Handbook of Research on Software-Defined and Cognitive Radio Technologies for Dynamic Spectrum Management

Naima Kaabouch
University of North Dakota, USA

Wen-Chen Hu
University of North Dakota, USA

A volume in the Advances in Wireless Technologies and Telecommunication (AWTT) Book Series

Information Science REFERENCE
An Imprint of IGI Global

Managing Director:	Lindsay Johnston
Managing Editor:	Austin DeMarco
Director of Intellectual Property & Contracts:	Jan Travers
Acquisitions Editor:	Kayla Wolfe
Production Editor:	Christina Henning
Development Editor:	Rachel Ginder
Typesetter:	Lisandro Gonzalez
Cover Design:	Jason Mull

Published in the United States of America by
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

CIP Data
Handbook of research on software-defined and cognitive radio technologies for dynamic spectrum management / Naima Kaabouch and Wen-Chen Hu, editors.
volumes cm
Includes bibliographical references and index.
ISBN 978-1-4666-6571-2 (hardcover) -- ISBN 978-1-4666-6572-9 (ebook) -- ISBN 978-1-4666-6574-3 (print & perpetual access) 1. Cognitive radio networks. 2. Radio frequency allocation--Management. I. Kaabouch, Naima, 1959- II. Hu, Wen Chen, 1960-
TK5103.4815.H36 2015
384.54'524--dc23
2014034430

This book is published in the IGI Global book series Advances in Wireless Technologies and Telecommunication (AWTT) (ISSN: 2327-3305; eISSN: 2327-3313)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 2
Cooperative Spectrum Sensing with Censoring of Cognitive Radios and MRC-Based Fusion in Fading and Shadowing Channels

Srinivas Nallagonda
National Institute of Technology – Durgapur, India

Sumit Kundu
National Institute of Technology – Durgapur, India

Sanjay Dhar Roy
National Institute of Technology – Durgapur, India

Gianluigi Ferrari
University of Parma, Italy

Riccardo Raheli
University of Parma, Italy

ABSTRACT

In this chapter, the authors study the performance of Cooperative Spectrum Sensing (CSS) with soft data fusion, given by Maximal Ratio Combining (MRC)-based fusion with Weibull faded channels, and Log-normal shadowed channels. More precisely, they evaluate the performance of a MRC-based CSS with Cognitive Radios (CRs) censored on the basis of the quality of the reporting channels. The performance of CSS with two censoring schemes, namely rank-based and threshold-based, is studied in the presence of Weibull fading, Rayleigh fading, and Log-normal shadowing in the reporting channels, considering MRC fusion. The performance is compared with those of schemes based on hard decision fusion rules. Furthermore, depending on perfect or imperfect Minimum Mean Square Error (MMSE) channel estimation, the authors analyze the impact of channel estimation strategy on the censoring schemes. The performance is studied in terms of missed detection probability as a function of several network, fading, and shadowing parameters.

DOI: 10.4018/978-1-4666-6571-2.ch002

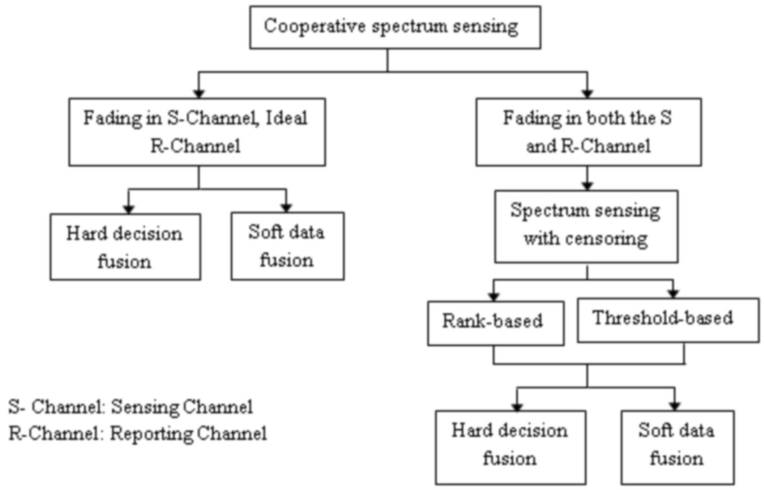
INTRODUCTION

There is huge demand of spectrum in this decade due to increase in internet traffic and other new services However, good part of the spectrum has already been licensed/ leased to different government, semi government and private organizations. Although, it can be noticed that the licensed and leased spectrums are not efficiently used and hence efficient spectrum allocation and utilization policies are required from spectrum traders and researchers.In order to deal with this conflict between spectrum scarcity and spectrum under-utilization, cognitive radio (CR) has been proposed as a revolutionary technology for the next generation of wireless communication networks (Mitola, 1999), (Haykin, 2005). In order to guarantee that the operation of the primary users (PUs) is not affected, the secondary users (SUs) need to sense the presence of active PUs: this process is referred to as *spectrum sensing*.

It is necessary to detect the presence of PUs accurately and quickly in order to find available unused spectrum, which is called *spectrum holes.* This is done by "Spectrum sensing" an important feature of CR technology. Accurate sensing of spectrum holes is a hard task because of the time-varying nature of wireless channels (Cabric, 2004), including fading and shadowing. Presence of multi-path fading or shadowing in the sensing (S) channel (S-channel) between a PU and a SU, may limit the successful detection of the PU by a single SU (Digham, 2003). The detection/sensing performance can be improved, by limiting the negative impact of fading, if different SUs are allowed to cooperate by sharing their local sensing information on the activity status of PUs: this is the essence of *cooperative spectrum sensing* (CSS) (Akyildiz, 2006), (Ghasemi, 2005), (Zhang, 2008). More precisely, CR systems allow the CR users[1] to sense the spectrum of PUs opportunistically without creating any intolerable interference to PUs. In many wireless applications, it is of great interest to check the presence and availability of an active communication link when the PU 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 a proper observation time window (Urkowitz, 1967), (Digham, 2003). Therefore, CSS using EDs improves the detection performance when all CR users sense the PU individually and send their sensing information via reporting (R) channels (R-channels) to a fusion center (FC). In CSS systems, the sensing information on the PUs's activity status sent by several CR users is combined at the 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 combining (Teguig, 2012), (Sun, 2011), (Nallagonda, 2013a) or (ii) hard combining (Choudhari, 2012(a)), (Choudhari, 2012(b)), (Choudhari, 2013), (Nallagonda, 2011b), (Nallagonda, 2012). In this book chapter, we focus on soft combining of spectrum sensing decisions from several CR users when the S- and R-channels are affected by fading and shadowing. Specifically, we study the impact of Weibull fading as well as Lognormal shadowing in the R-channels and the benefits of censoring the CR users on the basis of quality of the R-channels.

The rest of the chapter is organized as follows. Initially, we discuss on the background of this chapter: in particular, the motivation of the present work and the basics of CSS, along with existing works, are introduced. Next, we evaluate performance of CSS in faded environments (Rayleigh fading, Weibull fading, and Log-normal shadowing) under several hard and soft data fusion rules. We introduce the concept of censoring on the basis of the quality of R-channels, which is then incorporated into CSS systems. Specifically, two different censoring methods, such as rank-based and threshold-based censoring, have been analyzed under both perfect and imperfect channel estimation schemes. Finally, we conclude this chapter. The logical structure of the work presented in this chapter is shown in Figure 1.

Figure 1. Logical structure of the work in this chapter



BACKGROUND

Hard decision combining fusion rules, such as OR-logic, AND-logic, and Majority-logic, can be implemented at FC to make the final decision on the presence or on the absence of a PU (Ghasemi, 2007), (Zhang, 2008). The existing literature on ED, using a single CR user (Nallagonda, 2011a) or cooperative CR users (Nallagonda, 2011b), (Nallagonda, 2012) performing spectrum sensing with hard decision combining fusion rules, typically assumes the following models for the channels Rayleigh/ Rician/ Nakagami-*m*/ Weibull fading and Log-normal shadowing. In contrast to hard decision combining fusion rules, where the FC receives a 1-bit binary local decision from a CR, it is possible to apply soft data fusion at FC to improve the performance of CSS. According to a soft combining approach, CR users transmit the entire local sensing samples or the complete local test statistics (instead of sending just 1-bit binary decision), which are combined using any one of possible diversity combining techniques.

Our present study focuses not only on hard decision fusion rules but also on the soft data fusion rule assuming Weibull fading and log-normal shadowing environments. Weibull fading has been proved to exhibit an excellent fitting for indoor (Hashemi, 1993) and outdoor (Adawi, 1988) environments. The Weibull distribution reduces to Rayleigh distribution for a certain value of the fading parameter (Ismail, 2006). In (Fathi, 2012), the authors mentioned that existing receiver diversity techniques, such as equal gain combining (EGC) and maximal ratio combining (MRC), can be utilized for soft combining of local observations or test statistics at the FC. This has motivated us to evaluate the performance of CSS under soft data fusion in Weibull fading channels. Existing works mostly examine the CSS under various soft data combining fusion schemes, such as square law selection (SLS), MRC, square law combining (SLC), selection combining (SC) using ED in AWGN, Nakagami-*m* fading, Log-normal shadowing, and Rician fading channels (Teguig, 2012), (Sun, 2011), (Nallagonda, 2013a). For example, in (Niu, 2003), the likelihood ratio test (LRT) fusion is discussed in the case of wireless sensor networks. In (Ma, 2008), 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 signal-to-noise ratio (SNR) and reduces to MRC at low SNR. In (Choudhari, 2012(a)), the authors provide the performance analysis and comparison of hard decision (HD) and soft decision (SD)- based CSS in the presence of R-channel errors. The effects of channel errors are incorporated in the analysis through the bit error probability (BEP). A general expression for the detection probability with K-out-of-N fusion rule has been derived for HD fusion in the presence of R-channel error. While, for SD-based CSS, an optimal fusion rule with R-channel errors is derived and its distribution is established, SD-based CSS has been found to yield a significant performance gain with regard to conventional counting rule-based HD (i.e. K-out-of-N) even in the presence of channel BEP. If the BEP is above a certain value, then regardless of the received signal strength of a PU, the constraints on the probabilities of correct detection and false alarm cannot be met. Furthermore, it is shown that SD-based CSS is more robust in terms of channel BEP (Choudhari, 2012(a). In (Choudhari, 2013), the impact of error detection and error correction coding for cooperative sequential sensing by CRs has been shown. In particular, a distributed parallel detection network is considered, where each SU sends a soft decision in the form of quantized local LLRs to the FC. At each SU, the quantized LLRs are converted to bits using Gray mapping. These bits are then channel encoded and transmitted, using BPSK, to the FC. The reporting channels between the SUs and the FC induce errors in the decision statistics. Performance with a simple error correcting code yields a significant improvement (Choudhari, 2013). In Chaudhari (2012b), the authors evaluate the performance of sequential detection scheme for CSS in CRs with R-channel errors. The sequential local LLRs are transmitted through erroneous R-channels. The R-channels are modeled as a simple binary symmetric channel (BSC) that induces errors with a certain bit error probability (BEP). However, in (Choudhari, 2012a, Choudhari, 2013, Chaudhari, 2012b) CSS with distributed detection approach is mainly considered. In (Chen, 2014), the authors provide a tutorial on various cooperative techniques in cognitive networks, with emphasis on spectrum sensing and access based cooperation, interference constraint-based adaptive cooperative feedback, rate less network coding-based cooperative transmission.

