On the Efficiency of Distributed Spectrum Sensing in Ad-hoc Cognitive Radio Networks

Ioannis Glaropoulos and Viktoria Fodor
School of Electrical Engineering, KTH, Royal Institute of Technology,
Stockholm, Sweden
Email: {ioannisg,vfodor}@ee.kth.se

ABSTRACT

In this work we evaluate the efficiency of cooperative spectrum sensing to support cognitive radio operation, when sensing is assigned to the cognitive users, randomly located in the area of a primary network. We derive analytic expressions for sensing performance based on the traditional metrics of missed detection and false alarm probabilities, and show the existence of an optimal cooperation range. False alarm and missed detection probabilities, however, do not directly lead to performance degradation in the primary and low utilization in the cognitive system. We propose an interference model taking the cognitive access into account and optimize the sensing parameters in order to maximize the cognitive network capacity while satisfying the primary network interference constraints.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communication*

General Terms

Design,Performance

1. INTRODUCTION

Cognitive radio technology has been proposed to allow unlicensed (secondary) networks to access spectrum resources which are left unused by incumbent (primary) operators. The critical issue for allowing dynamic access in primary bands is to eliminate or limit the possibility of interference between the primary system and the secondary system. Secondary systems therefore need to include mechanisms for sensing the radio environment and detecting spectrum holes, within which cognitive operation will not create interference. Sensing accuracy and reliability, although crucial for cognitive actuation, are limited by electromagnetic signal attenuation due to path-loss and fading [1] and it has been shown that they can be significantly enhanced through sensor collaboration, an idea defined as distributed (or cooperative) sensing [2][3]. Energy detection has been mainly considered for local decision at the sensors, assuming lack of knowledge regarding primary users' transmission schemes, although lately more sophisticated detection methods have been proposed as well [4]. While most of these works assume that the quality of distributed sensing is independent of the sensor–primary transmitter distance, a distance dependent model has been proposed for regular sensor networks in [5]. Interference modelling in cognitive networks is addressed in [6] and [7]. The authors of [6] propose a way to model the interference between the primary and cognitive network, where the interference originates from imperfect spectrum sensing. They investigate the tradeoff between the capacity of the cognitive network and the interference caused to coexisting primary users. The paper assumes that a missed detection always results in interference and does not consider the interference between the primary and secondary users as distance-dependent. A recent interference modelling approach that takes the spatial distribution of the cognitive users into consideration is proposed in [7], where the authors model the accumulative interference to a primary user in the case of multiple simultaneous cognitive user transmissions. Employing a similar interference model we move a step further by optimizing distributed spectrum sensing for cognitive network capacity maximization. We give analytic formulation to determine the set of sensing parameters and level of inter-sensor cooperation that maximize the throughput of the cognitive users while guaranteeing that the average interference between the primary and cognitive users is below the acceptable limits.

The remainder of the paper is organized as follows. The considered networking scenario is described in Section 2. In Section 3 we provide analytical results for spectrum sensing performance along with numerical results. In section 4 we formulate the optimization problem to maximize cognitive network capacity under interference constraints, and evaluate the optimal system performance. Section 5 concludes the paper.

2. SCENARIO DESCRIPTION

Figure 1 depicts the networking scenario addressed in this paper. The primary and secondary (cognitive) users - mobile terminals and possibly base stations - are located in the same area. Secondary users (SU) are equipped with spectrum sensors and perform spectrum sensing in a cooperative way to assist the cognitive operation. Since neither the locations of the primary transmitters (PU) nor the locations

CoRoNet'09, September 21, 2009, Beijing, China.

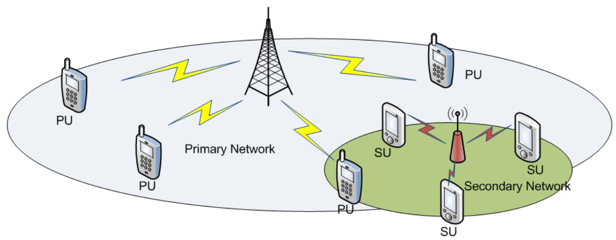

Figure 1: The considered scenario. Primary and secondary networks coexist in the same area, so the interference between them must be controlled.

of the primary receivers are known, secondary users have to collect spectrum availability information from the entire region where they can cause interference.

