Energy-Efficient Spectrum Sensing for Cognitive Radio Networks

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Energy-Efficient Spectrum Sensing for Cognitive Radio Networks

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Summary

Dynamic spectrum access employing cognitive radios has been proposed, in order to opportunistically use underutilized spectrum portions of a heavily licensed electromagnetic spectrum. Cognitive radios opportunistically share the spectrum, while avoiding any harmful interference to the primary licensed users. One major category of cognitive radios consists of is interweave cognitive radios. In this category, cognitive radios employ spectrum sensing to detect the empty bands of the radio spectrum, also known as spectrum holes. Upon detection of such a spectrum hole, cognitive radios dynamically share this empty band. However, as soon as the primary user appears in the corresponding band, cognitive radios have to vacate the band and look for a new spectrum hole. This way, reliable spectrum sensing becomes a key functionality of a cognitive radio network.

The hidden terminal problem and fading effects have been shown to limit the reliability of spectrum sensing. Distributed cooperative detection has therefore been proposed to improve the detection performance of a cognitive radio network. In this thesis, a distributed detection scheme based on hard fusion of local results is considered. Each cognitive radio senses the spectrum and sends the result to the fusion center, and there the final decision is made about the presence or absence of the primary user. Note that, in general, cognitive radios are low-power sensors and thus energy consumption becomes a critical issue.

In this thesis, several energy-efficient approaches are proposed, in order to minimize the maximum average energy consumption per sensor, while satisfying the sensing reliability of the cognitive radio network. The sensing reliability is defined by a lower bound on the probability of detection and an upper bound on the probability of false alarm. This way, the primary user is protected from the cognitive radio transmitters interference and also the chance of losing spectrum access through erroneous detection of the primary user in an empty band is constrained. First, a censoring scheme is considered where cognitive radios send their results to the fusion center only if they are deemed to be informative. Second, a combined censoring and truncated sequential sensing scheme is depicted which is shown to be more energy-efficient than the former case due to the sensing energy reduction. And third, a combined censoring and sleeping scheme is discussed where on top of censoring, each cognitive radio switches off its sensing module with a specific sleeping rate, in order to save energy both on transmission and sensing. It is shown that all the proposed schemes, particularly combined censoring and sleeping as well as censored truncated sequential sensing delivers significant energy savings. Further, we conclude that when a cognitive radio system is appropriately well-designed in terms of energy efficiency, increasing the number of cooperative cognitive sensors, not only improves the detection performance, but also reduces the average energy consumption of individual cognitive radios.

Finally, an optimal fusion strategy for energy-constrained hard-fusion based cognitive radio networks is presented, which optimizes the network throughput subject to a constraint on the average energy consumption of individual radios and a constraint on the amount of interference to the primary user. It is shown that the majority rule is either optimal or close to optimal in terms of the network throughput.

Glossary

Mathematical Notation

x	Scalar x
$\mathbf{x}$	Vector $\mathbf{x}$
$\mathbf{X}$	Matrix $\mathbf{X}$
$\mathbf{X}^T$	Transpose of matrix $\mathbf{X}$
$\mathbf{X}^H$	Hermitian transpose of matrix $\mathbf{X}$
$\mathbf{X}^{-1}$	inverse of matrix $\mathbf{X}$
$\Re\{x\}$	Real part of x
$\Im\{x\}$	Imaginary part of x
$\hat{x}$	Estimate of x
$\overline{x}$	Average of x
$\lvert x\rvert$	Modulus of x
$\lfloor x \rfloor$	Largest integer smaller or equal to x
$\lceil x \rceil$	Smallest integer larger or equal to x
$E(x)$	Expectation of random variable x
$Pr(x)$	Probability of x
σ_x^2	Variance of x
$\odot$	Hadamard (element-wise) product
$\mathscr{H}_0$	Absence of the primary user
$\mathscr{H}_1$	Presence of the primary user
h	Channel gain
s	Primary user signal modulus

s_i	Primary user signal at i-th time slot
w	Noise
$\mathscr{E}$	Calculated energy by the energy detector
P_f	Local probability of false alarm
P_d	Local probability of detection
λ	Detection threshold
λ_1	Lower detection threshold in censoring
λ_2	Upper detection threshold in censoring
a	Lower detection threshold in truncated sequential sensing
b	Upper detection threshold in truncated sequential sensing
N	Number of samples, Truncation Point
M	Number of cognitive radios
Q	Q-function
C_s	Sensing energy per sample
C_t	Transmission energy per bit
$\Gamma(x)$	Gamma function
$\Gamma(a,x)$	Incomplete gamma function
ρ	Average censoring rate
μ	Average sleeping rate
δ_0	Average censoring rate when the primary user is absent
δ_1	Average censoring rate when the primary user is present
γ	Signal-to-Noise-Ratio (SNR)
π_0	$Pr(\mathscr{H}_0)$, probability of the primary user absence
π_1	$Pr(\mathscr{H}_1)$, probability of the primary user presence
Q_F	Global probability of false alarm
Q_D	Global probability of detection
D_{FC}	Final decision at the fusion center
α	Probability of false alarm constraint
β	Probability of detection constraint
T_s	Sensing time
T_r	Reporting time

Acronyms and Abbreviations

ASN	Average sample number

Glossary

AWGN	Additive-white-Gaussian-noise
B	Bayesian criteria
CR	Cognitive radio, secondary user, cognitive sensor
FC	Fusion center
FCC	Federal Communications Commission
LLR	Log-likelihood ratio (test)
LRT	Likelihood ratio test
NP	Neyman-Pearson criteria
OFDM	Orthogonal frequency division multiplexing
PR	Primary user, licensed user
SPRT	Sequential probability ratio test
SNR	Signal-to-Noise Ratio
TDMA	Time-division-multiple-access

Contents

Chapter 1

Introduction

In this thesis, we consider designing energy-efficient spectrum sensing algorithms for cognitive radio networks. The purpose of this chapter is to motivate and introduce the problems addressed in the thesis, and describe our main contributions and the organization of the thesis.

1.1 Motivation

Wireless technologies have progressed rapidly during the recent years and have lead to a high demand for electromagnetic spectrum. The radio spectrum has been traditionally regularized for exploitation by licensed users, but as is depicted in Fig. 1.1 this policy now results in spectrum scarcity [4]. Meanwhile, recent studies on spectrum utilization show that large parts of the licensed spectrum are highly underutilized in vast geographical locations and time periods [1], [2], [3]. Figures 1.2 and 1.3 are examples of such studies. Dynamic spectrum access based on cognitive radios has been proposed in order to opportunistically use these underutilized spectrum portions [4]. Regulatory bodies are currently working on the standardization, regulation, and modeling of such technologies with the goal of reaching a higher spectrum efficiency and availability for future wireless technologies [5], [6], [7], [8]. This thesis is inspired by the FCC Report and Order permitting the operation of networks consisting of low-power devices and sensors in the VHF-UHF band [5] as well as by the IEEE 802.22 work group regulating the dynamic spectrum access for TV bands and wireless microphones [8]. More recently, standardization of dynamic spectrum sharing of the 2.36-2.4 GHz band for body sensor networks has been initiated by the FCC [6] where all secondary users are consisting of low-power wireless devices.

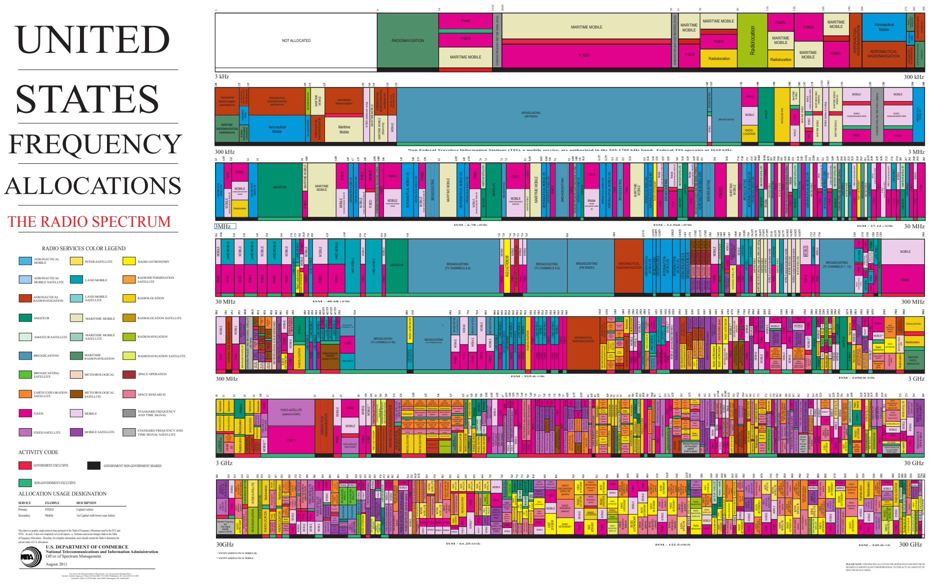
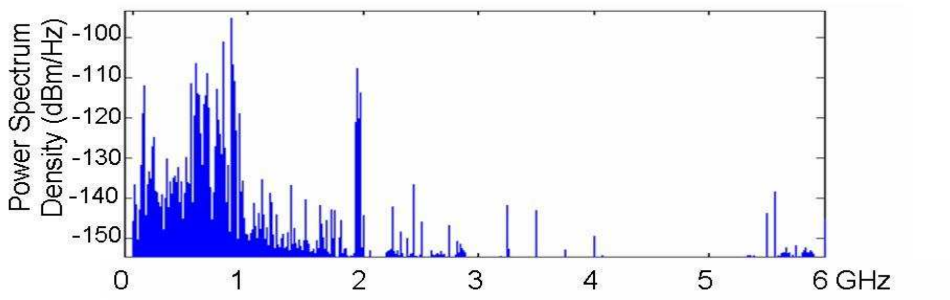


Figure 1.1: *The NTIA's Frequency Allocation Chart [5]*



Freq (GHz)	0~1	1~2	2~3	3~4	4~5	5~6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Figure 1.2: *Measurement of Spectrum Utilization (0-6 GHz) in the Downtown Berkeley [70]*

1.1.1 Cognitive radio

Cognitive radios are wireless radios that opportunistically share the spectrum while avoiding any imposed harmful interference to the primary licensed users. Depending on the way that cognitive radios tackle the problem of interference to the primary

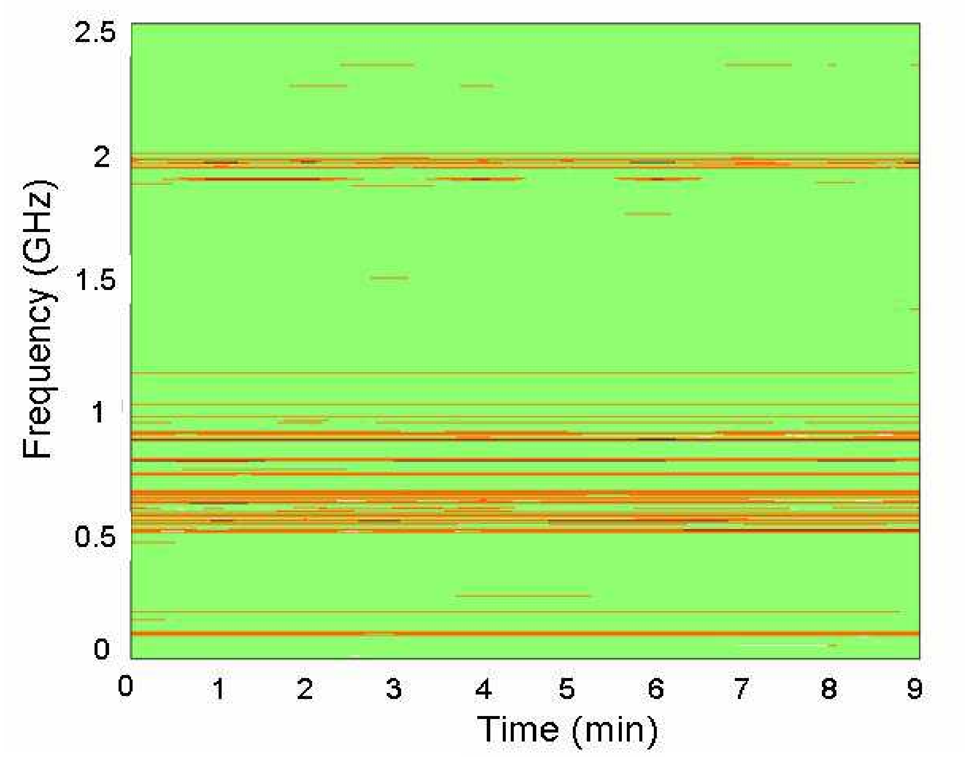


Figure 1.3: *Temporal Variation of the Spectrum Utilization (0-2.5 GHz) in the Downtown Berkeley [70]. Green color represents licensed user inactivity.*

user, three categories of cognitive radios are defined. These categories are underlay, overlay and spectrum-sensing (or interweave) cognitive radios.

In underlay and overlay systems, the cognitive radios are transmitting at the same time with primary users within the same band, while keeping their interference below a certain level as shown in Fig. 1.4. The difference between the underlay and overlay cognitive radios is that in the underlay systems, cognitive radios need to access the channel side information and in the overlay systems they need to have knowledge about the codebook side information and messages that the primary users send [69]. Several techniques have been proposed in order to accomplish this task. For example, an interference alignment scheme is considered in [85], in order to mitigate the effect of cognitive radio transmitters at the primary receiver, while cognitive transmitter signals remain resolvable at the cognitive receivers. [83] proposed a decode-and-forward technique where the secondary transmitters and receivers are able to decode the primary transmitter signal. The secondary transmitter regenerates the received primary signal and combines it with the secondary signal with a normalization factor. This data is then sent to the secondary receiver which can also be received by the primary receiver. It is shown that with a proper choice of the normalized factor, the outage probability of the primary transmitter remains the same or even better than for the case without spectrum coexistence. An extension of this technique to a case with multiple primary transmitters is considered in [84]. In [81] and [82], the secondary user spectrum is shaped in order to limit the amount of interference made to the primary user.

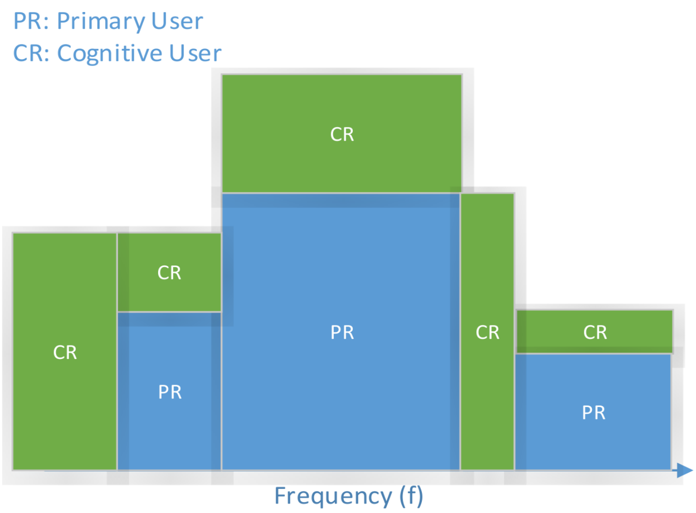


Figure 1.4: *Underlay and overlay cognitive radios*

Interweave cognitive radios, on the other hand, employ spectrum sensing to detect the empty portions of the radio spectrum as shown in Fig. 1.5 (also known as spectrum holes) at a certain time and geographical location. Upon detection of such a spectrum hole, cognitive radios dynamically share this hole by adapting their transmission power and modulation according to the available resources and the surrounding environment [78]. However, as soon as a primary user appears in the corresponding band, the cognitive radios have to vacate the band. This way, transmission is limited to the bands that are deemed to be empty in order to avoid interference to the primary users. In order to accomplish these tasks, a harmonious cooperation among cognitive users is required which is coordinated through a dedicated control channel [80]. In this thesis, our focus is on this category of cognitive radios and whenever we talk about a cognitive radio, we mean an interweave cognitive radio. A comparison of the different categories of cognitive radios is provided in Table 1.1 in terms of required cognition level, pros, and cons.

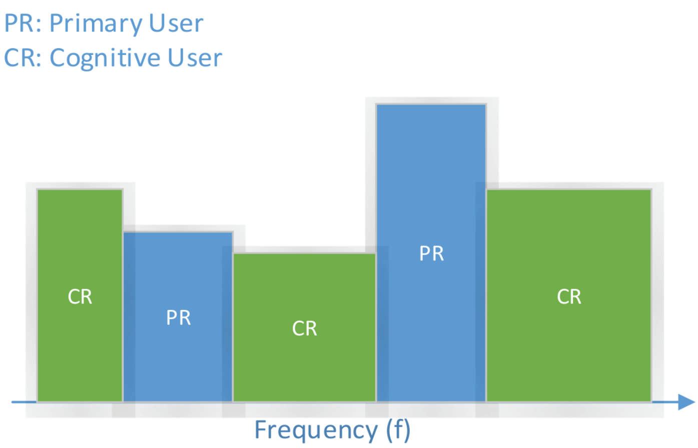


Figure 1.5: *Interweave cognitive radios*

Type of Cognitive Radio	Required Cognition Level	Pros	Cons
Interweave	Knowledge of spectrum holes	No knowledge about the primary user channel and signal is required. Partial knowledge about the primary signal such as cyclostationarity can improve the sensing reliability to an acceptable level.	Sensitive to the noise uncertainty, RF front-end impairments,... Part of the time frame is wasted on sensing.
Underlay	Knowledge of the primary channel	Concurrent transmission with primary signal is possible.	Acquiring perfect primary channel side information is difficult.
Overlay	Knowledge of the primary signal codebook	Achieving higher rates than the other two models. Concurrent transmission with primary signal is possible.	Acquiring knowledge of the primary codebook needs total cooperation from the primary user.

Table 1.1: *Comparison of the interweave, underlay, and overlay cognitive radios.*

1.1.2 Spectrum sensing

Considering the cognitive radio tasks mentioned above, finding a spectrum hole is the starting point for any cognitive activity. As such, reliable spectrum sensing becomes a key functionality of a cognitive radio network. It needs to be highly reliable to avoid any unacceptable interference to the primary user while fast to increase the achievable throughput of the cognitive radio system. Spectrum sensing has been studied extensively in literature. Denoting $\mathbf{r}$ as the received signal vector, $\mathbf{w}$ as the noise vector, $\mathbf{s}$ as the primary user signal vector and $\mathbf{h}$ as the channel gain vector between the primary transmitter and cognitive sensor, the goal of spectrum sensing is to solve a hypothesis testing problem as follows

$$\begin{aligned} \mathscr{H}_0 &: \ \mathbf{r} = \mathbf{w} \\ \mathscr{H}_1 &: \ \mathbf{r} = \mathbf{h} \odot \mathbf{s} + \mathbf{w}, \end{aligned} \tag{1.1}$$

where $\mathscr{H}_0$ denotes the primary user absence, $\mathscr{H}_1$ denotes the primary user presence, $\odot$ denotes the element-wise product.

Spectrum sensing techniques in order to solve (1.1) are generally categorized as matched filtering, energy detection, and feature (e.g., cyclostationarity) detection [12], [11]. Beyond these techniques, there are only a few sensing schemes such as compressive spectrum sensing, [77], which are mostly under investigation at the moment and are not yet adapted by the standardization bodies.

A matched filtering detection problem in general entails the following form

$$\Re\{\mathbf{s}^{\mathrm{H}} \odot \mathbf{h}^{\mathrm{H}} \mathbf{r}\} \underset{\mathscr{H}_0}{\overset{\mathscr{H}_1}{\gtrless}} \lambda, \tag{1.2}$$

where λ is the sensing threshold, $\Re$ denotes the real part, and H is the hermitian operation. Among the three main spectrum sensing categories, matched filtering gives the best performance but as is shown in (1.2), requires complete prior knowledge about the primary user signal $\mathbf{s}$ and the channel gain $\mathbf{h}$ which are not in general available at the cognitive sensor. Therefore, blind and semi-blind detection techniques are generally employed by the cognitive radios.

Energy detection is one of the most common blind detection techniques that does not need any prior information about the primary user signal and channel. The sensor collects a fixed number of samples at each sensing period, calculates the energy of these samples and compare it to a threshold in order to solve (1.1). Denoting N as the number of collected samples, the energy detector becomes

$$\mathscr{E} = \sum_{i=1}^{N} |r_i|^2 \underset{\mathscr{H}_0}{\overset{\mathscr{H}_1}{\gtrless}} \lambda, \tag{1.3}$$

where r_i is the i-th element of vector $\mathbf{r}$.

The detection performance of any detection technique is determined by its probability of false alarm and detection, denoted by P_f and P_d, respectively. These probabilities are defined as

$$P_f = Pr(\mathscr{H}_1|\mathscr{H}_0), \tag{1.4}$$

$$P_d = Pr(\mathscr{H}_1|\mathscr{H}_1), \tag{1.5}$$

where Pr denotes the probability. Therefore, the corresponding detection performance for energy detection, becomes

$$P_f = Pr(\mathscr{E} \geq \lambda|\mathscr{H}_0), \tag{1.6}$$

$$P_d = Pr(\mathscr{E} \geq \lambda|\mathscr{H}_1). \tag{1.7}$$

A common approach in order to determine the sensing threshold λ is to design the system so as to satisfy a certain probability of false alarm. The constant false alarm radar (CFAR) and Neyman-Pearson (NP) tests are two examples of such problem formulations. In order to determine λ for the energy detector with these criteria some information regarding the noise distribution is required. In general, the noise is assumed to be additive white Gaussian with zero mean and variance σ^2, which is to be estimated by the cognitive sensor. Since the noise variance estimation is erroneous, the sensing threshold is not exact and hence, below a certain signal-to-noise-ratio (SNR), the energy detector fails to detect the signal, even with an infinite number of samples [12].

The vulnerability of the energy detector to the noise variance estimation error leads to employing more computationally demanding semi-blind approaches categorized as feature detection. Usually, primary user signals contain certain features such as a pilot signal, a certain covariance structure, cyclostationarity and so on which can be used for detection. Ideally, such techniques are not susceptible to the noise variance estimation error. A review of these techniques is presented in [12] and [79]. Here, we briefly depict a general view of the cyclostationary detector as the most common approach which is employed for spectrum sensing in cognitive radios.

Cyclostationary processes are random processes for which the statistical properties such as the mean and autocorrelation change periodically as a function of time [72]. Many of the signals used in wireless communications and radar systems possess this property. Cyclostationarity may be caused by modulation and coding [72], or it may be intentionally produced to help channel estimation, equalization or synchronization such as the use of the cyclic prefix (CP) in an OFDM signal [73]. Here, we explain one of the cyclostationary detection techniques which uses the second-order time domain cyclostationary detector, [71].

A random process $x_k,\ k = 1, \ldots, N$ is wide-sense second-order cyclostationary if there exists a $K > 0$ such that

$$\mu_x(k) = \mu_x(k+K),\ \forall k,$$

and

$$R_x(k,\kappa) = R_x(k+K,\kappa),\ \forall(k,\kappa),$$

where $\mu_x(k) = E[x_k]$ is the mean value of the random process x_k, $R_x(k,\kappa) = E[x_k x^*_{k+\kappa}]$ is the autocorrelation function, and K is called the cyclic period.

Due to the periodicity of the autocorrelation $R_x(k,\kappa)$, it has a Fourier-series representation as follows [71],

$$R_x(k,\kappa) = \sum_{\alpha} R_x^{\alpha}(\kappa) e^{j\alpha k},$$

where the Fourier coefficients are

$$R_x^{\alpha}(\kappa) = \lim_{N\to\infty} \frac{1}{N} \sum_{k=0}^{N-1} R_x(k,\kappa) e^{-j\alpha k},$$

with α called the cyclic frequency and $R_x^{\alpha}(\kappa)$ called the cyclic autocorrelation function.

To check if $R_x^{\alpha}(\kappa)$ is null for a given candidate cycle, consider the following estimator of $R_x^{\alpha}(\kappa)$

$$\begin{aligned} \hat{R}_x^{\alpha}(\kappa) &= \frac{1}{N} \sum_{k=0}^{N-1} x_k x^*_{k+\kappa} e^{-j\alpha k} \\ &= R_x^{\alpha}(\kappa) + \varepsilon_x^{\alpha}(\kappa) \end{aligned} \tag{1.8}$$

where $\varepsilon_x^{\alpha}(\kappa)$ represents the estimation error which vanishes as $N \to \infty$. Due to the error $\varepsilon_x^{\alpha}(\kappa)$, the estimator $\hat{R}_x^{\alpha}(\kappa)$ is seldom exactly zero in practice, even when α

is not a cyclic frequency. This raises an important issue about deciding whether a given value of $\hat{R}_x^{\alpha}(\kappa)$ is "zero" or not. To answer this question statistically, we use the decision-making approach of [71].

In general, we consider a vector of $\hat{R}_x^{\alpha}(\kappa)$ values rather than a single value in order to check simultaneously for the presence of cycles in a set of lags κ.

Let $\kappa_1, \ldots, \kappa_\tau$ be a fixed set of lags, α be a candidate cyclic frequency, and

$$\begin{aligned}\hat{\mathbf{R}}_x = \big[&\Re\{\hat{R}_x^{\alpha}(\kappa_1)\}, \ldots, \Re\{\hat{R}_x^{\alpha}(\kappa_\tau)\},\\ &\Im\{\hat{R}_x^{\alpha}(\kappa_1)\}, \ldots, \Im\{\hat{R}_x^{\alpha}(\kappa_\tau)\}\big]\end{aligned}$$

represent a $1 \times 2\tau$ row vector consisting of cyclic correlation estimators from (1.8) with $\Re$ and $\Im$ representing the real and imaginary parts, respectively. If the asymptotic value of $\hat{\mathbf{R}}_x$ is given as $\mathbf{R}_x$ where

$$\begin{aligned}\mathbf{R}_x = \big[&\Re\{R_x^{\alpha}(\kappa_1)\}, \ldots, \Re\{R_x^{\alpha}(\kappa_\tau)\},\\ &\Im\{R_x^{\alpha}(\kappa_1)\}, \ldots, \Im\{R_x^{\alpha}(\kappa_\tau)\}\big],\end{aligned}$$

we can write $\hat{\mathbf{R}}_x = \mathbf{R}_x + \boldsymbol{\varepsilon}_x$ where

$$\begin{aligned}\boldsymbol{\varepsilon}_x = \big[&\Re\{\varepsilon_x^{\alpha}(\kappa_1)\}, \ldots, \Re\{\varepsilon_x^{\alpha}(\kappa_\tau)\},\\ &\Im\{\varepsilon_x^{\alpha}(\kappa_1)\}, \ldots, \Im\{\varepsilon_x^{\alpha}(\kappa_\tau)\}\big]\end{aligned}$$

is the estimation error vector.

In [71], the test statistic related to the cyclostationary detector has been derived as follows

$$D^{\mathrm{f}} = N\hat{\mathbf{R}}_x\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_x^H \tag{1.9}$$

where $\hat{\boldsymbol{\Sigma}}$ is the covariance matrix of $\hat{\mathbf{R}}_x$. In [71], it is shown that the test statistic D^{f} under the hypothesis $\mathscr{H}_0$, has a central chi-squared distribution, while under the hypothesis $\mathscr{H}_1$ follows a Gaussian distribution. Hence, for a large N we can write

$$D^{\mathrm{f}} \sim \begin{cases} \chi^2_{2\tau} & \text{under } \mathscr{H}_0 \\ \mathscr{N}(N\hat{\mathbf{R}}_x\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_x^H, 4N\hat{\mathbf{R}}_x\hat{\boldsymbol{\Sigma}}^{-1}\hat{\mathbf{R}}_x^H) & \text{under } \mathscr{H}_1 \end{cases}. \tag{1.10}$$

Having the asymptotic distribution of the test statistic D^{f}, we say that if $D^{\mathrm{f}} \geq \gamma$ we can declare that α is a cyclic frequency for some κ_n and therefore the primary user is present. Else, we declare that α is not a cyclic frequency and thus the primary user is absent, which means that this band is empty and can be used by the cognitive radio.

The probability of detection, P_d, and the probability of false alarm, P_f, can be obtained as

$$P_f = Pr(D_f \geq \gamma | \mathscr{H}_0) = \frac{\Gamma(\gamma/2, \tau)}{\Gamma(\tau)}, \tag{1.11}$$

$$P_d = Pr(D_f \geq \gamma | \mathscr{H}_1) = Q\left(\frac{\gamma - N\hat{\mathbf{R}}_x \hat{\mathbf{\Sigma}}^{-1} \hat{\mathbf{R}}_x^H}{\sqrt{(N\hat{\mathbf{R}}_x \hat{\mathbf{\Sigma}}^{-1} \hat{\mathbf{R}}_x^H)}} \right), \tag{1.12}$$

where $\Gamma(a)$ is the gamma function and $\Gamma(a,x)$ is the incomplete gamma function ($\Gamma(a,x) = \int_x^\infty t^{a-1} e^{-t} dt$).

Between feature and energy detection, energy detection is easier to implement and has a smaller computational complexity, while feature detection needs more computations but has a better performance particularly at low SNRs. A combination of the agile properties of energy detection and the reliability of cyclostationary detection (as a feature detection technique) in order to achieve a fast and reliable detection technique at low SNRs is considered in our paper on two-stage spectrum sensing [68]. Due to its simplicity and mathematical tractability, in this thesis, energy detection is employed for channel sensing. Table 1.2 depicts a summarizes the specifications, pros, and cons of the matched filtering, energy detection and feature detection.

Sensing Technique	Required Knowledge	Pros	Cons
Matched Filtering	Knowledge of the primary signal and channel	Optimal sensing performance	Acquiring knowledge of the primary signal and channel is difficult in practice.
Energy Detection	Knowledge of the noise variance	Very simple to implement, Fast sensing	Vulnerable to the noise uncertainty
Feature Detection	Knowledge of some features in the primary signal such as cyclostationarity	Highly reliable sensing performance	Complex in terms of implementation and computation, Slower sensing compared to the energy detection

Table 1.2: *Comparison of the matched filtering, energy detection and feature detection.*

1.1.3 Cooperative spectrum sensing

The hidden terminal problem and fading effects have been shown to limit the reliability of a single user spectrum sensing. Imagine a cognitive sensor is blocked or it is not located within the coverage range of a primary transmitter. It then fails to detect the presence of the primary user. On the other hand, the primary receiver may be located within the coverage area of the cognitive transmitter. In such a situation, the cognitive transmitter starts sending data while assuming the primary transmitter is idle and thus interferes with the primary user signal. Further, due to fading effects, the primary user signal might not be strong enough to be detected. Similar to the hidden terminal problem, this situation also leads to harmful interference to the primary user.

Distributed cooperative detection has therefore been proposed to improve the detection performance of a cognitive radio network [9], [10], by exploiting spatial diversity among signal observations at spatially distributed sensors. Several distributed detection frameworks are discussed in [14], [15]. In terms of configuration, distributed detection can be categorized under parallel, serial and tree configurations. The tree configuration is very similar to multi-hop sensor networks which is not the focus of this thesis. Among the serial and parallel configurations which are depicted in Figures 1.6 and 1.7, it is shown that the serial configuration has serious reliability issues due to a larger latency and its vulnerability to link failures. Therefore, due to its simplicity, low delay and higher reliability, a parallel detection configuration is considered in this thesis where each secondary radio continuously senses the spectrum in periodic sensing slots. A local decision is then made at the radios and sent to the fusion center (FC), which makes a global decision about the presence (or absence) of the primary user and feeds it back to the cognitive radios.

Several fusion schemes have been proposed in literature which can be categorized under soft and hard fusion strategies [13],[14]. Soft fusion requires several bits to be sent to the FC, while most of the hard fusion schemes require only one-bit transmissions. As a result, hard schemes are more energy-efficient than soft schemes,i.e., hard schemes consume less energy than soft ones. Further, in this thesis, energy detection is employed for channel sensing, which leads to a comparable detection performance for hard and soft fusion schemes [10]. From the above considerations, a hard fusion scheme is adopted in this thesis. A K-out-of-M fusion rule where M denotes the number of cooperating cognitive radios, is one of the most common hard fusion techniques. Employing this rule at the FC implies announcing the presence of the primary user, in case at least K cognitive radios out of M decides for the presence of the primary user. Special cases of this rule are the OR rule where $K = 1$, the AND rule where $K = M$ and the majority rule where $K = \lceil \frac{M}{2} \rceil$. The focus of this thesis in

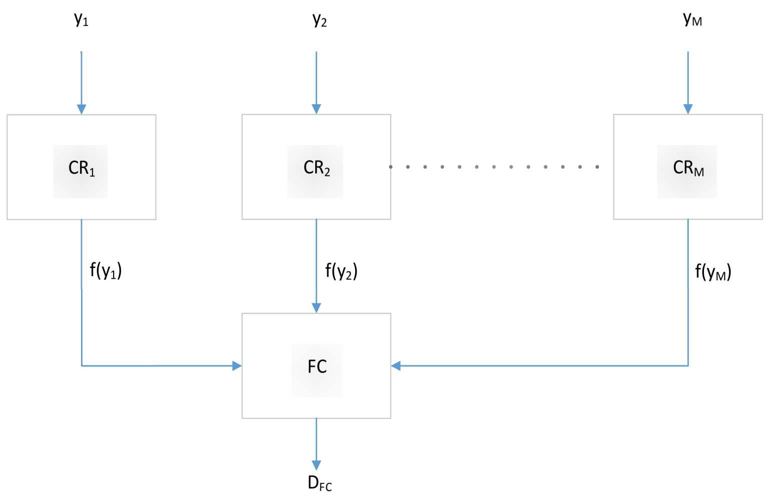


Figure 1.6: *Parallel configuration for distributed spectrum sensing*

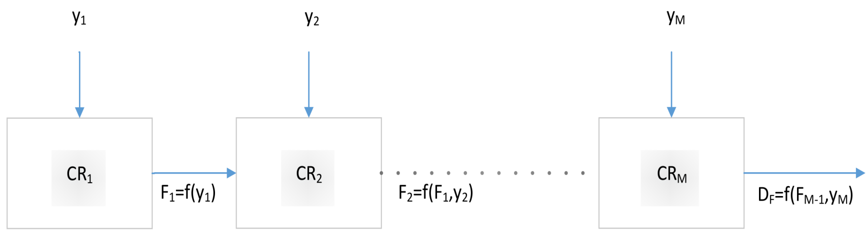


Figure 1.7: *Serial configuration for distributed spectrum sensing*

Chapters 2, 3 and 4 is on the OR and the AND rule, while in Chapter 5, a general K-out-of-M rule is considered as the decision fusion rule at the FC.

1.2 Problem Statement

As mentioned before, cooperative spectrum sensing improves the detection performance of the cognitive radio network. However, such a gain in performance comes with a resulting higher network energy consumption which is a critical factor in a low-power radio system. Minimizing the network energy consumption for cognitive radio networks is considered by us in [67], [24], [25], [26].

Although the network energy consumption is an important factor, considering the fact that cognitive radios are in general low-power sensors, the individual energy consumption of each cognitive radio is a much more critical issue, because the maximum energy consumption of a low-power radio is limited by its battery. As a result, designing energy-efficient spectrum sensing algorithms in order to limit the maximum energy consumption of a cognitive radio in a cooperative sensing framework is the focus of this thesis.

