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On the impact of primary traffic correlation in TV White Space☆

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ABSTRACT

In TV White Space, a secondary user must access periodically to a geolocated database to acquire the spectrum availability information. Furthermore, it can access on-demand to the database to update such an information. The more frequent are the on-demand accesses, the higher are the communication opportunities available to the secondary user but the higher is the induced overhead. Hence, in this manuscript, the on-demand access is investigated to a-priori determine whenever it is advantageous to perform it by accounting for the correlation exhibited by primary traffic patterns. To this aim, first the on-demand access is modeled through the general notions of reward and cost. Then, it is proved that the on-demand access maximizing the total reward available to the secondary user is a Markov Decision Process. Stemming from these results, a computational-efficient algorithm is designed. Finally, the theoretical analysis is validated through numerical simulations.

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1. Introduction

Nowadays, regulators worldwide are beginning to allow unlicensed access to unused segments of TV spectrum, known as TV White Space (TVWS) [1]. Secondary users (SUs) can access to the TVWS only if harmful interference on the primary users (PUs) is avoided. To this aim, the general consensus among FCC, Ofcom and ECC is on obviating the spectrum sensing [2–4] as the mechanism for the SUs to recognize and exploit portions of the TVWS spectrum whenever they are vacated by the licensed users. Instead, they require the SUs to periodically access to a geolocated database service [5–7], known as White Space DataBase (WSDB). Specifically, any SU must acquire the spectrum availability by accessing to a WSDB with a fixed timeframe. Within such a timeframe, the SU can freely access to the WSDB on-demand to update the spectrum availability information, but the specifics of the on-demand access are not detailed by the standards. The choice of whether or not to update the spectrum availability information through the on-demand access affects the overall performance of any secondary network. In fact, whenever the SU accesses to the WSDB, it can acquire some new knowledge on the current PU activities over the different channels. Hence, the more frequent are the on-demand accesses, the better the SU can exploit such availabilities to increase its communication opportunities. On the other hand, the more frequent are the on-demand accesses, the higher is the induced overhead.

Despite its importance, the on-demand database access issue in TVWS is still largely unexplored, since current research focuses on security issues [8], spectrum leasing [9], local sensing [10], or video streaming [11]. In [12] some preliminary results are obtained by assuming the PU traffic modeled as a Bernoulli process. Such an assumption is simplistic in TV scenarios, since the TV signal patterns are correlated [13,14], as confirmed by Fig. 1 reporting the PU

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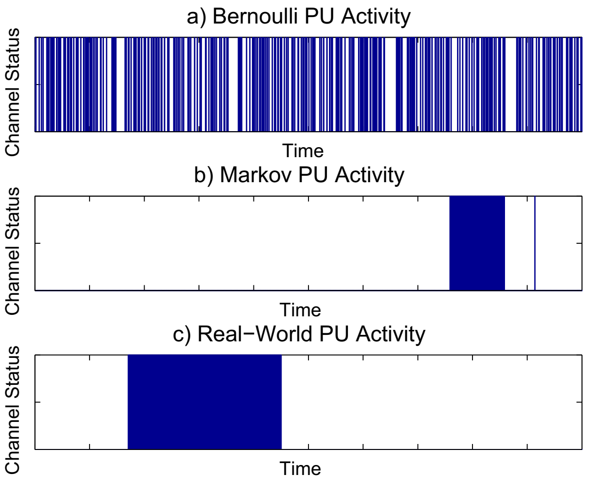

Fig. 1. PU activity pattern over 24 hours: (a) modeled as a Bernoulli process with parameter p modeling the PU on probability equal to 0.3; (b) modeled as a two-state Markov process with stationary distribution p modeling the PU on probability equal to 0.3; (c) measured in real world experiment [14]: channel 27, Zhongshan, Monday, Dataset 1.

activity experimentally measured [14] over a time interval equal to the timeframe between two mandatory database accesses as specified by FCC rulings [5], i.e., 24 h.

Hence, in the following, we investigate the on-demand database access by modeling the correlation among the PU traffic patterns through a two-state Markov process. As shown in Fig. 1, such a model is able to effectively describe the typical TVWS traffic patterns by properly setting the transition probabilities according to experimental measurements [14]. Specifically, the objective of this work is to determine *whenever it is convenient for an SU to access to the WSDB on-demand* in presence of correlated PU activity. This problem is not trivial, since the PU traffic correlation greatly complicates any theoretical analysis. Through the manuscript, we first model the WSDB accesses through the general notions of reward and cost. Then, by modeling the correlation among the PU traffic activities through a Markov process, we prove that the choice of the on-demand access maximizing the total reward available to the SU can be formulated as a Markov Decision Process. Furthermore, closed-form expressions for the decision transition probabilities are derived. Stemming from these results, we design a computational-efficient algorithm allowing any SU to a-priori establish whenever an on-demand access should be performed. Finally, we validate the analysis through numerical simulations.

