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

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Abstract In order to increase cognitive radios (CRs) 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 constructed. 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 (SS) decision-making process. In particular, a new Fittingness Factor-based strategy combining two 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 rate.

Keywords Spectrum management · Cognitive radio · Fittingness factor

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1 Context/Motivation

The cognitive radio (CR) 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 enhanced robustness by capitalizing on 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 been materialized in the form of increased efficiency by means of proper decision-making criteria in the spectrum selection (SS) 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 applications 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 proactive approach, to optimize both SS and spectrum mobility (SM) functionalities.

The remainder of this paper is organized as follows: in Sect. 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 Sect. 3 and a KM exploiting these statistics is developed in order to monitor the time-varying suitability of spectrum resources. Then, a new strategy following either a greedy or a proactive approach has been proposed in Sect. 4 to exploit the estimated fittingness factor values for the sake of optimizing both SS and SM functionalities. Results are presented in Sect. 5 firstly comparing performances are used, and secondly assessing the impact of the proposed decision making criteria. Conclusions are addressed in Sect. 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 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 KM that monitors the suitability of existing spectral resources to support the considered heterogeneous applications based on information retrieved from a knowledge database (KD).
2. The Decision-Making entity, which is responsible for assigning the appropriate pools to 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: SS, which will pick up a suitable pool for each communication whenever a new application request arrives, and SM, which will perform the reconfiguration of assigned pools whenever changes occur in the environment and better pools can be found for some applications.

In order to assess the suitability of spectral resources to support heterogeneous application requirements, 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]:

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

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 bit-rate by link l using pool $p\,(R(l, p))$ will depend on 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:

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

Let us note 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:

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

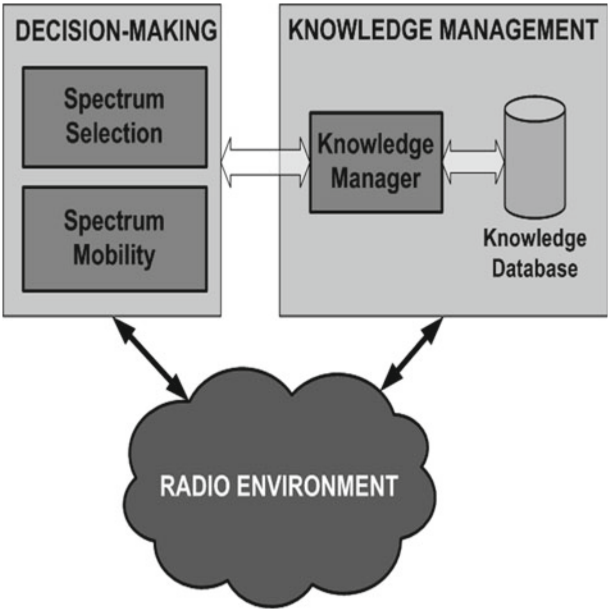

Fig. 1 Functional architecture of the proposed Fittingness Factor-based Spectrum Management Framework for CR Networks

where K is a shaping parameter and λ is a normalization factor that normalizes the maximum of the fittingness factor funtion to one, that is given by:

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

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 of $R(l, p)$ that are extracted from the radio environment about each active link/pool pair. Then, $F_{l,p}$ will be computed following either (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: LOW ($<\delta_{l,p}$) or HIGH ($>=\delta_{l,p}$), 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:

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

– 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:

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

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:

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

The proposed fittingness factor variability metrics ($P_{L,L}^{l,p}$ and $P_{H,H}^{l,p}$) can be used to determine the extent to which 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 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.

The KM keeps an estimation of $F_{l,p}$ values based on the set of 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 state of 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, respectively, 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 $\bar{F}_L^{l,p}$ or $\bar{F}_H^{l,p}$, the average $F_{l,p}$ values in the LOW and HIGH states, respectively, with probabilities $P_L^{l,p}(\delta_{l,p})$ and $1 - P_L^{l,p}(\delta_{l,p})$ (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).

The KM also captures relevant changes in these estimated values and informs the decision-making module for consideration.

