Chapter 1
Cooperative Spectrum Sensing with Censoring of Cognitive Radios in Fading Channel Under Majority Logic Fusion

Srinivas Nallgonda, Sanjay Dhar Roy, Sumit Kundu, Gianluigi Ferrari and Riccardo Raheli

Abstract In a cooperative spectrum sensing (CSS) scheme, the detection of the presence of activity of a primary user (PU) is improved by the fact that several cognitive radio (CR) users send, through reporting channels (R-channels), their sensed information on the activity of this PU to a common base station (BS). The benefits are particularly relevant in scenarios where the sensing channels (S-channels) towards the PU of interest of CR users are affected by severe fading or shadowing. However, in a CSS scheme with R channels affected by fading or shadowing as well, there may be erroneous reception, at the BS, of decisions from CR users: this can be counter-acted by using censoring of CR users. In this chapter, we discuss the performance of CSS with censoring of CR users based on their R-channels' statuses. Two schemes of censoring are considered: (i) rank-based censoring, where a pre-defined number of CR users, associated with the best R-channels, are selected; and (ii) threshold-based censoring, where CR users, whose R-channel fading coefficients exceed a pre-determined threshold, are selected. The performance of both censoring schemes is evaluated considering two different R-channel fading conditions: (i) Rayleigh fading and (ii) Nakagami-*m* fading. In both cases, majority logic fusion is considered at the BS (also denoted re-interpreted as fusion center, FC). The impact of various network parameters—such as censoring threshold, number of CR users, average S- and R-channels' SNRs, channel estimation (CE) quality, and fading severity—on the performance of the considered CSS schemes will be evaluated in terms of missed detection and total error probabilities.

Srinivas Nallagonda
ECE Department, NIT Durgapur, WB, India, e-mail: srinivas.nallagonda@gmail.com
Sanjay Dhar Roy
ECE Department, NIT Durgapur, WB, India, e-mail: sumit.kundu@ece.nitdgp.ac.in
Sumit Kundu
ECE Department, NIT Durgapur, WB, India, e-mail: sumit.kundu@ece.nitdgp.ac.in
Gianluigi Ferrari
Dept. of Information Engineering, University of Parma, Italy, e-mail: gianluigi.ferrari@unipr.it
Riccardo Raheli
Dept. of Information Engineering, University of Parma, Italy, e-mail: raheli@unipr.it

1.1 Introduction

Cognitive radio (CR) has been proposed [1] as a promising technique to solve the conflicts between spectrum scarcity and spectrum under utilization. CR systems allow CR users[1] to share the spectrum with primary users (PUs) either opportunistically or without creating any intolerable interference to PU. Spectrum sensing is an important feature of CR technology since it is necessary to detect the presence of PUs accurately and quickly in order to find availability of unused spectrum, i.e., the spectrum holes. Accurate sensing of spectrum holes is a hard task because of the time-varying nature of wireless channels [2], including fading and shadowing. Due to severe multipath fading in sensing channel (S-channel) between a PU and a CR user, the CR user may fail to detect the presence of the PU. The detection/sensing performance can be improved, by limiting the negative impact of fading, if different CR users are allowed to cooperate by sharing their detected information on the activity status of PUs: this is the essence of cooperative spectrum sensing (CSS). Therefore, CSS improves the detection performance when all CR users sense the PU individually and send their sensing information in the form of 1-bit binary decisions (1 or 0) via ideal (noiseless) reporting channels (R-channels) to a fusion centre (FC)—the FC corresponds to the base station (BS). In CSS schemes, the local decisions on PUs's activity status sent by several CR users are combined at FC to obtain a global decision. In general, the sensing information reported to the FC by several CR users can be combined in two different ways: through (i) soft or (ii) hard combining. According to a soft combining approach, CR users transmit the entire local sensing samples or the complete local test statistics which are combined using any one of possible diversity combining technique such as likelihood ratio test (LRT), maximal ratio combining (MRC), and equal gain combining (EGC) [3]-[5]. In [3] the authors consider soft information combining of the signals received via multiple antennas of a single CR. In [4], the LRT fusion is discussed in case of wireless sensor networks. In [6], an optimal soft combination scheme based on neyman-pearson (NP) criterion is proposed to combine the weighted local observations. The proposed scheme reduces to EGC at high SNR and reduces to MRC at low SNR. In the presence of hard combining, CR users make a local decision (hard decision on the PU activity status) and transmit the one bit decision for hard combining. A hard decision combining fusion rule—such as OR-logic, AND-logic, and majority-logic—is implemented at FC to make the final decision on the presence or absence of a PU [7]-[9].

In many wireless applications, it is of great interest to check the presence and availability of an active communication link when the signal is unknown. In such scenarios, one appropriate choice consists in using an energy detector (ED) which measures the energy in the received waveform over an observation time window [10]-[11]. The existing literature energy detector-based on single CR user [11]-[12] and cooperative CR users [13]-[16] spectrum sensing, typically assumes pop-

[1] Note that with the generic term CR we also refer to a secondary (cognitive) user (SU). The context eliminates any ambiguity.

ular fading models such as Rayleigh and Nakagami-*m* (*m* being the fading severity parameter). In these cases, R-channels are assumed to be ideal and S-channels are considered as Rayleigh and Nakagami-*m* fading channels. However, in many practical situations R-channels may not be noiseless (ideal) channels. Though most works on spectrum sensing assume noiseless R-channels [7]-[9], [12]-[16], the presence of fading in R-channels is likely to affect the decisions sent by CR users where the FC is far from CR users. If the R-channel connecting a CR user to the FC is heavily faded, the decision received at the FC is likely to be erroneous with respect to that transmitted by the CR user. If this is the case, it is better to stop transmitting decisions from such CR user and, thus, the use of censoring is expedient. The CR users whose R-channels are estimated as reliable by the FC are censored, i.e., they are allowed to transmit. The CR users which are not participating in improving the detection performance may be stopped, so that the system complexity can be reduced and the detection performance can be improved. This will further reduce the energy consumption for an energy-constrained network. Therefore, censoring of CR users is necessary to improve the performance of CSS. The R-channels are considered as noisy and Rayleigh faded in [17]-[18], in the context of a sensor network where sensors report their decisions to a FC. Censoring of sensors, as proposed in [19]-[20], and channel-aware censoring of sensors, as discussed in [21]-[21], can be well applied in the context of energy detection based CSS.

In our present discussion, we consider both R-channel and S-channel to be (i) Rayleigh faded and (ii) Nakagami-*m* faded. Similar fading scenario is considered in S-channel and R-channel i.e., both S-channel and R-channel as Rayleigh faded or Nakagami-*m* faded. Though all the CR users detect PUs using energy detectors, only those CR users censored based on quality of R-channels are allowed to transmit. The censoring decision is taken by FC based on estimation of R-channel. In [23], the performance of CSS systems with censoring of CR users under both majority-logic fusion and maximal ratio combining (MRC) fusion has been evaluated only in Rayleigh faded environments, considering CR users' censoring on the basis of the qualities of their R-channels. Using minimum mean square estimation (MMSE)-based estimation of the R-channels, the FC selects the subset of CR users among all the available ones (say K out of N) which have the highest channel coefficients, i.e., the CR users associated with best estimated channel coefficients are selected. However, in an alternative censoring scheme, based on channel thresholding, is considered and analyzed in [24] in the context of distributed detection in a (non-cognitive) sensor network where a number of sensors observe a common binary phenomenon. In [25], the performance of CSS schemes with channel thresholding-based censoring of CR users with Rayleigh fading and majority-logic fusion at the FC is evaluated. The investigation of majority-logic fusion schemes where both S- and R-channels are Nakagami-*m* faded is an interesting research extension. The Nakagami-*m* distribution provides flexibility in describing the fading severity of the channel and encompasses special cases such as Rayleigh fading (for m=1) [5].

In the current chapter, we consider the same system model of [23] and [25] and evaluate the performance of CSS with censoring of CR users based on quality of

R-channels. More precisely, we analyze the performance of CSS schemes with censored CR users in Nakagami-m faded environments (with special case given by Rayleigh faded environment), considering a network of N CR users. Each CR user makes local observation on the activity of the PU using energy detectors. We consider two schemes on channel quality-based censoring. The first scheme consists of rank-based censoring: using MMSE-based estimation of the R-channels, the FC selects the subset of CR users among all the available ones (say K out of N) which have the highest channel coefficients, i.e., the CR users associated with best estimated channel coefficients are selected. The second censoring scheme is threshold-based: a CR user is selected to transmit its decision if the estimated R-channel fading coefficient exceeds a given threshold (denoted as censoring threshold and indicated as C_{th}). The channel estimation is either perfect (no estimation error) or imperfect (with an estimation error). Accordingly, for each censoring strategy, there are two possibilities, namely perfect or imperfect channel estimation. The FC employs coherent reception to fuse the binary local decisions received from the censored CR users, in order to obtain a final decision regarding the presence or absence of PUs. Low complexity majority-logic fusion of the decisions received from the selected CR users is considered in present case. The overall probability of missed detection is selected as the key performance metric and is evaluated, through simulations, under several channel and network conditions.

The main contributions of this chapter can be summarized as follows.

- Closed-form expressions of the estimation error variances for Rayleigh and Nakagami-m fading channels are presented. These expressions are expedient to evaluate the performance of CSS with censoring based on imperfect channel estimation.
- The performance, in terms of missed detection and total error probabilities under both perfect and imperfect channel estimation strategies, is investigated. The effects of Nakagami-m fading, S- and R-channel SNRs on the performance of the considered CSS schemes are investigated.
- The impact of the R-channel estimation error on the detection performance in the considered fading scenarios is evaluted.
- Direct performance comparisons between perfect and imperfect channel estimation schemes, for various values of the main channel and network parameters, are carried out.
- In threshold-based censoring scenarios, novel analytical expressions, as functions of the censoring threshold C_{th}, for the selection of CR users are derived in Rayleigh and Nakagami-m fading channels. In particular, the probability mass functions (PMF) of the number of censored CR users is analyzed.
- The impact of the number of available CR users and of the average R-channel SNRs on the average missed detection and average total error probabilities of CSS schemes is investigated.
- In threshold-based censoring schemes, the impact of the censoring threshold on the average missed detection and average total error probability, with the derivation of an optimized censoring threshold.