To the best of our knowledge, this is the first work investigating the on-demand database access for TVWSs in presence of correlation among the PU traffic patterns.

The rest of the paper is organized as follows. In Section 2, we describe the network model along with some preliminaries. In Section 3, we design the optimal strategy, whereas in Section 4 we validate the analytical framework through numerical simulations. Finally, in Section 5, we conclude the paper.

2. Network model and preliminaries

In this section, we first describe the system model, and then we collect several definitions that will be used through the paper.

We consider a secondary network operating within the TVWS spectrum according to current regulations [5–7] and standards [15]. The SU time is organized into[1] L slots of duration T, with KT denoting the duration of a *database access period*. The database access period represents the time interval between two mandatory database accesses, i.e., K denotes the maximum number of consecutive time slots of duration T during which an SU is authorized to use the available TVWS spectrum without querying the database. Within a database access period KT, the SU can access on-demand to the WSDB for updating the spectrum availability information, which consists of a list of available channels and, for each channel, the duration of each authorization.

The spectrum is organized in M distinct channels, denoted with the set $\Omega = \{1, 2, \dots, M\}$. The PU activity within channel $i \in \Omega$ during an arbitrary time slot is modeled as a two-state Markov process, and hence the activities in subsequent time slots are correlated each other. In the arbitrary nth time slot, the ith channel is available with probability $p_i \triangleq P(S_i(n) = 1)$ where $S_i(n)$ denotes the status of the ith channel, whereas the ith channel is unavailable with probability $q_i \triangleq P(S_i(n) = 0) = 1 - p_i$. By denoting with $p_i(0|1) \triangleq P(S_i(n+1) = 0|S_i(n) = 1)$, $p_i(1|1) = 1 - p_i(0|1)$, $p_i(0|0) \triangleq P(S_i(n+1) = 0|S_i(n) = 0)$ and $p_i(1|0) = 1 - p_i(0|0)$ the transition probabilities,[2] and by accounting for the Markov chain property, the following relations hold: $q_i = p_i(0|1)/(p_i(0|1) + p_i(1|0))$, $p_i = p_i(1|0)/(p_i(0|1) + p_i(1|0))$. Furthermore, $\{N_i(n) = x_i(n)\}$ denotes the availability of the ith channel for $x_i(n)$ consecutive time slots starting from time slot n.

Definition 1 (Reward and cost)**.** The non-negative *channel reward*[3] r_i represents the quality of the ith channel. The non-negative *database access cost* c represents the overall overhead associated with a database access.

Remark. We note that the notions of reward and cost given above can model a variety of real-world scenarios, given that the two notions are commensurable in terms of dimension(s). As instance, if the reward models the achievable average number of bits successfully transmitted through the channel during an arbitrary time slot, the cost should model the average number of bits exchanged during a database access.

Remark. In the following, we consider r_i and c as dimensionless quantities. In such a way, the proposed model achieves the following key features: (a) it abstracts the derived results from the particulars; (b) it restricts our attention on the effects of the database access strategy; (c) it can be

[1] Physically, the time horizon LT represents the time interval during which the SU plans to opportunistically use the TVWS spectrum.

[2] The SU can estimate the transition probabilities through the past PU activity histories [16,17].

[3] In the following, without loss of generality, we assume the channel set Ω ordered according to the channel rewards, i.e., $r_i \geq r_{i-1}$ $\forall i = 2, \dots, M$.

easily applied to a variety of real-world scenarios by choosing the proper reward and cost measures. As instance, the cost/reward measures could account for the computation overhead or the power consumption as well as the query fee required by the database owner.

Definition 2 (Availability vector)**.** By accessing to the WSDB at time slot n, the SU obtains the *availability vector* $\mathbf{x}(n)$:

$$\mathbf{x}(n) = (x_1(n), x_2(n), \dots, x_M(n)) \tag{1}$$

with the mth component $x_m(n) \in [0, K]$ denoting the availability of the mth channel for $x_m(n)$ consecutive time slots starting from time slot n, i.e., $\{N_i(n) = x_i(n)\}$.

From Definition 2, $x_i(n) > 0$ if and only if $S_i(n) = 1$. Hence, the availability vector encloses both the information of the channel status and the consequently channel availability.

