

Provided for non-commercial research and education use.
Not for reproduction, distribution or commercial use.



This article appeared in a journal published by Elsevier. The attached copy is furnished to the author for internal non-commercial research and education use, including for instruction at the authors institution and sharing with colleagues.

Other uses, including reproduction and distribution, or selling or licensing copies, or posting to personal, institutional or third party websites are prohibited.

In most cases authors are permitted to post their version of the article (e.g. in Word or Tex form) to their personal website or institutional repository. Authors requiring further information regarding Elsevier's archiving and manuscript policies are encouraged to visit:

<http://www.elsevier.com/copyright>



Contents lists available at ScienceDirect

Physical Communication

journal homepage: www.elsevier.com/locate/phycom

Full length article

Binary power allocation for cognitive radio networks with centralized and distributed user selection strategies

Bassem Zayen^{a,*}, Majed Haddad^a, Aawatif Hayar^a, Geir E. Øien^b

^a Mobile Communications Group, Institut Eurecom, 2229 Route des Cretes, B.P. 193, 06904 Sophia Antipolis, France

^b Department of Electronics and Telecom, Norwegian University of Science and Technology, 7491 Trondheim, Norway

ARTICLE INFO

Keywords:

Cognitive radio network
Binary power allocation
Distributed algorithm
Capacity
QoS
Outage probability
Scheduling

ABSTRACT

Motivated by the desire for efficient spectral utilization, we present a novel algorithm based on binary power allocation for sum rate maximization in Cognitive Radio Networks (CRN). At the core lies the idea of combining multi-user diversity gains with spectral sharing techniques and consequently maximizing the secondary user sum rate while maintaining a guaranteed quality of service (QoS) to the primary system. We consider a cognitive radio network consisting of multiple secondary transmitters and receivers communicating simultaneously in the presence of the primary system. Our analysis treats both uplink and downlink scenarios. We first present a distributed power allocation algorithm that attempts to maximize the throughput of the CRN. The algorithm is simple to implement, since a secondary user can decide to either transmit data or stay silent over the channel coherence time depending on a specified threshold, without affecting the primary users' QoS. We then address the problem of user selection strategy in the context of CRN. Both centralized and distributed solutions are presented. Simulation results carried out based on a realistic network setting show promising results.

© 2008 Elsevier B.V. All rights reserved.

1. Introduction

The discrepancy between current-day spectrum allocation and spectrum use suggests that radio spectrum shortage could be overcome by allowing more flexible usage of spectrum. Flexibility would mean that radios could find and adapt to any immediate local spectrum availability. A new class of radios that are able to reliably sense the spectral environment over a wide bandwidth, detect the presence/absence of legacy users (primary users), and use the spectrum only if the communication does not interfere with primary users, is defined by the term *cognitive radio* [1]. Cognitive radio (CR) technology has attracted worldwide interest, and is believed to be a promising

candidate for future wireless communications in heterogeneous wideband environments.

Cognitive radio offers the opportunity to improve spectrum efficiency by detecting the primary user (PU) activity and adapting transmissions accordingly [1]. In current cognitive radio protocol proposals, the secondary user (SU) device listens to the wireless channel and determines, either in time or frequency, which part of the spectrum is unused. It then adapts its signal to fill this void in the spectrum domain. Thus, a SU device transmits over a certain time or frequency band only when no other user does, like in [2]. In the same context, it was shown in [3] how we can improve the overall system spectral efficiency compared to classical approaches by considering a *spectrum pooling* scenario. The contribution of some recent studies [4,5] has however also extended cognitive protocols to allow the SU to transmit *simultaneously* with the PU in the same frequency band. This is exactly the setup in this work, where the cognitive radio behavior is generalized to allow secondary

* Corresponding author. Tel.: +33 0 493008174; fax: +33 0 493008200.
E-mail addresses: bassem.zayen@eurecom.fr (B. Zayen),
majed.haddad@eurecom.fr (M. Haddad), aawatif.hayar@eurecom.fr
(A. Hayar), oien@iet.ntnu.no (G.E. Øien).

users to transmit simultaneously with PU as long as the level of interference to primary users remains within an acceptable range. Specifically, it is proposed in this paper to combine cognitive radio with multi-user diversity technology to achieve strategic spectrum sharing and self-organizing communications.

In most of the approaches above, the need may exist for centralized knowledge of all channel and interference state conditions for all nodes in the network. To circumvent this problem, the design of so-called *distributed* resource allocation techniques is crucial. Distributed optimization refers to the ability of each user to manage its local resources (e.g. rate and power control, user scheduling) based only on locally observable channel conditions such as the channel gain between the access point and a chosen user, and possibly locally measured noise and interference. A key example of multi-user resource allocation is that of power control, which serves as a means for both battery savings at the mobile, and interference management. In this work, we will focus on *binary* power control, since it has the advantage of leading towards simpler or even distributed power control algorithms [6]. In [7], it was also shown that the *optimal* power control with respect to maximal sum rate is always binary for a two-cell network, as well as in the low signal-to-interference ratio (SINR) regime for an N -cell (link) network [8]. In the general case when the number of cells (links) > 2 , it was also demonstrated by extensive computer simulations that a restriction to binary power levels yields only a negligible capacity loss [8].

A particularly noteworthy question in the context of cognitive radio, when we seek to optimize the secondary system capacity, is to guarantee a QoS to PUs. There are a large number of proposals for all communication layers treating the increase of restrictions to spectrum utilization [9], but the QoS issue still has not been clearly defined. In addition, it is unclear how secondary system opportunism, is compatible with the support of QoS for both cognitive radio systems and primary systems. The FCC proposed the concept of “*interference temperature*” as a way to have unlicensed transmitters share licensed bands without causing harmful interference. Rather than merely regulate transmitter power at fixed levels, as in the past, the scheme would have governed transmitter power on a variable basis calculated to limit the energy at victim receivers, where interference actually occurs. As a practical matter, however, the FCC abandoned the interference temperature concept recently [10] due to the fact that it is not a workable concept. While offering attractive promises, cognitive radios face various challenges, starting from defining the fundamental performance limits of this radio technology, in order to achieve the capability of using the spectrum in an opportunistic manner. Specifically, cognitive radio is required to determine the spectrum band allocation that meets the QoS requirements of different users. This decision can be made by assessing the channel capacity, known as the most important factor for spectrum characterization.

In this contribution, we will propose a different way to efficiently protect primary systems from SU interference, based on outage probability. The notion of *information*

outage probability, defined as the probability that the instantaneous mutual information of the channel is below the transmitted code rate, was introduced in [11]. Accordingly, the outage probability can be written as:

$$P_{\text{out}}(R) = P \{I(\mathbf{x}; \mathbf{y}) \leq R\}, \quad (1)$$

where $I(\mathbf{x}; \mathbf{y})$ is the mutual information of the channel between the transmitted vector \mathbf{x} and the received vector \mathbf{y} , and R is the target data rate in (bits/s/Hz). Reliable communication can therefore be achieved when the mutual information of the channel is strong enough to support the target rate R . Thus, a cognitive transmitter can adapt its transmit power p within the range of $[0; P_{\text{max}}]$ to fulfill the following two basic goals:

- *Self-goal*: Trying to transmit as much information for itself as possible,
- *Moral-goal*: Maintaining the primary users' outage probability unaffected.