- The performances of several hard-decision fusion strategies are also evaluated and compared with each other under various fading channels.

The rest of the chapter is organized as follows. In Section 1.2, the basics of CSS are introduced. In Section 1.3, the performance of CSS in faded environments (Rayleigh and Nakagami-*m*) under several hard decision fusion rules is studied. In Section 1.4, two different censoring methods such as Rank-based and threshold-based censoring have been analyzed under both perfect and imperfect channel estimation schemes. Finally, conclusions are drawn in Section 1.5.

1.2 Cooperative Spectrum sensing

Detection of PU by a single CR user may not be accurate due to impairment in S-channel or hidden node problem which necessitates the use of cooperation among many CR users. In such cases, as anticipated in Section 1.1, detection/sensing performance can be improved, by alleviating the effects of fading, if different CR users are allowed to cooperate by sharing their detection information, i.e., considering CSS. Therefore, CSS improves the detection performance where all CR users employ identical EDs and sense the PU individually and send their sensing information in the form of 1-bit binary decisions (1 or 0) via R-channels to FC. The hard decision combining fusion rule (OR, AND, and majority-logic fusion rules) is performed at FC using a counting rule to make the final decision regarding the presence or absence of a PU [7]-[9], [12], [15]. In case of soft decision combining, the CR users can transmit the entire local sensing samples or the complete local test statistics to FC. Existing receiver diversity techniques [3]-[5], such as LRT, EGC, and MRC, can be utilized at the FC for soft combining of local observations or test statistics. The performance of CSS with hard decision fusion in faded environments is investigated in the next section.

1.3 Impact of Fading on Cooperative Spectrum Sensing

The energy detection method is the common method for detection of unknown signals in noise [10]-[11]. The block diagram of an energy detector is shown in [10]-[11] which consist of one band pass filter (BPF), one signal squarer, one integrator and one decision device. The input BPF selects the center frequency and the corresponding bandwidth of interest (with width W). The output of the BPF filter is passed to a squaring device to measure the received energy. Then an integrator is placed to determine the observation interval, T. Finally, the output of the integrator, denoted as Y, is compared with a detection threshold to decide on the presence/absence of a PU signal. We assume that all CR users use the same energy detector and the identical threshold (denoted as λ). The received signal $x_i(t)$ at the input of the i-th CR user can be expressed as

$$x_i(t) = \begin{cases} n(t) & : H_0 \\ h_i(t)s(t) + n(t) & : H_1 \end{cases} \tag{1.1}$$

where $s(t)$ is the PU signal with energy E_s and $n(t)$ is the noise waveform. The noise $n(t)$ is modeled as a zero-mean white Gaussian random process. The Rayleigh faded S-channel coefficient for the i-th CR user is denoted as $h_i(t)$. H_1 and H_0 are the two hypotheses associated with presence and absence of a PU respectively. Each CR user has an energy detector to detect on the presence or absence of a useful signal.

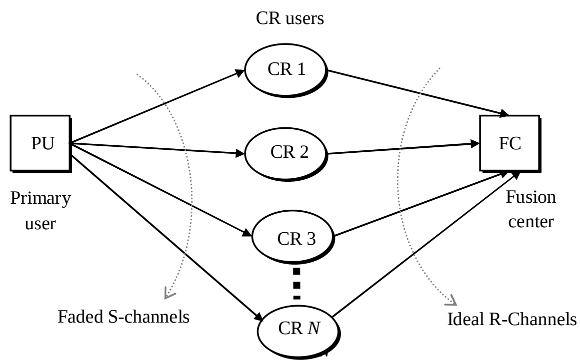

Fig. 1.1 Cooperative spectrum sensing network: illustrative scenario.

We consider a network of N CR users sensing the spectrum of a PU, as shown in Fig. 1.1. Each CR user makes its own decision regarding the presence of the PU, and forwards the binary decision (1 or 0) to FC for data fusion. We consider only one FC and all CR users are equipped with single antenna. The PU is located far away from all CR users. All CR users are assumed to be relatively close to each other. The distance between any two CR users is shorter than the distance between a PU and a CR user and the distance between a CR user and the FC. For simplicity, we assume that the average SNR in the S-channel is the same for each CR user. We consider that the S-channels are faded, while the R-channels are ideal channels (noiseless). According to the sampling theorem, the noise process can be expressed as follows [26]:

$$n(t) = \sum_{j=-\infty}^{\infty} n_j \operatorname{sinc}(2Wt - j) \tag{1.2}$$

where $\operatorname{sinc}(x) = \sin(\pi x)/(\pi x)$ and $n_j = n(j/(2W))$. One can easily show that

$$n_j \sim \mathcal{N}(0, N_{01}W); \forall j \tag{1.3}$$

where N_{01} is the one-sided noise power spectral density, W is the one-sided bandwidth and $\mathcal{N}(\mu, \sigma^2)$ is a Gaussian distribution with mean μ and variance σ^2.

When the PU is absent (i.e., H_0 is true), each CR user receives only the noise signal at the input of the ED and the noise energy can be approximated, over the time interval $(0,T)$, as follows [10]-[11]:

$$\int_0^T n^2(t)\,\mathrm{d}t = \frac{1}{2W}\sum_{j=1}^{2u} n_j^2 \tag{1.4}$$

where u is the time-bandwidth product. If we define $n'_j = n_j/\sqrt{N_{01}W}$, the decision statistic at i-th CR user, denoted as Y_i in case of H_0, can be written as [10]-[11]:

$$Y_i = \sum_{j=1}^{2u} n_j'^2. \tag{1.5}$$

In particular, Y_i is the sum of the squares of $2u$ standard Gaussian variates with zero mean and unit variance. Therefore, Y_i has a central χ^2 distribution with $2u$ degrees of freedom.

The same approach can be applied in the presence of the signal $s(t)$ of a PU, by replacing $\{n_j\}$ in (1.4) with $n_j + s_j$, where $s_j = s(j/(2W))$. In this case, the decision statistic Y_i has a non-central χ^2 distribution with $2u$ degrees of freedom and non-centrality parameter $2\gamma_{s,i}$ [10]-[11]. More precisely:

$$Y_i \sim \begin{cases} \chi^2_{2u} & : H_0 \\ \chi^2_{2u}(2\gamma_{s,i}) & : H_1 \end{cases} \tag{1.6}$$

In a non-faded environment, the detection and false alarm probabilities for the i-th CR user can be expressed as follows [16]-[7]:

$$P_{d,i} = \Pr[Y_i > \lambda | H_1] = Q_u\left(\sqrt{2\gamma_{s,i}}, \sqrt{\lambda}\right) \tag{1.7}$$

$$P_{f,i} = \Pr[Y_i > \lambda | H_0] = \Gamma(u, \lambda/2)/\Gamma(u) \tag{1.8}$$

where $\gamma_{s,i}$ is the instantaneous S-channel SNR, $\Gamma(\cdot)$ is the incomplete gamma function [27], and $Q_u(\cdot,\cdot)$ is the generalized Marcum Q-function of order u [28]. The expression for the probability of false alarm ($P_{f,i}$) for the i-th CR user, as given in equation (1.8), remains the same when fading is considered in the S-channel, owing to the independence of $P_{f,i}$ from the SNR $\gamma_{s,i}$. For a chosen value of $P_{f,i}$, the corresponding detection threshold λ can be set following equation (1.8). The ED thus compares Y_i with its preset detection threshold λ and takes a hard binary decision about the presence of a PU.

When h_i is time-varying, because of fading, equation (1.7) returns the probability of detection as a function of the instantaneous SNR $\gamma_{s,i}$. In this case, the average probability of detection at the i-th CR user can be derived by averaging (1.7) over fading statistics [7]-[9] and can be given the following expression:

$$\bar{P}_{d,i} = \int_0^\infty Q_u\left(\sqrt{2x}, \sqrt{\lambda}\right) f_\gamma(x)\,\mathrm{d}x \tag{1.9}$$

where $f_\gamma(x)$ is the probability density function (pdf) of γ under fading.

1.3.1 Rayleigh Fading Channel

If the received signal amplitude at the i-th CR user has a Rayleigh distribution, then the SNR ($\gamma_{s,i}$) has the following exponential pdf [5], [11]:

$$f_\gamma(\gamma_{s,i}) = \frac{1}{\bar{\gamma}_s}\exp\left(-\frac{\gamma_{s,i}}{\bar{\gamma}_s}\right) \qquad ;\gamma_{s,i} \geq 0 \tag{1.10}$$

where $\bar{\gamma}_s$ is the average SNR of the S-channel. The average P_d at the i-th CR user in this case, $\bar{P}_{d,i,Ray}$ can now be evaluated by substituting (1.10) in (1.9), thus obtaning:

$$\begin{aligned}\bar{P}_{d,i,Rayl} &= \exp\left(-\frac{\lambda}{2}\right)\sum_{k=0}^{u-2}\frac{1}{k!}\left(\frac{\lambda}{2}\right)^k + \left(\frac{1+\bar{\gamma}_s}{\bar{\gamma}_s}\right)^{u-1} \\ &\times\left(\exp\left(-\frac{\lambda}{2(1+\bar{\gamma}_s)}\right) - \exp\left(-\frac{\lambda}{2}\right)\sum_{k=0}^{u-2}\frac{1}{k!}\left(\frac{\lambda\bar{\gamma}_s}{2(1+\bar{\gamma}_s)}\right)^k\right).\end{aligned} \tag{1.11}$$

