A Novel Spectrum Selection Strategy for Matching Multi-Service Secondary Traffic to Heterogeneous Primary Spectrum Opportunities

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***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 this context, this paper proposes to exploit a statistical characterisation of Primary User (PU) activity to be retained in Radio Environment Maps (REMs) for spectrum selection purposes. The objective is to match multi-service secondary traffic to heterogeneous primary spectrum opportunities minimizing the SpHO (Spectrum handOver) rate. Specifically focusing on dependence structures potentially exhibited by primary ON/OFF periods, two spectrum selection criteria have been first proposed to benchmark the utility of the embedded statistical patterns in the REM. Results have shown that the one or the other criterion can introduce significant gains with respect to a random selection depending on the secondary configuration and characteristics of PUs. Therefore, a novel pro-active spectrum selection strategy combining the proposed criteria has been developed and proven to achieve in most of the cases the best performance for a given secondary service mix and the dependence level between primary ON/OFF periods.**

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 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 temporal, spectral and spatial correlations exist 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. In this respect, we have developed in [8] a framework that introduces a set of statistics that capture temporal dependency structures of ON/OFF periods, which can be stored in a REM. The reader is referred to [8] for considerations about how spectrum sensing measurements can be processed to obtain these statistics, the necessary time to ensure the statistical convergence of these metrics, etc.

The increase in the cognitive awareness level retained in the REM, particularly with respect to the temporal behavior of PUs, can make the cognitive operation much more efficient. In this respect, spectrum management tasks such as spectrum decision and spectrum mobility [9] can substantially benefit from the knowledge stored in the REM. Even though many recent proposals have dealt with diverse specific spectrum selection-related issues [10–16], to the best of our knowledge, none of them has attempted to exploit statistical dependence structures between primary ON/OFF periods.

In this context, the main objective of this paper is to attain a focused exploitation of primary-user statistical patterns capturing intra-channel dependence structures potentially exhibited by primary systems for optimising the specific task of spectrum selection. The identified primary behavior would make it possible to perform a pro-active spectrum selection strategy matching, when suitable, the available primary OFF periods to secondary traffic features. In this way, the usage of spectral resources could be improved while trying to avoid as much as possible the need for executing SpHOs (Spectrum Handovers) to vacate a channel when a PU appears. Therefore, the main contributions and advances with respect to the state-of-the art associated to this paper are two-fold: (1) To propose the usage of advanced statistics associated to heterogeneous primary-users and retaining such characterisations in a REM and (2) To exploit this knowledge by proposing a novel and comprehensive spectrum selection strategy able to suitably match multi-service secondary traffic to the observed spectrum opportunities and, therefore, benchmarking the utility of the knowledge retained in the REM.

The remainder of this paper is organized as follows: in Sec. II the system model is presented. In particular, it is proposed to characterise PUs through a set of statistical metrics stored in the REM. Sec. III proposes a set of principles for exploiting these statistical characterisations for the sake of optimizing spectrum selection. These principles are examined and assessed in Sec. IV through a set of case studies. Enlightened by this assessment, Sec. V proposes a more general spectrum selection strategy for matching multi-service secondary traffic to heterogeneous primary spectrum opportunities. Conclusions and possible extensions are addressed in Sec. VI.

II. System Model

Let consider a secondary access of M heterogeneous service types to a radio environment where PUs are operating on a set of channels of equal bandwidth B_P denoted as *C*. For each channel $i{\in}C$, the two discrete random sequences ON_i and OFF_i are introduced to respectively denote the sequences of PU 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 primary activity in the different channels are assumed to be independent.