In a cooperative spectrum sensing scenario, each cognitive radio consumes energy mainly on sensing the spectrum and then transmitting the raw or processed data to the FC. Decision fusion based on the received raw data from the cognitive radios is a centralized spectrum sensing scheme, which is the optimal scenario. However, such a centralized scheme demands a large bandwidth and high energy consumption for data transmission. On the other hand, decision fusion scenarios based on processed data need a lower communication overhead and transmission energy consumption. As mentioned earlier, processed data can be either one-bit hard results or quantized versions of some soft results such as log-likelihood ratios (LLRs). Denoting C_s as the sensing energy per sample, $\tilde{N}$ as the number of samples which can be either fixed or random, C_t as the transmission energy per bit and Q as the number of quantized bits, the energy consumption of a cognitive radio at one sensing slot, denoted by C, becomes

$$C = \tilde{N}C_s + QC_t. \tag{1.13}$$

The goal of any energy-efficient spectrum sensing algorithm is to reduce C through the reduction of the sensing energy, $\tilde{N}C_s$ or the transmission energy, QC_t while satisfying a certain detection performance constraint. In this thesis, a detection performance constraint is defined by a lower bound on the global probability of detection and an upper bound on the global probability of false alarm of the cognitive radio network. Such design constraints protect the primary user from harmful interference by the cognitive radios and limit the throughput loss of the cognitive network due to the false detection of the primary user, respectively. However, design constraints and problem formulations depend on the specific requirements of each scenario. In this thesis, three energy-efficient techniques are proposed in order to minimize the maximum average energy consumption per sensor in Chapters 2, 3, and 4. Further, the throughput of the cognitive radio network is maximized for a network consisting of energy-constrained cognitive radios in Chapter 5. Note that cognitive radios also consume energy by receiving the final decision from the FC. However, since this value is constant over all the sensing periods, it has not been considered in the energy model of (1.13).

Energy-efficient spectrum sensing algorithms can be categorized mainly under censoring, sequential sensing, sleeping and clustering schemes. In the following, a review of related works and the state-of-the-art related to energy-efficient spectrum sensing is considered for each category. Further, some of the available literature related to the optimization of spectrum sensing for energy-constrained cognitive radios are reviewed at the end of following section.

1.3 Related work

1.3.1 Censoring and sleeping

The idea behind distributed detection with censoring sensors lies in the fact that not all the local decision results are informative for the FC. Therefore, the transmission energy can be saved by avoiding sensors with not-informative results from communicating with the FC. Denoting $\mathscr{T}_j$ as the decision statistic of the j-th sensor, censoring is defined by a lower threshold λ_1 and an upper threshold λ_2 and the rule which dictates no decision transmission in case $\lambda_1 < \mathscr{T}_j < \lambda_2$. The definition of censoring may be slightly modified depending on the scenario, but the main idea is similar to the definition which is provided here.

Sleeping is another mechanism which achieves energy saving. Each sensor is turned off with probability μ (the sleeping rate) in a sensing slot. This way, both sensing and transmission energies are saved.

Censoring has been thoroughly investigated in wireless sensor networks and cognitive radios [17, 18, 19, 20, 21, 22, 23, 26]. It has been shown that censoring is very effective in terms of energy efficiency. In the early works, [19, 20, 21, 22], the design of censoring parameters including lower and upper thresholds has been considered and mainly two problem formulations have been studied. In the Neyman-Pearson (NP) case, the miss-detection probability is minimized subject to a constraint on the probability of false alarm and average network energy consumption [20, 21, 22]. In the Bayesian case, on the other hand, the detection error probability is minimized subject to a constraint on the average network energy consumption. It is shown that when the constraint on the probability of false alarm is low enough (NP case) or the probability of target presence is much lower than the one for target absence

(Bayesian case), a single-threshold censoring policy is optimal. These works have mainly considered a soft fusion scheme based on a likelihood ratio test (LRT) at the FC.

A censoring scheme for cognitive radios is considered in [17] where a censoring decision rule is employed to reduce the number of bits sent to the fusion center and so the bandwidth occupancy of the cognitive radio network. Each sensor calculates the energy of the collected samples and if it is deemed informative, then a bit indicating presence ("1") or absence ("0") of the primary user is sent to the FC. The informative region is defined by a lower threshold λ_1 and an upper threshold λ_2. In case $\lambda_1 < \mathscr{E} < \lambda_2$, no decision is made and no bit is sent to the FC. This way, the number of transmissions is reduced and so is the transmission energy. However, this paper looks at the problem only from a bandwidth point of view mainly trying to reduce the communication overhead. No systematic problem formulation is provided in order to design the system parameters. Furthermore, the fusion center in [17] makes no decision in case it does not receive any results from the cognitive users which is ambiguous in the sense that the FC has to make a final decision about the presence (or absence) of the primary user.

In [23], analytical expressions for the sensing parameters are given according to an NP setup for both soft and hard fusion schemes, but unlike [19]-[22] no constraint on the energy consumption is taken into account.

A combination of censoring and sleeping is considered in [18] with the goal of maximizing the mutual information between the state of signal occupancy and the decision state of the FC, but the energy efficiency of the system is not directly addressed.

A combined sleeping and censoring scheme is considered by us in [24], [25], [26], which can be viewed as the foundation of Chapter 4 in this thesis. The censoring scheme in these papers is similar to the one in [17] with a modification that the FC decides for the absence of the primary user in case that no result is received at the FC. On top of censoring, a sleeping mechanism is proposed where each cognitive radio turns off its sensing module with a probability μ. The probability of primary user presence or absence ($Pr(\mathscr{H}_1)$ or $Pr(\mathscr{H}_0)$) is assumed to be known under a knowledge-aided setup and unknown under a blind setup with the assumption that $Pr(\mathscr{H}_0) >> Pr(\mathscr{H}_1)$. The network energy consumption is minimized subject to a constraint on the probability of detection and false alarm. This approach is shown to reduce the network energy consumption dramatically. To the best of our knowledge, [26] is the first attempt to design a systematic energy-efficient algorithm for spectrum sensing in cognitive radio networks which laid a foundation for future works in this area including a major part of this thesis. As mentioned earlier, [24], [25], [26] are based on minimizing the network energy consumption. However, in low-power sensor networks, the individual energy consumption of each sensor is a more critical factor. Hence, in this thesis, minimizing the maximum average energy consumption per sensor is considered as the objective function (in Chapters 2, 3, and 4) or the average energy consumption of each cognitive radio is used as a constraint (in Chapter 5).

A sensing node and a joint sensing and decision node selection scheme is considered in [75] and [76], respectively. The network energy consumption is minimized subject to a detection performance constraint defined as in [26], in order to determine the sensing nodes from a pool of cognitive radios and further the decision nodes from the selected sensing nodes. The decision nodes are the nodes which send their result to the FC. Since the problem is to be solved by integer programming and such problems are in general NP hard, a convex relaxation is proposed in order to solve the problem as a real problem and later on map the solution from $[0,1]$ to $\{0,1\}$.

[86] considers censoring for a collaborative cyclostationary detection scheme in cognitive radio networks. The proposed cyclostationarity detection scheme is a generalization of [71], where sensors send their test statistics to the FC for a final decision about the presence or absence of the primary user. A similar censoring rule as in [22] and [19] is employed, in order to only transmit the test statistics which are deemed to be informative. It is shown that this way, the communication overhead reduces significantly, while the performance loss is low. One of the key advantages of collaborative cyclostationary detection is its robustness to the noise uncertainties. Incorporating the cooperative detection approach proposed in [86], in the combined censoring and sleeping scheme of [26], gives an even more energy-efficient reliable spectrum sensing technique at low SNRs.

1.3.2 Sequential sensing

Sequential detection as an approach to reduce the average number of sensors required to reach a decision is also studied comprehensively during the past decades [27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44]. In the context of distributed detection, the sensor observations are either spatially or temporally collected until the system comes up with a final decision [14], [35]. Intrinsic to every sequential sensing scheme, is a stopping rule and a terminal decision rule. The stopping rule is a function that determines when to stop collecting observations and therefore is a random variable. The terminal decision rule dictates which decision has to be made after the sequential test has stopped [35]. Since either the individual sensors or the FC can control the sequential test, two types of sequential detection can be recognized. When the FC manages the sequential test, [28], [30], [31], [34], [37], [40], [36], it either makes a decision or asks the sensors to send a new result. When the sequential test is carried out at the sensors, each sensor accumulates the samples sequentially and makes a decision about the presence or the absence of the target and then sends a binary decision to the FC [44], [38], [27], [32]. The other way to categorize sequential detection problems is based on the maximum number of samples that can be collected. In this context, we can distinguish between infinite horizon and finite horizon (or truncated) sequential detection [34] (the reader is referred to [14], [34] for a thorough analysis of distributed sequential detection). In [34], [33], each sensor collects a sequence of observations, constructs a summary message and passes it on to the FC and all other sensors. A Bayesian problem formulation comprising the minimization of the average error detection probability and sampling time cost over all admissible decision policies at the FC and all possible local decision functions at each sensor is then considered to determine the optimal stopping and decision rule. Further, algorithms to solve the optimization problem for both infinite and finite horizon are given. In [36], an infinite horizon sequential detection scheme based on the sequential probability ratio test (SPRT) at both the sensors and the FC is considered. Wald's analysis of error probability, [45], is employed to determine the thresholds at the sensors and the FC.

The design of a distributed sequential detection network under a communication bandwidth constraint is considered in [37]. Each sensor sends a quantized version of its observation to the FC and then the SPRT is employed to make the decision to stop or carry on sensing. The problem is formulated as to determine the distribution of the bandwidth among the sensors, the quantizer design, and the FC decision policy in order to minimize the average sample number (ASN). Incorporating [37] to increase the throughput of a cognitive radio system can be an interesting area of future research. [32] presents a distributed sequential sensing scheme where each sensor performs an SPRT and makes a decision. The decision is then sent to the FC and the FC announces the first incoming decision as the global decision. Henceforth, the global probability of detection and false alarm is equal to the ones at each sensor. This scheme can also be exploited to reduce the sensing and reporting time of the cognitive radio network thereby increasing the network throughput while decreasing the energy consumption.

A combination of sequential detection and censoring is considered in [42]. Each sensor computes the LLR of the received sample and sends it to the FC, if it is deemed to be in a certain region. The FC then collects the received LLRs and as soon as their sum is larger than an upper threshold or smaller than a lower threshold, the decision is made and the sensors can stop sensing. The LLRs are send in such a way that the larger LLRs are sent sooner. It is shown that the number of transmissions considerably reduces and particularly when the listening cost is high, this approach performs very well.

[31] proposes a sequential censoring scheme where an SPRT is employed by the FC and soft or hard local decisions are sent to the FC according to a censoring policy. It is depicted that the number of transmissions decreases but on the other hand the ASN increases. Therefore, [31] ignores the effect of listening on the energy consumption and focuses only on the transmission energy which for current low-power radios is comparable to the sensing energy. Further, the FC may not reach a decision in a reasonable time. Finally, the system in [31] asymptotically reaches a specific detection performance as the number of sensors grows, but this incurs a high total energy consumption by the system.

[38] considers a distributed sequential sensing scheme where each sensor employs the SPRT and upon reaching a decision, a binary result is sent to the FC. The FC then makes a final decision using a K-out-of-M rule. It is shown that for the same detection error probability, the detection performance of this sequential scheme is better than fixed-size sampling and furthermore the observation energy is proven to be lower. The optimal sensing thresholds are found by an iterative algorithm that solves a Bayesian risk problem.

Sequential spectrum sensing is also considered for cognitive radio design. An infinite horizon SPRT is employed in [41], [40], [39], [30] for different sensing techniques. It is shown that the sensing time dramatically reduces when employing sequential detection. The optimization of cognitive network throughput under a constraint on the miss-detection probability is solved in [28], [29] in order to find the optimal stopping and access policies. This approach is infinite horizon which is a not a valid assumption considering the limited sensing time of cognitive radios. Further, a binary result has to be sent to the FC for each collected observation sample which entails a high transmission energy consumption. Nevertheless, the considered optimization problem is matched to the cognitive radio system requirements and an extension of [28] for the finite horizon case can also be considered.

In [27], the sensing thresholds that minimize the ASN are derived subject to a constraint on the false alarm rate, miss-detection probability, outage probability and interference level. This method is particularly designed for systems with real-time traffic.

A truncated sequential sensing technique is employed in [44] to reduce the sensing time of a cognitive radio system. The thresholds are determined such that a certain probability of false alarm and detection are obtained. In this thesis, we are employing a similar technique, except that in [44], after the truncation point, a single threshold scheme is used to make a final decision, while in this thesis, the sensor decision is censored if no decision is made before the truncation point. Further, [44] considers a single sensor detection scheme which is not reliable particularly due to the hidden terminal problem.

1.3.3 Clustering

A cluster-based and a confidence voting approach to energy-efficient distributed sensing is proposed in [16]. In the cluster-based approach, a cognitive radio network is divided into several clusters based on their geometric location. Each cognitive radio sends its local decision to its assigned cluster head which makes a local cluster decision and sends it to the fusion center. This way, the energy consumption reduces due to the distance reduction by avoiding broadcasting every result to the fusion center directly. In the confidence voting approach, each user sends its local decision to the FC only if it is deemed confident enough. The secondary user looks for a consensus among the other users and if its result is in accordance with the majority opinion, it gains confidence, else its confidence level decreases. Each user can send its result to the FC only if its confidence level is above a certain threshold. However, these approaches are mainly protocol based schemes and the detection technique as well as the underlying problem formulation for system design parameters are not given.

1.3.4 Energy-constrained sensing

[65] considers the optimization of the cognitive radio network energy efficiency. Energy efficiency is defined as the ratio of the average network throughput over the average network energy consumption. Optimization of the energy efficiency is considered for two cases. In the former case, energy efficiency is optimized in order to find K in K-out-of-M rule, and in the latter case, the sensing threshold at the energy detector is derived by optimizing the energy efficiency. However, the combined optimization of K, M as well as the sensing threshold is not considered. Further, no typical performance constraint is considered for the optimization problem such as the probability of detection which is inherent in a cognitive radio design technique.

1.4 Contributions and outline of the thesis

In this section, we explain in detail what is the outline of each chapter and what are our key contributions.

Chapter 2

A fixed-sample size censoring scheme is considered in this chapter. Each cognitive radio collects the same number of samples, calculates the energy of the samples and if the calculated energy is deemed informative, one decision bit is sent to the FC. The calculated energy is informative, if it is lower than a lower threshold (λ_1) or larger than an upper threshold (λ_2), otherwise, no decision is sent to the FC. This way, the transmission energy of each cognitive radio is reduced. Our goal is to set the sensing parameters including λ_1 and λ_2 by minimizing the maximum average energy consumption per sensor subject to a constraint on the probability of detection and false alarm. This constraint is defined as a lower bound on the probability of detection and an upper bound on the probability of false alarm. The main result of this chapter is as follows

- For this approach, it is shown that a single-threshold censoring policy is optimal in terms of energy consumption for both the OR and AND rule. Moreover, a solution of the underlying problem is given for the OR and AND rule.

Fixed-size censoring is used as a benchmark for comparison in Chapter 3 where a sequential censoring scheme is introduced.

Chapter 3

This chapter is one of the major contributions of this thesis. In this chapter, for the first time, a combination of censoring and sequential sensing is introduced. The idea behind the censored truncated sequential spectrum sensing is to reduce the sensing energy as well as transmission energy of each cognitive radio, by introducing a sequential sampling technique. The contributions of this section are as follows

- A combination of censoring and truncated sequential sensing is proposed to save energy. The sensors sequentially sense the spectrum before reaching a truncation point, N, where they are forced to stop sensing. If the accumulated energy of the collected sample observations is in a certain region (above an upper threshold, a, or below a lower threshold, b) before the truncation point, a decision is sent to the FC. Else, a censoring policy is used by the sensor, and no bits will be sent. This way, a large amount of energy is saved for both sensing and transmission. In our thesis, it is assumed that the cognitive radios and fusion center are aware of their location and mutual channel properties.

- In terms of cognitive radio system design, the probability of detection limits the harmful interference to the primary user and the false alarm rate controls the loss in spectrum utilization. The ideal case yields no interference and full spectrum utilization, but it is practically impossible to reach this point. Hence, current standards determine a bound on the detection performance to achieve an acceptable interference and utilization level [8]. Our goal is to minimize the maximum average energy consumption per sensor subject to a specific detection performance constraint which is defined by a lower bound on the global probability of detection and an upper bound on the global probability of false alarm. To the best of our knowledge such a min-max optimization problem considering the average energy consumption per sensor has not yet been considered in literature.

- Analytical expressions for the underlying parameters are derived and it is shown that the problem can be solved by a two-dimensional search for both the OR and AND rule.

- To reduce the computational complexity for the OR rule, a single-threshold truncated sequential test is proposed where each cognitive radio sends a decision to the FC upon the detection of the primary user.

At the end of the chapter, several numerical results are provided which show that censored truncated sequential sensing outperforms censoring in terms of energy-efficiency for low-power cognitive radios and for the desired range of the detection performance. The material presented in Chapter 2 and Chapter 3 were published in part in the following journal and conference publications:

- S. Maleki and G. Leus, "Censored Truncated Sequential Spectrum Sensing for Cognitive Radio Networks," IEEE Journal on Selected Areas in Communications, vol.31, no.3, pp.364,378, March 2013

- S. Maleki and G. Leus, "Censored truncated sequential spectrum sensing for cognitive radio networks," 17th International Conference on Digital Signal Processing (DSP), 2011, vol., no., pp.1,8, 6-8 July 2011

Chapter 4

In this chapter, a combination of sleeping and censoring is introduced. On top of the fixed-size censoring as presented in Chapter 2, each sensor turns off its sensing module with probability μ (sleeping rate) at each sensing period. This way, a great deal of energy is saved on sensing and transmission. As in Chapter 2 and Chapter 3, the goal is to minimize the maximum average energy consumption per sensor subject to a lower bound on the probability of detection and an upper bound on the probability of false alarm. In this chapter, first the combined sleeping and censoring scheme is presented, followed by an analysis and problem formulation and several numerical results. Further, a case study based on IEEE 802.15.4 ZigBee is considered to evaluate the performance of the proposed approach for a practical scenario. Contributions of this chapter are as follows

- A combined sleeping and censoring scheme is proposed where each sensor turns off its sensing module with probability μ at each sensing period. In case the sensor is on, then a censoring policy is employed in order to send the decisions to the FC. In case the calculated energy is more than an upper threshold, λ_2, the decision is that the primary user is present. If the calculated energy turns out to be lower than a lower threshold, λ_1, then a decision is sent to the FC indicating the absence of the primary user. Else, no decision is made and nothing is sent to the FC.

- The underlying detection performance indicators including the global probability of false alarm and detection are derived for the OR and the AND rules.

- The problem is defined so as to minimize the maximum average energy consumption per sensor subject to a lower bound on the probability of detection and an upper bound on the probability of false alarm. As indicated before, such a min-max optimization problem has never been considered for the problem of energy-efficiency optimization in cognitive radio systems.

- It is shown that the optimal average energy consumption per sensor is obtained when the lower threshold is zero ($\lambda_1 = 0$) for the OR rule and approaching infinity ($\lambda_1 \to \infty$) for the AND rule. These are the same results as in fixed-size censoring in Chapter 2, but the beauty of the results in this chapter is that the same results holds with a combination of censoring and sleeping. This way, one of the three underlying arguments of the optimization problem including λ_1, λ_2 and μ is relaxed and the problem reduces to a two-dimensional optimization problem.

- It is shown that on top of reducing the main problem to a two-dimensional problem, using the interactions between λ_2 and μ, the problem can be reduced to a line-search problem over μ.

Chapter 5

This chapter considers the optimization of hard-combining cooperative spectrum sensing for energy-constrained cognitive radios. The goal is to find the optimal K-out-of-M fusion rule. A K-out-of-M rule is a hard fusion rule which decides for the presence of the primary user if at least K cognitive radios report the presence of a primary user to the FC. Note that the previously considered OR and AND rules are special cases of the K-out-of-M rule where $K = 1$ and $K = M$, respectively. The contributions of this chapter are as follows

- The throughput of the cognitive radio network is maximized subject to a constraint on the global probability of detection and energy consumption per cognitive radio in order to determine the optimal number of cognitive users M and K.

- It is shown that the underlying problem can be solved by a bounded two-dimensional search.

- It is assumed that the cognitive radios send their results to the FC in a time-division-multiple-access (TDMA) manner. Therefore, by optimizing the number of cognitive radios M, the reporting time of the cognitive radio and thus the network throughput is optimized.

The following journal and conference papers are published based on the material presented in this chapter:

- S. Maleki, S. P. Chepuri and G. Leus, “Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks”, Physical Communication (Elsevier Journal), Available online 20 July 2012, ISSN 1874-4907

- S. Maleki, S. P. Chepuri and G. Leus, “Energy and throughput efficient strategies for cooperative spectrum sensing in cognitive radios,” IEEE 12th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2011, pp.71,75, 26-29 June 2011

- S. Maleki, S. P. Chepuri and G. Leus, “Optimal hard fusion strategies for cognitive radio networks,” IEEE Wireless Communications and Networking Conference (WCNC), 2011, pp.1926,1931, 28-31 March 2011

Chapter 6

In this chapter, the conclusions of Chapters 2, 3, 4 and 5 are drawn and the main results are reviewed. Further, a couple of ideas for future works are presented in this chapter.

Chapter 2

Fixed-Size Censoring

Abstract

A fixed-sample size censoring scheme is considered in this chapter as benchmark for comparison of the censored truncated sequential technique which is proposed in Chapter 3. To design the underlying sensing parameters, the maximum average energy consumption per sensor is minimized subject to a lower bounded global probability of detection and an upper bounded false alarm rate. This way, both the interference to the primary user due to miss detection and the network throughput as a result of a low false alarm rate are controlled. To solve this problem, it is assumed that the cognitive radios and fusion center are aware of their location and mutual channel properties.

2.1 Introduction

Reliable spectrum sensing is a key functionality of a cognitive radio network. The hidden terminal problem and fading effects have been shown to limit the reliability of spectrum sensing. Distributed cooperative detection has therefore been proposed to improve the detection performance of a cognitive radio network [9], [10]. Due to its simplicity and small delay, a parallel detection configuration [14], is considered in this chapter where each secondary radio continuously senses the spectrum in periodic sensing slots. A local decision is then made at the radios and sent to the fusion center (FC), which makes a global decision about the presence (or absence) of the primary user and feeds it back to the cognitive radios. A dedicated control channel is considered to convey messages from the cognitive radios to the FC. Several fusion schemes have been proposed in the literature which can be categorized under soft and hard fusion strategies [14], [13]. Hard schemes are more energy efficient than soft schemes, and thus a hard fusion scheme is adopted in this chapter. More specifically, two popular choices are employed due to their simple implementation: the OR and the AND rule. The OR rule dictates the primary user presence to be announced by the FC when at least one cognitive radio reports the presence of a primary user to the FC. On the other hand, the AND rule asks the FC to vote for the absence of the primary user if at least one cognitive radio announces the absence of the primary user. In this chapter, energy detection is employed for channel sensing which is a common approach to detect unknown signals [13], [11], and which leads to a comparable detection performance for hard and soft fusion schemes [10].

Energy consumption is another critical issue. The maximum energy consumption of a low-power radio is limited by its battery. As a result, energy-efficient spectrum sensing limiting the maximum energy consumption of a cognitive radio in a cooperative sensing framework is the focus of this chapter. A fixed-sample size censoring scheme is considered as a benchmark (it is simply called the censoring scheme throughout the rest of the chapter) where each sensor employs a censoring policy after collecting a fixed number of samples. The censoring policy in this case works based on a lower threshold, λ_1 and an upper threshold, λ_2. The decision is only being made if the accumulated energy is not in (λ_1, λ_2). For this approach, it is shown that a single-threshold censoring policy is optimal in terms of energy consumption for both the OR and AND rule. Moreover, a solution of the underlying problem is given for the OR and AND rule.

2.2 Related work to censoring

Censoring has been thoroughly investigated in wireless sensor networks and cognitive radios [17, 18, 19, 20, 21, 22, 23, 26]. It has been shown that censoring is very effective in terms of energy efficiency. In the early works, [19, 20, 21, 22], the design of censoring parameters including lower and upper thresholds has been considered and mainly two problem formulations have been studied. In the Neyman-Pearson (NP) case, the miss-detection probability is minimized subject to a constraint on the probability of false alarm and average network energy consumption [20, 21, 22]. In the Bayesian case, on the other hand, the detection error probability is minimized subject to a constraint on the average network energy consumption. It is shown that when the constraint on the probability of false alarm is low enough (NP case) or the probability of target presence is much lower than the one for target absence (Bayesian case), a single-threshold censoring policy is optimal. Our fixed-sample size censoring scheme is different from these works in several aspects. First, they have mainly considered a soft fusion scheme based on a likelihood ratio test (LRT) at the FC while in this chapter, hard fusion OR and AND rules are considered. Second, the optimization problem in this chapter is different from the NP or Bayesian problems. Third, it is shown that in our scheme the optimal lower threshold is always zero and forth, an explicit solution of the underlying problem is given which has not yet been presented in the earlier works. A combination of censoring and sleeping is considered in [18] with the goal of maximizing the mutual information between the state of signal occupancy and the decision state of the FC, but the energy efficiency of the system is not directly addressed. Censoring for the specific application of cognitive radio is considered in [17], [23], [26]. In [17], a censoring rule similar to the one in this chapter is considered in order to limit the bandwidth occupancy of the cognitive radio network. Our fixed-sample size censoring scheme is different in two ways. First, in [17], the FC makes no decision in case it does not receive any decision from the cognitive radios which is ambiguous, since the FC has to make a final decision, while in this chapter, the FC reports the absence of a primary user, if no local decision is received at the FC. Second, we give a clear optimization problem and expression for the solution while this is not presented in [17]. In [23], analytical expressions for the sensing parameters are given according to an NP setup for both soft and hard fusion schemes, but unlike [19]-[22] no constraint on the energy consumption is taken into account. As a result, our optimization problem is different than the one in [23].

2.2.1 Organization

In this chapter, first, we introduce the system model, problem formulation and analysis for the OR rule in Section 2.3. An extension of censoring to the AND rule is considered in Section 2.4. The performance analysis of the fixed-size censoring considered in this chapter, will be presented together with the results of truncated sequential censoring in Chapter 3, Section 3.5. The conclusions of Chapters 2 and 3, are drawn in Section 3.6.

2.3 Fixed-size censoring analysis and problem formulation

A fixed-size censoring scheme is discussed in this section as a benchmark for the main contribution of the thesis in Chapter 3, which studies a combination of sequential sensing and censoring. A network of M cognitive radios is considered under a cooperative spectrum sensing scheme. A parallel detection configuration is employed as shown in Fig. 2.1. Each cognitive radio senses the spectrum and makes a local decision about the presence or absence of the primary user and informs the FC by employing a censoring policy. The final decision is then made at the FC by employing the OR rule. The AND rule will be discussed in Section 2.4. Denoting r_{ij} to be the i-th sample received at the j-th cognitive radio, each radio solves a binary hypothesis testing problem as follows

$$\begin{aligned} \mathscr{H}_0 &: \quad r_{ij} = w_{ij},\ i = 1,...,N,\ j = 1,...,M \\ \mathscr{H}_1 &: \quad r_{ij} = h_{ij}s_i + w_{ij},\ i = 1,...,N,\ j = 1,...,M \end{aligned} \tag{2.1}$$

where w_{ij} is additive white Gaussian noise with zero mean and variance σ_w^2. h_{ij} and s_i are the channel gain between the primary user and the j-th cognitive radio and the transmitted primary user signal, respectively. We assume two models for h_{ij} and s_i. In the first model, s_i is assumed to be white Gaussian with zero mean and variance σ_s^2, and h_{ij} is assumed constant during each sensing period and thus $h_{ij} = h_j,\ i = 1,\ldots,N$. In the second model, s_i is assumed to be deterministic and constant modulus $|s_i| = s,\ i = 1,\ldots,N,\ j = 1,\ldots,M$ and h_{ij} is an i.i.d. Gaussian random process with zero mean and variance $\sigma_{h,j}^2$. Note that the second model actually represents a fast fading scenario. Although each model requires a different type of channel estimation, since the received signal is still a zero mean Gaussian random process with some variance, namely $\sigma_j^2 = |h_j|^2\sigma_s^2 + \sigma_w^2$ for the former model and $\sigma_j^2 = s^2\sigma_{hj}^2 + \sigma_w^2$ for the latter model, the analyses which are given in the following sections are valid for both models. The SNR of the received primary user signal at the j-th cognitive radio is $\gamma_j = |h_j|^2\sigma_s^2/\sigma_w^2$ under the first model and $\gamma_j = s^2\sigma_{h,j}^2/\sigma_w^2$ under the second model. Furthermore, $h_{ij}s_i$ and w_{ij} are assumed statistically independent.

An energy detector is employed by each cognitive sensor which calculates the accumulated energy over N observation samples. Note that under our system model parameters, the energy detector is equivalent to the optimal LLR detector [13]. The

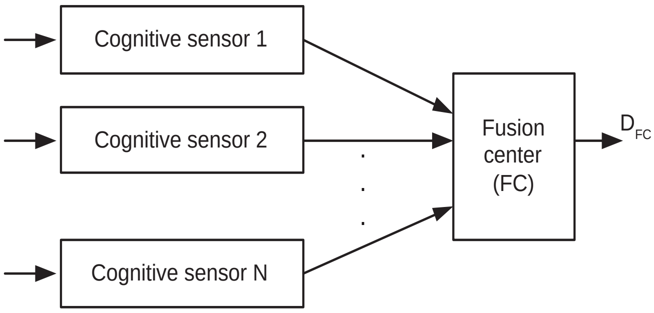


Figure 2.1: *Distributed spectrum sensing configuration*

received energy collected over the N observation samples at the j-th radio is given by

$$\mathscr{E}_j = \sum_{i=1}^{N} \frac{|r_{ij}|^2}{\sigma_w^2}. \tag{2.2}$$

When the accumulated energy of the observation samples is calculated, a censoring policy is employed at each radio where the local decisions are sent to the FC only if they are deemed to be informative [26]. Censoring thresholds λ_1 and λ_2 are applied at each of the radios, where the range $\lambda_1 < \mathscr{E}_j < \lambda_2$ is called the censoring region. At the j-th radio, the local censoring decision rule is given by

$$\begin{cases} \text{send 1, declaring } \mathscr{H}_1 & \text{if } \mathscr{E}_j \geq \lambda_2, \\ \text{no decision} & \text{if } \lambda_1 < \mathscr{E}_j < \lambda_2, \\ \text{send 0, declaring } \mathscr{H}_0 & \text{if } \mathscr{E}_j \leq \lambda_1. \end{cases} \tag{2.3}$$

It is well known [13] that under such a model, $\mathscr{E}_j$ follows a central chi-square distribution with $2N$ degrees of freedom under $\mathscr{H}_0$ and $\mathscr{H}_1$. Therefore, the local probabilities of false alarm and detection can be respectively written as

$$P_{f,j} = Pr(\mathscr{E}_j \geq \lambda_2 | \mathscr{H}_0) = \frac{\Gamma(N, \frac{\lambda_2}{2})}{\Gamma(N)}, \tag{2.4}$$

$$P_{d,j} = Pr(\mathscr{E}_j \geq \lambda_2 | \mathscr{H}_1) = \frac{\Gamma(N, \frac{\lambda_2}{2(1+\gamma_j)})}{\Gamma(N)}, \tag{2.5}$$

where $\Gamma(a,x)$ is the incomplete gamma function given by $\Gamma(a,x) = \int_x^{\infty} t^{a-1} e^{-t} dt$, with $\Gamma(a,0) = \Gamma(a)$.

Denoting $C_{s,j}$ and $C_{t,j}$ to be the energy consumed by the j-th radio in sensing per sample and transmission per bit, respectively, the average energy consumed for distributed sensing per user is given by,

$$C_j = NC_{s,j} + (1-\rho_j)C_{t,j}, \tag{2.6}$$

where $\rho_j = Pr(\lambda_1 < \mathscr{E}_j < \lambda_2)$ is denoted to be the average censoring rate. Note that $C_{s,j}$ is fixed and only depends on the sampling rate and power consumption of the sensing module while $C_{t,j}$ depends on the distance to the FC at the time of the transmission. Therefore, in this chapter, it is assumed that the cognitive radio is aware of its location and the location of the FC as well as their mutual channel properties or at least can estimate them. Defining $\pi_0 = Pr(\mathscr{H}_0)$, $\pi_1 = Pr(\mathscr{H}_1)$, $\delta_{0,j} = Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_0)$ and $\delta_{1,j} = Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_1)$, ρ_j is given by

$$\rho_j = \pi_0\delta_{0,j} + \pi_1\delta_{1,j}, \tag{2.7}$$

with

$$\delta_{0,j} = \frac{\Gamma(N,\frac{\lambda_1}{2})}{\Gamma(N)} - \frac{\Gamma(N,\frac{\lambda_2}{2})}{\Gamma(N)}, \tag{2.8}$$

$$\delta_{1,j} = \frac{\Gamma(N,\frac{\lambda_1}{2(1+\gamma_j)})}{\Gamma(N)} - \frac{\Gamma(N,\frac{\lambda_2}{2(1+\gamma_j)})}{\Gamma(N)}. \tag{2.9}$$

Denoting Q_{F}^{c} and Q_{D}^{c} to be the respective global probability of false alarm and detection, the target detection performance is then quantified by $Q_{\mathrm{F}}^{c} \leq \alpha$ and $Q_{\mathrm{D}}^{c} \geq \beta$, where α and β are pre-specified detection design parameters. Our goal is to determine the optimum censoring thresholds λ_1 and λ_2 such that the maximum average energy consumption per sensor, i.e., $\max_j\ C_j$, is minimized subject to the constraints $Q_{\mathrm{F}}^{c} \leq \alpha$ and $Q_{\mathrm{D}}^{c} \geq \beta$. Hence, our optimization problem can be formulated as

$$\begin{aligned} &\min_{\lambda_1,\lambda_2}\ \max_{j}\ C_j \\ &\text{s.t. } Q_{\mathrm{F}}^{c} \leq \alpha,\ Q_{\mathrm{D}}^{c} \geq \beta. \end{aligned} \tag{2.10}$$

In this section, the FC employs an OR rule to make the final decision which is denoted by D_{FC}, i.e., $D_{FC} = 1$ if the FC receives at least one local decision declaring 1, else $D_{FC} = 0$. This way, the global probability of false alarm and detection can be derived as

$$Q_{\mathrm{F}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_0) = 1 - \prod_{j=1}^{M}(1 - P_{f,j}), \quad (2.11)$$

$$Q_{\mathrm{D}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_1) = 1 - \prod_{j=1}^{M}(1 - P_{d,j}). \quad (2.12)$$

Note that since all the cognitive radios employ the same upper threshold λ_2, we can state that $P_{f,j} = P_f$ defined in (2.4). As a result, (2.11) becomes

$$Q_{\mathrm{F}}^{c} = 1 - (1 - P_f)^M. \quad (2.13)$$

Since the FC decides about the presence of the primary user only by receiving "1"s (receiving no decision from all the sensors is considered as absence of the primary user) and the sensing time does not depend on λ_1, it is a waste of energy to send zeros to the FC and thus, the optimal solution of (2.10) is obtained by $\lambda_1 = 0$. Note that this is only the case for fixed-size censoring, because the energy consumption of each sensor only varies by the transmission energy while the sensing energy is constant. This way (2.8) and (2.9) can be simplified to $\delta_{0,j} = 1 - P_f$ and $\delta_{1,j} = 1 - P_{d,j}$, and we only need to derive the optimal λ_2. Since there is a one-to-one relationship between P_f and λ_2, by finding the optimal P_f, λ_2 can also be easily derived as $\lambda_2 = 2\Gamma^{-1}[N, \Gamma(N)P_f]$ (where Γ^{-1} is defined over the second argument). Considering this result and defining $Q_{\mathrm{D}}^{c} = H(P_f)$, the optimal solution of (2.10) is given by $P_f = H^{-1}(\beta)$ as is shown in Appendix 2.A.

