

# Strengthening Radio Environment Maps with Primary-User Statistical Patterns for Enhancing Cognitive Radio Operation

F. Bouali, O. Sallent, J. Pérez-Romero and R. Agustí  
Theory of Signal and Communications Dept. (TSC)  
Universitat Politècnica de Catalunya(UPC), Barcelona, Spain  
Email: {faouzi.bouali, sallent, jorperez, ramon}@tsc.upc.edu

**Abstract**—In order to increase spectrum utilization efficiency, CRs (Cognitive Radios) have been introduced to reuse white spaces left unused by legacy services under the strict constraint of not interfering them. In order to fulfill this constraint while optimising spectrum utilisation, it is important to get knowledge about primary-user activity in order to devise proper strategies for secondary-user operation. In this context, this paper proposes to strengthen Radio Environment Maps (REM) with statistical patterns of primary systems that capture among others temporal dependence structures between activity (ON) and inactivity (OFF) periods. Convergence times for the different statistics are analysed. Then, a set of novel spectrum selection criteria exploiting these statistics are proposed and assessed to benchmark the usefulness of primary statistical patterns retained in the REM. Results show that significant performance gains can be achieved in terms of a reduction in the number of required spectrum hand-overs.

## I. CONTEXT/MOTIVATION

The CR (Cognitive Radio) paradigm has emerged as the solution to the problem of spectrum scarcity for wireless applications [1, 2]. It is the key technology that enables flexible, efficient and reliable spectrum use by adapting the radio operating characteristics to the real-time conditions of the environment.

In this context, there has been a recent trend towards improving the awareness level of CR systems by strengthening their observation sub-systems. Specifically, there has been an interest in recording, storing and accessing new relevant information about the external environment. For instance, Radio Environment Maps (REMs) have been proposed as new information sources that can assist cognitive operation by considering multi-domain environmental information [3–5]. REM is envisioned as an integrated space-time-frequency database consisting of multi-domain information, such as geographical features, available services, spectral regulations, locations and activities of radios, relevant policies, and experiences.

In a recent measurement campaign [6], it has been observed that primary channel vacancy durations are not independently distributed over time, and that significant spectral and spatial correlations can be found between channels of the same service. Focusing on the time perspective, other empirical measurements [7] have shown that, in addition to the expected daily/weekly periodicity of activity (ON) and inactivity (OFF) processes of the Primary Users (PUs), some correlation is observed between consecutive ON/OFF periods depending on the band of interest and the considered traffic conditions. Therefore, an increase in the cognitive awareness level retained in the REM, particularly with respect to the temporal behavior of PUs, can lead to a more efficient CR operation and corresponding spectrum utilization. In this respect, spectrum

management tasks such as spectrum decision and spectrum mobility [8] can substantially benefit from the knowledge stored in the REM.

Exploiting statistics about the temporal activity of PUs for the sake of optimising CR operation has been the subject of many recent proposals. To cite a few, a proactive spectrum access approach has been proposed in [9] where predictive statistical models of primary channel availability are built based on sensing reports. In [10], renewal theory has been applied on past channel observations in order to predict primary channel activity. In order to account for primary randomness, authors in [11] have first applied a simple classification method to qualify primary traffic as periodic or stochastic. Based on the detected randomness levels, remaining idle times of primary channels are differently estimated.

While all the above-mentioned proposals are based on a rough characterisation of PUs' activity, this paper aims at a more focused/accurate statistical characterisation that can be acquired offline and stored in a REM with a given level of accuracy. In particular, this paper tries to exploit hidden structures that may link primary ON/OFF periods. This would considerably improve the estimation reliability of idle times.

In this context, the main objective of this paper is to embed a REM with primary-user statistical patterns capturing intra-channel dependence structures potentially exhibited by primary ON/OFF periods for optimising the specific task of spectrum selection. This knowledge would make it possible to perform a pro-active spectrum selection strategy, trying to avoid as much as possible the need for executing Spectrum Handovers (SpHOs) to vacate a channel when a primary appears. Therefore, the main contributions and advances with respect to the state-of-the art associated to this paper are three-fold: (1) To propose the usage of advanced statistics that capture among others temporal dependence between ON/OFF periods and to retain such characterisation in the REM, (2) To make an analysis of convergence levels that can be achieved in the retained statistics in the REM for different primary activity profiles, and (3) To benchmark the utility of the retained knowledge exploiting it in the specific task of spectrum selection while quantifying performances' sensitivity to the level of convergence achieved in the acquired statistics.