1.3.2 Nakagami-m Fading Channel

If the received signal amplitude at the i-th CR user follows a Nakagami-m distribution, then $\gamma_{s,i}$ has the following gamma pdf [5], [11]:

$$f_\gamma(\gamma_{s,i}) = \left(\frac{m}{\bar{\gamma}_s}\right)^m \frac{\gamma_{s,i}^{m-1}}{\Gamma(m)}\exp\left(-\frac{m\gamma_{s,i}}{\bar{\gamma}_s}\right) \qquad ;\gamma_{s,i} \geq 0 \tag{1.12}$$

where m is the Nakagami fading parameter. The average probability of detection at the i-th CR user in the case of Nakagami-m channel $\bar{P}_{d,i,Nak}$ can be evaluated by substituting (1.12) in (1.9), obtaining:

$$\bar{P}_{d,i,Naka} = \alpha\left[G_1 + \beta\sum_{n=1}^{u-1}\frac{(\lambda/2)^n}{2n!}\,{}_1F_1\left(m; n+1; \frac{\lambda\bar{\gamma}_s}{2(m+\bar{\gamma}_s)}\right)\right] \tag{1.13}$$

where ${}_1F_1(\cdot;\cdot;\cdot)$ is the confluent hypergeometric function [27, Sec. 9.2]

$$\alpha = \frac{1}{\Gamma(m)2^{m-1}}\left(\frac{m}{\bar{\gamma}_s}\right)^m \tag{1.14}$$

$$\beta = \Gamma(m)\left(\frac{2\bar{\gamma}_s}{m+\bar{\gamma}_s}\right)^m \exp\left(-\frac{\lambda}{2}\right) \tag{1.15}$$

and

$$\begin{aligned} G_1 = {} & \frac{2^{m-1}(m-1)!}{\left(\frac{m}{\bar{\gamma}_s}\right)^m} \frac{\bar{\gamma}_s}{m+\bar{\gamma}_s} \exp\left(-\frac{m\lambda}{2(m+\bar{\gamma}_s)}\right) \left[\left(1+\frac{m}{\bar{\gamma}_s}\right)\left(\frac{m}{m+\bar{\gamma}_s}\right)^{m-1}\right. \\ & \left. \times L_{m-1}\left(-\frac{\lambda\bar{\gamma}_s}{2(m+\bar{\gamma}_s)}\right) + \sum_{n=0}^{m-2}\left(\frac{m}{m+\bar{\gamma}_s}\right)^n L_n\left(-\frac{\lambda\bar{\gamma}_s}{2(m+\bar{\gamma}_s)}\right)\right] \end{aligned} \tag{1.16}$$

where $L_n(\cdot)$ is the Laguerre polynomial of degree n [27, Sec. 8.970]. We can also obtain an alternative expression for $\bar{P}_{d,i,Ray}$ by setting m=1 in (1.13)—this expression is numerically equivalent to the one in (1.11). As already discussed in Section 1.3, all CR users in the network use identical EDs (with the same threshold λ) which make hard binary decisions and transmit them to the FC via noiseless R-channels.

Assuming independent decisions, the fusion rule according to which k-out of-N CR users are needed to make a final decision on the presence/absence of a PU can be characterized by a binomial distribution based on Bernoulli trials, where each trial represents the decision process of each CR user. The generalized formula for the overall probability of detection, according to a generic k-out of-N rule, is given by [8], [29]:

$$Q_d = \sum_{l=k}^{N} \binom{N}{l} \bar{P}_d^l (1-\bar{P}_d)^{N-l} \tag{1.17}$$

where $\bar{P}_d$ is the average probability of detection for each individual CR user as defined by generalized equation (1.9). The overall probability of detection under OR-fusion rule (i.e., 1 out of N rule) can be evaluated by setting $k=1$ in equation (1.17):

$$Q_{d,OR} = \sum_{l=1}^{N} \binom{N}{l} \bar{P}_d^l (1-\bar{P}_d)^{N-l} = 1-(1-\bar{P}_d)^N. \tag{1.18}$$

The performance with AND-fusion rule (i.e., N out of N rule) can be evaluated by setting $k=N$ in equation (1.17):

$$Q_{d,AND} = \sum_{l=N}^{N} \binom{N}{l} \bar{P}_d^l (1-\bar{P}_d)^{N-l} = \bar{P}_d^N. \tag{1.19}$$

Finally, for the case of majority-fusion rule, or simply for $(N/2+1)$ out of N rule, the probability of detection, denoted as $Q_{d,Maj}$, can be evaluated by setting $k = \lfloor N/2 \rfloor$ in equation (1.17).

The overall probability of false alarm (Q_f) for the considered fusion rules (OR, AND, and Majority fusion rules) can be evaluated by replacing $\bar{P}_d$ with P_f in equations (1.17), (1.18), and (1.19), respectively. It is of interest to observe that the probability of false alarm (P_f) is independent of the SNR (γ_s), so that it remains same for all fading channels. It may also be observed that in order to evaluate Q_d for a specific fading channel, we need to consider the appropriate expression for $\bar{P}_d$ (namely, $\bar{P}_{d,i,Ray}$ or $\bar{P}_{d,i,Naka}$ in equations (1.17) to (1.19)) to obtain the performance in Rayleigh or Nakagami-*m* channels, respectively.

In Fig. 1.2, the probability of detection Q_d is shown, as a function of the S-channel SNR, considering AND, OR, and majority logic hard decision fusion rules. For each fusion rule, Nakagami-*m* fading channel is considered. The OR and ma-

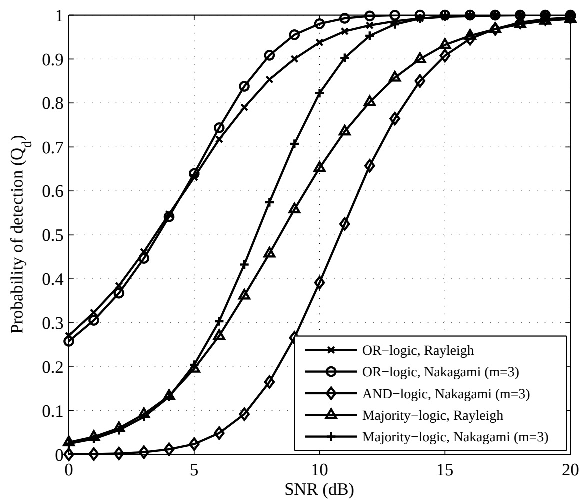

Fig. 1.2 Probability of detection as a function of the average S-channel SNR $(\bar{\gamma}_s)$, considering various fusion rules (OR, AND, majority logic). Both Rayleigh and Nakagami-*m* fading scenarios are considered. In all cases, N=3 CR users, Q_f =0.1, and u=5.

jority fusion rules for Rayleigh fading channel are also shown for comparison purposes. In all cases, there are N=3 cooperating CR users, Q_f =0.1, and u=5. In the case of CSS in a Nakagami-*m* fading channel, for a particular value of the average SNR (namely, 6 dB), the probability of detection is above 0.82, 0.36 and 0.01 for the OR, majority logic, and AND fusion rules, respectively. We can say that OR fusion rule performs better than the AND and the majority logic fusion rules. In the presence of Rayleigh fading, the CSS with OR fusion rule outperforms the schemes with the other fusion rules. Furthermore, in all cases of logic fusions we observe that the performance of CSS in Nakagami-*m* fading channel is better than the performance in Rayleigh fading channel—this is expected, as the Nakagami-*m* (with $m = 3$) fading is less severe than Rayleigh fading. Therefore, in the presence of such a Nakagami-*m* fading, the number of reliable S-channels is higher than the number in the Rayleigh fading case.

1.4 Censoring of CR user

As already discussed in Section 1.3, the performance of CSS, considering S-channels as noisy-faded and R-channels as ideal, has been well studied. However, in many practical situations R-channels may not be noiseless (ideal) channels. Though most works on spectrum sensing assume noiseless R-channels [7]-[9], [12]-[16], [29], the presence of fading in R-channels is likely to affect the decisions sent by CR users where the FC is far from CR users. If the R-channel connecting a CR user to the FC is heavily faded, the decision received at the FC is likely to be an erroneous version of that transmitted by the CR user. In such cases, it is better to stop transmitting decisions from this CR user and, thus, censoring is expedient in these scenarios. The CR users whose R-channels are estimated as reliable by the FC are censored, i.e., they are allowed to transmit. The CR users which are not participating in improving the detection performance may be stopped, so that system complexity can be reduced and the detection performance can be improved. Therefore, censoring of CR users is necessary to improve the performance of CSS. The cooperative spectrum sensing network with censoring of CR users is shown in Fig. 1.3. We assume that both S- and R-channels are modeled as noisy and faded.

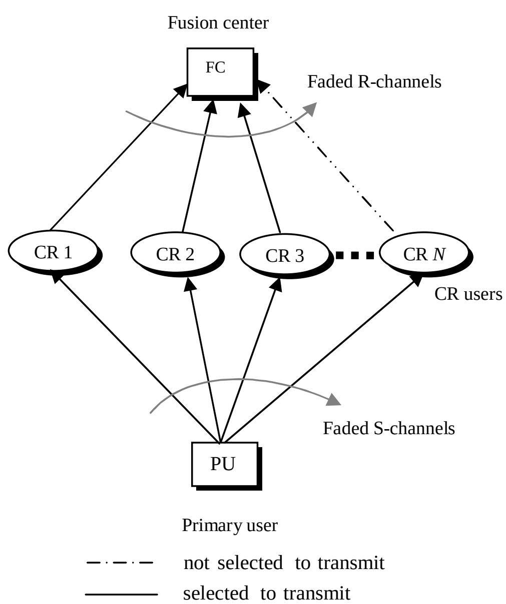

Fig. 1.3 Cooperative spectrum sensing network with censoring: illustrative scenario.

As anticipated in Section 1.1, in this section we study the performance of two censoring schemes, namely: (i) rank-based censoring and (ii) threshold- based censoring. The FC employs coherent reception to fuse binary local decisions received from censored CR users to obtain a final decision regarding the presence or absence of PUs. The overall probabilities of missed detection and total error are selected as the key performance metrics and are evaluated, through simulations, under several channel and network conditions. In [29], it is shown that the total error probability (given as the sum of the probabilities of missed detection and false alarm) is a decreasing function of number of available CR users in the network when majority-logic fusion is performed at the FC. One can easily expect that as the number of available CR users in the network increases, the performance of majority-logic fusion, in terms of total error probability, is better than that with AND-logic (where the probability of missed detection is a decreasing function of the probability of false alarm) and OR-logic (where the missed probability of detection is a decreasing function of the probability of false alarm) fusions. This is why, in the current section, low-complexity majority-logic fusion of the decisions received from the selected CR users is considered. A CR user takes an individual hard binary decision and, if censored, transmits its decision, using binary phase shift keying (BPSK) as modulation format, to the FC over the corresponding faded R-channel.