The generic 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 Secondary User (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, PU statistics 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. As discussed in [8], 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 $|.|$ 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 α 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, $\forall i{\in}C$ the following metrics can be considered:

- Average value of ON and OFF periods, $E(ON_i)$, $E(OFF_i)$.
- Variances of ON and OFF periods, $VAR(ON_i)$, $VAR(OFF_i)$.
- The empirical pdf (probability density function) of ON_i:
$$pdf_{ON}^i(B_i^a) = Pr\left[ON_i(j){\in}B_i^a\right], \forall a{\in}\{1..|B_i^{ON}|\} \quad (1)$$
- The empirical pdf of OFF_i:
$$pdf_{OFF}^i(B_i^b) = Pr\left[OFF_i(j){\in}B_i^b\right], \forall b{\in}\{1..|B_i^{OFF}|\} \quad (2)$$
- 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 $B_i^a{\in}B_i^{ON}$:
$$CP_{OFF,ON}^i(B_i^b, B_i^a){=}Pr\left[OFF_i(j){\in}B_i^b/ON_i(j){\in}B_i^a\right] \quad (3)$$

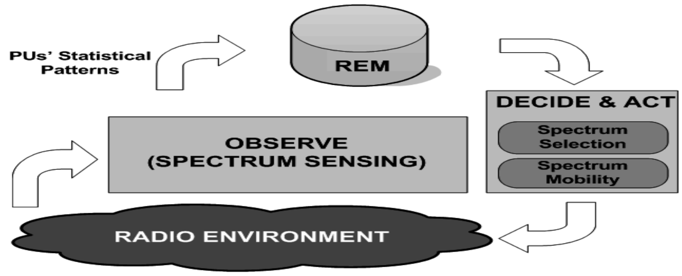


Fig. 1: Architecture of the proposed Primary-User Statistical Pattern Framework for Enhancing Cognitive Operation

- A proposed measure of dependence level between successive ON/OFF periods defined as:
$$DEP_i{=}\frac{1}{|B_i^{ON}|}\times \sum_{B_i^a\in B_i^{ON}} \max_{B_i^b\in B_i^{OFF}} \left(\delta_{a,b}{\times}CP_{OFF,ON}^i(B_i^b, B_i^a)\right) \quad (4)$$
where $\forall a{\in}\{1..|B_i^{ON}|\}$ and $\forall b{\in}\{1..|B_i^{OFF}|\}$, $\delta_{a,b}$ is a dependence indicator between B_i^a and B_i^b defined as:
$$\delta_{a,b} = \begin{cases} 1 \text{ if } CP_{OFF,ON}^i(B_i^b, B_i^a) > pdf_{OFF}^i(B_i^b), \\ 0 \text{ otherwise.} \end{cases} \quad (5)$$
Notice that only those buckets B_i^a such that $pdf_{ON}^i(B_i^a){\neq}0$ are considered in B_i^{ON} when calculating DEP_i in (4). The value of DEP_i will range from 0, corresponding to the case where ON and OFF periods are independent, to 1, corresponding to the case in which the OFF period is totally known from the preceding ON period.
- 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:
$$E(OFF_i/ON_i{\in}B_i^a){=} \sum_{B_i^b\in B_i^{OFF}} \hat{B}_i^b{\times}CP_{OFF,ON}^i(B_i^b, B_i^a) \quad (6)$$
where $\hat{B}_i^b$ is the center value of bucket B_i^b which is given by $\hat{B}_i^b{=}(b{-}0.5)\alpha E(OFF_i)$.

Depending on primary activity, useful knowledge about PUs can be inferred thanks to some of the above metrics. For instance, in case $VAR(OFF_i){=}0$ is observed, a deterministic primary inactivity pattern can be inferred and e.g. $E(OFF_i)$ would provide full estimation of primary OFF periods. Nevertheless, in a more general case of random primary inactivity, $E(OFF_i)$ may not be the best choice for characterising OFF periods if there are some patterns involving ON/OFF periods (e.g. dependencies between consecutive ON/OFF periods, between two successively observed OFF periods, etc). In this respect, DEP_i can be for instance used to evaluate how dependent consecutive ON/OFF periods are. The observation of a high DEP_i value would indicate that $E(OFF_i/ON_i{\in}B_i^a)$ would provide a much better estimator of actual OFF periods.