The remainder of this paper is organized as follows: in Sec. II the system model is presented including the statistical metrics stored in the REM. As an applicability example, Sec. III proposes to exploit REM's primary-user statistical patterns through a set of criteria for optimising spectrum selection. Sec. IV firstly focuses on assessing the proposed statistical characterisation, from the perspective of conver-

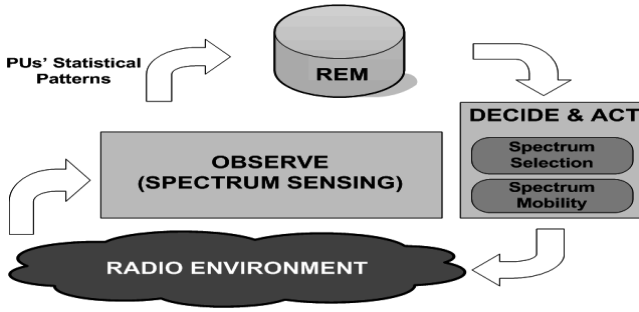


Fig. 1: Architecture for strengthening REMs with Primary-User Statistical Patterns for Enhancing Cognitive Operation

gence times needed for the different statistics. Afterwards, the resulting performances of the proposed spectrum selection criteria are evaluated. Conclusions and future directions are addressed in Sec. V.

## II. SYSTEM MODEL

Let consider a radio environment where PUs are operating on a spectrum modeled as  $C$  channels of equal bandwidth  $B_P$ . For each channel  $i \in \{1..C\}$ , the two discrete random sequences  $ON_i$  and  $OFF_i$  are introduced to respectively denote the sequences of activity and inactivity period lengths. At a given discrete time index  $j$ ,  $ON_i(j)$  and  $OFF_i(j)$  correspond to the length of the  $j$ -th activity and inactivity period, respectively. The time series representing the primary activity are independent across channels.

The functional architecture of the proposed framework is depicted in Fig. 1. Based on the observation of the environment, a statistical characterisation of the ON/OFF periods of the different channels is obtained and stored in the REM. This stored information will be used as input for the spectrum management decision-making process. In particular, whenever a new secondary service request arrives, the spectrum selection functionality at the SU will pick up a suitable channel for such communication. Similarly, whenever the SU detects the appearance of a PU, it must vacate the channel and perform a SpHO to another channel, if available. This is carried out by the spectrum mobility functionality.

Generally speaking, PUs' statistics that are stored in the REM can be classified into first-order metrics such as means or conditional probabilities or higher-order metrics such as variances or correlation functions. In order to offer a high scalability, it is proposed to make most of statistics characterising primary activity/inactivity period lengths structured in buckets. A bucket includes the ON (alternatively OFF) period durations falling in a given interval. Buckets for the ON periods are numbered as  $a \in \{1..|B_i^{ON}|\}$  so that  $B_i^a \in B_i^{ON}$  denotes the  $a$ -th bucket,  $B_i^{ON}$  the set of buckets and  $|\cdot|$  denotes the cardinality. The same applies to OFF periods numbered as  $b \in \{1..|B_i^{OFF}|\}$ ,  $B_i^b \in B_i^{OFF}$  denoting the  $b$ -th bucket and  $B_i^{OFF}$  the set of buckets. Bucket length is assumed to be a fraction  $\alpha$  of the average value of the corresponding distribution. This means that, considering for instance  $OFF_i$  distributions,  $\forall b \in \{1..|B_i^{OFF}|-1\}$ , bucket  $B_i^b$  is defined as  $B_i^b = [(b-1)\alpha E(OFF_i), b\alpha E(OFF_i)]$ , where  $E(OFF_i)$  denotes the average value of OFF period. The last bucket is assumed to be infinite of the form  $[(|B_i^{OFF}|-1)\alpha E(OFF_i), \infty[$ .