The motivation behind doing so is that, in any case, the PU will not necessarily need all those multi-rate systems. In fact, the primary user will experience the SU's interference, and as long as all its target rates (depending on its QoS) are achieved, it does not care about what it leaves more. In what follows, we adopt this setting and consider a CRN in which primary and secondary users both attempt to communicate, subject to mutual interference. We propose a distributed cognitive radio coordination that maximizes the CRN secondary rate while keeping the interference to the primary user acceptable. Our goal is to realize PU–SU spectrum sharing by optimally allocating SU transmit powers, in order to maximize the total SU throughput under interference and noise impairments, and short term (minimum and peak) power constraints, while preserving the QoS of the primary system. In particular, it is of interest to determine, in a distributed manner, the optimal noise/interference threshold above which SUs can decide to transmit without affecting the primary users' QoS. In such approaches, users individually make a decision on their transmit power so as to optimize their contribution to the system throughput. At the core of the distributed concept lies the idea that the interference is more predictable when the network is dense, and consequently the resource allocation problem of a given user is made more dependent on the average behavior, thus facilitating distributed optimization. At first sight, joint resource allocation does not lend itself easily to distributed optimization because of the strong coupling between the locally allocated resources and the interference created elsewhere in the CRN. Hence the maximization of a SU capacity taken individually will not in general result in the best overall network capacity, although we suggest later cases for which the outcomes for the centralized and distributed capacity optimization will differ little. Following the above trend, we will explore a distributed joint resource allocation framework and then analyze what would be the loss when considering a distributed strategy. Our study treats both downlink and uplink communications. In both cases, we will derive a distributed power allocation algorithm and address the QoS issues for the primary system from an outage point of view [12,13].

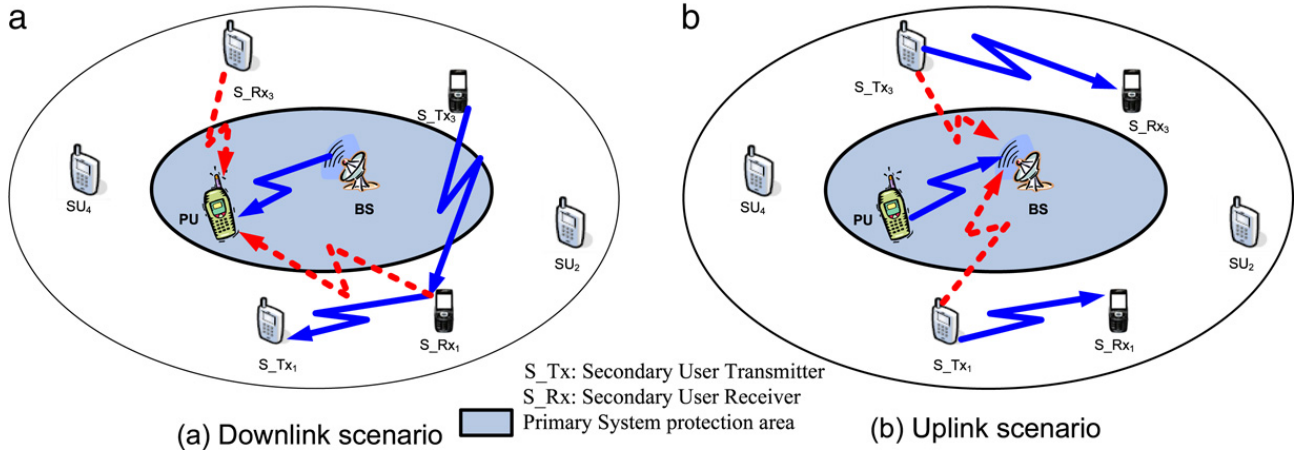


Fig. 1. The cognitive radio network with one primary user (PU) and $M = 4$ secondary users attempting to communicate with their respective pairs in an ad hoc manner during an primary system transmission, subject to mutual interference.

The rest of the paper is organized as follows. The next section describes the cognitive radio network. In Section 3, the proposed distributed power control algorithm is investigated in both the high and low SINR regimes, respectively. Section 4 includes the primary users' QoS issues. In Section 5, the centralized and the distributed user selection strategies are presented. Simulation results are provided in Section 6 and Section 7 concludes the paper.

2. The cognitive radio context

2.1. The system model

We consider a wireless CRN with a collection of users randomly distributed over the geographical area considered. Users can be both transmitters and receivers. By virtue of a scheduling protocol, one PU and M pairs of secondary users are simultaneously selected from these users to communicate at a given time instant, while others remain silent. The channel gains are assumed to be i.i.d. random variables. Throughout the paper, we will use the following notation:

- the index of SUs j lies between 1 and M ,
- $h_{pu,n}$ denotes the channel gain from the PU indexed by pu to a desired SU n ,
- $h_{pu,pu}$ denotes the channel gain between the base station (BS) and the PU,
- $h_{j,n}$ denotes the channel gain from SU j to a desired SU n ,
- the data destined from the primary system is transmitted with power p_{pu} .
- the data destined from SU j is transmitted with power p_j .

In the coverage area of the primary system, there is an *interference boundary* within which no SUs can communicate in an ad hoc manner. Thus, as can be seen in Fig. 1, for the impairment experienced by the primary system to be as small as possible, a SU must be able to detect very reliably whether it is far enough away from a primary base station, i.e., in the area of possible cognitive radio operation. The expression of the PU instantaneous capacity is

$$C_{pu} = \log_2 \left(1 + \frac{p_{pu} |h_{pu,pu}|^2}{\sum_{j=1}^M p_j |h_{j,pu}|^2 + \sigma^2} \right) \quad (2)$$

where σ^2 is the ambient noise variance. On the other hand, by making SUs access the primary system spectrum, the j th SU experiences interference from the PU and all neighboring co-channel SU links that transmit on the same band. Accordingly, the j th SU instantaneous capacity is given by:

$$C_j = \log_2 (1 + \text{SINR}_j); \quad \text{for } j = 1, \dots, M \quad (3)$$

where

$$\text{SINR}_j = \frac{p_j |h_{j,j}|^2}{\sum_{\substack{k=1 \\ k \neq j}}^M p_k |h_{k,j}|^2 + p_{pu} |h_{pu,j}|^2 + \sigma^2} \quad (4)$$

SUs need to recognize their communication environment and adapt the parameters of their communication scheme in order to maximize the cognitive capacity, expressed as

$$C_{\text{sum}} = \frac{1}{M} \sum_{j=1}^{\tilde{M}} C_j, \quad (5)$$

while minimizing the interference to the primary users, in a *distributed* fashion. The sum here is made over the \tilde{M} SUs allowed to transmit. Moreover, we assume that the coherence time is sufficiently large so that the channel stays constant over each scheduling period length. We also assume that SUs know the channel state information (CSI) of their own links, but have no information on the channel conditions of other SUs. No interference cancellation capability is considered. Power control is used for SUs both in an effort to preserve power and to limit interference and fading effects.