In (Han, 2013), the authors propose two novel quantization schemes to improve sensing performance considering soft decision fusion rule in CSS. In (Atlay, 2012), the authors consider the effect of imperfect R-channels on decision logics. In (Hamza, 2014), the authors find the global detection probabilities and secondary throughput through moment generating function (MGF)-based approach for the case of sensing with equal gain combining (EGC) in CSS. In particular, EGC is compared to MRC and situations where the former outperforms the latter are also identified. Sensing based on EGC always outperforms the sensing using orthogonal R-channels---such as TDMA---in terms of secondary throughput. Further, the effects of phase and synchronization errors on sensing performance are also evaluated in (Hamza, 2014). In (Abdi, 2013), a simulation study is conducted to optimize the linear SC scheme at the FC jointly with as a function of following these parameters, the number of bits used by each node to quantize the local sensing outcomes and the power levels at which each node reports its sensing outcome to the FC. Thus, the authors propose to optimize the linear SC scheme at the FC jointly with two significant mechanisms at reporting phase. It is demonstrated that by joint consideration of reporting and fusion phases the error detection performance can be improved because of better exploitation of spatial/user diversities. In (Zhao, 2013(b)), the authors propose a new soft fusion scheme based on LLRs, which simplifies the analysis of the data at the FC, and allows to derive exact closed-form expressions for the probabilities of missed detection and false alarm. In (Cui, 2013), the authors consider a relay-based dual-stage collaborative spectrum sensing (DCSS) model that combines distributed and centralized approaches. Furthermore, an efficient fast sensing algorithm for a large scale CR network is derived which requires the smallest number of CR users for DCSS while satisfying the target detection error rate bound (Cui, 2013). In (Paula, 2014), the authors consider a CSS scheme using a distributed approach with a

FC in presence of unreliable R-channel. The impact of errors introduced by R-channels on decision rule is analyzed following the Bayesian risk criterion. However cooperative sensing can incur cooperation overhead in terms of extra sensing time, delay, energy, and operations devoted to cooperative sensing. A detailed survey on these issues has been presented in (Akyildiz, 2011), which specifically addresses the issues of cooperation method, cooperative gain, and cooperation overhead.

In existing ED-based CSS systems, i.e., CSS with hard decision combining (Nallagonda, 2011b), (Nallagonda, 2012) or CSS with soft data combining fusions (Nallagonda, 2013a), R-channels are assumed to be ideal and S-channels are considered as noisy and faded / shadowed channels. However, in many practical situations R-channels may also be affected by noise and fading / shadowing channel (Zhao, 2013), (Zou, 2011), (Ferrari, 2006). Although most works on spectrum sensing assume ideal R-channels (Nallagonda, 2011b), (Nallagonda, 2012), (Nallagonda, 2013a), the presence of fading or shadowing in R-channels is likely to affect the sensing information sent by CR users where the FC is far from them (Choudhari, 2012(a)). If the R-channel is heavily faded or shadowed, the sensing information 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 interrupt the transmission of sensing information 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 has the additional benefit of reducing the energy consumption in energy constrained network. Therefore, censoring of CR users is necessary to improve the performance of CSS. In (Zhao, 2013(a)), under the assumption of both S and R-channels are noisy and faded, a filter bank-based soft decision fusion (SDF) CSS system is proposed. In (Zou, 2011), a selective-relay based CSS scheme, assuming noisy and Rayleigh faded channels in both S- and R-channels, is proposed. Similar fading or shadowing conditions is considered in S and R-channels. For example, both S-channel and R-channel are noisy and Weibull faded or noisy and Log-normal shadowed. Although all the CR users detect PUs using EDs, only the CR users censored on the basis of the R-channel quality are allowed to transmit. The censoring decision is taken by the FC on the basis of estimation of R-channel. Using minimum mean square estimation (MMSE)-based estimation of the R-channels, the FC selects a subset of CR users among all the available ones (say P out of N) which have the highest channel coefficients, i.e. the CR users associated with best estimated channel coefficients are selected --- this approach is referred to as rank-based censoring (Nallagonda, 2013b). However, an alternative censoring scheme, based on channel thresholding (denoted also as threshold-based censoring and such that a CR user is selected to transmit its decision if the estimated R-channel fading coefficient exceeds a given threshold), is considered and analyzed in (Nallagonda, 2013c) (Nallagonda, 2013d). In (Nallagonda, 2014), the performance of CSS with both rank-based and threshold-based censoring is evaluated only with Rayleigh and Nakagami-*m* fading channels, considering majority-logic only at FC.

Channel estimation can be either perfect (no estimation error) or imperfect (with estimation errors). 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 global decision regarding the presence or the absence of PUs. In (Nallagonda, 2014), a probabilistic model for CR user selection is proposed for Rayleigh, and Nakagami-*m* faded channels. In the current chapter, we consider the same censoring concept of (Nallagonda, 2013b), (Nallagonda, 2014) and evaluate the performance of CSS with rank-based censoring of CR users, based on R-channels quality. Similarly, considering the concept of channel thresholding of (Nallagonda, 2013c), (Nallagonda, 2013d), (Nallagonda, 2014), we evaluate the performance of CSS with threshold-based censoring in the presence of Weibull fading, Log-normal shadowing in R-channels, with MRC and majority logic fusions at the FC. The investigation of majority-logic and MRC fusion schemes where both S- and R-channels are Weibull faded or Log-normal shadowed is an interesting research extension. Moreover, we develop the required analytical and simulation testbed for CSS, with both rank-based and threshold-based in the presence of Weibull faded, and Log-normal shadowed channels. In order to reach this goal, we develop closed-form expressions for the estimation error variance for Weibull fading channels. These expressions are useful to evaluate the performance of CSS with both censoring strategies in the presence of imperfect channel estimation. To the best of our knowledge, these expressions are not readily available in the literature. Along the way, we also develop probabilistic models of CR selection for Weibull faded, and Log-normal shadowed channels.

Our main contributions in the present chapter can be summarized as follows.

We carryout performance evaluation of soft data fusion (MRC-based) in Weibull faded channels as well as Log-normal shadowed channels. Furthermore, the performance of SD-based fusion is compared with that of HD-based fusion (typically; OR-logic, AND-logic, and majority-logic) and the impact of fading and shadowing on soft data fusion is investigated.

The performances of several hard-decision fusion rules are also evaluated and compared with each other in the presence of Weibull fading and Log-normal shadowing conditions.

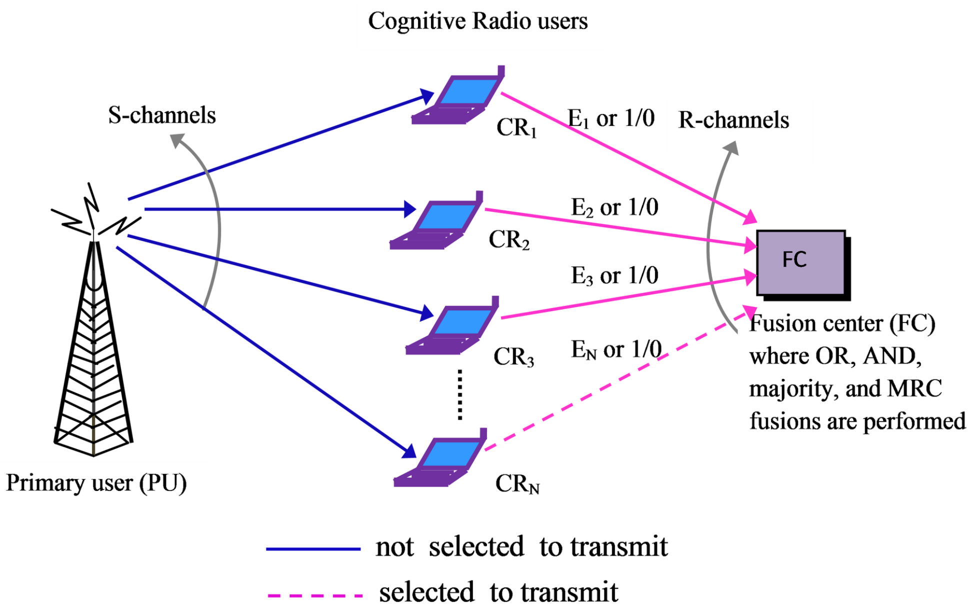
A closed-form expression for the estimation error variance with Weibull fading is presented. This expression is expedient to evaluate the performance of CSS with censoring based on imperfect channel estimation. The impact of the R-channel estimation error on the detection performance in the considered fading scenario is evaluated. Direct performance comparisons between perfect and imperfect channel estimation cases, for various values of the main channel and network parameters, are carried out.

The performance, in terms of missed detection probability, under both perfect and imperfect channel estimation conditions, is investigated. The effects of Weibull fading and Log-normal shadowing in S- and R-channel and the impact of channel SNRs on the performance of the considered CSS schemes are investigated. In threshold-based censoring scenarios, novel analytical expressions, as functions of the censoring threshold C_{th}, for the selection of CRs are derived in Weibull fading and Log-normal shadowing channels. In particular, the probability mass function (PMF) of the number of censored CRs is analyzed. The impact of the number of available CRs and the average R-channel SNRs on the average missed detection probability of CSS is investigated. In threshold-based censoring schemes, the impact of the censoring threshold on the average missed detection is discussed. Finally, the performance comparison between MRC fusion and majority logic fusion, for various network parameters, as well as the effect of imperfect channel estimation is also highlighted.

COOPERATIVE SPECTRUM SENSING

We consider a CSS network of N CRs, one PU and one FC, as shown in Figure 2. Each CR senses the PU individually using energy detector and sends its sensing information/data to the FC. Depending on the transmitted sensing information from each CR to FC, the FC employs HD combining fusion if it receives one bit binary values (1/0) from the CRs or soft data combining fusion if it receives energy values (E) from the CRs. Particularly, OR-logic, AND logic, majority-logic, and MRC fusion are performed separately at FC to make the global decision about the presence or the absence of the PU. In this chapter,

Figure 2. Cooperative spectrum sensing (CSS) system



we consider additive noise and Weibull fading or additive noise and shadowing in the S-channels, while R-channels are assumed as either (i) ideal channels (i.e., noiseless channels) or (ii) Weibull faded or Log-normal shadowed channels. Based on these two cases of interest, a CSS system can be classified as follows. In the first scenario, we assume that the R-channels are ideal and we evaluate the performance of CSS. In the second scenario, we consider fading or shadowing in the R-channels.

The received signal $x(t)$ at k-th CR can be represented as:

$$x_k(t) = \begin{cases} n_k(t) & H_0 \\ h_k s(t) + n_k(t) & H_1 \end{cases} \tag{1}$$

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 S-channel fading coefficient for the k-th CR is denoted as h_k. H_1 and H_0 are the two hypotheses associated with the presence and absence of a PU, respectively. When the PU is absent i.e., under hypotheses H_0, each CR receives only the noise signal at the input of the ED and the noise energy at k-th CR can be approximated over the time interval (0, T), as (Urkowitz, 1967), (Digham, 2003):

$$\int_0^T n_k{}^2(t)dt = \frac{1}{2W}\sum_{i=1}^{2u} n_{k_i}^2, \tag{2}$$

where u (=TW) is the time-bandwidth product, T is the observation time, and W is the one-sided bandwidth. Furthermore,

$$n_{k_i} \sim N(0, N_{01}W), \forall\, i. \tag{3}$$

where N_{01} is the one-sided noise power spectral density, and $N(\mu, \sigma^2)$ is a Gaussian random variable with mean μ and variance σ^2. The received signal energy under hypothesis H_0 at k-th CR, denoted as E_k, can be written as:

$$E_k = \sum_{i=1}^{2u} n_{k_i}'^2 \; ; \; n_{k_i}' = \frac{n_{k_i}}{\sqrt{N_{01}W}}, \tag{4}$$

The same approach can be followed to evaluate the received signal energy under hypothesis H_1 at the k-th CR by replacing n_{k_i} with $n_{k_i} + s_i$, where $s_i = s(\frac{i}{2W})$.