Definition 3 (System state)**.** At the nth time slot, the *system state* is represented by the pair $\mathbf{s}_n = (\mathbf{x}(\tilde{n}), \tilde{n})_n$, with $\tilde{n}$ denoting the time slot of the last database access and $\mathbf{x}(\tilde{n})$ denoting the availability vector obtained at time slot $\tilde{n}$. $\mathcal{S} = \{0, 1, \dots, K\}^M \times \{\max(n-K, 1), \dots, n\}$ denotes the set of system states at time slot n.

Definition 4 (Allowed action set)**.** When the system state is $\mathbf{s}_n = (\mathbf{x}(\tilde{n}), \tilde{n})_n$ at time slot n, the SU may choose an action a from the set of allowed actions $A_{\mathbf{s}_n}$, where:

$$A_{\mathbf{s}_n} = \begin{cases} \{0, 1\} & \text{if } \tilde{n} + K > n \\ \{0\} & \text{otherwise} \end{cases} \tag{2}$$

with:

- action $a = 0$ denoting the event “the SU accesses to the WSDB in the current time slot”;
- action $a = 1$ denoting the event “the SU does not access to the WSDB in the current time slot”.

In the following, $A = \{0, 1\}$ denotes the set of actions.

Remark. Through $A_{\mathbf{s}_n}$, we are able to model the regulatory requirement of a mandatory database access every K slots. Specifically, the database access is discretionary, i.e., $A_{\mathbf{s}_n} = \{0, 1\}$, when the mandatory database access requirement is satisfied, i.e., $\tilde{n} + K \geq n$. Differently, the database access is mandatory, i.e., $A_{\mathbf{s}_n} = \{0\}$, when the mandatory database access requirement is not satisfied, i.e., $\tilde{n} + K < n$.

We note that multiple SUs can choose to concurrently use the same channel, reported as available from the database. Hence, a proper interference avoidance technique should be adopted [18–20].

Definition 5 (System history)**.** At the nth time slot, the *system history* is represented by the vector $\mathbf{h}_n = (\mathbf{s}_n, \mathbf{s}_{n-1}, \dots, \mathbf{s}_1) \triangleq (\mathbf{s}_n, \mathbf{h}_{n-1})$.

Definition 6 (State probability)**.** The state probability $p(\mathbf{s}_n) = P(\bigcap_{i=1}^{M} \{N_i(n) = x_i\})$ denotes the probability of system state being $\mathbf{s}_n = (\mathbf{x}(n), n)_n$ by accessing to the WSDB at time slot n.

Definition 7 (Transition probability)**.** The transition probability $p(\mathbf{s}_{n+1}|\mathbf{h}_n, a)$ denotes the probability of system state being $\mathbf{s}_{n+1} = (\mathbf{y}, l)_{n+1}$ at time slot $n+1$ given that the SU choose action $a \in A_{\mathbf{s}_n}$ when the system history was $\mathbf{h}_n = (\mathbf{s}_n, \mathbf{h}_{n-1})$ at time slot n:

$$p(\mathbf{s}_{n+1}|\mathbf{h}_n, a) = p(\mathbf{y}, l|((\mathbf{x}, \tilde{n})_n, \mathbf{h}_{n-1}), a). \tag{3}$$

Definition 8 (Reward)**.** The reward $r(\mathbf{s}_n)$ denotes the instantaneous reward obtained by the SU when the system state is $\mathbf{s}_n = (\mathbf{x}, \tilde{n})_n$ at time slot n:

$$r(\mathbf{s}_n) = \begin{cases} -c + r_{\omega(\mathbf{s}_n)} & \text{if } \tilde{n} = n \\ r_{\omega(\mathbf{s}_n)} & \text{if } \tilde{n} \leq n \end{cases} \tag{4}$$

where $\omega(\mathbf{s}_n)$ denotes the highest-reward channel known to be available at time slot n when the system state is $\mathbf{s}_n$, i.e.:

$$\omega(\mathbf{s}_n) \triangleq \max_{m \in \Omega}\{m : x_m > n - \tilde{n}\}. \tag{5}$$

Definition 9 (Strategy)**.** A strategy $\pi : \mathcal{S} \to A$ is a function that maps any state $\mathbf{s}_n$ over the set of allowed actions $A_{\mathbf{s}_n}$, i.e., $\pi(\mathbf{s}_n) \in A_{\mathbf{s}_n}\ \forall \mathbf{s}_n \in \mathcal{S}$. In the following, $\mathcal{P}$ denotes the set of all strategies.

Remark. Generally, a strategy should depend on the whole system history $\mathbf{h}_n$ rather than on the system state $\mathbf{s}_n$. Nevertheless, by embedding within the system state $\mathbf{s}_n$ the temporal information (i.e., the time period) of the last database access through $\tilde{n}$, we obtain that the set of allowed actions $A_{\mathbf{s}_n}$ depends only on the current system state $\mathbf{s}_n$ according to (2). Hence, $\pi(\mathbf{s}_n) = \pi(\mathbf{h}_n)$.