Algorithm 1 Knowledge manager (KM)

Function KM()
for l=1 **to** L **do**
  for p=1 **to** P **do**
    if $F_{l,p}$ is LOW **then**
      if $P^{l,p}_{L,L}(\Delta k_{l,p}, \delta_{l,p}) \geq Thr\_LOW$ **then**
        $\hat{F}_{l,p} \leftarrow F_{l,p}$;
      else
        Estimate $F_{l,p}$ as follows:
$$\hat{F}_{l,p} = \begin{cases} \bar{F}^{l,p}_L & \text{with probability } P^{l,p}_L(\delta_{l,p}), \\ \bar{F}^{l,p}_H & \text{with probability 1-} P^{l,p}_L(\delta_{l,p}). \end{cases};$$
      end if
    else
      if $P^{l,p}_{H,H}(\Delta k_{l,p}, \delta_{l,p}) \geq Thr\_HIGH$ **then**
        $\hat{F}_{l,p} \leftarrow F_{l,p}$;
      else
        Estimate $F_{l,p}$ as follows:
$$\hat{F}_{l,p} = \begin{cases} \bar{F}^{l,p}_L & \text{with probability } P^{l,p}_L(\delta_{l,p}), \\ \bar{F}^{l,p}_H & \text{with probability 1-} P^{l,p}_L(\delta_{l,p}). \end{cases};$$
      end if
    end if
  end for
end for
return ($\{\hat{F}_{l,p}\}$);

4 Fittingness Factor in Spectrum Selection Decision-Making

The proposed fittingness factor function claims to have applicability in the SS 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 $F_{l,p}$ value up to the end of link session duration $T_{req,l}$. It is defined as follows:

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

where:

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

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

Note 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 SS and SM functionalities of the decision-making process are implemented using either the greedy or proactive criterion.

4.1 Spectrum Selection

Based on fittingness factor values estimated by the KM, the SS functionality selects a suitable spectrum pool for each radio link according to the Fittingness Factor-based SS algorithm described in Algorithm 2. Upon receiving a request for establishing a link l, the request is rejected if the set of available 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

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

Algorithm 2 Fittingness Factor-based Spectrum Selection

1: **if** application l request **then**
2:   **if** $Av\_Pools = \emptyset$ **then**
3:     Reject request;
4:   **else**
5:     Get $\{\hat{F}_{l,p}\}$ from the KM;
6:
$$p^*(l) = \begin{cases} p^*_{greedy}(l) \\ p^*_{proactive}(l) \end{cases};$$
7:   **end if**
8: **end if**

As detailed by Algorithm 3, the proposed fittingness factor-based SM 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 $F_{l,p}$ values. Following both triggers, the KM is first called in order to get an estimation of all $F_{l,p}$ 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 spectrum handover (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 reassigned to other links in the previous iterations of the loop of line 5 (line 8). Once all active links are explored, the list of assigned pools is updated to consider all SpHOs that need to be executed as a result of the algorithm (line 15).

Algorithm 3 Fittingness Factor-based Spectrum Mobility

if (application l^* ends) **or** (change in any active $F_{l,p}$) **then**
  Get $\{\hat{F}_{l,p}\}$ from the KM;
  $new\_Assigned \leftarrow \emptyset$;
  Sort $Active\_Links$ in the decreasing order of $R_{req,l}$;
  for l=1 **to** $|Active\_Links|$ **do**

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

    if (($\hat{F}_{l,p^*(l)}$ is LOW) **and** ($\hat{F}_{l,new\_p^*(l)}$ is HIGH)) **or**
    ($p^*(l) \in new\_Assigned$) **then**
      $p^*(l) \leftarrow new\_p^*(l)$;
      $new\_Assigned \leftarrow new\_Assigned \bigcup \{new\_p^*(l)\}$;
    else
      $new\_Assigned \leftarrow new\_Assigned \bigcup \{p^*(l)\}$;
    end if
  end for
  $Assigned \leftarrow new\_Assigned$;
end if

