Doctoral Dissertation

Interference Avoidance in MIMO Cognitive Radio Networks With Estimation Errors

Samuli Tiiro

Department of Electronic and Information Engineering
Graduate School of Engineering
Tokyo University of Agriculture and Technology

2014

Contents

List of Figures

List of symbols

A	scalar
$\boldsymbol{a}$	vector
$\boldsymbol{A}$	matrix
$\boldsymbol{I}_N$	$N \times N$ identity matrix
$\mathbb{C}$	complex plane
$(\cdot)^*$	complex conjugate
$(\cdot)^T$	transpose
$(\cdot)^H$	Hermitian transpose
$\\|\boldsymbol{a}\\|$	Euclidean norm of vector $\boldsymbol{a}$
$\det(\boldsymbol{A})$	determinant of matrix $\boldsymbol{A}$
$\mathrm{diag}(\boldsymbol{a})$	diagonal matrix with vector $\boldsymbol{a}$ on the diagonal
$\dim(\boldsymbol{A})$	dimension of the space spanned by the column vectors of $\boldsymbol{A}$
$\mathrm{null}(\boldsymbol{A})$	basis of the null space of matrix $\boldsymbol{A}$
$\mathrm{trace}(\boldsymbol{A})$	trace of matrix $\boldsymbol{A}$
$\Gamma(n)$	Gamma function
$(f * g)$	convolution functions f and g
$\mathrm{Prob}(X < \alpha)$	probability of random variable having a value less than α
$\mathcal{E}\{\cdot\}$	mathematical expectation
$\mathcal{CN}(\mu, \sigma^2)$	normal distribution with mean μ and variance σ^2
$\Gamma(k, \theta)$	Gamma distribution with shape parameter k and scale parameter θ
$\mathcal{CW}_p(n, \boldsymbol{R})$	complex Wishart distribution with n degrees of freedom and covariance matrix $\boldsymbol{R}$

List of abbreviations

3G	3rd Generation
4G	4th Generation
AM	Amplitude Modulation
BS	Basestation
BTS	Basestation Transceiver System
CPE	Customer-Premises Equipment
CPC	Cognitive Pilot Channel
CR	Cognitive Radio
CSI	Channel State Information
DFS	Dynamic Frequency Selection
DSA	Dynamic Spectrum Access
DSP	Digital Signal Processor
ETSI	European Telecommunications Standards Institute
FC	Fusion Center
FPGA	Field-Programmable Gate Array
IEEE	Institute of Electrical and Electronics Engineers
IMT	International Mobile Telecommunications
ISM	Industrial, scientific and medical
ITU	International Telecommunication Union
LTE	Long Term Evolution
MAC	Medium Access Control
MDL	Minimum Description Length
MIMO	Multiple-Input Multiple-Output
OFDMA	Orthogonal Frequency Division Multiple Access
OSA	Opportunistic Spectrum Access
QoS	Quality-of-Service
P2M2	Point to Multipoint
PHY	Physical layer

PSVD	Projected channel SVD
PU	Primary User
RF	Radio Frequency
RSS	Reconfigurable Radio Systems
SDR	Software-Defined Radio
SNR	Signal-to-Noise Ratio
SS	Spectrum Sharing
SU	Secondary User
SVD	Singular Value Decomposition
TPC	Transmit Power Control
TVWS	TV White Space
WiMAX	Worldwide Interoperability for Microwave Access
WRAN	Wireless Regional Area Network
WRC	World Radiocommunication Conference

Abstract

In recent years, due to the explosive growth of the number of new mobile wireless systems with increasingly high data rate requirements, we are facing the problem of spectrum scarcity. To facilitate new wireless services, frequency bands need to be allocated within the usable radio frequency (RF) spectrum. Furthermore, larger and larger bandwidths are required to cater the high data rate communications. However, the existing RF spectrum is already reserved for various government and commercial services. Because of this the introduction of new wireless services is difficult without changing the existing frequency allocation policies.

The spectrum scarcity issue has directed the research of future wireless communications towards more flexible and dynamic spectrum access techniques. The new wireless systems can take advantage of the licensed spectrum that is left unused by licensee or they can share the spectrum provided that they do not interfere with the licensed users. One of the techniques that has potential to achieve spectrum coexistence are cognitive radios (CRs) which have gained a significant amount of interest in the research community. CR terminals are able to sense the surrounding RF spectrum and adjust their operating parameters accordingly due to which they are a natural candidate for dynamic spectrum access (DSA) technology.

Several techniques based on CR and DSA methodologies have been proposed with a promise to achieve more efficient spectrum utilization. However, the gap between theory and practice still remains. While the concepts are simple, implementing them in practice is still hindered by several challenges. The goal of this work is to take one step closer to more practical applications.

In this work we focus on the issue of spectrum sharing and the coexistence of primary and secondary users. We consider multiple antenna based terminals which have become a mainstay in modern commercial wireless systems. By taking advantage of the spatial multiplexing capabilities of the multiantenna terminals, it is possible to achieve simultaneous primary and secondary transmissions by interleaving them in the spatial domain.

In practical applications, the difficulty of performing spatial spectrum sharing while protecting the primary users is due to the fact that the secondary network can only obtain information on the primary users by estimating it without any cooperation provided by the primary network. If no additional considerations are taken into account, this will result in prohibitive amount of interference to the primary users due to the secondary transmissions.

In this work, two sources of potential interference are tackled. First, channel estimation errors are considered which are the main cause of interference due to

the fact that without perfect channel state information (CSI), the secondary users are not able to perfectly orthogonalize their transmit signals with the interference channel. The second issue is incorrect allocation of spatial spectrum resources by the secondary users. If the secondary network is not able to accurately determine the number of transmit streams used by the primary system, it is possible that the secondary system incorrectly allocates too many transmit streams, some of which will overlap with the primary user's signal space and therefore will result in interference.

For the issue of spatial resource allocation, at first, cooperative estimation scheme is investigated in order to improve the estimation accuracy in the low signal-to-noise ratio region. A new decision fusion rule is proposed which is able to both improve the probability of correct estimation as well as to avoid interference to the primary user in the case of an error. To further avoid interfering with primary system when an error actually occurs or when only estimated CSI is available, a transmit power control method is proposed for the secondary users. In order to achieve more realistic characterization for the interference, it is modeled as a random variable and a probabilistic protection constraint is applied in order to guarantee desired interference outage probability for the primary user.

Chapter 1

Introduction

1.1 Background

1.1.1 Wireless communications and spectrum management

In 1865, James Clerk Maxwell postulated the existence of electromagnetic waves in his paper [1] with his famous equations and predicted that electricity, magnetism and light are all manifestations of the same physical phenomenon, electromagnetic field. Later, Maxwell's theory was confirmed by Heinrich Hertz who carried out a set of experiments with the antennas he had developed. Hertz was able to produce electromagnetic waves which would travel through free space and were then captured by a detector device. While Hertz himself did not realize the possible ramifications, his work combined with Maxwell's theory essentially laid out the foundation for wireless communications.

Hertz's proof of the existence of electromagnetic waves inspired other people to experiment on the new form of electromagnetic radiation. Among these were an Italian inventor and engineer, Guglielmo Marconi, who developed a wireless telegraph device capable of transmitting Morse coded messages over long ranges. After performing a series of demonstrations with his device for the British goverment, Marconi was able to gradually increase the operating range: the English channel was crossed in 1899 and the Atlantic ocean in 1901.

After Marconi's experiments, radio communication become popular and radios were used for example in naval communications where wire telegraphy was not an option. In the beginning of the twentieth century, the radio communication was completely unregulated and anyone possessing a radio transmitter could send messages over the whole frequency band. It has been estimated that in 1911 there were already over 10 000 radio amateurs in the United States alone. The first steps towards regulated spectrum use were taken with the Radio Act of 1912 which is a United States federal law stating that all radio stations in the United States must be licensed by the federal government and that seagoing vessels are required to continuously monitor frequencies reserved for distress signals. The bill followed shortly after the sinking of Titanic when several lives were lost due to the radio operators of a nearby ship being asleep [2].

In the beginning of the twentieth century, amplitude-modulated (AM) radio was invented by Reginald Fessenden and Lee de Forest. As opposed to the spark-gap based radio devices where one transmitter covers the entire spectrum, AM radio made it possible for several transmitters to send signals at the same time. Later in the 1920s, vacuum tube was invented which revolutionized the radio technology. Vacuum tubes played a key role in the development of electronic technology which caused a major push to the expansion and commercialization of radio communication applications such as radio broadcasting, television, large telephone networks and radar systems.

After the spread of radio communication technology, interference was quickly identified as an issue. The early radio devices based on the spark-gap technology were not able to efficiently control the frequency which set a limitation on the number of simultaneous transmitters within a geographical location. After the invention of tunable radio transmitters, frequency management became the means to achieve simultaneous transmissions on the radio spectrum and therefore take advantage of the potential of radio technology. The radio spectrum was eventually identified as a limited resource and in order to provide reliable operation by avoiding interference between transmitters, governmental agencies were established to be in charge of spectrum management.

Currently, the use of radio spectrum is regulated by goverments in most countries in process known as frequency allocation or spectrum allocation. Since the radio waves travel across national boundaries, international cooperation between countries is necessary. The International Telecommunication Union (ITU) is a specialized agency of the United Nations which is responsible for coordinating the shared global use of the radio spectrum. ITU organizes the World Radiocommunication Conference (WRC) every three to four years where the national regulatory agencies gather together to review and possibly revise the radio regulations and the international use of radio spectrum.

Even though current radio communication technology is leaps ahead of the capabilities of the first radio transmitters, the basic rules governing spectrum use have gone through very little evolution since they were established in the early twentieth century. From early on, the radio communication has been based on the premise that the radio spectrum is divided into portions separated by guard bands and different radio applications are assigned their own piece of the spectrum to operate on. These frequency allocation policies are usually very strict and they offer little flexibility due to the fact they are made on long term basis, covering large geographical areas, and with exclusive licenses.

While the static spectrum allocation policies have shown to be able to control interference between wireless communication systems and simplify the transmitter design by having them operate only on a designated frequency range, its lack of flexibility can make the introduction of new wireless services difficult. This problem has been highlighted in the recent years by the explosive increase in the number of wireless terminals, introduction of new communication technologies and operators. The frequency bands suitable for commercial radio services have already been allocated to legacy systems for the most part making the available bands scarce and sought after resources. Obtaining operating rights has become increasingly expensive as seen for example in the United Kingdom's 4G spectrum auction for Long Term Evolution (LTE) services which raised 3.62 billion dollars. Although it seems like the usable radio spectrum has already been exhausted, preliminary measurements [3] have shown that for the most part the allocated spectrum is highly underutilized. Results from more recent spectrum measurement campaigns around the world have shown similar results which confirms that spectrum scarcity problem is in fact a result of strict frequency allocation policy instead of actually overloading the usable radio spectrum. While the static spectrum allocation policy was applicable in the past, it is now evident that in order to support future wireless technologies and to efficiently make use of the available radio spectrum, a policy reform is in place. This situation has been acknowledged and it has motivated the development of new, more flexible spectrum access policies which can eventually take over the currently applied inefficient static spectrum allocation schemes.

1.1.2 Dynamic spectrum access

Inefficient utilization of the available radio spectrum has sparked interest in spectrum management methods which are able to overcome the limitations of static spectrum allocation policies. Number of initiatives and activities have been put in motion in regulatory [4–9], research as well as economic [10,11] communities in order to improve spectrum utilization. The methods that attempt to share spectrum among wireless services, technologies and operators and aiming to improve the overall spectrum utilization are gathered under the umbrella term Dynamic Spectrum Access (DSA). Examples of spectrum sharing have existed in various applications in the past [12] but it has become increasingly popular topic since the spectrum scarcity issue was identified.