2.2. The cognitive radio protocol

Under this scheme, we allow SUs to transmit simultaneously with the PU as long as the interference from the SUs

to the PU that transmits on the same band remains within an acceptable range. Specifically, we impose the condition that SUs may transmit simultaneously with the PU as long as the PU in question does not have its QoS affected in terms of outage probability. We consider that PUs operate at a desired rate (depending on their respective QoS demands). Based on PU channel statistics, we determine the outage failure, in other words the probability that the PU of interest is actually under that rate. From a practical point of view, the outage probability as well as the requested rate can be broadcasted before the start of the communication by the primary system base station, and is used as a preamble for the PU to get informed which data rate is requested. This preamble can also be overheard by SUs who can then learn about these outage values.

One basic assumption throughout this paper is that a SU can vary its transmit power, under short term (minimum and peak) power constraints, in order to maximize the cognitive capacity, while maintaining a QoS guarantee to the primary user. The idea of the binary on/off power control is simple, as well as yielding quasi-optimal results in a number of cases [8]. As such, it constitutes a promising tool for making spectrum sharing a reality. Besides complexity reduction, an important additional benefit of binary power control is to allow distributed optimization.

3. Binary power control algorithm

Secondary users offer the opportunity to improve the system throughput by detecting the PU activity and adapting their transmissions accordingly while avoiding the interference to the PU by satisfying the QoS constraint on outage. The motivation behind the proposed technique is that, by opportunistically adapting their transmit power with the guide of the proposed strategy, SUs can maximize the achievable sum rate under the constraint of maintaining the outage probability of the PU not degraded. Our goal within this work is thus to determine, under the assumption that the PU is oblivious to the presence of the cognitive users, which would be the cognitive system capacity (which can also be viewed as the total increase in system capacity (or spectral efficiency) due to the SUs' activity) and, at the same time, the maximum number of cognitive communication links allowed in such a system. We present a distributed algorithm for power allocation in the sense that it requires a SU to decide *distributively* to either transmit data or stay silent over the channel coherence time depending on a specified SNR threshold. The optimization problem can therefore be expressed as follows:

$$\text{Find } \{p_1^*, \dots, p_M^*\} = \arg \max_{p_1, \dots, p_M} C_{\text{sum}} \quad (6)$$

subject to:

$$\begin{cases} p_j \in \{0, P_{\max}\}, & \text{for } j = 1, \dots, M \\ P_{\text{out}} = \text{Prob} \{C_{pu} \leq R_{pu} \mid R_{pu}, q\} \leq q \end{cases} \quad (7)$$

where R_{pu} is the PU transmitted data rate. The key idea within the proposed iterative algorithm is, as in [6,14], to subsequently limit p_j to $\{0, P_{\max}\}$, i.e., to switch “off”

transmission in SUs' links which do not contribute enough capacity to outweigh the interference degradation caused by them to the rest of the network. We propose an adaptation of the distributed algorithm which allows a subset of controlled size \tilde{M} of the total number of SUs M to transmit simultaneously on the same sub-band. It turns out necessary to limit the number of SUs interfering with the primary user so as to guarantee the QoS for the primary system. A SU should be deactivated if this action results in an increase in the cognitive capacity of SUs or if its transmission violates the PU outage constraint. Let Ψ be the set of indices of all presently active SUs. Denoting the SU which is to be potentially turned off by m , the network capacity with and without SU turned off is given by the LHS and the RHS of (8a) respectively, and after simple manipulations (8c).

3.1. At high SINR regime

The CRN described in the previous subsection can be modeled by interference channels, due to the fact that SUs employ the same spectral resource in each link, giving rise to an interference-limited system. At high SINR regime, in all “on” SU, and assuming an interference-limited system, we can simplify condition (8c) (Box 1) as:

$$\begin{aligned} \text{SINR}_m &= \frac{p_m |h_{m,m}|^2}{p_{pu} |h_{pu,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k |h_{k,m}|^2} \\ &< \frac{\prod_{\substack{j \in \Psi \\ j \neq m}} \left(p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j}} p_k |h_{k,j}|^2 \right)}{\prod_{\substack{j \in \Psi \\ j \neq m}} \left(p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j \neq m}} p_k |h_{k,j}|^2 \right)} \quad (9) \\ &\Downarrow \\ &\frac{p_m |h_{m,m}|^2}{p_{pu} |h_{pu,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k |h_{k,m}|^2} < \frac{\prod_{\substack{j \in \Psi \\ j \neq m}} \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j}} p_k |h_{k,j}|^2}{\prod_{\substack{j \in \Psi \\ j \neq m}} \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j \neq m}} p_k |h_{k,j}|^2}. \quad (10) \end{aligned}$$

Suppose that devices operate in a dense network, i.e. a large number of SUs is distributed over a restricted geometrical area. Dense networks lend themselves to simplified modeling of the total interference experienced by any user, thanks to the large number of interference sources being averaged at the receiver [15]. Based on the observation that interference to any user in a large dense network is only weakly dependent on the user's position, we can approximate the interference term by an average interference gain, denoted by G^2 which is independent of the user location multiplied, by the total transmit power of active interferers:

$$\sum_{j=1}^M p_j |h_{n,j}|^2 \simeq G^2 \sum_{j=1}^M p_j = G^2 M P_{\max}, \quad \text{for all } n. \quad (11)$$

$$\sum_{j \in \Psi} \log_2 \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j}} p_k |h_{k,j}|^2} \right) < \sum_{\substack{j \in \Psi \\ j \neq m}} \log_2 \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j \neq m}} p_k |h_{k,j}|^2} \right) \quad (8a)$$

$$\begin{aligned} & \log_2 (1 + \text{SINR}_m) + \sum_{\substack{j \in \Psi \\ j \neq m}} \log_2 \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j}} p_k |h_{k,j}|^2} \right) \\ & < \sum_{\substack{j \in \Psi \\ j \neq m}} \log_2 \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j \neq m}} p_k |h_{k,j}|^2} \right) \end{aligned} \quad (8b)$$

$$\Rightarrow (1 + \text{SINR}_m) \prod_{\substack{j \in \Psi \\ j \neq m}} \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j}} p_k |h_{k,j}|^2} \right) < \prod_{\substack{j \in \Psi \\ j \neq m}} \left(1 + \frac{p_j |h_{j,j}|^2}{\sigma^2 + p_{pu} |h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j \neq m}} p_k |h_{k,j}|^2} \right) \quad (8c)$$

Box I.