Definition 10 (Expected total reward)**.** The expected total reward v^π obtained by the SU following the strategy π is:

$$v^\pi = \sum_{\mathbf{s}_1 = (\mathbf{x}(1), 1)_1 \in \mathcal{S}} p(\mathbf{s}_1)[r(\mathbf{s}_1) + v^\pi(\mathbf{h}_1)] \tag{6}$$

where $v^\pi(\mathbf{h}_1)$ denotes the *expected remaining reward* obtained starting from the system history $\mathbf{h}_1$, recursively defined as:

$$v^\pi(\mathbf{h}_n) = \begin{cases} \sum_{\mathbf{s}_{n+1} \in \mathcal{S}} p(\mathbf{s}_{n+1}|\mathbf{h}_n, \pi(\mathbf{s}_n))[r(\mathbf{s}_{n+1}) + v^\pi(\mathbf{h}_{n+1})] & n < L-1 \\ \sum_{\mathbf{s}_{n+1} \in \mathcal{S}} p(\mathbf{s}_{n+1}|\mathbf{h}_n, \pi(\mathbf{s}_n))[r(\mathbf{s}_{n+1})] & n = L-1 \end{cases} \tag{7}$$

Remark. The expected total reward v^π has been defined as a recursive function, with $v^\pi(\mathbf{h}_n)$ denoting the nth recursive step. Specifically, $v^\pi(\mathbf{h}_n)$ at the recursive step n is function of: (i) the past through $\mathbf{h}_n$; (ii) the present through $r(\mathbf{s}_{n+1})$; (iii) the future through $v^\pi(\mathbf{s}_{n+1}, h_n)$; (iv) the strategy π through $\pi(\mathbf{s}_n)$.

Definition 11 (Optimal strategy)**.** The *optimal strategy* $\pi^* \in \mathcal{P}$ is the strategy maximizing the expected total reward, i.e.,

$$v^{\pi^*} \triangleq \sup_{\pi \in \mathcal{P}} \{v^\pi\} \tag{8}$$

and we refer to $\pi^*(\mathbf{s}_n)$ as the optimal action for the state $\mathbf{s}_n$.

3. Optimal database access strategy

At first, in Section 3.1, we formulate the *optimal strategy* problem as a Markov Decision Process, and we prove there exists an optimal strategy with the attractive property of being deterministic. Then, in Section 3.2, we design a computational-efficient algorithm for finding such a strategy.

3.1. Accessing to the database as Markov Decision Process

Here, we prove with Theorem 1 that the problem of finding the optimal strategy can be formulated as a Markov Decision Problem. Stemming from this, we prove with Corollary 1 that there exists an optimal strategy which is both deterministic and Markovian.[4] The proof of Theorem 1 requires the following two lemmas.

Lemma 1 (State probability)**.** *The state probability $p(\mathbf{s}_n)$ is given by:*

$$p(\mathbf{s}_n)=\prod_{i=1}^{M}\left(p_{x_i}\prod_{k=1}^{x_i-1}p_i(1|1)\right) \tag{9}$$

with $\mathbf{s}_n=(\mathbf{x}(n),n)_n$, $p_{x_i}\triangleq p_i$ if $x_i>0$, $p_{x_i}\triangleq q_i$ otherwise.

Proof. By accounting for Definition 3 and by reasoning as in [22], one obtains[5]

$$p(\mathbf{s}_n)=\prod_{i=1}^{M}P(N_i(n)=x_i) \tag{10}$$

Since $P(N_i(n)=0)=q_i$ and $P(N_i(n)=x_i>0)=p_i(p_i(1|1))^{x_i-1}$, we have the thesis. □

Lemma 2 (Transition probability)**.** *The transition probability $p(\mathbf{s}_{n+1}|\mathbf{h}_n,a)$ is given by:*

$$p(\mathbf{s}_{n+1}|\mathbf{h}_n,a)=\begin{cases}\prod_{m=1}^{M}P(N(n+1)=y_i|N(\tilde{n})=x_i) & \text{if } a=0\\ =\begin{cases}1 & \text{if } \mathbf{s}_{n+1}=\mathbf{s}_n\\ 0 & \text{otherwise}\end{cases} & \text{if } a=1\end{cases} \tag{11}$$