III. Principles for Spectrum Selection

The basic idea of optimizing spectrum selection is to pick up the best channel for secondary operation (according to a given criterion). While this problem accepts some mathematical formulation, the dynamism in the radio environment, the heterogeneity in PU types as well as secondary traffic types and the fact that previous spectrum selection decisions condition future selections suggest that a heuristic approximation can initially be suitable in order to gain insight into the problem and devise the main principles to follow in this decision-making process. On the other side, one can anticipate that the formulation of a comprehensive and general spectrum selection strategy is complex, since there will not be a single criterion that will result suitable in the wide range of different scenarios and configurations that may arise in practice. Therefore, the methodology followed in this paper is a two-step approach: firstly, several main principles to drive the spectrum selection will be proposed and assessed in Sec. IV in order to derive their main dependencies with other system parameters, then, based on this assessment, a more generic spectrum selection strategy will be formulated in Sec. V.

As a basic principle, the knowledge retained in the REM about the PU traffic can be used to estimate the remaining free-time for each of the sensed-as-free channels. In particular, for each idle channel $i{\in}C$, it is assumed to track the duration of the last ON_i period assumed to fall in bucket B_i^a as well as the so-far observed duration of the current OFF_i period (denoted in the following as $Idle\_C^i$). The remaining OFF period (Rem_T^i) at a given time instant can be estimated by subtracting the so-far observed availability time ($Idle\_C^i$) from an estimation of the actual OFF period given the last observed ON period as follows:

$$Rem\_T^i{=}E(OFF_i/ON_i{\in}B_i^a) - Idle\_C^i \tag{7}$$

It is important to point out that $E(OFF_i/ON_i{\in}B_i^a)$ is considered here in order to formulate a more generic case for an estimator of actual OFF periods. In case no dependency is observed between consecutive ON/OFF periods (i.e. $DEP_i{=}0$), the statistic reduces to $E(OFF_i/ON_i{\in}B_i^a){=}E(OFF_i)$. In turn, as DEP_i increases and ON/OFF become more dependent, $E(OFF_i/ON_i{\in}B_i^a)$ becomes much more accurate than $E(OFF_i)$.

The introduced estimation of the remaining free-time for each of the sensed-as-free channels can be next considered in the spectrum selection decision-making process. One can expect that this knowledge can be beneficial with respect to a first reference spectrum selection criterion (*RandSS*) where a random selection among the idle channels would be performed. The *RandSS* would be a reasonable criterion in case there would not be a REM supporting the cognitive system and providing knowledge about PUs.

Apart from the reference random selection (*RandSS*), two spectrum selection criteria exploiting differently the estimated remaining free-time are proposed as follows:

$$i^*_{Crit_1}{=}\arg\max_i \left(Rem\_T^i\right) \tag{8}$$

$$i^*_{Crit_2}{=}\arg\min_i \left|Rem\_T^i - MHT_m\right| \tag{9}$$

where i^* and MHT_m respectively denote the selected channel and the Mean Holding Time (MHT) for the $m{-}th$ service type $\forall m{\in}\{1..M\}$.

Notice that while $Crit_1$ picks up the most available channel, $Crit_2$ takes into account the characteristics of the secondary service (in terms of MHT_m) trying to choose a channel whose remaining time fits with MHT_m. In this way, it intends to prevent that some secondary services use those channels that might be more suitable for other services.

IV. Assessment of Principles for Spectrum Selection

In order to gain insight into the proposed secondary spectrum selection principles, some simulations have been conducted using a controllable primary user activity pattern. Principles of estimating primary OFF periods will be first assessed. Based on that assessment, the proposed set of multi-service spectrum selection criteria will be evaluated for several primary traffic patterns and different secondary configurations.

