Thesis for the degree of Doctor of Philosophy

Model-Based Cognitive Radio Strategies

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Front cover illustration: Cognitive cycle, see Sec. 1.2.1

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To Toktam

Abstract

Many frequency bands for wireless services are severely underutilized by the primary users (PU) to which these bands are assigned. This motivates a new class of wireless communication devices known as cognitive radios (CR), which identify vacant spectrum and transmit accordingly. In this thesis, the PU traffic model knowledge as well as all the observations available to the CR are included in the CR transmission decisions. A transmission strategy is introduced that is based on comparing an a-posterior probability (APP) log-likelihood ratio (LLR) with a threshold. The objective is to maximize the utilization ratio (UR) subject to that the interference ratio (IR) is below a certain level. In papers A and B, we study CR transmission strategies that are based on all noisy observations of the PU activities, even when the CR itself is transmitting. Paper A demonstrates a more than 300% increase in UR over standard energy detection, for the same IR value, at the PU signal to CR noise power ratio (SNR) of -5 dB. Then, in paper B, we use a continuous-output hidden Markov model for the received signal and calculate an APP LLR based on this model. This paper shows that this strategy is the optimum in the sense of maximizing the UR, given a certain maximum allowed IR, among all CRs. Moreover, two practical schemes for calculating the transmission threshold are introduced. Numerical results show that the first method yields a threshold that is close to optimum when the PU use a large fraction of the available spectrum (i.e., when the PU activity level is high). The second method is analytically proven to always give a valid threshold. Simulation results show a 116% improvement in UR with PU state estimation over energy detection, at an SNR of -3 dB and IR level of 10%. In paper C, we extend paper B to consider that PU activities cannot be observed when CR is transmitting, in other words they are censored. This new strategy, entitled CLAPP, calculates a new LLR, which is compared with a threshold. This threshold is computed with a bisection search method. Simulation results show that CLAPP has a 52% gain in UR over the best censored energy detection scheme for a maximum IR level of 10% and an SNR of -2dB. In paper D, we introduce new time-varying thresholds for sequential spectrum sensing. These new thresholds, for an SNR of -10 dB, in comparison with standard sequential detection with parallel (fixed) thresholds with similar probabilities of misdetection and false alarm, performs 54% faster in terms of maximum detection time (90 percentile). **Keywords:** Spectrum utilization, cognitive radio, sequential detection, censorship, CLAPP.

Acknowledgments

> When there is no turning back, then we should concern ourselves only with the best way of going forward.
> Paulo Coelho – The Alchemist

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List of Included Publications

This thesis is based on the following appended papers:

Paper A
K. Haghighi, E. G. Ström, and E. Agrell, "An LLR-based cognitive transmission strategy for higher spectrum reutilization," *Proc. IEEE Global Telecommunications Conference (Globecom '11)*, Houston, Texas, USA, Dec. 2011.

Paper B
K. Haghighi, E. G. Ström, and E. Agrell, "On optimum causal cognitive spectrum reutilization strategy,"*IEEE Journal on Selected Areas in Communications*, vol. 30, no. 10, pp. 1911–1921, Nov. 2012.

Paper C
K. Haghighi, E. G. Ström, and E. Agrell, "Sensing or transmission: Causal cognitive radio strategies with censorship," submitted to *IEEE Transactions on Wireless Communications*, Sep. 2013.

Paper D
K. Haghighi, A. Svensson, and E. Agrell, "Wideband Sequential Spectrum Sensing with Varying Thresholds," *Proc. IEEE Global Telecommunications Conference (Globecom '10)*, Miami, Florida, USA, Dec. 2010.

List of Additional Related Publications

Publications by the author not included in this thesis:

1. K. Haghighi, "Cognitive Sensing and Transmission Strategies," *Licentiate thesis*, Chalmers University of Technology, Nov. 2011.

2. M. Rashidi, K. Haghighi, A. Panahi, and M. Viberg, "A NLLS based sub-Nyquist rate spectrum sensing for wideband cognitive radio," in *Proc. IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN)*, Aachen, Germany, pp. 545–551, May 2011.

3. M. Khanzadi, K. Haghighi, and T. Eriksson, "Optimal modulation for cognitive transmission over AWGN and fading channels," in *Proc. European Wireless*, Vienna, Austria, April 2011.

4. M. Rashidi, K. Haghighi, A. Owrang, and M. Viberg, "A wideband spectrum sensing method for cognitive radio using sub-Nyquist sampling," in *Proc. Digital Signal Processing Workshop and IEEE Signal Processing Education Workshop DSP/SPE*, Sedona, Arizona, USA, Jan. 2011.

5. M. Khanzadi, K. Haghighi, A. Panahi, and T. Eriksson, "A novel cognitive modulation method considering the performance of primary user," in *Proc. Conference on Wireless Advanced (WiAD)*, London, UK, June 2010.

6. D. Noguet, K. Haghighi, Y. A. Demessie, L. Biard, A. Bouzegzi, M. Debbah, P. Jallon, M. Laugeois, P. Marques, M. Murroni, J. Palicot, C. Sun, S. Thilakawardana, and A. Yamaguchi, "Sensing techniques for cognitive radio - state of the art and trends," IEEE, White Paper SCC41 P1900.6, Apr. 2009.

Contents

Acronyms

3G	Third generation of mobile telecommunications technology
ADC	Analog to digital converter
APP	A posteriori probability
ASN	Average sample number
CFAR	Constant false-alarm rate
CLAPP	Censored a posteriori probability log-likelihood ratio
CR	Cognitive radio
CTMC	Continuous-time Markov chain
DSA	Dynamic spectrum access
ECDF	Empirical cumulative distribution function
ETSI	European Telecommunications Standards Institute
FCC	Federal Communications Commission
HMM	Hidden Markov model
IR	Interference ratio
LLR	Log-likelihood ratio
MAC	Medium access control
MDP	Markov decision process
MIMO	Multiple input multiple output
NSF	National Science Foundation
POMDP	Partially observed Markov decision process
PU	Primary user
R&D	Research and development
RF	Radio frequency
SMM	Semi-Markov model
SNR	Signal to noise ratio, i.e., PU signal to CR noise power ratio
UR	Utilization ratio

Part I

Introduction

Chapter 1

Background

In recent years, the explosive growth of the population, the cost of transportation, the demand for worldwide goods and services, and a lack of resources have put telecommunication networks in focus. The internet is stretching between different corners of the world. Every day, more and more devices are hooked up to the grid. This is due to the rise of machine-to-machine communication, which results in more devices being connected to the network than the number of people. Thus, networks are getting congested, and the demand for more data rates increases faster than before.

1.1 Demand for data rate is demand for the spectrum

Due to its convenience, mobility, and availability, wireless communication has become a necessity. Many people are now using mobile phones or other smart devices such as tablets and running their businesses or lives on the go. The mobile data traffic had a exponential growth and is expected to reach 11.2 EB (each Exabyte is 10^{18} bytes) in 2017 [1].

This revolution has accelerated since the introduction of the iPhone in 2007. Now thanks to high-speed internet over Wi-Fi or 3G (and recently 4G), users are enjoying streaming video on busses or even in the skies. Statistics show that video, which needs high speed and low delay, comprises more than 66.5% of the mobile data traffic [1]. Due to the ease of deployment in most growing countries, wireless data networks are growing much faster than wired networks. The United States already plans to bring wireless broadband internet access to 98% of Americans [2]. This is a huge demand for wireless networks and cannot be realized with the already congested frequency spectrum.

Spectrum is one of the most expensive commodities in the world. There are a lot of attempts to reach higher spectral efficiency by increasing modulation orders, increasing the channel coding rate, and multiple input multiple output (MIMO). However, these efforts are not scaling with the demand.

A lot of vacant spectrum is wasted due to one or many of the following factors

1. Inefficient use of spectrum due to system design, e.g., modulation and coding,

2. Inefficient use of spectrum due to hardware limitations, such as filters' sharpness, spectrum spilling due to nonlinearities in power amplifiers, spectrum growth due to the phase noise in radio frequency (RF) chains,

3. Certain traffic patterns of spectrum usage created by operators and their network users.

Academia and industries have spent a considerable amount of resources on research and development to address these issues. Modulations and codings are approaching the Shannon limits, which makes higher spectral efficiencies theoretically impossible [3]. On the other hand, hardware impairments limit the possibility of efficient use of frequency bands. Many of these hardware limitations can be mitigated by signal processing methods, which will increase the cost and complexity of such devices and are impractical for cheap and simple terminals.