When the received SNR of the primary user by the cognitive radios can be assumed to be the same, the local probabilities of detection will be all the same, i.e., $P_{d,j} = P_d = G(F^{-1}(P_f))$, and thus $Q_{\mathrm{D}}^{c} = 1 - (1 - P_d)^M = 1 - (1 - G(F^{-1}(P_f)))^M$. This way the optimal P_d is $P_d = 1 - (1 - \beta)^M$ and the optimal P_f is given by $P_f = F(G^{-1}(1 - (1 - \beta)^{1/M}))$. Note that such an assumption is considered a good assumption if the difference between the SNRs is less than 1 dB which holds in many practical situations [51], particularly when the cognitive radios are far from the primary user, while are relatively close to each other. Furthermore, by increasing the SNR, the optimal P_f decreases and so does the maximum average energy consumption per sensor. Therefore, one suboptimal solution of (2.10) is to assume that the SNR for all the cognitive radios is equal to the minimum SNR and to find the sensing parameters using the earlier mentioned P_f and P_d. This way we are certain that the probability of detection constraint is satisfied because $\beta \leq Q_{\mathrm{D}}^{c}(\gamma_{min} = \min\{\gamma_1, \ldots, \gamma_M\}) \leq$

$Q_{\mathrm{D}}^{c}(\gamma_1,\ldots,\gamma_M)$. Although, the censoring scheme gives a considerable energy saving as shown in Section 3.5, it only relies on the transmission energy minimization.

2.4 Extension to the AND rule

So far, we have mainly focused on the OR rule. However, another rule which is also simple in terms of implementation is the AND rule. According to the AND rule, $D_{FC} = 0$, if at least one cognitive radio reports a zero, else $D_{FC} = 1$. This way the global probabilities of false alarm and detection, can be written respectively as

$$Q_{\mathrm{F,AND}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_0) = \prod_{j=1}^{M}(\delta_{0,j} + P_{f,j}), \tag{2.14}$$

$$Q_{\mathrm{D,AND}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_1) = \prod_{j=1}^{M}(\delta_{1,j} + P_{d,j}). \tag{2.15}$$

Similar to the case for the OR rule, the problem is defined so as to minimize the maximum average energy consumption per sensor subject to a lower bound on the global probability of detection and an upper bound on the global probability of false alarm.

The optimization problem for the censoring scheme considering the AND rule at the FC, becomes

$$\begin{aligned} &\min_{\lambda_1,\lambda_2}\ \max_{j}\ C_j \\ &\text{s.t. } Q_{\mathrm{F,AND}}^{c} \leq \alpha,\ Q_{\mathrm{D,AND}}^{c} \geq \beta. \end{aligned} \tag{2.16}$$

where C_j is defined in (2.6). Since the FC decides for the absence of the primary user by receiving at least one zero and the fact that the sensing energy per sample is constant, the optimal upper threshold λ_2 is $\lambda_2 \to \infty$. This way, cognitive radios censor all the results for which $\mathscr{E}_j > \lambda_1$, and as a result (2.14) and (2.15) become

$$Q_{\mathrm{F,AND}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_0) = \prod_{j=1}^{M}\delta_{0,j}, \tag{2.17}$$

$$Q_{\mathrm{D,AND}}^{c} = Pr(D_{FC} = 1|\mathscr{H}_1) = \prod_{j=1}^{M}\delta_{1,j}. \tag{2.18}$$

where $\delta_{0,j} = Pr(\mathscr{E}_j > \lambda_1|\mathscr{H}_0)$ and $\delta_{1,j} = Pr(\mathscr{E}_j > \lambda_1|\mathscr{H}_1)$. Since the thresholds are the same among the cognitive radios, we have $\delta_{0,1} = \delta_{0,2} = \cdots = \delta_{0,M} = \delta_0$. Since there is a one-to-one relationship between λ_1 and δ_0, by finding the optimal δ_0, the optimal λ_1 can be easily derived. As shown in Appendix 3.E, we can derive the optimal δ_0 as $\delta_0 = \alpha^{1/M}$. We can confirm this result intuitively by considering the fact that by maximizing δ_0, $\delta_{1,j}$ is maximized and so is ρ_j, and the maximum δ_0 is equal to $\alpha^{1/M}$, which is independent from SNR. This result is very important in the sense that as far as the feasible set of (2.16) is not empty, the optimal solution of (2.16) is independent from the SNR. Note that the maximum average energy consumption per sensor still depends on the SNR via $\delta_{1,j}$ and is reducing as the SNR grows.

2.5 Summary and conclusions

In this chapter, a censoring scheme has been discussed where each sensor employs a censoring policy to reduce the energy consumption. We defined our problem as the minimization of the maximum average energy consumption per sensor subject to a global probability of false alarm and detection constraint for the AND and the OR rules. The optimal lower threshold is shown to be zero for the censoring scheme in case of the OR rule while for the AND rule the optimal upper threshold is shown to be infinity. Further, an explicit expression was given to find the optimal solution for the OR rule and in case of the AND rule a closed form solution has been derived.

The fixed-sample size censoring scheme which has been presented in this chapter is used as a benchmark in the following Chapter, where a combination of censoring and sequential sensing approaches is discussed which optimizes both the sensing and the transmission energy.

Appendix 2.A Optimal solution of (2.10)

Since the optimal $\lambda_1 = 0$, (2.8) and (2.9) can be simplified to $\delta_{0,j} = 1 - P_f$ and $\delta_{1,j} = 1 - P_{d,j}$ and so (2.10) becomes,

$$\begin{aligned} &\min_{\lambda_2} \max_j \left[NC_{s,j} + (\pi_0 P_f + \pi_1 P_{d,j})C_{t,j} \right] \\ &\text{s.t. } 1 - (1 - P_f)^M \leq \alpha,\ 1 - \prod_{j=1}^{M} (1 - P_{d,j}) \geq \beta. \end{aligned} \tag{2.19}$$

Since there is a one-to-one relationship between λ_2 and P_f, i.e., $\lambda_2 = 2\Gamma^{-1}[N, \Gamma(N)P_f]$ (where Γ^{-1} is defined over the second argument), (2.19) can be formulated as [46, p.130],

$$\begin{aligned} &\min_{P_f} \max_j \left[NC_{s,j} + (\pi_0 P_f + \pi_1 P_{d,j})C_{t,j} \right] \\ &\text{s.t. } 1 - (1 - P_f)^M \leq \alpha,\ 1 - \prod_{j=1}^{M} (1 - P_{d,j}) \geq \beta. \end{aligned} \tag{2.20}$$

Defining $P_f = F(\lambda_2) = \frac{\Gamma(N, \frac{\lambda_2}{2})}{\Gamma(N)}$ and $P_{d,j} = G_j(\lambda_2) = \frac{\Gamma(N, \frac{\lambda_2}{2(1+\gamma_j)})}{\Gamma(N)}$, we can write $P_{d,j}$ as $P_{d,j} = G_j(F^{-1}(P_f))$. Calculating the derivative of C_j with respect to P_f, we find that

$$\frac{\partial C_j}{\partial P_f} = \frac{\partial \left[C_{t,j}(\pi_0 P_f + \pi_1 P_{d,j}) \right]}{\partial P_f} = C_{t,j}\pi_0 + \frac{\partial P_{d,j}}{\partial P_f} \geq 0, \tag{2.21}$$

where we use the fact that

$$\begin{aligned} \frac{\partial P_{d,j}}{\partial P_f} &= \frac{-\frac{1}{2^N\Gamma(N)} 2\Gamma^{-1}[N, \Gamma(N)P_f]^{N-1} e^{2\Gamma^{-1}[N,\Gamma(N)P_f]/2(1+\gamma_j)} I_{\{2\Gamma^{-1}[N,\Gamma(N)P_f] \geq 0\}}}{-\frac{1}{2^N\Gamma(N)} 2\Gamma^{-1}[N, \Gamma(N)P_f]^{N-1} e^{2\Gamma^{-1}[N,\Gamma(N)P_f]/2} I_{\{2\Gamma^{-1}[N,\Gamma(N)P_f] \geq 0\}}} \\ &= e^{2\Gamma^{-1}[N,\Gamma(N)P_f](1/2(1+\gamma_j) - 1/2)} \geq 0. \end{aligned} \tag{2.22}$$

Therefore, we can simplify (2.20) as

$$\begin{aligned} &\min_{P_f} P_f \\ &\text{s.t. } 1 - (1 - P_f)^M \leq \alpha,\ 1 - \prod_{j=1}^{M} (1 - P_{d,j}) \geq \beta. \end{aligned} \tag{2.23}$$

which can be easily solved by a line search over P_f. However, since Q_D^c is a monotonically increasing function of P_f, i.e., $Q_\mathrm{D}^c = H(P_f) = 1 - \prod_{j=1}^{M}(1 - G_j(F^{-1}(P_f)))$

and thus $\frac{\partial Q_{\mathrm{D}}^{c}}{\partial P_f} = \frac{\partial Q_{\mathrm{D}}^{c}}{\partial P_{d,j}} \frac{\partial P_{d,j}}{\partial P_f} = \prod_{l=1,l\neq j}^{l=M}(1-P_{dl})\frac{\partial P_{d,j}}{\partial P_f} \geq 0$, we can further simplify the constraints in (2.23) as $P_f \leq 1-(1-\alpha)^{1/M}$ and $P_f \geq H^{-1}(\beta)$. Thus, we obtain

$$\begin{aligned}&\min_{P_f} P_f \\ &\text{s.t. } P_f \leq 1-(1-\alpha)^{1/M},\ P_f \geq H^{-1}(\beta).\end{aligned} \tag{2.24}$$

Therefore, if the feasible set of (2.24) is not empty, then the optimal solution is given by $P_f = H^{-1}(\beta)$.

Chapter 3

Censored Truncated Sequential Sensing

Abstract

A censored truncated sequential spectrum sensing technique is considered as an energy saving approach. To design the underlying sensing parameters, the maximum average energy consumption per sensor is minimized subject to a lower bounded global probability of detection and an upper bounded false alarm rate. This way both the interference to the primary user due to miss detection and the network throughput as a result of a low false alarm rate are controlled. To solve this problem, it is assumed that the cognitive radios and fusion center are aware of their location and mutual channel properties. We compare the performance of the proposed scheme with a fixed-sample size censoring scheme under different scenarios and show that for low-power cognitive radios, censored truncated sequential sensing outperforms censoring. It is shown that as the sensing energy per sample of the cognitive radios increases, the energy efficiency of the censored truncated sequential approach grows significantly.

3.1 Introduction

As in Chapter 2, a hard combining cooperative spectrum sensing technique based on the OR and the AND rule is considered in this chapter. Further, as in the rest of the thesis, energy detection is employed for channel sensing.

As mentioned earlier, energy consumption is a critical issue in cognitive radio networks. The maximum energy consumption of a low-power radio is limited by its battery. In this chapter, we are focusing on designing an energy-efficient algorithm for spectrum sensing. The spectrum sensing module consumes energy in both the sensing and transmission stages. In the previous chapter, we have introduced a technique in order to reduce the transmission energy. To achieve a better energy-efficiency, in this chapter and also in Chapter 4, we try to reduce both sensing and transmission energy.

A combination of censoring and truncated sequential sensing is proposed to save energy. The sensors sequentially sense the spectrum before reaching a truncation point, N, where they are forced to stop sensing. If the accumulated energy of the collected sample observations is in a certain region (above an upper threshold, a, or below a lower threshold, b) before the truncation point, a decision is sent to the FC. Else, a censoring policy is used by the sensor, and no bits will be sent. This way, a large amount of energy is saved for both sensing and transmission. In this chapter, it is assumed that the cognitive radios and fusion center are aware of their location and mutual channel properties.

Our goal is to minimize the maximum average energy consumption per sensor subject to a specific detection performance constraint which is defined by a lower bound on the global probability of detection and an upper bound on the global probability of false alarm. In terms of cognitive radio system design, the probability of detection limits the harmful interference to the primary user and the false alarm rate controls the loss in spectrum utilization. The ideal case yields no interference and full spectrum utilization, but it is practically impossible to reach this point. Hence, current standards determine a bound on the detection performance to achieve an acceptable interference and utilization level [8]. To the best of our knowledge such a min-max optimization problem considering the maximum average energy consumption per sensor has not yet been considered in literature.

3.1.1 Related work to sequential sensing

Sequential detection as an approach to reduce the average number of sensors required to reach a decision is also studied comprehensively during the past decades [27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44]. In the context of distributed detection, the sensor observations are either spatially or temporally collected until the system comes up with a final decision [14], [35]. Intrinsic to every sequential sensing scheme, is a stopping rule and a terminal decision rule. The stopping rule is a function that determines when to stop collecting observations and therefore is a random variable. The terminal decision rule dictates which decision has to be made after the sequential test has stopped [35]. Since either the individual sensors or the FC can control the sequential test, two types of sequential detection can be recognized. When the FC manages the sequential test, [28], [30], [31], [34],

[37], [40], [36], it either makes a decision or asks the sensors to send a new result. When the sequential test is carried out at the sensors, each sensor accumulates the samples sequentially and makes a decision about the presence or the absence of the target and then sends a binary decision to the FC [44], [38], [27], [32]. The other way to categorize sequential detection problems is based on the maximum number of samples that can be collected. In this context, we can distinguish between infinite horizon and finite horizon (or truncated) sequential detection [34] (the reader is referred to [14], [34] for a thorough analysis of distributed sequential detection). In [34], [33], each sensor collects a sequence of observations, constructs a summary message and passes it on to the FC and all other sensors. A Bayesian problem formulation comprising the minimization of the average error detection probability and sampling time cost over all admissible decision policies at the FC and all possible local decision functions at each sensor is then considered to determine the optimal stopping and decision rule. Further, algorithms to solve the optimization problem for both infinite and finite horizon are given. This chapter is different from [34] and [33] in the sense that we first consider a sequential detection scheme at each sensor and assume no communications among the sensors. Second, the optimization problem in this chapter is an energy optimization problem and is constrained, while in [34], [33], the problem is different and is unconstrained. In [36], an infinite horizon sequential detection scheme based on the sequential probability ratio test (SPRT) at both the sensors and the FC is considered. Wald's analysis of error probability, [45], is employed to determine the thresholds at the sensors and the FC. Our sensing scheme is different, since we consider a truncated sequential detection and our thresholds are determined based on an energy optimization problem which do not lead to Wald's thresholds. The design of a distributed sequential detection network under a communication bandwidth constraint is considered in [37]. Each sensor sends a quantized version of its observation to the FC and then the SPRT is employed to make the decision to stop or carry on sensing. The problem is formulated as to determine the distribution of the bandwidth among the sensors, the quantizer design, and the FC decision policy in order to minimize the average sample number (ASN). Incorporating [37] to increase the throughput of a cognitive radio system can be an interesting area of future research. [32] presents a distributed sequential sensing scheme where each sensor performs an SPRT and makes a decision. The decision is then sent to the FC and the FC announces the first incoming decision as the global decision.

Henceforth, the global probability of detection and false alarm is equal to the ones at each sensor. This scheme can also be exploited to reduce the sensing and reporting time of the cognitive radio network thereby increasing the network throughput while decreasing the energy consumption. A combination of sequential detection and censoring is considered in [42]. Each sensor computes the LLR of the received sample and sends it to the FC, if it is deemed to be in a certain region. The FC then collects the received LLRs and as soon as their sum is larger than an upper threshold or smaller than a lower threshold, the decision is made and the sensors can stop sensing. The LLRs are send in such a way that the larger LLRs are sent sooner. It is shown that the number of transmissions considerably reduces and particularly when the listening cost is high, this approach performs very well. However, this chapter employs a hard fusion scheme at the FC, our sequential scheme is finite horizon, and further a clear optimization problem is given to optimize the energy consumption. [31] proposes a sequential censoring scheme where an SPRT is employed by the FC and soft or hard local decisions are sent to the FC according to a censoring policy. It is depicted that the number of transmissions decreases but on the other hand the ASN increases. Therefore, [31] ignores the effect of listening on the energy consumption and focuses only on the transmission energy which for current low-power radios is comparable to the sensing energy. In this chapter, we consider the energy of both sensing and transmission and optimize the overall energy consumed by each sensor. Further, since our sequential scheme is truncated, a decision will always be made by the FC, while in [31], the FC may not reach a decision in a reasonable time. Finally, the system in [31] asymptotically reaches a specific detection performance as the number of sensors grows, but this incurs a high total energy consumption by the system. As shall be shown later on, in our sequential censoring scheme, the energy consumption saturates when the number of cognitive radios increases. [38] considers a distributed sequential sensing scheme where each sensor employs the SPRT and upon reaching a decision, a binary result is sent to the FC. The FC then makes a final decision using a K-out-of-M rule. It is shown that for the same detection error probability, the detection performance of this sequential scheme is better than fixed-size sampling and furthermore the observation energy is proven to be lower. The optimal sensing thresholds are found by an iterative algorithm that solves a Bayesian risk problem.

Sequential spectrum sensing is also considered for cognitive radio design. An infinite horizon SPRT is employed in [41], [40], [39], [30] for different sensing techniques. It is shown that the sensing time dramatically reduces when employing sequential detection. The optimization of cognitive network throughput under a constraint on the miss-detection probability is solved in [28], [29] in order to find the optimal stopping and access policies. This approach is infinite horizon which is a not a valid assumption considering the limited sensing time of cognitive radios. Further, a binary result has to be sent to the FC for each collected observation sample which entails a high transmission energy consumption. Nevertheless, the considered optimization problem is matched to the cognitive radio system requirements and an extension of [28] for the finite horizon case can also be considered. In [27], the sensing thresholds that minimize the ASN are derived subject to a constraint on the false alarm rate, miss-detection probability, outage probability and interference level. This method is particularly designed for systems with real-time traffic. A truncated sequential sensing technique is employed in [44] to reduce the sensing time of a cognitive radio system. The thresholds are determined such that a certain probability of false alarm and detection are obtained. In this chapter, we are employing a similar technique, except that in [44], after the truncation point, a single threshold scheme is used to make a final decision, while in this chapter, the sensor decision is censored if no decision is made before the truncation point. Further, [44] considers a single sensor detection scheme while we employ a distributed cooperative sensing system and finally, in this chapter an explicit optimization problem is given to find the sensing parameters.

3.1.2 Organization

The remainder of this chapter is organized as follows. In Section 3.2, the sequential censoring scheme system model and problem formulation for the OR rule. Analytical expressions for the underlying system parameters are derived and the optimization problem is analyzed in Section 3.3. In Section 3.4, sequential censoring schemes are presented and analyzed for the AND rule. We discuss some numerical results in Section 3.5. Conclusions are finally posed in Section 3.6.

3.2 System Model and Problem Formulation

Unlike Chapter 2, where each user collects a specific number of samples, in this section, each cognitive radio sequentially senses the spectrum and upon reaching a decision about the presence or absence of the primary user, it sends the result to the FC by employing a censoring policy as introduced in Chapter 2. The final decision is then made at the FC by employing the OR rule. The AND rule will be covered in Section 3.4. Here, a censored truncated sequential sensing scheme is employed where each cognitive radio carries on sensing until it reaches a decision while not passing a limit of N samples. We define $\zeta_{nj} = \sum_{i=1}^{n} |r_{ij}|^2/\sigma_w^2 = \sum_{i=1}^{n} x_{ij}$ and $a_i = 0,\ i = 1,\dots,p,\ a_i = \overline{a} + i\overline{\Lambda},\ i = p+1,...,N$ and $b_i = \overline{b} + i\overline{\Lambda},\ i = 1,...,N$, where $\overline{a} = a/\sigma_w^2$, $\overline{b} = b/\sigma_w^2$, $1 < \overline{\Lambda} < 1+\gamma_j$ is a predetermined constant, $a < 0$, $b > 0$ and $p = \lfloor -a/\sigma_w^2\overline{\Lambda} \rfloor$ [44]. We assume that the SNR γ_j is known or can be estimated. This way, the local decision rule in order to make a final decision is as follows

$$\begin{cases} \text{send 1, declaring } \mathscr{H}_1 & \text{if } \zeta_{nj} \geq b_n \text{ and } n \in [1,N], \\ \text{continue sensing} & \text{if } \zeta_{nj} \in (a_n, b_n) \text{ and } n \in [1,N), \\ \text{no decision} & \text{if } \zeta_{nj} \in (a_n, b_n) \text{ and } n = N, \\ \text{send 0, declaring } \mathscr{H}_0 & \text{if } \zeta_{nj} \leq a_n \text{ and } n \in [1,N]. \end{cases} \quad (3.1)$$

Fig. 3.1 depicts (3.1) schematically.

The probability density function of $x_{ij} = |r_{ij}|^2/\sigma_w^2$ under $\mathscr{H}_0$ and $\mathscr{H}_1$ is a chi-square distribution with 2 degrees of freedom. Thus, x_{ij} becomes exponentially distributed under both $\mathscr{H}_0$ and $\mathscr{H}_1$. Henceforth, we obtain

$$Pr(x_{ij}|\mathscr{H}_0) = \frac{1}{2} e^{-x_{ij}/2} I_{\{x_{ij} \geq 0\}}, \quad (3.2)$$

$$Pr(x_{ij}|\mathscr{H}_1) = \frac{1}{2(1+\gamma_j)} e^{-x_{ij}/2(1+\gamma_j)} I_{\{x_{ij} \geq 0\}}, \quad (3.3)$$

where $I_{\{x_{ij} \geq 0\}}$ is the indicator function.

Defining $\zeta_{0j} = 0$, the local probability of false alarm at the j-th cognitive radio, $P_{f,j}$, can be written as

$$P_{f,j} = \sum_{n=1}^{N} Pr(\zeta_{0j} \in (a_0, b_0), ..., \zeta_{n-1j} \in (a_{n-1}, b_{n-1}), \zeta_{nj} \geq b_n | \mathscr{H}_0), \quad (3.4)$$

whereas the local probability of detection, $P_{d,j}$, is obtained as follows

$$P_{d,j} = \sum_{n=1}^{N} Pr(\zeta_{0j} \in (a_0, b_0), ..., \zeta_{n-1j} \in (a_{n-1}, b_{n-1}), \zeta_{nj} \geq b_n | \mathscr{H}_1). \quad (3.5)$$

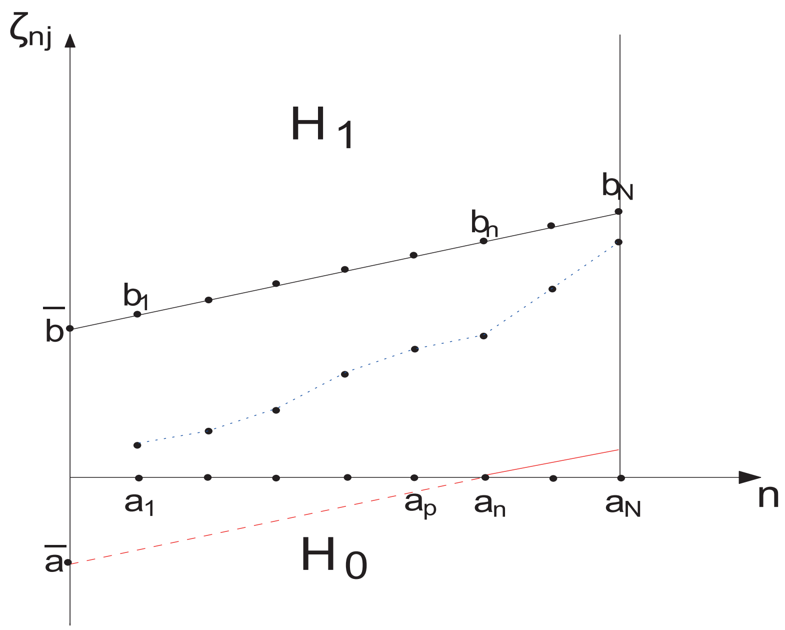


Figure 3.1: *Truncated sequential sensing procedure*

Denoting ρ_j to be the average censoring rate at the j-th cognitive radio, and $\delta_{0,j}$ and $\delta_{1,j}$ to be the respective average censoring rate under $\mathscr{H}_0$ and $\mathscr{H}_1$, we have

$$\rho_j = \pi_0 \delta_{0,j} + \pi_1 \delta_{1,j}, \tag{3.6}$$

where

$$\delta_{0,j} = Pr(\zeta_{1j} \in (a_1, b_1), ..., \zeta_{Nj} \in (a_N, b_N)|\mathscr{H}_0), \tag{3.7}$$

$$\delta_{1,j} = Pr(\zeta_{1j} \in (a_1, b_1), ..., \zeta_{Nj} \in (a_N, b_N)|\mathscr{H}_1). \tag{3.8}$$

The other parameter that is important in any sequential detection scheme is the average sample number (ASN) required to reach a decision. Denoting N_j to be a random variable representing the number of samples required to stop sensing, and this includes announcing the presence or absence of the primary user before the truncation point or reaching the truncation point where the sensing automatically stops, the ASN for the j-th cognitive radio, denoted as $\overline{N}_j$=$E(N_j)$, can be defined as

$$\overline{N}_j = \pi_0 E(N_j|\mathscr{H}_0) + \pi_1 E(N_j|\mathscr{H}_1), \tag{3.9}$$

where

$$\begin{aligned}
E(N_j|\mathscr{H}_0) &= \sum_{n=1}^{N} nPr(N_j = n|\mathscr{H}_0) \\
&= \sum_{n=1}^{N-1} n[Pr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{n-1j} \in (a_{n-1}, b_{n-1})|\mathscr{H}_0) \\
&- Pr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{nj} \in (a_n, b_n)|\mathscr{H}_0)] \\
&+ NPr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{N-1j} \in (a_{N-1}, b_{N-1})|\mathscr{H}_0), \qquad (3.10)
\end{aligned}$$

and

$$\begin{aligned}
E(N_j|\mathscr{H}_1) &= \sum_{n=1}^{N} nPr(N_j = n|\mathscr{H}_1) \\
&= \sum_{n=1}^{N-1} n[Pr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{nj} \in (a_{n-1}, b_{n-1})|\mathscr{H}_1) \\
&- Pr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{nj} \in (a_n, b_n)|\mathscr{H}_1)] \\
&+ NPr(\zeta_{0j} \in (a_0, b_0), \ldots, \zeta_{N-1j} \in (a_{N-1}, b_{N-1})|\mathscr{H}_1). \qquad (3.11)
\end{aligned}$$

Denoting again $C_{s,j}$ to be the sensing energy of one sample and $C_{t,j}$ to be the transmission energy of a decision bit at the j-th cognitive radio, the total average energy consumption at the j-th cognitive radio now becomes

$$C_j = \bar{N}_j C_{s,j} + (1 - \rho_j) C_{t,j}. \qquad (3.12)$$

Denoting Q_{F}^{cs} and Q_{D}^{cs} to be the respective global probabilities of false alarm and detection for the censored truncated sequential approach, we define our problem as the minimization of the maximum average energy consumption per sensor subject to a constraint on the global probabilities of false alarm and detection as follows

$$\begin{aligned}
&\min_{\bar{a}, \bar{b}} \max_{j} C_j \\
&\text{s.t. } Q_{\mathrm{F}}^{cs} \leq \alpha,\ Q_{\mathrm{D}}^{cs} \geq \beta. \qquad (3.13)
\end{aligned}$$

As in (2.11) and (2.12), under the OR rule that is assumed in this section, the global probability of false alarm is

$$Q_{\mathrm{F}}^{cs} = Pr(D_{\mathrm{FC}} = 1|\mathscr{H}_0) = 1 - \prod_{j=1}^{M} (1 - P_{f,j}), \qquad (3.14)$$

and the global probability of detection is

$$Q_{\mathrm{D}}^{cs} = Pr(D_{\mathrm{FC}} = 1|\mathscr{H}_1) = 1 - \prod_{j=1}^{M}(1 - P_{d,j}). \tag{3.15}$$

Note that since $P_{f,1} = \cdots = P_{f,M}$, it is again assumed that $P_{f,j} = P_f$ in this section.

In the following subsection, analytical expressions for the probability of false alarm and detection as well as the censoring rate and ASN are extracted.

3.3 Parameter and Problem Analysis

Looking at (3.4), (3.5), (3.6) and (3.9), we can see that the joint probability distribution function of $p(\zeta_{1j},\ldots,\zeta_{nj})$ is the foundation of all the equations. Since $x_{ij} = \zeta_{ij} - \zeta_{i-1j}$ for $i = 1,\ldots,N$, we have,

$$\begin{aligned} p(\zeta_{1j},\ldots,\zeta_{nj}) &= p(\zeta_{2j},\ldots,\zeta_{nj}|\zeta_{1j})p(\zeta_{1j}) \\ &= p(\zeta_{3j},\ldots,\zeta_{nj}|\zeta_{1j},\zeta_{2j})p(\zeta_{2j}|\zeta_{1j})p(\zeta_{1j}) \\ &= . \\ &= . \\ &= p(\zeta_{nj}|\zeta_{1j},\ldots,\zeta_{n-1j})\ldots p(\zeta_{1j}) \\ &= p(x_{nj})p(x_{n-1j})\ldots p(x_{1j}). \end{aligned} \tag{3.16}$$

Therefore, the joint probability distribution function under $\mathscr{H}_0$ and $\mathscr{H}_1$ becomes

$$p(\zeta_{1j},\ldots,\zeta_{nj}|\mathscr{H}_0) = \frac{1}{2^n}e^{-\zeta_{nj}/2}I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{nj}\}}, \tag{3.17}$$

$$p(\zeta_{1j},\ldots,\zeta_{nj}|\mathscr{H}_1) = \frac{1}{[2(1+\gamma_j)]^n}e^{-\zeta_{nj}/2(1+\gamma_j)}I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{nj}\}}, \tag{3.18}$$

where $I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{nj}\}}$ is again the indicator function.

The derivation of the local probability of false alarm and the ASN under $\mathscr{H}_0$ in this chapter are similar to the ones considered in [44] and [43]. The difference is that in [44], if the cognitive radio does not reach a decision after N samples, it employs a single threshold decision policy to give a final decision about the presence or absence of the cognitive radio, while in this chapter, no decision is sent in case none of the upper and lower thresholds are crossed. Hence, to avoid introducing a cumbersome detailed derivation of each parameter, we can use the results in [44] for our analysis with a small modification. However, note that the problem formulation in this chapter is essentially different from the one in [44]. Further, since in this chapter the distribution of x_{ij} under $\mathscr{H}_1$ is exponential like the one under $\mathscr{H}_0$, unlike [44], we can also use the same approach to derive analytical expressions for the local probability of detection, the ASN under $\mathscr{H}_1$, and the censoring rate.

Denoting E_n to be the event where $a_i < \zeta_{ij} < b_i,\ i = 1,...,n-1$ and $\zeta_{nj} \geq b_n$, (3.4) becomes

$$P_{f,j} = \sum_{n=1}^{N} Pr(E_n|\mathscr{H}_0). \tag{3.19}$$

where the analytical expression for $Pr(E_n|\mathscr{H}_0)$ is derived in Appendix 3.A.

Similarly for the local probability of detection, we have

$$P_{d,j} = \sum_{n=1}^{N} Pr(E_n|\mathscr{H}_1), \tag{3.20}$$

where the analytical expression for $Pr(E_n|\mathscr{H}_1)$ is derived in Appendix 3.B.

Defining $R_{nj} = \{\zeta_{ij}|\zeta_{ij} \in (a_i,b_i),\ i = 1,...,n\}$, $Pr(R_{nj}|\mathscr{H}_0)$ and $Pr(R_{nj}|\mathscr{H}_1)$ are obtained as follows

$$Pr(R_{nj}|\mathscr{H}_0) = \frac{1}{2^n} J^{(n)}_{a_n,b_n}(1/2),\ n = 1,...,N, \tag{3.21}$$

$$Pr(R_{nj}|\mathscr{H}_1) = \frac{1}{[2(1+\gamma_j)]^n} J^{(n)}_{a_n,b_n}(1/2(1+\gamma_j)),\ n = 1,...,N, \tag{3.22}$$

where $J^{(n)}_{a_n,b_n}(\theta)$ is presented in Appendix 3.C and (3.10) and (3.11) become

$$\begin{aligned} E(N_j|\mathscr{H}_0) &= \sum_{n=1}^{N-1} n(Pr(R_{n-1j}|\mathscr{H}_0) - Pr(R_{nj}|\mathscr{H}_0)) + NPr(R_{N-1j}|\mathscr{H}_0) \\ &= 1 + \sum_{n=1}^{N-1} Pr(R_{nj}|\mathscr{H}_0), \end{aligned} \tag{3.23}$$

$$\begin{aligned} E(N_j|\mathscr{H}_1) &= \sum_{n=1}^{N} n(Pr(R_{n-1j}|\mathscr{H}_1) - Pr(R_{nj}|\mathscr{H}_1)) + NPr(R_{N-1j}|\mathscr{H}_1) \\ &= 1 + \sum_{n=1}^{N-1} Pr(R_{nj}|\mathscr{H}_1). \end{aligned} \tag{3.24}$$

With (3.23) and (3.24), we can calculate (3.9). This way, (3.7) and (3.8) can be derived as follows

$$\delta_{0,j} = Pr(R_{Nj}|\mathscr{H}_0) = \frac{1}{2^N} J^{(N)}_{a_N,b_N}(1/2), \tag{3.25}$$

$$\delta_{1,j} = Pr(R_{Nj}|\mathscr{H}_1) = \frac{1}{[2(1+\gamma_j)]^N} J^{(N)}_{a_N,b_N}(1/2(1+\gamma_j)). \tag{3.26}$$

We can show that the problem (3.13) is not convex. Therefore, the standard systematic optimization algorithms do not give the global optimum for $\bar{a}$ and $\bar{b}$. However, as is shown in the following lines, $\bar{a}$ and $\bar{b}$ are bounded and therefore, a two-dimensional exhaustive search is possible to find the global optimum. First of all, we have $a < 0$ and $\bar{a} < 0$. On the other hand, if $\bar{a}$ has to play a role in the sensing system, at least one a_N should be positive, i.e., $a_N = \bar{a} + N\Delta \geq 0$ which gives $\bar{a} \geq -N\Delta$. Hence, we obtain $-N\Delta \leq \bar{a} < 0$. Furthermore, defining $Q^{cs}_{\mathrm{F}} = \mathscr{F}(\bar{a},\bar{b})$ and $Q^{cs}_{\mathrm{D}} = \mathscr{G}(\bar{a},\bar{b})$, for a given $\bar{a}$, it is easy to show that $\mathscr{G}^{-1}(\bar{a},\beta) \leq \bar{b} \leq \mathscr{F}^{-1}(\bar{a},\alpha)$ (where $\mathscr{F}^{-1}$ and $\mathscr{G}^{-1}$ are defined over the second argument).

Before introducing a suboptimal problem, the following theorem is presented.

Theorem 1. For a given local probability of detection and false alarm (P_d and P_f) and N, the censoring rate of the optimal censored truncated sequential sensing (ρ^{cs}) is less than the one of the censoring scheme (ρ^c).

Proof. The proof is provided in Appendix 3.D.