Transmissions between the CR users and the FC are carried out in two phases. In the first transmission phase, each CR user sends one training symbol to enable the FC to estimate all fading channel coefficients between FC and N number of CR users corresponding to N participating CR users. Minimum mean square estimation (MMSE) of the R-channel coefficients is obtained at the FC using training symbols sent by the CR users to the FC. The signal from the k-th CR user received at the FC is:

$$y_k = s_k h_k + n_k; \quad k \in \{1, 2, \cdots, N\} \tag{1.20}$$

where S_k is BPSK symbol ($\sqrt{E_b}$, -$\sqrt{E_b}$) indicating H_1 and H_0, respectively. The R-channel fading coefficient is denoted as h_k and $n_i \sim CN(0, \sigma_n^2)$ is the sample of AWGN. The complex Gaussian channel noise samples $\{n_k\}$ and faded R-channel coefficients $\{h_k\}$ are mutually independent. We assume that the FC estimates the k-th CR user's fading coefficient h_k according to an MMSE estimation strategy on the basis of the observable y_k as follows [22]-[24]:

$$\hat{h}_k = E\left[h_k|y_k\right] = \frac{\sqrt{E_b}}{E_b + \sigma_n^2} y_k. \tag{1.21}$$

We model the k-th R-channel estimation error ($\tilde{h}_k$) as the difference between the actual and the estimated k-th R-channel coefficients, i.e., $\tilde{h}_k = h_k - \hat{h}_k$, where h_k is the actual k-th R-channel coefficient while $\hat{h_k}$ is its estimate. The channel estimation is either perfect (with no estimation error) or imperfect (with estimation error). Accordingly, two censoring schemes are considered: one is based on perfect channel estimation ($\hat{h}_k = h_k$) while the other is based on imperfect channel estimation ($\hat{h}_k = h_k - \tilde{h}_k$). After the first phase, K (out of N) CR users, selected on the basis of rank-based censoring (the selected CR users are associated with the best K estimated channel coefficients) and threshold-based censoring (the selected K CR users have estimated channel coefficients exceeding the predefined threshold C_{th}). The FC informs the selected CR users via one-bit feedback (we assume that feedback channels are error-free). In the second transmission phase, the K selected CR users send their local binary BPSK modulated decisions to the FC over the corresponding R-channels. The fading coefficients of R-channels are assumed to be fixed over a symbol transmission time, as the channel is assumed to be slowly faded.

The signal, received from the k-th selected CR user, at the FC is [22]-[24]:

$$y_{k,d} = m_k h_k + n_{k,d}; \qquad k \in \{1, 2, \cdots, K\} \tag{1.22}$$

where the channel noise $n_{k,d} \sim CN(0, \sigma_n^2)$ and $m_k \in \{\sqrt{E_b}, -\sqrt{E_b}\}$ is the BPSK modulated binary decisions.

Since the communication channel is noisy and affected by fading, a decision received by the FC might differ from the one sent by the corresponding CR user. The decision received from the k-the selected CR user is

$$u_k = \begin{cases} 1 & \text{if the received decision in favor of } H_1 \\ 0 & \text{if the received decision in favor of } H_0 \end{cases} \tag{1.23}$$

where $k \in \{1, 2, \cdots, K\}$. The FC finally makes a global decision according to the following general majority logic-like fusion rule $u_0 = \Gamma(u_1, \cdots, u_K)$ [17]:

$$u_0 = \Gamma(u_1, \cdots, u_k) = \begin{cases} H_1 \quad if \ \sum\limits_{k=1}^{K} u_k > \frac{K}{2} \\ H_0 \quad if \ \sum\limits_{k=1}^{K} u_k < \frac{K}{2} \\ H_0 \ or \ H_1 \ if \ \sum\limits_{k=1}^{K} u_k = \frac{K}{2}. \end{cases} \tag{1.24}$$

In other words, if the number of decisions in favor of H_1 is larger than the number of decisions in favor of H_0, the FC takes a global decision in favor of H_1 and vice versa. Sometimes, if the number of decisions in favor of H_1 is equal to the number of decisions in favor of H_0, then the FC flips a coin and takes a decision in favor of either H_0 or H_0.

1.4.1 Rank-based Censoring

According to this censoring scheme, K (out of N) CR users—those with the best estimated channel coefficients (i.e., the highest ones)—are selected, as already discussed above section.

1.4.1.1 Rank-based Censoring in Rayleigh Faded Channel

The R-channel coefficient h_k (for the k-th selected CR user) is modeled as a zero-mean complex Gaussian random variable with variance $\sigma^2 = 1$ ($h_k \sim CN(0, \sigma^2)$), as in [22], and $n_k \sim CN(0, \sigma_n^2)$. The complex Gaussian channel noise samples $\{n_k\}$ and Rayleigh faded R-channel coefficients $\{h_k\}$ are mutually independent. For the k-th Rayleigh faded R-channel, the fading coefficient ($h_k = \alpha_k exp(j\theta_k)$, where $\theta_k \sim U(-\pi, \pi)$ can be expressed, in terms of h_{kI} and h_{kQ}, as

$$h_k = h_{kI} + jh_{kQ} \tag{1.25}$$

where $h_{kI} = \alpha_k \cos\theta_k$ and $h_{kQ} = \alpha_k \cos\theta_k$.

The amplitude $|h_k|$ is Rayleigh distributed only when $h_{kI}, h_{kQ} \sim CN(0, \sigma_n^2/2)$ [5]. The estimated k-th R-channel coefficient can be obtained by substituting (1.20) in (1.21), obtaining:

$$\begin{aligned}\hat{h}_k &= \frac{\sqrt{E_b}}{E_b + \sigma_n^2}\left(\sqrt{E_b}h_k + n_k\right) \\ &= \frac{E_b}{E_b + \sigma_n^2}h_k + \frac{\sqrt{E_b}}{E_b + \sigma_n^2}n_k\end{aligned} \tag{1.26}$$

where $h_k = h_{kI} + h_{kQ}$, with $h_{kI}, h_{kQ} \sim \mathcal{N}(0, 1/2)$ given by (1.26) (assuming normalized fading power $\mathbb{E}(\alpha^2) = 1$), and n_k is also complex Gaussian, i.e., $n_k = n_{kI} + n_{kQ}$ where $n_{kI}, n_{kQ} \sim \mathcal{N}(0, \sigma_n^2/2)$. From (1.26), the estimation error coefficient for the k-th R-channel $\tilde{h}_k = h_k - \hat{h}_k$ can be expressed as

$$\begin{aligned}\tilde{h}_k &= h_k\left(1 - \frac{E_b}{E_b + \sigma_n^2}\right) - \frac{\sqrt{E_b}}{E_b + \sigma_n^2}n_k \\ &= h_k\frac{\sigma_n^2}{E_b + \sigma_n^2} - \frac{\sqrt{E_b}}{E_b + \sigma_n^2}n_k.\end{aligned} \tag{1.27}$$

As seen from (1.27), the term $\tilde{h}_k$ is a complex quantity and can also be written in terms of real and imaginary parts, i.e.,

$$\tilde{h}_k = \tilde{h}_{kI} + j\tilde{h}_{kQ} \tag{1.28}$$

where

$$\begin{aligned}\tilde{h}_{kI} &= \frac{\sigma_n^2}{E_b + \sigma_n^2}h_{kI} - \frac{\sqrt{E_b}}{E_b + \sigma_n^2}n_{k,I} \\ \tilde{h}_{kQ} &= \frac{\sigma_n^2}{E_b + \sigma_n^2}h_{kQ} - \frac{\sqrt{E_b}}{E_b + \sigma_n^2}n_{k,Q}.\end{aligned}$$

From the theory of Gaussian random variables, it is well known that if $Z = aX + bY$ where $X \sim \mathcal{N}(m_X, \sigma_X^2)$ and $Y \sim \mathcal{N}(m_Y, \sigma_Y^2)$ then

$$Z \sim \mathcal{N}(m_Z, \sigma_Z^2); \quad m_Z = am_X + bm_Y, \sigma_Z^2 = a^2\sigma_X^2 + b^2\sigma_Y^2. \tag{1.29}$$

This implies that both $\tilde{h}_{kI}$ and $\tilde{h}_{kQ}$ that appear in (1.28) can be written in terms of their means and variances as follows:

$$\tilde{h}_{kI} \sim \mathcal{N}\left(0, \left(\frac{\sigma_n^2}{E_b+\sigma_n^2}\right)^2 \frac{1}{2} + \frac{E_b}{(E_b+\sigma_n^2)^2}\frac{\sigma_n^2}{2}\right) \tag{1.30}$$

$$\tilde{h}_{kQ} \sim \mathcal{N}\left(0, \left(\frac{\sigma_n^2}{E_b+\sigma_n^2}\right)^2 \frac{1}{2} + \frac{E_b}{(E_b+\sigma_n^2)^2}\frac{\sigma_n^2}{2}\right). \tag{1.31}$$

The mean and variance of $\tilde{h}_k$ are 0 and $\sigma^2_{\tilde{h},Rayl}$, respectively, i.e., $\tilde{h}_k \sim \mathcal{N}(0, \sigma^2_{\tilde{h},Rayl})$ [21]-[22], where

$$\begin{aligned}\sigma^2_{\tilde{h},Rayl} &= 2\left[\left(\frac{\sigma_n^2}{E_b+\sigma_n^2}\right)^2 \frac{1}{2} + \frac{E_b}{(E_b+\sigma_n^2)^2}\frac{\sigma_n^2}{2}\right] \\ &= \frac{\sigma_n^4 + E_b\sigma_n^2}{(E_b+\sigma_n^2)^2} = \frac{\sigma_n^2}{E_b+\sigma_n^2} \\ &= \left(1+\frac{E_b}{\sigma_n^2}\right)^{-1} = \frac{1}{1+\bar{\gamma}_R}. \end{aligned} \tag{1.32}$$

The k-th Rayleigh faded R-channel estimation error coefficient can be generated using the following distribution:

$$|\tilde{h}_k| = \sqrt{\tilde{h}_{kI}^2 + \tilde{h}_{kQ}^2}; \qquad \tilde{h}_{kI} \sim \mathcal{N}\left(0, \frac{\sigma^2_{\tilde{h},Rayl}}{2}\right), \quad \tilde{h}_{kQ} \sim \mathcal{N}\left(0, \frac{\sigma^2_{\tilde{h},Rayl}}{2}\right). \tag{1.33}$$

The following results are obtained using MATLAB-based simulations for both perfect and imperfect channel estimation schemes. S-channels and R-channels are both considered to be Rayleigh faded. The missed detection (Q_m) and the total error $(Q_m + Q_f)$ probabilities are evaluated considering the impact of several network parameters, such as the probability of false alarm (P_f) in each CR user, the average R-channel SNR $(\bar{\gamma}_R)$, and the average S-channel SNR $(\bar{\gamma}_s)$.