The constant G^2 depends only on the average amplitude of the channel gain and the pathloss. Though only an approximation, this model is supported by simulations. Accordingly, condition (10) becomes

$$\begin{aligned} & \frac{p_m |h_{m,m}|^2}{\sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq m}} p_k |h_{k,m}|^2} \\ & < \frac{\prod_{\substack{j \in \Psi \\ j \neq m}} G^2 \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j}} p_k}{\prod_{\substack{j \in \Psi \\ j \neq m}} G^2 \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j \neq m}} p_k} \end{aligned} \quad (12)$$

Let us denote $\tilde{M} = \text{card}\{\Psi\}$ and suppose¹ that $K = \frac{p_{pu}}{P_{\max}}$. As all “on” SUs transmit with P_{\max} , the m th SU will be active only if

$$\frac{|h_{m,m}|^2}{\sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq m}} |h_{k,m}|^2} > \left(\frac{\tilde{M} + K - 1}{\tilde{M} + K - 2} \right)^{\tilde{M}-1} \quad (13)$$

As the number of SUs increases, we get (as in [6])

$$\begin{aligned} \lim_{\tilde{M} \rightarrow \infty} \left(\frac{\tilde{M} + K - 1}{\tilde{M} + K - 2} \right)^{\tilde{M}-1} &= \left(\frac{\tilde{M} + K - 1}{\tilde{M} + K - 2} \right)^{\tilde{M}+K-2} \\ &\times \left(\frac{\tilde{M} + K - 1}{\tilde{M} + K - 2} \right)^{1-K} = e = 2.718281 \dots \end{aligned}$$

Thus, for a large network size, a SU will be active if its experimental signal-to-interference ratio is more than e ,

¹ Notice that for the case of uplink $K = 1$ since the PU is transmitting with $p_{pu} = P_{\max}$. However, in the downlink scenario, $K > 1$ since the power transmitted by the BS is generally greater than P_{\max} .

namely

$$\text{SIR}_m = \frac{p_m |h_{m,m}|^2}{|h_{i,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k |h_{k,m}|^2} > e. \quad (14)$$

3.2. At low SINR regime

The restriction to binary power levels yields in general only a negligible capacity loss. In addition, as stated before, it was shown in [8] that in the low SINR regime, i.e., where the approximation $\ln(1+x) \simeq x$ holds with good accuracy, binary power control is in fact always optimal. In the low SINR regime and starting from (8a), we get (15a). After simple manipulations and following (15c) (see Box II), the m th SU will now be active if

$$\begin{aligned} \text{SINR}_m &< \frac{\sum_{\substack{j \in \Psi \\ j \neq m}} p_j |h_{j,j}|^2}{P_{\max} G^2 (\tilde{M} + K - 2) + \sigma^2} \\ &\simeq \frac{P_{\max} G^2 (\tilde{M} - 1)}{P_{\max} G^2 (\tilde{M} + K - 2) + \sigma^2} \end{aligned} \quad (16)$$

where we use the same dense average network assumptions as in (11). Suppose, as in the high SINR regime, that we are in an interference-limited context. This would suggest that $\sigma^2 \ll P_{\max} G (\tilde{M} + K - 2)$ in the RHS of (16). As the number of SUs increases, we get

$$\lim_{\tilde{M} \rightarrow \infty} \left(\frac{\tilde{M} - 1}{\tilde{M} + K - 2} \right) = 1. \quad (17)$$

Thus, as previously done, a SU will be active if its experimental SIR is more than 1:

$$\text{SIR}_m = \frac{p_m |h_{m,m}|^2}{|h_{i,m}|^2 + \sum_{k \in k,m} p_k |h_{k,m}|^2} > 1. \quad (18)$$

$$\frac{p_m|h_{m,m}|^2}{\sigma^2 + p_{pu}|h_{pu,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k|h_{k,m}|^2} < \sum_{\substack{j \in \Psi \\ j \neq m}} \frac{p_j|h_{j,j}|^2}{\sigma^2 + p_{pu}|h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j \neq m}} p_k|h_{k,j}|^2} - \sum_{\substack{j \in \Psi \\ j \neq m}} \frac{p_j|h_{j,j}|^2}{\sigma^2 + p_{pu}|h_{pu,j}|^2 + \sum_{\substack{k \in \Psi \\ k \neq j}} p_k|h_{k,j}|^2} \quad (15a)$$

$$\frac{p_m|h_{m,m}|^2}{\sigma^2 + p_{pu}|h_{pu,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k|h_{k,m}|^2} < \sum_{\substack{j \in \Psi \\ j \neq m}} \left(\frac{p_j|h_{j,j}|^2}{\sigma^2 + \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j \neq m}} p_k|h_{k,j}|^2} - \frac{p_j|h_{j,j}|^2}{\sigma^2 + \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j}} p_k|h_{k,j}|^2} \right) \quad (15b)$$

$$\frac{p_m|h_{m,m}|^2}{\sigma^2 + p_{pu}|h_{pu,m}|^2 + \sum_{\substack{k \in \Psi \\ k \neq m}} p_k|h_{k,m}|^2} < \sum_{\substack{j \in \Psi \\ j \neq m}} \frac{p_j|h_{j,j}|^2}{\sigma^2 + \sum_{\substack{k \in \Psi \cup \{pu\} \\ k \neq j \neq m}} p_k|h_{k,j}|^2} \quad (15c)$$

Box II.

We thus confirm, as intuition would expect, that SUs under better SINR conditions would transmit only above a higher threshold than in the low-SINR regime.

4. Primary system QoS issues

In the current study, we adopt a QoS guarantee to the PU by means of an outage constraint. This knowledge can be obtained by two manners: In a centralized mode where the proposed system would require information from a third party (i.e. central database maintained by regulator or another authorized entity) to schedule incoming SUs. In a realistic network, centralized system coordination is hard to implement, especially in fast-fading environments and in particular if there is no fixed infrastructure for SUs, i.e., no back-haul network over which overhead can be transmitted between users. In fact, centralized channel state information for a dense network involves immense signaling overhead and will not allow the extraction of diversity gains in fast-fading channel components. To alleviate this problem, we propose a distributed method where SUs can get rid of PU knowledge. In a distributed framework, the information about the outage failure can be carried out by a band manager that mediates between the primary and secondary users [16], or can be directly fed back from the PU to the secondary transmitters through collaboration and exchange of the CSI between the primary and secondary users as proposed in [5]. To proceed further with the analysis and for the sake of emphasis, we introduce the PU average channel gain estimate G_{pu} based on the following decomposition:

$$h_{pu,pu} \triangleq G_{pu} * h'_{pu,pu}$$

where $h'_{pu,pu}$ is the random component of channel gain and represents the *normalized* channel impulse response tap. This gives us the following PU outage probability expression:

$$P_{out} = \text{Prob} \left\{ \log_2 \left(1 + \frac{p_{pu} G_{pu}^2 |h'_{pu,pu}|^2}{\sum_{j=1}^{\tilde{M}} p_j |h_{j,pu}|^2 + \sigma^2} \right) \leq R_{pu} \right\} \leq q$$

$$\begin{aligned} &\simeq \text{Prob} \left\{ \frac{p_{pu} G_{pu}^2 |h'_{pu,pu}|^2}{G_{su}^2 \sum_{j=1}^{\tilde{M}} p_j + \sigma^2} \leq 2^{R_{pu}} - 1 \right\} \leq q \\ &\simeq \text{Prob} \left\{ |h'_{pu,pu}|^2 \leq (2^{R_{pu}} - 1) \left(\frac{\tilde{M} G_{su}^2 P_{max} + \sigma^2}{G_{pu}^2 p_{pu}} \right) \right\} \leq q. \end{aligned} \quad (19)$$