Among the proposed spectrum access models, three main models can be identified [13]. Dynamic exclusive use model follows along the lines of static spectrum allocation policy in the sense that different frequency bands are exclusively licensed to different services, technologies and operators. The difference to the static policy is that some amount of flexibility is allowed in order to improve the spectrum efficiency. The spectrum licensees are allowed to sell or lease their share of the spectrum and they are allowed to choose what kind of services and technologies use their respective frequency band [14]. In this model the spectrum sharing is not required by the spectrum regulator but more efficient spectrum use is motivated by economic benefits. Dynamic spectrum allocation [15] is another approach that can also be categorized under the dynamic exclusive use model. In dynamic spectrum allocation, two or more radio networks share a block of frequency spectrum by taking advantage of spatial and temporal variations in the spectrum usage. Dynamic spectrum allocation resembles the static allocation policy in the sense that spectrum is allocated exclusively to the licensed services. The difference is that in dynamic spectrum allocation, the spectrum allocated to the licensees can adapt to the expected demand of the services sharing the same frequency band depending on time and location in relatively fast time scale.

Open spectrum access model [16] on the other hand proposes that instead of regulatory authority, the spectrum use is managed completely by its users. It has been theorized that by creating a basic set of rules for spectrum access the users are able to coordinate the spectrum use while avoiding interference between each other. The open spectrum access model has also faced criticsm as it has been suggested that it is possible for the users to take advantage of the common spectrum pool for their own benefit and thus degrade the overall spectrum utilization.

Hierarchical spectrum access model can be viewed as a combination of the two previous models. In hierarchical spectrum access model the users are divided into two categories: primary users who are licensed to access certain frequency band and secondary users who do not possess licensed frequency band. To realize efficient spectrum use in the hierarchical model, the secondary users are allowed to access the spectrum licensed to primary users by limiting the interfence the secondary spectrum access will generate. The interference can be avoided by requiring the secondary users to operate below the noise floor of the primary users. By spreading the secondary transmissions over a wide frequency band it is possible to achieve high data rate transmission (similar to spread spectrum and ultrawideband communications) albeit the drawback is that only short communication ranges can be covered due to the transmit power limitations. On the other hand, this approach has the benefit that it is not necessary to monitor primary user transmissions to avoid interference as long as secondary transmit power constraints can be met. If the secondary users are equipped with multiple antennas, it is also possible to meet the interference constraint by directing the secondary transmission away from the primary users. In this case the secondary users must be able to approximate interference resulting from secondary transmissions which can be done based on reciprocity if the primary communication can be observed. Another means to achieve spectrum sharing is to let the secondary users transmit using portions of the licensed spectrum that are left unused by the primary user. The variations in primary user spectrum utilization can result in spectrum holes at certain times or locations, also known as spectrum white space. If the secondary user is able to identify these spectrum holes, it is possible to exploit them for opportunistic spectrum access (OSA). [17]

While the dynamic exclusive access model can improve the overall spectrum utilization compared to the static access model, it leaves room for improvement as it can not adjust to the spectrum usage variations quickly enough. The open sharing model also has its problems as demonstrated by the interference generated by the multiple heterogenous technologies (such as cordless phones, Bluetooth devices and wireless local area networks) operating on the industrial, scientific and medical (ISM) band. Out of the three models presented, the hierarchical spectrum access is probably the most likely to be adopted in future wireless communication systems. The OSA model has been considered in a plethora of works on dynamic spectrum access techniques and secondary spectrum access by exploiting spectrum holes in time domain or geographical locations has been considered as a possible solution to the spectrum scarcity problem. With multiantenna terminals becoming increasingly popular in consumer wireless systems, the spectrum sharing techniques based on multiantenna techniques have also attracted attention recently. These techniques can be viewed as a combination of the interference constrained spectrum access and opportunistic spectrum. The DSA model considered for the remainder of this dissertation is based on multiantenna enabled OSA framework

1.1.3 Cognitive radio

DSA techniques have attracted a great deal of attention due to its potential to alleviate the spectrum scarcity problem by improving overall spectrum utilization. Moreover, DSA has been considered to have possible applications in other areas such as ad hoc, emergency and military networks [18–21]. The main technique that is generally considered as the enabler of DSA is Cognitive Radio (CR) which is often paired up with Software-Defined Radio (SDR) technology.

The term SDR was first introduced in 1992 by Joseph Mitola in his paper [22] where he described the architecture principles of the software-based transceiver he had been working on. SDR is essentially a radio communication system where the components that have been conventially implemented with specialized hardware (e.g. amplifiers, detectors, filters etc.) are instead implemented by software running on a general-purpose processor, Digital Signal Processor (DSP) or a Field-Programmable Gate Array (FPGA). The idea behind SDR is that by having most of the signal processing done in software it can support a variety of radio protocols as the RF chain is reconfigurable. The term CR was also introduced my Mitola in 1999 [23] and it is considered as one of the goals that the SDR platform should evolve into. CR is an intelligent, context-aware radio which is able to sense its surroundings. By learning from its environment, CR can then adjust its radio transmission parameters adaptively and autonomously.

The original concept of CR was somewhat general idea but the two main characteristics are easy to identify. First one is the learning ability, where the CR terminals capture information from the surrounding RF environment, and the second one is the reconfigurability where CR can dynamically adapt to the information it has observed. Therefore it is natural to consider CR in the context of DSA. CRs are able to detect possible spectrum holes within their coverage area which could then be utilized for secondary transmission without interfering with the primary users. CR can reconfigure various transmission parameters like operating frequency and bandwidth (to adapt to unused frequency bands), modulation and channel coding (to adapt to channel conditions) and transmission power (to control interference to primary users). DSA is one of the important applications of CR where the benefits of cognition-reconfiguration cycle can be realized.

1.1.4 Network architecture

A typical architecture of a CR network is illustrated in Figure 1.1. The CR network can be divided into two main groups, namely primary network and secondary network [24]. The primary network is defined as wireless network which has an exclusive license to access certain frequency band with a network infrastructure already in place, such as television broadcast network or a cellular network. The primary network is composed of primary users and a primary basestation. The primary users (or licensed users) are licensed to access their respective frequency. This access is controlled only by the primary basestation and it should not be affected by any of the unlicensed users. The primary users should not need any modification or additional functions to allow the coexistence of the unlicensed users and basestations. The primary basestation is a fixed network infrastructure component which has a spectrum license such as a basestation transceiver system (BTS) in a cellular system. The primary basestation does not have capability to support spectrum sharing with the secondary users, however, it is possible that it supports both legacy and new protocols for the primary network access of secondary users.

The secondary network (or unlicensed network) does not possess a license to operate in the desired frequency band. Therefore, the spectrum access is allowed only in an opportunistic manner. The secondary networks can be deployed either as a fixed infrastructure or as an ad hoc based network as shown in Figure 1.1. The secondary network is composed of secondary users, secondary basestation and a

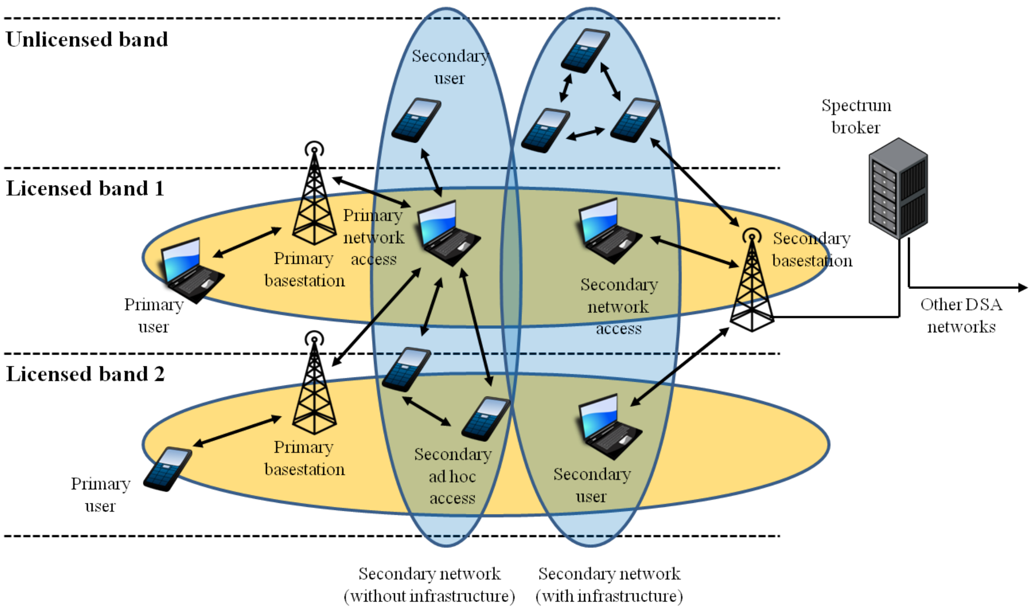

Figure 1.1: CR network architecture.

spectrum borker. The secondary users do not have a license to access the frequency band. Hence, DSA and CR functionalities are required so that the secondary users can access and share the licensed spectrum. The secondary basestation is a fixed infrastructure component with DSA capabilities and it provides a single hop connection to the users without spectrum license. Through the secondary basestation, the unlicensed users can access other networks. The spectrum broker (or a scheduling server) is a central network entity which manages the sharing of the spectrum resources among different secondary networks. The spectrum broker can be connected to each network and it can provide information on spectrum availability to enable the coexistence of multiple secondary networks [25–27].

The reference network found in Figure 1.1 consists of a primary network and both infrastructure and ad hoc based secondary networks. The networks operate under a spectrum environment which consists of licensed frequency bands and unlicensed frequency bands. In addition, the secondary users can communicate with each other either by accessing the secondary basestation or via multihop connections. Therefore we can consider three types of spectrum access in the CR network: primary network access where the primary users access primary basestations on the licensed frequency band, secondary network access where the secondary users access secondary base stations on both licensed and unlicensed frequency bands, and secondary ad hoc access where the secondary users communicate with each other on both licensed and unlicensed frequency bands without assistance from the secondary basestation. When secondary users access the licensed band, avoiding interference to the primary users is of great importance. In this case, the spectrum available to the secondary users depends on the primary user traffic as well as the interference from primary users located nearby. When accessing the unlicensed frequency bands, however, all of the network entities are considered equal and in this case the spectrum broker has an important role in managing the available spectrum in a fair manner among the secondary entities.

While the theory behind DSA concept is fairly simple, efficient and interference-free spectrum access in practice is very challenging. In order to realize this, a set specific functionality is required to locate the spectrum holes and manage their use.

Spectrum sensing is the function responsible for finding the portions of the spectrum which are available to the secondary users for opportunistic use. Spectrum sensing must also take care of detecting if the primary users appear while the secondary user is operating on the licensed frequency. It has been suggested that the secondary spectrum access could possibly be supported by the primary network by sharing real-time information on the licensed spectrum utilization [28]. This information could be broadcast to the secondary users for example by using the proposed cognitive pilot channel (CPC) [29–31]. This approach has the benefit that secondary users would be able to obtain perfect knowledge on the instantaneous spectrum usage, however it is possible that the changes required to facilitate the additional communication are not feasible if the primary network is based on legacy technology, for example. In this case, the secondary network is responsible for monitoring the primary network traffic and has to make decisions on when to access the spectrum and when to vacant the channel based on its own observations. Under such circumstances, spectrum sensing is the most important aspect to enable secondary spectrum access.

Spectrum sensing can be performed independently or in a cooperative fashion. In non-cooperative sensing, the secondary users make their own local observations on the spectrum utilization while in cooperative sensing, the sensing information can be exchanged between multiple users. In theory, cooperative sensing can achieve more accurate spectrum sensing and it offers benefits such as reducing the detection performance requirements of individual secondary users and mitigation of the degrading effects of multi-path fading and shadowing [32, 33]. Cooperative sensing can also be used to shorten the detection time of weak primary signals which results in improved frequency agility of the overall network [34, 35]. The downside of cooperative sensing is that it requires a dedicated control channel for exchanging the sensing information and it introduces additional signaling overhead which could pose a problem with primary networks where the spectrum utilization varies fast.