Therefore, more frequency bandwidth must eventually be allocated for public internet services. There is a lot of research and development going on for higher frequency bands. Nevertheless, due to propagation properties of higher bands, mainly bands below 10GHz can be used, for wide area coverage. Yet, almost all these bands are already licensed. Furthermore, in certain frequencies, the exclusive right of using spectrum is very expensive. Alone in Germany in 800 MHz band, an auction was held in May 2010 [4], and three operators paid 3.576 Billion euros for just 60 MHz which amounts for 59.6 Euros per Hz. Thus, spectrum is probably one of the most expensive commodities in the world. This induces a lot of research and discussions about dynamic spectrum auctioning and sharing.

However, studies have shown that many of these useful bands, which are not allocated for data/internet services, are not in use or are underutilized. Especially in certain geographical locations, licensed spectrum underutilization is more severe. In certain bands, 70% of time, spectrum is vacant [5]. Thus, there lies big hope in reusing vacant time-frequency slots, i.e., *spectrum white spaces*.

1.2 Cognitive radio

The need to reuse spectrum will give rise to a new paradigm in spectrum access, named opportunistic access, in which the spectrum is accessed whenever it is available. The enabling technology for opportunistic and dynamic spectrum access is software-defined radio [6, 7]. For the first time, J. Mitola and G. Q. Maguire [7] envisioned communication devices that adapt themselves to the spectrum [6] and coined the term *cognitive radio* (CR).

To use the spectrum efficiently, multiple users can share the same spectrum and transmit at different times. Some of the users are licensed users known as primary users (PU) and some are unlicensed secondary users known as cognitive radios (CR). Here, it should be noted that unlicensed does not mean unregulated. All users must be regulated by a regulatory body that enforces certain rules to protect other users from intentional and unintentional interferences. PUs are usually telecom operators or legacy radio equipment that have some method for sharing spectrum between each other and control the amount of interference. Thus, their medium access control (MAC) will allow them to be aware of each other and cooperate in controlling when and in which band to transmit. However, normally secondary use of spectrum refers to the other users that are either unaware or unable to join the same MAC as the PUs. Moreover, PUs have the high priority to use the spectrum and CRs must respect this right. This creates certain difficulty for CRs since they are unaware of the PUs' intentions to transmit or stop transmitting. Thus, one of the major challenges in implementing a CR network is to tackle this spectrum uncertainty. On top of that, all the natural limitations of wireless communication, such as channel fading uncertainty and receiver noise uncertainty, are still.

Applications of CR technology can be extended over different licensed bands. For instance, TV broadcasting is limited to certain hours. Global positioning system (GPS) satellites are in different orbital positions at different times of the day and have no (or weak) coverage indoors. In peace time, most military communication or sensing, e.g., radar, bands are either vacant or much less active.

1.2.1 Cognitive cycle

Cognitive radios perform a series of activities in order to achieve the spectrum reuse goal. These activities, which are known as the cognitive cycle [8, pp. 5], try to create an understanding of the radio spectrum and a plan for using it effectively. In the cognitive cycle as depicted in Fig. 1.1, which is a simplified version of the more complete cycle presented in [7], the spectrum sensing is responsible for creating a map of the current spectrum usage. The spectrum adaptation phase uses that

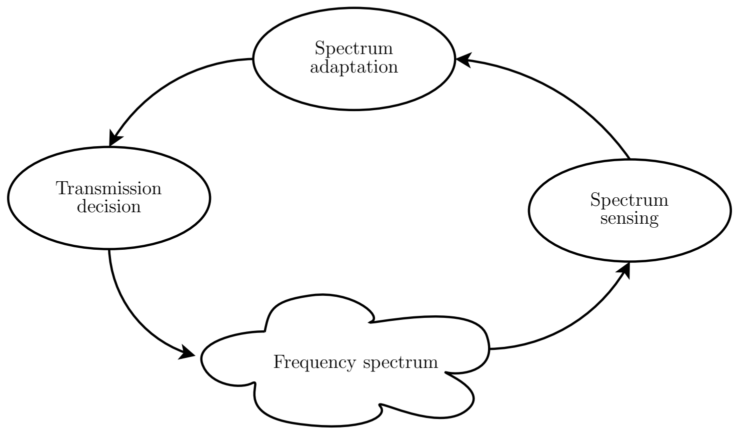

Figure 1.1: The cognitive cycle

map to adapt the CR transmission accordingly. For instance, if the CR intends to use OFDM, it can nullify the bands whose presence the PU has sensed. Finally, a transmission decision is made with respect to the CR traffic and adaptation results. The last arrow between transmission decision and frequency spectrum shows that CR decisions influence the spectrum. A simultaneous PU and CR transmission results in interference for the PU. And the PU might react by attempting to retransmit.

CR transmissions can, in some cases, be done without harming the primary transmission. Research has also been conducted on how to transmit in the same time-frequency slot as the PU, without increasing the probability of error for the PU [9] [10, Ch. 2], but this is beyond the scope of this thesis. Here, we assume that any CR transmission at the same time-frequency slot as the PU is harmful.

Thus, spectrum sensing plays a crucial role in the cognitive cycle. Due to high data-rate expectations, there is a need to reuse large chunks of the spectrum. Cognitive radios intended for such uses must employ wideband spectrum sensing.

1.2.2 Challenges and difficulties

In many cognitive radio applications, such as ultra-wideband detect-and-avoid, i.e., to detect existence of a narrowband PU and avoid that part of the band, the key limiting issue is spectrum sensing. Spectrum sensing is performed by a (normally) non-coherent receiver in the designated band [11]. In spectrum sensing, there exist several problems dependent on the setup, which include but are not limited to

- low PU signal to CR noise ratio (SNR) or wide-bandwidth scenarios [12],
- no information about the transmission type for the PUs of the band,
- hidden or exposed terminal cases as depicted in Fig. 1.2, i.e., the PU signal at the CR is weak. Thus, the CR might cause interference due to not receiving

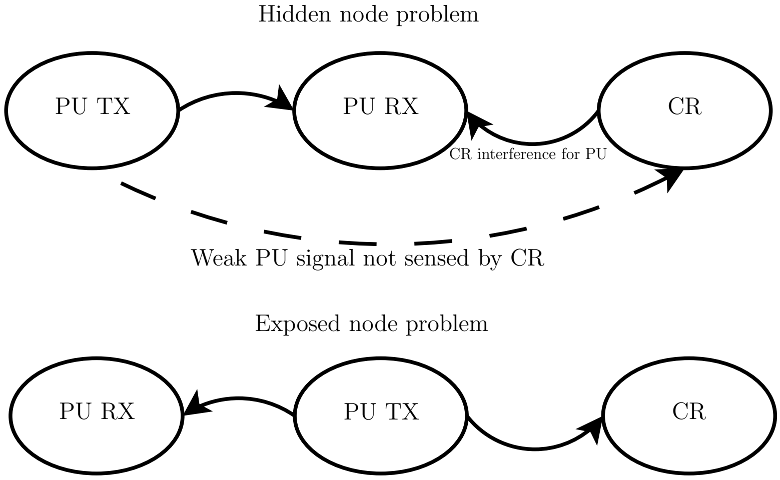

Figure 1.2: The hidden node and exposed node problems

PU signal or the PU signal at CR being strong, hence PU receiver is far from CR transmitter, which results in the over-protection of PU due to the detection of close PU transmission,

- bursty and hopping PUs, i.e., when the PU changes the band frequently and starts and stops transmissions in a random fashion.

Wideband spectrum sensing is a big challenge in itself, due to the large amount of noise contribution. In such situations where low PU signal to CR noise ratio might cause a larger detection delay or instead higher probabilities of misdetection, i.e., the probability that a PU is present and CR misses it, and false alarm, i.e., the probability that PU is absent and CR detects that it exists, inexpensive and less-complex methods such as energy detection are not enough. In addition, the capability of CRs utilizing energy detection spectrum sensing are limited by the so-called SNR wall, i.e., the SNR below which robust detection is impossible for the given detector [13]. This is due to the low received power of the PU signal at the CR receiver and uncertainties about signals, noise, and channels [14]. Specifically, in wideband spectrum sensing, this effect is more visible [15, 16]. This can ultimately result in large sensing delays. Nevertheless, spectrum opportunities appear and disappear quickly, and they depend on the occupancies in different bands. Moreover, a real cognitive radio, which according to the cognitive cycle [7, 17] should adapt itself to the dynamics of the spectrum, needs to be agile to react to the changes in the spectrum as quickly as possible [18]. However, in some cases such as energy detectors, agility compromises the accuracy of sensing the spectrum, which ultimately jeopardizes not only the interference level made for the PU but also reduces the spectrum reuse. Thus, a CR that can optimally incorporate all previous observations, and thus decides about transmission within a short time, is appealing. Sequential spectrum sensing, which accumulates more samples until it reaches one of two decision thresholds, has proven to be, on average, faster than traditional energy detection [19–21]. However, since detection time varies in sequential detection, it is not a good candidate for slotted CR systems in which the PU and CR are assumed to transmit in time slots.