From now on we assume for simplicity of analysis that the channel gains are i.i.d Rayleigh distributed. However, the results can be immediately translated into results for any other channel model by replacing by the appropriate probability distribution function. Continuing from (19), we have:

$$P_{out} \simeq \int_0^{(2^{R_{pu}} - 1) \left(\frac{\tilde{M} G_{su}^2 P_{max} + \sigma^2}{G_{pu}^2 p_{pu}} \right)} \exp(-t) dt \leq q. \quad (20)$$

Finally, we get the following outage constraint:

$$P_{out} \simeq 1 - \exp \left[- (2^{R_{pu}} - 1) \left(\frac{\tilde{M} G_{su}^2 P_{max} + \sigma^2}{G_{pu}^2 p_{pu}} \right) \right] \leq q \quad (21)$$

and the maximum number \tilde{M} of active “on” SUs that transmit with P_{max} is given by

$$0 \leq \tilde{M} \leq \frac{-\log(1 - q)}{(2^{R_{pu}} - 1)} \cdot \frac{G_{pu}^2 p_{pu}}{G_{su}^2 P_{max}} - \frac{\sigma^2}{G_{su}^2 P_{max}}. \quad (22)$$

By writing SNR = $\frac{G_{su}^2 P_{max}}{\sigma^2}$, Eq. (22) can be expressed as:

$$0 \leq \tilde{M} \leq \frac{-\log(1 - q)}{(2^{R_{pu}} - 1)} \cdot \frac{G_{pu}^2 p_{pu}}{G_{su}^2 P_{max}} - \frac{1}{\text{SNR}} = \tilde{M}_{theorie}. \quad (23)$$

The LHS in (23) prevents from obtaining a negative number of users when the SNR decreases significantly. The formula in (23) points out that the number of SUs allowed to transmit increases as their SNR increases.

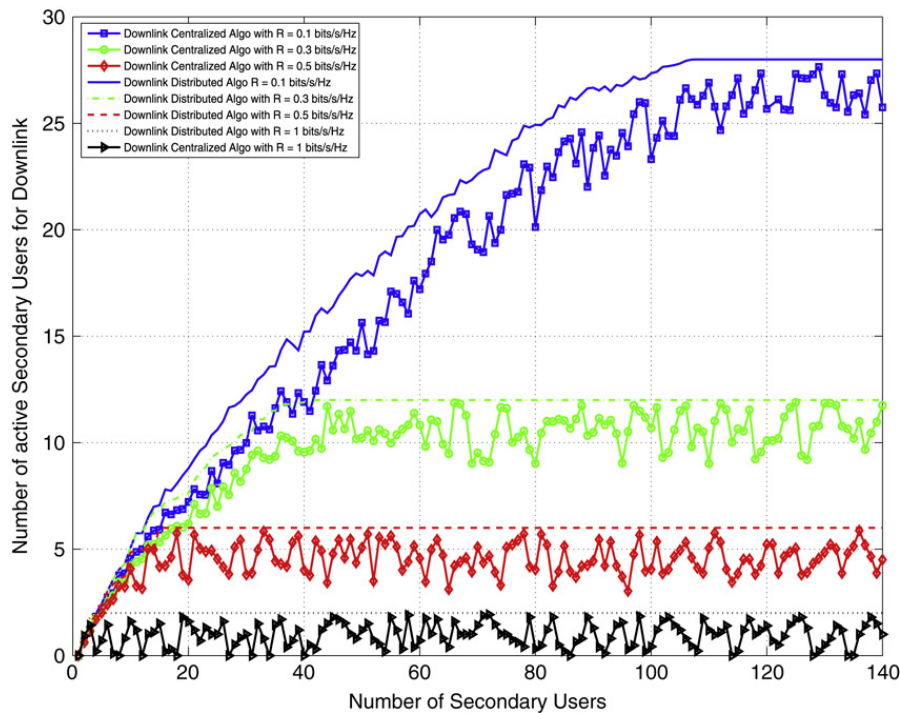


Fig. 2. Number of active secondary users vs. number of SUs for different rates and outage probability in the downlink.

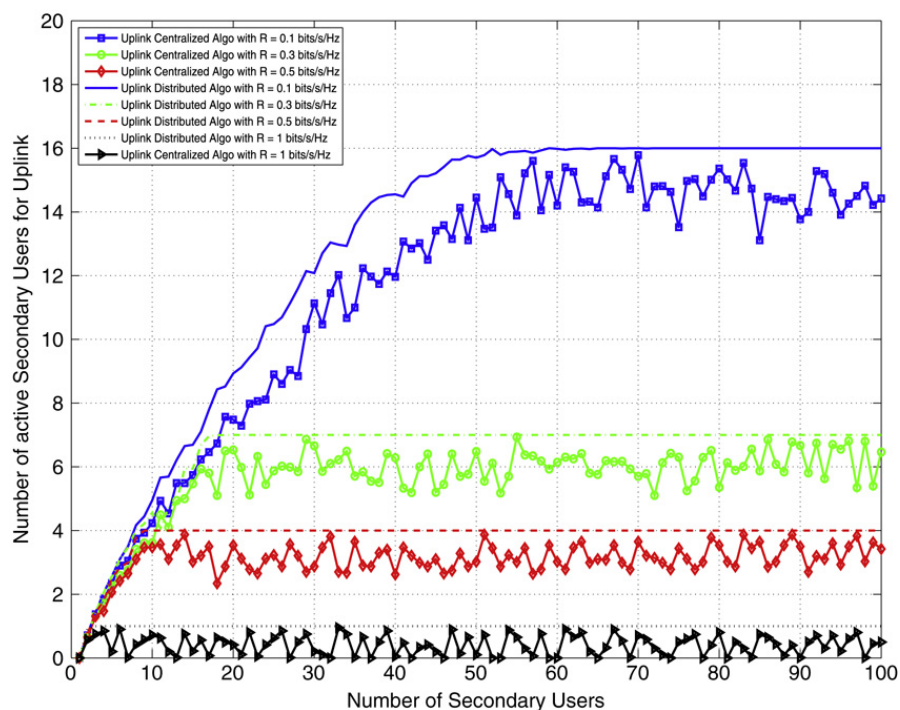


Fig. 3. Number of active secondary users vs. number of SUs for different rates and outage probability in the uplink.

5. User selection strategies

So far, we have studied a distributed approach for power allocation. With the same goal of maximizing the sum of user rates, let us now give some leads towards optimizing the resource by means of user selection. In what follows, we will present an algorithm where joint power allocation and channel-aware user selection are used, in view of maximizing the sum of user rates. The algorithm

can be implemented using a centralized controller who observes the global network and makes decisions, or through a distributed algorithm where each SU performs a distributed voting process.