Spectrum decision functionality is used to analyze the spectrum holes and decide the most suitable spectrum band for the secondary spectrum access. The detected spectrum holes are characterize in terms of parameters such as interference level, path loss, channel error rate and so on. Then, the best available frequency band is selected based on the user Quality of Service (QoS) requirements (data rate, error rate, etc.) and spectrum characteristics.

Spectrum sharing is used to provide fair spectrum access to the coexisting secondary users and networks by managing the access of the spectrum holes. This resembles the Medium Access Control (MAC) issue on traditional communication systems, however in DSA/CR applications specific MAC protocols are required [36].

Spectrum mobility is essential in order to avoid interference to the primary users. The secondary users must be able to vacant the channel in the case that primary users appears to access it and move the secondary transmission to another spectrum hole. Switching the operating band of the secondary transmission can also be triggered due to other reasons such is preservation or improvement of the QoS. The event of transitioning from a spectrum hole to another is also known as spectrum handover. The goal of spectrum mobility functionality is to provide seamless communication during the frequency band transitions while avoiding interference to the primary users.

1.1.5 Standardization activities

Standardization plays an important role in promoting the commercialization and deployment of DSA and CR based communication systems. The Institute of Electrical and Electronics Engineers (IEEE) has spearheaded the standardization initiatives but at the moment other international standardization organizations and industry associations such as the ITU, the Wireless Innovation Forum, the European Telecommunications Standards Institute (ETSI), and the European association for standardizing information and communication systems (Ecma International) are also working on development of DSA/CR related standards [37].

At the moment, the most popular standards on DSA/CR are the IEEE 802.22 standard for Wireless Regional Area Network (WRAN) using TV white space and the IEEE P1900 series of standards on dynamic spectrum management [38]. There are also other related activities within the IEEE and many other IEEE 802 standards include capabilities for DSA and CR techniques which have resulted from coexistence activities [39].

IEEE 802.22 was the first global standard based on the DSA/CR technology [40, 41]. The main target application of the standard is wireless broadband access in rural areas with performance similar to the fixed broadband access technologies deployed in urban and suburban areas. The standard defines physical (PHY) and MAC layers for unlicensed terminals to access the TV frequency bands on a non-interfering basis [42, 43] based on CR technology. The standard focuses on the TV white space (TVWS) due to its favorable propagation cahracteristics and the large coverage areas as well as the large amounts of available TVWS [44]. The standard specifies that the WRAN network should operate in a point to multipoint (P2MP) basis and the system consists of Basestations (BS) and Customer-Premises Equipment (CPE). The CPEs are connected to the BS via a wireless link and the BSs are responsible for controlling the medium access for all the CPEs connected to them. The PHY layer must be able to adapt to different conditions and it has to be able jump from channel to channel without transmission errors or losing CPEs. Flexibility is also required for being able to dynamically adjust the bandwidth, modulation and coding schemes. The modulation scheme considered for both uplink and downlink is Orthogonal Frequency Division Multiple Access (OFDMA) which is capable to achieve the fast adaptation required from both the CPEs and the BSs. By using a single TV channel with a bandwidth of 6 MHz, the achievable data rate is approximated to be 19 MBit/s at a 30 km distance. The standard also considers using multiple channels for transmission which results in higher overall bandwidth and thus improves the system performance. The MAC layer is based on CR technology as it is required that the system can adapt to changes in the spectrum utilization. The BS broadcasts on channels that can be used without interference and when a CPE is turned on, it can identify the channels that can be used to connect to the BS. The CPEs perform two types of spectrum sensing: in-band and out-of-band. In-band spectrum measurement consists of sensing the channel used by both the BS and the CPE and the out-of-band measurement is responsible for sensing the rest of the channels. Both spectrum measurements are performed on two types of granularity, namely fast sensing and fine sensing. Fast sensing is performed by both the CPE and the BS and the sensing speeds are less than 1 ms per channel. Based on the outcome of fast sensing mechanism, fine sensing is performed which is considerably slower, taking more than 25 ms per channel. The sensing mechanisms are used to determine if there are urgent transmissions taking place and if it is necessary to avoid interfering with them.

On the contrast to IEEE 802.22 which focuses on specific mechanisms in PHY and MAC layers, the IEEE P1900 series concentrates on architectural concepts and specifications for policy-based network management with DSA in a heterogeneous wireless access network composed of incompatible wireless technologies (3G/4G, WiFi, WiMAX). The series consists of six standards defining terminology and concepts (IEEE P1900.1), recommended practices for interference and coexistence analysis (IEEE P1900.2) and conformance evaluation of SDR software modules (P1900.3), architectural building blocks (P1900.4), policy language and architectures (P1900.5), spectrum sensing interfaces (P1900.6), and radio interface for DSA (P1900.7).

Coexistence issues have also been considered in other IEEE standardization activities and existing standards have been updated to include support for coexistence and unlicensed devices. The IEEE 802.11 standard, for example, now includes support for channel access and coexistence features using TVWS. New functionalities introduced include sensing of other transmitters (IEEE 802.11af [45]), Transmit Power Control (TCP) and Dynamic Frequency Selection (DFS) (IEEE 802.11h) and its extensions (IEEE 802.11y). Correspondingly, the IEEE 802.16h standard has introduced mechanisms to enable coexistence with systems with primary users [46]. The IEEE 802.19 standard addresses coexistence issues of unlicensed networks between different wireless standards under development within the IEEE (802.11, 802.15, 802.16 and 802.22).

Furthermore, other organizations besides the IEEE are also developing standards for DSA and CR systems. For example, ITU has released technical reports [47, 48] dealing with applying SDR techniques to International Mobile Telecommunications (IMT) 2000 standard for 3G communications and other mobile systems. ETSI is also working on Reconfigurable Radio Systems (RSS) standardization including CR technology and White Space (WS) access [49]. Ecma has also published a standard for portable devices operating on TVWS [50]. The standard specifies PHY and MAC layers and a number of primary user protection mechanisms which can be used to meet regulatory requirements.

Even though several activities have been initiated, the standardization of DSA and CR systems still requires a great deal of work. A great challenge for the standardization is the fact that the spectrum regulations differ from country to another. The fact that several organizations are independently on different further complicates the standardization issue.

1.2 Motivation

In the recent years, DSA and CR techniques have attracted a significant amount of interest as a potential solution to the spectrum scarcity problem where the demand for available spectrum increases while the reserved portions remain highly underutilized. DSA and CR can be used to alleviate this issue by having unlicensed secondary users to access the licensed spectrum opportunistically, without interfering with the licensed primary users. To realize interference-free unlicensed spectrum access, the secondary users are required to employ CR techniques such as spectrum sensing and spectrum sharing to detect the transmit opportunities and take advantage of them. In DSA networks, the secondary spectrum use is allowed only if the secondary users can guarantee QoS for the primary network, usually in terms of interference power.

In theory, the DSA and CR concept is simple, but putting it into practice is hindered by several challenges. While several prototypes [51–55] and experiments [56–58] have shown that there is potential for practical applications, there are still numerous issues that need to be investigated more. Identifying spectrum holes, effective but interference-free coexistence, managing spectrum opportunities among multiple secondary users have all been addressed in the literature but there are still many problems that prevent moving from theory to practice. For spectrum sensing there are methods varying from energy detectors to feature based detection to methods based on random matrix theory. However, it has still not been proven that accurate sensing can be achieved in low signal strength. Spectrum sharing methods have also been explored in great detail but a lot of the work is based on unrealistic assumptions on the available information or primary user cooperation, and so forth. Therefore, further investigation is required with more realistical approach.

The earlier studies on spectrum sharing were mostly based on opportunistical spectrum access in time and frequency domains. In temporal spectrum sharing, the secondary users attempt to identify time instants during which the primary users do not access the frequency band. Similarly, the frequency domain spectrum sharing attempts find vacant blocks on the licensed spectrum. As mentioned earlier, these methods can be combined by having the secondary users hop on time/frequency grid form a spectrum hole to another. The drawback of this approach is that in an area with high primary network traffic, it might not be possible to guarantee continuous operation for the secondary users. Therefore, coexistence methods where simultaneous primary and secondary transmissions can be realized on the same frequency band are desirable.

As mentioned earlier, the coexistence methods based purely on transmit control suffer from short transmission distances due to the strict interference constraints. Multiantenna based methods which avoid interference by directing the transmissions away from primary users by using beamforming, however, do not suffer from this. The signal processing required by multiantenna terminals tends to more complex but as most of the consumer wireless devices nowadays are equipped with multiple antennas it can deduced that the computational costs are not prohibitely high.

Multiantenna based spectrum sharing techniques where the interference is avoided with a combination of transmit beamforming and power control (sometimes called cognitive beamforming) have attracted some amount of interested in the research community in the recent years. The methods are very promising as ideally it is possible to achieve simultaneous secondary transmission while completely avoiding interference to the primary user. The ideal case, however, requires accurate information on channels between secondary and primary users. While obtaining channel state information (CSI) at the transmitter is trivial in regular wireless communications as it is possible to use pilot signals and feedback, it is significantly more difficult in a CR system. Generally it is unreasonable to expect assistance from the primary user especially if the goal is to coexist with a legacy system. Therefore, the task of estimating the channel between the secondary user and the primary user is left to the secondary user alone. As it is not possible to take advantage of pilot-based estimation, the channel estimation has to be performed blindly. Blind methods can not generally achieve the accuracy of conventional channel estimation methods and therefore it is very probable that significant estimation errors will occur. Under these circumstances, the secondary user must take additional measures to compensate for the interference resulting from the imperfect channel state information.

In this dissertation, the issue of multiantenna based spectrum sharing is investigated in the case where the unknown primary user parameters can not be accurately determined by the secondary user. The objective is to demonstrate that even with such uncertainties it is possible to protect the primary user from interference by sacrificing some of the achievable secondary user performance.

1.3 Thesis contributions

The main contribution of this dissertation is to provide a framework for the development of practical spectrum sharing that employ multiantenna techniques in the presence of channel and spatial degrees of freedom uncertainties. As opposed to the majority of related works, instead of setting a strict threshold for the interference we formulate a statistical primary user protection constraint based on the interference outage probability. This is a more realistic characterization for the interference in the presence of uncertainties which behave randomly in practice.

Furthermore, this dissertation addresses the issue of finding spectrum opportunities in the multidimensional signal space which has not been considered in the literature in a cognitive radio context. The issue is investigated in terms of both estimation as well transmission in the presence uncertains.

Since the constraint used to protect the primary user is defined in terms of probability, it is necessary to obtain expressions for the distribution of the interference power. In this dissertation, two kinds of estimation errors are considered and corresponding interference power distributions are derived. These expressions can prove to be useful in scenarios other than spectrum sharing, such as multiantenna enabled multiuser networks.

1.4 Thesis outline

The rest of the thesis is organized as follows. In Chapter 2, the problem of estimating the available spatial transmit opportunities is investigated. A cooperative secondary network operating in the vicinity of primary user terminal is considered. Before engaging transmission, the secondary users must determine the number of spatial streams they can allocate for transmission without interfering with the primary user. After obtaining individual estimates at each secondary user, the estimates are combined at a fusion center (FC) to extract spatial diversity. By improving the estimation accuracy, it is possible to effectively reduce the interference that would result from the secondary transmissions.

Chapter 3 deals with interference resulting from channel estimation errors. In order to mitigate the interference, additional transmit power constraints must be applied by the secondary users. To accomplish this, a statistical model for the estimation error is obtained. Based on the error statistics, it is then possible to derive the distribution for the interference power. The maximum transmit power that can satisfy the primary user protection constraint can then be obtained from the distribution. The results demonstrate that it is possible to protect the primary user even in the presence of channel estimation errors.