The performance of spectrum sensing is enhanced by collaborative sensing. We consider randomly located secondary users, but assume that they are aware of each others' relative locations, for instance with the help of GPS or by employing localization techniques [8]. Each secondary user collects spectrum measurements over a set of narrow frequency bands, e.g., according to OFDM subcarriers, and shares this information with other secondary users within the *cooperation area*. Secondary users then decide about the existence of primary transmitters based on the collected information.

We consider a secondary network where sensing information is exchanged over a dedicated low bitrate control channel. The secondary users operate in a time-slotted, slot-synchronized manner. They conduct spectrum measurements and share spectrum availability information at the beginning of a time-slot, and transmit in the second part of the time-slot, if free bands have been detected. The slot length is set based on the interference constraints of the primary system.

To limit the amount of information to be collected, we consider hard decision combining, that is, each sensor shares only its "only noise" or "signal present" decision. We evaluate the OR (occupied if at least one sensor decides for signal present) decision rule. For simplicity we consider energy detection to perform local hard decisions at each sensor.

3. SENSING PERFORMANCE

First we study the sensing performance of the ad-hoc secondary network that has been described in the above section, considering the probabilities of *false alarm* and *missed detection*. We first introduce the signal propagation model that will be employed in our analysis. Considering energy detection we derive formulas for local sensing performance, which will help us to evaluate the behavior of the cooperative sensing scheme in the last part of the section.

3.1 Channel model

For simplicity we will consider a Rayleigh flat-fading channel enhanced with log-normal shadowing, to account for large scale fading, as in [5]. Again, we model the wireless link between the transmitter and an arbitrary sensor l at a distance d_l by an equivalent baseband channel:

$$h_l = \frac{1}{(d_l/d_0)^{\eta/2}} e^{j\phi_l} \alpha_l \, 10^{\zeta_l/20}. \tag{1}$$

In (1) d_0 is a close-in reference, η is the path-loss exponent, α_l, ζ_l are a unit - variance Rayleigh and a lognormal distributed random variable respectively representing small scale fading and shadowing phenomena and ϕ_l is a random phase shift uniformly distributed in $[-\frac{\pi}{2}, \frac{\pi}{2}]$.

Since the correlation distance for small scale fading is in the order of tens of wavelengths, we can practically assume that Rayleigh variables are independent. Considering urban scenarios, shadowing correlation is distance dependent laying in the range between 5 and 50 meters [9] for carrier frequencies around 2GHz. For the purposes of our analysis we will assume that shadowing realizations for the different sensors are independent as well. Based on the derived results we will investigate to which extent this assumption is valid.

3.2 Cooperative sensing model

Our aim is to derive the sensing performance of the network of cognitive users as a function of the network density. The existence of an optimal cooperation range is expected, that jointly minimizes the probabilities of false alarm and missed detection. False alarm probability increases with cooperation radius as more users collaborate to make a decision. Detection probability, however, increases with cooperation radius up to a point when the users further away from the signal source are unable to contribute to the decision due to the low received energy.

As in [5] we assume that local sensing is performed under the formulation of a *binary hypothesis test*. We denote the "only noise" and "signal present" hypotheses by $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively. Considering energy detection technique, the local decision test at an arbitrary sensor l is given by:

$$y_l \triangleq \frac{1}{K}\sum_{k=1}^{K} |r_l\,[k]|^2 \quad \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \quad \gamma_0,$$

where r_l is the received signal down-converted to baseband, K is the total number of signal samples considered for one local decision and γ_0 is the selected *energy threshold* that is compared to the output of the energy detector. Then the probability density functions of the local test under $\mathcal{H}_0$ and $\mathcal{H}_1$ can be expressed as:

$$p_Y\left(y;\mathcal{H}_0\right) = \frac{1}{(\sigma/K)^{2K}\Gamma\left(K\right)} y^{K-1} e^{y/(\sigma/K)^2},$$

and

$$p_Y\left(y;\mathcal{H}_1/\alpha,\zeta\right) = \\ = \tfrac{1}{(\sigma/K)^2}\left(\tfrac{y}{q^2}\right)^{\frac{(K-1)}{2}} e^{-\frac{\left(q^2+y\right)}{(\sigma/K)^2}} I_{K-1}\left(\sqrt{y}\tfrac{2q}{(\sigma/K)^2}\right),$$

where we have used the quantity $q^2 \triangleq P_S K \frac{10^{\zeta_l}\alpha_l^2}{(d_l/d_0)^\eta}$, P_S is the transmitted signal power in the considered band, i.e. $P_S = |s|^2$, and $I_K\left(\cdot\right)$ is the K-th order Bessel modified function of the first kind.