In Fig. 1.4, the probability of missed detection is shown as a function of K. The performance of CSS with censoring under both perfect and imperfect channel estimation schemes is evaluated. Two values of S-channel average SNR (15 dB, 20 dB) and two values of R-channel average SNR (-5 dB, -7 dB) are considered. With both perfect and imperfect channel estimation, the probability of missed detection reduces for increasing values of the number of selected CR users, as well as of the S- and R-channel SNRs. The probability of incorrect reception from CR users at the FC reduces with higher R-channel SNR. As expected, for a given value of the R-channel SNR, Q_m is higher with imperfect channel estimation, as channel-based censoring leads to the selection of a group of CR users which may not be the best ones due to error in channel estimation. Furthermore, according to (1.32), an increase in the R-channel SNR leads to a decrease in estimation error variance and this, in turn, reduces the average estimation error. A reduced estimation error leads to a further reduction of Q_m. In particular, in the case of imperfect channel estimation with K= 10, Q_m decreases by 25.77% when the R-channel SNR increases

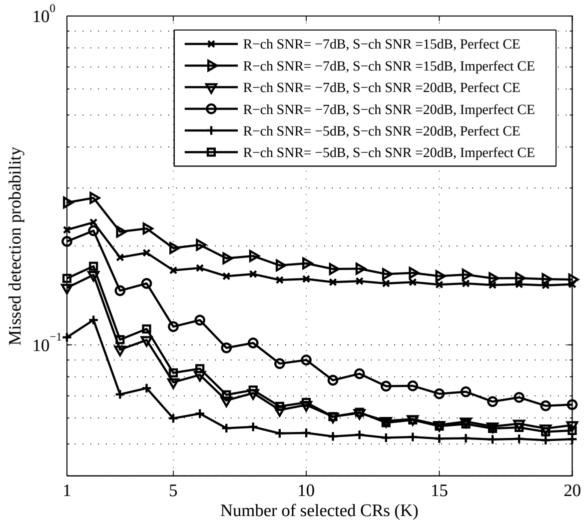

Fig. 1.4 Performance of CSS network with censoring of CR users under perfect and imperfect channel estimation for various values of average R-channel SNR $(\bar{\gamma}_R)$ and average S-channel SNR $(\bar{\gamma}_s)$ in Rayleigh fading (CE stands for channel estimation, N=20, P_f=0.05 and u=5).

from -7 dB to -5 dB. Similarly, in the case of perfect channel estimation, Q_m decreases by 17.80% for the same values of K and R-channel SNR. Higher values of the S-channel SNRs improves the detection of the PU at the CR user. For example, as the S-channel SNR increases from 15 dB to 20 dB, and K=10, Q_m decreases by 58.57%, and 49.15% in case of perfect and imperfect channel estimation, respectively. Under perfect channel estimation, by censoring, the FC selects CR users with best R-channel coefficients which means that decisions sent by selected CR users to the FC have low probability of getting flipped. As the FC uses a majority-logic fusion, it achieves a floor in the missed detection performance at a certain number of CR users, i.e., no further improvement in detection performance is obtained by increasing the number of CR users beyond this.

In Fig. 1.5, the total error probability is shown as a function of the number of selected CR users for various values of the probability of false alarm (P_f), and R-channel SNR. The number of available CR users is 20 and S-channel SNR is fixed at 20 dB. As the R-channel SNR increases from -7 dB to -5 dB, the total error probability reduces for both the cases of perfect channel and imperfect channel estimation. Higher R-channel SNR reduces probabilities of incorrect reception from CR users at the FC. As expected, for a given value of the R-channel SNR, the total error probability is higher with imperfect channel estimation, as channel-based censoring leads to the selection of a group of CR users which may not be the best ones due to error in channel estimaton. Furthermore, according to (1.32), an increase in

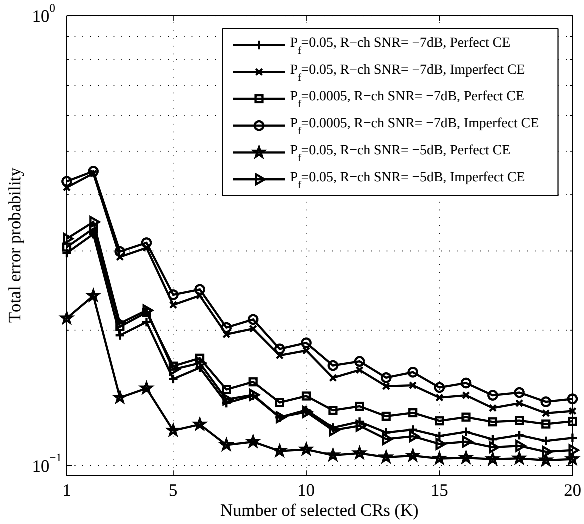

Fig. 1.5 Total error probability versus the number of selected CR users (K) under perfect and imperfect channel estimation for various values of $(\bar{\gamma}_R)$ and P_f in Rayleigh fading ($\bar{\gamma}_s$=20 dB, N=20, and u=5).

the R-channel SNR leads to a decrease in the estimation error variance $\sigma^2_{\tilde{h},Rayl}$ and this, in turn, reduces the average estimation error. A reduced estimation error leads to a further reduction of the total error probability as CR users with higher reliability in R-channels are selected. In particular, in case of perfect channel estimation, when the selected number of CR users is 10 and the R-channel SNR increases from -7 dB to -5 dB, the total error probability reduces by 18.28%. However, in case of imperfect channel estimation, the total error probability decreases by 26.97% for the same values of network parameters. Further the impact of P_f is also depicted in Fig. 1.5. Different P_f corresponds to setting of different threshold levels (λ) at an energy detector. In all cases, two values of P_f, namely 0.05 and 0.0005, are considered. As P_f increases from 0.0005 to 0.05, the total error probability decreases for both perfect and imperfect channel estimation. This is because as P_f increases from 0.0005 to 0.05 the value of detector threshold is lowered from 31 to 18. Thus number of decisions of CR users in favor of hypothesis H1 increases. So the total error probability decreases. For example, in case of imperfect channel estimation, as P_f increases from 0.0005 to 0.05 with the number of selected CR users is 10, the total error probability decreases by 3.84%, while in case of perfect channel estimation, the total error probability decreases by 6.86%.

1.4.1.2 Rank-based Censoring in Nakagami-*m* Faded Channel

The Nakagami-*m* distribution can be obtained from the Gamma distribution [3]. More precisely, if $X \sim gamma(r,s)$ then the k-th CR users' Nakagami-*m* fading channel coefficient (h_k) is obtained by setting $r = m$, $s = \Omega/m$ (Ω is the Nakagami-*m* fading power which is normalized to unity, i.e., Ω=1) and considering $h_k = \sqrt{X}$. The estimated k-th Nakagami-*m* faded R-channel coefficient can be expressed as $\hat{h}_k = h_k - \tilde{h}_k$ and, taking into account the independence between h_k and $\tilde{h}_k$, it follows that $\sigma^2_{\hat{h},Naka} = \sigma^2_{h,Naka} + \sigma^2_{\tilde{h},Naka}$, where $\sigma^2_{\hat{h},Naka}$ is the estimated variance of Nakagami-*m* fading coefficient $(\hat{h}_k)$, $\sigma^2_{h,Naka}$ is the actual variance of h_k and $\sigma^2_{\tilde{h},Naka}$ is the error variance of $\tilde{h}_k$. The analytical expressions for actual, estimated and error variance of Nakagami-*m* distribution can be derived using $\sigma^2_{h,Naka}$ as

$$\sigma^2_{h,Naka} = \Omega \left[1 - \frac{1}{m}\left(\frac{\Gamma(m+\frac{1}{2})}{\Gamma(m)}\right)^2\right] \tag{1.34}$$

$$\sigma^2_{\hat{h},Naka} = \hat{\Omega} \left[1 - \frac{1}{m}\left(\frac{\Gamma(m+\frac{1}{2})}{\Gamma(m)}\right)^2\right] \tag{1.35}$$

where $\hat{\Omega}$ is the estimated Nakagami-*m* fading power (which is not equal to 1). It can be shown that the error variance for Nakagam-*m* fading channel ($\sigma^2_{\tilde{h},Naka}$) is given as:

$$\sigma^2_{\tilde{h},Naka} = \frac{1}{(1+\bar{\gamma}_R)^2}\left[\Omega + \bar{\gamma}_R - \frac{\Omega}{m}\left(\frac{\Gamma(m+\frac{1}{2})}{\Gamma(m)}\right)^2\right]. \tag{1.36}$$

Setting m=1 and assuming $\Gamma(m+1/2) \cong 1$ in (1.36), one derives the expression for estimated error variance in Rayleigh channel ($\sigma^2_{\tilde{h},Rayl}$), which matches with equation (1.32).