with $\mathbf{s}_{n+1}=(\mathbf{y},l)_{n+1}$, $\mathbf{h}_n=(\mathbf{s}_n,\mathbf{h}_{n-1})$, $\mathbf{s}_n=(\mathbf{x},\tilde{n})_n$, and $P(N(n+1)=y_i|N(\tilde{n})=x_i)$ given by:

$$P(N(n+1)=y_i|N(\tilde{n})=x_i)=\begin{cases}\text{if } n+1<\tilde{n}+x_i\\ =\begin{cases}1 & \text{if } y_i=n+1-\tilde{n}-x_i\\ 0 & \text{otherwise}\end{cases}\\ \text{if } n+1=\tilde{n}+x_i\\ =\begin{cases}1 & \text{if } y_i=0\wedge\tilde{n}<K\\ 0 & \text{if } y_i>0\wedge\tilde{n}<K\\ p_i(0|1) & \text{if } y_i=0\wedge\tilde{n}=K\\ (p_i(1|1))^{y_i} & \text{if } y_i>0\wedge\tilde{n}=K\end{cases}\\ \text{if } n+1>\tilde{n}+x_i\\ =\begin{cases}P(S_i(n+1)=0|S_i(\tilde{n}+x_i)=0) & \text{if } y_i=0\\ P(S_i(n+1)=1|S_i(\tilde{n}+x_i)=0)(p_i(1|1))^{y_i-1} & \text{if } y_i>0\end{cases}\end{cases} \tag{12}$$

Proof. *Case $a=0$*: We have three cases. If $n+1<\tilde{n}+x_i$, i.e., if at time slot $\tilde{n}$ channel i was reported as available up to time slot $n+1$, then $n+1+y_i=\tilde{n}+x_i$. If $n+1=\tilde{n}+x_i$, i.e., if at time slot $\tilde{n}$ channel i was reported as available up to time slot n, then $y_i=0$ whenever $x_i<K$; differently, when $x_i=K$, one has $y_i=0$ with probability $p_i(1|0)$ and $y_i>0$ with probability $(p_i(1|1))^{y_i}$. Finally, if $n+1>\tilde{n}+x_i$, i.e., if at time slot $\tilde{n}$ channel i was reported as unavailable at time slot n, then $y_i=0$ with probability $P(S_i(n+1)=0|S_i(\tilde{n}+x_i)=0)$, whereas one has $y_i>0$ with probability $P(S_i(n+1)=1|S_i(\tilde{n}+x_i)=0)(p_i(1|1))^{y_i-1}$.

Case $a=1$: The thesis follows directly from Definition 3. □

Remark. From (11), it follows that $p(\mathbf{s}_{n+1}|\mathbf{h}_n,a)=p(\mathbf{s}_{n+1}|\mathbf{s}_n,a)$ for any $\mathbf{s}_n,\mathbf{s}_{n+1}\in\mathcal{S}$ and for any $a\in A$. Hence, the transition probability does not depend on the previous history given the current state $\mathbf{s}_n$.

Theorem 1 (Markov Decision Process)**.** *Finding the optimal strategy can be formulated as Markov Decision Process.*

Proof. It follows from Lemmas 1 and 2 by accounting for the Markov property of the state and transition probabilities. □

Corollary 1 (Deterministic strategy)**.** *There exists a Markovian deterministic strategy π^* achieving the supremum in (8), i.e., $v^{\pi^*}=\max_{\pi\in\mathcal{P}}\{v^\pi\}$.*

Proof. Since $A_{\mathbf{s}_n}$ is finite for any $\mathbf{s}_n$ and since the problem of finding π^* is a Markov Decision Process, by accounting for Section 4.3 in [21], there exists a strategy achieving the supremum in (8). Furthermore, since $\mathcal{S}$ is finite, by accounting for Proposition 4.4.3 in [21], there exists a deterministic strategy which is optimal. Finally, by accounting for Lemmas 1 and 2, we have the thesis. □

Insight 1. *Stemming from Corollary 1, there exists at least one deterministic strategy which is optimal under the expected total reward criterion. This is an important result since stochastic problems can be solved only through enumeration and evaluation of all the strategies, whereas deterministic systems can be solved in a more efficient way, as we will prove in Theorem 2.*

Corollary 2 (Expected remaining reward)**.** The *expected remaining reward* $v^\pi(\mathbf{h}_n)$ obtained by the SU starting from the system history $\mathbf{h}_n=(\mathbf{s}_n,\mathbf{h}_{n-1})$ at time slot n and following

[4] A strategy is *Markovian* when it depends on the current state rather than on the history, *deterministic* when it maps any state to a unique action, and *random* when it probabilistically maps any state to a subset of actions [21].

