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# Knowledge Management Framework for Robust Cognitive Radio Operation in Non-Stationary Environments

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***Abstract*—To increase cognitive radio operation efficiency, this paper proposes a new knowledge management functional architecture, based on the fittingness factor concept, for supporting spectrum management in non-stationary environments. It includes a reliability tester module that detects, based on hypothesis testing, relevant changes in suitability levels of spectrum resources to support a set of heterogeneous applications. These changes are captured through a set of advanced statistics stored in a knowledge database and exploited by a proactive spectrum management strategy to assist both spectrum selection and spectrum mobility functionalities. The results reveal that the proposed reliability tester is able to disregard the changes due to the intrinsic randomness of the radio environment and to efficiently detect actual changes in interference conditions of spectrum pools. Thanks to this support, the proposed spectrum management strategy exhibits substantial robustness when the environment becomes non-stationary, obtaining performance improvements of up to 75% with respect to the reference case that does not make use of the reliability tester functionality**

## I. Context/Motivation

The cognitive radio (CR) paradigm has led to the emergence of intelligent radios that automatically adjust their behavior based on active monitoring of the environment [1, 2]. In this context, the introduction of cognitive techniques for the management of wireless networks will lead to enhanced robustness by capitalizing on the learning capabilities intrinsic to cognitive systems. Strengthening these cognitive techniques is of great interest for optimizing cognitive management functions. Therefore, technical requirements of new cognitive management systems have been considered in many studies [3–5]. In particular, many recent proposals have attempted to develop new models and efficient architectures for building new cognitive management systems in emerging environments, such as the Future Internet (FI) [6] or the home environment [7]. The proven usefulness of cognitive capabilities has stimulated the initiation of many research projects (e.g., [8, 9]) and standardization activities (e.g., [10, 11]) to further strengthen and promote the use of cognitive management systems.

The flexibility provided by CR is of paramount importance to enable the so-called dynamic spectrum access (DSA), a new communication paradigm that proposes the use and sharing of available spectrum in an opportunistic manner to increase its usage efficiency. Not surprisingly, this topic has received a lot of interest in the recent literature (e.g., [12, 13]). The flexibility provided by spectrum agility has been materialized in the form of increased efficiency through proper spectrum selection criteria.

In this respect, we have proposed in [14, 15] a framework based on the fittingness factor concept to assess the suitability of a set of spectrum blocks to support a set of heterogeneous application requirements. An initial formulation of a fittingness-based spectrum management strategy was presented in [14] to benchmark the usefulness of the proposed framework in supporting cognitive operation. The strategy proposed in [14] was extended in [15] with the inclusion of several fittingness factor functions and spectrum selection criteria.

Therefore, the first main contribution of this paper is to extend the knowledge management functional architecture described in [15] to improve robustness of cognitive operation in non-stationary environments. The proposed architecture relies on a reliability tester (RT) that detects, based on hypothesis testing, relevant changes that may occur in radio and interference conditions, and updates a set of advanced statistics stored in a knowledge database (KD) to characterize available spectral resources accordingly. To the best of authors' knowledge, this is the first time the statistics hypothesis testing tool is adapted to probabilistically test for stationarity subject to the intrinsic randomness of the radio environment. A proactive spectrum management strategy exploiting KD data is proposed to assess the resulting performance under non-stationary conditions. Correspondingly, the second contribution of this paper is to benchmark the usefulness of the proposed RT to cope with non-stationarity of the environment from the spectrum management decision-making process perspective.

The remainder of this paper is organized as follows. A knowledge management functional architecture, integrating the fittingness factor concept, is proposed in Section. II to assist cognitive operation in non-stationary environments. Then, the RT is implemented in Section. III to detect changes that may arise in interference conditions of spectrum resources, and perform the required updates accordingly. A proactive spectrum management strategy that exploits these updates is proposed in Section. IV to support both spectrum selection and spectrum mobility functionalities. The results are presented in Section. V to firstly assess the capability of the RT to detect changes and, secondly evaluate robustness of the proposed spectrum management strategy when conditions become non-stationary. The conclusions are provided in Section. VI.