To avoid all the challenges with the spectrum sensing, some of the publications [22, Ch. 10] assume that spectrum opportunities are known input to the CR algorithm. This means that a CR just needs to have knowledge of its geographical position. Then it can look up a database that associates the positions to the spectrum availabilities. However, knowing the position and querying in that database needs extra equipment and further internet access, which makes the CR functionality and portability difficult.

1.3 Spectrum regulation for reuse

There are huge industrial and standardization activities going on side by side for the implementation of cognitive radio applications. The issue of dynamic spectrum reuse is even being considered at the highest political level, such that the White House Office of Science and Technology Policy, in cooperation with Federal Communication Commission (FCC), is drafting the policies and road map for dynamic spectrum access (DSA) in the U.S. [5].

In standardization, two tiers of national and international organizations are contributing. Frequency regulation bodies in different countries, such as the FCC in the U.S. and the Office of Communications (OFCOM) in U.K., are trying to define new use case models for unlicensed use of spectrum in the licensed bands [23, Ch. 4]. The second tier is international standardization organizations such as the international telecommunication union (ITU) and the European telecommunications standards institute (ETSI). They are playing a major role in the standardization of DSA and CR in the world. This is usually seen within the context of spectrum management, which is one of their activities. Spectrum management consists of [24, pp. 197–198]

1. Spectrum planning to allocate frequency bands for different services according to the international standards normally introduced by the ITU or ETSI,

2. Spectrum authorization for granting access to certain use by certain operators,

3. Spectrum engineering, which entails the development of standards for electromagnetic compatibility for equipment,

4. Spectrum monitoring and compliance to check whether all the users are using spectrum according to the regulations.

Unlicensed use of the spectrum in the licensed band such as TV bands enables the (re-)use of these bands. As an example, in 2008 the FCC released a report on the performance of devices operating in TV white spaces, which resulted in approving unlicensed use of white spaces [24, pp. 229–231].

Alongside the regulation, the IEEE, among others, is leading the technology standardization of such reuse not only by holding technical conferences such as DySPAN but also by having multiple standardization committees such as [23, pp. 45]

- IEEE SCC41/P1900 on next generation radio and spectrum management, to stimulate the research and development of CR,

- 802.22 for wireless rural access network for reuse of TV bands for internet provision in rural areas,

- 802.16h and 802.16.2 for coexistence in WiMax 802.16 licensed bands,

- 802.11 (Wi-Fi) subcommittees for coexistence and common channel framework operations.

1.4 Industrialization and standardization of dynamic spectrum access

Industrial use of CR is initiated by both research-funding organizations such as the national science foundation (NSF) and also by defense and military users such as the defense advanced research projects agency (DARPA). DARPA, in their Next generation communications program (XG), focuses on spectrum awareness, adaptive transmission and interference evaluation [23, Ch. 4]. The NSF and the European Union have funded many projects, such as GENI, E^3, WINNER+, WIP, SOCRATES, ROCKET, and ORACLE, that have addressed one or many of the issues in DSA and software-defined radio. The introduction of the unlicensed use of white spaces motivated big software companies such as Microsoft, Apple, and Google to actively engage in the development of technology, industrialization, and standardization for reuse of TV white spaces. Now some of these companies are in the process of creating and providing the geographical database for TV white space secondary use.

1.5 Scope of this thesis

This thesis highlights the importance of PU models and presents model-based CR transmission strategies for reutilizing frequency spectrum. In particular, we will focus on the CR transmission decision problem. That is, how the CR, based on noisy observations of the PU transmission, should decide whether to transmit or not. To treat this problem, we will use models for the PU data traffic, the PU transmitted signal, and the PU-CR channel. Clearly, we want simple models for mathematical tractability, but also models that reflects reality.

For the work presented in this thesis, the most important model is the PU data traffic model. It has been shown that Markov models fit real data traffic fairly well and are used in many CR research papers [25–31]. Knowledge of model parameter is necessary for the CR to fully exploit the PU activity model. In previous works, such as [32,33], the impact of model parameter estimation on the CR performance is evaluated, which, overall is quite promising. The development of the system model in this thesis from the discrete-output HMM in Paper A to the continuous-output HMM in Papers B and C, allows the CR to form a more accurate perception of the reality and better utilize the vacant spectrum. Markovian PU traffic models, are discussed in further detail in Chapter 2.

In the traditional implementations of cognitive radio, in which just the currently sensed received signal is considered for the transmission decision in the succeeding time slots, the important fact that PU traffic might be according to a certain model is ignored. Moreover, the CR hopes that its observation resembles the true transmission state of the PU and that the PU will not change its state in the period of CR transmission. Clearly, since this CR does not incorporate the PU transmission model in its decision, the performance of the CR may improve if the CR decision algorithm includes such a model. Markov decision process [25–28], the partially observed Markov decision process [29, 31] and some works on the prediction of the future state of the PU in [30, 34–36] were introduced before to exploit Markov models for CR. Papers A to C in this thesis belong to the latter class of predictive CRs. These papers introduced less complex algorithms, which in certain sense are optimal, and, in the case of Paper C, considering observation censorship due to the CR self transmissions. The use of Markov models and all the previous observations is shown to provide a considerable improvement in the performance of the CR.

To address the issue of low SNR in wideband spectrum sensing regimes, Paper D introduces a certain class of truncated sequential probability ratio test (SPRT) for spectrum sensing to ensure that the test would be terminated after a certain number of samples. Note that the SPRT has attracted a lot of attention due to its optimality in average sample number (ASN) in CR [37–45]. In standard SPRT, even though it is optimum in the sense of ASN, the maximum detection time can still be fairly large. To address this problem, we introduce sequential detectors with varying thresholds for energy-based spectrum sensing. These detectors are performing on average (or in 90 percentile sense) much faster than regular energy detection for the same probabilities of misdetection and false alarm. This enables agile and reliable spectrum sensing in low-SNR scenarios.

This thesis, introduces a set of models, metrics and tools for better identifying and reusing spectrum opportunities in time. Models, metrics and tools are designed in such a way to match reality as much as possible and at the same time they are based on solid and tractable math.

The upcoming chapters are structured as follows. We first introduce the PU traffic model in Chapter 2. Then, in Chapter 3, CR spectrum sensing is reviewed. In this chapter, the assumptions and their motivation for the CR model are also presented. Performance measures to judge the quality of a CR are established in Chapter 4. Chapter 5 describes the model-based CR transmission schemes. Finally, Chapter 6 wraps up the introduction of this thesis by listing the contributions and conclusions of this thesis and pointing out directions for future work.

Chapter 2

Primary user transmission model

As explained in the previous chapter, coexistence of CRs and PUs is deeply dependent on the behavior of the PU and knowledge about the PU transmissions present at the CR.

PUs can be any radio communication or sensing device such as mobile communication, global positioning system, or a radar. All of them share some features that can be exploited to facilitate the detection of their existence. These features can be as low-layer (physical layer) as

- periodicity of PU signal,
- carrier frequency and bandwidth,
- modulation format.

In contrast, they can be as high-layer as activity pattern, e.g., a scanning radar, which scans a certain geographical area periodically. These features can be exploited by secondary unlicensed users of the frequency spectrum to better utilize the temporal/spatial white spaces. From now on, all these features, which can distinguish a radio transmitter from white noise, are referred to as PU model features or simply the PU model. These features can vary in time or space. However, for a certain window of time or space, they might be fixed. Most of these features are known or can be estimated at the CR. For instance, in TV bands, the frequency, bandwidth, modulation, and even time of broadcasting is publicly known. Also, cell phone users have certain usage patterns throughout the day.

It might be preferable to use fewer of these features to have a rather general system that can handle many types of PU transmissions. One approach is to model some of the PU signal properties in the worst-case scenario with minimum knowledge about them.

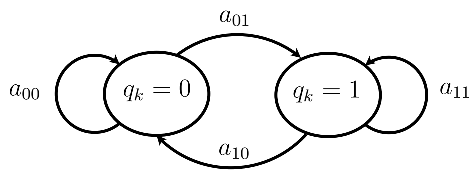

Figure 2.1: PU transmission model

This chapter is more about the PU traffic model rather than the signal model. The PU signal model and its properties will be explained in the next chapter together with the CR receiver signal model.

2.1 Markov model

Markov models, i.e., stochastic models in which the current state given the last state is independent of all previous states, is long in use for modeling many different processes [46]. From the early stages of the development of network activity models up to the latest development in cognitive radios [10, pp. 214–227], Markov models have been and are a major tool for modeling the activities of network users. Markov models, despite their simplicity, provide strong mathematical frameworks for modeling the behaviors of processes with memory. The use of a simple Markov model as the PU traffic model is described in this section.