In a non-faded environment (i.e., h_k =1) i.e., with only additive white Gaussian noise, the detection and false alarm probabilities for the k-th CR can be expressed as follows (Digham, 2003), (Nallagonda, 2011b), (Nallagonda, 2012):

$$P_{d,k} = P(E_{k1} > \lambda | H_1) = Q_u(\sqrt{2\gamma_{s,k}}, \quad \sqrt{\lambda}) \tag{5}$$

$$P_{f,k} = P(E_{k0} > \lambda \mid H_0) = \Gamma(u, \lambda/2) \,/\, \Gamma(u) \tag{6}$$

$$P_{m,k} = 1 - P_{d,k} \tag{7}$$

where $\gamma_{s,k}$ is the instantaneous SNR of k-th S-channel, $\Gamma(.,.)$ is the incomplete gamma function, and $Q_u(.,.)$ is the generalized Marcum Q-function. The expression for $P_{f,k}$ for the k-th CR, as given in (6), remains the same when fading is considered in the S-channel due to independence of $P_{f,k}$ from SNR. The detection threshold λ can be set for a chosen $P_{f,k}$ following (6). Equation (5) gives the probability of detection as a function of $\gamma_{s,k}$. However when h_k is varying due to fading, the average detection probability at k-th CR ($\bar{P}_{d,k}$) may be obtained by averaging (5) over fading or shadowing statistics (Ghasemi, 2005), (Nallagonda, 2011b), (Nallagonda, 2012)

$$\bar{P}_{d,k} = \int_0^{\infty} Q_u(\sqrt{2\gamma_s}, \quad \sqrt{\lambda}) f_{\gamma_s}(\gamma_s) d\gamma_s \tag{8}$$

where $f_{\gamma}(x)$ is the probability density function (PDF) of SNR under fading or shadowing.

RAYLEIGH FADING

In the Rayleigh faded scenario, the k-th S-channel fading coefficient h_k can be expressed as a function of the Gaussian in-phase X_1 and quadrature X_2 elements of the multipath components (Simon, 2014), (Nallagonda, 2011a, 2012):

$$|h_k| = |X_1 + jX_2| = \sqrt{X_1^{\ 2} + X_2^{\ 2}}\ ;\ X_{1,2} \sim N(0,\ \ 1/2)\,. \tag{9}$$

If the signal amplitude follows a Rayleigh distribution, then the SNR γ_s follows an exponential PDF given by (Simon, 2014):

$$f_{\gamma_s}(\gamma_s) = \tfrac{1}{\bar{\gamma}_s}\exp\left(-\tfrac{\gamma_s}{\bar{\gamma}_s}\right) \qquad \gamma_s \geq 0, \tag{10}$$

where $\bar{\gamma}_s$ is the average S-channel SNR. The average P_d in this case, $\overline{P}_{dRay}$, can be evaluated by substituting (10) in (8) (Nallagonda, 2014), (Digham, 2003), as

$$\overline{P}_{d,k,Ray} = \exp(-\tfrac{\lambda}{2})\sum_{k=0}^{m-2}\tfrac{1}{k!}(\tfrac{\lambda}{2})^k + (\tfrac{1+\bar{\gamma}_s}{\bar{\gamma}_s})^{m-1}$$

$$\times\left(\exp(-\tfrac{\lambda}{2(1+\bar{\gamma}_s)}) - \exp(-\tfrac{\lambda}{2})\sum_{k=0}^{m-2}\tfrac{1}{k!}(\tfrac{\lambda\bar{\gamma}_s}{2(1+\bar{\gamma}_s)})^k\right) \tag{11}$$

WEIBULL FADING

In the Weibull fading model, the k-th S-channel fading coefficient h_k can be expressed as a function of the Gaussian in-phase X_1 and quadrature X_2 elements of the multipath components (Hashemi, 1993) (Adawi, 1988), (Nallagonda, 2011b):

$$h_k = (X_1 + jX_2)^{2/v} \tag{12}$$

where v is the Weibull fading parameter and $j = \sqrt{-1}$. Let X be the magnitude of h_k, i.e., $X = \left|h_k\right|$. If $R = \left|X_1 + jX_2\right|$ is a Rayleigh distributed random variable, a Weibull distributed random variable can be obtained by transforming R and using (12) as

$$X = R^{2/v} \tag{13}$$

The PDF of the SNR (γ_s) in a Weibull faded channel is given by (Sagias, 2004) i.e.,

$$f_{\gamma_s}\left(\gamma_s\right) = c\left[\frac{\Gamma\left(p\right)}{\bar{\gamma}_s}\right]^c \gamma_s^{\,c-1} \exp\left[-\left\{\frac{\gamma_s \Gamma\left(p\right)}{\bar{\gamma}_s}\right\}^c\right] \tag{14}$$

where $c = v/2$ and $p = 1 + 1/c$. Furthermore, the average probability of detection $\bar{P}_{d,k,we}$ can be obtained by substituting (14) in (8).

LOG-NORMAL SHADOWING

In this case, we assume that the S-channel between PU and CR is shadow faded. The linear channel gain, h_k may be modeled by a log-normal random variable i.e. $h_k = e^X$ where X is a zero-mean Gaussian random variable with variance σ^2. Log-normal shadowing is usually characterized in terms of its dB-spread, σ_{dB} which is related to σ by $\sigma = 0.1\ln(10)\,\sigma_{dB}$. The PDF of SNR, γ_s, in Log-normal shadowing channel is given by (Simon, 2004)

$$f_{\gamma_s}\left(\gamma_s\right) = \frac{10}{\ln(10)\sqrt{2\pi}\sigma\gamma_s} \exp\left[-\frac{(10\log_{10}\gamma_s - \bar{\gamma}_s)^2}{2\sigma^2}\right] \tag{15}$$

Further, the average probability of detection $\bar{P}_{d,k,\ln}$ can be obtained by substituting (15) in (8).

The FC employs different hard decision and soft data combining fusion rules to attain a final decision from the received signals. Several types of hard decision fusion algorithms such as OR-logic, AND-logic, and majority-logic and soft data fusion such as MRC fusion are considered in the current text as described in the next section.

HARD DECISION FUSION RULES

In the case of HD, the CRs make the one-bit binary decision called local decision by comparing the received energy with a detection threshold λ. Several HD fusion rules, such as OR-rule, AND-rule, and majority-rules, can be implemented at the FC. Assuming independent decisions, the fusion problem, using k-out of-N CRs for decision, is described by a binomial distribution or is derived from Bernoulli trials where each trial represents the decision of each CR. The generalized formula for overall probability of detection Q_d at FC for the k-out of-N fusion rule is given by (Nallagonda, 2011b, 2012, 2014), (Ghasemi, 2007), (Zhang, 2008)

$$Q_d = \sum_{l=k}^{N} \binom{N}{l} \bar{P}_d^{\,l} \left(1 - \bar{P}_d\right)^{N-l}. \tag{16}$$

where $\bar{P}_d$ is the probability of detection for each individual CR as defined by (8).

The OR-logic fusion rule (i.e., 1-out of-N rule) can be evaluated by setting k=1 in (16)

$$Q_{d,OR} = \sum_{l=1}^{N} \binom{N}{l} \bar{P}_d^l \left(1 - \bar{P}_d\right)^{N-l} = 1 - (1 - \bar{P}_d)^N . \tag{17}$$

The AND-logic fusion rule (i.e., N-out of-N rule) can be evaluated by setting k=N in (16)

$$Q_{d,AND} = \sum_{l=N}^{N} \binom{N}{l} \bar{P}_d^l \left(1 - \bar{P}_d\right)^{N-l} = (\bar{P}_d)^N . \tag{18}$$

For the case of majority-rule (i.e., $N/2$ out of-N rule) the $Q_{d,\,MAJ}$ is evaluated by setting $k = \lfloor N / 2 \rfloor$ in (16). Similarly, the overall probability of false alarm Q_f for the generalized k-out of-N fusion rule can be evaluated by replacing $\bar{P}_d$ with P_f in (16).

SOFT DATA FUSION RULE

In the case of SD combining fusion, each CR forwards the entire sensing information (energy value, E) to the FC without performing any local decision. The FC employs soft data combining fusion and takes the final decision about the PU. The MRC fusion is considered in this chapter. First the energy value of the received signal at each CR is obtained using an ED. Next, all CRs send their respective energy values, with appropriate weighting, to the FC. Then the FC gathers all the data (energy values with appropriate weights) from all CRs, combines them, and makes a global decision by comparing the obtained value with a detection threshold, λ. The MRC fusion requires sensing channel state information to amplify the energy values. It may be observed that as we assume R-channels to be ideal, the MRC fusion rule at FC simply becomes the sum of the weighted signals received from all the CRs over their ideal R-channels. We also assume that signals sent by CRs over their R-channels are orthogonal, i.e., there is no interference amongst the signals sent by different CRs to the FC. Over AWGN channels, the probabilities of false alarm and correct detection under MRC fusion, are given by (Teguig, 2012), (Sun, 2011), (Nallagonda, 2013a)

$$Q_{f,MRC} = \frac{\Gamma(u, \lambda / 2)}{\Gamma(u)} \tag{19}$$

$$Q_{d,MRC} = Q_u(\sqrt{2\gamma_{s,MRC}}, \quad \sqrt{\lambda}) \tag{20}$$

where $\gamma_{s,MRC} = \sum_{i=1}^{N} \gamma_{s,i}$, denotes the instantaneous SNR at the output of the MRC combiner. However, in the presence of fading, the probability of correct detection can be found by averaging $Q_{d,MRC}$ given by (20) with respect to fading statistical distribution or, equivalently, over the SNR distribution as follows:

$$\bar{Q}_{d,MRC} = \int_0^\infty Q_{d,MRC}(\gamma_{s,MRC}, \lambda) f(\gamma_{s,MRC}) \; d\gamma_{s,MRC} \tag{21}$$

where $f(\gamma_{s,MRC})$ is the PDF of S-channel SNR under fading or shadowing.

Results

The following results are obtained using MATLAB-based simulations. The performance of CSS is evaluated in the presence of Weibull fading and Log-normal shadowing environments. The R-channels are assumed ideal. In particular, a performance comparison between HD and SD fusion rules at the FC is investigated.

In Figure 3 and Figure 4, the performance of CSS with hard decision and soft data fusion rules, respectively, is investigated. In particular, the performance is investigated through the use of complementary ROC curves, i.e., Q_m versus Q_f . In all cases, 3 CRs are considered and the performance is evaluated in Weibull fading environment (Figure 3) and Log-normal shadowing environments (Figure 4). In these figures, for comparison purposes, the curve for non-cooperation case (N=1) is also shown. It is obvious that the system with CSS among multiple CRs outperforms the system with a single CR (no-cooperation case), except for the AND rule. This is due to the fact that cooperation among the CRs cancels the negative effects of fading or shadowing in the S-channels as compared to the single CR case. It can be observed from both figures, that, for a particular value of Q_f, the performance with OR-rule is better than those with majority and AND-rules. It can also be seen, in both Weibull faded and Log-normal shadowed environments, that the schemes with MRC fusion outperforms all HD fusion rules. However, these benefits are obtained at the cost of a larger bandwidth for the reporting channel. On the other hand, HD fusion rules have a lower complexity. The impacts of fading and shadowing on the detection performance of MRC fusion are also investigated in Figure 3 and Figure 4, respectively. Sensing performance improves significantly for higher values of the Weibull fading parameter and lower values of the shadowing parameter. This is due to the fact that higher values of the fading parameter or lower values of the shadowing parameter reduce the severity of fading and shadowing in the S-channel.

