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A Fittingness Factor-based Spectrum Management Framework for Cognitive Radio Networks

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Abstract In order to increase CRs (Cognitive Radios) operation efficiency, there has been an increasing interest in strengthening awareness level about spectrum utilisation. In this respect, this paper proposes to exploit the fittingness factor concept to capture the suitability of spectral resources exhibiting time-varying characteristics to support a set of heterogeneous CR applications. First, a new knowledge management functional architecture for optimizing spectrum management has been built up. It integrates a set of advanced statistics capturing the influence of the dynamic radio environment on the fittingness factor. Then, a Knowledge Manager (KM) exploiting these statistics to monitor time-varying suitability of spectrum resources has been proposed to support the spectrum selection decision-making. In particular, a new Fittingness Factor-based strategy combining two Spectrum Selection (SS) and Spectrum Mobility (SM) functionalities has been proposed, following either a greedy or a proactive approach. Results have shown that, with a proper fittingness factor function, the greedy approach efficiently exploits the KM support at low loads and the SM functionality at high loads to introduce significant gains in terms of the user dissatisfaction probability. The proactive approach has been shown to maintain the introduced performance gain while minimizing the signalling requirements in terms of Spectrum HandOver (SpHO) rate.

Keywords Spectrum Management · Cognitive Radio · Fittingness Factor

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1 Context/Motivation

The CR (Cognitive Radio) paradigm has emerged as an intelligent radio that automatically adjusts its behavior based on the active monitoring of its environment [1, 2]. The introduction of cognitive techniques for the management of wireless networks will lead to robustness and the capitalization of the learning capabilities intrinsic to cognitive systems. Therefore, technical requirements of new cognitive management systems have been considered in many studies [3–5]. In particular, many recent proposals have tried to develop new models and efficient architectures for introducing cognitive management systems in emerging environments such as the Future Internet [6] or the home environment [7]. The underlying technical challenges have stimulated the initiation of many research projects (e.g. [8–10]) and standardization activities (e.g. [11, 12]) to further strengthen and promote the usage of cognitive management systems.

Radio Resource Management (RRM) functions are prime important in the specific context of CR and Dynamic Spectrum Access (DSA), a new communication paradigm proposing to use and share the spectrum in an opportunistic manner in order to increase spectrum usage efficiency. Not surprisingly, this topic has received a lot of interest in the recent literature [13–16]. The flexibility provided by spectrum agility has to be materialized in the form of an increased efficiency by means of proper decision-making criteria in the spectrum selection functionality.

In this respect, the main objective of this paper is to further strengthen awareness level in a cognitive system by exploiting the fittingness factor concept that captures the suitability of spectral resources exhibiting time-varying characteristics to support a set of heterogeneous CR applications. The use of the fittingness factor was proposed by the authors in [17]. In this paper, the previous work is extended by further developing the functional framework where the fittingness factor is used and the associated spectrum management strategies. In this perspective, the main contributions of this paper are two-fold: (1) To build up a new knowledge management functional architecture for optimizing the spectrum management decision-making process based on the fittingness factor. It includes a Knowledge Manager (KM) that monitors the time-varying suitability of spectrum resources to support heterogeneous services based on a set advanced statistics and observed fittingness factor values during CR operation. (2) To develop a spectrum management strategy exploiting the estimated suitability of spectrum resources, following either a greedy or a proactive approach, to optimize both spectrum selection and spectrum mobility.

The remainder of this paper is organized as follows: in Sec. 2, the system model is presented and the functional architecture of the proposed framework for assisting spectrum management is presented. After formulating two different fittingness factor functions, a set of statistics capturing their behavior are proposed in Sec. 3 and a Knowledge Manager (KM) exploiting these statistics is built up in order to monitor time-varying suitability of spectrum resources. Then, a new strategy following either a greedy or a proactive approach has been proposed in Sec. 4 to exploit the estimated fittingness factor values for the sake of optimizing both spectrum selection and spectrum mobility functionalities. Results are presented in Sec. 5 firstly comparing the performances when different fittingness functions are used, and secondly assessing the impact of the proposed decision making criteria. Conclusions and future directions are addressed in Sec. 6.