An iterative approach is adopted throughout the algorithm. Both centralized and distributed strategies are implemented. The centralized algorithm is referred to the one where PU's QoS constraint is guaranteed based on (19) while in the distributed algorithm, the PU's QoS

is insured by means of (23). The pseudo-code for the proposed approach is given in Algorithm 1 where $\tilde{M}_{\text{theorie}}$ is the number of SUs allowed to transmit ruled by (23). The algorithm is first initialized with a full power allocation vector. Each SU simultaneously measures its SIR, and depending on whether the SU is on high or low average SINR, respectively, it remains active or inactive during the next time slot based on (14), respectively (18). Similarly, at every iteration, inequalities (14) and (18) are evaluated for the SU in question based on the power allocation resulting from the previous iteration, and the power allocation vector is updated. Within each iteration, each PU verifies the outage probability constraint based on the resulting power allocation. The goal here is to compare the centralized approach to the distributed scheme in terms of users “on” and the average rate. The algorithm is run until the secondary sum capacity stabilizes or for a given number of iterations. The last SU entering the system is removed from the transmission. For future work, the selection strategies can be improved in order to select the user who affects the sum capacity more. In traditional

order to protect the primary user’s instantaneous rate. Therefore, it is essential for the cognitive user to obtain the message from the other SU in real time (via a broadcast channel), and to be strictly synchronized with the rest of SU. Obviously, SUs are supposed to be identified thanks to a specified beacon in the transmission. Specifically, we will consider a system where devices are scheduled no longer by the BS but by a specified SU. Under the user selection distributed protocol, cognitive users listen to the cognitive signaling channel broadcasted by the Cluster Head user and, depending on the constraints considered previously, determine, either in time or frequency, the SU allowed to transmit with P_{max} .

6. Numerical Results

To go further with the analysis, we resort to realistic network simulations. Specifically, we consider a cognitive radio network as described in Fig. 1 with one PU and M secondary users attempting to communicate during a transmission, subject to mutual interference. A hexagonal cellular system functioning at 1.8 GHz with a primary cell of radius $R = 1000$ m and a primary protection area of radius $R_p = 600$ m is considered. Secondary transmitters may communicate with their respective receivers of distances $d < R_p$ from the BS. Channel gains are based on the COST-231 path loss model [17] including log-normal shadowing with standard deviation of 10 dB, plus fast-fading assumed to be i.i.d. circularly symmetric with distribution $\mathcal{CN}(0, 1)$. The peak power constraint is given by $P_{\text{max}} = 1$ W while the power ratio K is taken equal to 10 for the downlink and equal to 1 for the uplink. This is justified in light of the fact that the power control transmitted by the BS is generally taken almost ten times the primary user transmitted power in multiple possible standards.

Figs. 2 and 3 show the behavior of the distributed strategy with respect to the centralized one for both uplink and downlink, respectively. It is shown that the distributed algorithm guarantees a good “protection” for the PU as compared to the centralized one. Generally, we found out that the distributed scheme presents almost 3 additional active SUs than the centralized scheme. Moreover, we also remark that the number of active users in the downlink in Fig. 2 always outperforms the uplink configuration in Fig. 3. This can be explained by the fact that, as far as the downlink system is considered, the power received from BS is K times the power in the uplink. This results in better PU’s QoS guarantee. In fact, at a rate $R = 0.3$ bits/s/Hz, 12 SUs are allowed to transmit in the downlink and 6 SUs in the uplink. We also remark that, asymptotically, i.e., as the number of SUs becomes large, the number of active SUs remains constant due to the influence of interference impairments on the PU’s QoS. This tends to confirm the intuition from formula (23) where the number of active SUs is always upper-bounded by $\tilde{M}_{\text{theorie}}$. In order to validate our theoretical derivation in Section 4, we compare the outage probability derived in (19) (referred to as centralized outage probability) to the distributed outage probability in (21) using $\tilde{M}_{\text{theorie}}$. As an example we carry out simulations for a rate $= 0.3$ bits/s/Hz. First, it is clear

Algorithm 1 Distributed Cognitive Radio Power Allocation (SINR, rate, target outage probability)

```

1:  $p_j^{(1)} = P_{\text{max}} \quad \forall j$  and  $\tilde{M}^{(1)} = M$ 
2: for  $it = 1 : IT_{\text{max}}$  do
3:   while  $\tilde{M}^{(it)} < \tilde{M}_{\text{theorie}}$  do
4:     for  $j = 1 : M$  do
5:        $\triangleright$  at high SINR regime
6:       if  $\text{SINR}_j^{(it)} > e$  then
7:          $p_j^{(it+1)} \leftarrow P_{\text{max}}$ 
8:       else  $p_j^{(it+1)} \leftarrow 0$ 
9:       end if
10:       $\triangleright$  at low SINR regime
11:      if  $\text{SINR}_j^{(it)} > 1$  then
12:         $p_j^{(it+1)} \leftarrow P_{\text{max}}$ 
13:      else  $p_j^{(it+1)} \leftarrow 0$ 
14:      end if
15:    end for
16:     $\triangleright$  outage constraint: centralized case
17:    if  $P_{\text{out}}^{(it+1)} \geq q$  then
18:       $\tilde{M}^{(it+1)} \leftarrow \tilde{M}^{(it)} - 1$ 
19:    end if
20:     $\triangleright$  outage constraint: distributed case
21:    if  $\tilde{M}^{(it)} \leq \tilde{M}_{\text{theorie}}$  then
22:       $\tilde{M}^{(it+1)} \leftarrow \tilde{M}^{(it)} - 1$ 
23:    end if
24:  end while
25: end for

```

systems, a centralized entity, for instance the BS, decides which user is allowed to transmit at each time slot. If the BS cannot schedule a user who contributes enough capacity to the system to outweigh the interference produced, it will remain silent on that specific time slot. However, in current cognitive radio protocols (e.g. the 802.22 Wireless Regional Area Network (WRAN) [18]), SUs are supposed to be willing to collaboratively relay their proper SIR in

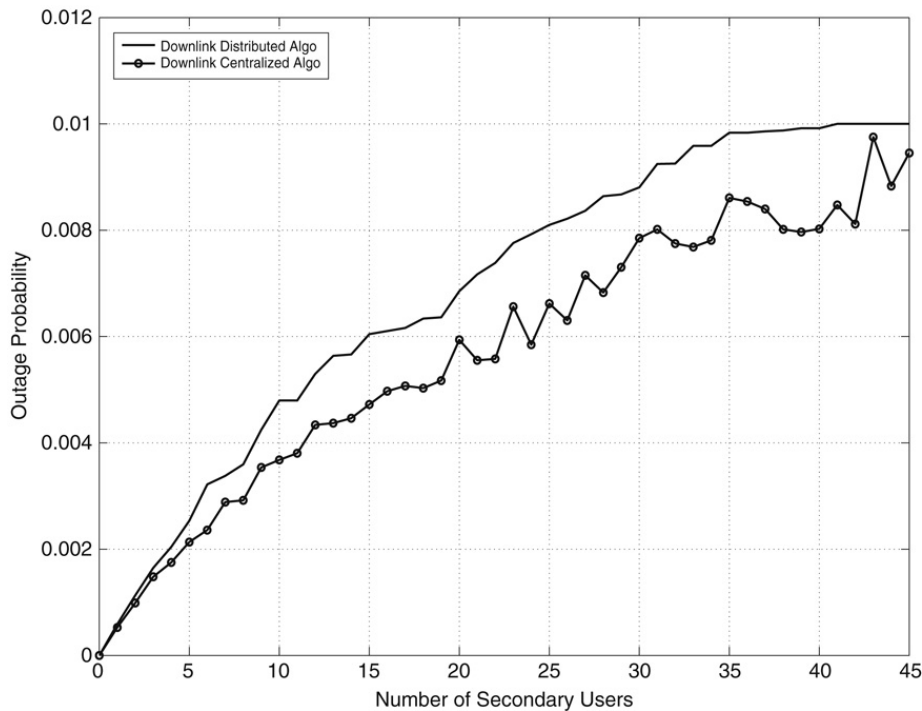


Fig. 4. The downlink outage probability as function of the number of secondary users for a target outage probability = 1% and a rate = 0.3 bits/s/Hz.