In Chapter 4, the interference resulting from incorrect allocation of transmit streams by the secondary users is considered. This is related to Chapter 2 and occurs when the estimation of allowable transmit streams fails. Similar to Chapter 3, the distribution of the resulting interference is obtained and it is used to determine the maximum transmit power that can satisfy the primary user protection. While this scenario presents additional challenges for the interference avoidance, it is possible to determine the maximum achievable secondary user performance.

Finally, the dissertation is concluded in Chapter 5. The results are reviewed and the implications and directions for future work are discussed.

Chapter 2

Estimating available spatial degrees of freedom

In this chapter a cooperative method for the estimation of the number of primary user transmit streams for cognitive radio networks is proposed. In cognitive radio systems, this information is essential in order to avoid interference to the primary system as well as to maximize the capacity for the secondary user. Here, a cooperative secondary network is considered where the secondary users estimate the number of streams and the independent estimates are then combined by a fusion center in order to take advantage of the spatial diversity. A decision fusion rule is proposed for this issue which takes advantage of the estimation bias of the minimum description length (MDL) algorithm. It is also demonstrated that the proposed method has the benefit of avoiding harmful interference in the case when the estimation results in an error.

2.1 Introduction

In recent years, the problem of spectrum scarcity has emerged and it is currently hindering the introduction of new wireless systems. The finite spectrum resources have already been reserved for existing licensed wireless network services and the rigid allocation policies offer very little flexibility to support new wireless communication systems. On the other hand, several measurements such as [3] confirm the fact that the reserved spectrum is utilized in a very unefficient manner. Depending on time and location, there is a possibility that the reserved spectrum is not used by the licensed primary users (PUs). Cognitive radio (CR) systems, which have been suggested as a possible solution to the spectrum scarcity problem, attempt to opportunistically exploit these temporal and spatial spectrum holes by using them for secondary transmissions. The premise is that secondary transmissions are allowed to use the licensed spectrum as long as they do not significantly interfere with the primary transmissions.

Multiple-input multiple-output (MIMO) systems, where the transmitter and the receiver are equipped with multiple antennas, have also gained a strong foothold among modern wireless communication systems. MIMO is an attractive technology as it enables higher data throughput capability without increasing the transmit power or the bandwidth. This technique, also known as spatial multiplexing, can achieve array gain and therefore improve the spectral efficiency of the system [59]. CR networks can also benefit from MIMO-enabled terminals as they make opportunistical spectrum allocation in the antenna domain possible. By orthogonalizing the secondary transmission space with the interference channel between the secondary users (SUs) and the PUs, it is ideally possible to achieve concurrent, interference-free secondary transmissions. Such transmission techniques have been explored in the existing literature such as [60], [61] and [62].

In the design of CR systems, the two main goals are protecting the PUs from the interference and maximizing the throughput for the secondary transmissions. In theory, the former does not pose an issue when the SUs employ orthogonal transmission methods. In practical systems, however, additional measures must be considered due to the fact that the knowledge of channels between the SUs and the PUs is not available for the SUs and it can be difficult to obtain due to the lack of assistance from the primary network. In related works, some solutions to this issue have been suggested in [63], [64], and [61]. The latter issue, while trivial in regular communications where the system parameters are readily available, also introduces additional challenges in the context of CR networks employing orthogonal transmissions. In order to maximize the thoughput for the secondary transmissions, the SUs must determine the number of spatial directions available for orthogonal transmission. Failure to do so will result either in inefficient spectrum usage or increased interference for the PUs, both of which conflict with our design goals.

In this chapter, we consider a CR network with multiple SUs who attempt to access the spectrum reserved for the primary system by using the orthogonal transmission technique. Before initiating the secondary transmissions, the SUs probe the channel and attempt to estimate the parameters required for efficient secondary spectrum allocation based on the signals transmitted by the PU. Since the SUs are sharing the licensed spectrum in the antenna domain, we consider the problem of estimating the available number of spatial degrees of freedom. In practice, this is directly related to the number of spatial streams transmitted by the PU. Therefore, we employ the well-known minimum description length (MDL) algorithm to accomplish this task. In order to improve the estimation accuracy, we consider cooperative estimation among the SUs where the independent estimates are combined to extract diversity gain. While both the stream number estimation and the decision fusion techniques are well investigated issues on their own, they have not been deeply investigated in a CR network context so far. Thus, in this chapter, we provide a brief study on the problem and show that by exploiting the estimation bias of the MDL algorithm it is possible to employ an unconventional decision fusion technique which provides significant performance gain over the conventional techniques, especially in low signal-to-noise ratio (SNR) conditions, as well as increased protection for the PU.

The rest of the chapter is organized as follows. In Section 2.2, we introduce the system model and assumptions, present the problem formulation and briefly cover the existing techniques that our work is based on. In Section 2.3, we discuss the decision fusion problem and outline our proposed method. Numerical results that confirm the validity of our proposal can be found in Section 2.4. Finally, the paper is concluded in Section 2.5.

2.2 System model

The CR network considered in this paper is illustrated in Fig. 2.1. The network consists of a single PU (although the system model can be easily extended to consider multiple PUs) and K SUs that attempt to opportunistically access the spectrum reserved for the PU. The PU terminal is equipped with M antennas and the SUs each have N antennas. The PU is assumed to communicate in a time-slotted manner, i.e., it alternates between transmitting and receiving modes. Moreover, it is assumed that the PU transmits using spatial multiplexing so that independent data streams are sent from each of its antennas. During the primary transmission, the SUs estimate the interference channel between the primary and the respective secondary terminals as well as other parameters, such as the number of independent streams transmitted by the PU. In addition, the CR network is connected to a fusion center (FC) which is used to aid the cooperative estimation. After estimating the PU parameters, the SUs transmit their respective estimates to the FC which then combines the independent estimates to obtain a final estimate and feeds it back to the SUs. The communication between the SUs and the FC is outside the scope of this paper, so we assume that error-free feedback channel is available which does not interfere with the PU. In practice, this can be realized by allocating a small amount of bandwidth from a frequency not used by the PU for the communication between the SUs and the FC.

The signal vector received at the kth SU terminal is expressed as

$$\boldsymbol{y}_k[n] = \boldsymbol{H}_k \boldsymbol{x}[n] + \boldsymbol{z}_k[n] \tag{2.1}$$

where $\boldsymbol{H}_k \in \mathbb{C}^{N \times M}$ is the channel from the PU to the kth SU, $\boldsymbol{x}[n] \in \mathbb{C}^M$ is the

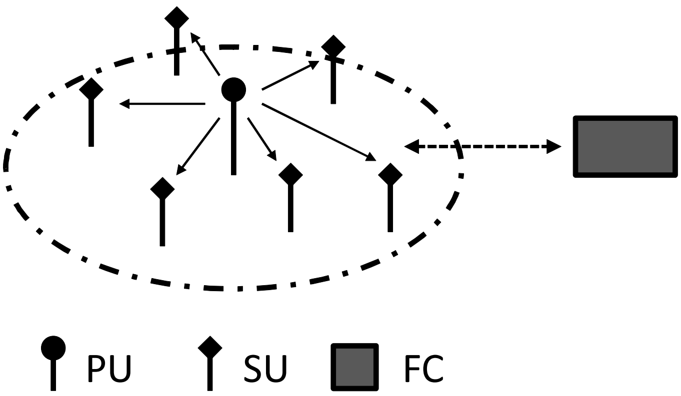

Figure 2.1: Cooperative cognitive radio network.

symbol vector transmitted by the PU, $\boldsymbol{z}_k[n] \in \mathbb{C}^N$ is the noise vector at the kth SU and n is the discrete time index. We consider a slow fading scenario where the channel matrices can be considered as constants during the primary transmission period and each $\boldsymbol{H}_k$ is modelled as independent and identically distributed (i.i.d.) standard Rayleigh fading channels. The effects of multipath fading, shadowing and pathloss are assumed to be included in the variation of the channel coefficients. In addition, the channels are assumed to be reciprocal, i.e., the reverse channel from the kth SU to the PU terminal can be expressed as $(\boldsymbol{H}_k)^T$. We also model signals transmitted by the PU so that $\boldsymbol{x}[n]$ are i.i.d. complex Gaussian vectors with zero mean and variance α. Similarly, the noise vectors $\boldsymbol{z}_k[n]$ are assumed to be i.i.d. complex Gaussian with zero mean variance σ_z^2.

During the secondary transmission phase, which takes place after the SUs have acquired the required transmission parameters, the SUs employ an orthogonal transmission method introduced in [60]. In orthogonal transmission, the SUs transmit over the orthogonal complement space of $(\boldsymbol{H}_k)^T$. Due to the orthogonality of the transmit channel and the interference channel, the secondary transmission will ideally result in no interference towards the PU. In practice, the SUs can obtain the orthogonal complement space as the basis of the null space of $(\boldsymbol{H}_k)^T$ from the covariance matrix of (2.1) which can be expressed as

$$\boldsymbol{R}_{yy}^k = \mathcal{E}\{\boldsymbol{y}_k[n]\boldsymbol{y}_k^H[n]\} = \alpha \boldsymbol{H}_k \boldsymbol{H}_k^H + \sigma_z^2 \boldsymbol{I} \tag{2.2}$$

where $\mathcal{E}\{\cdot\}$ denotes mathematical expectation over n and α and σ_z^2 are the received signal and noise powers, respectively. The basis of the null space of $(\boldsymbol{H}_k)^T$ can then be obtained as the complex conjugate of the eigenvectors of (2.2) that correspond to the $N - M$ smallest eigenvalues. The value $N - M$ also corresponds to the number of spatial degrees of freedom that can be used orthogonal secondary transmission.

In order to determine the dimension of the orthogonal complement space for the secondary transmission, knowledge of M is required at the SU terminals. In a CR network, however, the PU does not provide assistance to the secondary network and therefore this information must be estimated by the SUs. As the channel matrices $\boldsymbol{H}_k$ have full rank M, it follows that the ordered eigenvalues of (2.2) can be expressed as $\lambda_1 > \lambda_2 > \ldots > \lambda_M > \lambda_{M+1} = \ldots = \lambda_N = \sigma_z^2$. Therefore it is possible to determine the number of primary transmit streams from the eigenvalues of the covariance matrix.

In practice, the ideal covariance matrix (2.2) is not available due to finite number of samples observed by the SUs as well as the corrupting noise. Instead, the SUs use the respective sample covariance matrices

$$\hat{\boldsymbol{R}}_{yy}^{k} = \frac{1}{L}\sum_{n=1}^{L} \boldsymbol{y}_k[n]\boldsymbol{y}_k^H[n] \tag{2.3}$$

where L denotes the number of observed samples used. It follows that when using the sample covariance matrix, the smallest eigenvalues are no longer equal and it is not possible to accurately determine the number of transmit streams, M, anymore. However, it is possible to estimate this value by using the minimum description length (MDL) algorithm introduced in [65]. The MDL algorithm uses information theoretic criterion to select the model that is most likely for the given observation. This is done by minimizing the cost function

$$\mathrm{MDL}(m) = -L(N-m)\log\left(\frac{\prod_{i=m+1}^{N}\hat{\lambda}_i}{\sum_{i=m+1}^{N}\hat{\lambda}_i}\right)^{\frac{1}{L-M}} + \frac{1}{2}m(2N-m)\log(L) \tag{2.4}$$

where $\hat{\lambda}_i$ denotes the ith largest eigenvalue of the sample covariance matrix (2.3). The estimate at the kth SU, $\hat{M}_k$, is then obtained as $m \in \{0,\ldots,N-1\}$ which minimizes the corresponding MDL criterion, i.e., $\hat{M}_k = \arg\min_m \mathrm{MDL}(m)$.