The local false alarm and missed detection probabilities, $p_{fa} = Pr\{y > \gamma_0; \mathcal{H}_0\}$, $p_{md} = Pr\{y \le \gamma_0; \mathcal{H}_1\}$ with respect to the energy threshold γ_0 are given as in [5] – p_{md} averaged over the random variables α_l and ζ_l:

$$p_{fa} = \int_{\gamma_0}^{+\infty} p_Y\left(y;\mathcal{H}_0\right) dy, \tag{2}$$

$$p_{md} = \int_0^{\gamma_0} \int_0^{+\infty} \int_{-\infty}^{+\infty} p_Y\left(y; \mathcal{H}_1 | \alpha, \zeta\right) p\left(\zeta\right) p\left(\alpha\right) d\zeta d\alpha dy. \quad (3)$$

Next we derive the expressions for false alarm and missed detection probabilities under sensor cooperation, assuming that sensor measurements are uncorrelated. The presence of a transmitter at a given physical point O is determined by the secondary users within the circular area centered at O and with cooperation radius R_c. The number of secondary users in this area follows a Poisson distribution with parameter $\pi R_c^2 \rho$, where ρ denotes the secondary network density. Since the cognitive users are independently and uniformly distributed in the sensing area we can first determine the local probability of missed detection considering their spatial distribution. We consider a ring of width dr at distance r from O. The probability that a cognitive user lies within this – infinitely thin – ring is given by:

$$\mathbf{p}(r|R_c) = Pr\{\text{user lies in the ring at distance } r\} = \frac{2rdr}{R_c^2}.$$

The local missed detection probability for this user can be derived by averaging, considering its spatial distribution:

$$\mathbf{p}_{md}(R_c) = \int_0^{R_c} p_{md}(r)\mathbf{p}(r|R_c)dr = \int_0^{R_c} \frac{2}{R_c^2} r p_{md}(r) dr. \quad (4)$$

Considering cooperative sensing and OR decision rule, missed detection occurs if none of the users detect the signal within the area of cooperation, that is:

$$\begin{aligned} P_{MD}(R_c) &= Pr\{\text{all users miss detection}\} \\ &= \textstyle\sum_{i=0}^{\infty} \left[\mathbf{p}_{md}(R_c)\right]^i \cdot \left(\pi R_c^2 \rho\right)^i / i! \cdot e^{-\pi R_c^2 \rho} \\ &= \exp\{-2\pi\rho \textstyle\int_0^{R_c} r(1 - p_{md}(r))dr\}. \end{aligned} \quad (5)$$

False alarm under the same cooperative sensing scheme occurs if at least one of the users issues a false alarm in the area of cooperation:

$$\begin{aligned} P_{FA}(R_c) &= 1 - Pr\{\text{no user gives false alarm}\} \\ &= 1 - \textstyle\sum_{i=0}^{\infty} \left(1 - p_{fa}\right)^i \cdot \left(\pi R_c^2 \rho\right)^i / i! \cdot e^{-\pi R_c^2 \rho} \\ &= 1 - \exp\{-\pi R_c^2 \rho \ p_{fa}\}. \end{aligned} \quad (6)$$

Equations (5), (6) relate the sensing performance metrics to the average density ρ of the secondary network and the sensing radius R_c. Cooperative false alarm and missed detection depend also on local sensing performance which is a function of the selected energy threshold γ_0 and sensing time t_s that corresponds to the K samples that are considered in each decision.