We should note that, in censored truncated sequential sensing, a large amount of energy is to be saved on sensing. Therefore, as is shown in Section 3.5, as the sensing energy of each sensor increases, censored truncated sequential sensing outperforms censoring in terms of energy efficiency. However, in case that the transmission energy is much higher than the sensing energy, it may happen that censoring outperforms censored truncated sequential sensing, because of a higher censoring rate ($\rho^{cs} > \rho^c$). Hence, one corollary of Theorem 1 is that although the optimal solution of (2.10) for a specific N, i.e., $P_d = 1-(1-\beta)^{1/M}$ and $P_f = H^{-1}(\beta)$, is in the feasible set of (3.13) for a resulting ASN less than N, it does not necessarily guarantee that the resulting average energy consumption per sensor of the censored truncated sequential sensing approach is less than the one of the censoring scheme, particularly when the transmission energy is much higher than the sensing energy per sample.

Solving (3.13) is complex in terms of the number of computations, and thus a two-dimensional exhaustive search is not always a good solution. Therefore, in order to reach a good solution in a reasonable time, we set $a < -N\Delta$ in order to obtain $a_1 = \cdots = a_N = 0$. This way, we can relax one of the arguments of (3.13) and only solve the following suboptimal problem

$$\begin{aligned} &\min_{\bar{b}} \ \max_{j} \ C_j \\ &\text{s.t. } Q_{\text{F}}^{cs} \leq \alpha, \ Q_{\text{D}}^{cs} \geq \beta. \end{aligned} \tag{3.27}$$

Note that unlike Section 2, here the zero lower threshold is not necessarily optimal. The reason is that although the maximum censoring rate is achieved with the lowest $\bar{a}$, the minimum ASN is achieved with the highest $\bar{a}$, and thus there is an inherent trade-off between a high censoring rate and a low ASN, and a zero a_i is not necessarily the optimal solution. Since the analytical expressions provided earlier are very complex, we now try to provide a new set of analytical expressions for different parameters based on the fact that $a_1 = \cdots = a_N = 0$.

To find an analytical expression for $P_{f,j}$, we can derive $A(n)$ for the new paradigm as follows

$$A(n) = \underset{\Gamma_n}{\int \ldots \int} I_{\{0 \leq \zeta_{1j} \leq \zeta_{2j} \ldots \leq \zeta_{n-1j}\}} d\zeta_{1j} \ldots d\zeta_{n-1j}. \tag{3.28}$$

Since $0 \leq \zeta_{1j} \leq \zeta_{2j} \ldots \leq \zeta_{n-1j}$ and $a_1 = \cdots = a_N = 0$, the lower bound for each integral is ζ_{i-1} and the upper bound is b_i, where $i = 1, \ldots, n-1$. Thus we obtain

$$A(n) = \int_{\zeta_{0j}}^{b_1} \int_{\zeta_{1j}}^{b_2} \cdots \int_{\zeta_{n-2j}}^{b_{n-1}} d\zeta_{1j} d\zeta_{2j} \ldots d\zeta_{n-1j}, \tag{3.29}$$

which according to [43] is

$$A(n) = \frac{b_1 b_n^{n-2}}{(n-1)!}, \ n = 1, \ldots, N. \tag{3.30}$$

Hence, we have

$$P_{f,j} = \sum_{n=1}^{N} p_n A(n), \tag{3.31}$$

and $p_n = \frac{e^{-b_n/2}}{2^{n-1}}$. Similarly, for $P_{d,j}$, we obtain

$$\begin{aligned} B(n) &= \int_{\zeta_{0j}}^{b_1} \int_{\zeta_{1j}}^{b_2} \cdots \int_{\zeta_{n-2j}}^{b_{n-1}} d\zeta_{1j} d\zeta_{2j} \ldots d\zeta_{n-1j} \\ &= \frac{b_1 b_n^{n-2}}{(n-1)!}, \ n = 1, \ldots, N, \end{aligned} \tag{3.32}$$

and thus

$$P_{d,j} = \sum_{n=1}^{N} q_n B(n), \tag{3.33}$$

where $q_n = \frac{e^{-b_n/2(1+\gamma_j)}}{[2(1+\gamma_j)]^{n-1}}$. Furthermore, we note that for $a_1 = \cdots = a_N = 0$, $A(n) = B(n) = \frac{b_1 b_n^{n-2}}{(n-1)!}$, $n = 1, ..., N$.

It is easy to see that R_{nj} occurs under $\mathscr{H}_0$, if no false alarm happens until the n-th sample. Therefore, the analytical expression for $Pr(R_{nj}|\mathscr{H}_0)$ is given by

$$Pr(R_{nj}|\mathscr{H}_0) = 1 - \sum_{i=1}^{n} p_i A(i), \tag{3.34}$$

and in the same way, for $Pr(R_{nj}|\mathscr{H}_1)$, we obtain

$$Pr(R_{nj}|\mathscr{H}_1) = 1 - \sum_{i=1}^{n} q_i A(i). \tag{3.35}$$

Putting (3.34) and (3.35) in (3.23) and (3.24), we obtain

$$E(N_j|\mathscr{H}_0) = 1 + \sum_{n=1}^{N-1} \left\{ 1 - \sum_{i=1}^{n} p_i A(i) \right\}, \tag{3.36}$$

$$E(N_j|\mathscr{H}_1) = 1 + \sum_{n=1}^{N-1} \left\{ 1 - \sum_{i=1}^{n} q_i A(i) \right\}, \tag{3.37}$$

and inserting (3.36) and (3.37) in (3.9), we obtain

$$\overline{N}_j = \pi_0 \left(1 + \sum_{n=1}^{N-1} \left\{ 1 - \sum_{i=1}^{n} p_i A(i) \right\} \right) + \pi_1 \left(1 + \sum_{n=1}^{N-1} \left\{ 1 - \sum_{i=1}^{n} q_i A(i) \right\} \right). \tag{3.38}$$

Finally, from (3.34) and (3.35), the censoring rate can be easily obtained as

$$\rho_j = \pi_0 \left(1 - \sum_{i=1}^{N} p_i A(i) \right) + \pi_1 \left(1 - \sum_{i=1}^{N} q_i A(i) \right). \tag{3.39}$$

Having the analytical expressions for (3.27), we can easily find the optimal maximum average energy consumption per sensor by a line search over $\overline{b}$. Similar to the censoring problem formulation, here the sensing threshold is also bounded by $Q_{\mathrm{F}}^{cs-1}(\alpha) \leq \overline{b} \leq Q_{\mathrm{D}}^{cs-1}(\beta)$. As we will see in Section 3.5, censored truncated sequential sensing performs better than censored spectrum sensing in terms of energy efficiency for low-power radios.

3.4 Extension to the AND rule

So far, we have focused on the OR rule. However, another rule which is also simple in terms of implementation is the AND rule. According to the AND rule, $D_{FC} = 0$, if at least one cognitive radio reports a zero, else $D_{FC} = 1$. This way the global probabilities of false alarm and detection, can be written respectively as

$$Q^{cs}_{\mathrm{F,AND}} = Pr(D_{FC} = 1|\mathscr{H}_0) = \prod_{j=1}^{M}(\delta_{0,j} + P_{f,j}), \tag{3.40}$$

$$Q^{cs}_{\mathrm{D,AND}} = Pr(D_{FC} = 1|\mathscr{H}_1) = \prod_{j=1}^{M}(\delta_{1,j} + P_{d,j}). \tag{3.41}$$

Similar to the case for the OR rule, the problem is defined so as to minimize the maximum average energy consumption per sensor subject to a lower bound on the global probability of detection and an upper bound on the global probability of false alarm.

The optimization problem for the censored truncated sequential sensing scheme with the AND rule, becomes

$$\begin{aligned} &\min_{\bar{a},\bar{b}} \ \max_{j} \ C_j \\ &\text{s.t. } Q^{cs}_{\mathrm{F,AND}} \leq \alpha, \ Q^{cs}_{\mathrm{D,AND}} \geq \beta. \end{aligned} \tag{3.42}$$

where C_j is defined in (3.12). Similar to the OR rule, we have $-N\Delta \leq \bar{a} < 0$. Defining $Q^{cs}_{\mathrm{F,AND}} = \mathscr{F}_{\mathrm{AND}}(\bar{a},\bar{b})$ and $Q^{cs}_{\mathrm{D,AND}} = \mathscr{G}_{\mathrm{AND}}(\bar{a},\bar{b})$, for a given $\bar{a}$, we can show that $\mathscr{G}^{-1}_{\mathrm{AND}}(\bar{a},\beta) \leq \bar{b} \leq \mathscr{F}^{-1}_{\mathrm{AND}}(\bar{a},\alpha)$ (where $\mathscr{F}^{-1}_{\mathrm{AND}}$ and $\mathscr{G}^{-1}_{\mathrm{AND}}$ are defined over the second argument). Therefore, the optimal $\bar{a}$ and $\bar{b}$ can again be derived by a bounded two-dimensional search, in a similar way as for the OR rule. Note that, as in the *OR* rule, single threshold detection is not necessary optimal for the AND rule in censored truncated sequential sensing. However, to decrease the computational complexity, a sub-optimal line search with a single threshold is possible. In this case, the related parameters can be obtained by $b \to \infty$.

3.5 Numerical Results

A network of cognitive radios is considered for the numerical results. In some of the scenarios, for the sake of simplicity, it is assumed that all the sensors experience the same SNR. This way, it is easier to show how the main performance indicators including the optimal maximum average energy consumption per sensor, ASN and censoring rate changes when one of the underlying parameters of the system changes. However, to comply with the general idea of the paper, which is based on different received SNRs by cognitive radios, in other scenarios, the different cognitive radios experience different SNRs. Unless otherwise mentioned, the results are based on the single-threshold strategy for censored truncated sequential sensing in case of the OR rule.

In Fig. 3.2 the maximum energy consumption per sensor is optimized for $\gamma = 0dB$, $0.1 \leq \beta < 1$, $M = 5$, $C_{sj} = 1$ and $C_{tj} = 10$, $\alpha = 0.1$, and $\pi_0 = 0.2,\ 0.8$, and it is compared with the reference energy consumption where only censoring is employed by the cognitive radios. As we can see, the proposed censored truncated sequential scheme reduces the maximum energy consumption per sensor for both low and high π_0 as well as over the whole range of the detection probability constraint. Further, it is shown that the censored sequential scheme gives a higher energy efficiency than its censoring counterpart, particularly at high probability of detections. It is also shown that as π_0 increases, the maximum energy consumption per sensor decreases mainly due to a higher censoring rate.

Fig. 3.3 shows the optimal censoring rate versus β for the same scenario. Clearly, it is shown that the optimal censoring rate for higher π_0 is higher and further it is shown that the optimal censoring rate is slightly higher for censoring than for censored sequential sensing.

The optimal ASN versus β for the scenario of Fig. 3.2 is shown in Fig. 3.4. We can see that as π_0 increases the optimal ASN also increases which is expected due to the smaller probability of primary user appearance. Further, if the probability of detection increases, the ASN decreases, because the threshold $\bar{b}$ is lower for the higher detection rates and thus, cognitive radios sooner reach a decision.

Fig. 3.5 depicts the optimal maximum average energy consumption per sensor versus the number of cognitive radios for the OR rule. The SNR is assumed to be 0 dB, $N = 10$, $C_s = 1$ and $C_t = 10$. Furthermore, the probability of false alarm and detection constraints are assumed to be $\alpha = 0.1$ and $\beta = 0.9$ as determined by the IEEE 802.15.4 standard for cognitive radios [8]. It is shown for both high and low values of π_0 that censored sequential sensing outperforms the censoring scheme. Looking at Fig. 3.6 and Fig. 3.7, where the respective optimal censoring rate and

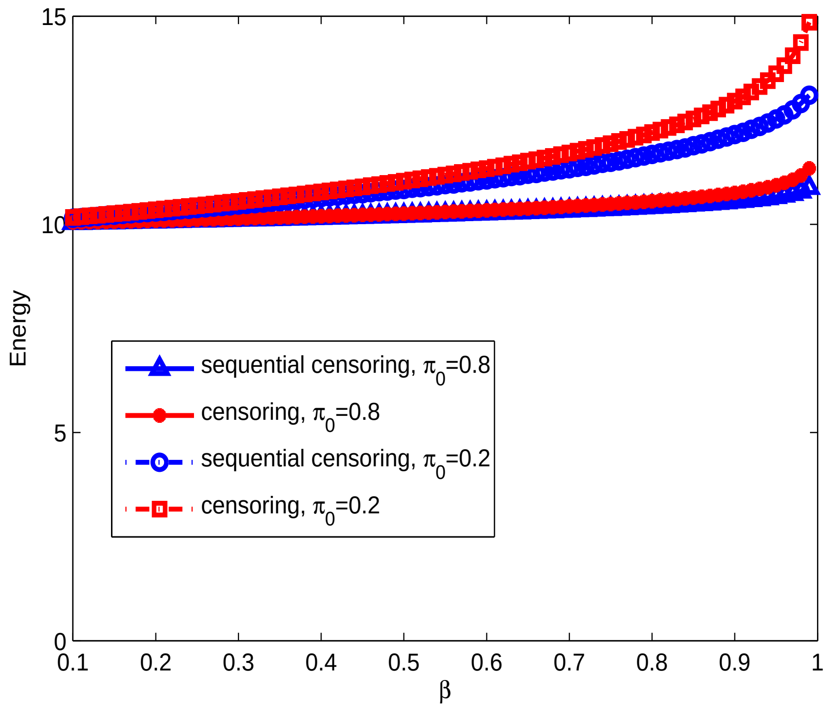


Figure 3.2: *Optimal maximum energy consumption per sensor versus β*

optimal ASN are shown versus the number of cognitive radios, we can deduce that the lower ASN is playing a key role in a lower energy consumption of the censored sequential sensing. Fig. 3.5 also shows that as the number of cooperating cognitive radios increases, the optimal maximum average energy consumption per sensor decreases and saturates, while as shown in Fig. 3.6 and Fig. 3.7, the optimal censoring rate and optimal ASN increase. This way, the energy consumption tends to increase as a result of ASN growth and on the other hand inclines to decrease due to the censoring rate growth and that is the reason for saturation after a number of cognitive radios. Therefore, we can see that as the number of cognitive radios increases, a higher energy efficiency per sensor can be achieved. However, after a number of cognitive radios, the maximum average energy consumption per sensor remains almost at a constant level and by adding more cognitive radios no significant energy saving per sensor can be achieved while the total network energy consumption also

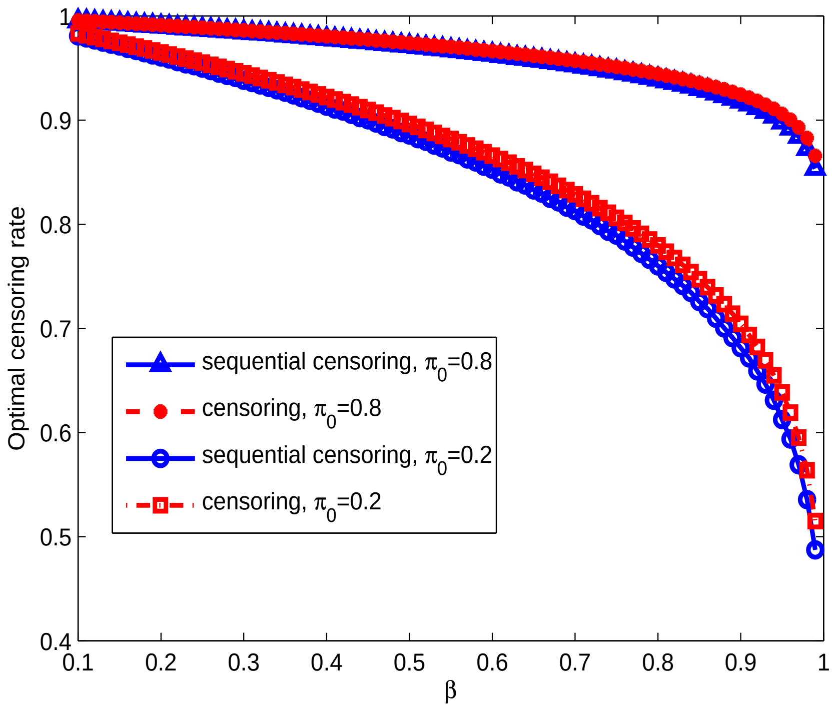


Figure 3.3: *Optimal censoring rate versus β*

increases.

Figures 3.8, 3.9 and 3.10 consider a scenario where $M = 5$, $N = 30$, $C_{s,j} = 1$, $C_{t,j} = 10$, $\alpha = 0.1$, $\beta = 0.9$ and π_0 can take a value of 0.2 or 0.8. The performance of the system versus SNR is analyzed in this scenario for the OR rule. The maximum average energy consumption per sensor is depicted in Fig. 3.8. As for the earlier scenario, censored sequential sensing gives a higher energy efficiency compared to censoring. While the optimal energy variation for the censoring scheme is almost the same for all the considered SNRs, the censored sequential scheme's average energy consumption per sensor reduces significantly as the SNR increases. The reason is that as the SNR increases, the optimal ASN dramatically decreases (almost 50% for $\gamma = 2$ dB and $\pi_0 = 0.2$). This shows that as the SNR increases, censored sequential sensing becomes even more valuable and a significant energy saving per sensor can be achieved compared with the one that is achieved by censoring. Since the SNR

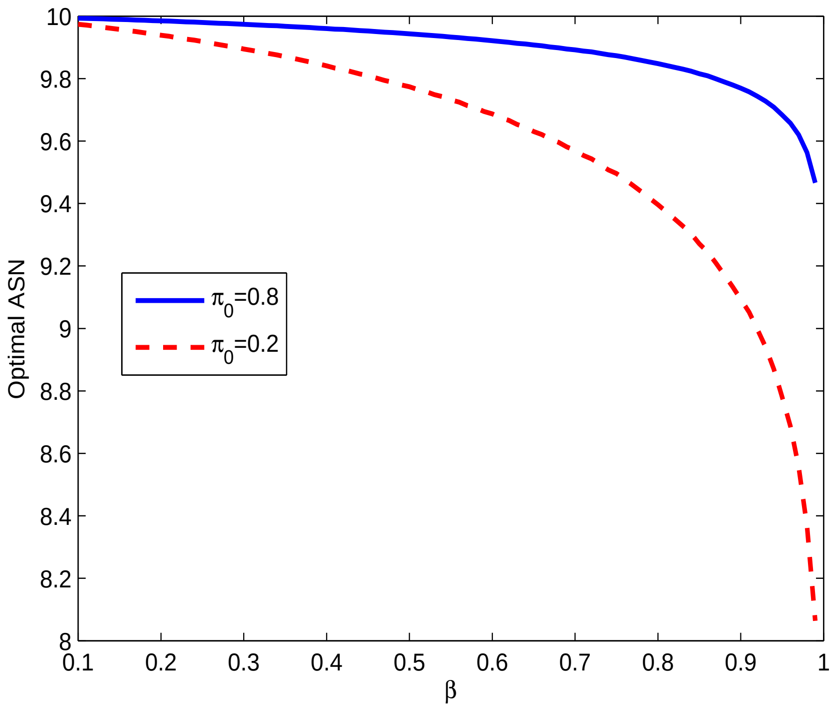


Figure 3.4: *Optimal ASN versus β*

changes with the channel gain ($|h_j|^2$ under the first model or $\sigma^2_{h,j}$ under the second model), from Fig. 3.8, the behavior of the system with varying $|h_j|^2$ or $\sigma^2_{h,j}$ can be derived, if the distribution of $|h_j|^2$ or $\sigma^2_{h,j}$ is known.

Figures 3.11 and 3.12 compare the performance of the single threshold censored truncated sequential scheme with the one assuming two thresholds, i.e, $\bar{a}$ and $\bar{b}$ for the OR rule. The idea is to find when the double threshold scheme with its higher complexity becomes valuable. In these figures, $M = 5$, $N = 10$, $\gamma = 0$ dB, $C_t = 10$, $\pi_0 = 0.2,\ 0.8$, and $\alpha = 0.1$, while β changes from 0.1 to 0.99. The sensing energy per sample, C_s in Fig. 3.11 is assumed 1, while in Fig. 3.12 it is 3. It is shown that as the sensing energy per sample increases, the energy efficiency of the double threshold scheme also increases compared to the one of the single threshold scheme, particularly when π_0 is high. The reason is that when π_0 is high, a much lower ASN can be achieved by the double threshold scheme compared to the single

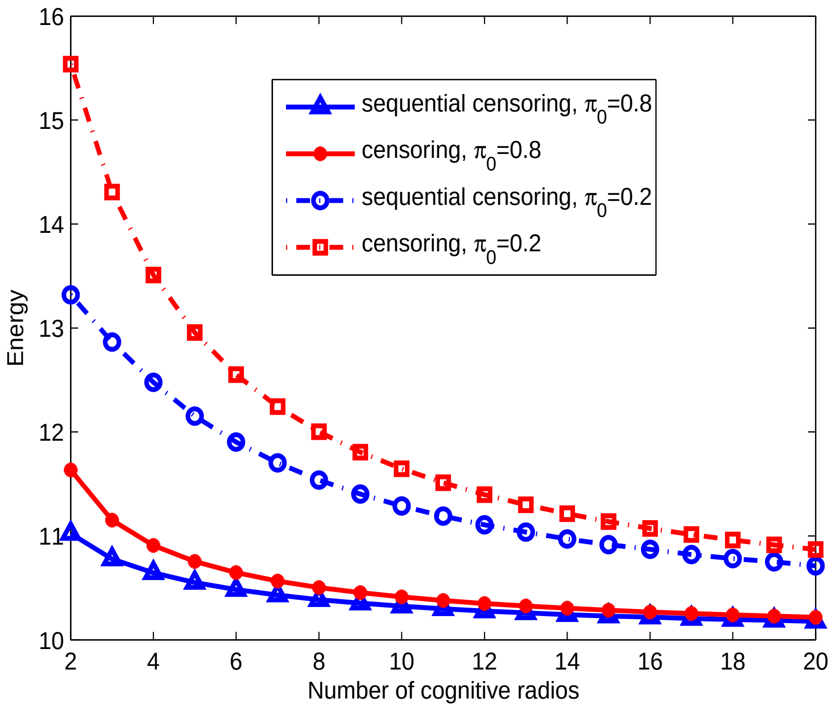


Figure 3.5: *Optimal maximum average energy consumption per sensor versus number of cognitive radios*

threshold one. This gain in performance comes at the cost of a higher computational complexity because of the two-dimensional search.

Fig. 3.13 depicts the optimal maximum average energy consumption per sensor versus the number of samples for the OR rule and for a network of $M = 5$ cognitive radios where each radio experiences a different channel gain and thus a different SNR. Arranging the SNRs in a vector $\boldsymbol{\gamma} = [\gamma_1, \ldots, \gamma_5]$, we have $\boldsymbol{\gamma}$ =[1dB, 2dB, 3dB, 4dB, 5dB]. The other parameters are $C_s = 1$, $C_t = 10$, $\pi_0 = 0.5$, $\alpha = 0.1$ and $\beta = 0.9$. As shown in Fig. 3.13, by increasing the number of samples and thus the total sensing energy, the sequential censoring energy efficiency also increases compared to the censoring scheme. For example, if we define the efficiency of the censored truncated sequential sensing scheme as the difference of the optimal maximum average energy consumption per sensor of sequential censoring and censoring divided by the opti-

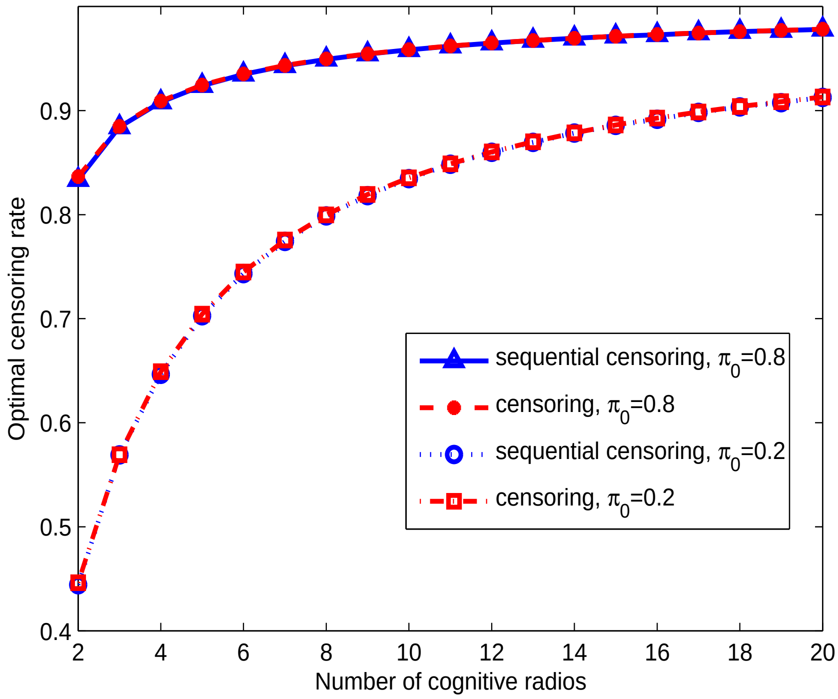


Figure 3.6: *Optimal censoring rate versus number of cognitive radios*

mal maximum average energy consumption per sensor of censoring, the efficiency increases approximately three times from 0.06 (for $N = 15$) to 0.19 (for $N = 30$).

In Fig. 3.14, the sensing energy per sample is $C_s = 1$ while the transmission energy C_t changes from 0 to 100. The goal is to see how the optimal maximum average energy consumption per sensor changes with C_t for the or rule and for a network of $M = 5$ cognitive radios with $\boldsymbol{\gamma}$ =[1dB, 2dB, 3dB, 4dB, 5dB]. The other parameters of the network are $N = 30$, $\pi_0 = 0.5$, $\alpha = 0.1$ and $\beta = 0.9$. The best saving for sequential censoring is achieved when the transmission energy is zero. Indeed, we can see that as the transmission energy increases the performance gain of sequential censoring reduces compared to censoring. However, in low-power radios where the sensing energy per sample and transmission energy are usually in the same range, sequential censoring performs much better than censoring in terms of energy efficiency as we can see in Fig. 3.14.

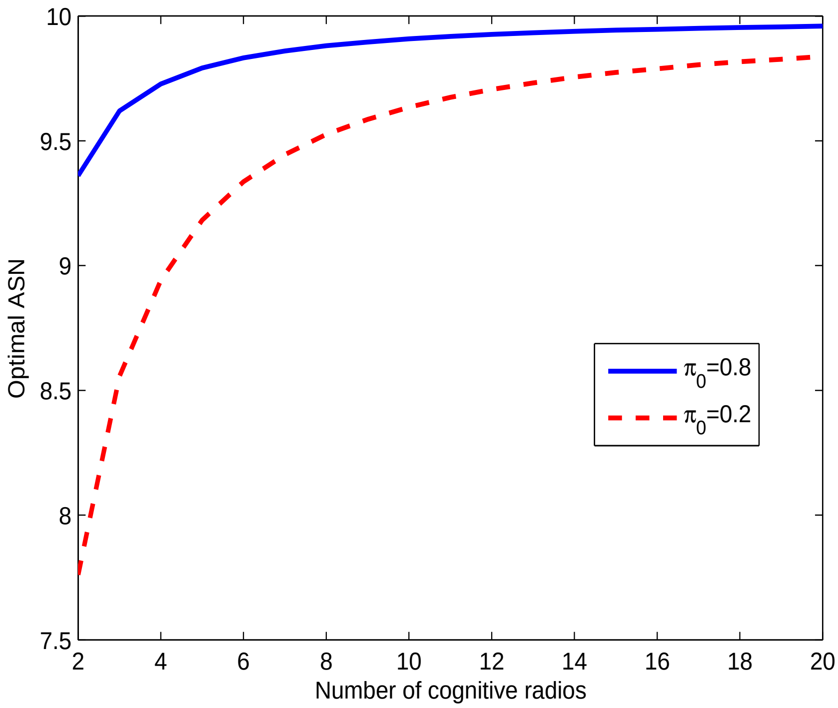


Figure 3.7: *Optimal ASN versus number of cognitive radios for the OR rule*

Fig. 3.15 depicts the optimal maximum average energy consumption per sensor versus the sensing energy per sample for both the AND and OR rule. For the sake of simplicity and tractability, the SNRs are assumed the same for $M = 50$ cognitive radios. The other parameters are assumed to be $N = 10$, $C_t = 10$, $\pi_0 = 0.5$, $\gamma = 0$ dB, $\alpha = 0.1$ and $\beta = 0.9$. For both fusion rules, the double threshold scheme is employed. We can see that the OR rule performs better for the low values of C_s. However, as C_s increases the AND rule dominates and outperforms the OR rule, particularly for high values of C_s. The reason that the OR rule performs better than the AND rule at very low values of C_s is that the optimal censoring rate for the OR rule is higher than the optimal censoring rate for the AND rule. However as C_s increases, the AND rule dominates the OR rule in terms of energy efficiency due to the lower ASN.

The optimal maximum average energy consumption per sensor versus π_0 is in-

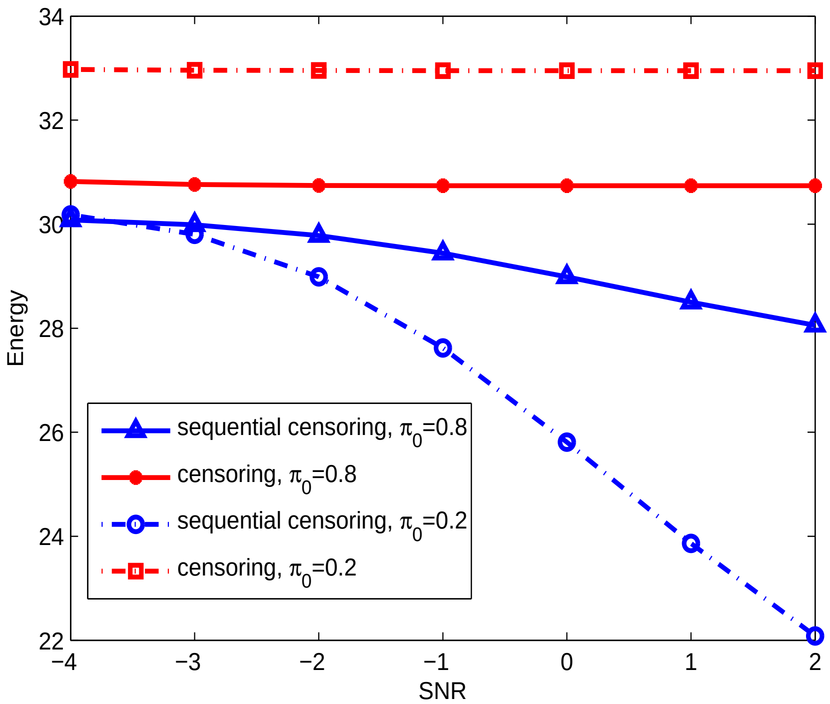


Figure 3.8: *Optimal maximum average energy consumption per sensor versus SNR*

vestigated in Fig. 3.16 for the AND and the OR rule. The underlying parameters are assumed to be $C_s = 2$, $C_t = 10$, $N = 10$, $M = 50$, $\gamma = 0$ dB, $\alpha = 0.1$ and $\beta = 0.9$. It is shown that as the probability of the primary user absence increases, the optimal maximum average energy consumption per sensor reduces for the OR rule while it increases for the AND rule. This is mainly due to the fact that for the OR rule, we are mainly interested to receive a ”1” from the cognitive radios. Therefore, as π_0 increases, the probability of receiving a ”1” decreases, since the optimal censoring rate increases. The opposite happens for the AND rule, since for the AND rule, receiving a ”0” from the cognitive radios is considered to be informative.

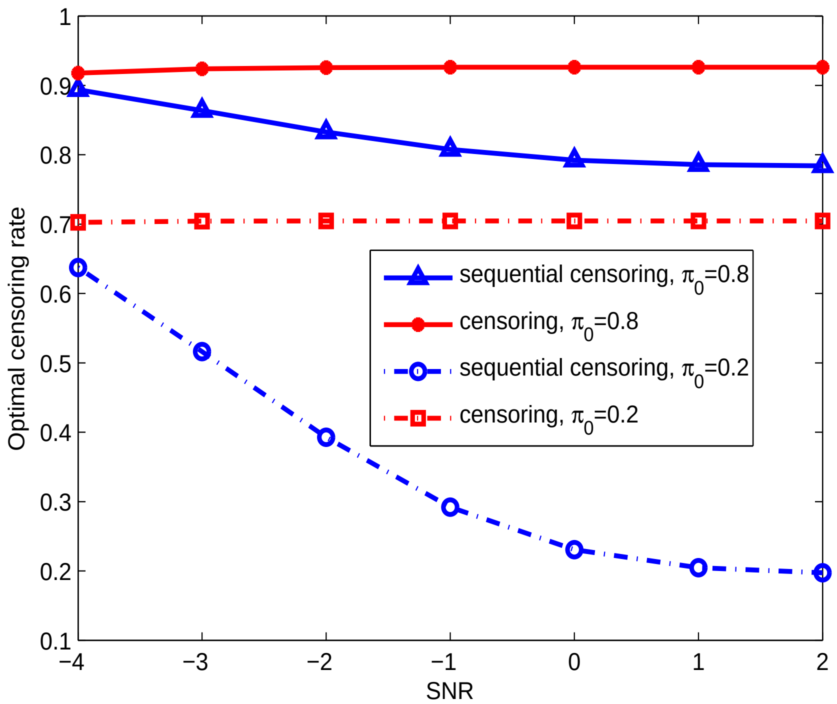


Figure 3.9: *Optimal censoring rate versus SNR*

3.6 Summary and conclusions

In Chapters 2 and 3, we presented two energy-efficient techniques for a cognitive sensor network. First, a censoring scheme has been discussed where each sensor employs a censoring policy to reduce the energy consumption. Then a censored truncated sequential approach has been proposed based on the combination of censoring and sequential sensing policies. We defined our problem as the minimization of the maximum average energy consumption per sensor subject to a global probability of false alarm and detection constraint for the AND and the OR rules. The optimal lower threshold is shown to be zero for the censoring scheme in case of the OR rule while for the AND rule the optimal upper threshold is shown to be infinity. Further, an explicit expression was given to find the optimal solution for the OR rule and in case of the AND rule a closed form solution has been derived. We have

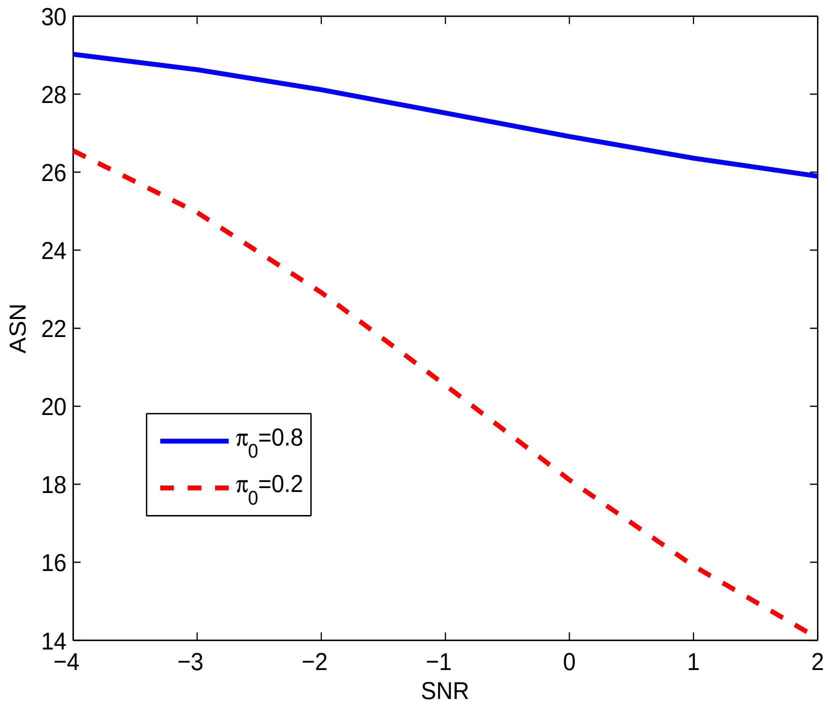


Figure 3.10: *Optimal ASN versus SNR for the OR rule*

further derived the analytical expressions for the underlying parameters in the censored sequential scheme and have shown that although the problem is not convex, a bounded two-dimensional search is possible for both the OR rule and the AND rule. Further, in case of the OR rule, we relaxed the lower threshold to obtain a line search problem in order to reduce the computational complexity.