2.3 Cooperative source number estimation and decision fusion

In a CR network where multiple SUs attempt to independently estimate the number of primary transmit streams, it is possible to take advantage of the increased spatial diversity and achieve more accurate estimation for the number of primary transmit streams. This can be realized by combining the K independent estimates at the FC. The final estimation result decided by the FC is expressed as $\hat{M} = f(\hat{M}_1,\ldots,\hat{M}_K)$ which is a function of the K independent estimates. The benefit of combining multiple estimates can be seen as a way to extract diversity gain, as the probability that all K channels simultaneously experience poor fading conditions is significantly smaller than in the case where there is only one SU.

As we are concerned with the problem of estimating the number of primary transmit streams, there are two possible error events we need to consider. The first one is underestimation, i.e., $P_0 := \{\hat{M} < M\}$ and the second one is overestimation, correspondingly $P_1 := \{\hat{M} > M\}$. Let us now study the implications of each case in our system model. As the number of available spatial directions is equal to $N - M$ it follows that in the event of P_0, the secondary network incorrectly decides that it can allocate more spatial directions for the secondary transmission than are actually available. This can have severe consequences in terms of PU protection as it results in the secondary signal space overlapping with the interference channel, and therefore it can cause significant amount of interference to the PU. On the other hand, in the case of P_1, the secondary network ends up using a number of spatial directions that is less than what is actually available. While this results in suboptimal spectrum allocation in terms of secondary transmission, it does not cause any additional interference to the PU. As the premise of CR systems is based on the agreement not to interfere with the primary transmissions, it can be said that out of the two possible error events P_1 is more favorable.

For conventional decision fusion systems, there are several fusion rules available in the literature. A common strategy to combine independent estimates is to use a voting-based fusion rule. Among the voting-based strategies, majority voting is a reasonable method for several systems. In majority voting, the fusion center decides in favor of the estimate which receives the highest number of votes among the K SUs. The majority voting method is in fact the optimal fusion rule when the number of sensors K is odd, the probabilities for each sensor to give the correct estimation result are equal, and the decisions among the K sensors are independent [66]. Using majority voting with unbiased estimates provides good results as it averages out the outlier estimates which have higher probability of being incorrect.

Here we consider the MDL algorithm for the task of estimating the number of primary transmit streams. The MDL algorithm is very popular method for source number estimation due to its simple implementation. However, because of the model inaccuracies, insufficiently small number of observed samples and observation noise, the MDL algorithm actually results in biased estimates [67]. This fact is illustrated in Fig. 2.2 where the error probabilities of the MDL algorithm can be seen in non-cooperative operation for various values of M. It can be seen that at low SNR the estimation errors are almost exclusively due to the underestimation event, P_0. As the SNR increases, the underestimation probability converges towards zero while the overestimation event, P_1, becomes more dominant. At high SNR region, the estimation errors can be seen to be mostly due to underestimation. As the MDL algorithm results in biased estimates, it can be seen that the estimation performance

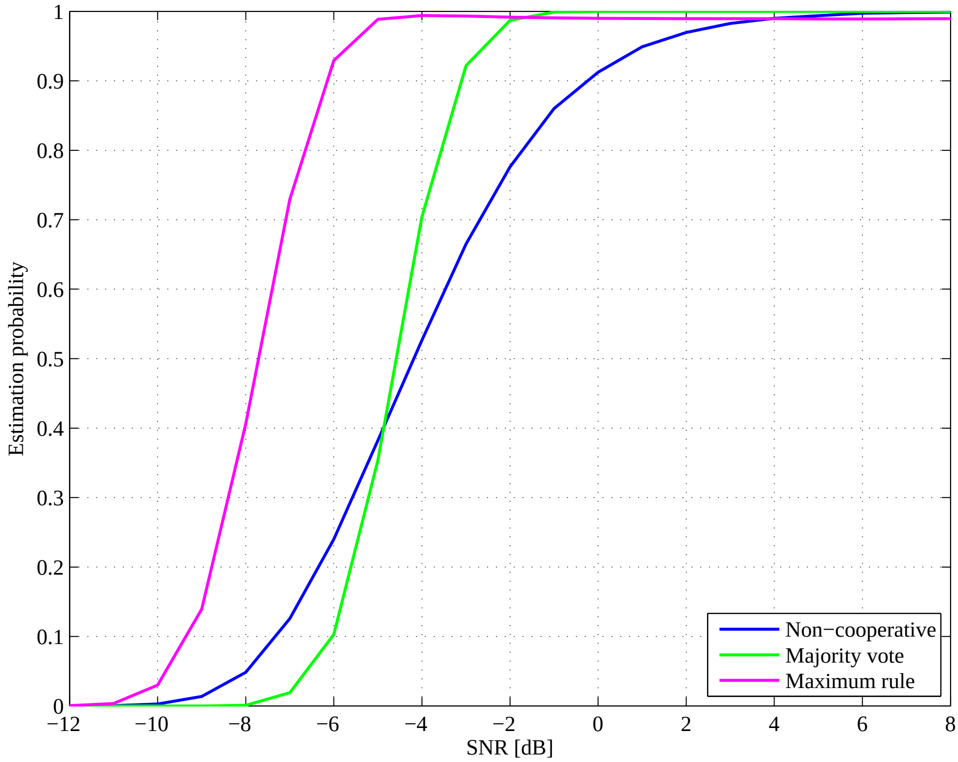

Figure 2.2: Error probabilities for the source number estimation in non-cooperative operation with $N = 5$ SU antennas, $M = \{1, 2, 3\}$ PU streams and $L = 100$ samples.

can be further improved from the majority voting rule. For example, applying the majority voting with the MDL at low SNR would result in erroneous estimate with high probability as it will average out the outliers. However, due to the estimation bias of the MDL algorithm, the estimates with higher values are actually more likely to be correct.

Due to the aforementioned issues, namely, underestimation resulting in additional interference to the PU and the MDL algorithm having negative bias in the low SNR region we are motivated to propose a new decision fusion rule. Our proposed fusion rule decides in favor of the largest estimate among the candidate estimates and it can be expressed as

$$\hat{M} = \max\{\hat{M}_1, \dots, \hat{M}_K\}. \tag{2.5}$$

The merits of the proposed fusion rule are twofold. First, at the low SNR region, we can achieve improved estimation accuracy as the fusion rule always decides in favor of the estimates with larger values which are most likely to be correct. Second, in the case where the fusion rule actually results in an erroneous decision, it will with high probability result in P_1 which is the desirable error event in terms of PU protection.

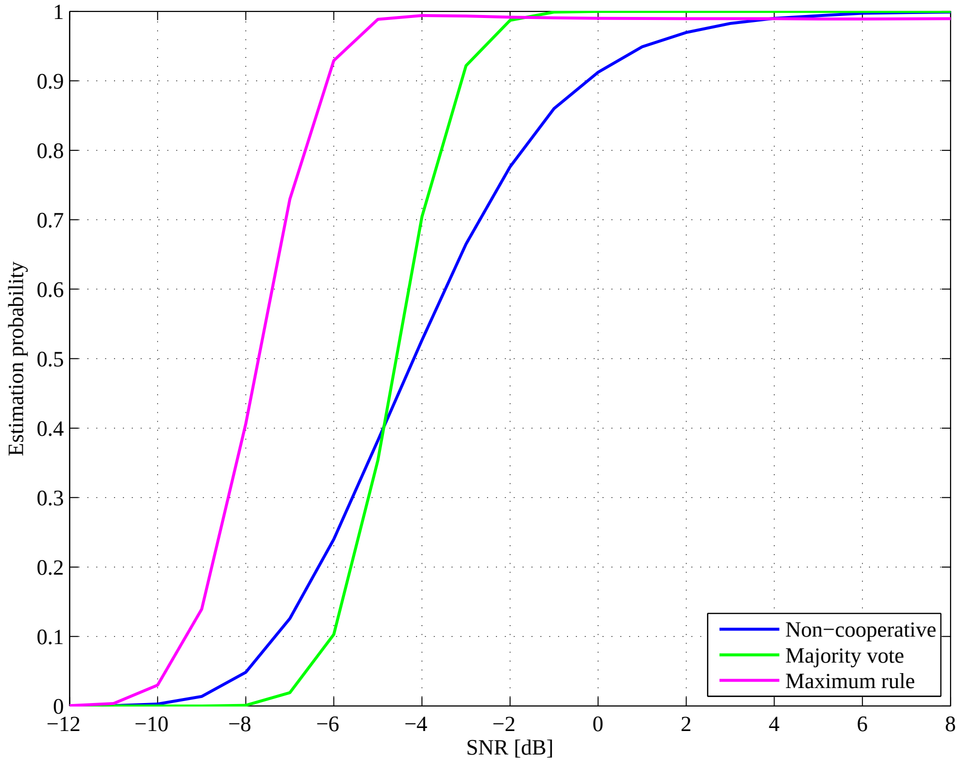

Figure 2.3: Estimation probabilities for the source number estimation in cooperative operation with $N = 5$ SU antennas, $M = 3$ PU streams and $L = 250$ samples.

2.4 Numerical results

In this section, we provide some numerical simulation results to verify the validity and the performance of our proposed decision fusion method. The performance of the proposed fusion rule was compared to the majority voting fusion, which is usually employed for similar problems. The system parameters considered for the simulations were $K = 10$ SU terminals each equipped with $N = 5$ antennas. For the PU, spatial multiplexing with $M = 3$ independent data streams were assumed. For computing the sample covariance matrix (2.3), each of the SUs used $L = 250$ samples. In addition, the SNR was defined as $\frac{\alpha}{\sigma_z^2}$ for the simulations and the results were obtained as the average over 100 000 Monte Carlo simulations.

First, the estimation probabilities of the fusion rules were evaluated and the results can be found in Fig. 2.3. In addition to the cooperative estimation results, the error probability of a non-cooperative SU was included as a comparison. It can be seen that the majority voting fusion rule results in improved estimation probability when the estimation probability of a single terminal exceeds 0.5, as expected. However, at low SNR the proposed maximum fusion rule achieves even better performance than the majority vote, approximately by a 3 dB margin. At high SNR, the maximum fusion exhibits a slight performance degradation which is

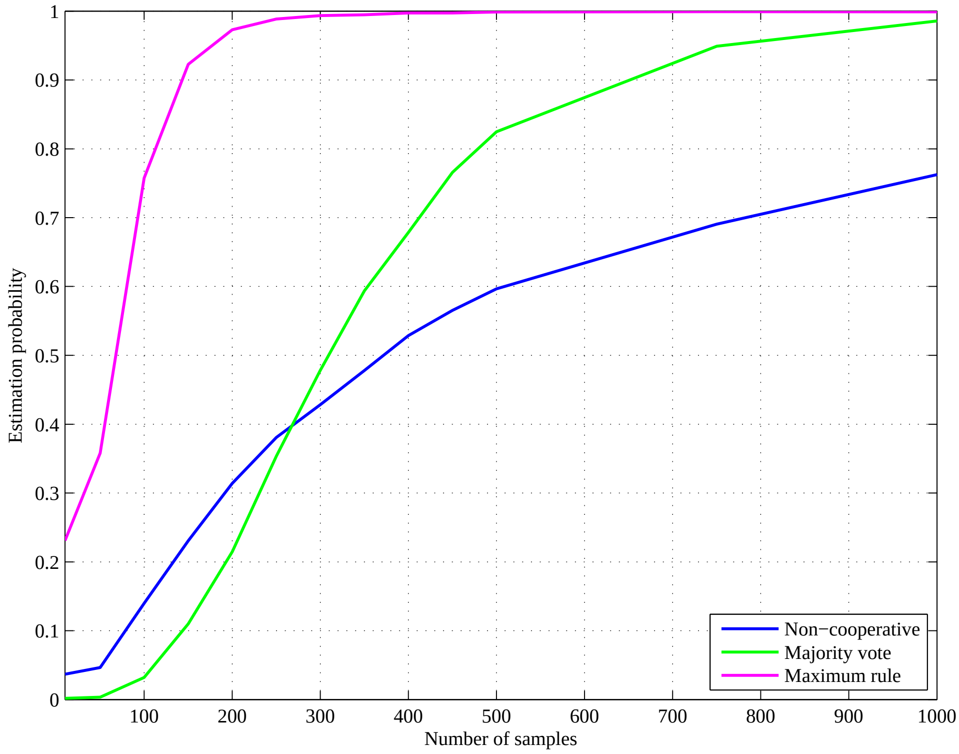

Figure 2.4: Estimation probabilities for the source number estimation in cooperative operation with $N = 5$ SU antennas, $M = 3$ PU streams at -5 dB SNR.

due to the fact the error events at high SNR are mostly due to the overestimation event, P_1.