2 System Model

Let us consider a set of L different radio links that need to be established between pairs of terminals and/or infrastructure nodes. The purpose of each radio link is to support a certain application. The l-th application is characterized in terms of a required bit-rate $R_{req,l}$ and a duration $T_{req,l}$. 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 for each of the L radio links. In order to accomplish this objective, the functional architecture depicted in Fig. 1 is proposed. It consists of the following entities:

1. The Knowledge Management entity, which is responsible for storing and managing the relevant knowledge obtained from the radio environment to be used in the decisions made by the Decision-Making entity. It is materialized by a Knowledge Manager (KM) that monitors the suitability of existing spectral resources to support heterogeneous services based on information retrieved from a Knowledge Database (KD).
2. The Decision-Making entity, which is responsible for assigning the appropriate pools to the different 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: Spectrum Selection (SS), which will pick up a suitable pool for each communication whenever a new service request arrives, and Spectrum Mobility (SM), which will perform the reconfiguration of assigned pools whenever changes occur in the environment and better pools can be found for some services.

In order to assess the suitability of spectral resources to support heterogeneous services, the so-called "Fittingness Factor" ($F_{l,p}$) is proposed as a metric capturing how suitable each p-th spectrum pool is for each l-th radio link/application. $F_{l,p}$ will particularly assess the suitability in terms of the bit rate that can be achieved operating in the spectrum pool p (denoted as $R(l,p)$) versus the bit rate required by the application l ($R_{req,l}$).

From a general perspective, the fittingness factor can be formulated as a function of the utility $U_{l,p}$ the l-th link can obtain from the p-th pool, where the utility is defined as [18]:

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

where ξ is a shaping parameter that allows the function to capture different degrees of elasticity of the application with respect to the required bit rate. The achievable

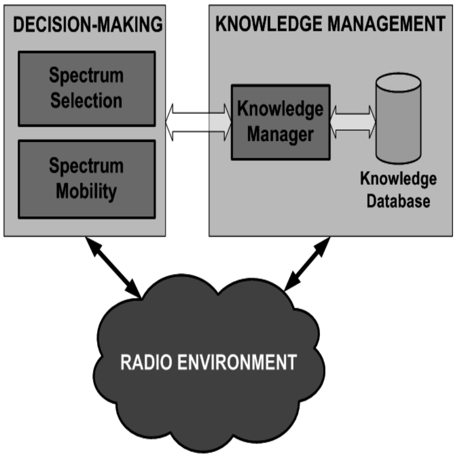


Fig. 1: Functional architecture of the proposed Fittingness Factor-based Spectrum Management Framework for Cognitive Radio Networks

bit-rate by link l using pool p ($R(l,p)$) will depend on the radio and interference conditions existing in pool p.

Based on the above concept, two different fittingness factor functions are defined:

- Fittingness factor function 1: It is the utility itself, that is:

$$F_{l,p} = f_1(U_{l,p}) = U_{l,p} \tag{2}$$

  Let us notice that $f_1(U_{l,p})$ is a monotonically increasing function of the ratio $\frac{R(l,p)}{R_{req,l}}$.
- Fittingness factor function 2: It is defined as:

$$F_{l,p} = f_2(U_{l,p}) = \frac{1 - e^{-\frac{K \times U_{l,p}}{\frac{R(l,p)}{R_{req,l}}}}}{\lambda} \tag{3}$$

  where K is a shaping parameter and λ is a normalization factor to ensure that the maximum of the fittingness factor is equal to 1, given by:

$$\lambda = 1 - e^{-\frac{K}{(\xi-1)^{\frac{1}{\xi}} + (\xi-1)^{\frac{1-\xi}{\xi}}}} \tag{4}$$

The proposed $f_2(U_{l,p})$ increases with $R(l,p)$ up to the maximum at $R(l,p) = \sqrt[\xi]{\xi - 1} \times R_{req,l}$. This means that $F_{l,p}$ decreases for $R(l,p) >> R_{req,l}$ which targets an efficient usage of spectral resources by reducing the value of the fittingness factor whenever the available bit rate is much higher than the required one.