A wide range of possible statistics of interest could be envisaged in the REM. For example,  $\forall i \in \{1..C\}$  the following metrics can be extracted during  $acq_{time}$  (acquisition time):

- Average value of ON and OFF periods,  $E(ON_i)$ ,  $E(OFF_i)$ . The corresponding DC (Duty Cycle) can be therefore estimated as:

$$DC_i = \frac{E(ON_i)}{E(ON_i) + E(OFF_i)} \quad (1)$$

- Variances of ON and OFF periods,  $VAR(ON_i)$ ,  $VAR(OFF_i)$ .
- The empirical pdf (probability density function) of  $ON_i$ :

$$pdf_{ON}^i(B_i^a) = Pr [ON_i(j) \in B_i^a], \forall a \in \{1..|B_i^{ON}|\} \quad (2)$$

- The empirical pdf (probability density function) of  $OFF_i$ :

$$pdf_{OFF}^i(B_i^b) = Pr [OFF_i(j) \in B_i^b], \forall b \in \{1..|B_i^{OFF}|\} \quad (3)$$

- The conditional probability of observing a certain duration of the OFF period given that a certain duration of the last ON period was observed. Specifically,  $CP_{OFF,ON}^i(B_i^b, B_i^a)$  is defined as the conditional probability of observing  $OFF_i$  in  $B_i^b \in B_i^{OFF}$  given that the last outcome of  $ON_i$  was observed in  $B_i^a \in B_i^{ON}$ :

$$CP_{OFF,ON}^i(B_i^b, B_i^a) = Pr [OFF_i(j) \in B_i^b / ON_i(j) \in B_i^a] \quad (4)$$

- The conditional mean of  $OFF_i$  given the last outcome of  $ON_i$  was observed in bucket  $B_i^a \in B_i^{ON}$  defined as follows:

$$E(OFF_i / ON_i \in B_i^a) = \sum_{B_i^b \in B_i^{OFF}} \hat{B}_i^b \times CP_{OFF,ON}^i(B_i^b, B_i^a) \quad (5)$$

where  $\hat{B}_i^b$  is the center value of bucket  $B_i^b$  which is given by  $\hat{B}_i^b = (b-0.5)\alpha E(OFF_i)$ .

In what follows, the practical exploitation of these statistics will be discussed for the specific task of spectrum selection.

## III. CASE STUDY: EXPLOITING REM'S PRIMARY-USER STATISTICAL PATTERNS FOR OPTIMISING SPECTRUM SELECTION

The basic idea of optimising spectrum selection is to pick up the best channel for secondary operation. This section considers optimising not only the first spectrum assignment (at spectrum selection events), but also all subsequent assignments (at spectrum mobility events). In order to achieve that, a proactive approach defining the best channel as the one that results in the least-likelihood for the appearance of a PU will be followed. In particular, for each idle channel  $i \in \{1..C\}$ , it is assumed to track the duration of the last observed ON period assumed to fall in bucket  $B_i^a$  as well as the so-far observed duration of the current OFF period (denoted as  $Idle\_C^i$ ) and we let  $i^*$  be the selected channel. First, a criterion that maximises the estimated remaining idle time ignoring all dependence effects is proposed as follows ( $Crit_1$ ):

$$i_{Crit_1}^* = \arg \max_i (E(OFF_i) - Idle\_C^i) \quad (6)$$

Next, a dependence-based spectrum selection criterion that selects the channel whose estimated remaining idle time is maximized given the last observed ON period is proposed as follows ( $Crit_2$ ):

$$i_{Crit_2}^* = \arg \max_i (E(OFF_i / ON_i \in B_i^a) - Idle\_C^i) \quad (7)$$

For both criteria, in the very specific case of multiple channels fulfilling the maximisation, the channel with lowest  $DC_i$  is selected. Finally, a reference criterion  $Ref.Crit$  is defined as a random selection among the idle channels.

#### IV. SIMULATION RESULTS

In order to validate the proposed methodology, the key assumptions and the set of primary activity time series to be used will be firstly introduced. This will allow the analysis of the different convergence times needed for the statistics retained in the REM. Enlightened by this analysis, the performance of the proposed spectrum selection criteria will be evaluated, initially, under fully-converged statistics. Finally, the sensitivity of the obtained performances to the level of convergence achieved in the considered statistics will be assessed.