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 with arrival rate λ_l and constant session duration $T_{req,l}$. Link #1 is associated to low-data-rate sessions ($R_{req,1} = 64$ Kbps, $T_{req,1} = 2$ min), while link #2 is associated to 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. The radio environment is modeled as a set of $P = 4$ spectrum pools. The available bandwidth at each pool is $BW_1 = BW_2 = 0.4$ MHz and $BW_3 = BW_4 = 1.2$ MHz. A heterogeneous interference situation is considered in which the total noise and interference power spectral density I_p experienced in each pool $p \in \{1, \ldots, P\}$ 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 $I_1(p)$ with transition probabilities P_{10} (i.e., probability of moving from I_1 to I_0 in a simulation step) and P_{01} (i.e., probability of moving from I_0 to I_1). In our specific case, it is assumed that pools #1 and #2 are always in state $I_0(p)$, while pools #3 and #4 alternate between $I_0(p)$ and $I_1(p)$ with transition probabilities of $P_{10} = 55.5 \times 10^{-5}$ and $P_{01} = 3.7 \times 10^{-5}$ for pool #3 and $P_{10} = 8.33 \times 10^{-3}$ and $P_{01} = 55.5 \times 10^{-5}$ for pool #4. Based on these probabilities, the average durations of the high interference state #3 and pools #4 are 0.5 h and 2 min, respectively, while the average durations of the low interference state for pools #3 and #4 are 7.5 h and 0.5 h, respectively. With this configuration, the achievable bit-rate by one link in pools #1 and #2 is $R(l, 1) = R(l, 2) = 128$ Kbps, while for pools #3 and #4, it alternates between $R(l, 3) = R(l, 4) = 1536$ Kbps for the $I_0(p)$ state, and $R(l, 3) = R(l, 4) = 96$ Kbps for the $I_1(p)$ state.

The system is observed during a simulation time of 300 days. Other simulation parameters are $\xi = 5$, $K = 1$, $\delta_{1,p} = 0.2$, $\delta_{2,p} = 0.8$, $Thr\_LOW = 0.8$ 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 SM decisions are made.
- $SS+SM$: This strategy jointly considers the SS and SM algorithms, so that it incorporates the reallocation flexibility associated to SM.

Both variants can use either the greedy or 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 SS 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, the procedure assigns the combinations of pools and active links that maximize the total instantaneous throughput at a given time instant k as follows:

$$\max\left(\sum_{active(l,p)} \min\left(R_{req,l}, R(l, p^*(1), k)\right)\right) \tag{14}$$

where $R(l, p^*(1), k)$ is the measured bit-rate $R(l, p^*(1))$ at time k.

5.3 Results

This section presents the performance evaluation of the different schemes introduced in Sect. 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.

Figure 2a 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 application 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 64 Kbps). Figure 2b plots the fraction of time during which 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. 2a, for low traffic loads below 0.6 Mbps, 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 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 or #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. 2b, where it can be seen that the

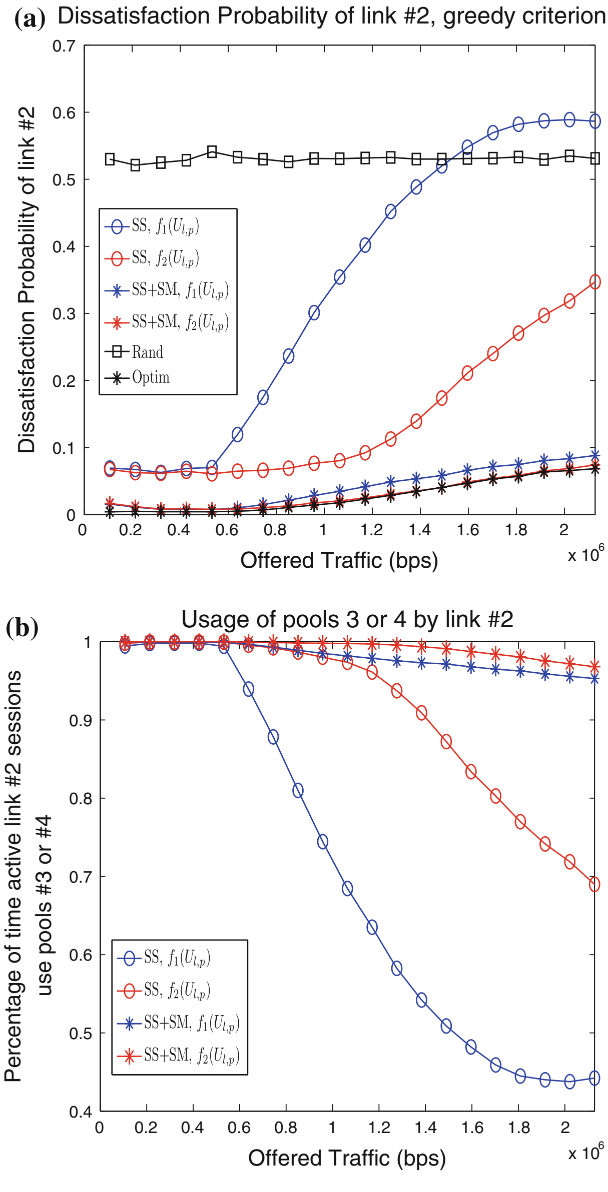

Fig. 2 Spectrum selection performance comparison for link #2. **a** Dissatisfaction probability. **b** Fraction of time that link #2 uses pools #3 or #4