3 Knowledge Management

3.1 Knowledge Database

In order to enable a global characterization of the suitability of a given pool p to a given link l based on the past history when using this pool, KD will retain some statistics of $F_{l,p}$. The database will be fed by measurements extracted from the radio environment in terms of $R(l,p)$ for active link/pool pairs. Then, $F_{l,p}$ will be computed following (2) or (3) and will be stored in the database together with the corresponding time stamp.

Considering that $F_{l,p}$ values can be associated to two states: HIGH ($\geq \delta_{l,p}$) or LOW ($< \delta_{l,p}$), the following statistics are also generated and stored in the database:

- The probability $P_L^{l,p}(\delta_{l,p})$ of observing a LOW fittingness factor:

$$P_L^{l,p}(\delta_{l,p}){=}Prob\left[F_{l,p}{<}\delta_{l,p}\right] \tag{5}$$

- The probability $P_H^{l,p}(\delta_{l,p})$ of observing a HIGH fittingness factor is then given by:

$$P_H^{l,p}(\delta_{l,p}){=}1{-}P_L^{l,p}(\delta_{l,p}) \tag{6}$$

- The average of observed LOW fittingness factor values:

$$\bar{F}_L^{l,p}{=}E\left(F_{l,p}|F_{l,p}{<}\delta_{l,p}\right) \tag{7}$$

- The average of observed HIGH fittingness factor values:

$$\bar{F}_H^{l,p}{=}E\left(F_{l,p}|F_{l,p}{\geq}\delta_{l,p}\right) \tag{8}$$

Furthermore, in order to monitor fittingness factor variability, the following statistical metrics are considered:

- Given $F_{l,p}$ is LOW at a given time instant k, the probability that $F_{l,p}$ will be LOW at each time instant up to time $k{+}\Delta k$ defined as follows:

$$P_{L,L}^{l,p}(\Delta k,\delta_{l,p}){=}Prob\left[F_{l,p}(k+j){<}\delta_{l,p},\forall j{\in}\{1..\Delta k\}|F_{l,p}(k){<}\delta_{l,p}\right] \tag{9}$$

  where $F_{l,p}(k)$ denotes the observed $F_{l,p}$ value at time k.
- Given $F_{l,p}$ is HIGH at a given time instant k, the probability that $F_{l,p}$ will be HIGH at each time instant up to time $k{+}\Delta k$ defined as follows:

$$P_{H,H}^{l,p}(\Delta k,\delta_{l,p}){=}Prob\left[F_{l,p}(k+j){\geq}\delta_{l,p},\forall j{\in}\{1..\Delta k\}|F_{l,p}(k){\geq}\delta_{l,p}\right] \tag{10}$$

The proposed fittingness factor variability metrics ($P_{L,L}^{l,p}$ and $P_{H,H}^{l,p}$) can be used to determine to which extent the fittingness factor is not likely to change after a certain time shift Δk.

3.2 Knowledge Manager

The KM plays a key role between the Knowledge Management and the Decision-Making domains of the proposed architecture. In this perspective, it manages the information retained in the KD in order to determine the knowledge about the environment that would be mostly relevant for supporting all decisions made by the decision-making entity.

Algorithm 1 Knowledge Manager (KM)

1: Function KM()
2: **for** l=1 **to** L **do**
3: **for** p=1 **to** P **do**
4: **if** $F_{l,p}$ is LOW **then**
5: **if** $P^{l,p}_{L,L}(\Delta k_{l,p}, \delta_{l,p}) \geq Thr\_LOW$ **then**
6: $\hat{F}_{l,p} \leftarrow F_{l,p}$;
7: **else**
8: Estimate $F_{l,p}$ as follows:
$$\hat{F}_{l,p} = \begin{cases} \bar{F}^{l,p}_{L} & \text{with probability } P^{l,p}_{L}(\delta_{l,p}), \\ \bar{F}^{l,p}_{H} & \text{with probability 1-}P^{l,p}_{L}(\delta_{l,p}). \end{cases};$$
9: **end if**
10: **else**
11: **if** $P^{l,p}_{H,H}(\Delta k_{l,p}, \delta_{l,p}) \geq Thr\_HIGH$ **then**
12: $\hat{F}_{l,p} \leftarrow F_{l,p}$;
13: **else**
14: Estimate $F_{l,p}$ as follows:
$$\hat{F}_{l,p} = \begin{cases} \bar{F}^{l,p}_{L} & \text{with probability } P^{l,p}_{L}(\delta_{l,p}), \\ \bar{F}^{l,p}_{H} & \text{with probability 1-}P^{l,p}_{L}(\delta_{l,p}). \end{cases};$$
15: **end if**
16: **end if**
17: **end for**
18: **end for**
19: return ($\{\hat{F}_{l,p}\}$);