## II. Functional architecture

The problem considered here is the selection of the spectrum to be assigned to a set of $L$ radio links that need to be established between pairs of terminals and/or infrastructure nodes. The purpose of the $l$-th radio link is to support the communication flow generated by a given application (e.g., voice, web browsing, or video call) whose requirements are expressed in terms of a required bit rate $R_{req,l}$ and duration

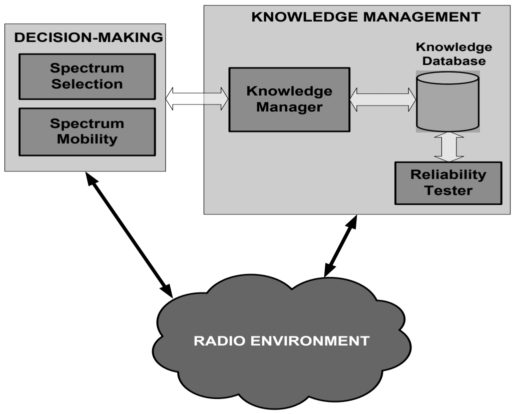



Fig. 1. Functional architecture of the proposed knowledge management framework

$T_{req,l}$. The available spectrum is modeled as a set of $P$ spectrum blocks (denoted in this paper as "pools") each of bandwidth $BW_p$. Based on radio link requirements and spectrum pool characteristics, the general aim is to efficiently assign a suitable spectrum pool to each of the $L$ radio links.

Based on the above considerations and inspired by the ETSI-RRS architecture [16], the functional architecture depicted in Fig. 1 is proposed. It consists in the following entities:

1) The knowledge management entity, which is responsible for storing and managing the information about the radio environment that is most relevant to the decision-making entity. It is composed of a knowledge manager (KM) that monitors the suitability of existing spectral resources to support the set of heterogeneous applications. The KM monitoring is based on information retrieved from a KD that stores a set of relevant statistics about the environment and the list of available spectrum pools. To detect relevant changes in these statistics when operating in non-stationary environments, the RT keeps analyzing a set of Key Performance Indicators (KPIs) from the radio environment, and may restart if needed the process of generating KD statistics.
2) The decision-making entity, which is responsible for assigning an appropriate pool to each of the established links. For that purpose, it interacts with the KM that will provide the relevant information for the decisions to be made. Decision making is split into two functional entities: the Spectrum Selection (SS) functionality, which will pick up a suitable pool for each communication whenever a new request for establishing a radio link arrives, and the Spectrum Mobility (SM) functionality, which will perform the reconfiguration of assigned pools whenever changes occur in the environment and better pools can be found for some links. In the latter case, the spectrum assignment can be modified through Spectrum HandOver (SpHO) procedures.

To assess the suitability of spectral resources to support different application requirements, the so-called "fittingness factor" ($F_{l,p}$) was considered in [14] as a metric capturing how suitable each $p$-th spectrum pool is in accordance with the bit rate requirements of the application supported by the $l$-th radio link ($R_{req,l}$). Specifically, the fittingness factor function is defined as:

$$F_{l,p}=\frac{1-e^{-\frac{K\times U_{l,p}}{\frac{R(l,p)}{R_{req,l}}}}}{\lambda} \tag{1}$$

where $R(l,p)$ is the achievable bit rate by link $l$ using pool $p$ that depends on the radio and interference conditions present in this pool, $K$ is a shaping parameter and $U_{l,p}$ is the following utility function:

$$U_{l,p}=\frac{\left(\frac{R(l,p)}{R_{req,l}}\right)^{\xi}}{1+\left(\frac{R(l,p)}{R_{req,l}}\right)^{\xi}} \tag{2}$$

$\xi$ is a shaping parameter that allows the function to capture different degrees of elasticity with respect to the required bit rate. Finally, $\lambda$ is a factor that normalizes the maximum of the fittingness factor to one that is given by:

$$\lambda=1-e^{-\frac{K}{(\xi-1)^{\frac{1}{\xi}}+(\xi-1)^{\frac{1-\xi}{\xi}}}} \tag{3}$$

The proposed $F_{l,p}$ function increases with $R(l,p)$ up to the maximum at $R(l,p)=\sqrt[\xi]{\xi-1}\times R_{req,l}$. It has been shown in [15] that this formulation of $F_{l,p}$ performs more efficient usage of spectral resources than just considering $F_{l,p}=U_{l,p}$, thanks to reducing the value of the fittingness factor whenever the available bit rate is much higher than the required one.