From (1.34), (1.35), and (1.36), it follows that

$$\hat{\Omega} = \frac{1 + \left(\frac{1}{1+\bar{\gamma}_R}\right) - \frac{1}{m}\left(1 + \left(\frac{1}{1+\bar{\gamma}_R}\right)^2\right)\left(\frac{\Gamma(m+\frac{1}{2})}{\Gamma(m)}\right)^2}{1 - \frac{1}{m}\left(\frac{\Gamma(m+\frac{1}{2})}{\Gamma(m)}\right)^2}. \tag{1.37}$$

The estimated Nakagami-*m* faded coefficient for the k-th CR user, in the case of imperfect channel estimation, can be generated using $\hat{h}_k = \sqrt{\left(gamma(m, \hat{\Omega}/m)\right)}$.

The following results are obtained using MATLAB-based simulations for both perfect and imperfect channel estimation schemes. The performance of CSS has been evaluated in Nakagami-*m* faded environment. S-channel and R-channel fading are considered to be same, i.e., Nakagami-*m* fading in S-channel and Nakagami-*m* fading in R-channel with same Nakagami parameter. The missed detection probability (Q_m) is evaluated by varying the Nakagami fading parameter m and the average R-channel SNR $\bar{\gamma}_R$.

In Fig. 1.6, the missed detection probability is analyzed as a function of the number of selected sensors. The impact of the Nakagami fading parameter (m) and of

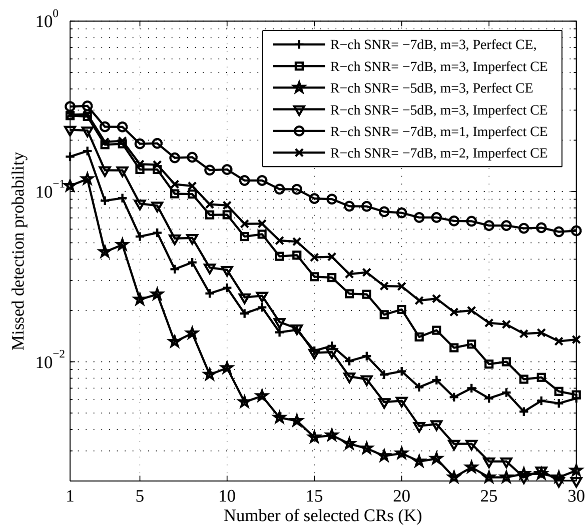

Fig. 1.6 Performance of CSS with censoring of CR users under perfect and imperfect channel estimation for various values of average R-channel SNRs $(\bar{\gamma}_R)$ in Nakagami-m faded environment, impact of fading parameter (m) on imperfect channel estimation is also depicted ($\bar{\gamma}_s$=20 dB, N=30, P_f=0.05 and u=5).

the average R-channel SNR, with both perfect and imperfect channel estimation, is analyzed. Two values of R-channel SNR (-5 dB and -7dB) and three different values of m (1, 2 and 3) are considered for this figure. The performance with $m = 1$ corresponds to that of Rayleigh fading as in Fig. 1.4. For increasing values of K, of the R-channel SNR, and of the parameter m, the missed detection probability (Q_m) decreases at the FC significantly, for both perfect and imperfect channel estimation. When the R-channel SNRs increase, the noise effect reduces in the R-channel so that the FC receives a larger number of correct decisions and this leads to a reduction in the missed detection probability. Higher values of the R-channel SNR reduces the probability of incorrect reception from CR users at the FC. As seen earlier in Fig. 1.4, for a given value of the R-channel SNR, the missed detection probability is higher with imperfect channel estimation than with perfect channel estimation. Furthermore, according to (1.36), an increase in the R-channel SNR leads to a decrease in the estimation error variance $\sigma^2_{\tilde{h},Naka}$ and this, in turn, reduces the average estimation error. A reduced estimation error leads to a further reduction of the missed detection probability. When fading parameter increases from 1 to 3, the fading severity in the channel decreases so that the FC receives more correct decisions which lead to further reduction in missed detection probability.

1.4.2 Threshold-based Censoring

In this censoring scheme, a CR user (say the k-th) is selected for transmission if the amplitude of the corresponding estimated R-channel fading coefficient $\hat{h}_k$ is above C_{th}. This approach involves two transmission phases: in the first phase, the FC estimates the R-channel corresponding to each CR user; in the second phase, the FC censors a CR user if the corresponding estimated channel coefficient exceeds a chosen threshold.

1.4.2.1 Threshold based Censoring in Rayleigh Faded Channel

If the amplitude of the estimated R-channel fading coefficient is a Rayleigh distributed random variable with parameter σ. The probability of selecting a CR user is [24]-[25]:

$$p = \Pr\left(|\hat{h}_k| > C_{th}\right) = \exp\left(-\frac{C_{th}^2}{2\sigma^2}\right). \tag{1.38}$$

The probability of selecting K CR users from N available CR users can then be expressed as follows [24]-[25]:

$$P(K) = \binom{N}{K} p^k (1-p)^{N-K} \tag{1.39}$$

where p is the probability of selecting a CR user which is obtained from equations (1.38).

Let $P_m(\text{error}|K)$ indicate the conditional missed detection probability when decisions from K CR users are fused. Given $P(K)$, the probability of selecting K CR users in (1.39), the average probabilities of missed and false detection can be expressed as follows [24]-[25]:

$$\bar{Q}_m = P(\text{missed detection}) = \sum_{K=0}^{N} P_m(\text{error}|K)P(K) \tag{1.40}$$

$$\bar{Q}_f = P(\text{false detection}) = \sum_{K=0}^{N} P_f(\text{error}|K)P(K). \tag{1.41}$$

Therefore, the average total error probability (an error occurs either with a missed detection or a false detection) can be expressed as follows:

$$\bar{Q} = \bar{Q}_m + \bar{Q}_f. \tag{1.42}$$

The average missed detection probability ($\bar{Q}_m$) and the average false alarm probability ($\bar{Q}_f$) are functions of the chosen censoring threshold C_{th}, as the PMF $\{P(K)\}$ of the number of censored CR users depends on C_{th}.

The following results are obtained, as in the previous sections, using MATLAB-based simulations. The performance of CSS for both perfect and imperfect channel estimation cases been evaluated in Rayleigh faded environments considering the impact of various network parameters, such as the censoring threshold (C_{th}), the number of available CR users (N), and the average R-channel SNRs $(\bar{\gamma}_R)$.

In Fig. 1.7, the binomially distributed PMF of the number of selected CR users is shown, for various values of the censoring threshold C_{th}, under both cases of perfect and imperfect channel estimation schemes in Rayleigh faded channel. It can

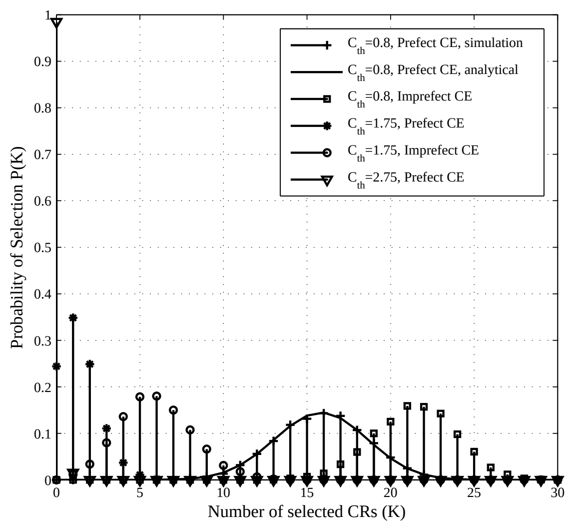

Fig. 1.7 PMF of the number of censored CR users for different censoring thresholds (C_{th}) under both perfect and imperfect channel estimation in Rayleigh faded channel.

be observed that for small values of the censoring threshold a larger number of CR users are likely to be selected, while the PMF tends to concentrate on small values for higher values of the censoring threshold for both the channel estimation (CE) cases. For example, for a censoring threshold of 0.8, it is seen that K= 16 CR users have highest probability (0.13) of being selected under perfect channel estimation scheme. Similarly, in case of imperfect channel estimation scheme it is found that K=21 CR users have highest probability (0.16) of being selected for the same value of C_{th}. It can also be observed that as the censoring threshold increases, the PMF moves towards the origin for both channel estimation schemes. This is due to the fact that increasing the censoring threshold decreases the number of selected CR users. The obtained results show that the PMF of the number of selected CR users under imperfect channel estimation shifts to the right side of the PMF of the number of selected CR users under perfect channel estimation for a particular value of censoring threshold. According to equation (1.32), in the case of imperfect channel estimation, depending on the estimation error a larger number of CR users can be selected, for a fixed value of R-channel SNR, with respect to the case with perfect channel estimation. The binomially distributed PMF of the number of selected CR users, as obtained through simulations, matches exactly with result obtained based on the analytical expression given in equation (1.38) and equation (1.39).

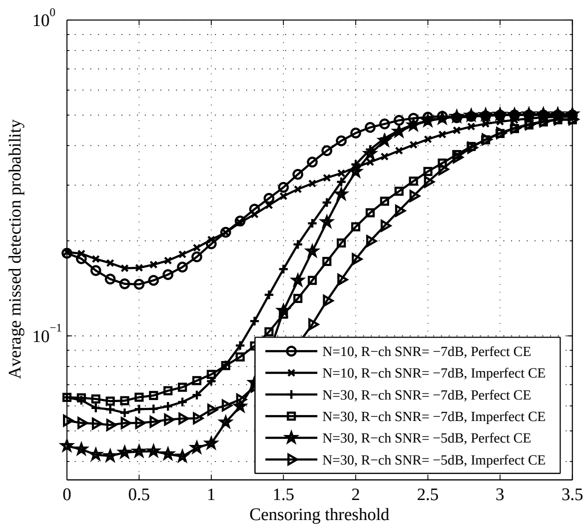

Fig. 1.8 Average missed detection probability as a function of C_{th} for various values of N and $\bar{\gamma}_R$ under perfect and imperfect channel estimation in Rayleigh fading channel ($\bar{\gamma}_s$ =20 dB, P_f=0.05, and u=5).