##### A. Assumptions

A secondary access to the  $C$  primary channels is considered.  $\lambda_i$  and  $\mu_i$  respectively denote the primary arrival and departure rates of the  $i$ -th channel  $\forall i \in \{1..C\}$ . As for secondary operation, inter-arrival and service duration processes are assumed to follow exponential distributions with arrival rate  $\lambda_S$  and mean holding time  $MHT$ . Considering a periodic sensing every  $\Delta T$ , a perfect sensing (free of miss-detections and false alarms) is assumed for the sake of simplicity. In the case a PU shows up in any of the opportunistically-accessed channels, the involved SU will be handed-over to another channel if there is any, or will be dropped if there is no channel available.

##### B. Primary Activity Time Series

In order to assess the behavior of the proposed statistical metrics and evaluate the performance of the proposed spectrum selection criteria, different sets of primary activity time series will be considered as benchmark for comparisons. Specifically, a set of fully-random activity time series free of any dependence between ON/OFF period durations will be first introduced. Then, another set of activity time series exhibiting strong dependence will be derived. For each set of time series, uniform and exponential distributions will be considered in order to introduce different levels of randomness variability.

1) *Fully-Random Primary Activity Time Series:*  $\{ON_i\}_{\forall i \in \{1..C\}}$  and  $\{OFF_i\}_{\forall i \in \{1..C\}}$  are randomly distributed, following either a uniform distribution (respectively in the intervals  $[\frac{1}{2\mu_i}, \frac{3}{2\mu_i}]$  and  $[\frac{1}{2\lambda_i}, \frac{3}{2\lambda_i}]$ ) or an exponential distribution (respectively with means  $\frac{1}{\mu_i}$  and  $\frac{1}{\lambda_i}$ )

2) *Fully-Dependent Primary Activity Time Series:* This class of primary activity time series is generated by forcing a full dependence between consecutive ON and OFF periods. In this case,  $ON_i$  is randomly distributed in accordance with the exponential or uniform distribution of the previous case, while  $OFF_i$  is obtained from every  $ON_i$  outcome based on the following mappings:

$$OFF_i = \begin{cases} OFF_i^{min} + \frac{(ON_i - ON_i^{min}) \times (OFF_i^{max} - OFF_i^{min})}{ON_i^{max} - ON_i^{min}} & (\text{uniform}) \\ OFF_i^{mean} \times \frac{ON_i}{ON_i^{mean}} & (\text{exponential}) \end{cases} \quad (8)$$

Where  $ON_i^{min}$  and  $ON_i^{max}$  (respectively  $OFF_i^{min}$  and  $OFF_i^{max}$ ) are the smallest and largest values of the uniformly-distributed  $ON_i$  (respectively  $OFF_i$ ), while  $ON_i^{mean}$  and  $OFF_i^{mean}$  respectively denote means of the exponentially-distributed  $ON_i$  and  $OFF_i$  period lengths. Even though the

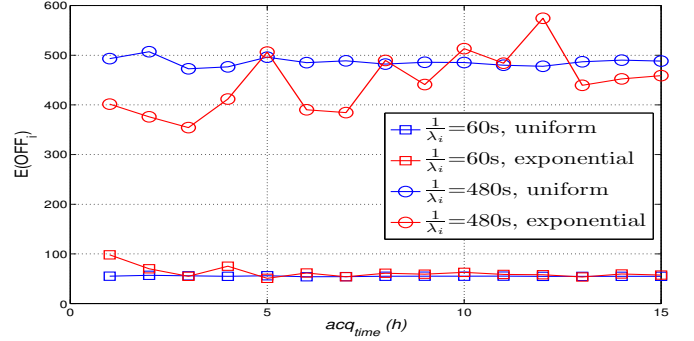


Fig. 2: Convergence of  $E(OFF_i)$

proposed mappings introduce strong dependence between successive ON/OFF periods, it is easy to prove that the resulting  $OFF_i$  are equally distributed to the fully-random case.