Spectrum Sensing with Censoring

As already discussed in above sections, in the first considered scenario, the performance of CSS, considering S-channels as noisy-faded and R-channels as ideal, has been well studied. However, in a more realistic scenario, R-channels may not be noiseless (ideal) channels. Though most works on spectrum sensing assume noiseless R-channels (Nallagonda, 2013b, 2013c, 2013d, 2014), the presence of fading or shadowing in R-channels is likely to affect the sensing information sent by CRs to FC. If the R-channel is heavily faded or shadowed, the sensing information received at the FC is likely to be an erroneous version of that transmitted by the CR. Under such conditions, it is wise to stop transmitting sensing

Figure 3. Performance comparison between hard decision (OR-rule, AND-rule, and majority-rule) and soft data (MRC) fusions under Weibull fading ($\overline{\gamma}_s$ =10 dB, u=5, N=3, and ideal R-channel)

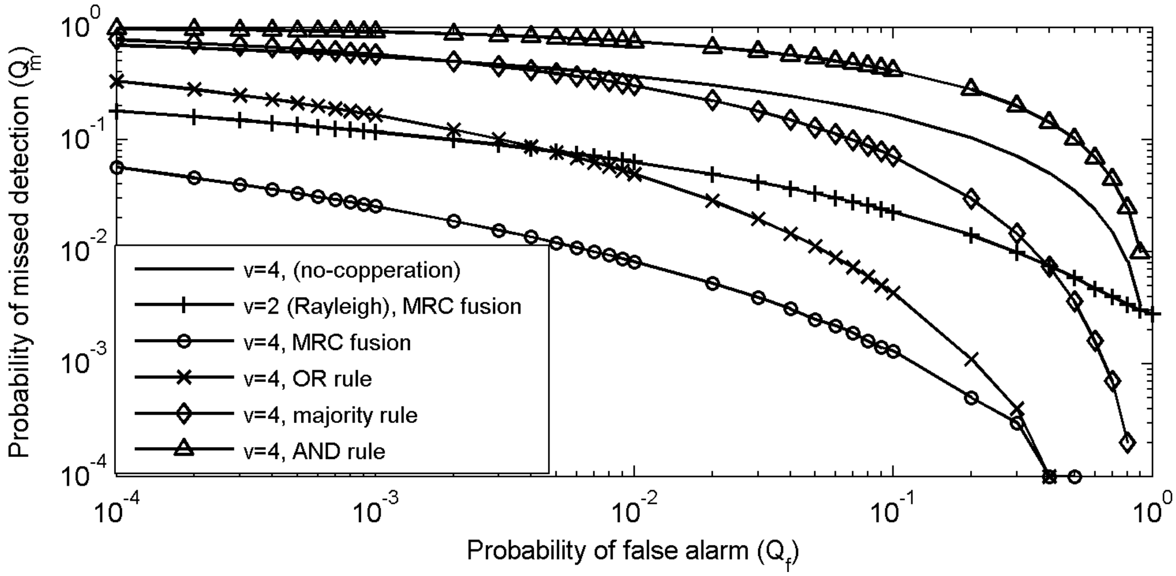
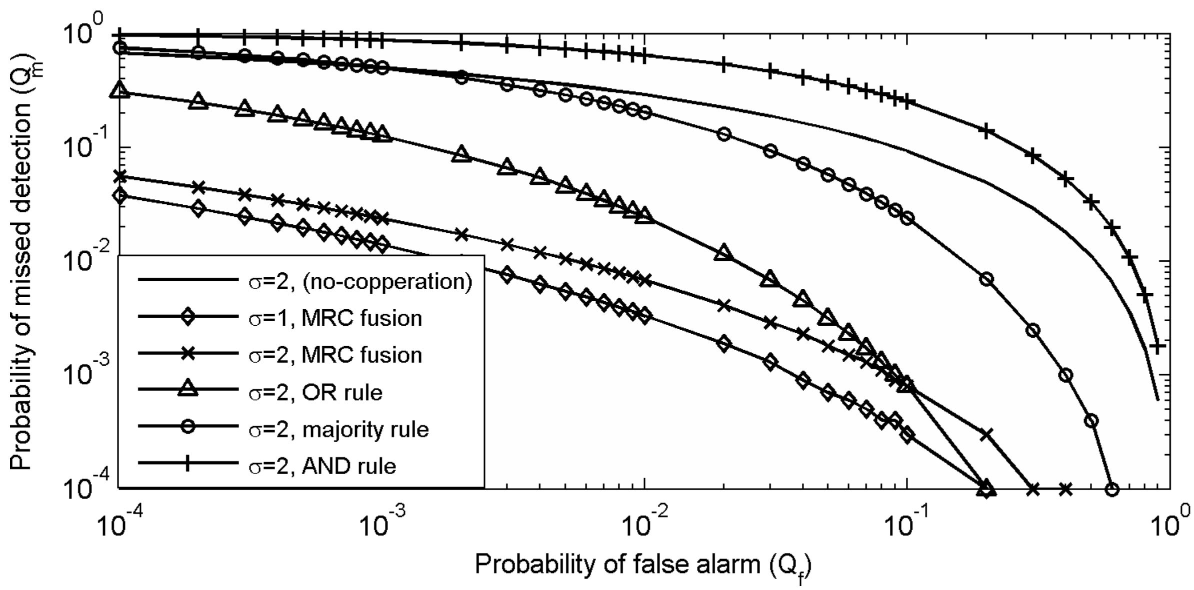


Figure 4. Performance comparison between hard decision (OR-rule, AND-rule, and majority-rule) and soft data (MRC) fusions under Log-normal shadowing ($\overline{\gamma}_s$ =10 dB, u=5, N=3, and ideal R-channel)



information from these CRs: censoring is thus expedient in such scenarios. The CRs whose R-channels are estimated as reliable by the FC are censored, i.e., they are allowed to transmit their sensing information, while the CRs with poor R-channels are stopped. This helps to reduce system complexity and to improve detection performance. Therefore, censoring of CRs is necessary to improve the performance of CSS. The CSS system with censoring is also shown in Figure 2.

In censoring-based CSS systems, we assume that both S-and R-channels are modeled as noisy and faded or noisy with shadowing. In this section, we study the performance of CSS with two censoring schemes, namely: (i) rank-based censoring and (ii) threshold-based censoring in the presence of Weibull fading and Log-normal shadowing. MRC and majority-logic fusion rules are considered at the FC on the reception of sensing information, received from censored CRs to obtain a global decision regarding the presence or the absence of PUs. The overall probability of missed detection is selected as the key performance metric and is evaluated, through simulations, under several channel and network conditions. A CR has its individual sensing information and, if censored, transmits its information, using binary phase shift keying (BPSK) as modulation format, to the FC over the corresponding faded or shadowed R-channel.

Transmissions between the CRs and the FC are carried out in two phases. In the first transmission phase, each CR sends one training symbol to enable the FC to estimate all fading or shadowing channel coefficients between the FC and *N* participating CRs. MMSE-estimation of the R-channel coefficients is carried out at the FC using training symbols sent by the CRs to the FC. The signal from the *k*-th CR received at the FC can be expressed as (Nallagonda, 2013b, 2013c, 2013d, 2014):

$$y_k = s_k h_k + n_k \quad k \in \left\{1, 2, \ldots, N\right\} \tag{22}$$

where $s_k = {}^{+}\!/_{-}\sqrt{E_b}$ is a BPSK signal corresponding to H_1 / H_0, respectively. The R-channel fading or shadowing coefficient is denoted as h_k and the R-channel noise is $n_k \sim CN\left(0, \tilde{A}_n^2\right)$. It should be observed that identical notation of h_k for both S- and R-channel coefficients is indicated which means that the same fading/shadowing parameter is considered in both S-and R-channels. The Gaussian channel noise samples $\left\{n_k\right\}$ and R-channel coefficients $\left\{h_k\right\}$ are mutually independent. We assume that the FC estimates the *k*-th CR's R-channel fading or shadowing coefficient h_k according to an MMSE estimation strategy on the basis of the observable y_k as follows (Nallagonda, 2013b, 2013c, 2013d, 2014):

$$\hat{h}_k = E[h_k \mid y_k] = \frac{\sqrt{E_b}}{E_b + \sigma_n^2} y_k$$

$$= \frac{E_b}{E_b + \sigma_n^2} h_k + \frac{\sqrt{E_b}}{E_b + \sigma_n^2} n_k . \tag{23}$$

The estimation error for *k*-th R-channel co-efficient can be expressed as $\tilde{h}_k = h_k - \hat{h}_k$

$$\tilde{h}_k = h_k \left(1 - \frac{E_b}{E_b + \sigma_n^2}\right) - \frac{\sqrt{E_b}}{E_b + \sigma_n^2} n_k$$

$$= h_k \frac{\sigma_n^2}{E_b + \sigma_n^2} - \frac{\sqrt{E_b}}{E_b + \sigma_n^2} n_k \,. \tag{24}$$

The channel estimation is either perfect $\left(\hat{h}_k = h_k, \tilde{h}_k = 0\right)$ or imperfect $\left(\hat{h}_k = h_k - \tilde{h}_k, \tilde{h}_k \neq 0\right)$. After the first phase of transmission, '*Z*' $\left(Z \leq N\right)$ CRs, out of '*N*' available CRs, are selected using any one of the two possible censoring schemes (i) *rank-based* (*Z*=*P*; the selected CRs are associated with the best *P* estimated channel coefficients, where $P \leq N$), and (ii) *threshold-based* (*Z*=*K*; the selected *K* CRs have estimated channel coefficients exceeding a predefined threshold C_{th} and the value of '*K*'. The FC informs the selected CRs via one-bit feedback (we assume that feedback channels are error-free).

In the second transmission phase, the selected CRs send their local binary BPSK modulated sensing information to the FC over the corresponding R-channels. The fading or shadowing coefficients of R-channels are assumed to be fixed over a symbol transmission time, as the channel is assumed to be slowly faded or shadowed. The signal, received from the *k*-th selected CR, at the FC is (Nallagonda, 2013b, 2013c, 2013d, 2014)

$$y_{k,d} = m_k h_k + n_{k,d}\,; \quad k \in \left\{1, 2, ..., Z\right\} \tag{25}$$

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

The MRC fusion rule depends on the R-channel estimates, the CR's performance indices, and incorporates the effect of channel estimation error. Assuming that the CRs have identical local performance indices and BPSK is the used modulation format, the MRC fusion rule can be obtained by simplifying the LRT fusion. In the case of ideal R-channel, as described earlier, the weights used for MRC depend on S-channel state information, while in present case the weights used for MRC fusion depend on R-channel state information. The LRT fusion can be written as follows (Nallagonda, 2013b, 2013d)

$$\Lambda = \prod_{k=1}^{N} \frac{f(y_{k,d} \mid H_1)}{f(y_{k,d} \mid H_0)}$$

$$= \prod_{k=1}^{N} \frac{\bar{P}_{d_k} + (1 - \bar{P}_{d_k}) e^{\frac{-4\sqrt{E_b}}{\sigma_w^2} \mathrm{Re}(y_{k,d} \hat{h}_k^*)}}{P_{f_k} + (1 - P_{f_k}) e^{\frac{-4\sqrt{E_b}}{\sigma_w^2} \mathrm{Re}(y_{k,d} \hat{h}_k^*)}} \tag{26}$$

where

$$\sigma_w^2 = E_b \sigma_{\tilde{h}}^2 + \sigma_n^2 = \frac{E_b \sigma_n^2}{E_b + \sigma_n^2} + \sigma_n^2,\ \bar{P}_{d_k} = \bar{P}_d,\ \ P_{f_k} = P_f \qquad \forall \quad k \tag{27}$$

In the case of perfect channel estimation, σ_w^2 is equal to σ_n^2 when the estimation error variance $\tilde{A}_{\tilde{h}}^2$ is zero. At very low R-channel SNRs both σ_n^2 and σ_w^2 tend to be very large. By taking a logarithm of both sides in (26) and using the approximations $e^{-x} \approx 1 - x$ and $\log(1+x) \approx x$ for small values of x, we can simplify the LRT rule as:

$$\Lambda_1 = \log(\Lambda) = \frac{2\sqrt{E_b}}{\sigma_w^2} \sum_{k=1}^{N} (\bar{P}_{d_k} - P_{f_k}) \operatorname{Re}(y_{k,d} \hat{h}_k^*) . \tag{28}$$

Under the assumption that the CRs have identical local performance indices, Λ_1 can be simplified further as follows (Nallagonda, 2013b, 2013d):

$$\Lambda_{MRC} = \sum_{k=1}^{N} \operatorname{Re}\left(y_{k,d} \, \hat{h}_k^* \right) \tag{29}$$

where $\hat{h}_k^*$ is the complex conjugate of the estimated channel coefficient $\hat{h}_k$ and the signal at the FC received from *k*-th selected CR is $y_{k,d}$ (given by Equation (25)) . Given $\hat{h}_k$, one can observe from (29) that Λ_{MRC} is a linear combination of Gaussian random variables and, therefore, has a Gaussian distribution. The FC can then take a decision in favor of H_1 or H_0 simply by comparing Λ_{MRC} with the threshold zero.