A. Assumptions

In order to account for heterogeneous spectrum opportunities, *K* primary-users using different sub-sets of channels are considered. Specifically, C_k denotes the set of channels operated by the $k{-}th$ PU so that $\cup_{k=1}^{K} C_k{=}C$. $\lambda_{p,k}$ and $\mu_{p,k}$ respectively denote the primary arrival and departure rates of the $k{-}th$ PU operating on all channels $i{\in}C_k$. The corresponding DC (Duty Cycle) is defined as:

$$DC_k{=}\frac{\lambda_{p,k}}{\lambda_{p,k}{+}\mu_{p,k}} \tag{10}$$

As for secondary operation, the $m{-}th$ service type will be denoted by $serv_m$ $\forall m{\in}\{1..M\}$. In order to vary secondary traffic loads, the mean holding time of each $serv_m$ (MHT_m) will be kept constant while varying the corresponding arrival rate (denoted as $\lambda_{s,m}$). Considering a periodic sensing every ΔT seconds, a perfect sensing (free of miss-detections and false alarms) is assumed for the sake of simplicity. If 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 Traffic Patterns

For simulation purposes, a controllable primary traffic time series is introduced for each channel $i{\in}C$. At a given time index *j*, the OFF period duration is generated based on the preceding ON period duration $ON_i(j)$ as follows:

$$OFF_i(j){=}p{\times}f(ON_i(j)){+}(1{-}p){\times}unif([OFF_i^{min},OFF_i^{max}]) \tag{11}$$

where $0{\leq}p{\leq}1$ is a probability that controls how dependent successive ON/OFF periods are, *unif[a,b]* denotes a uniformly distributed random variable in the range [a,b] and the function f is defined as:

$$f(x){=}OFF_i^{min}{+}\frac{(x{-}ON_i^{min}){\times}(OFF_i^{max}{-}OFF_i^{min})}{ON_i^{max}{-}ON_i^{min}} \tag{12}$$

With these definitions, it can be shown that $DEP_i{=}p$.

In the following assessment of principles, it is assumed that the statistics stored in the REM have achieved a good level of convergence. The reader is referred to [8] for aspects related to statistics' convergence (e.g. convergence time, operating bucket configuration, etc).

C. Assessment of Principles for Estimating Primary OFF Periods

This sections aims at analysing the key factors influencing estimation reliability of primary OFF periods. At a given moment of secondary operation, $\forall k{\in}\{1..K\}$ and $\forall i{\in}C_k$, Act_T^i

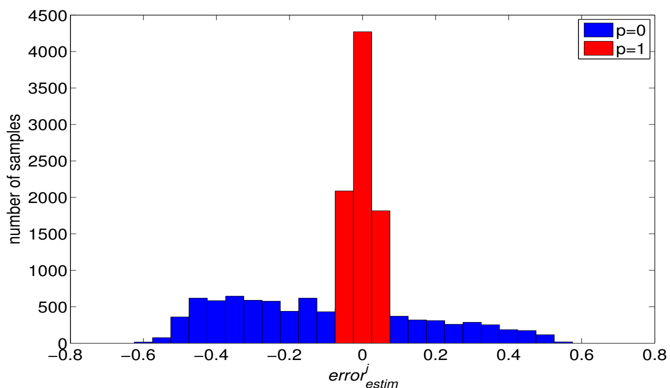


Fig. 2: Estimation reliability of OFF periods, $\frac{1}{\lambda_{p,k}}$=30s

is introduced to denote the actual remaining OFF period of channel i.