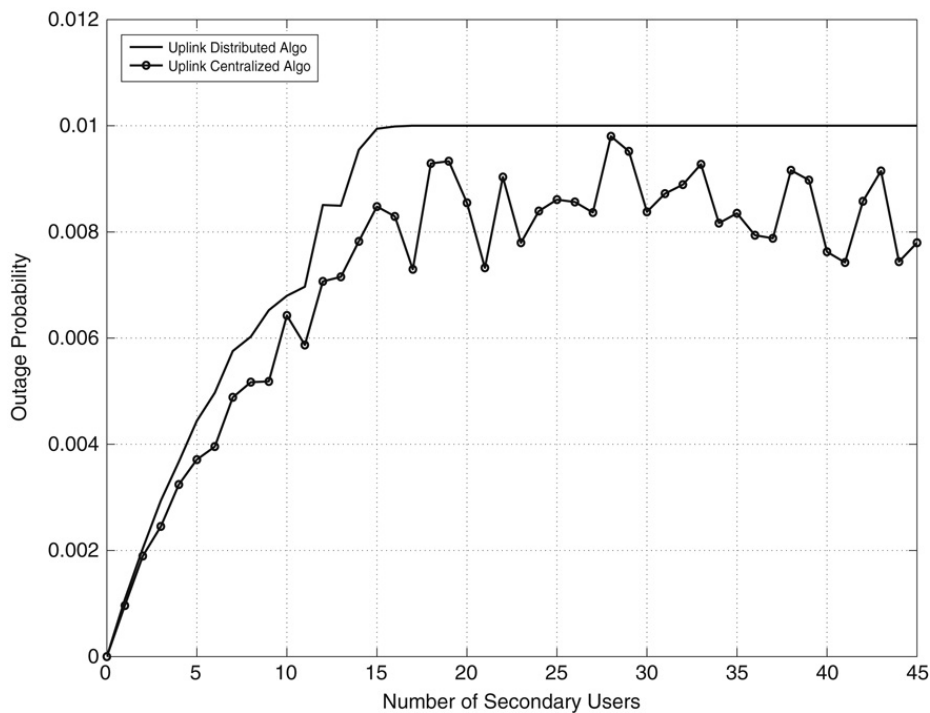


Fig. 5. The uplink outage probability as function of the number of secondary users for a target outage probability = 1% and a rate = 0.3 bits/s/Hz.

from Figs. 4 and 5 that the distributed outage probability always outperforms the centralized one. We also remark that, for the outage probability of interest (i.e., $q = 1\%$), the number of allowed SUs to transmit is equal to 6 for the uplink and 12 for the downlink. This is exactly what Figs. 2 and 3 show in the saturation state at a rate = 0.3 bits/s/Hz.

Fig. 6 depicts the sum secondary user capacity per user for both downlink and uplink as expressed in (5). As

expected, it is found that the capacity of the uplink system outperforms that of the downlink system. On the other hand, increasing the number of SUs yields significantly an increase in capacity because the increase in degree of freedom more than compensates for the decrease in SINR due to interference. However, reaching a certain number of SUs, the sum SU capacity per user decreases as the number of SUs increases. Notice here that, as the primary cell radius R and the primary protection area radius R_p decrease,

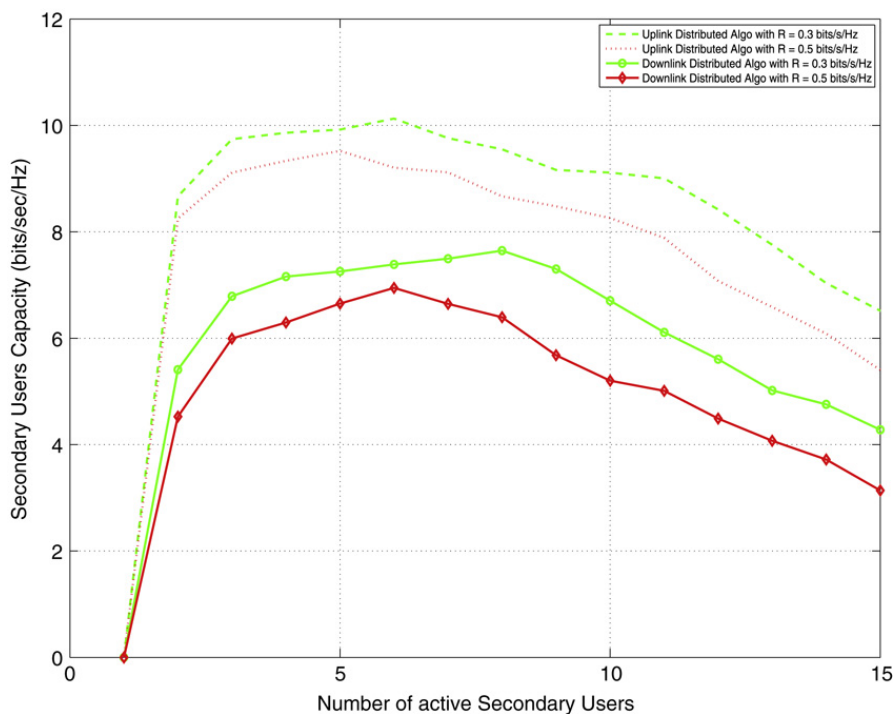


Fig. 6. Sum secondary user capacity per user vs. number of SUs for different rates.

the sum secondary user capacity per user becomes more sensitive to the interference impairments leading to a significant decrease in the sum secondary rate. The current curve claims that in CRN, when one attempts to maximize the number of active SUs, the cognitive capacity degrades asymptotically. Typically, there is a fundamental trade-off between cognitive capacity maximization and number of active SUs maximization.

7. Conclusion

In this paper, we explored the idea of combining multi-user diversity gains with spectral sharing techniques to maximize the secondary user sum rate while maintaining a QoS to a primary user. Both uplink and downlink scenarios are treated. Our contribution within this paper is two-fold. In the first part of the paper, we derived a distributed algorithm for power allocation under a cognitive capacity maximization criterion and minimum and peak power constraints. We found out that a secondary user can self-adapt its spectrum assignment to approximate a new optimal assignment in order to maximize the system spectral efficiency. We also investigated the QoS issues from an outage point of view. In the second part, we explored the user selection strategies. In this setting, centralized and distributed strategies are presented. Both theoretical and simulation results based on a realistic network setting are shown to exhibit interesting features in terms of CRN deployment while maintaining QoS for the primary system by means of outage probability. In particular, we showed that in such CRN, one should make a trade-off between cognitive capacity maximization and number of active SUs maximization.