[5] Without loss of generality, the channel statuses $S_i(n)$ and $S_j(n)$ are assumed independent $\forall\, i\neq j$, since, when the channel statuses are correlated, e.g., due to adjacent-channel use restriction [6,15], $S_i(n)$ represents either the status of the best channel belonging to a set of correlated channels (if the SU is equipped with a single radio interface) or the status of a set of correlated channels (if the SU is equipped with multiple radio interfaces).

the strategy π is equal to $v^{\pi}(\mathbf{s}_n)$, with:

$$v^{\pi}(\mathbf{s}_n) = \begin{cases} \sum_{\mathbf{s}_{n+1}} p(\mathbf{s}_{n+1}|\mathbf{s}_n, \pi(\mathbf{s}_n))[r(\mathbf{s}_{n+1}) + v^{\pi}(\mathbf{s}_{n+1})] \text{ if } n < L-1 \\ \sum_{\mathbf{s}_{n+1}} p(\mathbf{s}_{n+1}|\mathbf{s}_n, \pi(\mathbf{s}_n))[r(\mathbf{s}_{n+1})] \text{ if } n = L-1 \end{cases} \tag{13}$$

Proof. It follows from Theorem 1. □

Insight 2. *From Corollary 2, histories need not to be retained, i.e., $v^{\pi}(\cdot)$ is independent of the past given the current system state $\mathbf{s}_n$. Hence, the computation complexity of the optimal strategy search is reduced since, at time slot n, the number of possible states goes from $|\mathcal{S}|^n$ to $|\mathcal{S}|$, with $|\mathcal{S}| = (K+1)^{MK}$.*

3.2. Optimal deterministic strategy

Here, we prove with Theorem 2 that the optimal deterministic strategy π^* can be efficiently found through *Backward Induction*, i.e., by searching for each system state $\mathbf{s}_n$ the action achieving the maximum in (13), with n going from L to 1.

Theorem 2. *Given that the state is $\mathbf{s}_n$ at time slot n, the optimal action $\pi(\mathbf{s}_n)$ is any action $a \in A_{\mathbf{s}_n}$ achieving the maximum in:*

$$v^*(\mathbf{s}_n) = \max_{a \in A_{\mathbf{s}_n}} \{v^*(\mathbf{s}_n, a)\} \tag{14}$$

where:

$$v^*(\mathbf{s}_n, 0) = \begin{cases} \sum_{\mathbf{s}_{n+1}} p(\mathbf{s}_{n+1}|\mathbf{s}_n, 0)[r(\mathbf{s}_{n+1}) + v^*(\mathbf{s}_{n+1})] & n < L-1 \\ \sum_{\mathbf{s}_{n+1}} p(\mathbf{s}_{n+1}|\mathbf{s}_n, 0) r(\mathbf{s}_{n+1}) & n = L-1 \end{cases} \tag{15}$$

$$v^*(\mathbf{s}_n, 1) = \begin{cases} r(\mathbf{s}_n) + v^*(\mathbf{s}_{n+1}), \mathbf{s}_{n+1} = \mathbf{s}_n & n < L-1 \\ r(\mathbf{s}_n) & n = L-1 \end{cases} \tag{16}$$

Proof. It follows from Corollary Corollary 2 by accounting for Section 4.5 in [21]. □

Insight 3. *According to Theorem 2, the optimal strategy π^* can be found through Algorithm 1, whose complexity is upper bounded by $O(L|A||\mathcal{S}|^2) = O(2L(K+1)^{2MK})$, rather than through enumeration and evaluation of all the strategies. Since there are $(|A|^{|\mathcal{S}|})^{L-1}$ deterministic Markovian strategies, each with an evaluation complexity lower bounded by $O(L)$, Theorem 2 significantly reduces the problem complexity.*

Algorithm 1 .

```
// base step: n = L − 1
for s_{L−1} ∈ S do
    π*(s_{L−1}) = arg max_{a∈A_{s_{L−1}}} {v*(s_{L−1})}
end for
// inductive step: 1 < n < L − 1
for n = L − 2 : 2 do
    for s_n ∈ S do
        π*(s_n) = arg max_{a∈A_{s_n}} {v*(s_n)}
    end for
end for
// final step: n = 1
for s_1 ∈ S do
    π*(s_1) = 0
end for
```

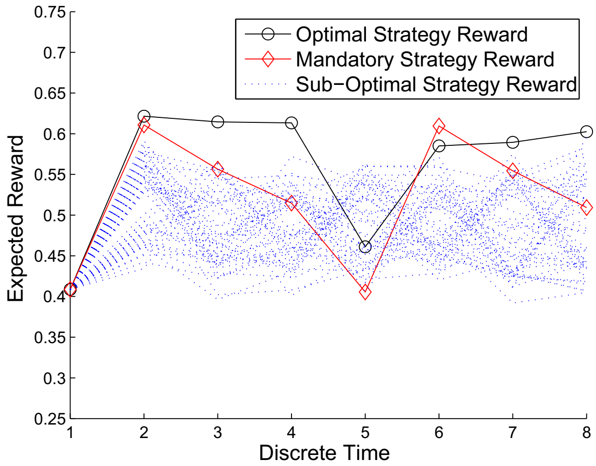

Fig. 2. Expected reward vs time for $M = 2$, $K = 4$, and $N = 8$.