Next, the estimation performance of the cooperative estimation methods was evaluated in terms of number of samples L used for estimating the sample covariance matrices. The result is shown in Fig. 2.4 where it can be confirmed that the non-cooperative operation as well as the cooperative methods with decision fusion benefit from increasing the number of observed samples. This due to the fact that the estimation performance of the MDL algorithm depends on both the SNR and the number of samples observed during the estimation. Increasing either one has the result of improving estimation accuracy. In addition, it can be seen that the cooperative estimation using the proposed maximum decision fusion rule benefits the most even with a very moderate increase in the number of samples. For example, at -5 dB to achieve estimation probability of approximately 0.7 only $L = 100$ samples are required, whereas the corresponding estimation performance with the majority voting rule requires more than $L = 400$ samples. This effect is due to the fact that the maximum fusion rule can operate at lower SNR as mentioned earlier.

Finally, the performance of the proposed maximum fusion rule was evaluated as a function of the number of SU terminals. In Fig. 2.5 it can be seen that at lower SNR of -8 dB, the performance increases almost linearly as the number of SU ter-

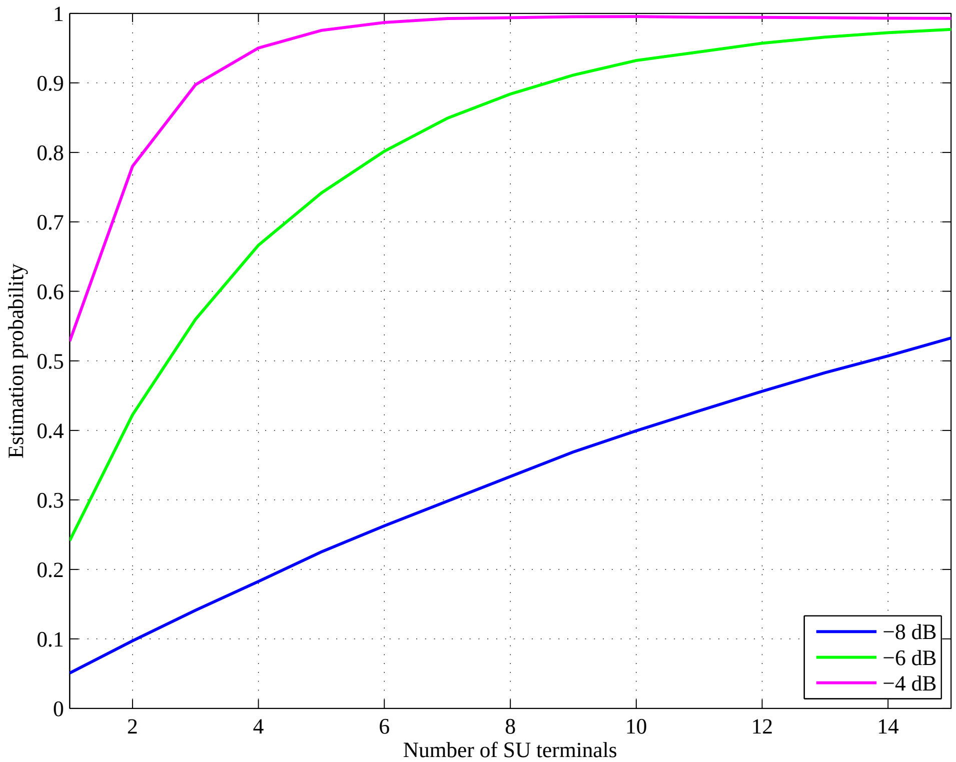

Figure 2.5: Estimation probabilities with maximum fusion rule in terms of the number of SUs each with $N = 5$ antennas, $M = 3$ PU streams and $L = 250$ samples.

minals increases because the probability that a correct estimate is found among the candidate estimates is low. At higher SNR levels where the estimation probability is higher, however, the increase in estimation probability grows significantly faster. For example, at -4 dB only $K = 8$ SU terminals are required for the maximum estimation probability.

2.5 Conclusion

Cognitive radio (CR) systems have been proposed as a promising solution to the spectrum scarcity problem due to their ability to opportunistically allocate unused spectrum resources for secondary transmissions. An important issue in CR-based spectrum sharing techniques is the problem of estimating the primary system parameters which are required for efficient operation while receiving no cooperation from the primary user (PU). In this paper, we considered a CR network where the secondary users (SUs) attempt to allocate unused spatial directions for secondary spectrum use. In order to do this while maximizing the secondary throughput and avoiding interference to the PU, it is necessary to determine the number of spatial streams transmitted by the PU. We considered cooperative stream number estimation to solve this problem where each SU in the secondary network first obtains independent estimates which are then combined into a final decision. We proposed a new decision fusion rule for this issue which takes into account and exploits the estimation bias of the minimum description length (MDL) algorithm. The benefits of the proposed method are improved estimation performance in the low signal-to-noise ratio (SNR) region and better protection for the PU in the case of an estimation error.

Chapter 3

Interference avoidance for spatial spectrum sharing with imperfect channel state information

In this chapter we propose a power control method for a multiple-input multiple-output (MIMO) based cognitive radio (CR) system with imperfect channel state information (CSI). In order to mitigate the interference caused by the channel estimation errors, we study the distribution of the channel estimation error and it effects on the SU's precoding matrix. We also analyze the statistics of the interference power resulting from the channel estimation. Based on empirically obtained error distributions, we provide an approximation for the error distribution which is used to obtain an analytical expression for the interference power distribution. With the interference power, it is possible to constrain the SU's transmit power in way that the resulting interference can be guaranteed to stay below the interference threshold with desired probability. Therefore, it is possible to improve the PU protection in the presence of channel estimation errors.

3.1 Introduction

In spectrum sharing, the secondary user (SU) attempts to transmit using the licensed frequency band reserved for to the primary user (PU). With MIMO-enabled SU terminals it is ideally possible to realize concurrent secondary and primary transmission without interfering with the primary system. However, to achieve completely interference free secondary transmission, perfect knowledge of the interference channel is required in order to orthogonalize the SU's transmit signals. Practical systems can not rely on this unrealistic assumption and they have to the estimate the required CSI. Furthermore, in CR systems the channel estimation is hampered by the fact that the PU can not be expected to provide any assistance and therefore, for example, conventional pilot-based channel estimation methods are out of the question.

Due to estimation errors, it is not possible to achieve perfectly orthogonal secondary transmission and, therefore, interference will be caused to the PU. In order to reduce the interference enough to provide sufficient PU protection, additional countermeasures must be considered. In practice, this means that the SU has to limit its transmit power so that the interference will remain below the allowed threshold. In the existing literature, some works have considered this issue already. In [63], the authors applied a bounded error model for the problem and provided a robust beamforming solution, however the problem of CSI estimation was not considered and it was assumed that the error bounds are available at the SU. In [61], the authors proposed a method to estimate the required CSI and also demonstrated that the average interference can be constrained by applying a first-order approximation for the perturbation due to the estimation error. Most of the related works attempt to protect the PU only by constraining the interference power, however, since the estimation error is a random process, it is more natural to define the protection constraint in terms of the probability of exceeding the threshold. This leads to a constraint that is reminiscent of outage probability. It also allows us to exert more control over the resulting interference, therefore enabling more flexible spectrum utilization.

In this chapter we will investigate the performance of a MIMO-based spectrum sharing system where only estimated CSI is available at the SU. Before engaging in transmission, the SU probes the channel during PU transmission and obtains the CSI by estimating it from the transmitted PU signals. For the estimation, we apply a similar technique as proposed in [61] where the null space of the interference channel is estimated from the sample covariance matrix. In order to mitigate the interference resulting from imperfect CSI, we propose a power control method which can provide desired PU protection in the presence of CSI errors. As opposed to previous works, we define the protection constraint in terms of the probability of exceeding the interference threshold. In order to satisfy the probabilistic protection constraint, we analyze the distribution of the CSI errors as well as the interference to obtain the density function for the interference from where the maximum allowable transmit powers can be solved.

The rest of the chapter is organized as follows. In Section 3.2, we describe the system model and define the protection constraint. Section 3.3 presents the existing techniques that we are using in this work. In Section 3.4, we provide analysis for the channel estimation errors as well as the interference power and formulate the proposed power control method. The validity of our analysis as well as the performance of the proposed method are evaluated by numerical simulations in Section

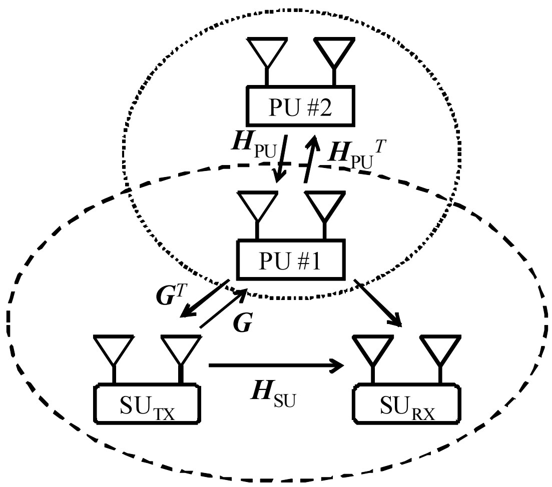

Figure 3.1: Cognitive radio network with two primary users and a secondary transmitter receiver pair.

3.5. Finally, the chapter is concluded in Section 3.6.

3.2 System model

The system model considered in this chapter is depicted in Fig. 3.1. Here the CR network consists of two PU transceivers, PU #1 and PU #2, and secondary transmitter-receiver pair. For the sake of simplicity, we assume that PU #2 is outside the covarage area of the SU transmitter so that we only need to cancel the interference towards PU #1. It is, however, trivial to extend the system model to consider multiple PU terminals within the SU coverage. Furthermore, we assume that the SU terminals are outside the coverage area of PU #2 so that we can focus on estimating the interference channel between the SU and PU #1. The coverage areas of the secondary and primary systems are represented in Fig. 3.1 by dashed and dotted lines, respectively.

The transmit and receive terminals are equipped with M and N transmit antennas, respectively, and the secondary transmission channel is denoted by $\boldsymbol{H}_{\text{SU}} \in \mathbb{C}^{N\times M}$. Correspondingly, the PU terminals have M_{PU} antennas each and the channel from PU #2 to PU #1 is denoted by $\boldsymbol{H}_{\text{SU}} \in \mathbb{C}^{M_{\text{PU}}\times M_{\text{PU}}}$. The interference channel from the SU transmitter to PU #1 is denoted by $\boldsymbol{G} \in \mathbb{C}^{M_{\text{PU}}\times M}$. The interference channel from PU #2 to the SU receiver is not explicitly modeled as the roles of the SU transmitter and receiver can be reversed due to the symmetrical situation. All the related channels are assumed to be reciprocal so that, for example, the channel from PU #1 to the SU transmitter can be expressed as $\boldsymbol{G}^T$. All the channels are assumed to be Rayleigh distributed with their elements following the distributions $\mathcal{CN}(0, \sigma_H^2)$ for the transmission channels $\boldsymbol{H}_{\text{PU}}$ and $\boldsymbol{H}_{\text{SU}}$, and $\mathcal{CN}(0, \sigma_G^2)$ for the interference channel $\boldsymbol{G}$.