Generation of Estimated and Estimated Error Coefficients for *k*-th R-Channel

In this section, we discuss methods for generating the estimated R-channel coefficient ($\hat{h}_k$) and estimated error coefficient ($\tilde{h}_k$) for Rayleigh, Weibull faded, and Log-normal shadowed R-channels. To the best of our knowledge, the error variance expression for Weibull fading channel is not readily available in the literature.

Estimation Error in Rayleigh Channel

For *k*-th Rayleigh faded R-channel, the estimation error is a zero-mean complex Gaussian random variable with the following variance (Nallagonda, 2013b, 2013d, 2014):

$$\sigma_{\tilde{h},R}^2 = \left(\frac{E_b}{\sigma_n^2} + 1 \right)^{-1} \tag{30}$$

At this point, the *k*-th Rayleigh faded R-channel estimation error coefficient can be generated according to the following equations:

$$|\tilde{h}_k| = \sqrt{\tilde{h}_{kI}^{\ 2} + \tilde{h}_{kQ}^{\ 2}}\ ;\ \tilde{h}_{kI} \sim N\left(0, \quad \frac{\sigma^2_{\tilde{h},\mathrm{R}}}{2}\right),\ \tilde{h}_{kQ} \sim N\left(0, \quad \frac{\sigma^2_{\tilde{h},\mathrm{R}}}{2}\right). \tag{31}$$

Estimation Error in Weibull Fading Channel

For the *k*-th Weibull faded R-channel, the actual fading coefficient h_k can be expressed, in terms of in-phase (h_{kI}) and quadrature (h_{kQ}) components as

$$h_k = (h_{kI} + jh_{kQ})^{2/v} \tag{32}$$

where *v* is the Weibull fading parameter (also denoted as shape parameter). The amplitude or envelope $| h_k |$ is Weibull distributed only when $h_{k,I,Q} \sim N(0, \sigma^2 / 2);\ \sigma^2 = 1$. The mean and variance of h_k are

$$\mu_{h,we} = E[h_k]_{we} = w\Gamma(1 + 1 / v) \tag{33}$$

$$\sigma^2_{h,we} = w^2\Gamma(1 + 2 / v) - w^2\Gamma(1 + 1 / v)^2 \tag{34}$$

where w is the scale parameter. The estimated *k*-th Weibull faded R-channel coefficient ($\hat{h}_k$) can be generated by substituting (32) in (23) as

$$\hat{h}_k = \frac{E_b}{E_b + \sigma^2_n}(h_{kI} + jh_{kQ})^{2/v} + \frac{\sqrt{E_b}}{E_b + \sigma^2_n} n_k. \tag{35}$$

Finally, the estimated Weibull fading coefficient can be generated by substituting h_{kI}, $h_{kQ} \sim N(0, 1 / 2)$ in (35) and $n_k = n_{kI} + jn_{kQ}$, where $n_{kI}, n_{kQ} \sim N(0, \sigma^2_n / 2)$. From (35), the estimation error coefficient for the *k*-th Weibull faded R-channel $\tilde{h}_k (= h_k - \hat{h}_k)$ can be generated by substituting (32) in (24) as

$$\tilde{h}_k = \frac{\sigma^2_n}{E_b + \sigma^2_n}(h_{kI} + jh_{kQ})^{2/v} - \frac{\sqrt{E_b}}{E_b + \sigma^2_n} n_k. \tag{36}$$

The mean and variance of $\tilde{h}_k$ can be evaluated by using (33), and (34) as

$$E[\tilde{h}_k]_{we} = \frac{1}{1 + \bar{\gamma}_r} w\Gamma(1 + 1 / v) \tag{37}$$

$$\sigma^2_{\tilde{h},we} = \frac{1}{(1+\bar{\gamma}_r)^2}\left[\bar{\gamma}_r + w^2\Gamma(1+2/v) - w^2\Gamma(1+1/v)^2\right]$$

$$= \frac{1}{(1+\bar{\gamma}_r)^2}\left[\bar{\gamma}_r + \sigma^2_{h,we}\right] \tag{38}$$

For v=2, the term $\sigma^2_{h,we}$ in (38) is equal to the variance of a Rayleigh distributed random variable, which is assumed to be equal to one and (38) gives an alternative expression for estimated error variance in Rayleigh channel ($\sigma^2_{\tilde{h},R}$), which matches with (30).

Estimation Error in Log-Normal Shadowing Channel

For the k-th Log-normal shadowing R-channel, the actual Log-normal coefficient h_k can be expressed as follows: if X is a zero-mean Gaussian RV with variance σ^2, i.e., $X \sim N(0,\sigma^2)$, then a log-normal coefficient can be modeled as $h_k = \exp(X)$. Finally, the Log-normal shadowing coefficient can be generated by using σ of $X \sim N(0,\sigma^2)$ as $\sigma = 0.1\ln(10)\sigma_{dB}$, where σ_{dB} is the shadowing parameter, generally expressed in terms of its dB-spread. The estimated shadowing coefficient for the k-th R-channel ($\hat{h}_k$) can be generated by substituting $h_k = \exp(X)$, where $X \sim N(0,(0.1\ln(10)\sigma_{dB})^2)$, and $n_k = n_{kI} + jn_{kQ}$, where $n_{kI}, n_{kQ} \sim N(0,\sigma^2_n/2)$ in (23), as follows:

$$\hat{h}_k = \frac{E_b}{E_b+\sigma^2_n}\exp(X) + \frac{\sqrt{E_b}}{E_b+\sigma^2_n}(n_{kI} + jn_{kQ}) \tag{39}$$

From (39), the estimation error $\tilde{h}_k$ for k-th R-channel can be generated by substituting the shadowing coefficient h_k and the complex Gaussian noise coefficient n_k in (24) as follows:

$$\tilde{h}_k = \frac{\sigma^2_n}{E_b+\sigma^2_n}\exp(X) - \frac{\sqrt{E_b}}{E_b+\sigma^2_n}(n_{kI} + jn_{kQ}) \tag{40}$$

Due to analytical complexity, it may not be possible to simplify further the Equations (35), (36), (39), and (40).

Rank-Based Censoring

According to this censoring scheme (Nallagonda, 2013b, 2013d, 2014), P (out of N) CRs—those with the best estimated channel coefficients (i.e., the highest ones)—are selected. More precisely, using MMSE-based estimation of the R-channels, the amplitudes of the N estimated R-channel coefficients are sorted in decreasing order and the FC selects the P CRs ($P \leq N$) which have highest estimated R-channel coefficients i.e., CRs associated with best estimated R-channel coefficients are selected. The FC fuses the sensing information, received as BPSK signal from the P selected CRs, to obtain a final decision on the presence or absence of the PU. The overall probability of missed detection can be evaluated by using MRC fusion.

The following results are obtained using MATLAB based simulations. The performance of CSS with rank-based censoring for both perfect and imperfect channel estimation cases has been evaluated in Weibull faded and Log-normal shadowed environments. Particularly, the overall missed detection probability (Q_m) is evaluated as function of number (P) of selected CRs, considering the impact of average S-channel SNR ($\bar{\gamma}_s$) and the average R-channel SNRs ($\bar{\gamma}_r$). The results for majority-logic fusion are also shown for comparison purpose.

In Figure 5 and Figure 6, the performance of CSS with rank-based censoring is evaluated in the presence of Weibull fading and Log-normal shadowing, respectively. In both figures, Q_m is shown as a function of number(P) of selected CRs. The results are shown for both the cases with perfect and imperfect channel estimations by performing MRC fusion at FC in both the figures. For comparison purposes, the curves for majority-logic fusion are shown. In Figure 5, the impact of $\bar{\gamma}_r$ and $\bar{\gamma}_s$ on missed detection performanceis investigated. Two values of $\bar{\gamma}_r$ (-8 dB, -6 dB) and two values of $\bar{\gamma}_s$ (15 dB, 20 dB) are considered. When any one of the parameters P, $\bar{\gamma}_r$ and $\bar{\gamma}_s$ increases, Q_m reduces with both perfect and imperfect channel estimations. The probability of incorrect reception from CRs at FC reduces with higher $\bar{\gamma}_r$. As expected, for a given value of the $\bar{\gamma}_r$, Q_m is higher with imperfect channel estimation, as channel-based censoring leads to the selection of a group of CRs which may not be the best ones due to channel estimation errors. Furthermore, according to (38), an increase in $\bar{\gamma}_r$ leads to a decrease in estimation error variance $\sigma^2_{\tilde{h},weib}$ and this, in turns, reduces the average estimation error. A reduced estima-

Figure 5. Performance of CSS in terms of Q_m under perfect and imperfect channel estimation for different values of $\bar{\gamma}_r$, and $\bar{\gamma}_s$ in Weibull faded (v=4) environment (u=5, P_f=0.05, N=30, and rank-based censoring).

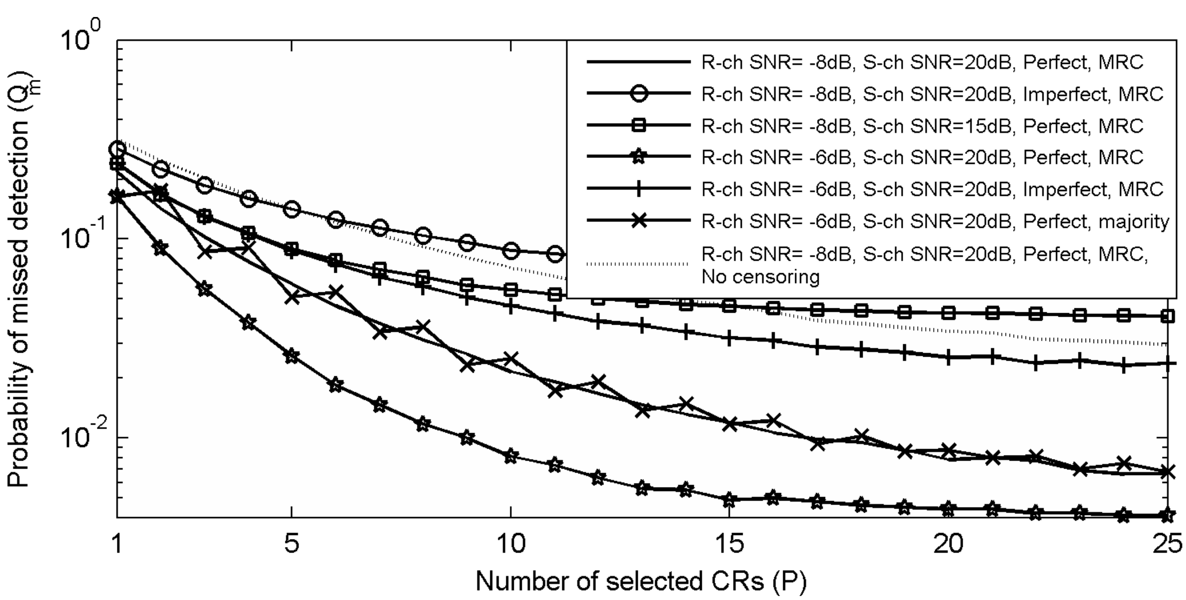
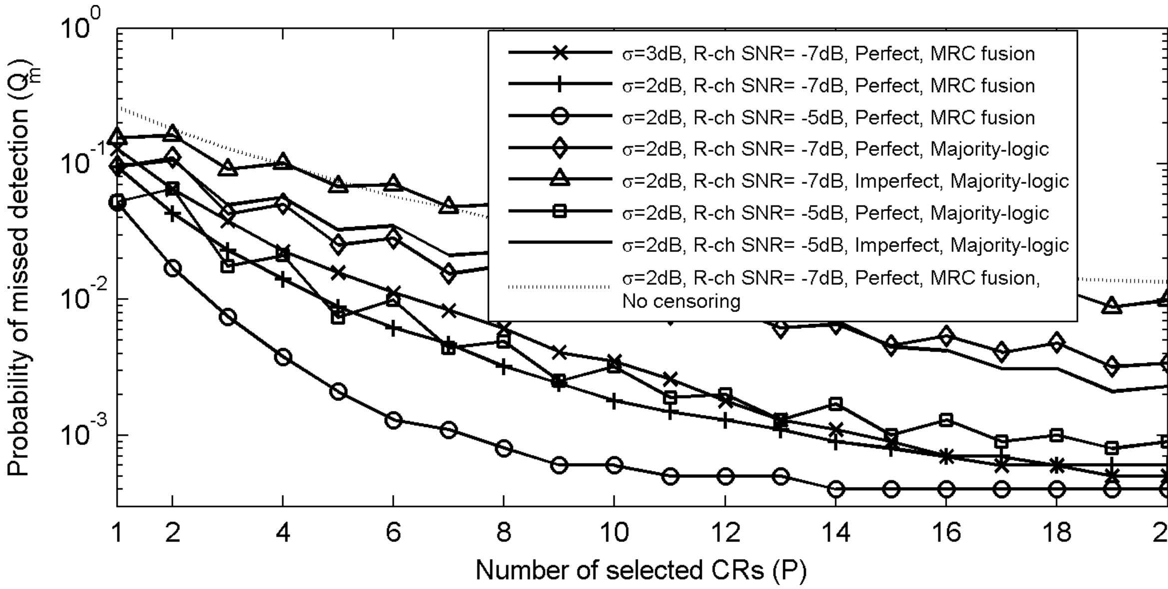