4. Performance evaluation

In this section, we validate the theoretical results derived in Section 3 by simulating a secondary network operating within the TVWS in urban scenarios, i.e., for small values of M [13].

In the first experiment, we compare the performance of the proposed optimal strategy (Algorithm 1) with those obtained through different database access strategies. More specifically, Fig. 2 presents the expected reward given in (4) as a function of the discrete time. The adopted simulation set is as follows: $M = 2$, $K = 4$, $L = 8$, $c = 0.25$,[6] $r_i = (2i+1)/M$, $p_i(0|1) = 0.1$ and $p_i(1|0) = 0.5$ for any i, and we consider the following rewards: (i) the *Optimal Strategy Reward*, i.e., the reward achieved by the strategy found out with Algorithm 1; (ii) the *Mandatory Strategy Reward*, i.e., the reward achievable by a strategy following the mandatory rulings, i.e., not performing on-demand accesses; (iii) the *Sub-Optimal Strategy Reward*, i.e., the reward achievable by a randomly-selected strategy performing on-demand accesses. First, we note that there exist time slots, such as $n = 5, 6$, during which the optimal strategy does not achieve the highest expected reward. This is reasonable since Algorithm 1 aims at discovering the strategy π^* assuring the highest expected total reward v^{π^*}, i.e., the highest expected reward over the whole time horizon L. In fact, by averaging the expected reward over the time, the strategy singled out by Algorithm 1 achieves the highest expected total reward, as confirmed by the next experiment shown in Fig. 3. Furthermore, we observe that the expected reward achieved by the *optimal strategy reward* exhibits local minima for $n = 1, 5$. This is reasonable and it agrees with

[6] $c = 0.25$ and $r_i = 0.75$ represent the case in which the database access wastes one third of the available bandwidth.

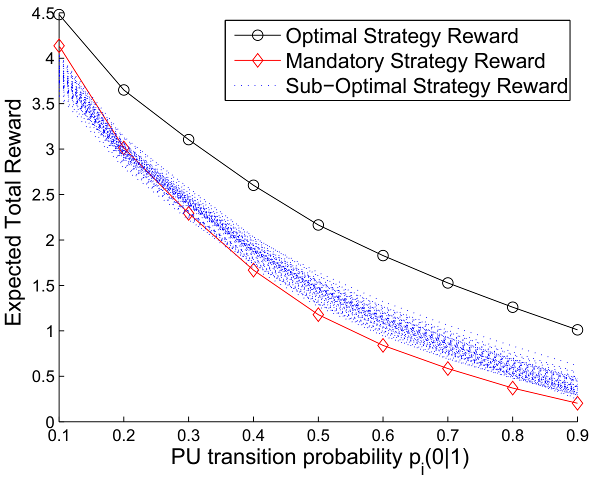

Fig. 3. Expected total reward vs time for $M = 2$, $K = 4$, and $N = 8$.

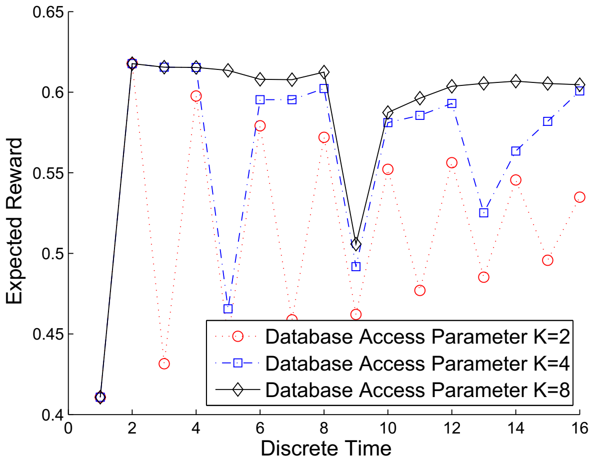

Fig. 4. Expected reward vs time for different values of the database access parameter K.

the requirement of a mandatory database access every $K = 4$ time slots starting from the first time slot, as confirmed by the experiment shown in Fig. 4.