Both KD and KM blocks are implemented based on the fittingness factor concept. Specifically, the KD is fed by measurements of $R(l,p)$ extracted from the radio environment, from which the current value of $F_{l,p}$ will be computed following (1), and will be stored in the database together with the corresponding time stamp indicating when the measurement was obtained. Furthermore, the set of advanced statistics proposed in [14] to monitor fittingness factor variability are generated and stored in the database based on the previously obtained measurements of $R(l,p)$ and $F_{l,p}$. This allows having in the KD a characterization of each pool/link based on the history of using this pool. Based on KD data, the KM keeps an estimation of $F_{l,p}$ values (denoted as $\hat{F}_{l,p}$) following the algorithm proposed in [14].

## III. Reliability Tester

To detect changes in the radio and interference conditions of the different spectrum pools, the RT monitors the reliability of stored KD data. Whenever a relevant change is detected, KD statistics are regenerated under the new conditions.

The RT detects changes by monitoring pools used by active link sessions. A change is judged as relevant if it has a significant impact on the performance perceived by the end-user evaluated in terms of a set of KPIs (e.g., the achievable bit rate $R(l,p)$, the dissatisfaction probability and the number of SpHOs). To carry out this procedure, the RT considers first an initial estimate of each $KPI$ computed based on a sequential analysis of its observed sample mean over the established link sessions (let $\overline{KPI}$ denote this initial mean estimate). Then, the RT gradually increases the sample size (denoted as $S$) as new link sessions are established, and updates the observed sample mean ($\overline{KPI}$), sample variance ($\sigma$) and $\gamma$ confidence interval defined as

$$Prob\left[KPI\in[KPI_{min},KPI_{max}]\right]=\gamma \tag{4}$$

Assuming large-sample conditions (typically in the order of $S>30$), $KPI_{min}$ and $KPI_{max}$ are given by:

$$KPI_{min}=\overline{KPI}-z\times\frac{\sigma}{\sqrt{S}} \tag{5}$$

$$KPI_{max}=\overline{KPI}+z\times\frac{\sigma}{\sqrt{S}} \tag{6}$$

where $z=\phi^{-1}(1-\frac{1-\gamma}{2})$ and $\phi(.)$ denotes the cumulative normal distribution function. Note that as the sample size $S$ increases, $KPI$ tends to converge and the interval $[KPI_{min}, KPI_{max}]$ gets narrower.

To achieve a good level of convergence in each $KPI$, the sequential analysis is performed until the width of the $\gamma$ confidence interval becomes smaller than a fraction $0<\rho<1$ of the sample mean ($\overline{KPI}$), that is:

$$\overline{KPI}_{max}-\overline{KPI}_{min}<\rho\times\overline{KPI} \tag{7}$$

After meeting this stopping rule, $\overline{KPI}$ becomes the initial estimate, and the current value $S$ of the window size is kept.

Then, the RT starts a procedure of monitoring possible changes in the average value of $KPI$ based on the statistical technique known in the literature as binary hypothesis testing [17]. Specifically, a null hypothesis ($H_0$) is introduced to claim that there is no difference between the initial average value ($\overline{KPI}$) and a new average value continuously updated based on a moving window of the same size $S$. Let $\widehat{KPI}$ denote this new average value and $\left[\widehat{KPI}_{min}, \widehat{KPI}_{max}\right]$ be its corresponding $\gamma$ confidence interval. As long as $H_0$ holds, KD statistics are assumed to be valid. On the contrary, the alternative hypothesis ($H_1$) claims that there is a difference between the initial and new average values, and thus KD statistics are no longer valid.