The relative estimation error is defined as the difference between Rem_T^i and the actual remaining time Act_T^i relative to the average OFF period duration ($\frac{1}{\lambda_{p,k}}$):

$$error^i_{estim}{=}\lambda_{p,k}\times\left(Rem\_T^i-Act\_T^i\right) \quad (13)$$

Focusing on a given primary-user k operating with $\frac{1}{\lambda_{p,k}}{=}30s$, Fig. 2 plots the histogram of $error^i_{estim}$ for different primary-user traffic patterns, characterised by the parameter p in the primary source generation process. It is worth pointing that, for $p{=}0$, $E(OFF_i/ON_i{\in}B^a_i){=}E(OFF_i)$ while for $p{=}1$, $E(OFF_i/ON_i{\in}B^a_i)$ gives the actual OFF_i. This is clearly reflected in Fig. 2, where for $p{=}0$, the rough estimation of the actual remaining OFF period results in an absolute value of the relative estimation error above 0.3 about 50% of the time. On the contrary, for primary traffic sources exhibiting stronger dependence levels ($p{=}1$), the observed estimation error histogram concentrates to the origin because $E(OFF_i/ON_i{\in}B^a_i)$ exploits the dependence between successive ON and OFF periods making OFF period estimation much more accurate. Notice that the fact that $error^i_{estim}{\neq}0$ for $p{=}1$ is due to the resolution of buckets. As a matter of fact, $error^i_{estim}$ tends to zero as buckets get squeezed.

Given that the accuracy in the estimation of OFF periods depends on dependence level between ON/OFF periods and it can be different for each channel, it is proposed to introduce a compensation factor β_i in (8) and (9) so that the spectrum selection decision is not biased by the estimation error:

$$i^*_{Crit_1}{=}\arg\max_i\left(\beta_i{\times}Rem\_T^i\right) \quad (14)$$

$$i^*_{Crit_2}{=}\arg\min_i\left|\beta_i{\times}Rem\_T^i-MHT_m\right| \quad (15)$$

D. Performance Evaluation of Spectrum Selection Criteria

This section aims at getting an insight into the relevance of the proposed spectrum selection criteria as far as multi-service secondary spectrum selection is concerned. Considering the case study described in Table I, performances of the proposed criteria will be evaluated for different primary traffic patterns. Since both $Crit_1$ and $Crit_2$ are pro-active in terms of subsequent SpHO events, it is proposed to evaluate spectrum selection performances in terms of the overall SpHO rate (i.e. total number of SpHO/s). Notice that even though the compensation factor β_i used by $Crit_1$ and $Crit_2$ is in general a function of DEP_i, it is assumed for the sake of simplicity that $\beta_i{=}0.95$.

TABLE I: Considered case study

	Parameter	Definition	Value
PUs	C	Set of primary channels	{1−16}
	K	Number of PUs	2
	C_1	Set of channels of the 1^{st} PU	{1−4}
	C_2	Set of channels of the 2^{nd} PU	{5−16}
	$\frac{1}{\lambda_{p,1}}$	Average OFF period of the 1^{st} PU	15s
	$\frac{1}{\lambda_{p,2}}$	Average OFF period of the 2^{nd} PU	60s
	DC_k	Duty Cycle	0.2
SUs	M	Number of secondary service types	2
	MHT_1	Mean holding time of $serv_1$	15s
	MHT_2	Mean holding time of $serv_2$	60s
	$\triangle T$	Sensing period	0.1s

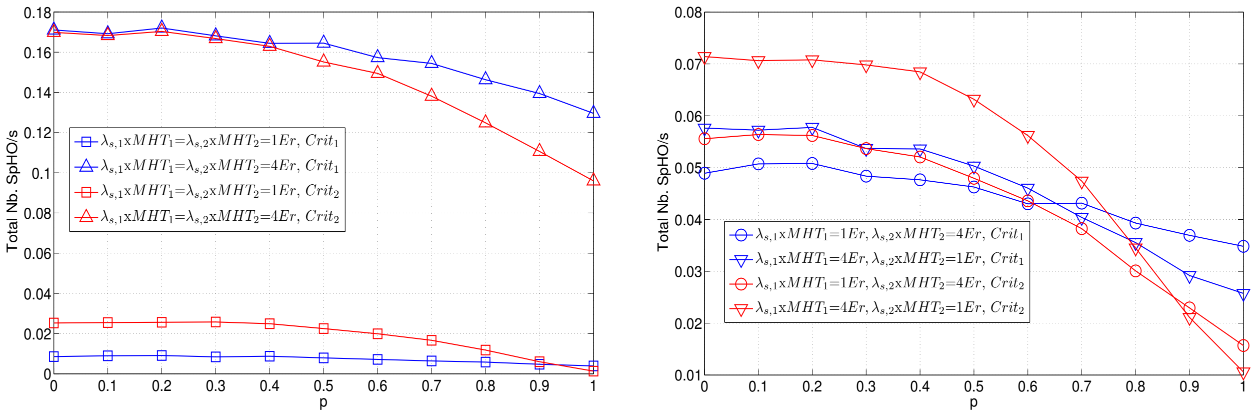
TABLE II: Spectrum selection performances of $RandSS$