Acknowledgements

The work reported herein was partially supported by the projects GRACE and Sendora.

References

- [1] J. Mitola, Cognitive radio: An integrated agent architecture for software defined radio, in: Doctor of Technology, Royal Inst. Technol. (KTH), Stockholm, Sweden, 2000.
- [2] R.W. Brodersen, A. Wolisz, D. Cabric, S.M. Mishra, D. Willkomm, Corvus, A Cognitive radio approach for usage of virtual unlicensed spectrum, UC Berkeley White Paper, July 2004.
- [3] M. Haddad, A.M. Hayar, M. Debbah, Spectral efficiency of spectrum-pooling systems, *IET Commun.* 2 (6) (2008) 733–741.
- [4] N. Devroye, P. Mitran, V. Tarokh, Achievable rates in cognitive channels, *IEEE Trans. Inform. Theory* 52 (5) (2006) 1813–1827.
- [5] A. Jovicic, P. Viswanath, Cognitive radio: An information-theoretic perspective, in: IEEE International Symposium on Information Theory, Seattle, USA, July 2006.
- [6] S.G. Kiani, G.E. Øien, D. Gesbert, Maximizing multi-cell capacity using distributed power allocation and scheduling, in: Proc. IEEE Wireless Communications and Networking Conference, Hong Kong, China, March 2007.
- [7] A. Gjendemsjø, D. Gesbert, G.E. Øien, S.G. Kiani, Optimal power allocation and scheduling for two-cell capacity maximization, in: 4th International Symposium on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, Boston, MA, April 2006.
- [8] D. Gesbert, G.E. Øien, S.G. Kiani, A. Gjendemsjø, Anders adaptation, coordination and distributed resource allocation in interference-limited wireless networks, *Proc. IEEE* 95 (12) (2007).
- [9] J.M. Peha, Approaches to spectrum sharing, *IEEE Commun. Mag.* 43 (2) (2005) 10–12.
- [10] <http://hraunfoss.fcc.gov/edocspublic/attachmatch/FCC-07-78A1.doc>.
- [11] L.H. Ozarow, S. Shamai, A.D. Wyner, Information theoretic considerations for cellular mobile radio, *IEEE Trans. Veh. Technol.* 43 (5) (1994) 359–378.
- [12] M. Haddad, A.M. Hayar, G.E. Øien, S.G. Kiani, Uplink distributed binary power allocation for cognitive radio networks, in: proceeding of CrownCom 2008, Singapore, 2008.

- [13] M. Haddad, A.M. Hayar, G.E. Øien, Downlink Distributed Binary Power Allocation for Cognitive Radio Networks, in: proceeding of PIMRC 2008, Cannes, France, 2008.
- [14] S.G. Kiani, D. Gesbert, Maximizing the capacity of large wireless networks: Optimal and distributed solutions, in: Proc. ISIT, Seattle, USA, July 2006.
- [15] S.G. Kiani, D. Gesbert, Optimal and distributed scheduling for multicell capacity maximization, IEEE Trans. Wirel. Commun. 7 (1) (2008) 288–297.
- [16] J.M. Peha, Approaches to spectrum sharing, IEEE Commun. Mag. 43 (2) (2005) 1012.
- [17] Urban transmission loss models for mobile radio in the 900 and 1800 MHz Bands, EURO-COST Std. 231, 1991.
- [18] The charter of IEEE 802.22, the Working Group on Wireless Regional Area Networks (WRANs). <http://www.ieee802.org/22/>.



Bassem Zayen received his Engineering degree in telecommunications at ENIT (Ecole Nationale d'Ingénieurs de Tunis) in 2004 and his master degree in communication systems in 2005. He worked on his graduation project with the group TSI at ENST-Paris. In 2005, he did a seven-month internship within the framework of the RNRT ARTUS project at ENST-Paris. He was a member in the research unit Signaux et Systèmes (U2S) at ENIT from September 2005 to September 2007, where he worked on adaptative multi-equalization on light complexity for radio-mobile channels. Meanwhile, he gave courses in telecommunications for two years at ENIT. In October 2007 he joined the Mobile Communications Department of Eurecom Institute where he is currently pursuing a Ph.D. under the supervision of Professor Aawatif Menouni. His research focuses on Cognitive Radio for the European project SENDORA (SEnsor Network for Dynamic and cOgnitive Radio Access).



Majed Haddad was born in Sousse, Tunisia. He received the Telecommunication Engineering Degree from ENIT (National School of Engineering Sciences) in June 2004. In October 2004, he entered the Master of Communications Systems SiCom in the University of Nice Sophia Antipolis (UNICE), Nice, France. From March to October 2005, he pursued his internship in IMRA-Europe in Sophia Antipolis, France, where he worked on MIMO Systems in impulsive environment. Since December 2005, he has been

pursuing his Ph.D. thesis at Mobile Communications Department in EU-RECOM under the supervision of Aawatif Menouni and Merouane Debba, registered at Ecole Nationale Supérieure de Telecommunication Paris (ENST-Paris), Paris, France. His work focuses on Radio Cognitive in heterogeneous wireless communication systems for the French National RNRT project GRACE (Gestion de Spectre et Radio Cognitive).



Aawatif Hayar received the "Agrégation Génie Electrique" from Ecole Normale Supérieure de Cachan in 1992. She received the "Diplôme d'Etudes Approfondies" in Signal processing Image and Communications and the degree of Engineer in Communications Systems and Networks from ENSEEIHT de Toulouse in 1997. She received with honors the Ph.D. degree in Signal Processing and Communications from Institut National Polytechnique de Toulouse in 2001. She is currently a research and teaching associate in the mobile communications department. Her research interests include array of UWB channel measurements modeling and characterization, Multiple access technique (ChDMA) and localization algorithms based on UWB signaling, Mobile and Wireless communications (GSM, WCDMA, TD/CDMA, LTE, etc.), reconfigurable radio architectures and Radio Resources Power/Resource allocations strategies for Software Defined Radio and Cognitive Radio.



Geir E. Øien was born in Trondheim, Norway in 1965. He received the MScEE and the Ph.D. degrees, both from the Norwegian Institute of Technology in Trondheim, Norway, respectively in 1989 and 1993. From 1994 to 1996 he was an Associate Professor with Stavanger University College in Stavanger, Norway. In 1996, he joined NTNU as an Associate Professor, and in 2001 was promoted to Full Professor. During the academic year 2005–2006 he was visiting professor with Institut Eurécom in Sophia Antipolis, France. Prof. Øien participates in, manages, and coordinates a number of national and international projects and networks of collaboration. His current research interests are in communication theory, information theory, and signal processing for wireless communications and sensor networks, with particular emphasis on link adaptation, power control, radio resource allocation, interference mitigation, dynamic spectrum access, and cross-layer design. He is a senior member of the IEEE.