Consider now the case when the primary system introduces constraints on the missed detection probability and sensing time. Then we can derive the optimal set of parameters (R_c^*, γ_0^*) that minimize the probability of false alarm, and thus maximize the throughput of the cognitive system:

$$\begin{aligned} &\text{find} \quad R_c^*, \gamma_0^* \\ &\text{minimize} \quad P_{FA}(R_c, t_s, \gamma_0) \\ &\text{subject to} \quad P_{MD}(R_c, t_s, \gamma_0) \leq P_{MD}^{(\max)}, \ t_s = T_s, \end{aligned} \quad (7)$$

where $P_{MD}^{(\max)}$ and T_s denote the constraint values. The optimization problem (7) can be solved numerically by assuming strong duality and applying the KKT optimality conditions [10].

Since cognitive users are located randomly in the service area, the spatial distances between the sensing points can not be controlled, and sensing observations may be correlated. The derivation of the joint probability distribution of the sensing observations is however computationally very expensive. A simple way to evaluate the possible effect of correlated observations is to estimate the percentage of inter-sensor distances $D_{i,j}$ that are shorter than a reference distance d_{corr} which implies that correlation in measurements is significant and must be considered. We calculated some representative values according to the guidelines in [11] and the results are shown in Figure 2. Note that due to the random location, the ratio of sensors with correlated measurements does not depend on density ρ, however, it decreases with increasing cooperation radius R_c.

3.3 Sensing performance evaluation

In this section we present the results on the sensing performance in a single frequency band B_s of the ad-hoc cognitive network when the primary network is a 802.11 WLAN. Table 1 summarizes the system parameters which we consider, unless otherwise noted. Figure 3 shows the parameter plot of both performance metrics under given cognitive user density. Each missed detection – false alarm probability pair corresponds to a specific γ_0 value. The different curves in the figure correspond to different cooperation radii, i.e. to different levels of sensor cooperation. As expected, a maximum performance can be achieved for a certain value of R_c; increasing R_c above a certain level decreases sensing quality. We can see that the cooperation radius has to be ca. 200m. Considering the small ratio of correlated measurements for such a cooperation radius, as shown in Figure 2, we can conclude that the actual system performance lies quite close to the one derived above, based on the assumption on independent sensor observations.

Table 1: Parameter Values for WLAN Case Study

Case Study	WLAN
Signal Bandwidth (W)	20MHz (all channels)
Signal Power (P_0)	15dBm
Path Loss (η)	4.5
Shadowing (μ, σ^2)	0dBm, 10dB
AWGN Power (σ^2)	-96dBm
$P_{MD}^{(\max)}$	10^{-3}
Maximum Sensing Time (T_s)	0.25msec
Number of Samples (K)	100
Sensed Band Size (B_s)	200kHz
Signal Power in Sensed Band ($P_0 B_s / W$)	-5dBm
Prohibited area radius ($R_{\mathcal{I}}$)	300m

In Figure 4 the relation between the average network density and the resulting probability of false alarm – derived from (7) – is depicted for different constraints on sensing time and missed detection. Clearly, for high sensing quality – $P_{FA} < 10\%$ – and strict system constraints a high secondary network density is required.

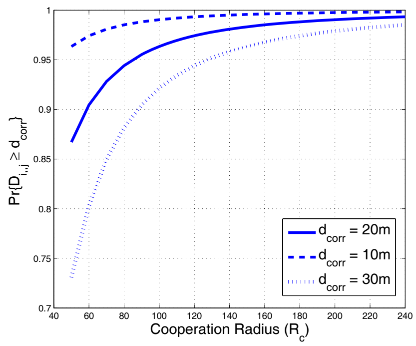

Figure 2: Probability that the Euclidean distance between two sensors inside the sensing area lies above the correlation threshold d_{corr}.

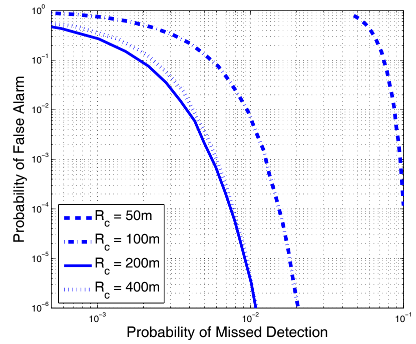

Figure 3: P_{FA} with respect to P_{MD} for different levels of cooperation and with average density $\rho = 400$ Users/km^2.