Figure 6. Performance of CSS in terms of Q_m under perfect and imperfect channel estimation for different values of σ, and $\bar{\gamma}_r$ in Log-normal shadowing environment (u=5, P_f=0.05, N=30, and rank-based censoring).



tion error leads to a further reduction of Q_m. In particular, in case of imperfect channel estimation with P=15, Q_m decreases by 59.16% when $\bar{\gamma}_r$ increases from -8 dB to -6 dB. Similarly, in the case of perfect channel estimation, Q_m decreases by 53.76% for the same values of P and $\bar{\gamma}_r$. Higher $\bar{\gamma}_s$ improves the detection of the PU at the CR. For example, in the case of perfect channel estimation with P=12 and $\bar{\gamma}_r$ =-8 dB, as $\bar{\gamma}_s$ increases from 15 dB to 20 dB, Q_m decreases by 73.96%. We observe from Figure 5 that missed detection performance with MRC fusion is better than the performance with majority-logic fusion in both the cases of channel estimations. For example, in case of perfect channel estimation, for P=12, $\bar{\gamma}_r$ = -6 dB and $\bar{\gamma}_s$ =20 dB, Q_m with MRC is 58.47% lower than Q_m with majority-logic fusion. In Figure 6, the missed detection is evaluated for various values of shadowing parameter (σ in dB) and $\bar{\gamma}_r$. It is seen that there is a significant impact of shadowing parameter on missed detection performance. More precisely, the performance degrades for higher value of σ due to increase in value of σ, S/R-channels undergo severe effect of shadowing so that quality of S/R-channels become very poor and erroneous transmission/reception occurs. The Q_m reduces with increase in the value of $\bar{\gamma}_r$ due to reduction of noise effect in the R-channel. Further, MRC fusion provides better performance than majority-logic fusion, though MRC fusion depends on channel estimation. From both Figure 5 and Figure 6, it is observed that in case of majority logic fusion, zigzag nature of the curve may be attributed due to occurrence of tie at FC in the case of even number of selected CRs. However in the case of no censoring, the missed detection probability is seen to be high.

Threshold Based Censoring

In this censoring scheme (Nallagonda, 2013c, 2013d, 2014), a CR (say the k-th) is selected for transmission if the amplitude of the corresponding estimated R-channel coefficient $\hat{h}_k$ is above a censoring threshold (C_{th}). This approach involves two transmission phases: in the first phase, the FC estimates the R-channel corresponding to each CR using MMSE; in the second phase, the FC censors a CR if the corresponding estimated channel coefficient exceeds a chosen threshold C_{th}. In this section, novel analytical expressions, as functions of C_{th}, for the selection of CRs are derived in different channels such as Weibull fading, and Log-normal shadowing channels. The threshold based selection of CRs in the case of Rayleigh faded R-channels is analyzed in (Nallagonda, 2013c, 2013d, 2014). In particular, the probability mass functions (PMF) of the number of censored CRs; the expression for the average missed detection ($\bar{Q}_m$) and false alarm ($\bar{Q}_f$) probabilities are analyzed in the context of Rayleigh fading in R-channel.

Threshold Based Censoring in Weibull Fading and Log-Normal Shadowing Channels

If the amplitude of estimated R-channel fading coefficient is a Weibull distributed random variable, the cumulative distribution function (CDF) of Weibull distributed random variable in terms of C_{th} can be derived as

$$F_{we}(C_{th}) = 1 - \exp(-\{C_{th} / \Omega\}^{v}); \quad C_{th} \geq 0 \tag{41}$$

where v is the Weibull fading parameter which ranges from 1 to ∞ and $\Omega = 1$. Now the probability of selecting a CR in Weibull faded R-channel can be derived as

$$\begin{aligned} p_{we} &= \Pr(|\hat{h}_k| > C_{th}) \\ &= 1 - F_{we}(C_{th}) \\ &= \exp(-\{C_{th} / \Omega\}^{v}) \end{aligned} \tag{42}$$

Similarly, in case of Log-normal shadowing, amplitude of estimated R-channel coefficient is a Log-normal distributed random variable, so the CDF of Log-normal distributed RV in terms of C_{th} can be derived as

$$F_{we}(C_{th}) = \frac{1}{2} erfc\left(-\frac{\ln C_{th}}{\sigma\sqrt{2}}\right); \quad C_{th} \geq 0 \tag{43}$$

where erfc (.) is complementary error function, σ is the Log-normal shadowing parameter generally expressed in dB. Then the probability of selecting a CR for Log-normal shadowing channel can be derived as

$$p_{\ln} = \Pr\left(| \hat{h}_k | > C_{th} \right) = 1 - \frac{1}{2} erfc\left(-\frac{\ln C_{th}}{\sigma\sqrt{2}} \right) \quad (44)$$

The probability of selecting K number of CRs from N available CRs can now be expressed by utilizing the binomial distribution function as follows (Nallagonda, 2013c, 2013d, 2014)

$$P(K) = \binom{N}{K} p^K (1-p)^{(N_1 - K)} \quad (45)$$

where p is p_{we} or $p_{\ln}$ depends on censoring in Weibull or log-normal channels.

Let $P_m(\text{error} \mid K)$ indicates the conditional missed detection probability when sensing information from K number of CRs are fused using MRC fusion. Given $P(K)$, the probability of selecting K number of CRs in (45), the average probabilities of missed detection and false alarm can be expressed following (Nallagonda, 2013c, 2013d, 2014) as:

$$\bar{Q}_m = P(\text{missed detection}) = \sum_{K=0}^{N_1} P_m(\text{error} \mid K)\ P(K) \quad (46)$$

$$\bar{Q}_f = P(\text{false alarm}) = \sum_{K=0}^{N_1} P_f(\text{error} \mid K)\ P(K) \quad (47)$$

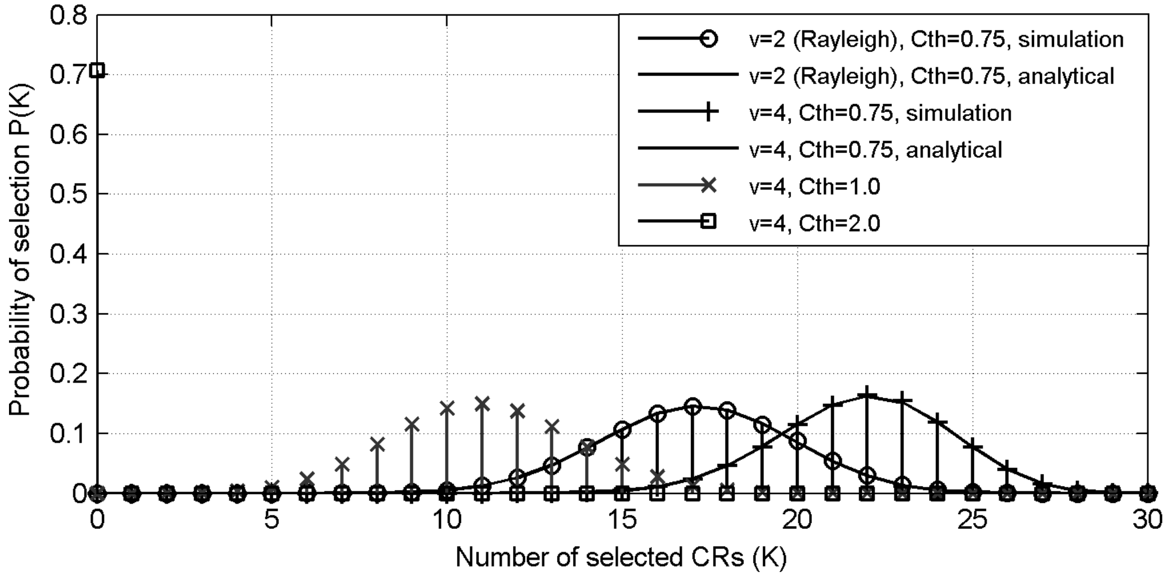
The $\bar{Q}_m$ and $\bar{Q}_f$ are the function of chosen C_{th}, as the probability of mass function (pmf) {$P(K)$} of the number of censored CRs depends on C_{th}. It may be noted that $P_m(\text{error} \mid K)$ and $P_f(\text{error} \mid K)$ are evaluated here considering sensing information from K selected CRs.

Results

The following results are obtained, as in the previous sections, using MATLAB based simulations. The performance of CSS with threshold based censoring for both the perfect and imperfect channel estimation cases has been evaluated in Weibull fading and Log-normal shadowing environments. The average missed detection probability is evaluated as a function of C_{th} considering the impact of various network parameters, such as the Weibull fading parameter (v), shadowing parameter (σ in dB), the number of available CR users (N), and the average R-channel SNRs ($\bar{\gamma}_r$).