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 more available for link #2 usage, resulting in

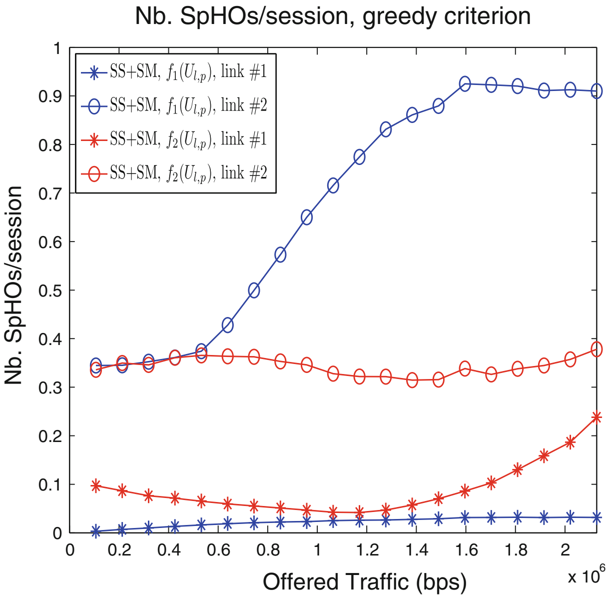

Fig. 3 Average number of SpHOs/session

a much lower dissatisfaction probability. To illustrate allocations made by the two functions, it can be observed in Fig. 2b 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. 2a between SS and $SS + SM$). The reason is that, for low loads, it occurs very rarely that a link is not allocated the pool with the highest fittingness factor because of being occupied 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 inappropriate allocations made by the 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 signalling requirements due to 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. Note 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 number of required SpHOs for link #1).

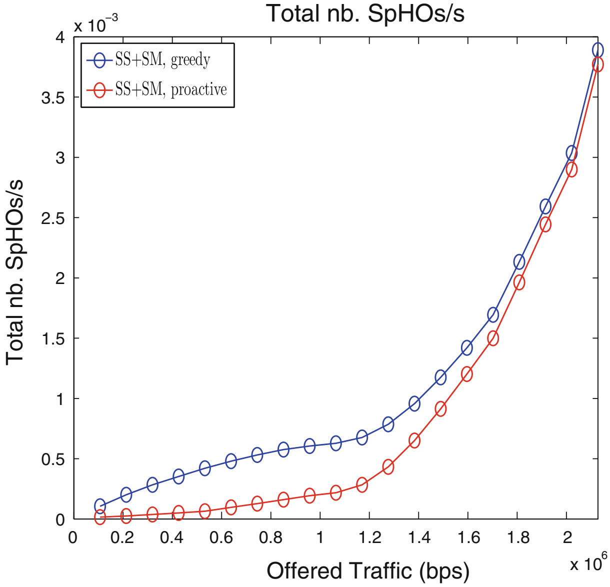

Fig. 4 Impact of decision-making criterion

Another relevant observation in Fig. 2a is that the strategy $SS + SM$ using $f_2(U_{l,p})$ 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 85–100 % (Fig. 2a). Note 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 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 performance, a comparison between the greedy and proactive criteria introduced in Sect. 4 is next presented. Only the function $f_2(U_{l,p})$ is considered for both criteria, together with the strategy $SS + SM$.

Figure 4 plots the total requirements in terms of SpHO rate for both the greedy and 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. 2a 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 and #4, the proactive criterion tends to prioritize pool #3 exhibiting much longer durations of the state HIGH (7.5h for poos #3 versus 0.5h for pool #4). 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 and #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 application. It particularly includes a set of advanced statistics to capture the influence of the dynamic radio environment on the fittingness factor. These statistics are exploited by a KM entity that supports two Fittingness Factor-based SS and SM 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 85–100 %) with respect to a random selection scheme.

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