On one side, the KM keeps an estimation of $F_{l,p}$ values based on the statistics available at the KD. These estimated values, denoted as $\hat{F}_{l,p}$ and obtained following Algorithm 1, are provided upon request to the decision-making module. The estimate $\hat{F}_{l,p}$ is determined based on whether the $F_{l,p}$ stored in the KD is likely to be the same that was obtained $\Delta k_{l,p}$ time units before (this is checked in the conditions of lines 5 and 11 with respect to the significance thresholds Thr_LOW and Thr_HIGH). In such case, $\hat{F}_{l,p}$ is set to the last measured value $F_{l,p}$ (lines 6 and 12). Otherwise, $\hat{F}_{l,p}$ is randomly set to either either $\bar{F}^{l,p}_{L}$ or $\bar{F}^{l,p}_{H}$, the average $F_{l,p}$ values in the LOW and HIGH states, respectively, with probabilities $P^{l,p}_{L}(\delta_{l,p})$ and $1-P^{l,p}_{L}(\delta_{l,p})$ (lines 8 and 14). Once all link/pool pairs are explored, the list of all estimated fittingness factor values ($\{\hat{F}_{l,p}\}$) is returned back to the decision-making entity (line 19).

On the other side, the KM captures relevant changes in these estimated values and informs the decision-making module for consideration.

4 Fittingness Factor in Spectrum Selection Decision-Making

The proposed fittingness factor function claims to have applicability in the spectrum selection decision-making process whose aim is to allocate, for a given application l, the best spectrum pool $p^*(l)$. In this respect, two fittingness factor-based criteria are proposed:

– Greedy criterion: It selects the pool with the largest fittingness factor among the set of available pools (Av_Pools):

$$p^*_{greedy}(l) = \arg \max_{p \in Av\_Pools} \left(\hat{F}_{l,p}\right) \tag{11}$$

– Proactive criterion: It selects the pool that maximizes the likelihood of observing a HIGH $F_{l,p}$ up to the end of the link session duration $T_{req,l}$. It is defined as follows:

$$p^*_{proactive}(l) = \arg \max_{p \in Av\_Pools} \left(p(\hat{F}_{l,p})\right) \tag{12}$$

where:

$$p(\hat{F}_{l,p}) = \begin{cases} P^{l,p}_{H,H}(\Delta k_{l,p} + T_{req,l}, \delta_{l,p}) & \text{if } \hat{F}_{l,p} \text{ is HIGH,} \\ 0 & \text{otherwise.} \end{cases} \tag{13}$$

In the very specific case of multiple channels fulfilling the maximization, the pool with the highest $\hat{F}_{l,p}$ is selected.

Notice that unlike the greedy criterion that simply maximizes the instantaneous fittingness factor value a link can immediately get, the proactive criterion selects the pool that would be most likely to provide a HIGH fittingness factor value during the whole link session.

In what follows, both the spectrum selection and spectrum mobility functionalities of the decision-making process are implemented using either the greedy or the proactive criterion.

4.1 Spectrum Selection (SS)

Based on the fittingness factor values determined by the KM, the spectrum selection functionality selects a suitable spectrum pool for each radio link according to the Fittingness Factor-based Spectrum Selection algorithm described in Algorithm 2. 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 all $F_{l,p}$ values is obtained from the KM (line 5). Based on provided $\hat{F}_{l,p}$ values, the best spectrum pool $p^*(l)$ is selected following either the greedy or the proactive criterion (line 6).

4.2 Spectrum Mobility (SM)

In order to further adjust CR behavior to changes in spectrum resources suitability, the spectrum mobility functionality can be executed whenever better pools can be found for some services. Spectrum mobility is considered on a global perspective jointly optimizing all assignments in order to improve the overall pool usage efficiency.