One simple Markov model is a discrete-state discrete-time Markov chain consisting of two states of on and off, which can be considered as the most basic transmission model. It is presented in Fig. 2.1. The PU is alternating between active and idle states, $q_k = 1$ and $q_k = 0$. This Markov chain can be mathematically expressed with transition probabilities $a_{i,j} = \Pr\{q_{k+1} = j | q_k = i\} > 0$ for $i, j \in \{0, 1\}$, where q_k denotes the PU state in time slot k. The initial distribution of the states is assumed to be in a steady state [46] and is defined as

$$\begin{aligned}\boldsymbol{\pi} &\triangleq \begin{bmatrix} \pi_0 & \pi_1 \end{bmatrix} \triangleq \begin{bmatrix} \Pr\{q_k = 0\} & \Pr\{q_k = 1\} \end{bmatrix} \\ &= \begin{bmatrix} \frac{a_{10}}{a_{01}+a_{10}} & \frac{a_{01}}{a_{01}+a_{10}} \end{bmatrix}, \; k = 0, 1, 2, \cdots \end{aligned} \tag{2.1}$$

The transition matrix is

$$\mathbf{A} \triangleq \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix}, \; a_{00} + a_{01} = a_{10} + a_{11} = 1. \tag{2.2}$$

These probabilities can be easily estimated by observing for a long enough period such that the PU arrives in a steady state.

This model inherently assumes some properties such as

- PU time slots have a fixed and predefined size,
- PU transmissions are done in bursts of an integer number of time slots,
- PU has periods of idle slots in between transmissions which are also an integer number (more than zero).

Indeed, not all PUs have these properties. However, in the next chapter, when we discuss our adopted CR model, these assumptions are motivated. Many kinds of telecommunication network traffic can be adequately represented as Markov models, for example, the following

- human conversation on the phone is followed by silences for listening,
- many wired networks are using Ethernet protocol (IEEE 802.3), which is a frame-based protocol with a fixed frame size,
- most data networks use TCP/IP (Transmission Control Protocol / Internet Protocol), which involves packet transmission and acknowledgements of received or failed transmission and retransmissions,
- normal video content is served after video coding compression with known encoders such as H.264, which has a standard format and flow of data,
- web traffic normally consists of a request and many pieces of replies, depending on the web page contents.

All of them have some properties in common such as bursty transmissions, fixed slot lengths, and non-zero idle periods. Moreover, these activities, given their last state, are independent of states long before. These are just some of the reasons that make Markov models suitable for modeling PU activities in the frequency spectrum. Moreover, measurement campaigns have confirmed the Markov model hypothesis for PU traffic [47] [29].

Throughout this thesis, we consider this simple two-state Markov chain as the PU traffic model.

Many other Markov-based models, such as semi-Markov models, continuous-time Markov chains, and embedded Markov models, are also introduced in the literatur [31] [48]. Some of them are briefly reviewed in the next section.

2.2 Other PU models

Of course, the PU traffic can be modeled as just bursty traffic. Thus, one way is to use the latest observation of the spectrum as the only knowledge about the state of the spectrum. The simple standard energy detection based CRs, which decide whether to transmit or not by comparing the energy in a certain band for a fixed period with a threshold, is one of the simple methods not assuming any specific PU [8, Ch. 10]. In the next chapter, this type of CR and its properties will be explained in detail.

Another approach for addressing the PU traffic model is to have a geographical database (lookup table) of known PU activities. This is mostly useful when there is a scheduled broadcast, e.g., TV broadcasting [22, pp. 347].

For radio communication networks, like any other telecommunication network, one simple method to model the arrival of the entities (nodes, packets, cells, ...) can be a Poisson process. Other processes, such as Pareto distribution processes or Weibull distribution processes, are also proposed. Another class of processes that model network traffic is models such as embedded Markov models. In this class, one can refer to models such as interrupted Poisson process, semi-Markov models, and Markov modulated Poisson processes [49].

Indeed, the two-state Markov chain, as explained in the previous section, is a very simplified model. Much research has been devoted to exploring other, more sophisticated models that give more degrees of freedom. One class of these advanced models is the semi-Markov models (SMM). SMMs are a generalization of Markov models. The transitions in a SMM are time-dependent and random. It was shown in [48] that this model matches certain Wi-Fi traffic. However, dealing with any arbitrary distribution of the transition time is quite difficult and thus a more simplified version can be used instead. An example of simplified SMMs for which all holding times, i.e., the time spent in one state, are exponentially distributed, are called continuous-time Markov chains.

One of the reasons why Markov processes are so interesting is their application to the Markov decision process (MDP). MDPs are processes in which the state of the system is influenced by their decisions. If the state of the system is not observed directly, but only through another random process, it is called a partially observed MDP (POMDP). These decision-making tools are briefly reviewed in Chapter 5.

Chapter 3

Cognitive radio and spectrum sensing model

In this chapter, first, the structure of the CR that this thesis is based upon, is presented. Then, the assumptions related to this model are reviewed. We cover the whole signal path from PU traffic until a CR transmission decision is made.

In Chapter 2, we introduced the PU traffic model and established a simple two-state Markov model for it. In this chapter, we discuss the PU signal from the perspective of the CR.

3.1 Spectrum sensing

Any communication system, including CR systems, is comprised of three basic components: transmitter, receiver, and the channel in-between. In CR scenarios, there are no intentions for the CR to transmit to the PU, or vice versa. Since the CR is interested in re-utilizing the time-frequency vacancies, the CR has to locate the available spectrum by capturing the current state of the PU. To do so, three components involved in a CR system model can be defined, the PU transmission model, the PU-CR channel, and the CR spectrum sensing. Spectrum sensing forms the CR perspective from the PU signal. There are many different types of spectrum sensing in the CR community [11, 22]. Generally, CR spectrum sensing is designed to address one or more of the following challenges

- hardware limitations such as filters imperfectness, ADC (analog to digital converter) low resolution and dynamic range and limited complexity DSPs (digital signal processor), and sampling rate,
- the hidden PU problem, as depicted in Fig. 1.2, in which the CR is not able to sense the PU signals with low power or PUs with low probability of intercept

features such as spread spectrum signals,

- spectrum agility to be able to react to the spectrum changes very fast.

As explained in the previous chapter, the more information available of the PU signal model, the better CR perception from the PU activities. The CR is interested in an accurate model of the PU signal, e.g., orthogonal frequency-division multiplexing (OFDM) signal with certain parameters. Knowing an accurate model would be very helpful for spectrum sensing, e.g., one can use simply a matched filter detector matched to the PU signal [22, pp. 267]. However, depending on any specific model may cause robustness or sensitivity issues.

If certain information about the periodicity of the signal exists, a cyclostationary feature detector can be used [50]. Some knowledge regarding the PU transmission in narrowband can be exploited by wavelet feature extraction [22, pp. 272–273]. Another simple (low-complexity) spectrum sensing method is energy detection. It measures the energy in a time slot after passing the received signal through a bandpass filter and sampling. Another recent method in spectrum sensing is the application of random matrix theory. In this method, either the ratio of the largest eigenvalue of the sample covariance matrix to the smallest one or the average eigenvalue to the minimum one is compared with a threshold [51].

Spectrum sensing can be performed in different setups, e.g., single-node vs. networked, centralized vs. distributed, and sequential vs. fixed-sample-size. To mitigate the problem of the hidden PU node, the spectrum sensing can be performed by cooperation between CR nodes, spatially apart. This cooperation can be done in a distributed fashion, or a central fusion center.

One can make the spectrum sensing more agile by performing it sequentially, i.e., continue sampling until the decision variable reaches one of two thresholds [11, 19]. It was shown that sequential spectrum sensing is on average four times faster, for the same probabilities of misdetection and false alarm, than a fixed-sample-size detector, which was earlier referred to as energy detection [19, pp. 53–56]. This scheme enables the CR to sense in wideband or low-SNR scenarios.

Spectrum sensing, in this thesis, is based on a simple energy detection. So, the complete block diagram of the CR side will be according to Fig. 3.1. In this setup, the received signal is down-converted and filtered in the designated band. Then, the energy and a decision variable, e.g., the log-likelihood ratio (LLR) of energy samples, are calculated. By comparing this decision variable with a threshold, a decision for transmission is finally made. The decision for transmission in the next slot is denoted by u_{k+1} in this thesis and is equal to zero or one for no transmission or transmission, respectively. We cover the details of this model in the next sections

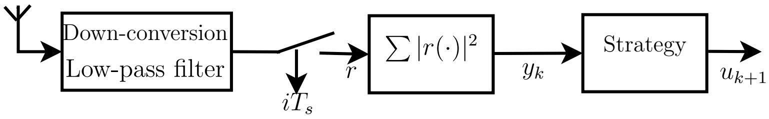

Figure 3.1: Cognitive radio block diagram

in this chapter. Details about the strategy for deciding to transmit are given in Chapter 5.