Different scenarios regarding transmission and sensing energy per sample as well as SNR, number of cognitive radios, number of samples and detection performance constraints were simulated for low and high values of π_0 and for both the OR rule and the AND rule. It has been shown that under the practical assumption of low-power radios, sequential censoring outperforms censoring. We conclude that for high values of the sensing energy per sample, despite its high computational complexity, the double threshold scheme developed for the OR rule becomes more attractive. Further, it is shown that as the sensing energy per sample increases compared to the

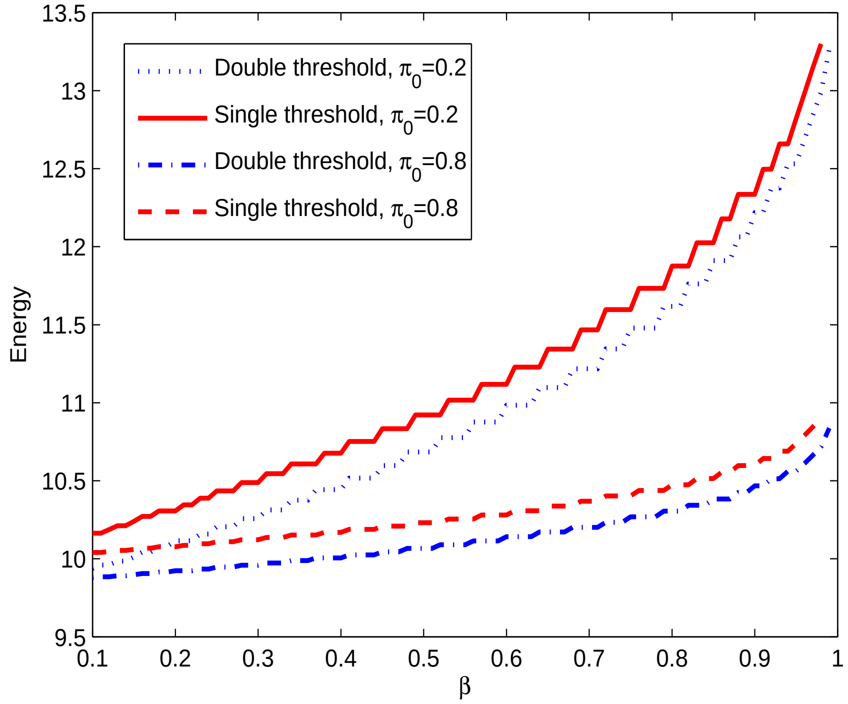


Figure 3.11: *Optimal maximum average energy consumption per sensor versus probability of detection constraint, β, for the OR rule and $C_s = 1$*

transmission energy, the AND rule performs better than the OR rule, while for very low values of the sensing energy per sample, the OR rule outperforms the AND rule.

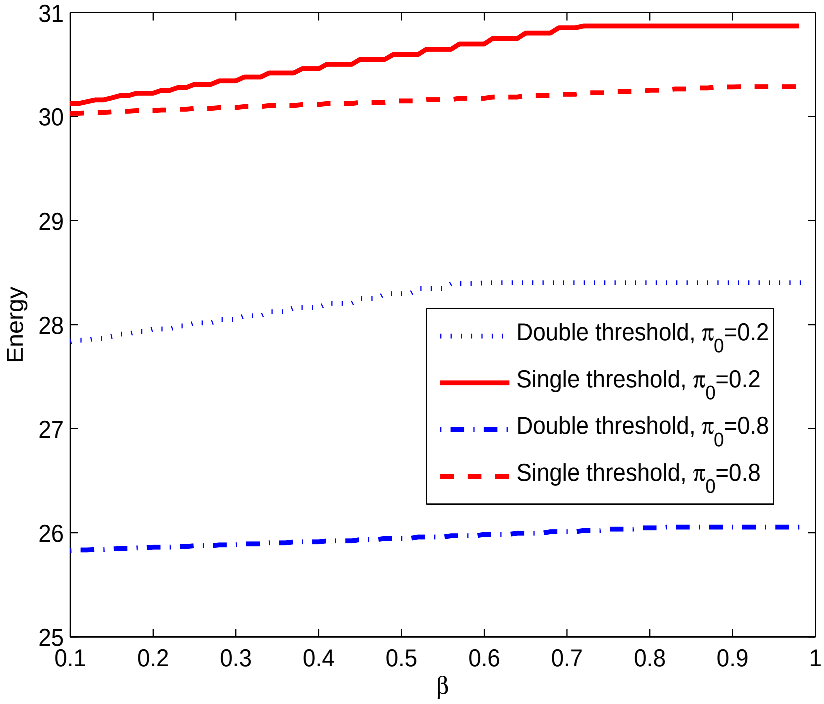


Figure 3.12: *Optimal maximum average energy consumption per sensor versus probability of detection constraint, β, for the OR rule and $C_s = 3$*

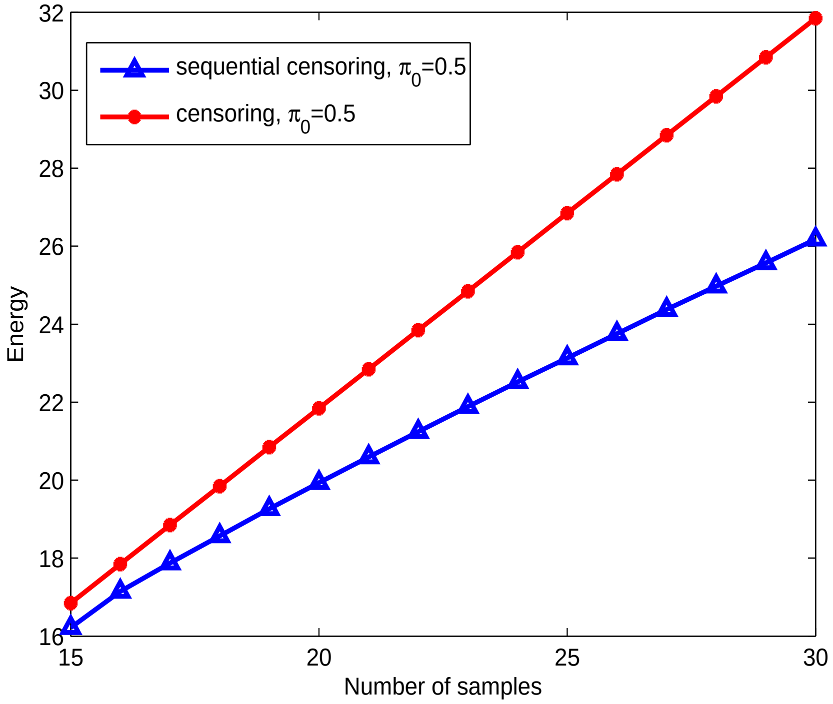


Figure 3.13: *Optimal maximum average energy consumption per sensor versus number of samples for the OR rule*

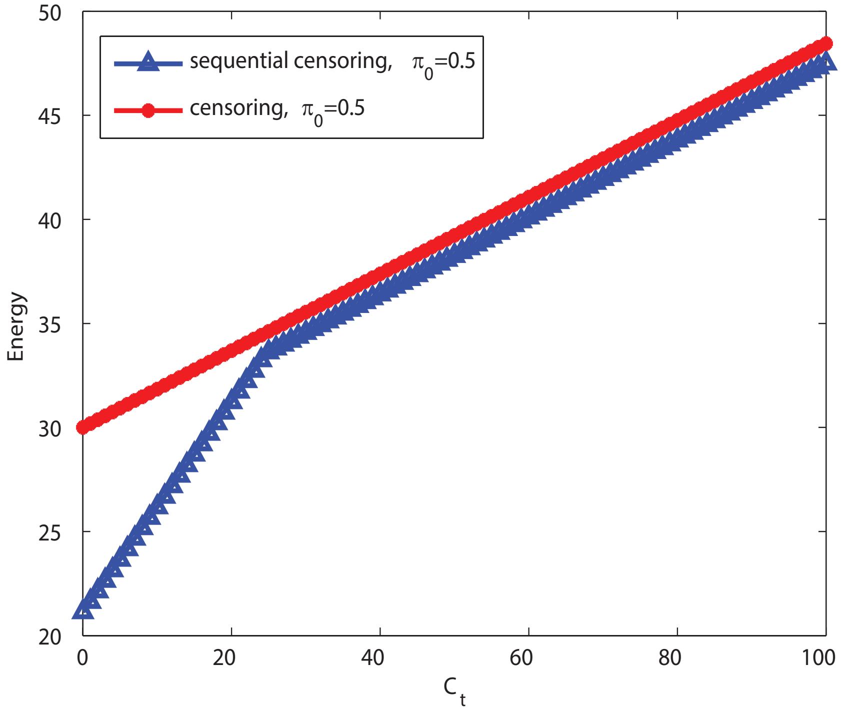


Figure 3.14: *Optimal maximum average energy consumption per sensor versus transmission energy for the OR rule*

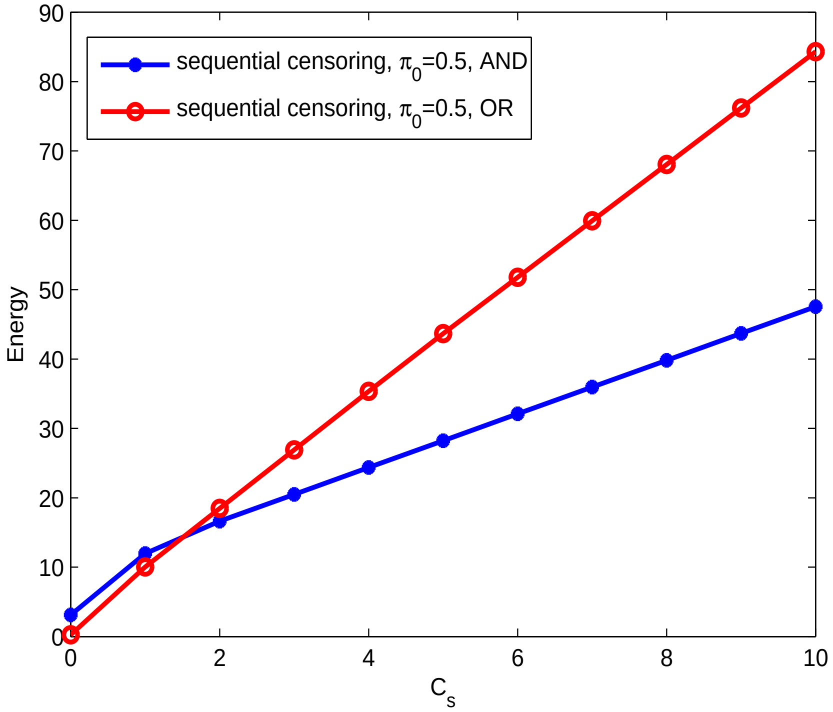


Figure 3.15: *Optimal maximum average energy consumption per sensor versus sensing energy per sample for AND and OR rule*

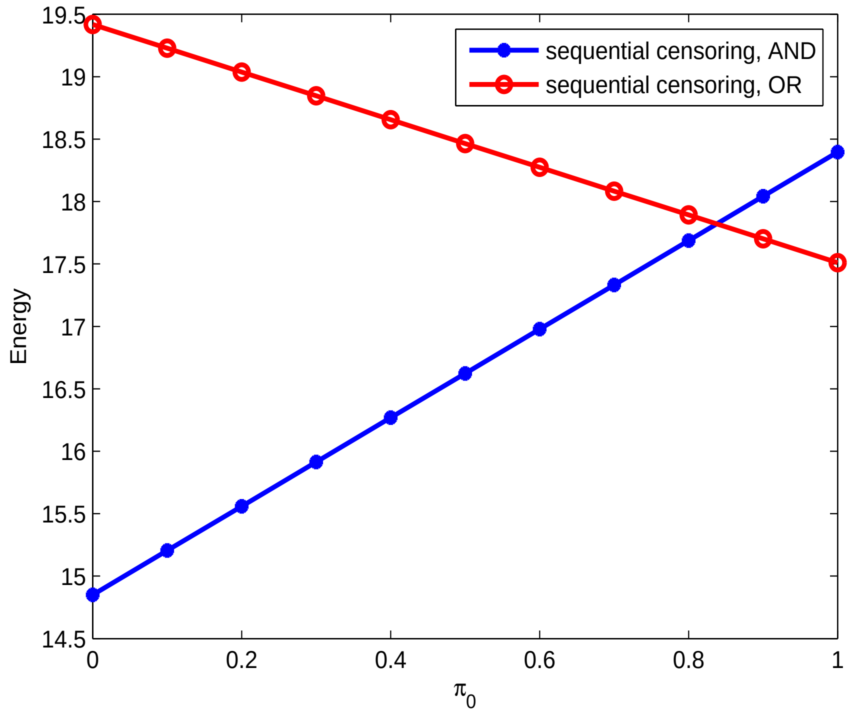


Figure 3.16: *Optimal maximum average energy consumption per sensor versus π_0 for AND and OR rule*

Appendix 3.A Derivation of $Pr(E_n|\mathscr{H}_0)$

Introducing $\Gamma_n = \{a_i < \zeta_{ij} < b_i,\ i = 1,...,n-1\}$ and $p_n = \frac{1}{2^{n-1}}e^{-b_n/2}$, we can write

$$\begin{aligned} Pr(E_n|\mathscr{H}_0) &= \underset{\Gamma_n}{\int \cdots \int} \int_{b_n}^{\infty} \frac{1}{2^n} e^{-\zeta_{nj}/2} I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{nj}\}} d\zeta_{1j}\ldots d\zeta_{nj} \\ &= p_n \underset{\Gamma_n}{\int \cdots \int} I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{n-1j}\}} d\zeta_{1j}\ldots d\zeta_{n-1j}. \end{aligned} \tag{3.43}$$

Denoting $A(n) = \underset{\Gamma_n}{\int \cdots \int} I_{\{0\le\zeta_{1j}\le\zeta_{2j}\ldots\le\zeta_{n-1j}\}} d\zeta_{1j}\ldots d\zeta_{n-1j}$, we obtain

$$A(n) = \begin{cases} \frac{b_1 b_n^{n-2}}{(n-1)!},\ n_1^{p+1} \\ \left[f^{(n-1)}_{\boldsymbol{a}_0^{n-1}}(b_{n-1}) - I_{\{n\ge3\}} \sum_{i=0}^{n-3} \frac{(b_{n-1}-b_{i+1})^{n-i-1}}{(n-i-1)!} 2^i e^{\frac{b_{i+1}}{2}} Pr(E_{i+1}|\mathscr{H}_0)\right],\ n_{p+2}^{q+1} \\ \left[f^{(n-1)}_{\boldsymbol{a}_0^{n-1}}(b_{n-1}) - \sum_{i=0}^{n} f^{(n-1-i)}_{\boldsymbol{\psi}^{n-1}_{i,a_{n-1}}}(b_{n-1}) 2^i e^{\frac{b_{i+1}}{2}} Pr(E_{i+1}|\mathscr{H}_0)\right],\ n_{q+2}^{N} \end{cases}, \tag{3.44}$$

where n_x^y denotes $n = x, x+1, \ldots, y-1, y$, and $\boldsymbol{a}_0^{n-1} = [a_0, \ldots, a_{n-1}]$. Denoting q to be the smallest integer for which $a_q \le b_1 < b_q$, and c and d to be two non-negative real numbers satisfying $0 \le c < d$, $a_{n-1} \le c \le b_n$ and $a_n \le d$, $\eta_0 = 0$, $\boldsymbol{\eta}_k = [\eta_1,...,\eta_k]$, $0 \le \eta_1 \le ... \le \eta_k$, the functions $f^{(k)}_{\boldsymbol{\eta}_k}(\zeta)$ and the vector $\boldsymbol{\psi}^n_{i,c}$ in (3.44) are as follows

$$\begin{aligned} f^{(k)}_{\boldsymbol{\eta}_k}(\zeta) &= \textstyle\sum_{i=0}^{k-1} \frac{f_i^{(k)}(\zeta-\eta_{i+1})^{k-i}}{(k-i)!} + f_k^{(k)} \\ f_i^{(k)} &= f_i^{(k-1)},\ i = 0,...,k-1,\ k \ge 1 \\ f_k^{(k)} &= -\textstyle\sum_{i=0}^{k-1} \frac{f_i^{(k-1)}}{(k-i)!}(\eta_k - \eta_{i+1})^{k-i},\ f_0^{(0)} = 1, \end{aligned} \tag{3.45}$$

$$\boldsymbol{\psi}^n_{i,c} = \begin{cases} [\underbrace{b_{i+1},...,b_{i+1}}_{q}, \underbrace{a_{q+i+1},...,a_{n-1},c}_{n-q-i}],\ i \in [0, n-q-2] \\ [\underbrace{b_{i+1},...,b_{i+1},c}_{n-i}],\ i \in [n-q-1, s-1] \\ b_{i+1}\mathbf{1}_{n-i},\ i \in [s, n-2] \end{cases}, \tag{3.46}$$

with s denoting the integer for which $b_s < c \le b_{s+1}$ and $f^{(0)}_{\boldsymbol{\eta}_k}(\zeta) = 1$.

Appendix 3.B Derivation of $Pr(E_n|\mathscr{H}_1)$

Introducing $q_n = \frac{1}{[2(1+\gamma_j)]^{n-1}} e^{-b_n/2(1+\gamma_j)}$, we can write

$$\begin{aligned} Pr(E_n|\mathscr{H}_1) &= \int_{\Gamma_n} \cdots \int \int_{b_n}^{\infty} \frac{1}{[2(1+\gamma_j)]^n} e^{-\zeta_{nj}/2(1+\gamma_j)} I_{\{0 \le \zeta_{1j} \le \zeta_{2j} \ldots \le \zeta_{nj}\}} d\zeta_{1j} \ldots d\zeta_{nj} \\ &= q_n \int_{\Gamma_n} \cdots \int I_{\{0 \le \zeta_{1j} \le \zeta_{2j} \ldots \le \zeta_{n-1j}\}} d\zeta_{1j} \ldots d\zeta_{n-1j}. \end{aligned} \tag{3.47}$$

Denoting $B(n) = \int_{\Gamma_n} \ldots \int I_{\{0 \le \zeta_{1j} \le \zeta_{2j} \ldots \le \zeta_{n-1j}\}} d\zeta_{1j} \ldots d\zeta_{n-1j}$, and using the notations of Appendix 3.A, we obtain

$$B(n) = \begin{cases} \frac{b_1 b_n^{n-2}}{(n-1)!}, & n_1^{p+1} \\ \left[f_{\boldsymbol{a}_0^{n-1}}^{(n-1)}(b_{n-1}) - I_{\{n \ge 3\}} \sum_{i=0}^{n-3} \frac{(b_{n-1}-b_{i+1})^{n-i-1}}{(n-i-1)!} [2(1+\gamma_j)]^i e^{\frac{b_{i+1}}{2(1+\gamma_j)}} Pr(E_{i+1}|\mathscr{H}_1) \right], & n_{p+2}^{q+1} \\ \left[f_{\boldsymbol{a}_0^{n-1}}^{(n-1)}(b_{n-1}) - \sum_{i=0}^{n-3} f_{\boldsymbol{\psi}_{i,a_{n-1}}^{n-1}}^{(n-1-i)}(b_{n-1}) [2(1+\gamma_j)]^i e^{\frac{b_{i+1}}{2(1+\gamma_j)}} Pr(E_{i+1}|\mathscr{H}_1) \right], & n_{q+2}^{N} \end{cases} . \tag{3.48}$$

Appendix 3.C Analytical expression for $J^{(n)}_{a_n,b_n}(\theta)$

Under $\theta > 0,\ n \geq 1$ and $0 \leq \zeta_{1j} \leq \ldots \leq \zeta_{nj},\ \zeta_{ij} \in (a_i, b_i),\ i = 1, \ldots, n$, the function $J^{(n)}_{a_n,b_n}(\theta)$ is defined as (3.49), where using the notations of Appendix 3.A, we have (3.50) with $I^{(0)} = 1$ and (3.51), [44].

$$J^{(n)}_{a_n,b_n}(\theta) = \sum_{i=1}^{n} \theta^{-i} \left[f^{(n-i)}_{\boldsymbol{a}_0^{n-i}}(a_n) e^{-\theta a_n} - f^{(n-i)}_{\boldsymbol{a}_0^{n-i}}(b_n) e^{-\theta b_n} \right] - I_{\{n \geq 2\}} \sum_{k=0}^{n-2} g^{(k)}_{a_n,b_n}(\theta), \quad (3.49)$$

$$g^{(k)}_{c,d} = \begin{cases} I^{(k)} \left[\theta^{k-n} e^{-\theta b_{k+1}} - \sum_{i=1}^{n-k} \theta^{-i} f^{(n-k-i)}_{b_{k+1}\mathbf{1}_{n-k-i}}(d) e^{-\theta d} \right],\ c \leq b_1,\ k \in [0, n-2] \\ I^{(k)} \sum_{i=1}^{n-k} \theta^{-i} \left[f^{(n-k-i)}_{\boldsymbol{\psi}^{n-i}_{k,c}}(c) e^{-\theta c} - f^{(n-k-i)}_{\boldsymbol{\psi}^{n-i}_{k,d}}(d) e^{-\theta d} \right],\ c > b_1,\ k \in [0, s-1] \\ I^{(k)} \left[\theta^{k-n} e^{-\theta b_{k+1}} - \sum_{i=1}^{n-k} \theta^{-i} f^{(n-k-i)}_{b_{k+1}\mathbf{1}_{n-k-i}}(d) e^{-\theta d} \right],\ c > b_1,\ k \in [s, n-2] \end{cases}, \quad (3.50)$$

$$I^{(n)} = \begin{cases} f^{(n)}_{\boldsymbol{a}_0^n}(b_n) - I_{\{n \geq 2\}} \sum_{i=0}^{n-2} \frac{(b_n - b_{i+1})^{n-i}}{(n-i)!} I^{(i)},\ n \in [1, q] \\ f^{(n)}_{\boldsymbol{a}_0^n}(b_n) - \sum_{i=0}^{n-2} f^{(n-i)}_{\boldsymbol{\psi}^n_{i,a_n}}(b_n) I^{(i)},\ n \in [q+1, \infty) \end{cases}. \quad (3.51)$$

Appendix 3.D Proof of Theorem 1

Assume that P_f and P_d are the respective given local probability of false alarm and detection. Denoting ρ^c as the censoring rate for the optimal censoring scheme (2.24), we obtain $1-\rho^c = \pi_0 P_f + \pi_1 P_d$, and denoting ρ^{cs} as the censoring rate for the optimal censored truncated sequential sensing (3.13), based on what we have discussed in Section 2, we obtain $1-\rho^{cs} = \pi_0(P_f + \mathscr{L}_0(\overline{a},\overline{b})) + \pi_1(P_d + \mathscr{L}_1(\overline{a},\overline{b}))$. Note that $\mathscr{L}_k(\overline{a},\overline{b}),\ k=0,1$, represents the probability that $\zeta_n \leq a_n,\ n=1,\ldots,N$ under $\mathscr{H}_k$ which is non-negative. Hence, we can conclude that $1-\rho^{cs} \geq 1-\rho^c$ and thus $\rho^c \geq \rho^{cs}$.

Appendix 3.E Optimal solution of (2.16)

Since the optimal $\lambda_2 \to \infty$, (3.40) and (3.41) can be simplified to $Q^c_{\text{F,AND}} = \delta_0^M$ and $Q^c_{\text{D,AND}} = \prod_{j=1}^M \delta_{1,j}$ and so (2.16) becomes,

$$\begin{aligned} &\min_{\lambda_1} \max_j \left[NC_{s,j} + (\pi_0(1-\delta_0) + \pi_1(1-\delta_{1,j}))C_{t,j} \right] \\ &\text{s.t. } \delta_0^M \le \alpha, \ \prod_{j=1}^M \delta_{1,j} \ge \beta. \end{aligned} \tag{3.52}$$

Since there is a one-to-one relationship between λ_1 and δ_0, i.e., $\lambda_1 = 2\Gamma^{-1}[N,\Gamma(N)\delta_0]$ (where Γ^{-1} is defined over the second argument), (3.52) can be formulated as [46, p.130],

$$\begin{aligned} &\min_{\delta_0} \max_j \left[NC_{s,j} + (\pi_0(1-\delta_0) + \pi_1(1-\delta_{1,j}))C_{t,j} \right] \\ &\text{s.t. } \delta_0^M \le \alpha, \ \prod_{j=1}^M \delta_{1,j} \ge \beta. \end{aligned} \tag{3.53}$$

Defining $\delta_0 = F_{\text{AND}}(\lambda_1) = \frac{\Gamma(N,\frac{\lambda_1}{2})}{\Gamma(N)}$ and $\delta_{1,j} = G_{\text{AND,j}}(\lambda_1) = \frac{\Gamma(N,\frac{\lambda_1}{2(1+\gamma_j)})}{\Gamma(N)}$, we can write $\delta_{1,j}$ as $\delta_{1,j} = G_{\text{AND},j}(F^{-1}(\delta_0))$. Calculating the derivative of C_j with respect to δ_0, we find that

$$\frac{\partial C_j}{\partial \delta_0} = \frac{\partial \left[C_{t,j}(\pi_0(1-\delta_0) + \pi_1(1-\delta_{1,j})) \right]}{\partial \delta_0} = -C_{t,j}\pi_0 + \frac{\partial (1-\delta_{1,j})}{\partial \delta_0} \le 0, \tag{3.54}$$

where we use the fact that

$$\begin{aligned} \frac{\partial \delta_{1,j}}{\partial \delta_0} &= \frac{-\frac{1}{2^N\Gamma(N)} 2\Gamma^{-1}[N,\Gamma(N)\delta_0]^{N-1} e^{2\Gamma^{-1}[N,\Gamma(N)\delta_0]/2(1+\gamma_j)} I_{\{2\Gamma^{-1}[N,\Gamma(N)\delta_0]\ge 0\}}}{-\frac{1}{2^N\Gamma(N)} 2\Gamma^{-1}[N,\Gamma(N)\delta_0]^{N-1} e^{2\Gamma^{-1}[N,\Gamma(N)\delta_0]/2} I_{\{2\Gamma^{-1}[N,\Gamma(N)\delta_0]\ge 0\}}} \\ &= e^{2\Gamma^{-1}[N,\Gamma(N)\delta_0](1/2(1+\gamma_j)-1/2)} \ge 0. \end{aligned} \tag{3.55}$$

Therefore, we can simplify (3.53) as

$$\begin{aligned} &\max_{\delta_0} \delta_0 \\ &\text{s.t. } \delta_0^M \le \alpha, \ \prod_{j=1}^M \delta_{1,j} \ge \beta. \end{aligned} \tag{3.56}$$

Since $Q^c_{\text{D,AND}}$ is a monotonically increasing function of δ_0, i.e., $Q^c_{\text{D,AND}} = H_{\text{AND}}(\delta_0) = \prod_{j=1}^M (G_{\text{AND},j}(F^{-1}_{\text{AND}}(\delta_0)))$ and thus $\frac{\partial Q^c_{\text{D,AND}}}{\partial \delta_0} = \frac{\partial Q^c_{\text{D,AND}}}{\partial \delta_{1,j}} \frac{\partial \delta_{1,j}}{\partial \delta_0} = \prod_{l=1,l\neq j}^{l=M} (\delta_{1l}) \frac{\partial \delta_{1,j}}{\partial \delta_0} \ge 0$, we can further simplify the constraints in (3.56) as $\delta_0 \leq \alpha^{1/M}$ and $\delta_{1,j} \geq H^{-1}(\beta)$. Thus, we obtain

$$\begin{aligned} &\max_{\delta_0} \delta_0 \\ &\text{s.t. } \delta_0 \leq \alpha^{1/M},\ \delta_{1,j} \geq H^{-1}(\beta). \end{aligned} \tag{3.57}$$

Therefore, if the feasible set of (3.57) is not empty, then the optimal solution is given by $\delta_0 = \alpha^{1/M}(\beta)$.

Chapter 4

Combined Censoring and Sleeping

Abstract

In conventional distributed sensing approaches, as the detection performance improves with the number of radios, so does the network energy consumption. However, since cognitive radios are mostly low-power radios, the individual energy consumption of each radio is a more critical issue than the total energy consumption. In the previous chapters, we have introduced a fixed-size censoring and a truncated sequential censoring scheme in order to minimize the maximum average energy consumption per sensor. In this chapter, we consider a combined sleeping and censoring scheme as an energy-efficient spectrum sensing technique for cognitive sensor networks. Our objective is to minimize the maximum energy consumption per sensor subject to constraints on the detection performance, by optimally choosing the sleeping and censoring design parameters. The constraint on the detection performance is given by a minimum target probability of detection and a maximum permissible probability of false alarm. Depending on the availability of prior knowledge about the probability of primary user presence, two cases are considered. The case where a priori knowledge is not available defines the blind setup; otherwise the setup is called knowledge-aided. By considering a sensor network based on IEEE 802.15.4/ZigBee radios, we show that significant energy savings can be achieved by the proposed scheme.

4.1 Introduction

In this chapter, we consider a distributed spectrum sensing system comprising of a fusion center (FC) and a number of cognitive sensors that carry out sensing in dedicated, periodic sensing slots. Energy detection is used for spectrum sensing in this chapter. The sensing results of each cognitive radio are collected at the FC, which makes a global decision on the occupancy of the channel using a fusion rule.

Schemes based on soft and hard fusion have been considered in the past [10] (the reader is referred to [14] for an extensive treatment of distributed detection). It has been shown in [10] that the performance of hard fusion schemes is comparable to that of soft fusion schemes in a number of practical settings. We shall hence limit our attention to hard decision based spectrum sensing, since the energy cost of sending one bit per decision is smaller than sending multiple bits per decision for a soft decision scheme.

We propose a combination of sleeping and censoring as an energy saving mechanism for spectrum sensing. In this scheme, when in sleep mode, each radio switches off its sensing transceiver and incurs no observation costs or transmission costs. Censoring involves transmitting detection results only when they are in a certain information region. Our goal is to minimize the maximum average energy incurred by the individual cognitive radios to perform spectrum sensing while maintaining a global detection performance by determining the optimum sleeping and censoring parameters. The constraints on the detection performance are specified by a minimum target probability of detection and a maximum permissible probability of false alarm. We consider two cases based on the availability of prior knowledge about the probability of primary user presence. For the case that the prior probabilities are not available, a blind setup is defined. When the prior probabilities are available, a knowledge-aided setup is described. Systematic algorithms for obtaining the optimum sleeping and censoring parameters are proposed for both setups. We then consider a network of IEEE 802.15.4/ZigBee radios to evaluate the efficiency of our proposed scheme. Resulting simulation results show that large energy savings can be obtained in comparison to traditional spectrum sensing schemes.

4.1.1 Related works

Censoring has been considered in the context of wireless sensor networks and cognitive radios [17], [19], [20], [21], [22] and shown to be effective in saving energy. The design of censoring regions under different optimization settings related to the detection performance has been considered in [19]-[22] for minimization of the miss detection probability with constraints on the false alarm rate and the network energy consumption. Further, [19], [20] and [22] consider minimization of the detection error probability subject to the network energy consumption. The combination of sleeping and censoring was considered in [18], with the goal of maximizing the mutual information between the state of signal occupancy and the decision state of the fusion center. Censoring for cognitive radios is considered in [17] where a censoring decision rule similar to our scheme is employed to reduce the number of bits sent to the fusion center and so the bandwidth occupancy of the cognitive radio network. Our scheme is different in three ways. First, we consider a combination of sleeping and censoring and give closed-form analytical expressions for the probability of detection and false alarm. Second, we give a clear problem formulation and necessary algorithms to solve the problem in order to design the sensing parameters which is not given in [17]. Third, in [17], only the knowledge-aided setup is considered for analysis while we also consider the blind setup. Finally, the fusion center in [17] makes no decision in case it does not receive any results from the cognitive users which is ambiguous in the sense that the FC has to make a final decision about the presence (or absence) of the primary user. In this chapter, if no results are reported to the FC, we assume that the primary user is not present. A sleeping technique is employed in [54] where the sleeping policy is controlled by learning from the past channel observations. As shall be shown, the optimization problems resulting from our work differ from these mentioned past works; we lay constraints on the detection performance while the maximum average energy consumption per sensor is minimized.

4.1.2 Organization

The remainder of the chapter is organized as follows. In Section 4.2, we describe distributed spectrum sensing based on sleeping and censoring and formulate energy-efficient distributed sensing as an optimization problem for the blind and knowledge-aided setups. Expressions for the global probability of detection and false alarm are then derived in Section 4.3. In Section 4.4, the problem is analyzed and systematic algorithms are proposed to solve the underlying optimization problems for both setups. We present numerical results to show the energy savings obtained by the proposed scheme in Section 4.6. Conclusions are drawn in Section 4.7.

4.2 System Model

The basics of the system model including the primary user signal distribution, noise, channel gain and hypothesis definitions in this chapter are the same as the ones in

Chapters 2 and 3, which are introduced in Section 2.3 as in (2.1). An energy detector is employed by each cognitive sensor that calculates the accumulated energy over N observation samples. The received energy collected over the N observation samples at the j-th radio is given by

$$\mathscr{E}_j = \sum_{i=1}^{N} \frac{|r_{ij}|^2}{\sigma_w^2}. \tag{4.1}$$

Afterwards a censoring policy is employed at each radio [19], [22]. Censoring thresholds λ_1 and λ_2 are applied at each of the radios. The range $\lambda_1 < \mathscr{E}_j < \lambda_2$ is called the censoring region. At the j-th radio, the local censoring decision rule is given as

$$\begin{cases} \text{send 1, declaring } \mathscr{H}_1 & \text{if } \mathscr{E}_j \geq \lambda_2, \\ \text{no decision} & \text{if } \lambda_1 < \mathscr{E}_j < \lambda_2, \\ \text{send 0, declaring } \mathscr{H}_0 & \text{if } \mathscr{E}_j \leq \lambda_1. \end{cases} \tag{4.2}$$

It is well known that under the model (4.1), $\mathscr{E}_i$ follows a central chi-square distribution with $2N$ degrees of freedom under $\mathscr{H}_0$ and $\mathscr{H}_1$, [13].

Based on the above decision rule, the local probabilities of false alarm and detection can be respectively written as

$$P_{f,j} = Pr(\mathscr{E}_j \geq \lambda_2 | \mathscr{H}_0) = \frac{\Gamma(N, \frac{\lambda_2}{2})}{\Gamma(N)} \tag{4.3}$$

and

$$P_{d,j} = Pr(\mathscr{E}_j \geq \lambda_2 | \mathscr{H}_1) = \frac{\Gamma(N, \frac{\lambda_2}{2(1+\gamma_j)})}{\Gamma(N)} \tag{4.4}$$

where $\Gamma(a,x)$ is the incomplete gamma function given by $\Gamma(a,x) = \int_x^\infty t^{a-1}e^{-t}dt$, with $\Gamma(a,0) = \Gamma(a)$.