As detailed by Algorithm 3, the proposed Fittingness Factor-based Spectrum Mobility is triggered whenever a previously selected pool by SS at link establishment is no longer the best in terms of $\hat{F}_{l,p}$ for the corresponding active link. This may happen whenever some active pools are released or experience some change in their $F_{l,p}$. Following both triggers, the KM is first called in order to get an estimation of all $F_{l,p}$

Algorithm 2 Fittingness Factor-based Spectrum Selection

if service l request **then**
  if Av_Pools=$\emptyset$ **then**
    Reject request;
  else
    Get $\{\hat{F}_{l,p}\}$ from the KM;

$$p^*(l)= \begin{cases} p^*_{greedy}(l) \\ p^*_{proactive}(l) \end{cases} ;$$

  end if
end if

Algorithm 3 Fittingness Factor-based Spectrum Mobility

1: **if** (service l^* ends) **or** (change in any active $F_{l,p}$) **then**
2:   Get $\{\hat{F}_{l,p}\}$ 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:

$$new\_p^*(l)= \begin{cases} p^*_{greedy}(l) \\ p^*_{proactive}(l) \end{cases} ;$$

7:     **if** (($\hat{F}_{l,p^*(l)}$ is LOW) **and** ($\hat{F}_{l,new\_p^*(l)}$ is HIGH)) **or**
8:     ($p^*(l) \in new\_Assigned$) **then**
9:       $p^*(l) \leftarrow new\_p^*(l)$;
10:       $new\_Assigned \leftarrow new\_Assigned \bigcup \{new\_p^*(l)\}$;
11:     **else**
12:       $new\_Assigned \leftarrow new\_Assigned \bigcup \{p^*(l)\}$;
13:     **end if**
14:   **end for**
15:   $Assigned \leftarrow new\_Assigned$;
16: **end if**

values ($\{\hat{F}_{l,p}\}$) (line 2). The algorithm then explores the list of currently active links ($Active\_Links$) in the decreasing order of the 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 actually used pool ($p^*(l)$) and the currently best pool in terms of $\hat{F}_{l,p}$ ($new\_p^*(l)$) (line 7). Specifically, if $F_{l,p^*(l)}$ is LOW and $F_{l,new\_p^*(l)}$ is HIGH, a SpHO from $p^*(l)$ to $new\_p^*(l)$ is performed since $new\_p^*(l)$ fits better link l. The same SpHO should be performed in case $p^*(l)$ is no longer available to link l after being preempted during previous reassignments (line 8). Once all active links are explored, the list of assigned pools is updated according to performed SpHOs (line 15).

5 Performance Evaluation

5.1 Simulation Model

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

Performances are evaluated using a system-level simulator operating in steps of 1s. The radio environment is modeled as a set of P=4 spectrum pools. The available bandwidth at each pool is BW_1=BW_2=$0.4MHz$ and BW_3=BW_4=$1.2MHz$. A heterogeneous interference situation is considered in which the total noise and interference power spectral density I_p experienced in each pool $p \in \{1..P\}$ is assumed to follow a two-state discrete time Markov chain jumping between a state of low interference $I_0(p)$ and a state of high interference $I_1(p)$. In our specific case, pools $\#1$ and $\#2$ are always in state $I_0(p)$ while pools $\#3$ and $\#4$ randomly alternate between $I_0(p)$ and $I_1(p)$ with transition probabilities for pool $\#3$ P_{10}=55.5×10^{-5} (i.e. probability of moving from state I_1 to I_0 in a simulation step) and P_{01}=3.7×10^{-5} (i.e. probability of moving from state I_0 to I_1) and for pool $\#4$ P_{10}=8.33×10^{-3} and P_{01}=55.5×10^{-5}. Based on these probabilities, the average duration of the high interference state is $0.5h$ for pool $\#3$ and $2min$ for pool $\#4$ while the average duration of the low interference state is $7.5h$ for pool $\#3$ and $0.5h$ for pool $\#4$. With this configuration, the achievable bit-rate by one link in pools $\#1$ and $\#2$ is $R(l,3)$=$R(l,4)$=$128Kbps$, while for pools $\#3$ and $\#4$, it alternates between $R(l,3)$=$R(l,4)$=$1536Kbps$ for the $I_0(p)$ state, and $R(l,3)$=$R(l,4)$=$96Kbps$ for the $I_1(p)$ state.