3.1.1 Sequential probability ratio test with parallel thresholds

The SPRT has particular characteristics, mentioned earlier in this chapter, which are appealing in the context of cognitive radio research, where the primary goal is to make use of under-utilized radio spectrum.

In the Wald model [52], a test statistic, normally a probability ratio or a function of it, is accumulated until it reaches one of two (or many) thresholds γ_{0_i} and γ_{1_i} as depicted in Fig. 3.2. Here, it is assumed that the threshold functions are designed such that the longest detection time is (much) shorter than the PU slot time. If the test statistic passes the lower threshold γ_{0_i}, the test will announce no PU signal ($\hat{q}_k = 0$), and if the test statistic passes the upper threshold γ_{1_i} a PU signal detection is announced ($\hat{q}_k = 1$). After making a decision, a new test will start.

3.1.2 Sequential spectrum sensing with varying thresholds

The Wald SPRT algorithm is well known in the spectrum sensing literature. However, its downside is apparent when there is a mismatch between design and actual parameters of the distributions, or when there is a change of distribution in the middle of the test (which is not normally studied in the CR context). Under these conditions, the maximum number of samples needed by the SPRT to reach a decision could be rather high [53–57]. In this thesis, we introduce a certain class of truncated SPRTs in spectrum sensing to ensure that the test would be terminated at a certain number of samples. Two different types of this class of thresholds are studied, and it was shown with these truncating thresholds, without too much loss in ASN, in 90% of the cases the detection time is improved.

3.2 PU transmission model from CR perspective

The goal of developing a CR is to exploit time-frequency vacancies. To take advantage of time-frequency slots that are not used by the PU, the CR must be aware of the PU activities. In the rest of this thesis, it is assumed that the CR has a full buffer to reuse the spectrum whenever it is available.

3.2.1 Network of PUs or CRs

The CR will receive the PU signal, which is attenuated by the PU-CR channel, where also noise may be added. If there is more than one PU in the vicinity of the CR, the aggregated signal will be received at the CR antenna. It is reasonable to assume that PUs operating in the same frequency band and are co-located, belong to the same network, and thus from a CR point of view can be modeled as a single entity. Since the protection of each one of the PUs is as important as the others, a network of PUs can be represented by a single but more active PU. If there exists a network of synchronized, centralized cooperative CRs that observe PU(s), it can see the PUs as operating on a single Markov model. It should be noted that this assumption will reduce the complexity of the design. However, to design an optimum system, a multi-PU model must be considered.

3.2.2 PU-CR fading channel

Another factor in modeling the PU-CR interaction is the channel in-between. Wireless channel gains are normally considered as random fading processes, such as Rayleigh, Rician, Nakagami, etc. [58,59]. For simplicity, it can be assumed that the fading gain is constant and known to the CR during the operation of this CR.

Another approach to modeling the fading process is to include the fading in the PU transmission model. Thus, whenever the channel is in a deep fade, it is assumed that there is no PU transmission, no matter what the real state of the PU is. Furthermore, in the case where there is no deep fade, the standard PU transmission model will be deployed. However, there is a caveat to this approach. If the PU-CR channel is in fade, the CR cannot sense PU activities. Now if the channel between the CR transmitter and PU receiver is not in fade, interference is inevitable.

With this brief introduction, a simple two-state Markov model can be used to represented a wide range of PU transmissions, PU network activities, and even fading channels. Furthermore, a simple Markov model will simplify the mathematical analysis for the rest of the derivations. In the next sections, the simplified two-state Markov model will be presented as the PU transmission model.

3.2.3 Slotted PU and CR activity

In this thesis, the PU transmissions are assumed to be slotted, since in most of today's digital communication systems, transmissions are confined to within a packet, frame, or generally a block structure of some minimum length T_{F}. It is assumed that the CR is expecting PU activities and vacancies in much smaller slots of length $T \ll T_{\mathrm{F}}$.

As discussed in Section 2.1, the existence of a PU transmission in slot k, i.e., during time $t \in [kT, (k+1)T)$, is denoted by the state $q_k = 1$, and its absence is denoted by $q_k = 0$.

Smaller slot sizes T improve the agility of the CR to adapt its transmission to the PU activity. In this thesis, for simplicity, we will assume that the CR slots are synchronized to the PU slots. However, due to the small slot length T of the CR in comparison to the PU frame length T_{F}, any mismatch in synchronization will not cause major performance degradation.

3.3 Signal and noise models

Due to the noise and other channel impairments, the CR is unable to directly observe q_k. This gives rise to three different models used in the included papers. After that, in the Section 3.3.2, the idea of observation censorship due to the CR transmission is modeled.

3.3.1 Sampling receiver

In the following sections, the uncertainties in signal and noise are modeled as Gaussian random processes. The receiver front end is an energy detector whose output y_k is written as

$$y_k \triangleq \sum_{i=0}^{K-1} \left| r\left(kT + iT_s\right)\right|^2 \tag{3.1}$$

where $r(\cdot)$ is the complex envelope of received signal low-pass filtered to the PU signal bandwidth W, T is the period in which energy is collected, and T_s is the sampling time. The energy samples are accumulated, and K is the total number of samples in each CR time slot. In the block diagram in Fig. 3.1, i and k denote the time index for the received signal and the CR slot index, respectively.

We assume that the received PU signal can be modeled as a Gaussian random process. The Gaussian PU signal model is commonly assumed in the literature [38], [6], and it is reasonable for many combinations of PU signal formats and channels

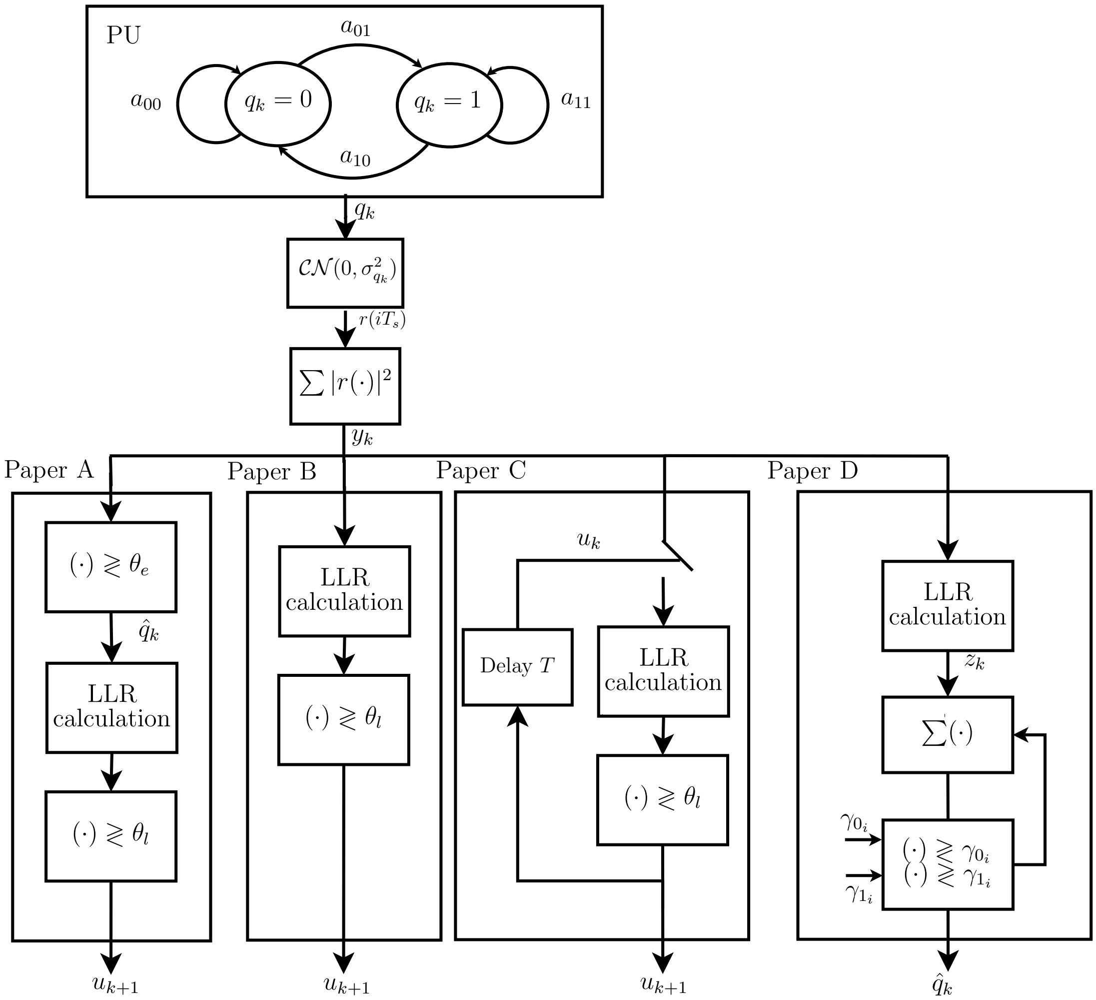

Figure 3.2: Signal model for four papers

(fading as well as nonfading). Assuming the PU signal to be a Gaussian signal is a worst-case scenario. Any other signal model improves the fundamental limits on performance of spectrum sensing. A Gaussian signal model can also be seen in practice, e.g., the OFDM signal is very close to Gaussian.