Let us define a transmission frame consisting of T_{frame} symbols, during which the channel estimation and secondary transmission take place. We also assume a slow fading static scenario so that the channels can be considered to remain constant during a single transmission frame. The transmission frame can be furthermore divided into two parts. In the beginning of the frame there is a period when the SU attempts to estimate the interference channel. We denote the length of this estimation period by T_{est}. After obtaining the channel estimate, the SU can engage in secondary transmission while canceling the interference towards the PU for the remainder of the transmission frame. The SU transmission period is T_{trans} symbols and thus we have the relation $T_{\text{frame}} = T_{\text{est}} + T_{\text{trans}}$.

The goal of the SU is to design a capacity maxiziming transmit covariance matrix $\boldsymbol{S} = \boldsymbol{A}\boldsymbol{\Sigma}\boldsymbol{A}^H \in \mathbb{C}^{M\times M}$, where $\boldsymbol{A} \in \mathbb{C}^{M\times d}$ is the transmit precoding matrix for the SU and d denotes the number of spatial streams used, and $\boldsymbol{\Sigma} = \operatorname{diag}(\sigma_1^2, \ldots, \sigma_d^2) \in \mathbb{R}^{d\times d}$ is the power allocation matrix where σ_i^2 is the transmit power allocated for the ith stream. The capacity maximization is constrained by the maximum transmit power at the SU, P_{SU}, but in order to cancel the interference we also have to take into account the PU protection constraint. Instead of simply constraining the interference in terms of power, we wish to constraint the probability of the interference exceeding the threshold γ. By formulating the protection constraint this way, we attempt to achieve more realistic interference characterization and also be able to exert more control over the interference at the PU. Now, the capacity maximization problem can be defined as follows

$$\max_{\boldsymbol{C}} \quad \log_2 \det(\boldsymbol{I}_N + \boldsymbol{H}_{\text{SU}}\boldsymbol{C}\boldsymbol{H}_{\text{SU}}^H/\sigma_z^2) \tag{3.1}$$

$$\text{subject to} \quad \operatorname{Prob}(I_P \le \gamma) = 1 - P_{\text{out}} \tag{3.2}$$

$$\operatorname{trace}(\Sigma) \le P_{\text{SU}} \tag{3.3}$$

where (3.2) is the PU protection constraint, σ_z^2 is the noise power at the SU receiver, I_P is the interference power ath the PU and P_{out} is the desired probability at which the interference threshold is allowed to be exceeded, and (3.3) is the SU's transmit power constraint.

3.3 Spectrum sharing and channel estimation

In this section, we introduce the conventional methods that are considered in this work. First, in Section 3.3.1 we describe the orthogonal transmission method for the SU as well as the corresponding capacity achieving transmit covariance design. In Section 3.3.2, we explain the channel estimation method which can be used in order to obtain the required CSI for the interference cancellation.

3.3.1 Spectrum sharing with orthogonal transmission

In conventional spectrum sharing techniques, some form of CSI on the interference channel is required to be available at the SU. Methods that rely purely on power control require full CSI in order to evaluate the resulting interference at the CSI and methods that also employ null steering need the CSI to orthogonalize the SU transmit signals with the interference channel.

In [60], the authors presented various SS methods based on cognitive beamforming. One of them, termed as projected channel SVD (PSVD) enables secondary transmission over an orthogonal channel while completely negating the interference caused to the PU. In PSVD, only the basis of the complement space of the interference channel matrix $\boldsymbol{G}$ is required for the ortogonal transmission.

In PSVD, the secondary channel $\boldsymbol{H}_{\mathrm{SU}}$ is first projected onto the null space of the interference channel $\boldsymbol{G}$ in order to obtain projected channel as

$$\boldsymbol{H}_{\perp} = \boldsymbol{H}_{\mathrm{SU}} \left(\mathrm{null}\left(\boldsymbol{G}\right) \mathrm{null}\left(\boldsymbol{G}\right)^{H} \right), \tag{3.4}$$

where null$(\cdot)$ denotes the basis of the null space of its matrix argument, i.e., a matrix composed of a set of vectors that span the null space. Since it follows that $\boldsymbol{H}_{\perp}$ is orthogonal to the interference channel, the SU can transmit over the projected channel without interfering with the PU.

To maximize the SU capacity with PSVD, singular value decomposition based transmission (SVD) [68] over the projected channel is performed. That is, the SU obtains the precoding matrix from the SVD of the projected channel $\boldsymbol{H}_{\perp} = \boldsymbol{U}_{\perp}\boldsymbol{\Sigma}_{\perp}\boldsymbol{V}_{\perp}^{H}$ by setting $\boldsymbol{A} = [\boldsymbol{v}_{\perp 1} \dots \boldsymbol{v}_{\perp d}]$, where $\boldsymbol{v}_{\perp i},\ i = 1, \dots, d$ are the right singular vectors that correspond to the d largest singular values, and the power allocation matrix $\boldsymbol{\Sigma}$ can be obtained by performing waterfilling over $\boldsymbol{H}_{\perp}$ with respect to the transmit power constraint (3.3).

It should be noted that the PSVD-based secondary transmission is only possible when enough spatial degrees of freedom are available. In other words, the dimension of the null space of the interference channel should satisfy $\dim\left(\mathrm{null}\left(\boldsymbol{G}\right)\right) \geq 1$. In practice, this condition is satisfied for uncorrelated channels when $M > M_{\mathrm{PU}}$ which we assume holds for the rest of the chapter. This assumption increases the required processing costs at the SU but it is considered to be a reasonable cost in order to realize concurrent secondary transmission [62].

3.3.2 Interference channel estimation

For estimating the interference channel, the authors in [61] described a technique where the SU can obtain the partial CSI required to perform the orthogonal transmission from the covariance matrix of the signals observed during the primary transmission. In order to obtain the channel knowledge for the PSVD, i.e., $\mathrm{null}(\boldsymbol{G})$, the SU has to estimate it during the primary transmissions. Therefore, we define the signal received by the SU transmitter during the estimation period as

$$\boldsymbol{y}_{\mathrm{SU}}[n] = \begin{cases} \boldsymbol{G}^T \boldsymbol{x}_{\mathrm{PU}}[n] + \boldsymbol{z}_{\mathrm{SU}}[n] & n \in \mathcal{N} \\ \boldsymbol{z}_{\mathrm{SU}}[n] & \text{otherwise} \end{cases}, \qquad n = 0, \dots, T_{\mathrm{est}} - 1 \tag{3.5}$$

where $\boldsymbol{x}_{\mathrm{PU}}[n]$ denote the signals sent by PU #1 during the estimation period. The signals are assumed to be i.i.d. zero mean complex Gaussian with covariance matrix $\sigma_s^2 \boldsymbol{I}_{M_{\mathrm{PU}}}$. The noise vector at SU transmitter is denoted by $\boldsymbol{z}_{\mathrm{SU}}[n]$ and it is assumed to be complex Gaussian noise with the covariance matrix $\sigma_z^2 \boldsymbol{I}_M$. Moreover, the received SNR at the SU transmitter is defined as $\rho_{\mathrm{est}} = \frac{\sigma_s^2}{\sigma_z^2}$ and $\sigma_s^2 = \frac{P_1}{M_{\mathrm{PU}}}$ where P_1 is the transmit power of PU #1. The time instants of the estimation period during which PU #1 transmits a signal are denoted by $\mathcal{N} \subset \{n = 0, \dots, T_{\mathrm{est}} - 1\}$. Moreover, the portion of the estimation period that is occupied by PU #1 transmission is expressed as $\alpha = \frac{|\mathcal{N}|}{T_{\mathrm{est}}}$, where $|\mathcal{N}|$ denotes the cardinality of $\mathcal{N}$. When $n \ni \mathcal{N}$, PU #1 is assumed to be in the receiver mode, or equivalently, neither one of the PUs is transmitting. In this work, we focus on the case where $\alpha = 1$. Similar system has been considered, for example, in [62].

The covariance matrix of the signal received at the SU transmitter during the estimation period can now be expressed as

$$\boldsymbol{R}_{yy} = \mathcal{E}\left\{\boldsymbol{y}_{\mathrm{SU}}[n]\boldsymbol{y}_{\mathrm{SU}}^H[n]\right\} = \alpha\sigma_s^2 \boldsymbol{G}^T \boldsymbol{G}^* + \sigma_z^2 \boldsymbol{I}_M \tag{3.6}$$

where $\mathcal{E}\{\cdot\}$ denotes mathematical expectation. The covariance matrix $\boldsymbol{R}_{yy}$ shares the null space with $\boldsymbol{G}$ [69] which was required to obtain the orthogonal channel projection in (3.4). Therefore, by estimating $\boldsymbol{R}_{yy}$ by using the sample covariance matrix of the received signal vector (3.5) we can also obtain an estimate for the null space of $\boldsymbol{G}$. The sample covariance matrix was shown in [70] to be the maximum likelihood estimate of $\boldsymbol{R}_{yy}$ and it can be expressed as

$$\hat{\boldsymbol{R}}_{yy} = \frac{1}{T_{\mathrm{est}}} \sum_{n=0}^{T_{\mathrm{est}}-1} \boldsymbol{y}_{\mathrm{SU}}[n]\boldsymbol{y}_{\mathrm{SU}}^H[n]. \tag{3.7}$$

The estimate for $\text{null}\,(\boldsymbol{G})$ can now be obtained from the eigenvalue decomposition of sample covariance matrix

$$\hat{\boldsymbol{R}}_{yy} = \boldsymbol{V}_R \boldsymbol{\Sigma}_R \boldsymbol{V}_R^H \tag{3.8}$$

by finding the eigenvectors in $\boldsymbol{V}_R^*$ that correspond to the $M - M_{\text{PU}}$ smallest eigenvalues. It is assumed that the SU has knowledge about M_{PU} which in practice can be estimated from the sample covariance matrix $\hat{\boldsymbol{R}}_{yy}$ [65].

3.4 Interference analysis

In this section, we first provide the analysis required by the problem and then present our proposed power control method. In Section 3.4.1 the interference power statistics are derived. Section 3.4.2 discusses how the precoding matrix error is modelled in this work. Finally, in Section 3.4.3 we propose a power control method for the SU to limit the interference under channel estimation error.