Nevertheless, differences that may be observed between these two average values do not always imply invalidity of KD statistics but may be just the result of the pure chance of the experiment. Therefore, the hypothesis testing procedure should ensure with a certain probability that only those differences caused by an actual change in the scenario (e.g., appearance of a new external interferer) are detected. This means, on the one hand, that the probability of selecting $H_1$ when $H_0$ actually holds (the so-called Type I error in hypothesis testing terminology [18]) should be kept below a maximum level $\alpha$. On the other hand, the probability of selecting $H_0$ when $H_1$ actually holds (the so-called type II error) should also be kept below a maximum level $\beta$.

Depending on the objective to achieve, different strategies may be followed to strike a balance between $\alpha$ and $\beta$ [18]. In our specific case, it is proposed to select $H_0$ when confidence intervals of the two average values overlap and $H_1$ otherwise. This minimizes as much as possible the significance level $\alpha$ while keeping $\beta$ at an acceptable level, which reduces the risk of useless regeneration of KD data.

Finally, the obtained hypothesis testing results for each of the considered KPIs are combined to decide about the reliability of the whole KD data. Specifically, we consider in this paper that, if $H_1$ is selected for at least one of the considered KPIs, the whole KD data is judged as unreliable, so it is regenerated. In such case, the RT sets $S$ to zero and loops back to the sequential analysis procedure described in the beginning of this section to recalculate all the initial estimates $\overline{KPI}$ under the new conditions. In this case, the KM will continue using old KD statistics until the new statistics become available.

## IV. Spectrum Management Decision-Making

The proposed fittingness factor function is applied to the SS decision-making process. The aim of this process is to allocate, for a given link $l$, the best spectrum pool $p^*(l)$ among the list of available pools ($Av\_Pools$), i.e., those that are not currently assigned to any other link, to support the corresponding application.

Enlightened by the comparative study of several SS criteria conducted in [15], the following proactive criterion is considered in this paper:

$$p^*(l) = \arg\max_{p\in Av\_Pools}\left(g(\hat{F}_{l,p})\right) \tag{8}$$

The function $g(\hat{F}_{l,p})$ assesses the likelihood of observing a HIGH $F_{l,p}$ value (i.e., above a certain threshold $\delta_{l,p}$) up to the end of session duration $T_{req,l}$ as follows:

$$g(\hat{F}_{l,p})=\begin{cases}P^{l,p}_{H,H}(\Delta k_{l,p}+T_{req,l},\delta_{l,p}) & \text{if } \hat{F}_{l,p} \text{ is HIGH } (\geq\delta_{l,p})\\ 0 & \text{if } \hat{F}_{l,p} \text{ is LOW } (<\delta_{l,p})\end{cases} \tag{9}$$

where $\Delta k_{l,p}$ and $P^{l,p}_{H,H}(k,\delta_{l,p})$ denote the number of time units since the $F_{l,p}$ stored in the KD was obtained and the probability that $F_{l,p}$ will be HIGH after $k$ time units given that $F_{l,p}$ is initially HIGH, respectively.

In what follows, both SS and SM functionalities of the decision-making process are implemented.

### A. Spectrum Selection

The proposed proactive fittingness factor-based SS algorithm is described in Algorithm 1. It is executed every time the start of a new application requires the establishment of a radio link to support communication. Upon receiving a request for establishing a link $l$, the request is rejected if the set of available pools ($Av\_Pools$) is empty (line 3). Otherwise, an estimation of $F_{l,p}$ values is obtained from the KM (line 5). Based on provided data, the available spectrum pool $p^*(l)$ that maximizes the likelihood of observing a HIGH $F_{l,p}$ value up to the end of link session duration $T_{req,l}$ is selected (lines 6 and 7).

### B. Spectrum Mobility

The SM functionality attempts to ensure highly efficient allocation of available spectrum pools to each of the established radio links. Therefore, whenever an event that might have influence on the SS decision-making process occurs, the SM will be executed to trigger possible changes in spectrum assignment, i.e., SpHOs. Such events include (1) a spectrum pool being released due to finalization of the corresponding application, or (2) a change in suitability of available spectrum pools being detected.