In order to achieve more energy saving, on top of censoring, a sleeping policy is applied. Each sensor turns of its sensing module with a sleeping rate denoted by μ. This way, we make sure that in average at each sensing period, $(1-\mu)M$ users are ON. Denote $C_{s,j}$ and $C_{t,j}$ to be the energy consumed by the j-th radio in sensing per sample and transmission per bit, respectively. Our cost function is then given by the average energy consumed per sensor as follows

$$C_j = (1-\mu)(NC_{s,j} + C_{t,j}(1-\rho_j)), \tag{4.5}$$

where $\rho_j = Pr(\lambda_1 < E_i < \lambda_2)$ is denoted to be the censoring rate.

We shall assume that $\mu \neq 0$ and $\rho_j \neq 0$. The sensing energy $C_{s,j}$ constitutes the energy consumed in listening and collecting one observation sample. The transmission energy $C_{t,j}$ is the energy required to transmit the one-bit local decision to the FC.

Denote Q_{D} and Q_{F} to be the respective global probability of detection and false alarm. The target detection performance is then quantified by: $Q_{\mathrm{F}} \leq \alpha$ and $Q_{\mathrm{D}} \geq \beta$. Here, α and β are pre-specified detection design parameters. In practice, it is desirable to have α close to zero and β close to unity. These conditions respectively ensure that the cognitive sensor network can exploit empty channels and that primary users are not interfered with. Our goal is to determine the optimum sleeping rate μ and the censoring thresholds λ_1 and λ_2 such that $\max_j C_j$ in (4.5) is minimized subject to the constraints $Q_{\mathrm{F}} \leq \alpha$ and $Q_{\mathrm{D}} \geq \beta$. Note that ρ_j is a function of λ_1 and λ_2. Hence our optimization problem can be formulated as follows:

$$\begin{aligned} &\min_{\mu,\lambda_1,\lambda_2} \ \max_j C_j \\ &\text{s.t. } Q_{\mathrm{F}} \leq \alpha,\ Q_{\mathrm{D}} \geq \beta. \end{aligned} \tag{4.6}$$

Depending on the prior knowledge about the respective prior probabilities, $\pi_0 = Pr(\mathscr{H}_0)$ and $\pi_1 = Pr(\mathscr{H}_1)$, of the hypotheses $\mathscr{H}_0$ and $\mathscr{H}_1$, we consider two different cases.

4.2.1 Blind Problem Formulation

First, we assume that π_0 and π_1 are unknown, and that π_1 is much smaller than π_0, reflecting channel under-utilization. Therefore, we assume $\pi_0 \to 1$. In this case, we can follow the definition of [22] for the censoring rate under the blind Neyman-Pearson (NP) setup

$$\rho_j^{\mathrm{NP}} = Pr(\lambda_1 < \mathscr{E}_j < \lambda_2 | \mathscr{H}_0).$$

Using (4.3), we may write ρ_j^{NP} as

$$\rho_j^{\mathrm{NP}} = \frac{\Gamma(N, \frac{\lambda_1}{2})}{\Gamma(N)} - \frac{\Gamma(N, \frac{\lambda_2}{2})}{\Gamma(N)}. \tag{4.7}$$

where we can see $\rho_1^{\mathrm{NP}} = \rho_2^{\mathrm{NP}} = \cdots = \rho_M^{\mathrm{NP}} = \rho^{\mathrm{NP}}$. This way we obtain $C_1 = C_2 = \cdots = C_M = C^{\mathrm{NP}}$ Denoting $Q_{\mathrm{D}}^{\mathrm{NP}}$ and $Q_{\mathrm{F}}^{\mathrm{NP}}$ to be the respective global probability of detection and false alarm under the blind setup, (4.6) becomes

$$\begin{aligned}&\min_{\mu,\lambda_1,\lambda_2} C^{\mathrm{NP}}\\&\text{s.t. } Q_{\mathrm{F}}^{\mathrm{NP}} \leq \alpha,\ Q_{\mathrm{D}}^{\mathrm{NP}} \geq \beta.\end{aligned} \tag{4.8}$$

4.2.2 Knowledge-Aided Problem Formulation

Here, we assume that π_0 and π_1 are known. In practice, estimates of π_0 and π_1 can be obtained via spectrum measurements. In this case, we can follow the definition of [22] for the censoring rate under the knowledge-aided Bayesian (B) setup

$$\begin{aligned}\rho_j^{\mathrm{B}} &= Pr(\lambda_1 < \mathscr{E}_j < \lambda_2)\\&= \pi_0 Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_0) + \pi_1 Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_1)\\&= \pi_0\delta_{0,j} + \pi_1\delta_{1,j}\end{aligned} \tag{4.9}$$

where $\delta_{0,j}$ and $\delta_{1,j}$ can be written using (4.3) and (4.4) as

$$\begin{aligned}\delta_{0,j} &= Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_0)\\&= \frac{\Gamma(N,\frac{\lambda_1}{2})}{\Gamma(N)} - \frac{\Gamma(N,\frac{\lambda_2}{2})}{\Gamma(N)},\end{aligned} \tag{4.10}$$

$$\begin{aligned}\delta_{1,j} &= Pr(\lambda_1 < \mathscr{E}_j < \lambda_2|\mathscr{H}_1)\\&= \frac{\Gamma(N,\frac{\lambda_1}{2(1+\gamma_j)})}{\Gamma(N)} - \frac{\Gamma(N,\frac{\lambda_2}{2(1+\gamma_j)})}{\Gamma(N)}.\end{aligned} \tag{4.11}$$

Denote $Q_{\mathrm{D}}^{\mathrm{B}}$ and $Q_{\mathrm{F}}^{\mathrm{B}}$ to be the respective global probability of detection and false alarm under the knowledge-aided setup. Hence, our optimization problem becomes

$$\begin{aligned}&\min_{\mu,\lambda_1,\lambda_2} \max_j C_j^{\mathrm{B}}\\&\text{s.t. } Q_{\mathrm{F}}^{\mathrm{B}} \leq \alpha,\ Q_{\mathrm{D}}^{\mathrm{B}} \geq \beta.\end{aligned} \tag{4.12}$$

In the following section, we derive analytically the expressions for $Q_{\mathrm{D}}^{\mathrm{NP}}$, $Q_{\mathrm{F}}^{\mathrm{NP}}$, $Q_{\mathrm{D}}^{\mathrm{B}}$ and $Q_{\mathrm{F}}^{\mathrm{B}}$.

4.3 Detection Performance Analysis

Each cognitive radio that is awake listens to the channel in dedicated sensing slots. An awake cognitive radio computes the received signal energy and locally decides on the presence or absence of the licensed system based on the decision rule in (4.2). If it comes up with a decision, then it sends its decision result to the FC. The FC employs an OR rule to make the final decision denoted by D_{FC}. That is, $D_{FC} = 1$ if the FC receives at least one local decision declaring 1, else $D_{FC} = 0$. The AND rule is discussed in Section 4.5. Let the number of awake cognitive radios be L. The probability of false alarm for the blind setup, $Q_{\mathrm{F}}^{\mathrm{NP}}$ can now be written as

$$\begin{aligned} Q_{\mathrm{F}}^{\mathrm{NP}} &= Pr(D_{FC} = 1, L \geq 1|\mathscr{H}_0) \\ &= \sum_{L=1}^{M} Pr(D_{FC} = 1, L|\mathscr{H}_0) \\ &= \sum_{L=1}^{M} Pr(L|\mathscr{H}_0) Pr(D_{FC} = 1|\mathscr{H}_0, L) \\ &= \sum_{L=1}^{M} \begin{pmatrix} M \\ L \end{pmatrix} \mu^{M-L}(1-\mu)^L \\ &\times Pr(D_{FC} = 1|\mathscr{H}_0, L) \\ &= \sum_{L=1}^{M} \begin{pmatrix} M \\ L \end{pmatrix} \mu^{M-L}(1-\mu)^L \\ &\times [1 - \prod_{j=1}^{L}(1 - P_{f,j})], \end{aligned} \tag{4.13}$$

where $P_{f,j}$ is given by (4.3). In the above expression, $Pr(L|\mathscr{H}_0)$ is the probability that there are L cognitive radios awake conditioned on hypothesis $\mathscr{H}_0$. Since, $P_{f,1} = P_{f,2} = \cdots = P_{f,M} = P_f$, using the binomial expansion theorem, we obtain

$$Q_{\mathrm{F}}^{\mathrm{NP}} = 1 - [1 - (1-\mu)P_f]^M. \tag{4.14}$$

This can be easily explained by the OR rule based global probability of false alarm when considering $P_{fl}^{\mathrm{NP}} = (1-\mu)P_f$ to be the local probability of false alarm including the censoring and sleeping policies.

The global probability of detection for the blind setup, $Q_{\mathrm{D}}^{\mathrm{NP}}$, can be derived in a similar way. We have

$$\begin{aligned} Q_{\mathrm{D}}^{\mathrm{NP}} &= Pr(D_{FC}=1, L\geq 1|\mathscr{H}_1) \\ &= \sum_{L=1}^{M} Pr(D_{FC}=1, L|\mathscr{H}_1) \\ &= \sum_{L=1}^{M} Pr(L|\mathscr{H}_1) Pr(D_{FC}=1|\mathscr{H}_1, L) \\ &= \sum_{L=1}^{M} \begin{pmatrix} M \\ L \end{pmatrix} \mu^{M-L}(1-\mu)^L \\ &\times [1-\prod_{j=1}^{L}(1-P_{d,j})] \end{aligned} \tag{4.15}$$

where $P_{d,j}$ is given by (4.4). This also can be explained by the OR rule based global probability of detection when considering $P_{dlj}^{\mathrm{NP}} = (1-\mu)P_{d,j}$ to be the local probability of detection including the censoring and sleeping policies.

Denoting $P_{fl}^{\mathrm{B}} = (1-\mu)P_f$ to be the local probability of false alarm including the censoring and sleeping policies, the global probability of false alarm for the knowledge-aided scenario, $Q_{\mathrm{F}}^{\mathrm{B}}$, can be written as

$$\begin{aligned} Q_{\mathrm{F}}^{\mathrm{B}} &= Pr(D_{FC}=1, L\geq 1|\mathscr{H}_0) \\ &= 1-\left\{1-P_{fl}^{\mathrm{B}}\right\}^M \\ &= 1-\left\{1-(1-\mu)P_f\right\}^M, \end{aligned} \tag{4.16}$$

where P_f is given by (4.3).

Denoting $P_{dlj}^{\mathrm{B}} = (1-\mu)P_{d,j}$ to be the local probability of detection including the censoring and sleeping policies, the global probability of detection for the knowledge-aided scenario, $Q_{\mathrm{D}}^{\mathrm{B}}$, can be derived in a similar way. We obtain

$$\begin{aligned} Q_{\mathrm{D}}^{\mathrm{B}} &= Pr(D_{FC}=1, L\geq 1|\mathscr{H}_1) \\ &= \sum_{L=1}^{M} \begin{pmatrix} M \\ L \end{pmatrix} \mu^{M-L}(1-\mu)^L \times [1-\prod_{j=1}^{L}(1-P_{d,j})] \end{aligned} \tag{4.17}$$

where $P_{d,j}$ is given by (4.4).

In the following section, we analyze the optimization problems (4.8) and (4.12) given the expressions for the constraints derived in this section and we propose an algorithm to solve them.

4.4 Problem Analysis

In this section, first (4.12) is analyzed in order to find a systematic solution for the system parameters, namely the sleeping rate and censoring thresholds for the two setups. Later we show that a modified version of the solution given for (4.12) can be used as a solution for (4.8).

To analyze (4.12), it is more convenient to rewrite it in the following format

$$\begin{aligned} &\min_{\mu,\lambda_1,\lambda_2} \max_{j} (1-\mu)\left[NC_{s,j} + C_{t,j}(1-\rho_j^{\mathrm{B}})\right] \\ &\text{s.t. } 1-[1-(1-\mu)P_f]^M \leq \alpha \\ &\sum_{L=1}^{M} \binom{M}{L} \mu^{M-L}(1-\mu)^L \times [1-\prod_{j=1}^{L}(1-P_{d,j})] \geq \beta. \end{aligned} \tag{4.18}$$

Since the FC only decides for the presence of the primary user by receiving "1"s, sending "0"s is not optimal in terms of energy efficiency. Therefore, $\lambda_1 = 0$ is the optimal solution of (4.18). Using this result, we can relax one of the arguments of the problem. When $\lambda_1 = 0$, we obtain

$$\begin{aligned} 1-\delta_0 &= P_f, \\ 1-\delta_{1,j} &= P_{d,j}. \end{aligned} \tag{4.19}$$

Hence, (4.18) is given by

$$\begin{aligned} &\min_{\mu,\lambda_2} \max_{j} (1-\mu)\left[NC_{s,j} + C_{t,j}(\pi_0 P_f + \pi_1 P_{d,j})\right] \\ &\text{s.t. } 1-[1-(1-\mu)P_f^2]^M \leq \alpha \\ &Q_{\mathrm{D}}^{\mathrm{B}} \geq \beta. \end{aligned} \tag{4.20}$$

Since changing the order of min and max operations does not change the optimal solution of (4.20), we can rewrite the problem as follows

$$\begin{aligned}&\max_{j}\min_{\mu,\lambda_2}(1-\mu)\left[NC_{s,j}+C_{t,j}(\pi_0 P_f+\pi_1 P_{d,j})\right]\\&\text{s.t. } 1-[1-(1-\mu)P_f^2]^M\le\alpha\\&Q_D^B\ge\beta.\end{aligned}\tag{4.21}$$

Assume that μ is fixed to μ^*. Then (4.21) will reduce to the following problem

$$\begin{aligned}&\max_{j}\min_{P_f}(1-\mu^*)\left[NC_{s,j}+C_{t,j}(\pi_0 P_f+\pi_1 P_{d,j})\right]\\&\text{s.t. } P_f\le\frac{1-(1-\alpha)^{1/M}}{(1-\mu^*)}\\&Q_D^B\ge\beta.\end{aligned}\tag{4.22}$$

Defining $F(\lambda_2)=\frac{\Gamma(N,\frac{\lambda_2}{2})}{\Gamma(N)}$, we can write P_d as $P_{d,j}=F(\lambda_2/(1+\gamma_j))$. Calculating the derivative of C_j^B with respect to P_f, we find that $\frac{\partial C_j^B}{\partial P_f}=(1-\mu^*)\frac{\partial\left[C_{t,j}(\pi_0 P_f+\pi_1 P_{d,j})\right]}{\partial P_f}=(1-\mu^*)\left[C_{t,j}\pi_0+\frac{\partial P_{d,j}}{\partial P_f}\right]\ge 0$ where we used the fact that $\frac{\partial P_{d,j}}{\partial P_f}\ge 0$. Therefore we can write (4.22) as follows

$$\begin{aligned}&\min_{P_f}P_f\\&\text{s.t. } P_f\le\frac{1-(1-\alpha)^{1/M}}{(1-\mu^*)}\\&Q_D^B\ge\beta\end{aligned}\tag{4.23}$$

Looking at (4.23) we can find that

$$F(G^{-1}(\beta))\le P_f\le\alpha'/1-\mu^*\tag{4.24}$$

where $G(\lambda_2)=Q_D^B$ and $\alpha'=1-(1-\alpha)^{1/M}$. Thus, we find that for every μ^*, $P_f^*=F(G^{-1}(\beta))$. Therefore, our optimization problem reduces to the following unconstrained line search problem

$$\max_{j}\min_{\mu}(1-\mu)\left[NC_{s,j}+C_{t,j}(\pi_0 F(G^{-1}(\beta))+\pi_1 F(G^{-1}(\beta)/(1+\gamma_j))\right]\tag{4.25}$$

Looking carefully at (4.25), we find that we can use the same optimization problem for the blind setup by considering $\pi_0=1$ ($\pi_1=0$). In other words, the blind setup is just a special case of the knowledge-aided setup. This is the approach that we will adopt in the simulations for both setups.

4.5 Extension to the AND Rule

As in Chapters 2 and 3, here we analyze the performance of the combined sleeping and censoring for the AND rule. Here, we provide the analysis for the knowledge-aided case. The analysis for the blind problem formulation is then straightforward. According to the AND rule, $D_{FC} = 0$, if at least one cognitive radio reports a zero, else $D_{FC} = 1$. This way, the global probabilities of false alarm and detection are as follows

$$Q_{\text{F,AND}}^{\text{B}} = Pr(D_{FC} = 1|\mathscr{H}_0) \tag{4.26}$$

$$= \prod_{j=1}^{M} \Big[\mu + (1-\mu)(\delta_{0,j} + P_{f,j})\Big] \tag{4.27}$$

$$= \prod_{j=1}^{M} \Big[1 - (1-\mu)(1 - \delta_{0,j} - P_{f,j})\Big], \tag{4.28}$$

$$Q_{\text{D,AND}}^{\text{B}} = Pr(D_{FC} = 1|\mathscr{H}_1) \tag{4.29}$$

$$= \prod_{j=1}^{M} \Big[\mu + (1-\mu)(\delta_{1,j} + P_{d,j})\Big] \tag{4.30}$$

$$= \prod_{j=1}^{M} \Big[1 - (1-\mu)(1 - \delta_{1,j} - P_{d,j})\Big]. \tag{4.31}$$

Since $P_{f1} = P_{f2} = \cdots = P_{fM} = P_f$ and $\delta_{01} = \delta_{02} = \cdots = \delta_{0M} = \delta_0$ the global probability of false alarm becomes

$$Q_{\text{F,AND}}^{\text{B}} = \Big[\mu + (1-\mu)(\delta_0 + P_f)\Big]^M \tag{4.32}$$

$$= \Big[1 - (1-\mu)(1 - \delta_0 - P_f)\Big]^M \tag{4.33}$$

We define our problem in order to find the underlying arguments $(\lambda_1, \lambda_2, \mu)$, so as to minimize the maximum average energy consumption per sensor subject to a constraint on the probabilities of false alarm and detection. As in the previous scenarios, the constraints on the probabilities of false alarm and detection are defined by an upper bound α and a lower bound β respectively. This way, the problem is written as follows

$$\begin{aligned} &\min_{\mu,\lambda_1,\lambda_2} \max_j C_j^{\mathrm{B}} \\ &\text{s.t. } Q_{\mathrm{F,AND}}^{\mathrm{B}} \leq \alpha,\ Q_{\mathrm{D,AND}}^{\mathrm{B}} \geq \beta. \end{aligned} \tag{4.34}$$

Since, the FC decides for $\mathscr{H}_0$ only by receiving zeros, the optimal solution of (4.34) is attained by $\lambda_2 \to \infty$. This way, the global probabilities of false alarm and detection reduce to

$$Q_{\mathrm{F,AND}}^{\mathrm{B}} = \Big[1-(1-\mu)(1-\delta_0)\Big]^M, \tag{4.35}$$

$$Q_{\mathrm{D,AND}}^{\mathrm{B}} = \prod_{j=1}^{M}\Big[1-(1-\mu)(1-\delta_{1,j})\Big]. \tag{4.36}$$

Inserting (4.35) and (4.36) in (4.34) and relaxing λ_2 using the fact that $\lambda_2 \to \infty$ is optimal, we obtain

$$\begin{aligned} &\min_{\mu,\lambda_1} \max_j (1-\mu)(NC_{s,j} + C_{t,j}(1-\rho_j^B)) \\ &\text{s.t. } \Big[1-(1-\mu)(1-\delta_0)\Big]^M \leq \alpha,\ \textstyle\prod_{j=1}^{M}\Big[1-(1-\mu)(1-\delta_{1,j})\Big] \geq \beta, \end{aligned} \tag{4.37}$$

where $\rho_j^B = \pi_0\delta_0 + \pi_1\delta_{1,j}$. Since there is a one-to-one relation between λ_1 and δ_0, we can rewrite (4.37) as follows

$$\begin{aligned} &\min_{\mu,\delta_0} \max_j (1-\mu)(NC_{s,j} + C_{t,j}(1-\pi_0\delta_0+\pi_1\delta_{1,j})) \\ &\text{s.t. } \Big[1-(1-\mu)(1-\delta_0)\Big]^M \leq \alpha,\ \textstyle\prod_{j=1}^{M}\Big[1-(1-\mu)(1-\delta_{1,j})\Big] \geq \beta, \end{aligned} \tag{4.38}$$

For a given $\mu = \mu^*$, (4.38) becomes

$$\begin{aligned} &\min_{\delta_0} \max_j (1-\mu^*)(NC_{s,j} + C_{t,j}(1-\pi_0\delta_0+\pi_1\delta_{1,j})) \\ &\text{s.t. } \Big[1-(1-\mu^*)(1-\delta_0)\Big]^M \leq \alpha,\ \textstyle\prod_{j=1}^{M}\Big[1-(1-\mu^*)(1-\delta_{1,j})\Big] \geq \beta. \end{aligned} \tag{4.39}$$

Since $\delta_{1,j}$ is a monotone increasing function of δ_0, the optimal solution of (4.39) is obtained by solving the following problem

$$\begin{aligned}&\max_{\delta_0}\delta_0\\&\text{s.t. }\Big[1-(1-\mu^*)(1-\delta_0)\Big]^M\leq\alpha,\ \prod_{j=1}^M\Big[1-(1-\mu^*)(1-\delta_{1,j})\Big]\geq\beta.\end{aligned}\tag{4.40}$$

Therefore, if the feasible set of (4.40) is not empty, then the maximum δ_0 in this feasible set, determines the optimal δ_0. From the first constraint in (4.40), we find $\delta_0 \leq 1-\frac{1-\alpha^{1/M}}{1-\mu^*}$. Assuming $Q^B_{\text{D,AND}} = G(\mu,\delta_0)$, we have $\frac{\partial G(\mu,\delta_0)}{\partial\delta_0} = \frac{\partial G(\mu,\delta_0)}{\partial\delta_{1,j}}\frac{\partial\delta_{1,j}}{\partial_0} \geq 0$, where we used the fact that $\frac{\partial G(\mu,\delta_0)}{\partial\delta_{1,j}} \geq 0$. This way, from the second constraint in (4.40), we obtain $\delta_0 \geq G^{-1}(\mu^*,\beta)$, where the inverse function is defined over the second argument in $G(\mu,\delta_0)$. Based on this discussion, (4.40) reduces to

$$\begin{aligned}&\max_{\delta_0}\delta_0\\&\text{s.t. }G^{-1}(\mu^*,\beta)\leq\delta_0\leq1-\tfrac{1-\alpha^{1/M}}{1-\mu^*}.\end{aligned}\tag{4.41}$$

Therefore, if the feasible set of (4.41) is not empty then the optimal δ_0 is obtained by $\delta_0 = 1-\frac{1-\alpha^{1/M}}{1-\mu^*}$. Inserting the optimal δ_0 for a given μ in (4.38), we obtain the following line search problem in order to determine the optimal μ and consequently δ_0 and λ_1.

$$\min_{\mu}\ \max_j(1-\mu)(NC_{s,j}+C_{t,j}(1-\pi_0(1-\tfrac{1-\alpha^{1/M}}{1-\mu})-\pi_1F_{j,\text{AND}}(1-\tfrac{1-\alpha^{1/M}}{1-\mu})))\tag{4.42}$$

where $F_{j,\text{AND}}(\delta_0) = \delta_{1,j}(\delta_0)$. In search for the optimal μ, we should note that $\mu \leq \alpha^{1/M}$ which comes from the fact that $1-\frac{1-\alpha^{1/M}}{1-\mu} \geq 0$ and also $G(\mu, 1-\frac{1-\alpha^{1/M}}{1-\mu}) \geq \beta$.

4.6 Numerical Results

4.6.1 Case Study for IEEE 802.15.4/ZigBee

Here, a case study is considered in order to verify the performance of the proposed combined sleeping and censoring scheme. A Chipcon CC2420 transceiver based on the IEEE 802.15.4/ZigBee standard [48] is considered to compute the energy consumption in sensing and transmission. This low-power radio with a data rate upto 250 Kbps is aimed to work as a wireless personal area network up to ranges of

100 m. Our cognitive sensor network comprises of such radios arranged in a circular field with a radius of 70 m, uniformly distributed along the circumference with the FC located in the center. We model the wireless channel between the cognitive sensor and the FC using a free-space path loss model. This means that the signal power attenuation is inversely proportional to the square of the distance d between the transmitter and receiver.

The energy consumption analysis that is presented here is based on the transceiver model developed in [49]. The sensing energy for each decision consists of two parts: the energy consumption involved in listening over the channel and making the decision and the energy consumption of the signal processing part for modulation, signal shaping, etc. The former contribution depends on the number of samples taken during the detection time. We choose $N = 5$, corresponding to a detection time of 1 μs. Considering the fact that the typical circuit power consumption of ZigBee is approximately 40 mW, the energy consumed for listening is approximately 40 nJ. The processing energy related to the signal processing part in the transmit mode for a data rate of 250 kbps, a voltage of 2.1 V, and current of 17.4 mA is approximately 150 nJ/bit. Since we use one bit per decision, the sensing energy of each cognitive sensor is $C_s = 190$ nJ [24], [25].

The transmitter dissipates energy to run the radio electronics and the power amplifier. Following the model in [49] and [50], to transmit one bit over a distance d, the radio spends:

$$C_t(d) = C_{t-elec} + e_{amp} d^2 \tag{4.43}$$

where C_{t-elec} is the transmitter electronics energy and e_{amp} is the amplification required to satisfy a given receiver sensitivity level. Assuming a data rate of 250 kbps and a transmit power of 20 mW, $C_{t-elec} = 80$ nJ. The e_{amp} to satisfy a receiver sensitivity of -90 dBm at an SNR of 10 dB is 40.4 pJ/m^2 [24], [25].

Two sets of values were chosen for the a priori probabilities: $\pi_0 = 0.2, \pi_1 = 0.8$ and $\pi_0 = 0.8, \pi_1 = 0.2$. In Fig. 4.1, we show the optimal maximum average energy consumption per sensor for different values of the probability of detection constraint, β. Here, $M = 5$, SNR $= 10$ dB and $\alpha = 0.1$. As is clear, a combined sleeping and censoring scheme consumes less than half the energy as would be consumed if a distributed spectrum sensing such as in [10] were employed. Furthermore, we see that when π_0 is much higher than π_1, the blind setup gives a performance close to the one of the knowledge-aided setup.

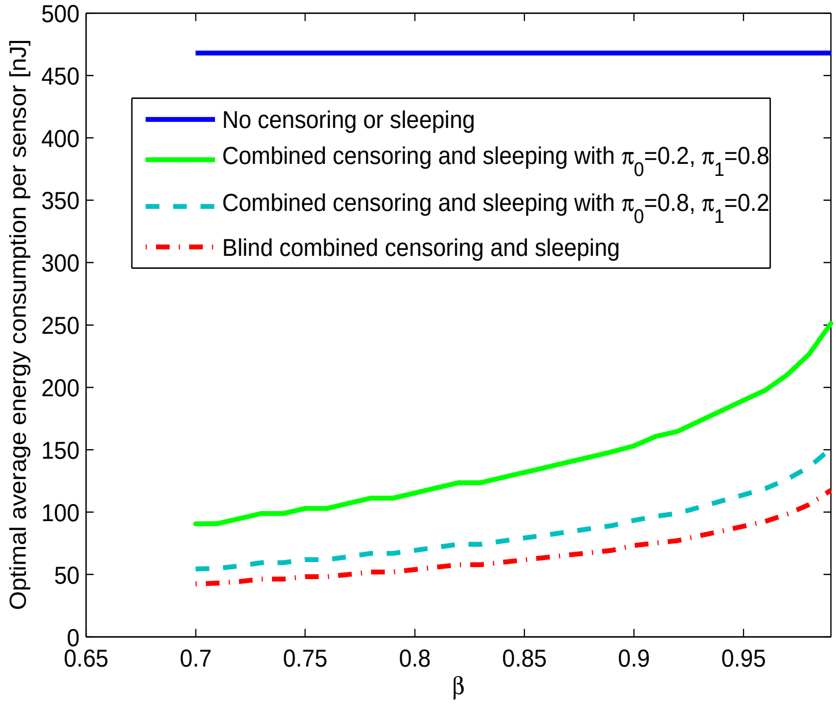


Figure 4.1: *Comparison of energy consumption for different setups.*

In Fig. 4.2, we show the optimal maximum average energy consumption per sensor as the number of cognitive sensors in the network is increased. Here, $\alpha = 0.1$ and $\beta = 0.9$. Without sleeping or censoring, the maximum energy consumption per sensor scales linearly with the number of cognitive sensors. However with a sleeping and censoring scheme, the optimal maximum energy consumption reduces as the number of cognitive radios increases. Again, it is shown that the blind setup gives a lower bound of the system energy consumption for a certain detection performance.

Fig. 4.3 shows the optimal censoring and sleeping rate for different values of the probability of detection constraint β and $\alpha = 0.1$. Since the sensing energy of a ZigBee network is much higher than its transmission energy, the optimal value for the sleeping rate is attained at μ_{max} for different values of β. That is why in Fig. 4.3, the sleeping rate is shown to have the same value for different a priori probabilities π_0 and π_1 as well as for the blind setup. However, it is shown that the censoring

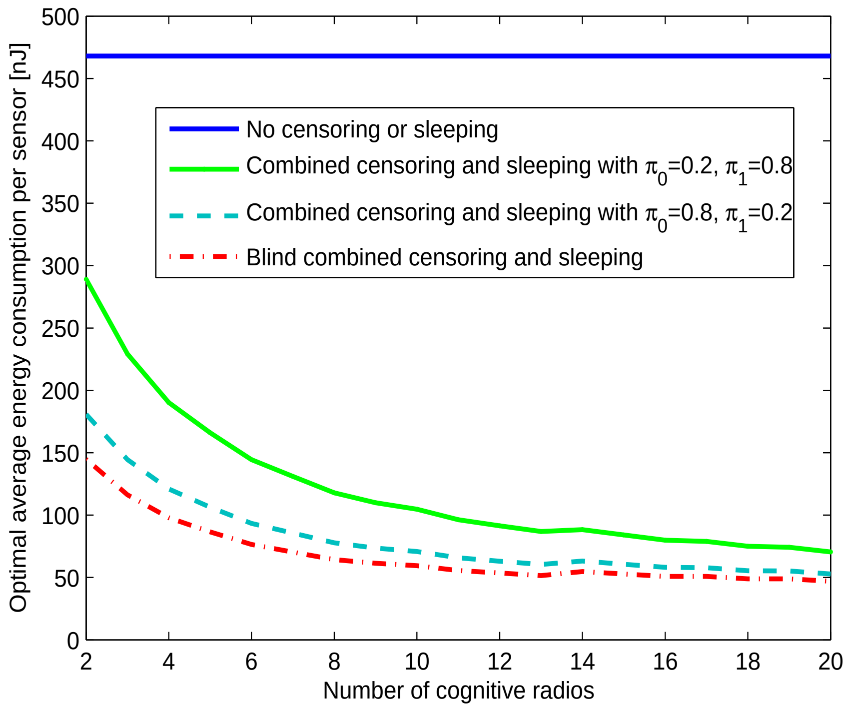


Figure 4.2: *Energy scaling with number of cognitive sensors for different setups.*

rate changes with the a priori probabilities. It is clear that the optimal censoring rate increases with π_0 and is the largest for the blind setup ($\pi_0 = 1$).

In Fig. 4.4, we finally show how the optimal censoring and sleeping rates change with respect to the number of users for $\alpha = 0.1$ and $\beta = 0.9$. For this figure, the blind setup is used for the simulations. It is shown that as the number of users increases, the optimal sleeping rate increases dramatically in order to keep the system energy consumption as stable as possible. However, the optimal censoring rate saturates after a limited number of users.

4.6.2 Performance comparison of the OR and AND rules

A performance comparison of the OR and AND rules is considered in this section. Unless mentioned otherwise, the setup is the same as the case study for IEEE

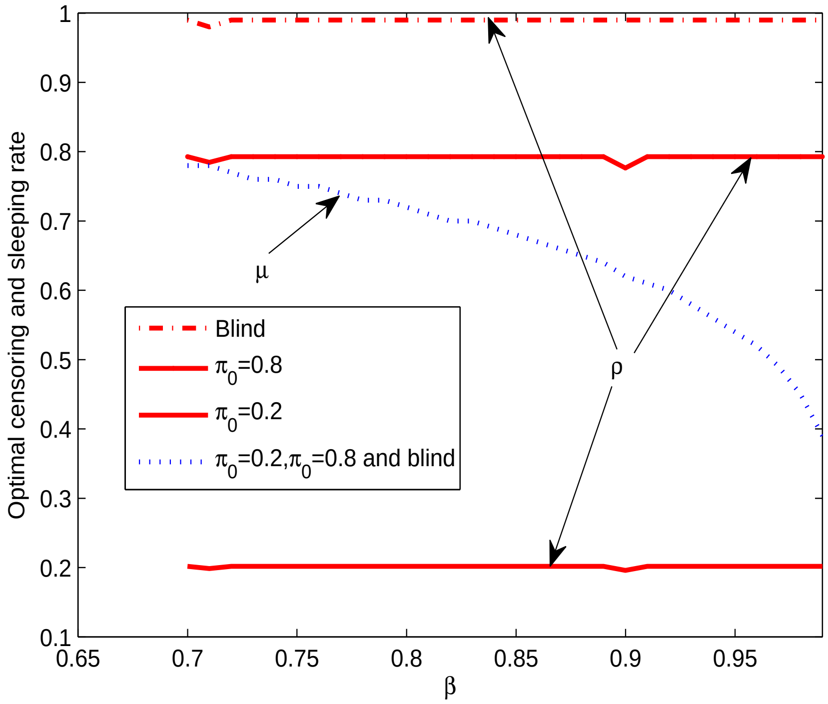


Figure 4.3: *Optimal censoring and sleeping rate for different setups*

802.15.4/ZigBee. In all the simulations, the number of cognitive radios is $M = 5$, the number of samples is $N = 5$ and the SNR is $\gamma = 10$ dB.

In Figures 4.5, 4.6 and 4.7, the optimal average energy consumption per sensor is depicted versus the probability of primary user absence, π_0. In these figures, the probability of false alarm constraint $\alpha = 0.1$, and the probability of detection constraint $\beta = 0.9, 0.99$, and 0.8 respectively, in Figures 4.5, 4.6 and 4.7. We can see, as π_0 increases, the average energy consumption per sensor reduces for the OR rule, while for the AND rule, it increases. The reason is that, in the lower values of π_0 for the OR rule, on average, a higher number of transmissions occur compared to the higher values of π_0, because the FC in the case of the OR rule only receives 1s from the users. In contrast to the OR rule, for the AND rule, the probability that cognitive users transmit their results to the FC increases by increasing π_0, since the probability of sending 0s to the FC increases. Therefore, the average energy consumption per

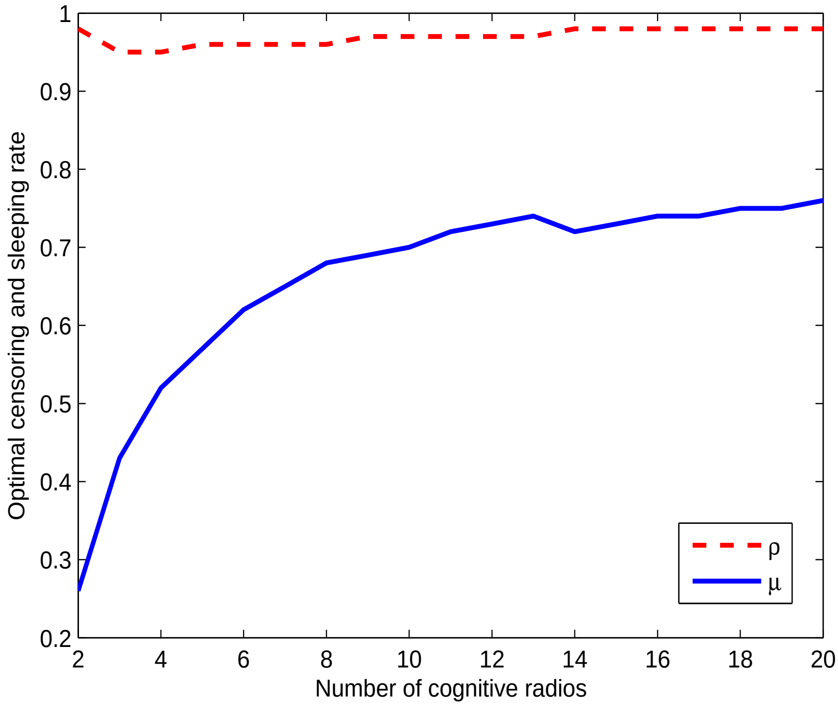


Figure 4.4: *Optimal censoring and sleeping rate with number of cognitive radios for the blind setup*

sensor decreases and increases with π_0, for the OR and AND rules, respectively.