Fig. 1.8 shows the impact of censoring threshold on the average missed detection probability, under perfect and imperfect channel estimation. Two different values of the average R-channel SNR (-5 dB and -7 dB) and two values of the available number of CR users (i.e. N=10 and 30) are considered. It can be seen from the figure that as the censoring threshold increases, the average missed detection probability attains a minimum value in corespondence to an "optimal" censoring threshold, beyond which it increases and finally saturates to 0.5. The optimum censoring threshold is found to be different for the cases with perfect and imperfect channel estimation strategies and it depends on the number N of CR users and on the average R-channel SNR. For example, in the case of perfect channel estimation, as seen from the figure that an optimum censoring threshold is found to exist near 0.5 for N=10 and average R-channel SNR=-7 dB. Similarly, in case of imperfect channel estimation as seen from the figure an optimum censoring threshold is found to exist near 0.4 for N=10 and average R-channel SNR=-7 dB. This behavior of the average missed detection probability is due to the changing PMF of the number of censored CR users for various values of the censoring threshold. For very small values of the threshold, even unreliable links tend to be selected, and the average probability of missed detection is rather high. On the other hand, as the censoring threshold is increased to a very high level, no CR user is selected to transmit, i.e. $P(0) = 1$, and the FC takes a decision by flipping a fair coin resulting in an average missed detection probability of 0.5. Therefore, there exists an optimal value of the censoring threshold, in correspondence to which the average probability of missed detection is minimized. Further, as expected, it can be seen that a larger number of CR users, as well as a higher average R-channel SNR, leads to a reduced average missed detection probability in correspondence to the optimized censoring threshold.

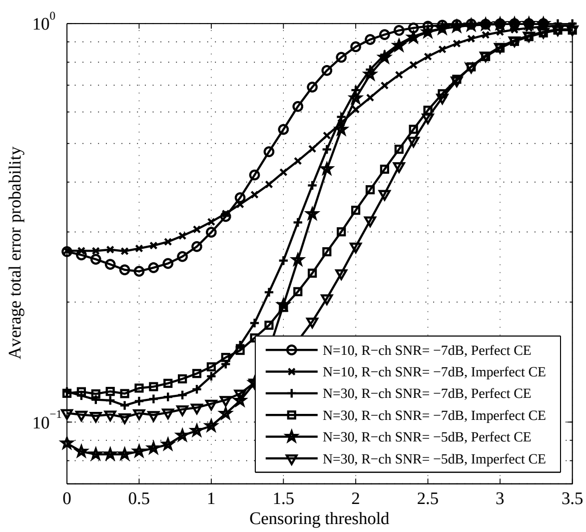

Fig. 1.9 Average total error probability as a function of C_{th} for various values of N and $\bar{\gamma}_R$ under perfect and imperfect channel estimation in Rayleigh fading channel ($\bar{\gamma}_s$=20 dB, P_f=0.05, and u=5).

Fig. 1.9 shows the impact of censoring threshold on the average total error probability (sum of average missed detection and average false alarm probabilities) under perfect and imperfect channel estimation. As censoring threshold increases, the average total error probability attains a minimum value at an ‘optimal’ censoring threshold level and thereafter increases with further increase in censoring threshold to finally attain a value of 1.0 (average missed detection probability reaches a value of 0.5 and average false alarm probability reaches a value of 0.5). There exists an optimal value of the censoring threshold, in correspondence to which the average total error probability is minimized. It can be seen that a high value of R-channel SNR as well as higher number of CR users leads to a reduced average total error probability in correspondence to the optimized C_{th} for both perfect and imperfect channel estimation cases. The optimum censoring threshold is found to be different for perfect and imperfect cases. For example, in perfect channel estimation case, the optimum censoring threshold is found to exist near 0.3 for N=30 and average R-channel SNR of 5 dB. Similarly, in imperfect channel estimation case, the optimum censoring threshold is found to exist near 0.4 for N=30 for the same value of R-channel SNR.

1.4.2.2 Threshold-based Censoring in Nakagami-*m* Faded Channel

If the amplitude of estimated R-channel fading coefficient is a Nakagami-*m*-distributed random variable, the probability of selecting a CR user can be expressed as follows:

$$p = \Pr\left(|\hat{h}_k| > C_{th}\right) = 1 - \frac{\gamma\left(m, \frac{m}{\Omega} C^2{}_{th}\right)}{\Gamma(m)} \tag{1.43}$$

where $\gamma(s,x) = \int_0^x t^{s-1}\, e^{-t}\, \mathrm{d}t$ is the lower incomplete gamma function. The performance in Nakagami-*m* faded R-channels can be evaluated by substituting the expression of p given by (1.43) into (1.39), (1.40), (1.41), and (1.42). More details are presented in the following.

As before, the following results are obtained using MATLAB-based simulations. The performance of CSS has been evaluated for both perfect and imperfect channel estimation schemes in Nakagami-*m* faded environments for various network parameters, such as the Nakagami fading parameter, the censoring threshold (C_{th}), the number of available CR users (N), and the average R-channel SNRs $(\bar{\gamma}_R)$.

In Fig. 1.10, the binomially-distributed PMF of the number of selected CR users is shown for various values of the censoring threshold C_{th}. The impact of the Nakagami fading parameter m on the PMF is investigated. It can be observed that for small values of the censoring threshold, larger numbers of CR users are likely to be censored, while the PMF tends to concentrate on small values for higher values of the censoring threshold as observed in case of Rayleigh fading case in Fig. 1.7. It is also observed that when m increases, larger numbers of CR users are likely to be censored. The binomially distributed PMF of the number of selected CR users as obtained based on our simulation testbed matches exactly with result obtained based on the analytical expression given in equations (1.39) and (1.43), which validates our simulation testbed. The binomially distributed PMF of the number of selected CR users as obtained for m=1 matches exactly with result obtained for Rayleigh (Fig. 1.7) under perfect channel estimation.

Fig. 1.11 shows the effects of Nakagami fading parameter, number of available CR users in the network, and R-channel SNR on the average missed detection probability under both perfect and imperfect channel estimations. We observe that for a fixed value of C_{th} when fading parameter as well as R-channel SNR increase, the

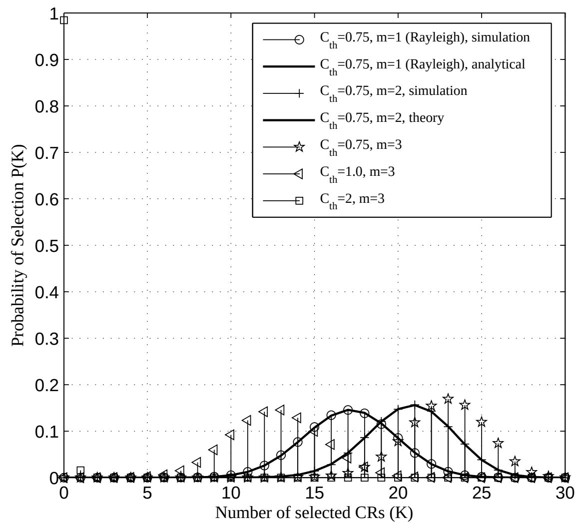

Fig. 1.10 PMF of the number of censored CR users for different censoring thresholds (C_{th}) under perfect channel estimation in Nakagami-*m* faded channel.

average probability of missed detection decreases for both perfect channel estimation and imperfect channel estimation. When R-channel SNR increases, the effect of noise reduces in the channel so that the FC receives more correct decisions which leads to reduction in average missed detection probability. As expected, for a given value of the R-channel SNR, the total error probability is higher with imperfect channel estimation. Furthermore, according to (1.36), an increase in the R-channel SNR leads to a decrease in the estimation error variance $\sigma^2_{\tilde{h},Naka}$ and this, in turn, reduces the average estimation error. A reduced estimation error leads to a further reduction of the average missed detection probability. When fading parameter increases from 1 to 3, the fading severity in the R-channel as well as in S-channel decreases so that the FC receives more correct decisions which leads to reduction in average missed detection probability. We observe that the results obtained for fading parameter m=1 match exactly with the results obtained for Rayleigh fading as shown in Fig. 1.8. As in the case of Rayleigh faded channel, an optimal censoring threshold exists in present Nakagami-*m* fading case also, which minimizes the average probability of missed detection. Further this optimum threshold also depends on the number of CR users, fading parameter (m), average R-channel SNR, and channel estimation schemes i.e., perfect and imperfect estimation.

In Fig. 1.12, the impact of censoring threshold, number of available CR users and R-channel SNR on the average total error probability (sum of average missed detection and average false alarm probabilities) is shown for Nakagami-*m* fading. The performance comparison between perfect and imperfect channel estimation is

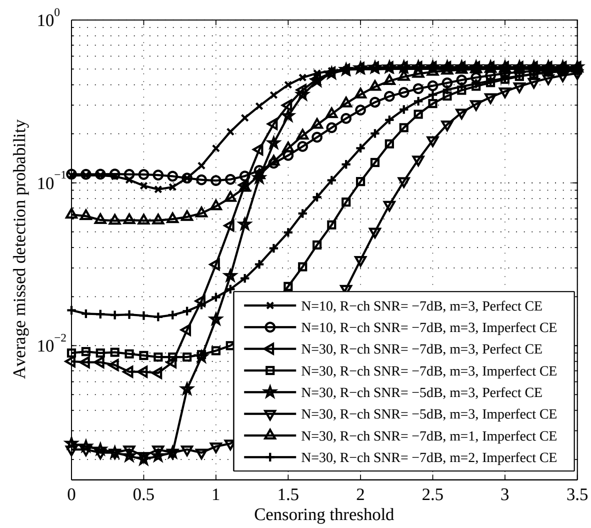

Fig. 1.11 Average missed detection probability as a function of C_{th} for various values of N, m and $\bar{\gamma}_R$ under perfect and imperfect channel estimation in case of Nakagami-*m* fading ($\bar{\gamma}_s$=20 dB, P_f=0.05, and u=5).

evaluated. It is seen from the figure that as C_{th} increases, the average total error probability attains a minimum value at an optimal C_{th} level and thereafter increases with further increase in C_{th} to finally attain a value of 1.0 (both average missed detection probability and average false alarm probability reach a value of each 0.5). The optimal value of C_{th}, in correspondence to minimum average total error probability is found to depend on channel and network parameters.