##### C. Convergence of REM's Statistics

In the following, the impact of the acquisition time ( $acq_{time}$ ) on the retained statistics in the REM is analysed. The analysis considers the statistical metrics  $E(OFF_i)$  and  $E(OFF_i/ON_i \in B_i^a)$  defined in Sec. II since they are not equally sensitive to  $acq_{time}$ . Since  $E(OFF_i/ON_i \in B_i^a)$  is as well dependent on bucket setting, the bucket configuration has been first studied and an operating configuration that looks for a balance between statistics' accuracy and computational complexity has been determined. It corresponds to  $N_B^{opr} = |B_i^{ON}| = |B_i^{OFF}| = 31$  and  $\alpha^{opr} = 0.1$ .

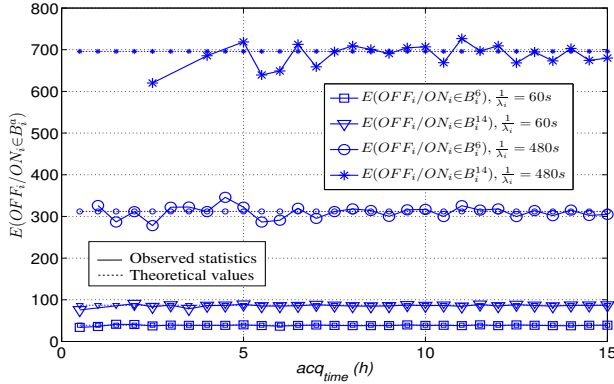
Thanks to this bucket configuration, convergence times of the different statistics can be analysed. Fig. 2 plots the time evolution of  $E(OFF_i)$  for different values of the primary traffic arrival rate  $\lambda_i$ . It is first observed that  $E(OFF_i)$  is much more stable for shorter  $\frac{1}{\lambda_i}$ . This is basically due to the fact that for a given  $acq_{time}$  as  $\frac{1}{\lambda_i}$  gets longer, there are less samples of  $OFF_i$  and the range of  $OFF_i$  outcomes gets wider.

With respect to convergence speed,  $E(OFF_i)$  is relatively stable after  $acq_{time} = 2h$  for all the considered  $\frac{1}{\lambda_i}$  of uniform distributions. However, it fluctuates much more for exponential distributions especially when long  $\frac{1}{\lambda_i}$  are considered. This is due to the higher variability of exponential distributions making random outcomes deviate much from their means.

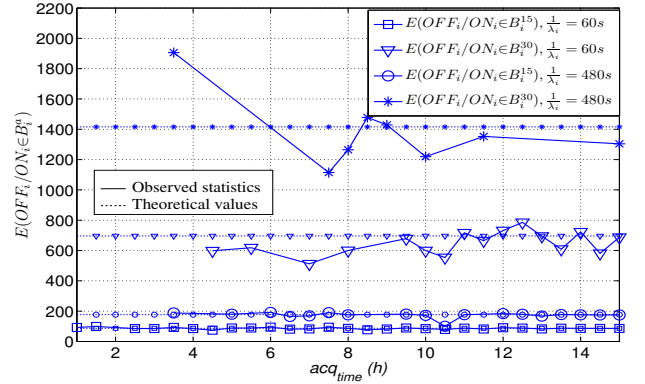
Next, the more challenging convergence of the conditional mean  $E(OFF_i/ON_i \in B_i^a)$  is considered. As a matter of fact, the estimation accuracy in this case does not only depend on  $acq_{time}$ , but also on the number of possible combinations of successively observed ON/OFF buckets. In order to better illustrate this, fully-dependent time series whose ON/OFF mapping results in only  $N_B^{opr}$  out of the  $N_B^{opr^2}$  possible combinations are considered. As a matter of fact,  $\forall a \in \{1..|B_i^{ON}|\}$  and  $\forall b \in \{1..|B_i^{OFF}|\}$ , the theoretical  $CP_{OFF,ON}^i(B_i^b, B_i^a)$  is given in the particular case of the mapping defined in (8) by:

$$CP_{OFF,ON}^i(B_i^b, B_i^a) = \begin{cases} 1 & \text{if } a = b, \\ 0 & \text{otherwise.} \end{cases} \quad (9)$$