The proposed proactive fittingness factor-based SM algorithm is described in Algorithm 2. The algorithm is triggered whenever a previously selected pool by SS at link establishment is no longer the best in terms of $g(\hat{F}_{l,p})$ for the corresponding active link. This may happen whenever some active pools are released or experience some change in their $F_{l,p}$ values. Following both triggers, an estimation of $F_{l,p}$

values is obtained from the KM (line 2). The algorithm then explores the list of currently active links ($Active\_Links$) in the decreasing order of required throughputs ($R_{req,l}$) in order to prioritize the neediest links. The decision to reconfigure or not each active link is based on a comparison between the in use pool ($p^*(l)$) and the currently best pool in terms of $g(\hat{F}_{l,p})$ ($new\_p^*(l)$) (line 8). Specifically, if $\hat{F}_{l,p^*(l)}$ is LOW and $\hat{F}_{l,new\_p^*(l)}$ is HIGH, an SpHO from $p^*(l)$ to $new\_p^*(l)$ is performed since $new\_p^*(l)$ fits better link $l$. Finally, as reflected in the condition of line 9, the same SpHO should be performed if $p^*(l)$ is no longer available to link $l$ after being reassigned to another active link in the previous iterations of the loop of line 5. Once all active links have been explored, the list of assigned pools is updated according to performed SpHOs (line 16).

**Algorithm 1** Fittingness Factor-based SS

1: **if** application $l$ request **then**
2:     **if** $Av\_Pools{=}\emptyset$ **then**
3:         Reject request;
4:     **else**
5:         Get $\{\hat{F}_{l,p}\}_{1\leq p\leq P}$ from the KM;
6:         Compute $g\left(\hat{F}_{l,p}\right)_{1\leq p\leq P}$;
7:         $p^*(l) \leftarrow \arg \max_{p\in Av\_Pools} \left(g\left(\hat{F}_{l,p}\right)\right)$;
8:     **end if**
9: **end if**

**Algorithm 2** Fittingness Factor-based SM

1: **if** (application $l^*$ ends) **or** (change in any active $F_{l,p}$) **then**
2:     Get $\{\hat{F}_{l,p}\}_{1\leq L\leq l,1\leq p\leq P}$ from the KM;
3:     $New\_Assigned \leftarrow \emptyset$;
4:     Sort $Active\_Links$ in the decreasing order of $R_{req,l}$;
5:     **for** $l$=1 **to** $|Active\_Links|$ **do**
6:         Compute $g\left(\hat{F}_{l,p}\right)_{1\leq p\leq P}$;
7:         $new\_p^*(l) \leftarrow \arg \max_{p\in Av\_Pools} g\left(\hat{F}_{l,p}\right)$;
8:         **if** (($\hat{F}_{l,p^*(l)}$ is LOW) **and** ($\hat{F}_{l,new\_p^*(l)}$ is HIGH)) **or**
9:         ($p^*(l){\in}new\_Assigned$) **then**
10:             $p^*(l) \leftarrow new\_p^*(l)$;
11:             $New\_Assigned \leftarrow New\_Assigned \bigcup \{new\_p^*(l)\}$;
12:         **else**
13:             $New\_Assigned \leftarrow new\_Assigned \bigcup \{p^*(l)\}$;
14:         **end if**
15:     **end for**
16:     $Assigned \leftarrow New\_Assigned$;
17: **end if**

## V. Simulation results

### A. Simulation model

To evaluate the effectiveness of the proposed framework in assisting in the spectrum management decision-making process, $L$=2 radio links are considered. Each radio link generates sessions with arrival rate $\lambda_l$ and constant session duration $T_{req,l}$. Link #1 is associated with low-data-rate sessions ($R_{req,1}{=}64\,Kbps$ and $T_{req,1}{=}2\,min$), while link #2 is associated with high-data-rate sessions ($R_{req,2}{=}1\,Mbps$ and $T_{req,2}{=}20\,min$).