	$\lambda_{s,1}{\times}MHT_1$	$\lambda_{s,2}{\times}MHT_2$	Nb. SpHO/s
Extreme loads	1	1	0.66
	4	4	0.63
Intermediate loads	1	4	1.05
	4	1	0.51

Fig. 3 plots spectrum selection performances of $Crit_1$ and $Crit_2$ for the whole range of possible values of p for a given set of secondary traffic mixes. For a better visualisation, the figure is split into Fig. 3(a) for the extreme traffic loads (i.e. either low load or high load of both service types) and Fig. 3(b) for the intermediate traffic loads. Performances of *RandSS* for the considered traffic loads are separately given by Table II since they are independent from p.

The first observation is that for all considered traffic loads, the gains $Crit_1$ and $Crit_2$ are introducing with respect to *RandSS* are significant. Gains ranging around 70% are observed for independent ON/OFF periods ($p{=}0$). As p increases, the accuracy of $E(OFF_i/ON_i{\in}B^a_i)$ in estimating OFF periods gets improved and gains rise up to around 100%. Next, a comparison between $Crit_1$ and $Crit_2$ performances is performed in the following.

- Low traffic loads: Results show that for low traffic loads of both service types ($\lambda_{s,1}{\times}MHT_1{=}\lambda_{s,2}{\times}MHT_2{=}1Er$) (Fig. 3(a)), $Crit_1$ is outperforming $Crit_2$ regardless of the dependence level at hand (p). This is due to that fact that, at such low load conditions, there are often some available channels whose remaining OFF period lengths (Rem_T^i) are longer that the MHT of the secondary request at hand. The assignment of the largest estimated Rem_T^i (i.e. $Crit_1$) basically picks the most available among these channels meaning that no subsequent SpHO will be experienced. On the contrary, assigning a channel whose Rem_T^i tightly fits MHT (i.e. $Crit_2$) can result in more SpHOs if the reliability of OFF period estimation in not perfect. Specifically, as it has been observed in Sec. IV-C, for low dependence levels (small p), $E(OFF_i/ON_i{\in}B^a_i)$ is just providing a rough estimation of actual OFF periods. This means that $Crit_2$ can assign to $serv_1$ requests channels whose remaining OFF period (Rem_T^i) were over-estimated and were wrongly supposed to fit MHT_1. This increases the number of unnecessary SpHOs compared to $Crit_1$. As the dependence level (p) increases, the estimation reliability is improved, the number of unnecessary SpHOs performed by $Crit_2$ is reduced, and $Crit_1$ and $Crit_2$ performances get closer.