Introducing  $CP_{OFF,ON}^i(B_i^b, B_i^a)$  into (5), the obtained theoretical expected value  $E(OFF_i/ON_i \in B_i^a) = \hat{B}_i^a$  will be used as a reference for convergence in the different cases. Fig. 3 illustrates the convergence of some  $E(OFF_i/ON_i \in B_i^a)$  towards these theoretical values for an increasing  $acq_{time}$  where



(a) Uniform distributions



(b) Exponential distributions

Fig. 3: Convergence of  $E(OFF_i/ON_i \in B_i^a)$  for some selected values of  $B_i^a$ 

$a \in \{6, 14\}$  for uniform distributions and  $a \in \{15, 30\}$  for exponential distributions. It turns out that  $E(OFF_i/ON_i \in B_i^a)$  converges more slowly than  $E(OFF_i)$  for both the considered distributions. Considering for instance  $acq_{time}=4h$ , all observed  $E(OFF_i/ON_i \in B_i^a)$  get to 95% of their theoretical values for the uniform case. As far as exponential distributions are considered,  $E(OFF_i/ON_i \in B_i^a)$  values are in some cases below 90% of their theoretical values even after long values of  $acq_{time}$ . This is basically due to the higher variability of exponential distributions making slower the exploration of successive ON/OFF bucket combinations.

#### D. Performance Evaluation of Spectrum Selection Criteria under Fully-Converged REM's Statistics

This section analyses the impact of the considered statistics over the proposed spectrum selection criteria. Since both  $Crit_1$  and  $Crit_2$  are pro-active in terms of SpHO events, it is proposed to evaluate their performances in terms of number of SpHO per secondary call. Furthermore,  $Crit_1$  and  $Crit_2$  performance gains are defined as the percentages of reduction in the number of SpHO with respect to  $Ref.Crit$ . Initially, performances are analysed for  $acq_{time}=15h$ , where convergence has been achieved in most of the cases.

Considering the simulation parameters specified in Table I and a common duty cycle ( $DC_i=DC, \forall i \in \{1..C\}$ ) for the sake of simplicity, Fig. 4 illustrates performances of all introduced criteria with different primary/secondary traffic conditions for both fully-random and fully-dependent primary activity time series. As far as fully-random data are concerned, it is observed that both advanced criteria ( $Crit_1$  and  $Crit_2$ ) outperform the random selection ( $Ref.Crit$ ) with equal gains. While  $Crit_1$  outperforms  $Ref.Crit$  thanks to the estimation of the remaining OFF time,  $Crit_2$  can not further improve the estimation accuracy since the occupancy data ( $ON_i$ ) do not exhibit any useful dependence. As a matter of fact, free of any dependence  $E(OFF_i/ON_i \in B_i^a)=E(OFF_i)$  so both  $Crit_1$  and  $Crit_2$  turn out to be the same.

Notice that the introduced gains have different orders of magnitude depending on the considered distribution. While they range from 50% to 100% for uniform distributions (Fig. 4(a)), they are between 10% and 50% for exponential distributions (Fig. 4(b)). This is justified by the lower variability of uniform distributions making both  $E(OFF_i)$  and  $E(OFF_i/ON_i \in B_i^a)$  reliable estimators of actual OFF periods

TABLE I: Simulation Parameters

	C	i	$\frac{1}{\lambda_i}$ (s)	$\frac{1}{\mu_i}$ (s)
PUs' parameters	16	1-4	15	60,27.8,15
		5-8	30	120,55.7,30
		9-12	60	240,111.60
		13-16	120	480,222.8,120
SUs' parameters	$\Delta T$ (s)	MHT (s)	$\frac{1}{\lambda_S}$ (s)	
	0.1	6,24	6	

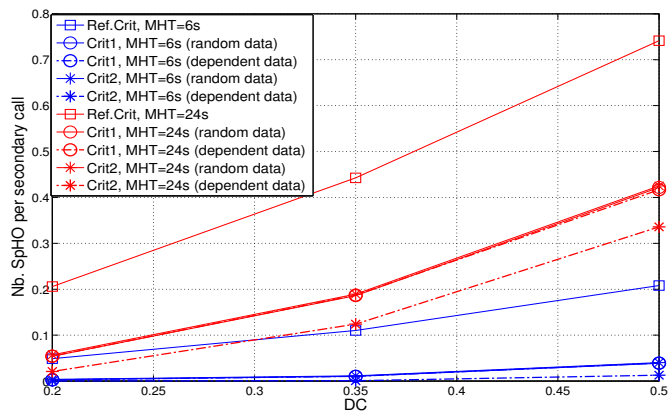
as their outcomes are not deviating much from their means.