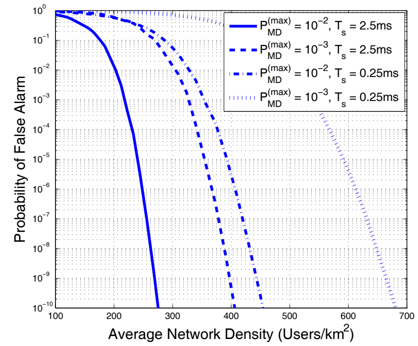

Figure 4: P_{FA} with respect to average network density for different constraints on P_{MD} and sensing time.

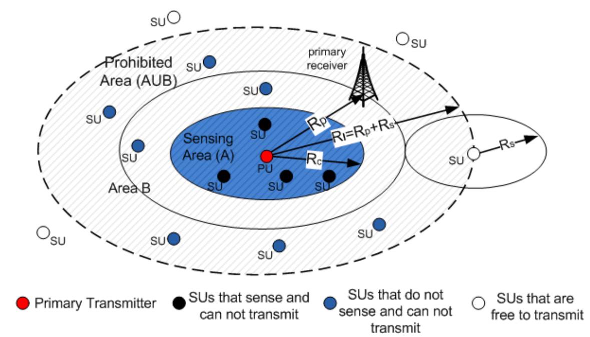

Figure 5: Interference modelling. Radius $R_{\mathcal{I}}$ defines the disk that corresponds to the prohibited area of a PU, which is defined by the communication ranges of the primary and secondary users.

4. SYSTEM OPTIMIZATION FOR INTERFERENCE

In this section of the paper we discuss how sensing parameters can be optimized in order to maximize the *cognitive capacity* available for the secondary users while limiting the *interference* between the primary and the secondary system.

4.1 Interference management

Figure 5 illustrates the main principles of the considered interference management. The primary and secondary networks coexist in the same geographical area, with secondary users operating in multiple spectrum bands. A transmitting primary user is surrounded by a *prohibited area*, within which secondary transmissions on the same frequency would cause unacceptable interference. Considering the worst case scenario – the primary receiver associated with the particular transmitter lies in the border of the primary transmission range – the radius of the prohibited area $R_{\mathcal{I}}$ is defined by the power transmission characteristics of primary and secondary users, associated with transmission ranges R_p and R_s respectively. In the rest of the analysis we will assume that these characteristics for primary and secondary users are fixed and so the radius $R_{\mathcal{I}}$ is fixed and known to the secondary users.

The secondary users try to detect the primary transmissions through spectrum sensing. Once a primary user is detected, the secondary users that lie inside the prohibited area of the detected primary user cease transmission in the respective band.

The bands available for secondary communication are the ones for which cooperative sensing did not result in a "signal present" decision, i.e. a correct detection or a false alarm. These bands are assigned to the secondary users, ensuring that each user receives at most one band. For simplicity we assume that the secondary users can successfully communicate over the assigned bands, even if they are simultaneously used by primary users (i.e. miss-detected bands).

Consider now the situation shown in Figure 5. A primary user starts transmitting in a primary band $\mathcal{W}$ at an arbitrary point in time. The primary user will encounter interference, $\{\mathcal{I}\}$, on band $\mathcal{W}$, if *i)* spectrum sensing on band $\mathcal{W}$ results in a missed detection, and *ii)* during the following time interval this band is assigned to a secondary user, that lies inside its prohibited area, for cognitive operation. Spectrum sensing for the location of the considered primary user is conducted by secondary users inside the area $\mathcal{A}$ – determined by the cooperation radius R_c – as shown in Figure 5. Area $\mathcal{B}$ is the area where secondary users do not sense for the primary user but cause interference to it if they are transmitting on frequency $\mathcal{W}$. The union of $\mathcal{A}$ and $\mathcal{B}$ constitutes the prohibited area for the considered primary user.

4.2 Interference and cognitive capacity model

The formulation of the optimization problem is based on the modelling assumptions in section 4.1. First consider that there exist N_1 and N_2 secondary users in areas $\mathcal{A}$ and $\mathcal{B}$ respectively, assuming $R_{\mathcal{I}} \geq R_c$. Let the N_1 secondary users in $\mathcal{A}$ use the available sensing time (t_s) in order to sense M different bands of bandwidth B_s, $\mathcal{W}_1, \ldots, \mathcal{W}_M$. So the available sensing time for each band $\mathcal{W}_i$ will be $t_{s,i} = t_s/M, i = 1 \ldots M$. We assume here that all secondary users in the considered area sense the same set of bands. Let $\mathcal{W} \in \{\mathcal{W}_1, \ldots \mathcal{W}_M\}$, that is, the primary user transmits in only one of the sensed bands. To take the feasibility of sensing into account, we limit the number of bands $M \leq M_{\max}$. Note that in this formulation we fix the number of occupied bands to one, since we are interested in the interference on that particular band. An extension with the primary network load as parameter is possible and will be subject of future work.