If we select T_s such that $T_s \gg 1/W$, then the samples $r(iT_s)$ are approximately statistically independent. Note that K is constrained as $K \leq T/T_s$.

In state $q_k = 0$, the noise $n(iT_s) \sim \mathcal{CN}(0, \sigma_0^2)$ is a zero-mean complex circular Gaussian sample with variance σ_0^2, and the received signal will be $r(iT_s) = n(iT_s)$. Thus, y_k is, after normalization, chi-square distributed with $2K$ degrees of freedom.

Since noise and channel uncertainties exist in the CR observation of the PU signal, the true PU state from Fig. 3.2 is not observable. Depending on the state of the PU, a continuous energy level that consists of noise only, or signal plus noise, is observed. This model corresponds to a continuous-output hidden Markov model (HMM) depicted in Fig. 3.2. In Paper A, for further simplification, the energy is

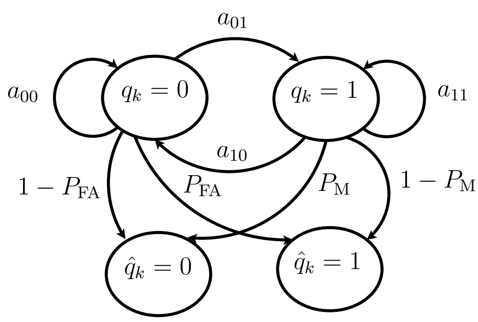

Figure 3.3: Discrete-output HMM model in Paper A

thresholded to give an estimate of the current PU state. Thus, the system model corresponding to Paper A is a discrete-output HMM presented in Fig. 3.3.

3.3.2 Simultaneous or separate sensing and transmission

In papers A and B, we assume that spectrum sensing is possible also when the CR is transmitting. One can achieve this by, e.g., self-interference cancellation if the CR transmission power is small enough. Previously, the transmission and reception in the same band at the same time has been shown to be possible, in theory, e.g., in [60] as well as in practice, e.g., in [61].

However, usually, due to the hardware limitation, e.g., complexity and cost, there is only one antenna and a duplexer that alternates between transmission and reception. This stops the CR from observing all the PU states. We say that the PU observations are *censored*.

Of course, the CR's intention is to transmit whenever the PU is not active, i.e., it is in $q_k = 0$. But this cannot always be achieved due to the noise and PU signal uncertainties. Further, if there exists any observation censorship, the job is even more difficult. Eventually, a collision might happen. From the CR point of view, whenever $u_k = 1$, the PU state is censored. This censorship causes the following problems for CR decision making

- the CR cannot observe all PU activities,
- the censorship of observation is dependent on the previous CR transmission decisions and ultimately on all previous PU states,
- statistics of CR decision variables vary a lot with just changing the threshold.

Thus, the strategies provided in papers A and B cannot address the scenario with the observation censorships. In paper C, we address this scenario with censorship, which calls for a new decision variable and algorithm for computing it.

Chapter 4

Performance measures

The purpose of a CR is to reuse radio spectrum as efficiently as possible. To judge CRs and compare them, we need performance metrics. No matter how well the spectrum sensing is performed, a CR is not able to perfectly predict the future activities (states) of the PU in advance. Thus, the CR will eventually interfere with the PU. The amount of this interference should be kept below a certain level. These measures can compare CRs from different perspectives, such as

- performance of CR spectrum sensing,
- performance of CR in presence of PU with certain transmission model,
- performance of CR transmitter to CR receiver link,
- the amount of interference of CR(s) for PU(s) or vice versa,
- the delay corresponding to performing spectrum sensing,
- the power consumption of the CR.

This thesis cannot cover all these items. The performance measures related to the contributions in this thesis are covered in the next two sections. After that, some other metrics are presented in the last section of this chapter.

4.1 Performance of spectrum sensing

Spectrum sensing is a detection algorithm performed to determine what is the current state of the PU. Thus, it inherits the same performance measures used in detection theory. Detection, which is embraced in the radar area, has long been used for identifying and testing the presence of a target. The performance of radar is measured by the probabilities of misdetection (P_{M}) and false alarm (P_{FA}), which are used in the field of hypothesis testing or detection. Normally, to design a detector, one keeps the probability of false alarm fixed and minimizes the probability of misdetection, so-called constant false alarm rate.

The performance of a detector can be characterized by plotting the probability of $1-P_{\mathrm{M}}$ vs. P_{FA}, which is called receiver operating characteristic (ROC) [19, pp. 56]. The ROC is also used for characterizing and evaluating spectrum sensing algorithms. A detector with a higher ROC is normally preferable.

In the context of CR, the probability of misdetection is related to the risk of interference with the PU. The probability of false alarm can represent the spectrum opportunities that are missed by the CR. Thus, P_{M} and P_{FA} can be written as

$$\begin{aligned} P_{\mathrm{M}} &= \Pr\{\hat{q}_k = 0 \mid q_k = 1\}, \\ P_{\mathrm{FA}} &= \Pr\{\hat{q}_k = 1 \mid q_k = 0\} \end{aligned}$$

where $\hat{q}_k$ is the PU state estimate at the CR after observing energy samples from the PU signal up to y_k. The next section will demonstrate better measures that depend on the PU traffic.

Another factor that comes into play, is when one uses sequential detectors for spectrum sensing [11, 19]. These algorithms do not take a fixed number of samples for making a detection. The number of samples varies test by test and is a random variable. These detectors can achieve a given probability of misdetection and false alarm (under certain SNR conditions) by adjusting their thresholds. However, depending on the shape of the thresholds, the distributions of the detection time may differ. One can compare the mean detection time or a certain percentile of detection time.

4.2 Model-based performance metrics

The CR is interacting with the PU in the spectrum. Thus, considering the performance of a CR without considering the interacting PU is not enough. To have a reasonable measure for assessing CR performance, one might consider the interference caused by the CR for the PU and the spectrum vacancies not used by the PU and utilized by the CR. To achieve that, we have introduced two new measures called interference ratio (IR) and utilization ratio (UR). The CR's goal is to take advantage of any spectral opportunities and transmit in them. However, due to channel and noise uncertainties, it may create unintentional interference for the PU. The CR transmission strategy decision is denoted by u_{k+1}, where $u_{k+1} = 0$ and $u_{k+1} = 1$ represent no transmission and transmission, respectively, in slot $k+1$. This decision u_{k+1}, in the most general case, is a function of y_1, y_2, $\ldots$, y_k. Interference will happen whenever the CR transmits at the same time as the PU. Thus, the interference ratio (IR) ρ is defined as [62]

$$\rho \triangleq \Pr\{u_{k+1} = 1 | q_{k+1} = 1\}. \tag{4.1}$$

Utilization of the spectrum occurs whenever the CR transmits in a vacant time–frequency slot. Thus, we define the spectral utilization ratio (UR) as

$$\eta \triangleq \Pr\{u_{k+1} = 1 | q_{k+1} = 0\}. \tag{4.2}$$

Any CR would like to have a strategy that keeps ρ below a specified level, say $\rho_{\max}$, and at the same time maximizes the utilization ratio η. Hence, we call a transmission scheme that maximizes η while $\rho \leq \rho_{\max}$, an optimal transmission strategy for the given model parameters. Usually, increasing η causes ρ to increase.

Designing a CR system based on the definition of UR and IR is advantageous compared to designing one based on P_{FA} and P_{M} because the CR does not have to over-protect the PU for the sake of not violating the IR requirement and thus might increase UR. Another property of IR and UR is the relationship with known communication metrics such as rate and probability of error. Without any particular assumption on the CR's modulation and coding, a CR average rate, as defined in Paper A, Sec. III-B, is calculated based on UR and IR as

$$R = R_b(\eta\pi_0 + \rho\pi_1) = R_b\left(\pi_0(\eta - \rho) + \rho\right), \tag{4.3}$$

where R and R_b are the average CR transmission rate in bit/s and the data rate for continuous CR transmission in bit/s, respectively. Thus, for small $\rho\pi_1/\pi_0$, R is approximated by $R_b\pi_0\eta$. In the same way, the probability of error can be derived for the CR as

$$\begin{aligned}\Pr\{\text{error}\} =& \big(\Pr\{\text{error}|q_{k+1} = 0, u_{k+1} = 1\}\eta\pi_0 \\ &+ \Pr\{\text{error}|q_{k+1} = 1, u_{k+1} = 1\}\rho\pi_1\big)/(\eta\pi_0 + \rho\pi_1).\end{aligned} \tag{4.4}$$

The first term in (4.4) includes the probability of error in the absence of the PU transmissions, and the second term includes the probability of error in the presence of a PU transmission. In this thesis, the focus is mainly on the UR and IR.