Considering next fully-dependent primary activity time series, it is observed that both  $Ref.Crit$  and  $Crit_1$  are performing equally to the previous case while  $Crit_2$  succeeds in exploiting the increased dependence level to clearly outperform  $Crit_1$ . Notice that the resulting absolute gain  $Crit_2$  is introducing w.r.t  $Ref.Crit$  ranges from 50% to 100% and is independent of the considered distribution. Nevertheless, it is observed that the absolute gain of  $Crit_2$  is distributed differently for each of the considered distributions. As a matter of fact, the gain of  $Crit_2$  w.r.t  $Crit_1$  is up to 15% of the absolute gain of  $Crit_2$  for uniform distributions (Fig. 4(a)) while it reaches 70% for exponential data (Fig. 4(b)). This basically means that variability level does not change the absolute gain of  $Crit_2$  but simply redistributes it: a low-variability level makes the gain of  $Crit_1$  w.r.t  $Ref.Crit$  dominate the gain of  $Crit_2$  w.r.t  $Crit_1$ , while a high-variability level results in the opposite distribution.

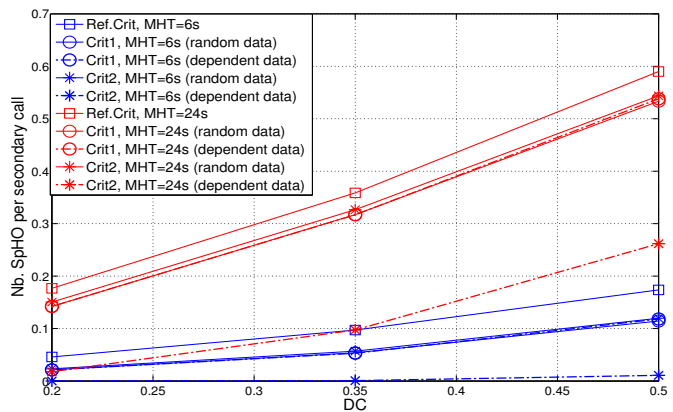
#### E. Impact of Convergence of REM's Statistics on Spectrum Selection Performance

In order to evaluate the impact of the level of convergence achieved in REM's statistics on the obtained performances,  $acq_{time}$  has been gradually decreased while checking the corresponding performances. It is worth to highlight that, as the obtained results have shown, spectrum selection performances converge much faster than their corresponding statistics. For instance, considering the worst case of exponential distributions and  $MHT=24s$ , Fig. 5 plots performances of all criteria while decreasing  $acq_{time}$  for dependent data. The results show that  $acq_{time}=3h$  results in stable results for both criteria in spite of the previously observed fluctuations of  $E(OFF_i)$  and  $E(OFF_i/ON_i \in B_i^a)$ . It has been checked and omitted for the sake of brevity that for lower randomness levels (e.g. uniform distributions), performances tend to stabilize





(a) Uniform Primary Activity Time Series



(b) Exponential Primary Activity Time Series

Fig. 4: Spectrum selection performance evaluation for  $acq_{time}=15h$

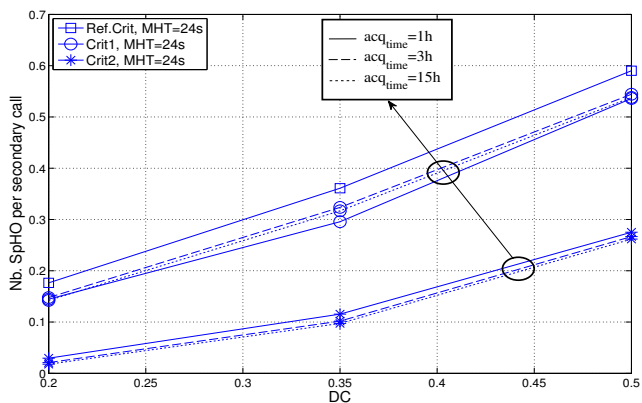


Fig. 5: Sensitivity to  $acq_{time}$ , dependent exponential data

for  $acq_{time}$  of few tens of seconds. The observed better stability of spectrum selection performances compared to their corresponding statistics is justified by the fact that even though further increasing  $acq_{time}$  improves the estimation accuracy of the considered statistics, the introduced gains are usually smaller than the differences between OFF periods of different channels, keeping unchanged the selected channel.