Let $P(\mathcal{I}|(N_1, N_2))$ express the probability of interference to the primary user, conditioned on the number of secondary users present. Since the number of secondary users in the two areas are independent Poisson variables with the same intensity rate we can write:

$$\begin{aligned} &P(\mathcal{I}|(N_1, N_2)) = \\ &\quad = Pr\{\text{ miss. det.}|N_1\} \cdot Pr\{\text{use}|N_1, N_2\}. \end{aligned} \tag{8}$$

In the following we derive the expressions for both factors in (8). Based on *OR* decision rule, we get:

$$\begin{aligned} &Pr\{\text{ miss. det.}|N_1\} = \\ &\quad = \textstyle\prod_{i=1}^{N_1} Pr\{\text{ miss. det. from node } i\} = (\mathbf{p}_{md}(R_c))^{N_1}. \end{aligned} \tag{9}$$

Furthermore, the probability that band $\mathcal{W}$ will be assigned for cognitive operation to one of the secondary users in the prohibited area for the rest of the time slot is given by:

$$\Pr\{use|(N_1, N_2)\} = \sum_{j=0}^{M-1} \min\{1, \frac{N_1 + N_2}{j+1}\} \cdot P_{fr}(j), \tag{10}$$

where $P_{fr}(j)$ defines the probability that j out of the $M-1$ bands are available for cognitive operation after sensing (excluding the considered band $\mathcal{W}$). A band $\mathcal{W}_i$ – out of the $M-1$ initially available ones – may not be available for cognitive use if spectrum sensing in this band during the sensing period resulted in a false alarm. Since the probability of false alarm is independent for each sensed band, we get the following expression for $\Pr_{fr}(j)$:

$$\begin{aligned} P_{fr}(j) &= \Pr\{j \text{ bands detected free}\} \\ &= \tbinom{M-1}{j}(p_{fa}^{(N_1)})^{M-1-j}(1 - p_{fa}^{(N_1)})^j, \end{aligned} \tag{11}$$

where $p_{fa}^{(N_1)}$ is defined as:

$$\begin{aligned} p_{fa}^{(N_1)} &= \Pr\{\text{False alarm in a single band}|N_1\} \\ &= 1 - (1 - p_{fa}(t_s/M))^{N_1}. \end{aligned} \tag{12}$$

Notice in (9) and (12) that $\mathbf{p}_{md}(R_c)$ and $p_{fa}^{(N_1)}$ also depend on the available sensing time for each band $\mathcal{W}_i$, which is a function of the total sensing time, t_s, and the number of sensed bands, M.

The expected interference between the primary user and the secondary network is given by the following formula:

$$\begin{aligned} &P(\mathcal{I}) = \\ &\quad = \textstyle\sum_{N_1=0}^{\infty}\sum_{N_2=0}^{\infty} P(\mathcal{I}|(N_1, N_2)) \cdot \mathbf{p}_{N_1}\mathbf{p}_{N_2} \\ &\quad = \textstyle\sum_{N_1=0}^{\infty}\sum_{N_2=0}^{\infty}[P(\mathcal{I}|(N_1, N_2)) \cdot \\ &\quad\quad \cdot \tfrac{(|\mathcal{A}|\rho)^{N_1}}{N_1!}e^{-(|\mathcal{A}|\rho)}\tfrac{(|\mathcal{B}|\rho)^{N_2}}{N_2!}e^{-(|\mathcal{B}|\rho)}]. \end{aligned} \tag{13}$$

where $P(\mathcal{I}|(N_1, N_2))$ is given by (8) based on the derivations in (9), (10) and (11) and $\mathbf{p}_{N_1}$ and $\mathbf{p}_{N_2}$ define the probabilities of having N_1 and N_2 in areas $\mathcal{A}$ and $\mathcal{B}$ respectively. Notice again that these probabilities depend on the sizes of the areas, denoted as $|\mathcal{A}|$ and $|\mathcal{B}|$, corresponding to radii R_c and $R_{\mathcal{I}}$ respectively. In the less realistic case, $R_c > R_{\mathcal{I}}$, problem formulation is similar – with $N_1 + N_2$ being the number of users that cooperate in sensing, while only N_2 being the interfering ones.