(a) Extreme Traffic loads

(b) Intermediate Traffic loads

Fig. 3: Performance evaluation of spectrum selection criteria

- High traffic loads: As far as high traffic loads are considered ($\lambda_{s,1}\times MHT_1$=$\lambda_{s,2}\times MHT_2$=$4Er$) (Fig. 3(a)), it is observed that $Crit_2$ outperforms $Crit_1$ for all dependency levels (p). At such high traffic loads, it is less likely to find a channel whose remaining OFF period can fit MHT, which makes inevitable assigning secondary requests to channels to be switched-off. This means that wrong "fit" that may be performed by $Crit_2$ due to estimation inaccuracy is not likely to result in unnecessary SpHOs. Nevertheless, the "fit" performed by $Crit_2$ tends to assign C_1 channels to $serv_1$ and C_2 channels to $serv_2$, which results in a better assignment.
- Intermediate traffic loads: For intermediate traffic loads and mixes (Fig. 3(b)), it is observed that relative performances of $Crit_1$ and $Crit_2$ strongly depend on the dependency level p at hand. Specifically, for low dependency levels, $Crit_1$ is performing better while $Crit_2$ is preferable for high dependency levels. This means that there is a threshold at which relative performances are reversed, and this threshold is dependent on the traffic loads. Considering for instance $\lambda_{s,1}\times MHT_1$=$4Er$ and $\lambda_{s,2}\times MHT_2$=$1Er$, $Crit_1$ is better up to p=0.8.

V. Combined Spectrum Selection Strategy

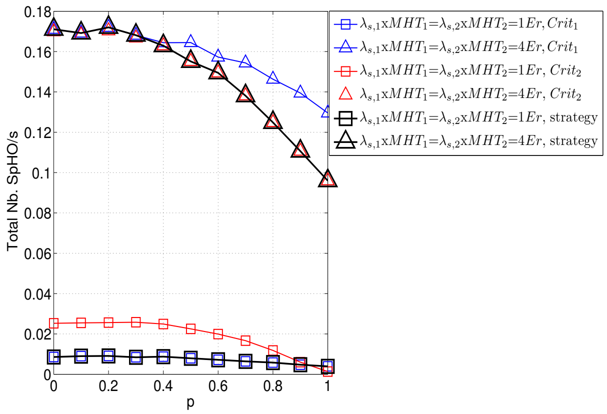
Enlightened by the assessment of principles conducted in Sec. IV, which has shown that the suitable spectrum selection criterion depends on a number of aspects such as characteristics of primary users, level of dependence exhibited by primary traffic, secondary service mix, etc., this section develops a combined spectrum selection strategy for better exploiting statistical metrics provided by the REM, thus matching multi-service secondary traffic to heterogeneous primary spectrum opportunities. The inputs of the considered strategy are, on the one hand, the statistical characterisation of the different channels in terms of $E(OFF_i/ON_i{\in}B_i^a)$ and the dependence level DEP_i obtained from the REM. It is assumed for the sake of simplicity that all channels have the same dependence level (DEP_i=$DEP, \forall i{\in}C$). The algorithm uses, on the other hand, as inputs the secondary traffic load levels of the different services as well as their characterisations in terms of MHT.

As detailed by the pseudo-code of Algorithm 1, it is assumed that secondary service types are served in the increasing order of their indices (loop in line 2). For the service at hand (the *m*-th one), the remaining OFF period of the set of available channels (av_list) is first estimated by subtracting the so-far observed availability time ($Idle\_C^i$) from the expected OFF period given the last observed ON period (line 4). Once all Rem_T^i are estimated, the list of potential channels for assignments to $serv_m$ (*Candidates*) is built differently depending on the dependence level provided by the REM. Specifically, if DEP is below a given threshold DEP_{thr}, the list of candidate channels for assignments to $serv_m$ is built using $Crit_1$ (i.e. picking channels that maximize Rem_T^i) (line 7). Otherwise, *Candidates* is constructed using $Crit_2$ (i.e. by channels that best fit MHT_m) (line 9). As it has been identified in Sec. IV-D, the threshold DEP_{thr} for deciding about the significance of the dependency level at hand is a function (denoted as g) of traffic loads of both service types to capture the fact that the convenience of one or other criterion depends on the specific traffic loads. Finally, in the very specific case of multiple channels in *Candidates*, the channel with lowest DC is selected (line 11).