The system is observed during a simulation time of 300 days. Other simulation parameters are ξ=5, K=1, $\delta_{1,p}$=0.2, $\delta_{2,p}$=0.8, Thr_LOW=0.8 and Thr_HIGH=0.1.

5.2 Benchmarking

In order to assess the influence of the different components of the proposed framework, the following variants will be compared:

- SS: This variant only considers the use of the SS algorithm supported by the KM module, and no spectrum mobility decisions are made.
- SS+SM: This strategy considers jointly the spectrum selection and the spectrum mobility algorithms, so that it incorporates the reallocation flexibility associated to SM.

Both variants can use either the greedy or the proactive criterion. The use of either fittingness factor function 1 or 2 will be also considered in the analysis.

Apart from the considered variants, the following reference schemes are introduced for benchmarking purposes:

- Rand: This implements only the spectrum selection module of Fig. 1 and performs a random selection among available pools. Neither SM nor KM modules are used.
- Optim: This scheme is an upper bound theoretical reference. In each simulation step, it redistributes all pools among active links to perform the following maximization of the total number of transmitted bits at a given time instant k, defined

as:

$$\max\left(\sum_{active(l,p)} \min\left(R_{req,l}, R(l,p,k)\right)\right) \tag{14}$$

where $R(l,p,k)$ is the measured bit-rate $R(l,p)$ at time k.

5.3 Results

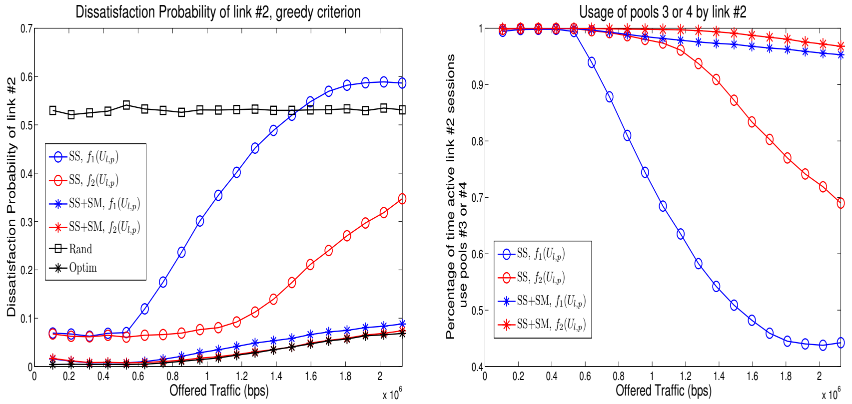
This section presents the performance evaluation of the different schemes introduced in Sec. 5.2. The target of the analysis is two-fold: (1) to benchmark the performance of the proposed variants (SS and SS+SM) with respect to the reference Rand and Optim schemes, and (2) to compare the proposed fittingness factor functions. The greedy criterion is initially considered for the sake of simplicity.

Fig. 2(a) plots the dissatisfaction probability of link $\#2$ (i.e. the most demanding in terms of required bit rate) as a function of the total offered traffic load $\lambda_1 \times T_{req,1} \times R_{req,1} + \lambda_2 \times T_{req,2} \times R_{req,2}$. It is defined as the probability of observing a bit rate below the service requirement $R_{req,l}$. Results for link $\#1$ are not presented since it is all the time satisfied (i.e., the bit rate is always above the requirement of 64Kbps). Fig. 2(b) plots the fraction of time that link $\#2$ uses pools $\#3$ or $\#4$. When using these pools in the low interference state, link $\#2$ will be satisfied. In turn, link $\#2$ will be dissatisfied whenever it is allocated pools $\#1$ or $\#2$ or pools $\#3$ or $\#4$ in the high interference state.