Performance is evaluated using a system-level simulator operating in steps of 1 s under the following assumptions:

- $P$=4 spectrum pools are considered.
- The noise and interference power spectral density $I(p)$ experienced in each pool $p{\in}\{1,\ldots,P\}$ follows a two-state discrete time Markov chain jumping between a state of low-interference $I_0(p)$ and a state of high-interference $I_1(p)$.
- To assess robustness in front of changes in interference conditions, the simulation is assumed to start with a given statistical pattern of $I(p)$ in each of the considered spectrum pools. Then, at a certain point of time, some of these interference patterns are altered. Table I shows durations of the two possible states of $I(p)$ with the corresponding bit rates before and after the change. Note that, after the change, statistical patterns of pools #1 and #3 are swapped.

Furthermore, the procedure of detecting changes described in Section. III is performed by the RT based the following subset of KPIs observed for each link $l$:

- The average dissatisfaction probability (i.e., probability of experiencing a bit rate $R(l,p)$ below the requirement $R_{req,l}$), $Dissf(l)$.
- The average number of SpHOs performed per session, $SpHO(l)$.

The system is observed till establishing $65,000$ sessions for each link. The change in interference conditions occurs for all simulations after establishing $22,000$ sessions for each link. The other simulation parameters are $\xi$=5, $K$=1, $\delta_{1,p}$=0.2, $\delta_{2,p}$=0.9, $\rho$=0.1, and $\gamma$=0.95.

### B. Benchmarking

To assess the influence of the proposed RT, the following variants are compared:

- *SS+SM*: This approach makes use of both the SS and SM functionalities, but does not include the RT to detect possible changes and regenerate KD statistics in case.
- *SS+SM+RT*: This is the complete approach that includes the SS, SM and RT functionalities.

### C. RT capability to detect changes

This section evaluates the capability of the RT to detect relevant changes in the radio and interference conditions of the different spectrum pools.

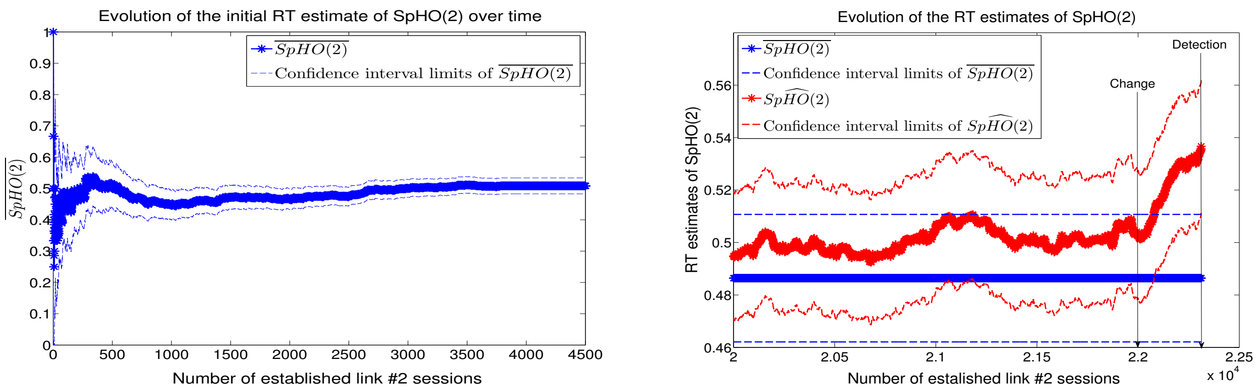
Fig. 2(a) plots the temporal evolution of the initial RT estimate of the number of SpHOs/session for link #2 ($\overline{SpHO(2)}$) with the corresponding confidence interval shown in dashed lines for a traffic load of $L_l{=}\lambda_l{\times}T_{req,l}{=}1\,Er, l{\in}\{1,2\}$. The time evolution on the x-axis is shown in terms of the number of established link #2 sessions according to the generation process described in Section. V-A. Note that only $SpHO(2)$ is considered because this is the KPI for which $H_1$ is selected by the RT after the change occurs.