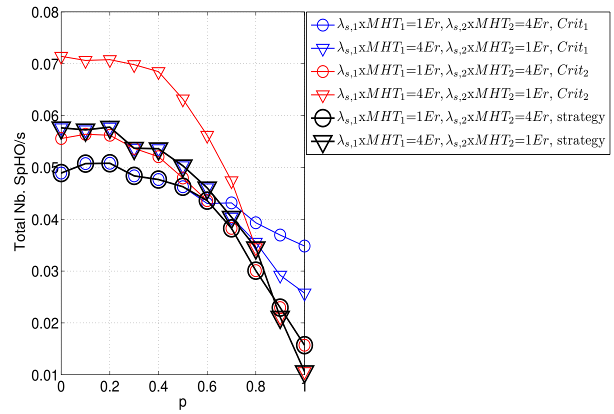
Considering the case study described in Table I, the function g defining the dependency threshold DEP_{thr} has been fit based on previous simulations using a polynomial regression model with an overall Root Mean Squared Error (RMSE) of 0.1. Based on this model, Fig. 4 makes a comparison between performances of $Crit_1$, $Crit_2$ and the combined strategy for the whole range of possible values of p for different secondary traffic mixes. As pointed out previously, performances are measured in terms of the overall SpHO rate. It can be seen that the combined strategy efficiently switches between $Crit_1$ and $Crit_2$. As a result, it achieves in most of the cases the best performance among $Crit_1$ and $Crit_2$ for a given secondary traffic mix and every dependence level.

Algorithm 1 Combined Spectrum Selection Strategy

1: $\{Rem\_T^i\}_{i\in C} \leftarrow 0, Candidates \leftarrow \emptyset$;
2: **for** m=1 **to** 2 **do**
3:   **for** i=1 **to** $|av\_list|$ **do**
4:     $Rem\_T^i \leftarrow E(OFF_i/ON_i{\in}B_i^a) - Idle\_C^i$;
5:   **end for**
6:   **if** $DEP{<}DEP_{thr}{=}g(\lambda_{s,1}\times MHT_1, \lambda_{s,2}\times MHT_2)$ **then**
7:     $Candidates \leftarrow \{i \in av\_list/i{=}i^*_{Crit_1}\}$;
8:   **else**
9:     $Candidates \leftarrow \{i \in av\_list/i{=}i^*_{Crit_2}\}$;
10:   **end if**
11:   $i^*_{m,strategy} \leftarrow \arg\min_{j\in Candidates}(DC_j)$;
12: **end for**



(a) Extreme Traffic loads



(b) Intermediate Traffic loads

Fig. 4: Performance evaluation of the combined spectrum selection strategy

VI. Conclusions and Proposed Extensions

In order to improve CR's operation, this paper has proposed the usage of advanced statistics associated to heterogeneous primary-users and retaining such characterisations in a REM. Specifically, statistical patterns that capture among others hidden dependence structures potentially exhibited by primary ON/OFF periods have been formulated and developed. In order to benchmark the utility of such knowledge in a REM, two spectrum selection criteria exploiting differently the formulated patterns have been proposed in a multi-secondary service context. Results have shown that in case a REM supporting the cognitive system and providing such knowledge about primary users is available, both of the proposed criteria can introduce significant gains (ranging from 70% to 100%) with respect to a random selection among idle channels. Furthermore, it has been identified that the suitable spectrum selection criterion depends on a number of aspects such as composition and characteristics of primary users, level of dependence exhibited by primary traffic, secondary service mix, etc. Therefore, a novel pro-active spectrum selection strategy combining the proposed criteria to suitably match multi-service secondary traffic to heterogeneous spectrum opportunities has been proposed. Explicitly exploiting primary dependence metrics provided by the REM and a characterisation of secondary service types in terms of MHT and traffic mix, the proposed strategy has been proven to efficiently switch between the different criteria for a given secondary traffic mix and a given level of dependence. As part of future work, it is proposed to extend this work to support the non-continuous channel aggregation feature of LTE-advanced systems and exploit inter-channel dependence structures.

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.

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