To express the efficiency of the cognitive operation we define the *effective cognitive capacity* as the ratio of spectrum resources that are available for cognitive access over the sum of resources requested by the secondary users, that is:

$$\phi = \frac{\min\{\#\text{ free bands}, \#\text{ requested bands}\}}{\#\text{ requested bands}}. \tag{14}$$

The number of bands available for cognitive use depends on the total number of sensed bands, M, and the probabilities of false alarm and missed detection as a result of spectrum sensing in area $\mathcal{A}$. Consequently, we get:

$$\begin{aligned} &\phi(M, N_1, N_2) = \\ &\quad = \tfrac{\min\{\Pr\{\text{miss det.}|N_1\} + (M-1)\cdot(1-p_{fa}^{(N_1)}), N_1+N_2\}}{N_1+N_2}. \end{aligned} \tag{15}$$

Similar to (13) the expected effective cognitive capacity $\overline{\phi}(M)$ is derived by averaging based on the secondary user distributions in areas $\mathcal{A}$ and $\mathcal{B}$.

Although it is not shown in (15), $\overline{\phi}(M)$ is also a function of total sensing time t_s, decision threshold γ_0 and cooperation radius R_s, so it is related to all the system design parameters that we wish to optimize. Finally, our optimization problem can be formulated in the following way:

$$\begin{aligned} &\text{find } M^*, \;\; R_c^*, \;\; \gamma_0^* \\ &\text{maximize } \overline{\phi}(M, t_s, R_c, \gamma_0) \\ &\text{subject to } Pr\{\mathcal{I}\} \leq P_{\mathcal{I}}^{(\max)} \\ &\qquad M \leq M_{\max}\;,\; t_s = T_s, \end{aligned} \tag{16}$$

where $P_{\mathcal{I}}^{(\max)}$ denotes the interference constraint for the primary system. In the next section we present evaluation results that are based on a numerical solution of the above optimization problem.

4.3 Cognitive network performance

In this section we evaluate how the system parameters affect the cognitive network performance and derive the achievable effective cognitive capacity for various average densities. Our numerical study is based on the WLAN case study, deriving the values for the necessary parameters from Table 1. The particular value for $R_{\mathcal{I}}$ has been chosen based on practical transmission ranges in WLANs and considering that the secondary users have similar transmission properties with the WLAN users of the primary system. $M_{\max}$ has been chosen equal to 100 bands while the total sensing time for all M bands, t_s, has now been chosen 2.5ms. Figure 6 illustrates the relation between cognitive capacity and the total number of sensed bands. We observe that the capacity can have local maximum in the considered range of M. This happens as even though the actual free capacity increases, the sensing performance degrades due to shorter sensing periods for each band, thus increasing false alarm in those bands. Note that in the unrealistic case that M approaches the infinity, the network capacity will tend to 1, since then the probability of interference tends to zero even without sensing.

In Figure 7 the relation between secondary network density and effective cognitive capacity is depicted for different

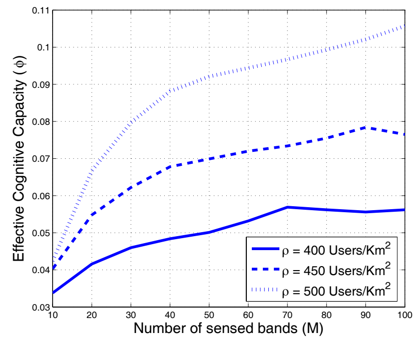

Figure 6: Effective cognitive capacity with respect to the total number of sensed frequency bands (M). $P_{\mathcal{I}}^{(\mathbf{max})} = 10^{-3}$**.**