The results show that $\overline{SpHO(2)}$ tends to converge as more link #2 sessions are established. Specifically, the stopping rule of (4) is met after establishing around $3,700$ sessions. At this point of time, the initial $\overline{SpHO(2)}$ estimate and its confidence interval are frozen, and the RT starts to watch the second moving-average estimate ($\widehat{SpHO}(2)$).

Fig. 2(b) plots the temporal evolution of $\widehat{SpHO}(2)$ and its corresponding confidence interval around the considered change. The initial $\overline{SpHO(2)}$ estimate is also shown for comparison purposes. The results show that, before the change occurs, the moving average estimate $\widehat{SpHO}(2)$ oscillates close

TABLE I
INTERFERENCE CONDITIONS OF THE DIFFERENT POOLS BEFORE AND AFTER THE CHANGE

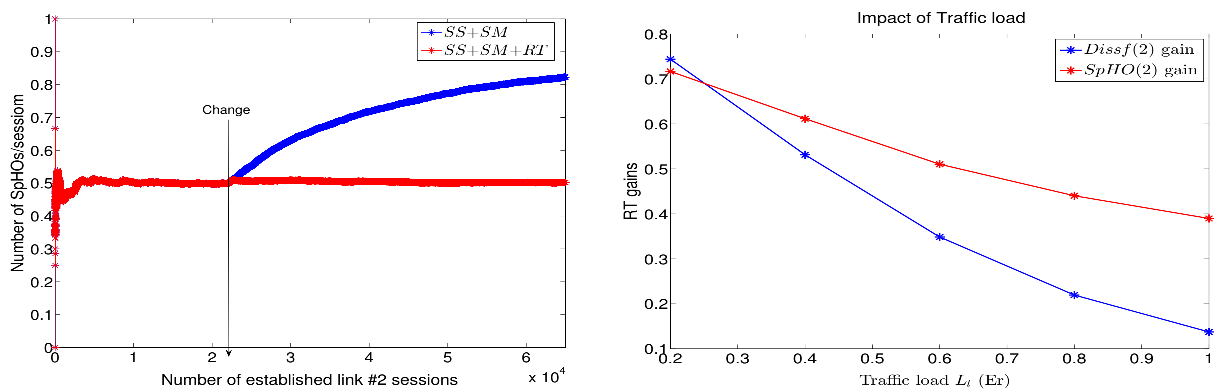
| pool | Before the change | | | | After the change | | | |
|---|---|---|---|---|---|---|---|---|
| | $I_0$ | | $I_1$ | | $I_0$ | | $I_1$ | |
| | Duration | $R(l,p)[Kbps]$ | Duration | $R(l,p)[Kbps]$ | Duration | $R(l,p)[Kbps]$ | Duration | $R(l,p)[Kbps]$ |
| 1 | $\infty$ | 512 | - | - | $7.5\,h$ | 1536 | $0.5\,h$ | 96 |
| 2 | $\infty$ | 512 | - | - | $\infty$ | 512 | - | - |
| 3 | $7.5\,h$ | 1536 | $0.5\,h$ | 96 | $\infty$ | 512 | - | - |
| 4 | $0.5\,h$ | 1536 | $2\,min$ | 96 | $0.5\,h$ | 1536 | $2\,min$ | 96 |




(a) initially

(b) around the considered change

Fig. 2. Evolution of the RT estimates of $SpHO(2)$




(a) Number of SpHOs/session

(b) Impact of traffic load on RT gains

Fig. 3. Analysis of SS performance for link #2

to $\overline{SpHO(2)}$ due to the intrinsic randomness of radio conditions. Nevertheless, the RT disregards these oscillations and selects $H_0$ because confidence intervals of the two estimates are still overlapping. After the change occurs, $\widehat{SpHO}(2)$ starts to deviate much from $\overline{SpHO(2)}$ till their confidence intervals no longer overlap. At this moment, $H_1$ is selected for $SpHO(2)$ and the considered change is detected by the RT. It is worth mentioning that only one wrong change (Type I error) is detected during the whole simulation, thus showing the efficiency of the proposed hypothesis testing strategy in Section. III in minimizing useless regeneration of KD data.