Further, in Fig. 4.5, an interesting behavior in optimal average energy consumption per sensor is shown with π_0. We can see that for $\pi_0 < 0.5$, the AND rule outperforms the OR rule, while for $\pi_0 > 0.5$, it is vice versa, and for $\pi_0 = 0.5$, both rules almost behave the same. The same behavior can be shown to happen when $\alpha + \beta = 1$. We can see in Figures 4.6 and 4.7, that with increasing or decreasing β, the crossing point where the OR rule starts to outperform the AND rule moves to the right or the left of $\pi_0 = 0.5$.

Figures 4.8 and 4.9 show the optimal average energy consumption per sensor versus the transmission energy as the distance between cognitive radios changes from 0 to 70 m for ZigBee. In other words, these figures depict the performance of the combined censoring and sleeping scheme as the ratio C_s/C_t decreases for the OR

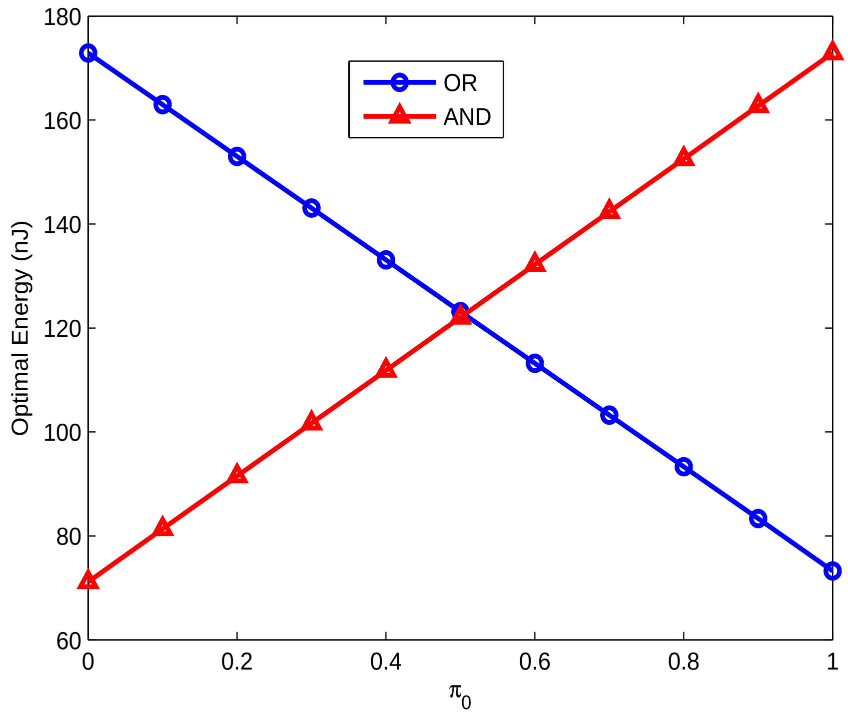


Figure 4.5: *Optimal average energy consumption per sensor versus the probability of primary user absence for $\alpha = 0.1$ and $\beta = 0.9$*

and the AND rules. The other parameters in these figures are $\alpha = 0.1$, $\beta = 0.99$, $\pi_0 = 0.2$ for Fig. 4.8, $\pi_0 = 0.8$ for Fig. 4.9, $M = 5$, $N = 5$ and $\gamma = 10$ dB. We can see that in Fig. 4.8 where the probability that the sensors send a 0 to the FC for the AND rule is low compared to the case of sending 1s for the OR rule, the AND rule outperforms the OR rule significantly.

In contrast to the case in Fig. 4.8, in Fig. 4.9, the probability of primary user absence is $\pi_0 = 0.8$ and therefore the probability of sending 0s to the FC for the AND rule is much higher compared to the scenario in Fig. 4.8 and thus, by increasing the transmission energy, C_t, the average energy consumption per sensor increases dramatically for the AND rule and after a certain C_t, the performance of the AND rule becomes lower than the one for the OR rule in terms of energy efficiency.

In Fig. 4.10, the optimal average energy consumption per sensor is depicted ver-

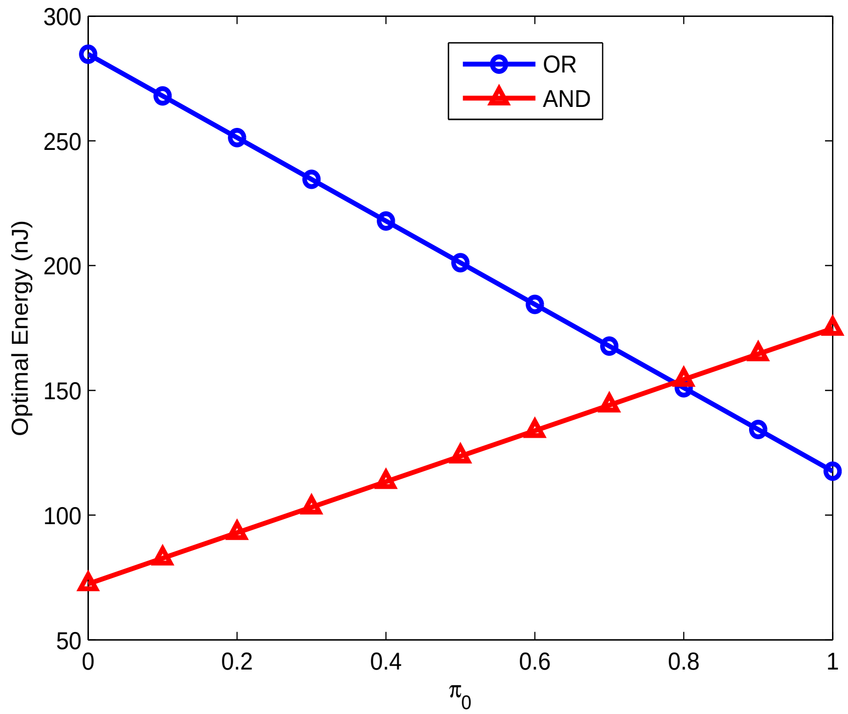


Figure 4.6: *Optimal average energy consumption per sensor versus the probability of primary user absence for* $\alpha = 0.1$ *and* $\beta = 0.99$

sus the sensing energy C_s for $\pi_0 = 0.2$ and $\pi_0 = 0.8$, in order to compare the performance of the OR and the AND rules. In this figure, $M = 5$, $N = 5$, $\gamma = 10$ dB, $\alpha = 0.1$ and $\beta = 0.99$, but unlike previous scenarios, a general radio technology is assumed where $C_t = 1$ and C_s changes from 0 to 10. We can see that the AND rule outperforms the OR rule as C_s increases, which is a similar behavior as the ones in Figures 4.8 and 4.9. Therefore, for the constraints considered in this figure, the AND rule seems a better choice compared to the OR rule, particularly when the sensing energy is much higher compared to the transmission energy. However, as we have seen in the previous figures, the value of π_0 plays a big role in determining the optimal rule when $\alpha = 0.1$ and $\beta = 0.9$. These constraints are basically defined as the cognitive radio system requirements by the current standards. For these values, as we observe this section, the OR rule is optimal for $\pi_0 > 0.5$ while the AND rule is

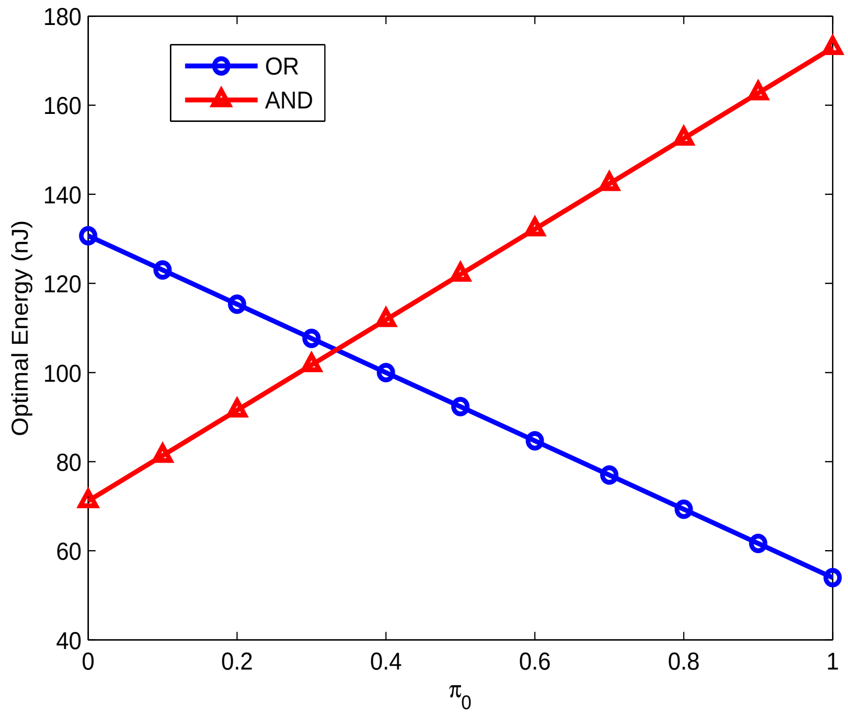


Figure 4.7: *Optimal average energy consumption per sensor versus the probability of primary user absence for* $\alpha = 0.1$ *and* $\beta = 0.8$

optimal for $\pi_0 < 0.5$.

4.7 Summary and conclusions

We presented an energy-efficient distributed spectrum sensing technique based on the combination of censoring and sleeping policies. Depending on the knowledge of the a priori probability of primary user presence, a Neyman-Pearson (blind setup) and Bayesian (knowledge-aided setup) formulation was obtained with the goal of minimizing the maximum average energy consumption per sensor subject to a global detection performance constraint for the OR and the AND rules. We then derived analytical expressions for the global probabilities of detection and false alarm for each setup and each rule. In seeking a systematic solution for the obtained optimiza-

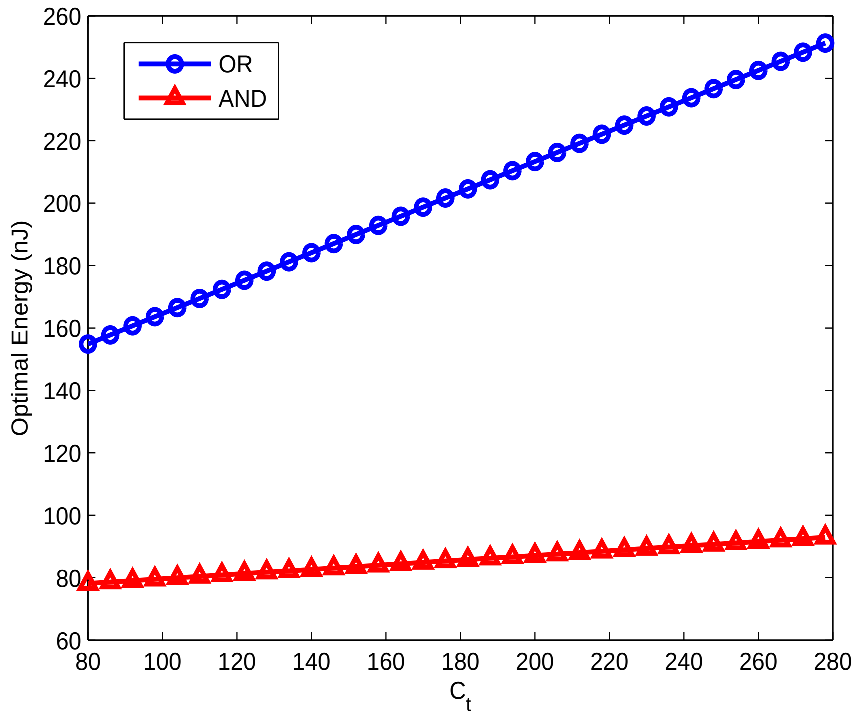


Figure 4.8: *Optimal average energy consumption per sensor versus the transmission energy with* $\alpha = 0.1$, $\beta = 0.99$, $C_s = 190$ *nJ and* $\pi_0 = 0.2$

tion problems, we showed that the resulting optimization problem can be reduced to a line search problem for both setups and both rules.

We considered a case study with IEEE 802.15.4/ZigBee radios for numerical results. It was shown that the average energy consumption per sensor is reduced significantly. We further compared the performance of the OR and the AND rule in terms of energy efficiency. It was shown that as the ratio between sensing energy and transmission energy increases, the AND rule can perform much better than the OR rule for some specific detection performances. However, depending on the probability of a primary user being absent, the sensing energy, the transmission energy and the detection performance constraint, sometimes the OR rule preforms better than the AND rule, particularly when the probability of primary user absence is high and sensing and transmission energies are either comparable or the transmission energy

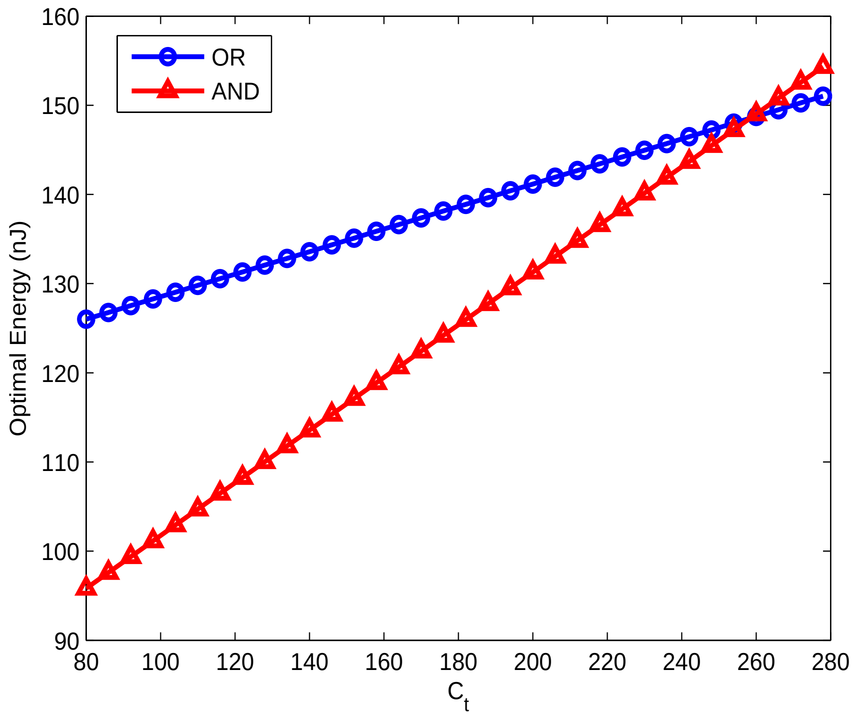


Figure 4.9: *Optimal average energy consumption per sensor versus the transmission energy with* $\alpha = 0.1$*,* $\beta = 0.99$*,* $C_s = 190$ *nJ and* $\pi_0 = 0.8$

is higher than the sensing energy. For desired constraints in cognitive radio system, the OR rule performs better than the AND rule for $\pi_0 > 0.5$ while the AND rule performs better than the OR rule for $\pi_0 < 0.5$.

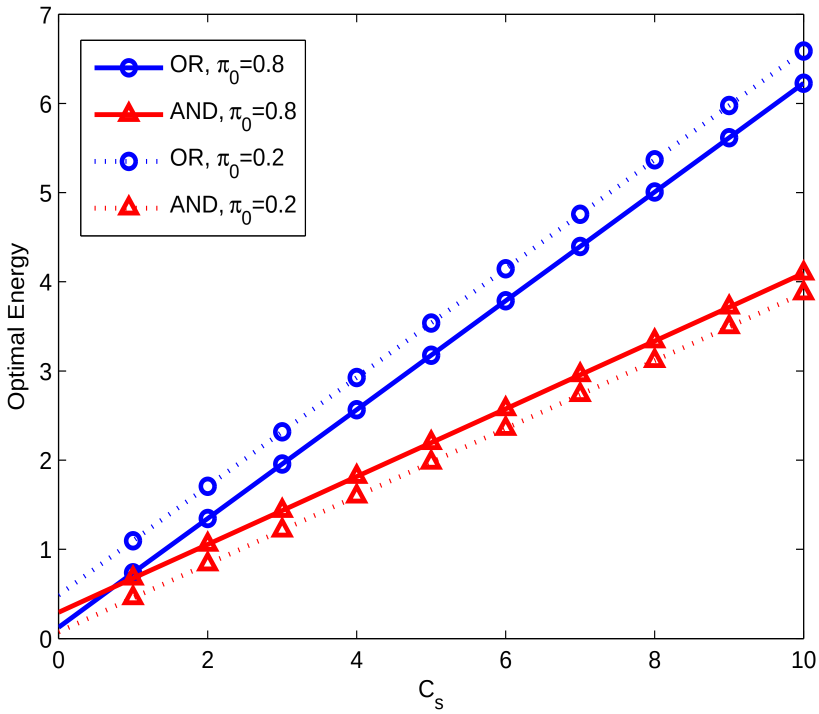


Figure 4.10: *Optimal average energy consumption per sensor versus the sensing energy with* $\alpha = 0.1$, $\beta = 0.99$, $C_t = 1$

Chapter 5

Optimization Hard Fusion Strategies

Abstract

The detection reliability of a cognitive radio network improves by employing a cooperative spectrum sensing scheme. However, increasing the number of cognitive radios entails a growth in the cooperation overhead of the system. Such an overhead leads to a throughput degradation of the cognitive network. Since current cognitive radio networks consist of low-power radios, the energy consumption is another critical issue. In the previous chapters, we have optimized the average energy consumption per sensor subject to certain detection performance constraints for the OR and the AND rules. In this chapter, throughput optimization of the hard fusion based sensing using the K-out-of-M rule is considered. We maximize the throughput of the cognitive radio network subject to a constraint on the probability of detection and energy consumption per cognitive radio in order to derive the optimal number of users, the optimal K and the best probability of false alarm. The simulation results based on the IEEE 802.15.4/ZigBee standard, show that the majority rule is either optimal or almost optimal in terms of the network throughput.

5.1 Introduction

In this chapter, we consider a cognitive radio network where each cognitive user senses a specific frequency band in a fixed sample size detection period and makes a local decision about the primary user presence. The results are then sent to a fusion center (FC) in consecutive time slots by employing a time-division-multiple-access (TDMA) approach. The final decision is made at the FC. Although, several fusion schemes have been proposed in literature [14],[33], we consider a hard fusion scheme due to its improved energy and bandwidth efficiency. Among them, the OR and AND rules have been studied extensively in literature. The OR and AND rules are special cases of the more general K-out-of-M rule with $K = 1$ and $K = M$, respectively. In a K-out-of-M rule, the FC decides the target presence, if at least K out of M sensors report to the FC that a target is present [14].

Optimization of the K-out-of-M rule based spectrum sensing is considered in this chapter. The optimal K and optimal M is derived for a throughput optimization setup. The sensing time of the individual cognitive radios is given but the reporting time which is directly related to the number of cognitive users is unknown.

The throughput of the cognitive radio network is maximized subject to a constraint on the global probability of detection and energy consumption per cognitive radio in order to determine the optimal number of cognitive users M and K. It is shown that the underlying problem can be solved by a bounded two-dimensional search. As we will discuss later, the reporting time of the cognitive radio system is directly proportional to M and thus by deriving the optimal M, the reporting time is also optimized.

5.1.1 Related works

Cooperative spectrum sensing optimization is studied extensively in the literature. The sensing-throughput trade-off is studied in [55], [56]. The optimal sensing time is determined by maximizing the cognitive radio throughput subject to the probability of detection constraint in [55]. An extended version of [55] including K as an argument of optimization is discussed in [56]. This chapter is different from [56], in the sense that in our throughput optimization setup with a given sensing time, the combined optimization of the reporting time and K is discussed, and further the energy consumption per cognitive radio is included as an additional constraint in this chapter. [57] depicts an optimal spectrum sensing scheme where the sensing efficiency of a cognitive radio network is maximized subject to an interference constraint. The sensing efficiency is defined as the transmission time divided by the total cognitive radio time frame. However, this work also ignored the effect of the reporting time on the sensing efficiency of the cognitive radio network.

The reporting time optimization is studied in [58], [59]. [58] optimizes the cognitive radio network throughput subject to a detection probability constraint in order to find the optimal sensing and reporting time. An extension of [58] to a general K-out-of-M rule based spectrum sensing is considered by us in [59]. The difference is that in [59] and this chapter, the sensing time is assumed to be given. In this chapter, a combined optimization of M and K is given while optimization of K is ignored in [58] and [59]. In contrast to [59], we include a constraint on the energy consumption per cognitive radio in this chapter. As shall be shown in Section 5.3, this additional constraint requires new algorithms to solve the problem. [65] considers the optimization of the cognitive radio network energy efficiency. Energy efficiency is defined as the ratio of the average network throughput over the average network energy consumption. Optimization of the energy efficiency is considered for two cases. In the former case, energy efficiency is optimized in order to find K and in the latter case, the sensing threshold at the energy detector is derived by optimizing the energy efficiency. However, the combined optimization of K, M as well as the sensing threshold is not considered. Further, no typical performance constraint is considered for the optimization problem such as the probability of detection which is inherent in a cognitive radio design technique.

5.1.2 Organization

The remainder of this chapter is organized as follows. The considered cooperative sensing configuration and its underlying system model are presented in Section 5.2. The problem formulation is discussed and analyzed in Section 5.3. We depict some numerical results based on the IEEE 802.15.4/ZigBee standard in Section 5.4 and draw our conclusions in Section 5.5.

5.2 System Model

We consider a network with M identical cognitive radios under a cooperative spectrum sensing scheme. Each cognitive radio senses the spectrum periodically and makes a local decision about the presence of the primary user based on its own observations. To avoid any false detections of the secondary users instead of a primary user, the secondary users are silent during the sensing period. The local decisions are to be sent to the FC in consecutive time slots based on a TDMA scheme. The FC employs a hard decision fusion scheme over a soft fusion one due to its higher energy and bandwidth efficiency along with a reliable detection performance that is asymptotically similar to that of a soft fusion scheme [10].

To make local decisions about the presence or absence of a primary user, each cognitive radio solves a binary hypothesis testing problem, by choosing $\mathscr{H}_1$ in case the primary user is present and $\mathscr{H}_0$ when the primary user is absent. Denoting r_i

as the i-th sample received by the cognitive radio, w_i as the noise and s_i as the primary user signal, the hypothesis testing problem can be represented by the following model,

$$\begin{aligned} \mathscr{H}_0 &: r_i = w_i,\ i = 1,\dots,N \\ \mathscr{H}_1 &: r_i = s_i + w_i,\ i = 1,\dots,N \end{aligned} \tag{5.1}$$

where the noise and the signal are assumed to be i.i.d. Gaussian random processes with zero mean and variance σ_w^2 and σ_s^2, respectively, and the received signal-to-noise-ratio (SNR) is denoted by $\gamma = \frac{\sigma_s^2}{\sigma_w^2}$.

Each cognitive radio employs an energy detector in which the accumulated energy of N observation samples is compared with a predetermined threshold denoted by λ as follows

$$\mathscr{E} = \sum_{i=1}^{N} |r_i|^2 \underset{\mathscr{H}_0}{\overset{\mathscr{H}_1}{\gtrless}} \lambda. \tag{5.2}$$

For a large number of samples we can employ the central limit theorem, and the decision statistic is distributed as [10]

$$\begin{aligned} \mathscr{H}_0 &: \mathscr{E} \sim \mathscr{N}(N\sigma_w^2, 2N\sigma_w^4), \\ \mathscr{H}_1 &: \mathscr{E} \sim \mathscr{N}(N(\sigma_w^2+\sigma_s^2), 2N(\sigma_w^2+\sigma_s^2)^2). \end{aligned} \tag{5.3}$$

Denoting P_f and P_d as the respective local probabilities of false alarm and detection, $P_f = Pr(\mathscr{E} \geq \lambda | \mathscr{H}_0)$ and $P_d = Pr(\mathscr{E} \geq \lambda | \mathscr{H}_1)$ are given by

$$P_f = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right), \quad P_d = Q\left(\frac{\lambda - N(\sigma_w^2+\sigma_s^2)}{\sqrt{2N(\sigma_w^2+\sigma_s^2)^2}}\right). \tag{5.4}$$

The reported local decisions are combined at the FC and the final decision regarding the presence or absence of the primary user is made according to a certain fusion rule. Several fusion schemes have been discussed in literature [33]. Due to its simplicity in implementation, lower overhead and energy consumption, we employ a K-out-of-M rule to combine the local binary decisions sent to the FC. Thus, the resulting binary hypothesis testing problem at the FC is given by, $I = \sum_{i=1}^{M} D_i < K$ for $\mathscr{H}_0$ and $I = \sum_{i=1}^{M} D_i \geq K$ for $\mathscr{H}_1$, where D_i is the binary local decision of the i-th cognitive radio which takes the binary value ‘0’ if the local decision supports the absence of the primary user and ‘1’ for the presence of the primary user. For the sake of analytical simplicity, we assume that all the cognitive radios experience the same SNR and each cognitive radio employs an identical threshold λ to make the decision. Such an assumption on the SNR is a valid assumption when the SNR difference is less than 1 dB [51]. This way, the global probability of false alarm (Q_{F}) and detection (Q_{D}) at the FC are given by

$$\begin{aligned} Q_{\mathrm{D}} &= \sum_{i=K}^{M} \binom{M}{i} P_d^i (1-P_d)^{M-i}, \\ Q_{\mathrm{F}} &= \sum_{i=K}^{M} \binom{M}{i} P_f^i (1-P_f)^{M-i}. \end{aligned} \tag{5.5}$$

We can rewrite (5.5) using the binomial theorem as follows,

$$\begin{aligned} Q_{\mathrm{F}} &= 1-\psi(K-1,P_f,M) \\ Q_{\mathrm{D}} &= 1-\psi(K-1,P_d,M) \end{aligned} \tag{5.6}$$

where ψ is the regularized incomplete beta function as follows,

$$\begin{aligned} \psi(K,p,n) &= I_{1-p}(n-K,K+1) \\ &= (n-K)\binom{n}{K}\int_0^{1-p} t^{n-K-1}(1-t)^K \, dt \end{aligned}$$

Denoting P_x as the local probability of detection or false alarm and Q_x as the global probability of detection or false alarm, we can define $P_x = \psi^{-1}(K,1-Q_x,M)$ as the inverse function of ψ in the second variable.

Each cognitive radio employs periodic time frames of length T for sensing and transmission. The time frame for each cognitive radio is shown in Fig. 5.1. Each frame comprises two parts namely a sensing time required for observation and decision making and a transmission time denoted by T_x for transmission in case the primary user is absent. The sensing time can be further divided into a time required for energy accumulation and local decision making denoted by T_s and a reporting time where cognitive radios send their local decisions to the FC. Here, we employ a TDMA based approach for reporting the local decision to the FC. This way, we avoid collisions among the reported data from the cognitive radios. Hence, denoting T_r as the required time for each cognitive radio to report its result, the total reporting time for a network with M cognitive radios is MT_r .

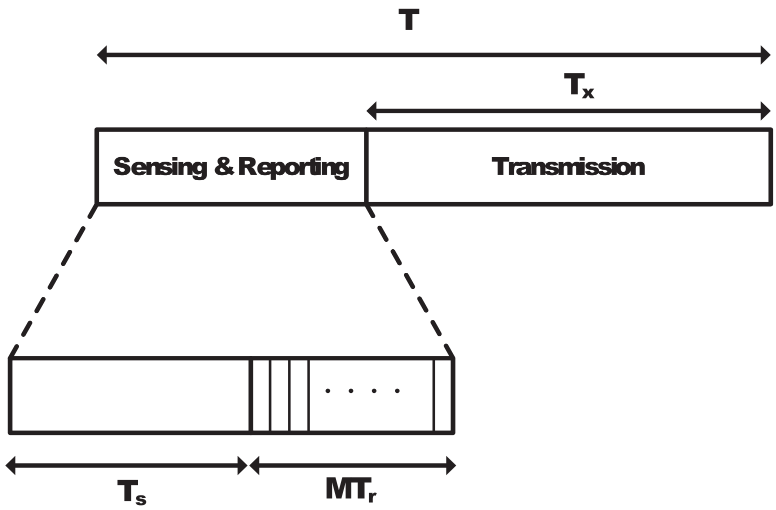


Figure 5.1: *Cognitive radio time frame*

Considering the above structure of a cognitive radio time frame, we define the throughput of the cognitive radio network, R_{CR}, by

$$R_{\mathrm{CR}} = \pi_0 \left(\frac{T - T_s - MT_r}{T}\right)(1 - Q_{\mathrm{F}})\mathscr{C}_0 Pr(success|\mathscr{H}_0) + \pi_1 \left(\frac{T - T_s - MT_r}{T}\right)(1 - Q_{\mathrm{D}})\mathscr{C}_1 Pr(success|\mathscr{H}_1) \quad (5.7)$$

where $\mathscr{C}_0$ and $\mathscr{C}_1$ are the cognitive radio capacity under $\mathscr{H}_0$ and $\mathscr{H}_1$, respectively, $\pi_0 = Pr(\mathscr{H}_0)$, $\pi_1 = Pr(\mathscr{H}_1)$ and $Pr(success|H_i),\ i = 0,1$ is the probability that the cognitive radio can successfully send its data to the cognitive receiver upon the detection of a spectrum hole or miss detection of a primary user. Upon the correct detection of a spectrum hole, since the whole bandwidth is free for the cognitive radio, $Pr(success|\mathscr{H}_0) \to 1$, but in case of miss detection of a primary user, since the bandwidth is almost occupied completely by the primary user, $Pr(success|\mathscr{H}_1) \to 0$. This way, the second part of R_{CR} is negligible. Therefore, in this chapter, after normalizing with π_0 and $\mathscr{C}_0$, the first part of R_{CR} denoted by R is considered as the throughput of the cognitive radio network and is given by

$$R = \left(\frac{T - T_s - MT_r}{T}\right)(1 - Q_{\mathrm{F}}). \quad (5.8)$$

The energy consumption of each cognitive radio is another critical element in a low-power cognitive radio network. Denoting P_s and P_t to be the sensing and transmission power respectively, the average energy consumption at each cognitive radio, E, is defined as follows

$$E = P_s T_s + P_t T_r + \pi_0 (1 - Q_{\mathrm{F}}) P_t (T - T_s - MT_r) + \pi_1 (1 - Q_{\mathrm{D}}) P_t (T - T_s - MT_r). \quad (5.9)$$

Note that here we assume that the transmission power to report the results to the FC and the data transmission power are the same. This assumption is particularly valid in situations where the FC is the data receiver as well or the transmission power of the cognitive transmitter is constant.

In the following section, a throughput optimization setup is considered to optimize the K-out-of-M rule based spectrum sensing subject to a constraint on the probability of detection and average energy consumption per cognitive radio.

5.3 Analysis and Problem Formulation

The cooperative sensing performance improves with the number of cognitive users. However, a larger number of cooperating users leads to a higher reporting time and hence a lower network throughput. Further, in a low-power cognitive radio network, the energy consumption of each cognitive radio is constrained. Therefore, it is desirable to find the optimal number of users and fusion rule that satisfies a certain detection performance and energy consumption by optimizing the cognitive radio network throughput. The cognitive radio throughput depends on the specific choice of the K-out-of-M rule. In this section, we consider a setup where the network throughput is maximized subject to a constraint on the probability of detection and energy consumption per cognitive radio to find the system parameters including the number of users, the optimal K-out-of-M rule and the probability of false alarm.

The sensing-throughput trade-off has been extensively studied in literature, e.g.[55, 56, 57]. However, the combined reporting time and K-out-of-M rule optimization attracted less attention while it is a critical factor in the cognitive radio throughput. Reducing the reporting time leads to an increase in the throughput of the cognitive radio network. In a TDMA based scheme, the reporting time directly corresponds to the number of cognitive radios. As such, M becomes an argument of the optimization in the following discussions. Here, we fix the sensing time, T_s, and focus on optimizing the reporting time MT_r where $T_r = \frac{1}{R_b}$, with R_b the cognitive radio transmission bit rate. The other important factor is the parameter K in the K-out-of-M rule. For a given M, it is shown that different values of K lead to different throughputs. Thus, the optimization of K along with M is an important issue in cognitive network design. Naturally, also the local sensing threshold, λ, which is related to the local probability of false alarm, P_f, is part of the optimization problem. Avoiding harmful interference to the primary user is one of the requirements of a cognitive radio network. Cognitive radios interfere with the primary user if they miss the detection of the primary user. Therefore, it is desirable that the probability of detection is lower bounded. Finally, most cognitive radio networks consist of low-power radios. Hence, the energy consumption of each cognitive radio should also be constrained. To summarize, we define our problem as an optimization of the network throughput over K, M and P_f (or λ) subject to the constraint on the probability of detection and average energy consumption per cognitive radio as follows:

$$\begin{aligned} \max_{M,K,P_f} \quad & \left(\frac{T - T_s - MT_r}{T}\right)(1 - Q_\mathrm{F}) \\ & \text{s.t. } Q_\mathrm{D} \geq \beta \\ & 1 \leq M \leq \left\lfloor \frac{T - T_s}{T_r} \right\rfloor \\ & 1 \leq K \leq M \\ & E \leq E_\mathrm{max} \end{aligned} \tag{5.10}$$

where E is defined in (5.9) and E_max is the energy constraint.

For a given M and K, the optimization problem reduces to

$$\begin{aligned} \max_{P_f} \quad & (1 - Q_\mathrm{F}) \\ \text{s.t. } & Q_\mathrm{D} \geq \beta \\ & E \leq E_\mathrm{max} \end{aligned} \tag{5.11}$$

which can be further simplified to

$$\begin{aligned} \min_{P_f} \quad & Q_\mathrm{F} \\ \text{s.t. } & P_d \geq \psi^{-1}(K-1, 1-\beta, M) \\ & E \leq E_\mathrm{max} \end{aligned}$$

and is equivalent to finding the minimum P_f in the feasible set of the problem. Since the probability of false alarm grows with the probability of detection, the minimum P_f considering the probability of detection constraint is the P_f that satisfies $P_d = \psi^{-1}(K-1, 1-\beta, M)$. In this case, P_f is given by

$$P_f = Q\left(\frac{N\sigma_s^2 + Q^{-1}(\psi^{-1}(K-1,1-\beta,M))\sqrt{2M(\sigma_s^2+\sigma_w^2)^2}}{\sqrt{2M\sigma_w^4}}\right) \tag{5.12}$$

Since Q_{F} and Q_{D} increase as P_f grows, E decreases with P_f. Therefore, from the energy viewpoint, the probability of false alarm is desired to be as high as possible. The minimum P_f in this case is the one that satisfies $E = E_{\max}$. Denoting $P_f(\beta)$ as the P_f that satisfies $P_d = \psi^{-1}(K-1, 1-\beta, M)$ and $P_f(E_{\max})$ as the P_f that satisfies $E = E_{\max}$, the optimal P_f denoted by $\tilde{P}_f$ is $\tilde{P}_f = \max\{P_f(\beta), P_f(E_{\max})\}$.