As seen in Fig. 2(a), for low traffic loads below 0.6Mbps, a very important reduction of the dissatisfaction probability compared to Rand is observed for both $f_1(U_{l,p})$ and $f_2(U_{l,p})$. This is because the KM component allows a proper exploration of the different pools to identify the changes in their interference conditions. Therefore, the most suitable pools are allocated to the different applications and, as a result, the dissatisfaction probability improves. The similar performance of $f_1(U_{l,p})$ and $f_2(U_{l,p})$ can be justified by the fact that, for this low traffic load, either pool $\#3$ and $\#4$ uses to be available for link $\#2$, even if function $f_1(U_{l,p})$ tends to allocate these pools to link $\#1$. This is reflected in Fig. 2(b), where it can be seen that the usage of pools $\#3$ or $\#4$ by link $\#2$ (when it is active) is close to 1 for both fittingness factor functions

When load increases above 0.6 Mbps, performance degrades more significantly for $f_1(U_{l,p})$ than for $f_2(U_{l,p})$. This is because $f_1(U_{l,p})$ tends to allocate pools $\#3$ and $\#4$ to link $\#1$ sessions, which forces link $\#2$ sessions to use pools $\#1$ and $\#2$ that are not able to provide the required bit rate. On the contrary, $f_2(U_{l,p})$ prioritizes pools $\#1$ and $\#2$ for link $\#1$ sessions and thus pools $\#3$ and $\#4$ tend to be available for link $\#2$ usage, resulting in a much lower dissatisfaction probability. To illustrate the different allocation made by the two functions, it can be observed in Fig. 2(b) that the usage of pools $\#3$ or $\#4$ by the most demanding link $\#2$ is much higher with $f_2(U_{l,p})$ than with $f_1(U_{l,p})$.

With respect to the role of SM, for low loads, its use leads to small improvements for both fittingness factor functions (see the comparison in Fig. 2(a) between SS and SS+SM). The reason is that, for low loads, it occurs very rarely that a link is not allocated to the pool with the highest fittingness factor because of being occupied



(a) Dissatisfaction probability

(b) Fraction of time that link $\#2$ uses pools $\#3$ or $\#4$

Fig. 2: Spectrum selection performance comparison for link $\#2$

by another link. Consequently, there is no need to perform SpHOs towards a better pool except in the case when the interference increases in the allocated pool, which justifies the small improvement observed when comparing SS and SS+SM. On the contrary, when traffic load increases, the introduction of SM leads to a significant performance gain. The reason is that, whenever link $\#2$ sessions are assigned to pools $\#1$ or $\#2$ due to the unavailability of pools $\#3$ and $\#4$, the SM algorithm succeeds in reconfiguring these sessions to use pools $\#3$ and $\#4$ after they got released. In case of $f_2(U_{l,p})$, the unavailability of pools $\#3$ and $\#4$ for link $\#2$ usage occurs mainly due to the high traffic load. Nevertheless, in case of $f_1(U_{l,p})$, the unavailability of pools $\#3$ and $\#4$ may also be caused by the inefficient allocation of these pools to link $\#1$ sessions which justifies the higher improvement SM is introducing in this case. Correspondingly, it can be observed that the difference in dissatisfaction probability between $f_1(U_{l,p})$ and $f_2(U_{l,p})$ becomes smaller when strategy SS+SM is considered. The reason is that the inappropriate allocations made by function $f_1(U_{l,p})$ can be compensated by the reassignments made by SM when these pools are released. However, this comes at the expense of an increase in the signalling requirements due to the executed SpHOs. This is shown in Fig. 3 that plots the number of SpHOs per link session experienced by SS+SM for both fittingness factor functions. Notice in particular that there is a very important reduction in the number of required SpHOs for link $\#2$ when function $f_2(U_{l,p})$ is used (at the expense of a slight increase in the SpHO required for link $\#1$).

