Control, and Computing*, 2004.

[17] M. Bkassiny and S. K. Jayaweera, "Optimal channel and power allocation for secondary users in cooperative cognitive radio networks," in *Special Session on Advanced Radio Access Techniques for Energy-Efficient Communications in 2nd International Conference on Mobile Lightweight Wireless Systems*, Barcelona, Spain, May 2010.

[18] R. D. Smallwood and E. J. Sondik, "The optimal control of partially observable Markov processes over a finite horizon," *Operations Research*, vol. 21, no. 5, pp. 1071 –1088, Sept.-Oct. 1973.

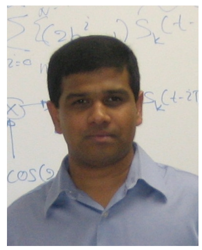
[19] D. Li and X. Sun, *Nonlinear Integer Programming*, 1st ed. Springer, 2010.

[20] L. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257 –286, feb 1989.

[21] J. Baker, "The dragon system–an overview," *Acoustics, Speech and Signal Processing, IEEE Transactions on*, vol. 23, no. 1, pp. 24 – 29, Feb 1975.

[22] L. E. Baum and G. R. Sell, "Growth functions for transformations on manifolds," *Pac. J. Math.*, vol. 23, no. 2, pp. 211 – 227, 1968.

Yang Li received the B.E. degree in Electrical Engineering from the Beijing University of Aeronautics and Astronautics, Beijing, China, in 2005 and the M.S. degree in Electrical Engineering from New Mexico Institute of Mining and Technology, Socorro, New Mexico, USA in 2009. He is currently working towards the PhD degree in Electrical Engineering at the Communication and Information Sciences Laboratory (CISL), Department of Electrical and Computer Engineering at the University of New Mexico, Albuquerque, NM, USA. His current research interests are in cognitive radios, spectrum sensing, cooperative communications, and dynamic spectrum access.



Sudharman K. Jayaweera (S'00, M'04, SM'09) received the B.E. degree in Electrical and Electronic Engineering with First Class Honors from the University of Melbourne, Australia, in 1997 and M.A. and PhD degrees in Electrical Engineering from Princeton University in 2001 and 2003, respectively. He is currently an assistant Professor in Electrical Engineering at the Department of Electrical and Computer Engineering at University of New Mexico, Albuquerque, NM. From 2003-2006 he was an assistant Professor in Electrical Engineering at the Department of Electrical and Computer Engineering at Wichita State University. Dr. Jayaweera is currently an associate editor of EURASIP Journal on Advances in Signal Processing. His current research interests include cooperative and cognitive communications, information theory of networked-control systems, statistical signal processing and wireless sensor networks.

Mario Bkassiny (S'06) received the B.E. degree in Electrical Engineering and the M.S. degree in Computer Engineering both from the Lebanese American University, Lebanon, in 2008 and 2009, respectively. He is currently working towards the PhD degree in Electrical Engineering at the Communication and Information Sciences Laboratory (CISL), Department of Electrical and Computer Engineering at the University of New Mexico, Albuquerque, NM, USA. His current research interests are in cognitive radios, distributed learning and reasoning, cooperative communications, dynamic spectrum leasing and game theory.

Keith A. Avery is the Program Lead for the Integrated Microsystems program at the Air Force Research Laboratory focusing on advanced packaging and optoelectronics for space. He received his BS degree from DeVry Institute of Technology in 1983. For the first 12 years of his career he worked in the commercial sector designing digital and analog circuits for commercial, industrial, and telephony applications. Prior to joining AFRL he worked as a government contractor performing design activities for space experiments, advanced packaging techniques, and radiation effects on micro-electronics. During his career he has increased his level of responsibility for design activities and program management. He has authored or co-authored numerous papers on designs for space and radiation effects. Mr. Avery is a member of IEEE/NPSS and AIAA.