4.3 Other performance metrics

In different publications, many well-known measures are introduced [8,10,22]. Here, some of them are reviewed. In the CR optimization problem, researchers considered short-term and long-term power constraints. Usually, a Gaussian CR-PU channel is considered and the amount of interference the CR causes for the PU is measured in the received CR power at the PU receiver. In these situations, usually, the performance of CR is also characterized in rate (or even capacity) for a given Gaussian channel. So, the purpose of CR is to adapt its power to a certain level, at which PU can safely transmit while at the same time maintaining a rate that is feasible for the CR.

In [63], the notions of achievable rate and capacity for cognitive networks were used. Information-theoretic measures can express the bounds for CR performance in the presence of cooperative and non-cooperative PUs.

Indeed, as in any other communication system, in cognitive radio scenarios, the performance of PU link or CR link can be specified in rate and probability of error [9].

Chapter 5

Model-based CR transmission strategy

Cognitive radios are designed to serve the purpose of exploiting the vacant time–frequency slots in the spectrum. This quest has some major obstacles in the way.

The first and foremost issue with reacting to the spectrum state change is causality, i.e., the CR only observes the spectrum state that has already past. This makes it more difficult for the CR to find the time-frequency holes ahead of time. Unless the PU conveys its future states prior to transmission to the CR (or there exist tables of PU operations), the CR is not able to know PU states ahead of time, with certainty. In this case, the PU traffic model can play a crucial role in predicting the future vacancies of the spectrum. The models discussed in this thesis, as explained in Chapter 2, are based on the Markov model and thus they are stochastic. This means that, even with PU statistical model knowledge, the predicted PU state might not match the actual PU transmission state. Fortunately, observing a large enough number of PU states, normally through another random process, e.g., channel or noise, can give the CR a pretty good perception of PU activity and its potential future states. Moreover, one can estimate the SNR and PU model parameter by just observing the received signal.

On top of the PU traffic uncertainty, there are all the uncertainties of PU-CR channel and CR receiver noise. They occlude the CR's perception of the PU state. The job for the CR, without having the exact previous PU states, is much more difficult. Thus, in the presence of channel and noise uncertainties, having an accurate signal model that includes the PU traffic is highly desirable.

As explained in Chapters 3 and 4, the intention of the CR is to reuse spectrum with a strategy that decides whether to transmit or not. This strategy, given all the previous observations from PU and CR transmission decisions, makes a decision denoted by u_{k+1}, which can be zero or one. In this chapter, the methods introduced in this thesis as well as some other spectrum reutilization methods are reviewed.

5.1 Markov-model-based strategies

The Markovian behavior of network entities, as discussed in Chapter 2, makes Markov models a good choice for modeling PU data traffic in CR networks [64]. In this section, we briefly review two classes that are based on Markov model assumptions for PU traffic. This first class of such attempts are based on Markov decision processes (MDP). MDP is a process in which transition probabilities between states are dependent on the action taken. In MDP, there exists an immediate reward function received after transition between two states [65]. Now the goal is to maximize the reward by choosing proper actions. With the help of optimization methods such as value iteration or policy iteration, an appropriate policy can be found. MDPs have been implemented in dynamic spectrum access [26, 39, 66, 67].

When perfect knowledge of PU states is not available to the CR, an extension of MDP, which is called partially observed MDP (POMDP), is applicable. Thus, POMDP does not have direct access to the Markov states, but rather observes them through another random process, e.g., noise. POMDP better captures the difficulties of uncertainties in the PU-CR channel and CR receiver noise. A lot of research has been done that focuses on CRs based on POMDP, such as [29, 31, 68–71]. Often, exact solutions of POMDPs are computationally intractable. Hence, there exist several approximate solutions such as grid-based algorithms or principle component analysis.

The second path in the model-based CR strategies, which we used in this thesis, is prediction-based strategies. In this class, the strategy predicts the next PU state(s) using one or all observations up to the current one [34, 35, 72]. There exist different spectrum prediction methods, such as HMM-based, neural-network-based, Bayesian-inference-based, moving-average-based, and autoregressive-model-based [72]. Markov models play a crucial role in many strategies [36]. The strategies provided in the contributions of this thesis are in this class. In Papers A and B, we developed a dynamic spectrum access strategy entitled a-posteriori probability log-likelihood ratio (APP-LLR)-based spectrum reutilization strategy. In Paper C, we extend the strategy to the case where CR is unable to sense during its own transmission and those observations are censored, so-called censored a-posteriori probability log-likelihood ratio (CLAPP).

5.2 APP-LLR-based strategy

There are many challenges associated with CR, mainly due to the spectrum sensing problems. We introduce a new model for the inclusion of the PU model in decision making regarding CR transmission. This model not only includes the last

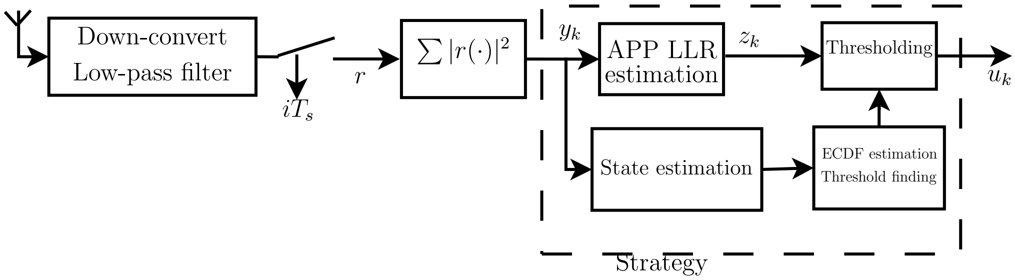

Figure 5.1: Proposed APP-LLR based opportunistic access strategy

energy observation but also takes all observations before the last one into account. This method considers all information available both in the system model, and the observations from the spectrum.

The proposed system is depicted in the block diagram presented in Fig. 5.1. In this figure, after sampling a down-converted filtered signal, its energy is calculated and accumulated for a certain given period. Based on the energy of the signal, the a-posteriori probability (APP) LLR is computed. For the transmission strategy, a threshold is needed as follows

$$u_{k+1} = \begin{cases} 1, & \text{if } z_k \leq \theta_1 \\ 0, & \text{if } z_k > \theta_1 \end{cases}, \tag{5.1}$$

where $z_k \triangleq \log \frac{\Pr\{q_{k+1}=1|\mathbf{y}_k\}}{\Pr\{q_{k+1}=0|\mathbf{y}_k\}}$, θ_1 and $\mathbf{y}_k \triangleq [y_1, y_2, \cdots, y_k]$ are the *a posteriori log-likelihood ratio*, the threshold for z_k, and all observations up to kth slot, respectively. In Papers A and B, we use the same model with minor modifications. In Paper A, the threshold can be calculated with a closed-form expression. In Paper B, to find the threshold, we can calculate the inverse empirical cumulative distribution function (ECDF) of the LLRs at the level of allowed interference ratio for the samples, which are corresponding to the next state of the PU being one. However, knowledge of the PU state, even for a training period, is not available in practical situations. Thus, it is needed to estimate the PU states for a certain training period, based on estimated PU states, estimate the ECDF of the LLR values. For this period of threshold estimation, the forward-backward method is used for PU state estimation [46].

5.3 CLAPP

As it was explained in Section 3.3.2, due to the hardware limitations, usually, the CR cannot sense and transmit in the same band at the same time. Thus, the whole energy samples vector $\mathbf{y}_k$ is not available and some energy samples are missing. This calls for revisiting the procedure of calculating the LLRs and also of finding the threshold. The transmission strategy has access to the spectrum's energy y_k only when $u_k = 0$. In other words, the CR will observe the list $\mathbf{y}'_k$,

$$\mathbf{y}'_k \triangleq \begin{cases} \mathbf{y}'_{k-1}, & \text{if } u_k = 1, \\ [\mathbf{y}'_{k-1} \quad y_k], & \text{if } u_k = 0 \end{cases}, k = 1, 2, \ldots, \tag{5.2}$$

where $\mathbf{y}'_0 = [\ ]$, i.e., an empty list. Obviously, the length of $\mathbf{y}'_k$ is smaller than or equal to k. Here, the LLRs shall be calculated based on $\mathbf{y}'_k$. However, $\mathbf{y}'_k$ is very different from $\mathbf{y}_k$ and thus also its CDF. The reason is that the distribution of $\mathbf{y}'_k$ is dependent on the previous CR transmissions.