In summary, the RT probabilistic detector, based on hypothesis testing, enables to properly filter those changes related to the intrinsic randomness of the radio environment and to efficiently detect relevant changes in the scenario.

*D. Performance evaluation*

This section evaluates the performance of the proposed strategy in front of changes in the interference conditions under which KD statistics were generated.

Fig. 3(a) shows the online evolution of the average number of SpHOs performed per link #2 session ($SpHO(2)$). A traffic load of $L_l$=1 $Er, l\in\{1,2\}$ is initially considered. To analyze the impact of RT, both variants $SS$+$SM$ and $SS$+$SM$+$RT$ are considered. The corresponding dissatisfaction probability ($Dissf(2)$) is not shown because it is exhibiting a similar behavior.

The results show that, after the change in interference conditions, the use of RT functionality results in a significant reduction of the number of performed SpHOs (Fig. 3(a)). At the end of the simulation, the observed reduction is of about 40%. The reason for this improvement is that, before the change, both strategies are mainly assigning pools #1 and #2 to link #1 and pools #3 and #4 to link #2. After the change, the strategy $SS$+$SM$ without any support from the RT still relies on the out-of-date KD statistics previously generated, so it continues to exclude pool #1 and assign pool #3 to link #2 sessions. This turns out to be a wrong decision because, according to the new conditions after the change, pool $\#1$ should be assigned instead of pool $\#3$ that becomes, from now on, unable to support the bit rate requirements of link $\#2$. Correspondingly, much more frequent SpHOs are required to change pool $\#3$ whenever it is assigned. On the contrary, when RT is used (*SS+SM+RT*), new KD statistics are generated after detecting the change. As a consequence, the $\hat{F}_{l,p}$ estimates provided by the KM prevent the SS from further assigning pool $\#3$ to link $\#2$ in the future. Instead, pool $\#1$, which allows a much better bit rate under the new interference conditions, is assigned to link $\#2$. This results in a significant gain in the number of performed SpHOs (Fig. 3(a)). Note that the performance obtained with RT after the change remains approximately the same as before the change. This equal performance is because the change shown in Table I does not change the overall set of pools but just swaps interference patterns of pools $\#1$ and $\#3$. Consequently, if KD statistics are properly updated after the change, the strategy *SS+SM+RT* should be able to find the proper combination of pools and active links that keeps the same performance that existed before the change.

Next, the impact of the traffic load on observed performance is analyzed. RT gains are defined as the percentages of reduction in the number of performed SpHOs and dissatisfaction probability of link $\#2$, respectively, when using *SS+SM+RT* with respect to *SS+SM*. Fig. 3(b) plots observed RT gains at the end of the simulation (i.e., after establishing $65,000$ sessions) for different traffic loads.

The results show that, for low traffic loads, the RT is introducing significant gains (around 75%) in terms of both $SpHO(2)$ and $Dissf(2)$. This improvement is because, after the change, *SS+SM+RT* is able to disregard pool $\#3$ and assign instead pool $\#1$ to link $\#2$ based on the new KD statistics as previously explained. As traffic load increases, RT gains gradually decrease to reach 40% and 15% in terms of $SpHO(2)$ and $Dissf(2)$, respectively. This reduction is because, for higher traffic loads, more link sessions are simultaneously active and spectrum pools become used most of the time, which marginalizes the impact of the wrong assignments that may be performed by *SS+SM* based on old KD statistics.

## VI. Conclusions

This paper has proposed a new knowledge management functional architecture, based on the fittingness factor concept, for supporting spectrum management in non-stationary environments. It includes a RT that detects, based on hypothesis testing, relevant changes in interference conditions subject to the intrinsic randomness of the radio environment and updates, when needed, a set of advanced statistics stored in a KD. Based on these statistics, a proactive strategy combining SS and SM functionalities is proposed. The results have shown that the proposed RT efficiently detects actual changes in the environment. Thanks to the RT support, the proposed spectrum management strategy exhibits substantial robustness when radio and interference conditions become non-stationary, obtaining performance improvements of up to 75% with respect to the reference case that does not make use of the RT, thus proving the utility of the proposed framework from the spectrum management perspective.

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