Inserting $\tilde{P}_f$ in (5.10) for a given K, we obtain a line search optimization problem as follows

$$\begin{aligned} \max_{M} \quad & \left(\frac{T - T_s - MT_r}{T}\right)(1-\tilde{Q}_f) \\ \text{s.t. } & 1 \le M \le \left\lfloor \frac{T-T_s}{T_r} \right\rfloor \end{aligned} \tag{5.13}$$

where $\tilde{Q}_f = 1 - \psi(K-1, \tilde{P}_f, M)$. Similarly inserting $\tilde{P}_f$ in (5.10) for a given M, we obtain a line search optimization problem as follows

$$\begin{aligned} \max_{K} \quad & \left(\frac{T - T_s - MT_r}{T}\right)(1-\tilde{Q}_f) \\ \text{s.t. } & 1 \le K \le M \end{aligned} \tag{5.14}$$

Since both M and K are bounded, a two-dimensional search utilizing (5.10) can be carried out if both M and K are unknown. Further, employing (5.13) and (5.14), an alternating optimization algorithm is possible that in general converges faster than a two-dimensional search, but is suboptimal.

5.4 Numerical Results

A cognitive radio network with several secondary users is considered for the simulations. A Chipcon CC2420 transceiver based on the IEEE 802.15.4/ZigBee standard is considered to compute the sensing and transmission power as well as the data rate

[24]. Our cognitive radio network comprises of such radios arranged in a circular field with a radius of 70 m. This way, the data rate is $R_b = 250$ Kbps, the sensing power is $P_s = 2.1\text{V} \times 17.4\text{mA}$ and the transmission power is $P_t = 20$ mW [24]. Each cognitive radio accumulates $N = 275$ observation samples in the energy detector to make a local decision. In [52], it is shown that for $N \geq 250$, the normal approximation of the calculated energy under $\mathscr{H}_0$ and $\mathscr{H}_1$ performs close to the real values. The received SNR at each cognitive user is assumed to be $\gamma = -7dB$. Unless mentioned otherwise, we take $T = 105$ μsec, $T_s = 45$ μsec and $T_r = 1/R_b = 4$ μsec. The constraints are defined so as to satisfy the current cognitive radio standard requirements [66].

Fig. 5.2 depicts the optimal throughput versus $E_{\max}$ for $\beta = 0.9, 0.95$ and $\pi_0 = \pi_1 = 0.5$. Note that since T_s is given, here the throughput is normalized with respect to $T - Ts$ instead of T. We can see that as $E_{\max}$ increases, the optimal throughput increases up to a certain point. After this point the optimal throughput becomes saturated. The reason is that as E_{max} increases, for a given M and K, $P_f(E_{\max})$ decreases up to a point after which $\max\{P_f(\beta), P_f(E_{\max})\} = P_f(\beta)$ and the optimal point becomes independent from $E_{\max}$. As β increases, $P_f(\beta)$ also increases, thus the turning point where $\max\{P_f(\beta), P_f(E_{\max})\}$ changes from $P_f(E_{max})$ to $P_f(\beta)$ occurs for a lower E_{max}.

In Fig. 5.3, the optimal throughput versus the probability of detection constraint, β, is considered for different values of π_0 and $E_{\max}$. In this figure, $E_{l,\max}$ and $E_{u,\max}$ denote the lower and upper bounds on the $E_{\max}$ for the considered range of β. For example, in case $\pi_0 = 0.2$, for $E_{\max}$ less than 1970 nJ, the feasible set of (5.10) is empty and for $E_{\max}$ more than 2100 nJ, the optimal throughput does not increase anymore. It is depicted that as π_0 increases, $E_{l,\max}$ increases as well. Assume that for a certain π_0, $E_{\max}$, M and K, we define $\beta = P_f(E_{\max})$ and we chose β as the probability of false alarm of the system. We keep all the parameters the same and only increase the π_0. Since in a cognitive radio system, $Q_{\text{F}} \ll Q_{\text{D}}$, we obtain $(1 - Q_{\text{F}})P_t(T - T_s - MT_r) \gg (1 - Q_{\text{D}})P_t(T - T_s - MT_r)$. Therefore, by increasing π_0, we increase the larger term more than that we decrease the smaller term and so E increases and passes $E_{\max}$. That is why we need to increase $E_{l,\max}$ in order to make (5.10) feasible for a higher π_0. Furthermore, we can see that as β decreases, the optimal throughput increases up to a certain point after which the optimal throughput saturates to a certain level. With a similar explanation as given

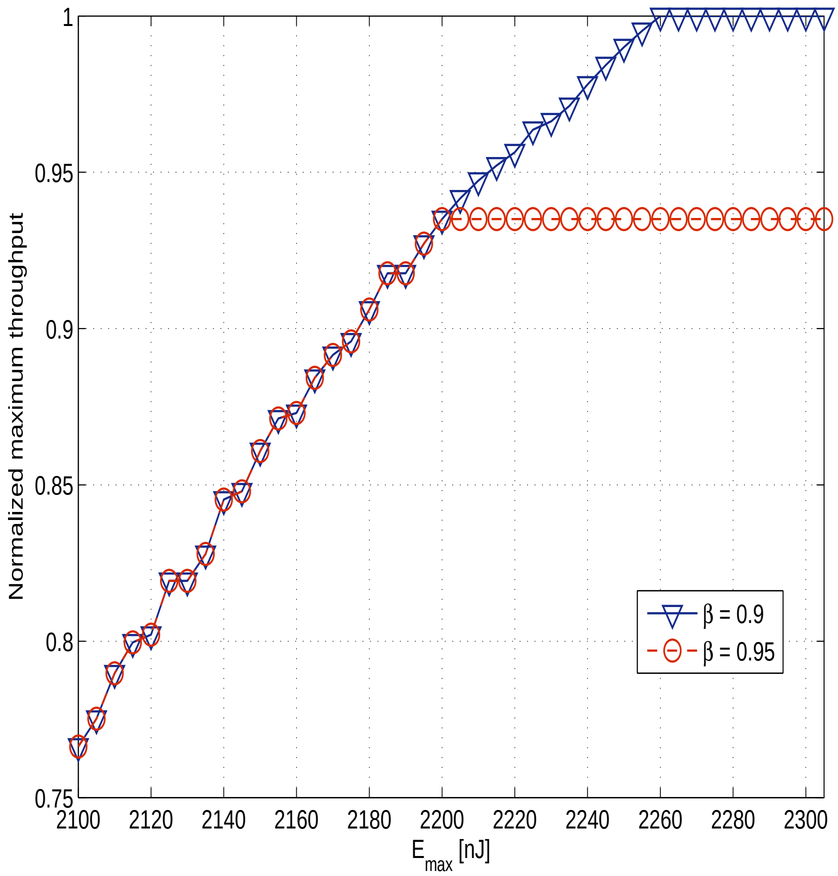


Figure 5.2: *Optimal throughput versus* $E_{\max}$

for Fig. 5.2, for the highest feasible β in the range $E_{l,\max} \leq E_{\max} \leq E_{u,\max}$, we have $\max\{P_f(\beta), P_f(E_{\max})\} = P_f(\beta)$. As β decreases, $P_f(\beta)$ also decreases and thus the optimal throughput increases up to the point where $\max\{P_f(\beta), P_f(E_{\max})\}$ becomes $P_f(E_{\max})$. After that point, the optimal throughput becomes independent from β.

Fig. 5.4 depicts the throughput versus the number of cognitive users and K for a detection constraint equal to $\beta = 0.97$, $E_{\max} = 2300$ nJ and $\pi_0 = 0.5$. It is shown that the optimal throughput is a quasi-concave function of M and K and thus there is a unique optimal point. The mathematical investigation of quasi-concavity is subject

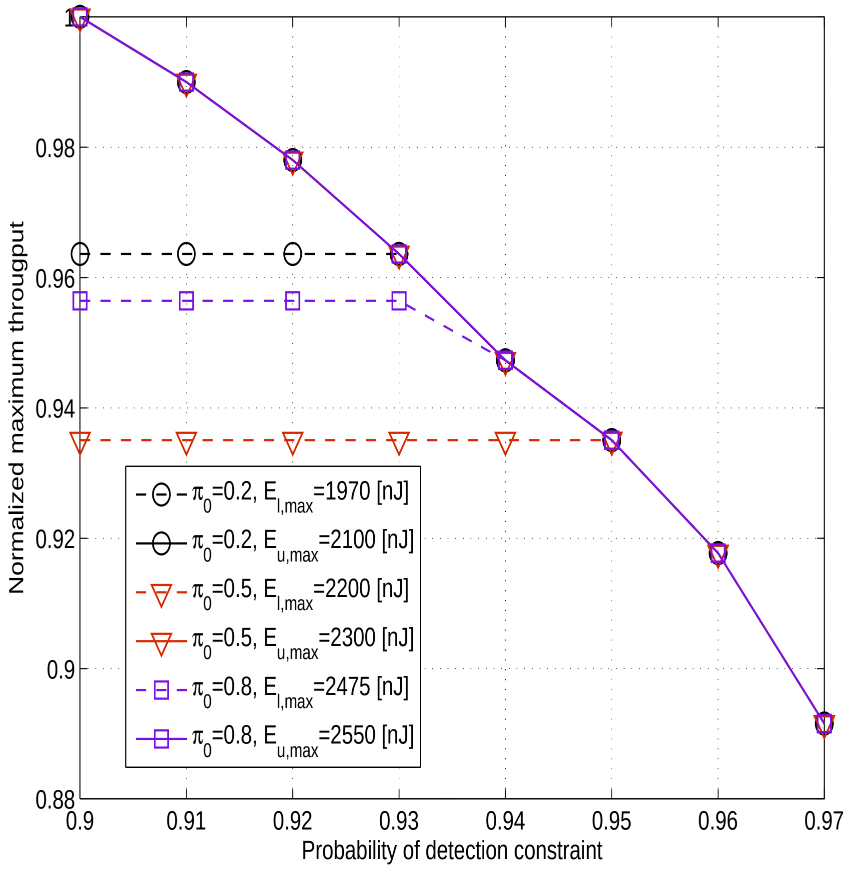


Figure 5.3: *Optimal throughput versus probability of detection constraint*

of future work. Further, it is evident that the choice of M and K has a dramatic impact on the cognitive network throughput.

In Fig. 5.5, the optimal M and K are depicted versus the probability of detection constraint. In this figure, $T = 0.5$ msec and $E_{\max}$=6500 nJ. It is shown that for the desired range of the detection rate constraint, the majority rule is either optimal or nearly optimal.

Fig. 5.6 depicts the optimal M and K versus $E_{\max}$. In this figure, $T = 0.5$ msec and $\beta = 0.95$. We can see that similar to the previous scenario, the majority rule is

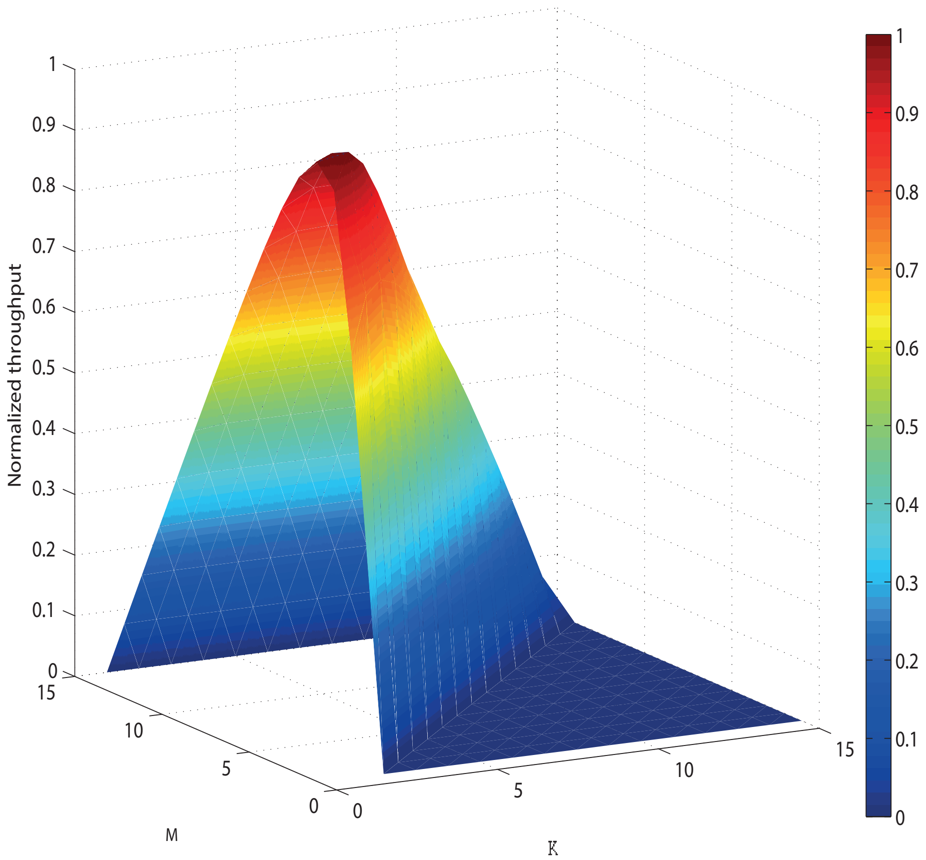


Figure 5.4: *Throughput versus M and K*

optimal.

5.5 Summary and conclusions

In this chapter, the network throughput is maximized subject to a detection rate and energy constraint in order to find the optimal reporting time, K and probability of false alarm. We have shown that the problem can be solved by a bounded two-dimensional search. It is also shown that as the energy constraint reduces, the optimal

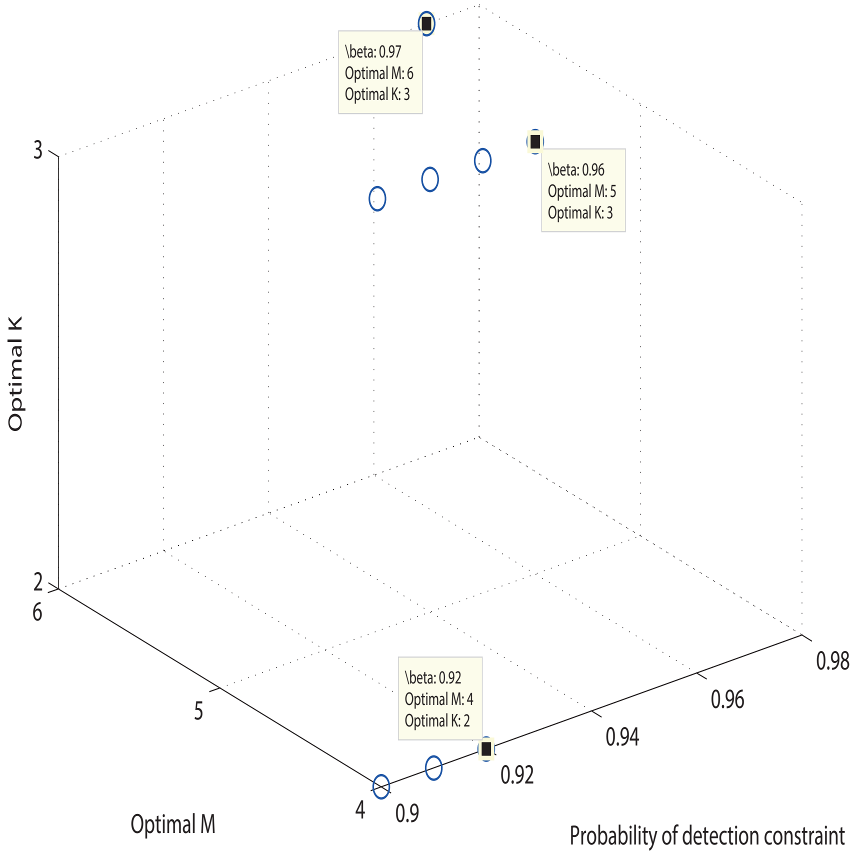


Figure 5.5: *Optimal M and K versus the probability of detection constraint*

throughput also reduces while reducing the probability of detection constraint for the same energy constraint leads to a higher throughput. Furthermore, we have shown that in the desired range of the probability of detection constraint, the majority rule is either optimal or nearly optimal in terms of the cognitive network throughput.

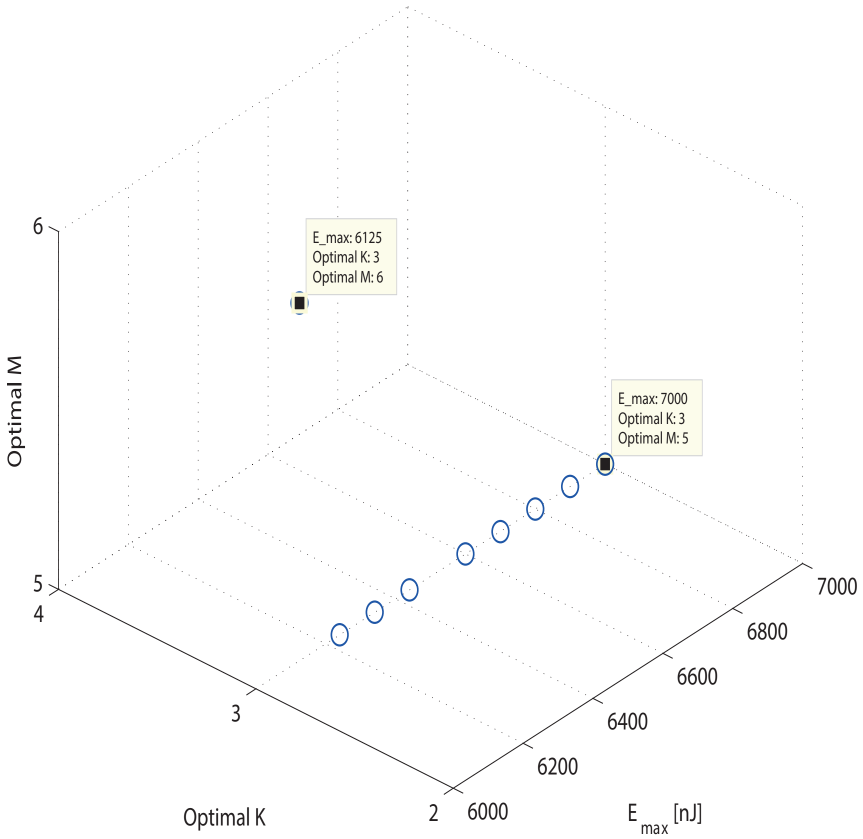


Figure 5.6: *Optimal M and K versus the maximum average energy consumption per cognitive radio*

Chapter 6

Conclusions and Future Works

In this chapter, we draw the conclusions and review the main achieved results of Chapters 2, 3, 4 and 5. We further propose some ideas for future works.

6.1 Chapters 2, 3 and 4

In this thesis, the problem of energy-efficiency for spectrum sensing in cognitive radio networks was considered. A cognitive radio network was defined as a set of M cognitive radios which receive conditionally independent observations from a primary user and cooperatively decide about the presence or absence of the primary user by making a final decision at the fusion center (FC) based on the received local decisions of each sensor at the FC. It was elaborated that in this process, each user spends energy on sensing as well as transmitting the local decision to the FC.

In Chapters 2, 3 and 4, we developed three techniques in order to minimize the maximum average energy consumption per sensor. Denoting ϕ as the set of parameters defining the associated sensing policy, $C_j(\phi)$ as the average energy consumption of the j-th cognitive radio which employs ϕ as sensing parameters, $Q_D(\phi)$ as the global probability of detection and $Q_F(\phi)$ as the probability of false alarm, we defined our problem as follows

$$\begin{aligned} &\min_{\phi} \max_{j} C_j(\phi) \\ &Q_F(\phi) \leq \alpha \\ &Q_D(\phi) \geq \beta \end{aligned}$$

It was elaborated that the lower bound (β) on the probability of detection, represents an upper bound on the amount of interference made to the primary user, and the upper bound (α) on the probability of false alarm, represents a lower bound on the cognitive network throughput.

In Chapter 2, a fixed-size censoring scheme was considered. The local decision rule of each cognitive radio was defined based on a censoring policy where each sensor could only make a decision if the calculated energy is less than a lower threshold (λ_1) or larger than an upper threshold (λ_2). Therefore, in this case $\phi = (\lambda_1, \lambda_2)$. It was shown that for the OR rule, the optimal lower threshold is zero ($\lambda_1 = 0$) and for the AND rule, the optimal upper threshold is infinity ($\lambda_2 \to \infty$). Further, an explicit expression was given to find the optimal solution for the OR rule and in case of the AND rule, a closed form solution has been derived.

We proposed our novel censored truncated sequential spectrum sensing scheme in Chapter 3. We let each sensor sequentially collect the observation samples instead of the fixed-sample size paradigm of Chapter 2. Each sensor calculated the energy of the collected samples until a certain point and compared it with a lower threshold at time i (a_i) and an upper threshold at time i (b_i). In case that the calculated energy passed any of these thresholds, a decision was made, otherwise a new sample was collected for a new comparison. In case the sensor could not reach a decision by time N (truncation point), the sensing process stopped and no decision was made. This way, both the transmission and sensing energy consumption of each cognitive radio was optimized. In this case $\phi = \left\{(a_i, b_i),\ i = 1, \ldots, N\right\}$.

We further derived the analytical expressions for the underlying parameters in the censored sequential scheme and showed that although the problem is not convex, a bounded two-dimensional search is possible for both the OR rule and the AND rule. Further, in case of the OR rule, we relaxed the lower threshold to obtain a line search problem in order to reduce the computational complexity.

Different scenarios regarding transmission and sensing energy per sample as well as SNR, number of cognitive radios, number of samples and detection performance constraints were simulated for low and high values of π_0 and for both the OR rule and the AND rule. It has been shown that under the practical assumption of low-power radios, sequential censoring outperforms censoring. We can conclude that for high values of the sensing energy per sample, despite its high computational complexity, the double threshold scheme developed for the OR rule becomes more attractive. Further, it was shown that as the sensing energy per sample increases compared to the transmission energy, the AND rule performs better than the OR rule, while for very low values of the sensing energy per sample, the OR rule outperforms the AND rule.

A combined censoring and sleeping scheme was depicted in Chapter 4. Each sensor turned off its sensing module with sleeping rate μ, and if it was on, a censoring policy as introduced in Chapter 2 was employed in order to send the local decisions to the FC. In this case, $\phi = (\mu, \lambda_1, \lambda_2)$. Similar to the fixed-size censoring, it was shown that the optimal average energy consumption per sensor is attained by $\lambda_1 = 0$ for the OR rule and $\lambda_1 \to \infty$ for the AND rule. This way, the number of arguments for optimization has reduced to two.

In seeking a systematic solution for the obtained optimization problems, we showed that the resulting optimization problem can be reduced to an unconstrained line search problem over μ for both the OR and AND rule.

We considered a case study with IEEE 802.15.4/ZigBee radios for numerical results. It was shown that the average energy consumption per sensor is reduced significantly. We further compared the performance of the OR and the AND rule in terms of energy efficiency. It was shown that as the ratio between sensing energy and transmission energy increases, the AND rule can perform much better than the OR rule for some specific detection performances. However, depending on the probability of a primary user being absent, the sensing energy, the transmission energy and the detection performance constraint, sometimes the OR rule preforms better than the AND rule, particularly when the probability of primary user absence is high and sensing and transmission energies are either comparable or the transmission energy is higher than the sensing energy. For desired constraints in cognitive radio system, the OR rule performs better than the AND rule for $\pi_0 > 0.5$ while the AND rule performs better than the OR rule for $\pi_0 < 0.5$.

One of the very interesting results for all the presented energy-efficient algorithms in Chapters 2, 3 and 4 was that increasing the number of cognitive radios, leads to a reduction in the average energy consumption per sensor which is of high importance for low-power radios. Therefore, increasing the number of cognitive radios (with conditionally independent observations), not only increases the detection performance and reliability of a cognitive radio network, but also leads to lower energy consumption in each radio by employing any of the proposed or presented energy-efficient techniques in this thesis.

6.2 Chapter 5

In this chapter, we have tried to find an answer to the question of the optimal K-out-of-M rule in a cognitive radio network. In search for such an answer, we defined our problem so as to maximize the network throughput subject to a constraint on the probability of detection and average energy consumption per sensor. As in the previous scenarios, the constraint on the probability of detection puts an upper bound on the amount of interference made to the primary user by cognitive radios while the constraint on energy consumption makes sure that the system has enough resources able to perform sensing and data transmission with an acceptable reliability and quality.

We have shown that the problem can be solved by a bounded two-dimensional search over the number of cognitive radios M and the fusion rule parameter K. We have also shown that as the energy constraint reduces, the optimal throughput also reduces while reducing the probability of detection constraint for the same energy constraint leads to a higher throughput. Furthermore, we have shown that in the desired range of the probability of detection constraint, the majority rule is either optimal or nearly optimal in terms of the cognitive network throughput.

6.3 Suggestions for Future Works

6.3.1 Energy harvesting spectrum sensing

In this thesis, it is assumed that the cognitive radios consist of low-power sensors with a fixed battery level. In the current low-power wireless sensors, it is possible to include some energy harvesting techniques in order to gain energy from different sources such as solar batteries [88], [89], [90]. These techniques are particularly important for real-time applications, where we need reliable resources in order to accomplish a task. Designing spectrum sensing algorithms for energy harvesting cognitive radio is a very good potential of research for future work [91], [92], [93].

6.3.2 Energy-efficient feature detection

We have employed energy detection as the spectrum sensing technique throughout this thesis. Although the energy detector is very simple to implement and mathematically easy to track, at the low SNRs, the detection performance of energy detectors reduces significantly and below a certain SNR (depending on the noise uncertainty), they are not able to detect the primary user signal. Feature detectors on the other hand, try to detect certain features of the primary user signal such as cyclostationarity. This way, they tackle the problem of low performance at low SNRs due to the noise uncertainty. In general, feature detectors are harder to implement and demand a much higher sensing time than energy detectors. This way, the energy consumption due to sensing increases significantly and at the same time, the network throughput reduces due to a lower transmission time. [86] considers a collaborative cyclostationary detection with censoring which reduces the transmission energy of the cognitive radio system. Designing energy-efficient feature detectors which also offer a good throughput is a nice area for future research.

6.3.3 Energy and computational efficient wide-band spectrum sensing

In this thesis, we have focused on spectrum sensing in narrow-band channels. However, at a system level, spectrum sensing over a wide-band spectrum is often more desirable. First, a cognitive radio can have an overview of the available resources over a wide band of frequencies and can adapt its transmission to the best ones. Second, in case that a currently accessed band becomes unavailable, moving to the next band is faster and the agility of the sensing increases. Third, the transmission scheme in a cognitive radio might need a wide band of frequencies, which can e.g. be obtained by OFDM modulation. In this case, virtually only wide-band sensing can be a solution to find available resources. Several techniques have been proposed to perform wide-band spectrum sensing including sub-Nyquist sampling recovery techniques [12]. However, energy-efficient design of wide-band spectrum sensing is almost a non-touched area of research. Since the computational complexity of current wide-band sensing techniques is high, energy-efficient or better computationally efficient wide-band sensing is also an open area of research. [94] considers this issue from a MAC layer viewpoint where each sensor based on its available energy resources, decides weather to sense, where in the spectrum to sense and weather to access by maximizing the throughput. However, this scheme is based on multi-channel narrow-band sensing which is different than the wide-band sensing schemes where the whole wide band of frequencies is considered at the same time.

6.3.4 Agile search schemes

As we mentioned earlier, a cognitive radio should be able to switch to a new spectrum hole in case the current accessed band becomes available. This process should be fast while reliable to save energy and increase the cognitive radio throughput. Agility of search schemes are particularly important in real-time applications where cognitive radios can not wait for a long time to transmit their data. Designing fast and reliable spectrum hole search schemes such as the one in [87] is also a good direction for further research.

6.3.5 Energy-efficient cross layer design

Note that in this thesis, we did not address the design of protocols employed in the cognitive sensor network - in particular, the medium access protocol that individual sensors use to transmit their detection results to the FC. Optimizing the design of the protocol jointly with spectrum sensing could lead to additional energy savings [95], [96]. For example, in case of the OR rule in censored truncated sequential sensing, the whole sensing process can be stopped as soon as one cognitive radio reports one.

6.3.6 Energy-efficient decentralized spectrum sensing

Decentralized spectrum sensing without fusion center is a growing research topic [97, 98, 99]. Such schemes are particularly important when energy resources are limited. In general, each sensor either makes a local decision by employing its own information as well as its immediate neighborhood information (diffusion techniques [101]) or participates in reaching a consensus among all the sensors (consensus techniques [100]). Energy-efficient design of distributed estimation algorithms is considered for example in a selective communication approach presented in [64], which is based on the optimal selective transmission policy in energy-constrained sensor networks discussed in [102]. Energy-efficient design of decentralized spectrum sensing without fusion center, employing selective transmission or other energy saving techniques is also a good topic for further investigation.

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Samenvatting

Deze thesis richt zich op het dynamisch gebruik van het spectrum door middel van cognitieve radios, om op een opportune manier toegang te verkrijgen tot het spectrum dat bijna volledig gelicentieerd is. Cognitieve radios delen het spectrum op een opportune wijze en proberen zo weinig mogelijk schadelijke interferentie te genereren voor de primaire gelicentieerde gebruikers. Een belangrijke klasse van cognitieve radios bestaat uit zogenaamde verweven cognitieve radios. In die klasse tasten de cognitieve radios het spectrum af op zoek naar lege spectrale banden ook wel gaten genaamd. Als zo een spectraal gat wordt ontdekt, wordt dit dynamisch verdeeld onder de cognitieve radios. Maar zodra er een primaire gebruiker in dit gat opduikt, moeten de cognitieve radios deze band zo snel mogelijk verlaten en op zoek gaan naar een nieuw gat. Op die manier is het aftasten van het spectrum een belangrijke functionaliteit van een cognitief radionetwerk.

De betrouwbaarheid waarmee het spectrum kan worden afgetast wordt beperkt door verscholen zenders en variaties in propagatiekanalen. Gedistribueerde detectie met behulp van meerdere sensoren kan echter de detectie van gaten verbeteren. In deze thesis wordt zo een gedistribueerd detectiesysteem gebaseerd op harde detectie onderzocht. Iedere cognitieve radio tast het spectrum af en zendt zijn resultaat naar een fusiecentrum, waar de uiteindelijke beslissing wordt genomen of er een primaire gebruiker aanwezig is of niet. Merk op dat cognitieve radios veelal sensoren zijn met een laag vermogen en dus speelt het energieverbruik een belangrijke rol.

In deze thesis worden verschillende energie-efficinte methodes voorgedragen om het spectrum af te tasten. De voorgestelde methodes minimaliseren het maximale energieverbruik per sensor zonder de detectiebetrouwbaarheid van het cognitieve ra-

dionetwerk te schaden. Deze betrouwbaarheid wordt gedefinieerd door middel van een minimale detectiekans en een maximale kans op een vals alarm. Op die manier wordt de primaire gebruiker beschermd tegen de interferentie van de cognitieve radio en wordt de kans op het missen van een spectraal gat door een foute detectie beperkt. Ten eerste wordt er een censuurtechniek voorgesteld waarbij cognitieve radios enkel informatieve boodschappen naar een fusiecentrum sturen. Ten tweede wordt er een combinatie aangedragen van de censuurtechniek en een eindige-lengte sequentile detectietechniek. Deze combinatie is energiezuiniger dan de pure censuurtechniek omwille van de reductie van de detectie-energie. Ten derde wordt er een combinatie onderzocht van de censuurtechniek en een slaapmechanisme waarbij de cognitieve radios, naast het niet versturen van onbeduidende informatie, zichzelf met een bepaalde zogenaamde slaapkans uitschakelen om op die manier energie te besparen, detectie-energie zowel als transmissie-energie. In de thesis wordt aangetoond dat met alle voorgestelde technieken veel energie kan bespaard worden, vooral dan met de combinatie van de censuurtechniek en de eindige-lengte sequentile detectietechniek en de combinatie van de censuurtechniek en het slaapmechanisme. Verder wordt er geconcludeerd dat wanneer een cognitief radiosysteem op de juiste manier energiezuinig wordt ontworpen, dan zal een toename van het aantal samenwerkende gebruikers niet alleen het detectieresultaat verbeteren maar ook het gemiddelde energieverbruik van de individuele sensoren verminderen.

Tenslotte wordt er een optimale fusietechniek voorgesteld voor cognitieve radionetwerken gebaseerd op energiezuinige harde fusie. Deze techniek optimaliseert de datasnelheid behoudens een beperking van het gemiddelde energieverbruik van de individuele radios en een beperking van de interferentie die de primaire gebruikers ondervinden. Het is aangetoond dat de meerderheidsregel optimaal of bijna optimaal is wat betreft de datasnelheid.

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Curriculum Vitae

Sina Maleki was born on September 1983 in Zaherdan, Iran. He received the bachelor in science degree in electrical engineering from Iran University of Science and Technology, Tehran, Iran, in 2006, and the master of science degree in electrical and telecommunication engineering with cum laude from Delft University of Technology, Delft, The Netherlands, in 2009. From July 2008 to April 2009, he was an intern student at the Philips Research Center, Eindhoven, The Netherlands, working on spectrum sensing for cognitive radio networks. He then joined the Circuits and Systems Group at the Delft University of Technology as a research scientist till Jan 2011. From Jan 2011 to May 2013, he had been working on his PhD studies in the same group under supervision of Prof. Geer Leus. Since August 2013, he joined Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, where he is currently a research associate working on cognitive radio for satellite communications. He has served as a reviewer for several journals and conferences.

List of Publications

Journals

Accepted

- S. Maleki and G. Leus, "Censored truncated sequential spectrum sensing for cognitive radio networks", *IEEE Journal on Selected Areas in Communications*, vol.31, no.3, pp.364-378, March 2013

- S. Maleki, S. P. Chepuri and G. Leus, "Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks", to appear in *Elsevier Physical Communication*

- S. Maleki, A. Pandharipande and G. Leus, "Energy-efficient distributed spectrum sensing for cognitive sensor networks", *IEEE Sensors Journal*, vol.11, no.3, pp.565-573, March 2011 (Top 10 most downloaded papers in IEEE Sensors Journal in year 2011)

In Preparation

- S. Maleki et al., "Min-max energy-efficient spectrum sensing for cognitive radio networks"

- S. Maleki et al., "Multi-stage detection: analysis and performance optimization"

- N. Pan, S. Maleki, R. Arroyo-Valles and G. Leus, “Optimal power allocation for energy harvesting cognitive radio networks”

Conferences

Accepted

- R. Arroyo-Valles, S. Maleki and G. Leus, “A Censoring strategy for decentralized estimation in energy-constrained adaptive diffusion networks”, *IEEE SPAWC 2013*, Darmstadt, Germany, June 2013

- S. Maleki and G. Leus, “Censored truncated sequential spectrum sensing for cognitive radio networks”, *IEEE DSP 2011*, Corfu, Greece, July 2011 (*Invited Paper*)

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- R. Arroyo-Valles, S. Maleki and G. Leus, “Distributed wideband spectrum sensing for cognitive radio networks”