1.5 Conclusions

In this chapter, the performance of cooperative spectrum sensing (CSS) using energy detection with and without censoring in Rayleigh and Nakagami-*m* faded channels has been investigated. The performance of a few hard decision fusion rules (OR-logic, AND-logic, and majority-logic) has been analyzed in a comparative way, considering meaningful performance metrics and evaluating the impact of several system parameters. Our results show that the CSS using energy detection and no censoring achieves highest probability of detection with OR-logic fusion, with respect to majority-logic and AND-logic fusions, under the same average SNR conditions in both Rayleigh and Nakagami-*m* fading channels. We have also investigated the performance of CSS with CR users censored on the basis of the quality

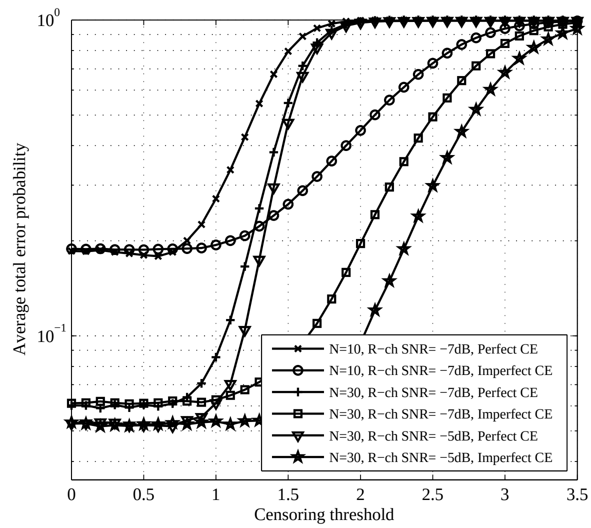

Fig. 1.12 Average missed detection probability as a function of C_{th} for various values of N, and $\bar{\gamma}_R$ under perfect and imperfect channel estimation in case of Nakagami-m fading ($\bar{\gamma}_s$=20 dB, m=3, P_f=0.05, and u=5).

of the R-channels, considering both Rayleigh and Nakagami-*m* faded channels. The performance with perfect and imperfect channel estimation has been analyzed, in a comparative way, under majority-logic fusion. Our results show that missed detection and total error probabilities reduce for increasing values of the number of selected CR users, regarless of the channel estimation quality (perfect or imperfect). However, in the presence of perfect channel estimation no further improvement, in terms of missed detection and total error probabilities, is obtained by increasing the number of CR users beyond a given limit. The Nakagami-*m* fading parameter and the R-/S-channel SNRs have a significant impact on the missed detection probability. With Rayleigh fading and majority-logic fusion, as the false alarm probability at each CR user increases, the total error decreases for both perfect and imperfect channel estimation. The censoring threshold for the selection of CR users has a significant impact on the average missed detection probability. Depending on the configuration of relevant network parameters, such as the available number of CR users and the average R-channel SNRs, there exists an optimal censoring threshold, which corresponds to the minimum average missed detection and total error probabilities, for both perfect and imperfect channel estimation. The framework presented in this paper is useful in designing a cooperative spectrum sensing scheme able to prolong, by minimizing the number of "useless" transmission acts, the lifetime of an energy-constrained cognitive radio network.

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Srinivas Nallagonda received his B.E. degree in Electronics and Communication Engineering in 2006 from Osmania University, Hyderabad, India and M.Tech. degree in Telecommunication Engineering from NIT Durgapur, India in 2009. He joined as Ph.D. Scholar in NIT Durgapur in 2010. His research interests include Fading Models, Diversity Techniques and Spectrum Sensing in

Cognitive Radio Networks. As of today, he has published twenty (20) research papers in various international conferences and journals.

Sanjay Dhar Roy received his B.E. (Hons.) degree in Electronics and Telecommunication Engineering in 1997 from Jadavpur University, Kolkata, India and M.Tech. degree in Telecommunication Engineering in 2008 from NIT Durgapur. He received his Ph. D. degree from NIT Durgapur in 2011. He worked for Koshika Telecom Ltd. from 1997 to 2000. After that he joined the Department of Electronics and Communication Engineering, National Institute of Technology Durgapur as a Lecturer in 2000 and is currently an Assistant Professor there. His research interests include Radio Resource Management, Handoff, and Cognitive Radio Networks. As of today, he has published sixty (60) research papers in various journals and conferences. Dr. Dhar Roy is a member of IEEE (Communication Society) and is a reviewer of IET Communications, Electronics Letters and Journal of PIER, IJCS, Wiley, International Journal of Electronics, Taylor & Francis. Dr. Dhar Roy is also a reviewer for IEEE Globecom, IEEE VTC, and IEEE PIMRC etc.

Sumit Kundu received his B.E. (Hons.) degree in Electronics and Communication Engineering in 1991 from NIT, Durgapur, India and M.Tech. degree in Telecommunication Systems Engineering and Ph. D. in Wireless Communication Engineering from IIT Kharagpur, India respectively. He has been a faculty in the department of ECE, National Institute of Technology, Durgapur since 1995 and is currently a Professor there. His research interests include Cognitive Radio Networks focusing on Spectrum Sensing and Spectrum Sharing issues, Cooperative Communications in Cognitive Radio Networks, Wireless Sensor Networks. He has published extensively in several leading international journals and conferences. He is a senior member of IEEE (Communication Society) and is a reviewer of several IEEE and other reputed journals.

Gianluigi Ferrari (http://www.tlc.unipr.it/ferrari) was born in Parma, Italy, in 1974. He received his "Laurea" and PhD degrees from the University of Parma, Italy, in 1998 and 2002, respectively. Since 2002, he has been with the University Parma, where he currently is an Associate Professor of Telecommunications. He was a visiting researcher at USC (Los Angeles, CA, USA, 2000-2001), CMU (Pittsburgh, PA, USA, 2002-2004), KMITL (Bangkok, Thailand, 2007), and ULB (Brussels, Belgium, 2010). Since 2006, he has been the Coordinator of the Wireless Ad-hoc and Sensor Networks (WASN) Lab (http://wasnlab.tlc.unipr.it/) in the Department of Information Engineering of the University of Parma.

As of today he has published more than 180 papers in leading international journals/conferences and 19 book chapters. He is coauthor of 7 books, including "Detection Algorithms for Wireless Communications, with Applications to Wired and Storage Systems" (Wiley: 2004), "Ad Hoc Wireless Networks: A Communication-Theoretic Perspective" (Wiley: 2006-technical best seller), "LDPC Coded Modulations" (Springer: 2009), and "Sensor Networks with IEEE 802.15.4 Systems: Distributed Processing, MAC, and Connectivity" (Springer: 2011). He edited the book "Sensor Networks: where Theory Meets Practice" (Springer: 2010). His research interests include wireless ad hoc and sensor networking, adaptive digital signal processing, and communication theory. He participates in several research projects funded by public and private bodies.

Prof. Ferrari is a co-recipient of: a best student paper award at IWWAN'06; a best paper award at EMERGING'10; an award for the outstanding technical contributions at ITST-2011; the best paper award at SENSORNETS 2012; the best paper award at EvoCOMNET 2013. The WASNLab team won the first Body Sensor Network (BSN) contest, held in conjunction with BSN 2011. He acts as a frequent reviewer for many international journals and conferences. He acts also as a technical program member for many international conferences. He currently serves on the Editorial Boards of several international journals. He was a Guest Editor of the 2010

EURASIP JWCN Special Issue on "Dynamic Spectrum Access: From the Concept to the Implementation." He is an IEEE Senior Member.

Riccardo Raheli received the Dr. Ing. degree (Laurea) in Electrical Engineering "summa cum laude" from the University of Pisa in 1983, the Master of Science degree in Electrical and Computer Engineering with full marks from the University of Massachusetts at Amherst, USA, in 1986, and the Doctoral degree (Perfezionamento) in Electrical Engineering "summa cum laude" from the Scuola Superiore S. Anna, Pisa, in 1987. From 1986 to 1988 he was a Project Engineer with Siemens Telecomunicazioni, Milan. From 1988 to 1991, he was a Research Professor at the Scuola Superiore S. Anna, Pisa. In 1990, he was a Visiting Assistant Professor at the University of Southern California, Los Angeles, USA. Since 1991, he has been with the University of Parma, as a Research Professor, Associate Professor since 1998 and Full Professor since 2001. In this role, he was Chairman of the Communication Engineering Program Committee from 2002 to 2010 and Member of the Scientific Committee of CNIT (Consorzio Nazionale Interuniversitario per le Telecomunicazioni) from 2000 to 2005.

He has also been Member of the Executive Committee of CNIT since 2008 and Member of the Scientific Committee of the Doctoral School in Engineering and Architecture since 2011. His scientific interests are in the general area of Information and Communication Technology, with special attention toward systems for communication, processing and storage of information. His research has lead to numerous international publications in journals, conference proceedings, as well as a few industrial patents. He is coauthor of a few scientific monographs such as "Detection Algorithms for Wireless Communications, with Applications to Wired and Storage Systems" (John Wiley & Sons, 2004) and "LDPC Coded Modulations" (Springer, 2009). He is supervising coauthor of the paper which received the "2006 Best Student Paper Award in Signal Processing & Coding for Data Storage" from the Communications Society of the Institute of Electrical and Electronics Engineers (IEEE).

He served on the Editorial Board of the IEEE Transactions on Communications from 1999 to 2003. He was Guest Editor of a special issue of the IEEE Journal on Selected Areas in Communications (JSAC) published in 2005. He served on the Editorial Board of the European Transactions on Telecommunications (ETT) from 2003 to 2008. He was Guest Editor of a special issue of the IEEE Journal of Selected Topics in Signal Processing (JSTSP) published in 2011. He served as Co-Chair of the General Symposium on Selected Areas in Communications at the International Communications Conference (ICC 2010), Cape Town, South Africa and the Communication Theory Symposium at the Global Communications Conference (GLOBECOM 2011), Houston, Texas, USA. He has also served on the Technical Program Committee of many international conferences such as ICC, GLOBECOM, IEEE Intern. Symp. Power-Line Commun. and its Appl. (ISPLC), European Signal Processing Conf. (EUSIPCO) and others.