In Figure 7, the binomially distributed probability mass fusion (PMF) of the number of selected CRs is shown for different values of v and C_{th} under perfect channel estimation. We observe that as v increases from 2 to 4, the binomially-distributed PMF is shifted right side i.e. more number of CRs is selected by reducing the fading severity in the R-channel. The binomially distributed PMF of the number of selected CR users as obtained for v=2 matches exactly with result obtained for Rayleigh (Figure 7.7, Nallagonda, 2014) under perfect channel estimation. In the same figure, the effects of C_{th} on the probability of select-

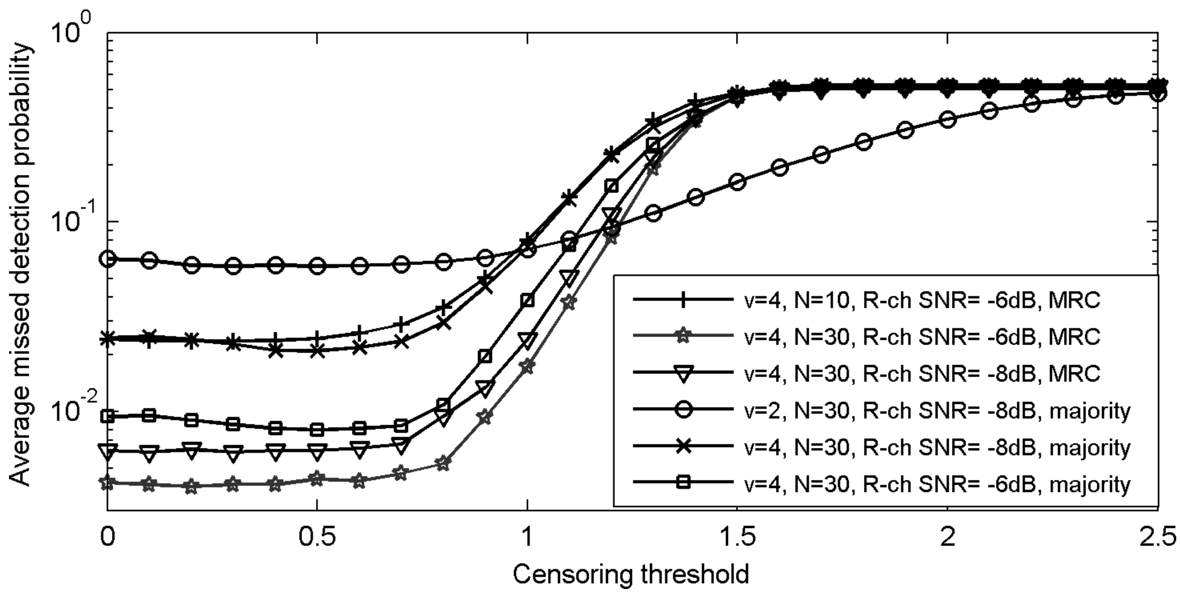
Figure 7. PMF of the number of selected CR users for different values of v, and C_{th}, under perfect channel estimation in Weibull faded environment (N=30)



ing K number of CRs, i.e., on the value of $P(K)$, is also shown. It can be observed that for small values of C_{th}, a larger number of CRs is likely to be selected, while the PMF tends to concentrate around small values for higher values of C_{th}. For example, for v=4, and C_{th}=0.75, it is seen that K=22 CRs have highest probability (0.17) of being selected. One can also observe that as C_{th} increases, the PMF moves towards origin. This is due to the fact that a larger value of C_{th} decreases the number of selected CRs. If the value of C_{th} is increased to a very high level (say C_{th} =3.5), no CR is selected to transmit, i.e., the probability of selecting no CR is equal to 1 ($P(0) = 1$). The binomially distributed PMF of the number of selected CRs obtained with our simulation test bed confirms that obtained based on the analytical expression (Equation 42 followed by Equation 45). This validates our analytical framework.

In Figure 8, $\bar{Q}_m$ is shown as a function of the C_{th} in presence of Weibull fading. Various values of N (i.e. N=10, and 30) and of $\bar{\gamma}_r$ ($\bar{\gamma}_r$=-8 dB, -6 dB) are considered. Two fusion rules such as majority-logic fusion and MRC fusion have been performed separately at FC. The performance comparison between these two fusions is evaluated considering perfect channel estimation case. It can be seen from this figure that as C_{th} increases $\bar{Q}_m$ attains a minimum value for an 'optimal' C_{th} level and thereafter increases with further increase in C_{th} to finally attain a value of 0.5. This behavior of $\bar{Q}_m$ is due to the changing PMF of the number of censored CRs for various values of C_{th}. For very small values of the C_{th}, even unreliable links tend to be selected, and $\bar{Q}_m$ is rather high. On the other hand, as C_{th} is increased to a very high level, no CR is selected to transmit, i.e. $P(0)$ =1, and the FC takes a decision by flipping a fair coin resulting in $\bar{Q}_m$ of 0.5. Therefore, there exists an optimal value of C_{th}, in correspondence to which $\bar{Q}_m$ is minimized. It can be seen that a larger value of N leads to a reduced $\bar{Q}_m$ in correspondence to the optimized value of C_{th}. In particular, for C_{th}=0.5 and $\bar{\gamma}_r$=-6 dB, $\bar{Q}_m$ decreases by 81.81% when N increases from 10 to 30. When $\bar{\gamma}_r$ increases, the FC receives a larger number of correct decisions (large

Figure 8. Average missed detection probability ($\bar{Q}_m$) as a function of C_{th} for various values of v, N, and $\bar{\gamma}_r$ under perfect channel estimation in Weibull fading ($\bar{\gamma}_s$ =20 dB, P_f=0.05, and u=5)



number of CRs selected) and this, in turn, leads to a reduction in $\bar{Q}_m$. The optimum value of C_{th} depends on network parameters. Furthermore, the MRC fusion-based CSS outperforms the majority-logic fusion-based CSS for the same values of network parameters.

Figure 9. and Figure 10 show the impacts of σ on binomially-distributed PMF of the number of selected CRs, and on the average missed detection performance, respectively. Different values of σ (σ

Figure 9. PMF of the number of selected CR users for different values of σ and C_{th} under perfect channel estimation in Log-normal shadowing environment (N=30).

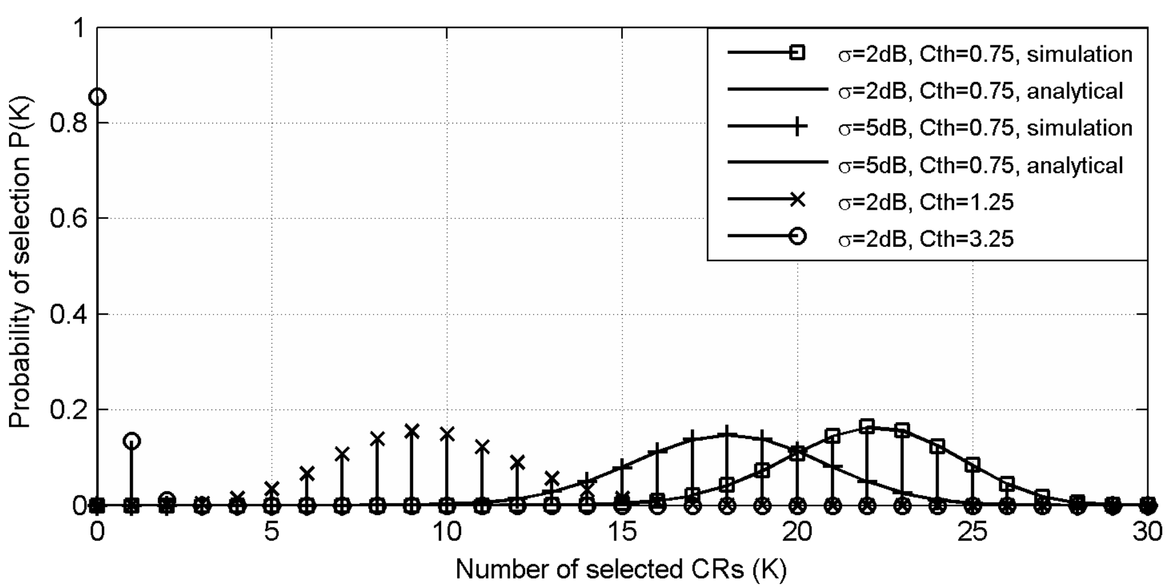
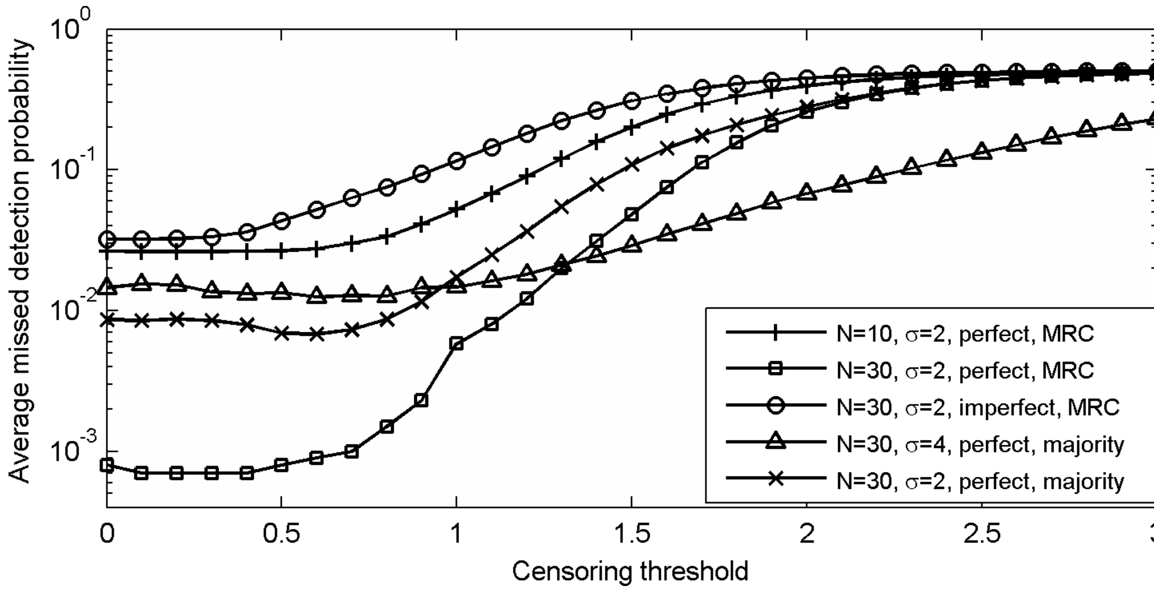


Figure 10. Average missed detection probability ($\bar{Q}_m$) as a function of C_{th} for various values of N, and σ under perfect and imperfect channel estimations in Log-normal shadowing ($\bar{\gamma}_s$=20 dB, $\bar{\gamma}_r$=-8 dB P_f=0.05, and u=5).



=2 dB, 4 dB, and 5 dB) are considered for these figures. In Figure 9, it is seen that when σ increases from 2 to 5, the PMF is shifted towards origin, it means that probability of selecting K number of CRs decreases due to increase in severity of shadowing effect in the R-channel. Due to this reason, the missed detection performance degrades with increase in parameter σ from 2 to 4 as shown in Figure 10. In Figure 10, the performance is evaluated by performing majority-logic, and MRC fusions individually at FC. We observe that there is an improvement in performance of CSS by increasing number of CRs in the network. The binomially distributed PMF of the number of selected CR users as obtained based on our simulation test bed matches exactly with result obtained based on the analytical expression given in equations (Equation 44 followed by Equation 45), which validates our simulation test bed. Furthermore, in presence of shadowing also, the MRC fusion provides better results as compared to the results with majority-logic fusion.

The considered framework can be applied to a spectrum overlaid cognitive radio network where secondary users need to identify spectrum holes. Our censoring scheme saves energy by not allowing transmissions from CRs whose R-channels are deeply faded. The scheme is energy efficient—even though the FC, which is not energy constrained, needs to spend some energy for MRC operation.

FUTURE RESEARCH DIRECTIONS

Future work might be to perform censoring not only on basis of R-channel quality but also to consider reliability of CR's decisions along with R-channel quality. Thus censoring could be done on the basis of some combined metric assigning appropriate weight to each of R-channel quality and decision reliability of CR. Further censoring could be pursued to achieve certain target objectives such as energy efficiency, a given level of sensing throughput, agility etc.

CONCLUSION

In this chapter, the performance of cooperative spectrum sensing (CSS) using energy detection with and without censoring in Weibull fading and Log-normal shadowing channels has been investigated. The performance of a few hard decision fusion rules (OR-rule, AND-rule, and majority-rule) and a soft data fusion rule (MRC fusion) has been analyzed in a comparative way, considering meaningful performance metrics and evaluating the impact of several system parameters. Our results show that in case of CSS with CRs using ED achieves the lowest probability of missed detection with MRC fusion, as compared to OR-rule, AND-rule, majority-rule fusions, under the same conditions in both the Weibull and Log-normal shadowing channels. We have also investigated the performance of CSS with CRs censored on the basis of the quality of the R-channels, considering both Weibull and Log-normal shadowing channels. The performance with perfect and imperfect channel estimation has been analyzed, in a comparative way, under MRC fusion. Our results show that missed detection probability reduces for increasing values of the number of selected CRs, regardless of the channel estimation quality (perfect or imperfect). However, in the presence of perfect channel estimation no further improvement, in terms of missed detection probability, is obtained by increasing the number of selected CRs beyond a given limit. The fading parameter and the R-/S-channel SNRs have a significant impact on the missed detection probability. The censoring threshold for the selection of CRs has a significant impact on the average missed detection probability. Depending on the configuration of relevant network parameters, such as the available number of CRs, fading/shadowing parameters, and the average R-channel SNRs, there exists an optimal censoring threshold, which corresponds to the minimum average missed detection probability, for both the perfect and imperfect channel estimation. The framework presented in this chapter is useful in designing a cooperative spectrum sensing scheme able to prolong the lifetime of an energy-constrained cognitive radio network by minimizing the number of less useful transmissions.