Fig. 3 presents the expected total reward as a function of the PU transition probability $p_i(0|1) \triangleq P(S_i(n+1) = 0|S_i(n) = 1)$ for the same simulation set adopted for Fig. 2. We first observe that, for any considered value of the PU transition probability $p_i(0|1)$, the designed access strategy outperforms significantly all the other considered strategies. This confirms that: (i) the choice of the database access strategy is crucial for the performance of any secondary network operating within the TVWS; (ii) a significant performance gain can be obtained with the optimal strategy design. Furthermore, we observe that, the higher is the probability $p_i(0|1)$ of channel i becoming unavailable, the higher is the gain assured by the designed strategy. In fact, the higher is $p_i(0|1)$, the less likely a given channel remains available, and hence the higher is the impact of a good strategy in terms of achievable reward.

In Fig. 4 we present the expected reward as a function of the discrete time for three different values of the database access parameter K, i.e., 2, 4 and 8, when $M = 2$ and $N = 16$. We observe that each curve exhibits a local minimum every K time slots, confirming so the considerations made for Fig. 2. Furthermore, Fig. 5 presents the expected total reward as a function of the PU transition probability $p_i(0|1)$ for the same simulation set adopted for Fig. 4. We observe that the expected reward increases as the database access parameter K increases. This is reasonable and it agrees with the reward definition (4): the higher is K, the less frequent the mandatory cost c is charged to the SU. Finally, Fig. 6 presents the expected total reward as a function of the PU transition probability $p_i(0|1)$ for three different values of the database access cost c, i.e., 0.1, 0.25 and 0.4, when $M = 2$, $K = 4$ and $N = 16$. We observe that the expected total reward linearly decreases as the database access cost increases, in agreement with the theoretical results derived in Section 3. Furthermore, the considerations made for Fig. 3 regarding the importance of a proper strategy design hold in this case as well.

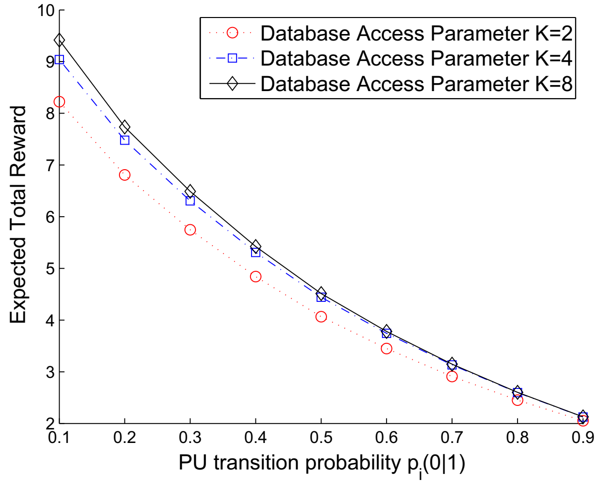

Fig. 5. Expected total reward vs time for different values of the database access parameter K.

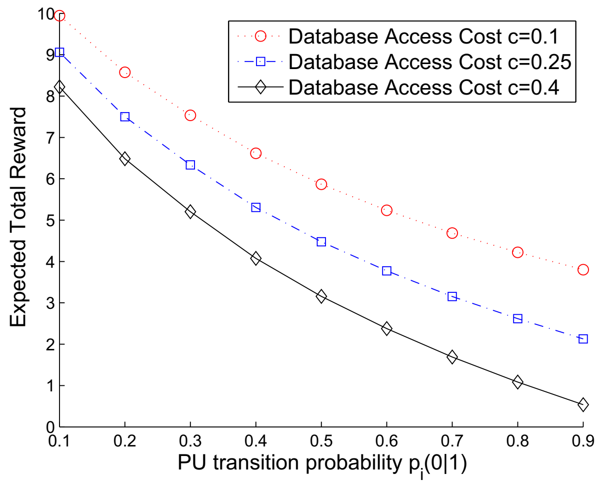

Fig. 6. Expected total reward vs time for different values of the database access cost c.

5. Conclusions

In TVWS, an SU can access on-demand to a geolocated database to update the spectrum availability information. The more frequent are the on-demand accesses, the higher can be the communication opportunities available to the SU but the higher is the induced overhead. For this, in this manuscript, the on-demand access is investigated to a-priori determine whether to access or not by accounting for the correlation exhibited by primary traffic patterns. Specifically, is proved that the on-demand access maximizing the communication opportunities available to the SU is a Markov Decision Process. Stemming from these results, a computational-efficient algorithm maximizing the communication opportunities is designed. Numerical simulations validate the theoretical analysis with a case study. As future work, we will explore the design of reward and cost metrics from a database point of view.

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