In the CLAPP algorithm, we calculate the LLRs based on a statistic from available observations. This statistic is calculated recursively. When observations are missing, CR is using the prior knowledge to predict the PU future states. The details are developed in Paper C.

In this strategy, we use the same idea as APP-LLR to decide whether to transmit or not by thresholding CLAPP LLRs. However, in this strategy, choosing a threshold influences which observations must be censored and thus the LLRs. The threshold is found by a bisection search method. To do so, we need the IR as a function of model parameters (a_{01}, a_{10}, σ_0^2 and σ_1^2) and the threshold. Given the model information, we can calculate the IR numerically. Bisection needs a condition of monotonicity of IR as a function of the threshold, which is demonstrated in Paper C.

Chapter 6

Contributions and conclusions

This thesis aims to propose robust and reliable algorithms with low complexity for spectrum sensing and reutilization. To reach this goal, we developed a set of model-based strategies that allow a CR to coexist with a PU operating based on a Markov chain.

First, we start with a discrete-output hidden Markov model (HMM) in Paper A. In this model, the two-state Markov model is at the heart. The PU signal, after passing through a noise process, is estimated by thresholding. This model is presented in Fig. 3.3. In this figure, P_{FA} and P_{M} represent probability of false alarm, and misdetection, respectively caused by thresholding.

The next step in improving the signal model is to model a received signal by a continuous-output HMM process in Paper B, which is presented in Fig. 3.2. This model is more accurate, since there is no hard decision making early in the signal model, unlike discrete-output HMM.

The Paper C signal model, which is depicted in Fig. 3.2, takes the model in paper B to a new, more practical level. Paper C considers that the PU signal is not observed, i.e., censored, during CR's own transmissions. Thus, the PU signal observations are not only influenced by noise and PU transmission uncertainties, but are also disrupted by CR transmissions.

A number of contributions were introduced for covering the decision-making part of the cognitive cycle. It is shown that the inclusion of a model for the PU allows the spectrum utilization to increase considerably, which is due to the fact that the integration of the PU model into the the CR transmission strategy will enable the CR to have a credible estimation of PU states.

6.1 Contributions

The main contributions of this thesis are found in three appended papers.

6.1.1 Paper A: An LLR-based cognitive transmission strategy

In this paper, we use a hidden Markov model to form a framework for modeling the behavior of CRs in the presence of the PU and all the uncertainties. Additionally, a benchmark for evaluation of CR performance is introduced. Then, using this foundation and these measures, a new CR transmission strategy is designed and implemented. This new design ensures that the vacant spectrum is optimally used conditioned on that the level of interference for the PU, due to all uncertainties in the model, does not exceed a certain level. We demonstrate a more than 300% increase in UR compared to simple energy detection for up to 1% allowed IR at the SNR of -5 dB.

6.1.2 Paper B: On optimum cognitive spectrum reutilization strategy

This paper presents an a-posteriori LLR-based cognitive transmission strategy, which maximizes the spectrum utilization ratio for a given PU transmission model and allowed interference ratio. In Paper B, we generalize the discrete-output HMM in Paper A to a continuous-output HMM. Two methods for calculating the threshold for this strategy in practical situations are presented. One of them performs well when the PU activity level is high, for all SNRs, or when the PU activity level is small and the SNR is high. We prove that the other method never violates the allowed IR. In addition, an upper bound for the UR of any CR strategy is presented. Simulation results show an improvement of more than 116% in UR compared to energy detection at an SNR of -3 dB and IR level of 10% for the threshold that guarantees no IR violation.

6.1.3 Paper C: Sensing or Transmission

This paper extends the contribution in Paper B by considering that the CR can either transmit or sense but not both at the same time. In this scenario, the observations during CR transmissions are censored. This calls for a new algorithm that handles missing observations. In this paper we introduced a new strategy (CLAPP), which uses the prior information whenever an observation is censored. Previously, some statistics, e.g., forward and backward variables, for censored observations in the following cases, were calculated [73]. However, there were no statistics calculated from all censored observation through a deterministic strategy to the best of our knowledge. In CLAPP, LLRs also indicate how much the CR can safely continue to transmit before sensing, without interfering with the PU transmissions more that $\rho_{\max}$. Thus, CLAPP inherently saves energy for sensing. Moreover, CLAPP provides an easy way to compute LLRs with low complexity.

CLAPP simulation results show a 52% gain in UR over the best censored energy detection scheme for a maximum IR level of 10% and an SNR of -2 dB.

6.1.4 Paper D: Wideband sequential spectrum sensing with varying thresholds

In this contribution, sequential detectors with varying thresholds are used for energy-based spectrum sensing. The performance of this class of sequential spectrum sensors is evaluated in terms of the probabilities of false alarm, misdetection and detection distributions. This performance is compared with the standard fixed thresholds introduced by Wald [52]. It is shown that for an SNR of -10 dB, among tests with Wald and triangular thresholds with similar probabilities of misdetection and false alarm, triangular performs 54% faster, in terms of maximum detection time (90 percentile).

6.2 Conclusions

This thesis introduces strategies that include a PU model and all the observations available at the CR even if some PU observations are censored by CR transmissions. To evaluate the performance of CR in the presence of a PU, the UR and IR performance metrics are introduced. Simulation results show a considerable improvement in the CR performance, in terms of UR, by utilizing the PU state model and all the previous observations. We have proven that APP-LLR is the optimum strategy when all the energy samples are observed. In addition, an upper bound for all CR strategies operating in the presence of a Markov-model-based PU is derived.

The models and methods introduced in this thesis alongside other state-of-the-art technologies such as software-defined radio can be used to remedy major CR challenges mainly SNR wall issues. Inclusion of the PU traffic model in the CR transmission decisions and using sequential agile spectrum sensing can makes the CR more useful. Furthermore, since the models and methods introduced in this thesis are simple, they can be applied to a broad range of applications and PU networks. Even one might consider these strategies to be deployed in current network infrastructures to use spectrum, licensed or unlicensed, more effectively. A crucial point in the deployment of these tools is the knowledge of model parameters. It is mentioned that these parameters can be estimated fairly accurately. Thus, real-world implementation of these strategies, specially CLAPP, is feasible due to their simplicity.

Another challenge regarding utility of strategies, provided in this thesis, is calculating thresholds. Given the model parameter knowledge, one can compute the thresholds for corresponding scenarios. However, storing thresholds in a big lookup table, for given parameters, is not practical.

Moreover, the performance measures introduced in Chapter 4, UR and IR, can be used for evaluation of CR performance by regulatory organizations, e.g., FCC or PTS.

To summarize, the overall advantages and disadvantages with the methods developed in this thesis are as follows.

Advantages

- By employing a simple two-state Markov model for the PU traffic, we gain the advantage of being able to predict the future behavior of the PU to some degree with moderate CR complexity.
- Strategies have low complexity and can be implemented rather easily.
- In the CLAPP algorithm consideration of observation censorship due to self transmissions makes it appropriate for less expensive implementations.
- Introduction of UR and IR, as performance metrics, makes assessment of a CR performance, from a regulatory standpoint, more practical.

Disadvantages

- A more accurate model for the PU traffic would lead to better prediction of the PU, but at the price of more CR complexity and sensitivity to model errors,
- The current framework treat all CR transmissions as harmful to the PU receiver. A better modeling of the CR-to-PU receiver channel could enable more spectral re-utilization,
- These strategies are dependent to the model parameters and proper thresholds. In real-world applications, these parameters should be estimated fairly well to enable high performance

6.3 Future work

We tried to choose a general framework for modeling the PU and CR. There still exist some assumptions or considerations that can be further improved or generalized. In this section, some examples of future extensions to this thesis are reviewed.

In Chapter 2, a simple two-state Markov model and some other Markov-based models are introduced as candidates for PU traffic model. Throughout this thesis, a two-state Markov model is used. One way that might potentially improve the performance of the system in more complex PU traffic is the use of semi-Markov models.

Another extension to the PU traffic model is modeling multiple PUs on the same band as well as modeling multi-band PU(s). One can even include the CR traffic model into the transmission strategy.

As explained before, knowledge of the model parameters is important in this thesis. The effects of the model parameter estimation on the strategies performance, specially CLAPP, can be studied. Moreover, this estimation error can be included in the strategies to have more robust strategies.

Chapter 3 reviews the CR signal model. In this thesis, we have used energy detection as the spectrum sensing. If there exists more information about the PU signal, a matched filter can be used instead. This can increase the SNR and improve the UR of the system considerably.

In addition Chapter 3 also includes the PU-CR channel in the PU model and channel gain influencing the SNR. To better capture the channel behavior, the channel can also be independently modeled. One can even consider two-state Markov models for all the channels between PUs' and CRs' transmitters and receivers.

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