REFERENCES

Abdi, Y., & Ristaniemi, T. (2013). Joint reporting and linear fusion optimization in Collaborative Spectrum Sensing for cognitive radio networks. In *Proceedings of 9th International Conference on Information, Communications and Signal Processing (ICICS)*. Academic Press. doi:10.1109/ICICS.2013.6782816

Adawi, N. S. (1988). Coverage prediction for mobile radio systems operating in the 800/900 MHz frequency range. *Transactions on Vehicular Technology*, *37*(1), 3–72. doi:10.1109/25.42678

Akyildiz, I. F., Lee, W. Y., Vuran, M. C., & Mohanty, S. (2006). Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Computer Networks*, *50*(13), 2127–2159. doi:10.1016/j.comnet.2006.05.001

Altay, C., Yilmaz, H. B., & Tugcu, T. (2012). Cooperative sensing analysis under imperfect reporting channel. In *Proceedings of IEEE Symposium on Computers and Communications (ISCC)*. IEEE. doi:10.1109/ISCC.2012.6249392

Cabric, S. D., Mishra, S. M., & Brodersen, R. W. (2004). Implementation issues in spectrum sensing for cognitive radios. In *Proceedings of the Asilomar Conference on Signals, Systems, and Computers*, (*Vol. 1*, pp. 772-776). Academic Press. doi:10.1109/ACSSC.2004.1399240

Chaudhari, S., & Koivunen, V. (2013). Impact of reporting-channel coding on the performance of distributed sequential sensing. In *Proceeding of IEEE 14th Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*. IEEE.

Chaudhari, S., & Lunden, J., & Koivunen, V. (2012a). Cooperative Sensing with Imperfect Reporting Channels: Hard Decisions or Soft Decisions. *IEEE Transactions on Signal Processing*. doi:10.1109/TSP.2011.2170978

Chaudhari, S., Lunden, J., & Koivunen, V. (2012b). Effects of quantization and channel errors on sequential detection in cognitive radios. In *Proceeding of 46th Annual Conference on Information Sciences and Systems (CISS)*. CISS.

Cui, C., & Wang, Y. (2013, October). Analysis and Optimization of Sensing Reliability for Relay-Based Dual-Stage Collaborative Spectrum Sensing in Cognitive Radio Networks. *Wireless Personal Communications*, *72*(4), 2321–2337. doi:10.1007/s11277-013-1152-6

Digham, F. F., Alouini, M. S., & Simon, M. K. (2003). On the energy detection of unknown signals overfading channels. In *Proceedings of the International conference on Communications*, (*Vol. 5*, pp. 3575-3579). Academic Press.

Fathi, Y., & Tawfik, M. H. (2012). Versatile performance expression for energy detector over á-µ generalized fading channels. *Electronics Letters*, *48*(17), 1081–1082. doi:10.1049/el.2012.1744

Ferrari, G., & Pagliari, R. (2006). Decentralized binary detection with noisy communication links. *Transactions on Aerospace Electronic Systems*, *42*(4), 1554–1563. doi:10.1109/TAES.2006.314597

Ghasemi, A., & Sousa, E. S. (2005). Collaborative spectrum sensing for opportunistic access in fading environments. In *Proceedings of the International Symposium on Dynamic Spectrum Access Networks* (pp. 131-136). Baltimore, MD: Academic Press. doi:10.1109/DYSPAN.2005.1542627

Ghasemi, A., & Sousa, E. S. (2007). Opportunistic spectrum access in fading channels through collaborative sensing. *Journal on Selected Areas in Communications*, *2*(2), 71-82.

Hamza Mohamed, D., Aissa, S., & Aniba, G. (2014). Equal Gain Combining for Cooperative Spectrum Sensing in Cognitive Radio Networks. *IEEE Transactions on Wireless Communications*. doi:10.1109/TWC.2014.2317788

Han, W., Li, J., Li, Z., Si, J., Zhang, Y. (2013). Efficient Soft Decision Fusion Rule in Cooperative Spectrum Sensing. *IEEE Transactions on Signal Processing*, *61*(8), 1931-1943. doi:10.1109/TSP.2013.2245659

Hashemi, H. (1993). The indoor radio propagation channel. *Proceedings of the IEEE*, *81*(7), 943–968. doi:10.1109/5.231342

Haykin, S. (2005). Cognitive radio: Brain-empowered wireless communications. *Journal on Selected Areas in Communications*, *23*(2), 201–220. doi:10.1109/JSAC.2004.839380

Ismail, M. H., & Matalgah, M. M. (2006). BER analysis of BPSK modulation over the Weibull fading channel with CCI. In *Proceedings of the Vehicular Technology Conference* (pp. 1-5). Montreal, Canada: Academic Press. doi:10.1109/VTCF.2006.334

Ma, J., Zhao, G., & Li, Y. (2008). Soft combination and detection for cooperative spectrum sensing in cognitive radio networks. *Transactions on Wireless Communications*, *7*(11), 4502–4507. doi:10.1109/T-WC.2008.070941

Mitola, J., & Maguire, G. (1999). Cognitive radio: Making software radios more personal. *Personal Communications*, *6*(4), 13–18. doi:10.1109/98.788210

Nallagonda, S., Shravan kumar, B., Roy, S. D., & Kundu, S. (2013a). Performance of cooperative spectrum sensing with soft data fusion schemes in fading channels. In *Proceedings of the India Conference* (pp. 1-5). IIT Kanpur. doi:10.1109/INDCON.2013.6725924

Nallagonda, S., Roy, S. D., & Kundu, S. (2011a). Performance of energy detection based spectrum sensing in fading channels. In *Proceedings of the Computer & Communication Technology* (pp. 575-580). Allahabad, India: Academic Press. doi:10.1109/ICCCT.2011.6075107

Nallagonda, S., Roy, S. D., & Kundu, S. (2011b). Performance of Cooperative Spectrum Sensing in Rician andWeibull Fading Channels. In *Proceedings of the India Conference* (pp. 1-5). Hyderabad, India: Academic Press.

Nallagonda, S., Roy, S. D., & Kundu, S. (2012). Performance of cooperative spectrum sensing in Fading Channels. In *Proceedings of the Recent Advances in Information Technology* (pp. 1-6). ISM Dhanbad. doi:10.1109/RAIT.2012.6194506

Nallagonda, S., Roy, S. D., & Kundu, S. (2013b). Performance evaluation of cooperative spectrum sensing with censoring of cognitive radios in Rayleigh fading channel. *Wireless Personal Communications*, *70*(4), 1409–1424. doi:10.1007/s11277-012-0756-6

Nallagonda, S., Roy, S. D., Kundu, S., Ferrari, G., & Raheli, R. (2013c). Cooperative spectrum sensing with censoring of cognitive radios in Rayleigh fading under majority logic fusion. In *Proceedings of the National Conference on Communications* (pp. 1-5). IIT Delhi. doi:10.1109/NCC.2013.6487926

Nallagonda, S., Roy, S. D., Kundu, S., Ferrari, G., & Raheli, R. (2013d). Performance of MRC fusion based cooperative spectrum sensing with censoring of cognitive radios in Rayleigh fading channel. In *Proceedings of the Wireless Communications and Mobile Computing Conference* (pp. 30-35). Sardinia, Italy: Academic Press. doi:10.1109/IWCMC.2013.6583530

Nallagonda, S., Roy, S. D., Kundu, S., Ferrari, G., & Raheli, R. (2014). Cooperative spectrum sensing with censoring of cognitive radios in fading channel under majority logic fusion. In F. Bader & M. G. Di Benedetto (Eds.), Cognitive Communications and Cooperative HetNet Coexistence (pp. 133-161), Springer International Publishing. doi:10.1007/978-3-319-01402-9_7

Niu, R., Chen, B., & Varshney, P. K. (2003). Decision fusion rules in wireless sensor networks using fading statistics. In *Proceedings of the Annual Conference on Information Sciences and Systems* (pp. 1-6). The Johns Hopkins University.

Paula, A. D., & Panazio, C. (2014). Cooperative spectrum sensing under unreliable reporting channels. Elsevier.

Sagias, N. C., Karagiannidis, G. K., & Tombras, G. S. (2004). Error-rate analysis of switched diversity receivers in Weibull fading. *Electronics Letters*, *40*(11), 681–682. doi:10.1049/el:20040479

Simon, M. K., & Alouini, M. S. (2004). *Digital Communication over Fading Channels* (2nd ed.). John Wiley and Sons. doi:10.1002/0471715220

Sun, H., Nallanathan, A., Jiang, J., & Wang, C. X. (2011). Cooperative spectrum sensing with diversity reception in cognitive radios. In *Proceedings of the International Conference on Communications and Networking in China* (216-220). Harbin, China: Academic Press. doi:10.1109/ChinaCom.2011.6158151

Teguig, D., Scheers, B., & Nir, V. L. (2012). Data fusion schemes for cooperative spectrum sensing in cognitive radio networks. In *Proceedings of the Military Communications and Information Systems Conference* (pp. 1-7). Gdansk, Poland: Academic Press.

Urkowitz, H. (1967). Energy detection of unknown deterministic signals. *Proceedings of the IEEE*, *55*(4), 523–531. doi:10.1109/PROC.1967.5573

Zhang, W., Mallik, R. K., & Letaief, K. B. (2008). Cooperative spectrum sensing optimization in cognitive radio networks. In *Proceedings of the International conference on Communications* (pp. 3411-3415). Beijing, China: Academic Press. doi:10.1109/ICC.2008.641

Zhao, N., Pu, F., Xu, X., & Chen, N. (2013). Optimization of multi-channel cooperative sensing in cognitive radio networks. *IET Communications*, *7*(12), 1177–1190. doi:10.1049/iet-com.2012.0748

Zhao, Y., Kang, G., Wang, J., Liang, X., & Liu, Y. (2013). A soft fusion scheme for cooperative spectrum sensing based on the log-likelihood ratio. In *Proceedings of IEEE 24th International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC)*. IEEE. doi:10.1109/PIMRC.2013.6666688

Zou, Y., Yao, Y. D., & Zheng, B. (2011). A selective-relay based cooperative spectrum sensing scheme without dedicated reporting channels in cognitive radio networks. *Transactions on Wireless Communications*, *10*(4), 1188–1198. doi:10.1109/TWC.2011.021611.100913

KEY TERMS AND DEFINITIONS

Cooperative Spectrum Sensing: A technique where the Cognitive radios share their individual sensing information to improve the over all sensing information about the primary user.

Fading Channels: A wireless communication channel undergoing fading which may either be due to multipath propagation, referred to as multipath induced fading, or due to shadowing from obstacles affecting the wave propagation, sometimes referred to as shadow fading.

Fusion Rules: Schemes for combining local decisions to obtain a global decision.

Censoring: Allowing to send information.

Missed Detection: The situation of not detecting the PU/ target.

MRC (Maximal Ratio Combining): Is a diversity combining technique in which signals from several branch or channel are added together with the gain of each channel is made proportional to the rms signal level and inversely proportional to the mean square noise in that channel.

MMSE: In signal processing, a minimum mean square error (MMSE) estimator is an estimation method which minimizes the mean square error (MSE) of the estimated value and the actual value of a desired random variable. This is a common measure of estimator quality.

ENDNOTE

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