## V. CONCLUSIONS AND FUTURE WORK

In order to improve CR's operation, it has been proposed to strengthen REMs with primary-user statistical patterns that capture among others intra-channel dependence structures potentially exhibited by primary systems. After assessing some general aspects of the introduced metrics, the convergence times needed for the different types of statistics have been analysed. Then, a novel spectrum selection criterion exploiting dependence between consecutive primary ON/OFF periods has been proposed as a case study benchmarking the usefulness of the statistical patterns retained in the REM. The proposed criterion has been proven to significantly outperform a random scheme as well as a statistical scheme that neglects all dependence effects. The sensitivity of the obtained results has been finally evaluated for different convergence levels of the statistics retained in the REM. Results show substantial robustness to partially-converged REM's statistics. As part of future work, we plan to evaluate the sensitivity of the obtained performances to sensing imperfection, and validate the proposed approach with real-world spectrum measurements.

## ACKNOWLEDGEMENTS

This work was partly supported by the European Commission in the framework of the FP7 FARAMIR Project (Ref. ICT-248351) and by the Spanish Research Council and FEDER funds under ARCO grant (ref. TEC2010-15198) The support from the Spanish Ministry of Science and Innovation (MICINN) under FPI grant BES-2009-017934 is hereby acknowledged.

## REFERENCES

- [1] J. Mitola III and G. Q. Maguire, Jr., "Cognitive radio: making software radios more personal," *Personal Communications, IEEE*, vol. 6, no. 4, pp. 13–18, aug. 1999.
- [2] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201–220, Feb. 2005.
- [3] Y. Zhao, L. Morales, J. Gaeddert, K. K. Bae, J.-S. Um, and J. H. Reed, "Applying radio environment maps to cognitive wireless regional area networks," april 2007, pp. 115–118.
- [4] J. Riihijärvi, P. Mähönen, M. Petrova, and V. Kolar, "Enhancing cognitive radios with spatial statistics: From radio environment maps to topology engine," june 2009, pp. 1–6.
- [5] Z. Youping, L. Bin, and J. H. Reed, "Network support - the radio environment map," in *Cognitive Radio Technology*, B. A. FETTE, Ed. Elsevier, 2006.
- [6] D. Chen, S. Yin, Q. Zhang, M. Liu, and S. Li, "Mining spectrum usage data: a large-scale spectrum measurement study," in *Proceedings of the 15th annual international conference on Mobile computing and networking*, ser. MobiCom '09. ACM, 2009, pp. 13–24.
- [7] M. Wellens, J. Riihijärvi, and P. Mähönen, "Empirical time and frequency domain models of spectrum use," *Physical Communication*, vol. 2, no. 1-2, pp. 10–32, 2009.
- [8] I. F. Akyildiz, W.-Y. Lee, and K. R. Chowdhury, "Spectrum management in cognitive radio ad hoc networks," *Netw. Mag. of Global Internetwkg.*, vol. 23, no. 4, pp. 6–12, 2009.
- [9] P. A. Kumar Acharya, S. Singh, and H. Zheng, "Reliable open spectrum communications through proactive spectrum access," in *Proceedings of the first international workshop on Technology and policy for accessing spectrum*, ser. TAPAS '06. New York, NY, USA: ACM, 2006.
- [10] L. Yang, L. Cao, and H. Zheng, "Proactive channel access in dynamic spectrum networks," *Physical Communication*, vol. 1, no. 2, pp. 103–111, 2008.
- [11] M. Hoyhtya, S. Pollin, and A. Mammela, "Performance improvement with predictive channel selection for cognitive radios," in *Cognitive Radio and Advanced Spectrum Management, 2008. CogART 2008. First International Workshop on*, 2008, pp. 1–5.