Another relevant observation in Fig. 2(a) is that the proposed SS+SM strategy with $f_2(U_{l,p})$ performs very closely to the upper-bound optimal scheme for all load conditions, mainly thanks to the support of the KM and SM components. The gain observed by SS+SM with respect to the Rand scheme (measured as the reduction in dissatisfaction probability) ranges from 85% to 100% (Fig. 2(a)). Notice that a slight degradation is observed for SS+SM when $f_1(U_{l,p})$ is used. This is due to a higher number of SM executions caused by the inefficient allocation of pools. As a matter of fact, whenever link $\#2$ sessions are inefficiently assigned pools $\#1$ or $\#2$, some

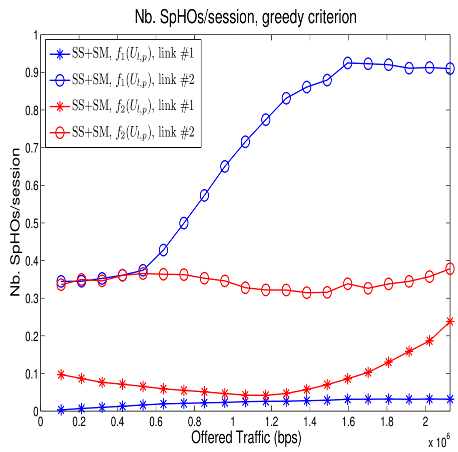


Fig. 3: Average number of SpHOs/session

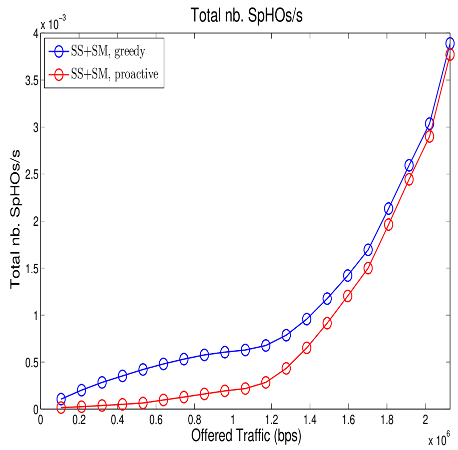


Fig. 4: Impact of decision-making criterion

time is spent before SM reconfigures these sessions to use pools $\#3$ or $\#4$ which slightly increases the dissatisfaction probability.

Enlightened by the above analysis, it can be concluded that function $f_2(U_{l,p})$ provides a more efficient resource allocation resulting in a better dissatisfaction probability and less SpHO signalling requirements.

In order to evaluate the impact of the decision making criterion on the obtained performances, a comparison between the greedy and proactive criteria introduced in Sec. 4 is next presented. Only the function $f_2(U_{l,p})$ is considered for both criteria, together with strategy SS+SM.

Fig. 4 plots the total requirements in terms of SpHO rate for both the greedy and the proactive criteria as a function of the total offered traffic load. It is worth mentioning that the performance in terms of dissatisfaction probability reveals a very similar performance for both criteria with the same result shown in Fig. 2(a) for SS+SM with $f_2(U_{l,p})$.

The results in Fig. 4 show that, from low-to-medium traffic loads, the proactive criterion strongly outperforms the greedy criterion. This is because, among pools $\#3$ or $\#4$, the proactive criterion tends to prioritize pool $\#3$ exhibiting much longer durations of the state HIGH (0.5h for pool $\#4$ versus 7.5h for pool $\#3$). Therefore, it becomes less likely to experience a state change from $I_0(p)$ to $I_1(p)$ during link session which considerably reduces the number of executed SpHOs. As traffic load becomes high, pools $\#3$ or $\#4$ become occupied most of the time which marginalizes the effect of giving priority to pool $\#3$.

6 Conclusions

This paper has proposed a new knowledge management functional architecture, based on the fittingness factor concept, for optimizing spectrum management to support a set of heterogeneous services. It includes a set of advanced statistics capturing the influence of the dynamic radio environment on the fittingness factor. These statistics are exploited by a Knowledge Manager (KM) entity that supports two Fittingness Factor-based Spectrum Selection and Spectrum Mobility functionalities. The impact of two different formulations of the fittingness factor and two decision-making criteria has been analyzed. It has been obtained that a proactive decision-making combined with fittingness factor function 2 allows performing an efficient resource allocation in terms of both dissatisfaction probability and SpHO signalling requirements. Specifically, achieved performance in terms of dissatisfaction probability is very close to the upper-bound optimal scheme and introduces significant gains (ranging from 85% to 100%) with respect to a random selection scheme.

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