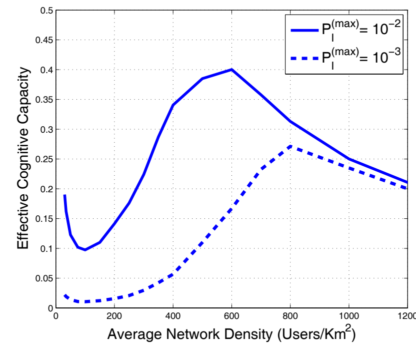

Figure 7: Effective cognitive capacity with respect to average secondary network density.

values of primary system interference bound. We observe that as user density increases, the effective cognitive capacity reaches a highest point which corresponds to the higher probability that a secondary user will be allocated a spectrum band for cognitive operation at an arbitrary time slot. For higher densities the sensing improvement is not adequate to satisfy the increasing number of users in the system. For lower densities we observe that there exist a point when capacity is minimized as a result of low sensing quality. However, as the density further decreases, the existing users receive a higher capacity because of their low number. The capacity maximization and minimization points depend on the system parameters, i.e. the total sensing time and the maximum number of sensed bands. Finally, we observe that for high user densities the capacity of the system does not depend much on the interference bound as a result of high spectrum sensing efficiency. Based on this result we conclude that cognitive networks may need to control the network density, forming parallel sub-networks, each operating over a different primary frequency range.

5. CONCLUSION

In this paper we addressed the problem of detecting low power primary signals in order to assist opportunistic spectrum access. We considered the scenario where the sensing process was assigned to the secondary user terminals which were considered to be randomly located in the designated area where the primary and secondary networks coexist. We presented analytical results for spectrum sensing performance with respect to network density and design characteristics and concluded that secondary network density must be quite high, so as to achieve a good sensing quality. We then investigated the effective capacity of the cognitive network and shown that while the highest cognitive capacity is achieved at high densities, the performance of low density networks is acceptable as well.

6. ACKNOWLEDGMENTS

This work was supported in part by the European Community's Seventh Framework Programme (FP7/2007-2013) under grant agreement no 216076 (SENDORA).

7. REFERENCES

[1] A. Sahai, N. Hoven, S. M. Mishra, and R. Tandra. Fundamental tradeoffs in robust spectrum sensing for opportunistic frequency reuse. Technical report, Berkeley, 2006.

[2] E. Visotsky, S. Kuffner, and R. Peterson. On collaborative detection of tv transmissions in support of dynamic spectrum sharing. In *Proc. IEEE 1st Symposium on Dynamic Spectrum Access Networks (DySPAN'05)*, 2005.

[3] N. Sahai, A. Hoven, and R. Tandra. Opportunistic spectrum use for sensor networks: the need for local cooperation. *Berkeley Wireless Research Center*, 2006.

[4] S. Chaudhari, V. Koivunen, and H.V. Poor. Distributed autocorrelation-based sequential detection of ofdm signals in cognitive radios. *CrownCom'08*, May 2008.

[5] V. Fodor, I. Glaropoulos, and L. Pescosolido. Detecting low-power primary signals via distributed sensing to support opportunistic spectrum access. In *Proccedings of IEEE ICC'09, Germany*, 2009.

[6] Won-Yeol Lee and I.F. Akyildiz. Optimal spectrum sensing framework for cognitive radio networks. *Wireless Communications, IEEE Transactions on*, 7(10):3845–3857, October 2008.

[7] M. Timmers, S. Pollin, A. Dejonghe, A. Bahai, L. Van der Perre, and F. Catthoor. Accumulative interference modeling for distributed cognitive radio networks. *Journal of Communications*, April 2009.

[8] C. Taylor, A. Rahimi, J. Bachrach, H. Shrobe, and A. Grue. Simultaneous localization, calibration, and tracking in an ad hoc sensor network. In *Information Processing in Sensor Networks, 2006. IPSN 2006. The Fifth International Conference on*, 2006.

[9] D.S. Baum, J. Hansen, and J. Salo. An interim channel model for beyond-3g systems: extending the 3gpp spatial channel model (scm). In *Vehicular Technology Conference, 2005. VTC 2005-Spring. 2005 IEEE 61st*, May-1 June 2005.

[10] Stephen Boyd and Lieven Vandenberghe. *Convex Optimization*. Cambridge University Press, 2004.

[11] M. G. Kendall and P. A. P. Moran. *Geometrical Probability*. Charles Griffin & Company Ltd., 1963.