3.4.1 Interference power analysis

The average interference power due to the secondary transmission at the first PU terminal can be expressed as

$$\bar{I}_P = \mathcal{E}\left\{\|\boldsymbol{G}\tilde{\boldsymbol{A}}\boldsymbol{\Sigma}^{1/2}\boldsymbol{x}_{\text{SU}}[n]\|^2\right\}, n = T_{\text{est}}, \ldots, T_{\text{frame}} - 1, \tag{3.9}$$

where $\tilde{\boldsymbol{A}} = \boldsymbol{A} + \Delta\boldsymbol{A}$ is the erroneous precoding matrix and $\Delta\boldsymbol{A}$ is the error term, $\boldsymbol{x}_{\text{SU}}[n] = (x_1[n], \ldots, x_M[n])^T \in \mathbb{C}^M$ is the symbol vector transmitted by the SU at time instant n and $\boldsymbol{\Sigma}^{1/2} = \text{diag}\,(\sigma_1 \ \ldots \ \sigma_d)$. The covariance matrix of the transmit vector before precoding and power allocation is $\mathcal{E}\left\{\boldsymbol{x}_{\text{SU}}[n]\boldsymbol{x}_{\text{SU}}^H[n]\right\} = \boldsymbol{I}_M$, so (3.9) can be approximated by

$$\begin{aligned} \bar{I}_P &\approx \text{trace}\left(\boldsymbol{G}\tilde{\boldsymbol{A}}\boldsymbol{\Sigma}\tilde{\boldsymbol{A}}^H\boldsymbol{G}^H\right) && (3.10)\\ &= \text{trace}\left(\boldsymbol{G}\Delta\boldsymbol{A}\boldsymbol{\Sigma}\Delta\boldsymbol{A}^H\boldsymbol{G}^H\right) && (3.11)\\ &= \text{trace}\left(\boldsymbol{\Sigma}\Delta\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{A}\right) && (3.12) \end{aligned}$$

where (3.11) follows from the fact that $\boldsymbol{G}$ and $\boldsymbol{A}$ are orthogonal, and (3.12) follows from the cyclic property of the matrix trace. Due to the matrix trace it suffices to only consider the diagonal elements of the matrix argument in (3.12) which can also be expressed as

$$\left(\boldsymbol{\Sigma}\Delta\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{A}\right)_{ii} = \sigma_i^2\Delta\boldsymbol{a}_i^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{a}_i,\ i = 1, \ldots, d \tag{3.13}$$

where $\Delta\boldsymbol{a}_i$ denotes the ith column of the matrix $\Delta\boldsymbol{A}$.

For given precoding matrix error $\Delta\boldsymbol{A}$, we can now obtain the distribution of (3.13) over all realizations of $\boldsymbol{G}$. It can be seen that the matrix product $\boldsymbol{G}^H\boldsymbol{G} \sim \mathcal{CW}_M\left(M_{\mathrm{PU}}, \sigma_G^2\boldsymbol{I}_M\right)$. From [71] we have the following result for Wishart matrices: if $\boldsymbol{W} \sim \mathcal{CW}_m\left(n, \boldsymbol{R}\right)$ and $\boldsymbol{B} \in \mathbb{C}^{k\times m}$ with rank k, then $\boldsymbol{B}\boldsymbol{W}\boldsymbol{B}^H \sim \mathcal{CW}_k\left(n, \boldsymbol{B}\boldsymbol{R}\boldsymbol{B}^H\right)$. Therefore we have $\Delta\boldsymbol{a}_i^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{a}_i \sim \mathcal{CW}_1\left(M_{\mathrm{PU}}, \sigma_G^2\|\Delta\boldsymbol{a}_i\|^2\right)$ which reduces to a Gamma distributed scalar. Thus, the diagonal elements of $\Delta\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{A}$ are distributed as

$$\left(\Delta\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{A}\right)_{ii} \sim \Gamma\left(M_{\mathrm{PU}}, \sigma_G^2\|\Delta\boldsymbol{a}_i\|^2\right), \qquad i = 1, \ldots, d \tag{3.14}$$

and due to the scaling property of the Gamma distribution it follows that

$$\left(\boldsymbol{\Sigma}\Delta\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\Delta\boldsymbol{A}\right)_{ii} \sim \Gamma\left(M_{\mathrm{PU}}, \sigma_i^2\sigma_G^2\|\Delta\boldsymbol{a}_i\|^2\right), \qquad i = 1, \ldots, d. \tag{3.15}$$

Therefore, as the composite interference power (3.12) is a sum of d random variables each of which is distributed according to (3.15), its probability density function can be expressed as a d-fold convolution of Gamma density functions

$$f_{\overline{I}}(x) = (f_1(x) * \ldots * f_d(x))(x), \tag{3.16}$$

where

$$f_i(x; m, \lambda_i) = \frac{1}{\Gamma(m)\lambda_i^m}x^{m-1}e^{-\frac{x}{\lambda_i}}, \qquad x > 0;\ m, \lambda_i \geq 0;\ i = 1, \ldots, d \tag{3.17}$$

and $m = M_{\mathrm{PU}}$ and $\lambda_i = \sigma_i^2\sigma_G^2\|\Delta\boldsymbol{a}_1\|^2$.

3.4.2 Precoding matrix error

As mentioned earlier in Section 3.3.2, the SU obtains the required CSI by using the sample covariance matrix in (3.7). As the SU only has a limited number of samples available for the estimation combined with the fact that the observed vectors are corrupted with noise, the SU can only obtain an erroneous estimate for the null space of the interference channel. The SU then computes the precoding matrix according to Section 3.3.1 using the estimated CSI, which results in a precoding matrix that is not completely orthogonal to the interference channel $\boldsymbol{G}$. As shown in the previous section, in addition to the SU's transmit power, the interference power observed at the PU depends on the random estimation error through the precoding matrix.

$$
\begin{aligned}
f_i(x|\alpha,\beta,m,k,\theta_i) =& \int_0^\infty f_i(x|m,\lambda) g_i(\lambda|\alpha,\beta,k,\theta_i) d\lambda \\
=& \int_0^\infty \frac{1}{\Gamma(m)\lambda^m} x^{m-1} e^{-\frac{x}{\lambda}} \frac{1}{2\Gamma(k)\theta_i^k} (\alpha\beta)^{-\frac{1}{2}k} \lambda^{\frac{1}{2}k-1} e^{-\frac{\sqrt{\lambda}}{\theta_i\sqrt{\alpha\beta}}} d\lambda \\
=& \frac{(\alpha\beta)^{-\frac{1}{2}k} x^{m-1}}{2\Gamma(m)\Gamma(k)\theta_i^k} \int_0^\infty \lambda^{\frac{1}{2}k-m-1} e^{-\left(\frac{x}{\lambda}+\frac{\sqrt{\lambda}}{\theta_i\sqrt{\alpha\beta}}\right)} d\lambda, \\
& \geq 0; m,k,\theta_i,\alpha,\beta > 0
\end{aligned} \tag{3.19}
$$

Although the error in the precoding matrix depends on the parameters ρ_{est} and T_{est} during the estimation period, it is essentially a random process due to the observation noise and the transmitted symbol sequences. The exact distribution of the error is unfortunately difficult to obtain because of the non-linear transformations required for the computation of the precoding matrix. Therefore, we have empirically obtained the first-order statistics of the precoding matrix error by simulating the estimation process for various values ρ_{est} and T_{est}. The corresponding error vector magnitudes were then obtained as the averages, $\overline{\|\Delta \boldsymbol{a}_i\|}$, over 10 000 Monte Carlo iterations. In the following we assume that these empirically obtained values are available at the SU in order to perform the interference compensation.

As can be seen from (3.15), the distribution of the interference power depends on the magnitudes of the precoding matrix error vectors $\|\Delta \boldsymbol{a}_i\|$. In fact, the estimated precoding vectors $\tilde{\boldsymbol{a}}_i$ consist of a component that lies in the space spanned by the true precoding vectors $\boldsymbol{a}_i$ and a component that lies in the corresponding complement space. In our case it suffices to only consider the latter as the former will not contribute to the interference power due to orthogonality. Therefore, we can obtain the error component by projecting the erroneuos precoding matrix onto the complement space of the true precoding matrix as $\Delta \boldsymbol{A} = (\boldsymbol{I}_M - \boldsymbol{A}\boldsymbol{A}^H)\tilde{\boldsymbol{A}}$. The numerical results for the distribution of $\|\Delta \boldsymbol{a}_1\|$ can be seen in Fig. 3.2, where the cumulative distribution function is shown for various T_{est} and ρ_{est} pairs. The simulations were performed for $M = 4$ and $M_{\text{PU}} = 3$ and empirical cumulative distribution was obtained by simulating the estimation process for 10 000 trials.

In order to take the randomness of precoding matrix error into account, we need to approximate the probability density function of $\|\Delta \boldsymbol{a}_i\|$. It was observed that the Gamma distribution with parameters $k = M$ and $\theta_i = \frac{\overline{\|\boldsymbol{a}_i\|}}{M}$ provides a decent approximation. The rationale for the parameters of the approximation is the fact that $\boldsymbol{a}_i \in \mathbb{C}^M$ and the length of a random vector can be expressed in terms of Gamma distribution with the mean of $\mu = k\theta_i$. The approximated distributions are also plotted in Fig. 3.2. It can be seen that when the estimation SNR is high, the approximation is quite good for both $T_{\text{est}} = 50$ and $T_{\text{est}} = 500$. On the other hand,

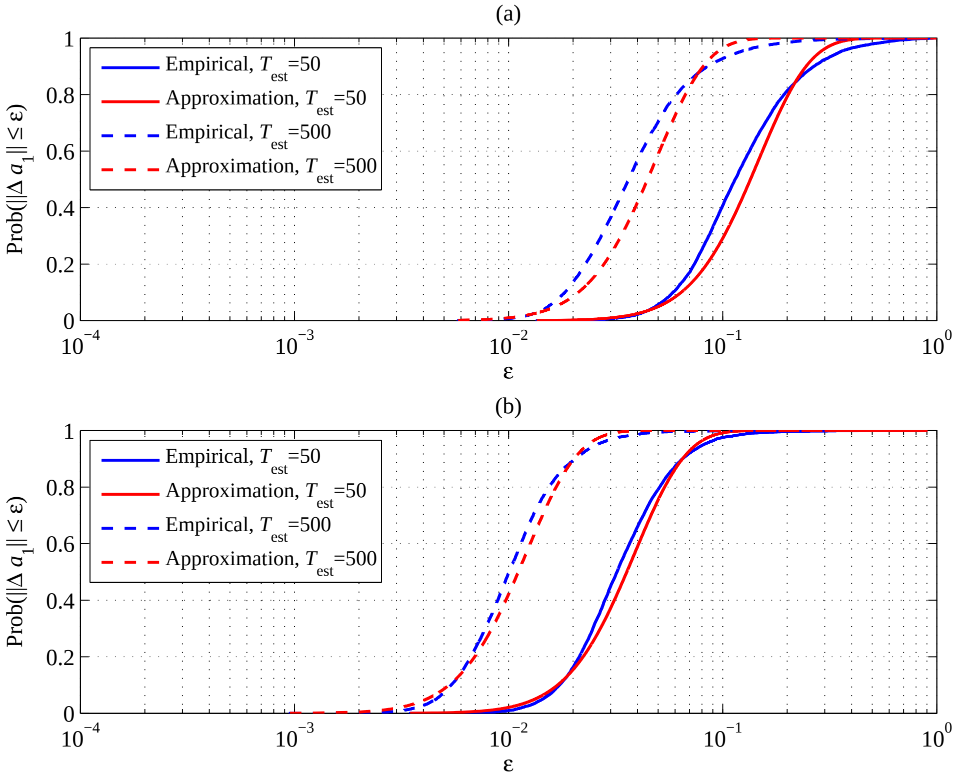

Figure 3.2: Empirical cumulative distribution function of $\|\Delta \boldsymbol{a}_1\|$ and the corresponding approximation for $M = 4$ and $M_{\mathrm{PU}} = 3$ with (a) $\rho_{\mathrm{est}} = 10$ dB and (b) $\rho_{\mathrm{est}} = 20$ dB.

with lower estimation SNR the mismatch becomes larger and some accuracy is lost for both simulated estimation period lengths.

Because the scale parameters λ_i in (3.17) depend on the estimation error, we would like to obtain the corresponding compound distribution where the error distribution is taken into account. Therefore, we must first derive the probability density function for λ_i. Recall from earlier that the distribution of $\|\Delta \boldsymbol{a}_i\|$ can be approximated as $\Gamma(k, \theta_i)$, where $k = M$ and $\theta_i = \frac{\|\Delta \boldsymbol{a}_i\|}{M}$. It follows that the distribution of λ_i can now be obtained by transforming the Gamma distribution. Let us redefine $\lambda_i = \alpha\beta X^2$, where $X \sim \Gamma(k, \theta_i)$ and we can obtain the density function $g_i(\lambda)$ for λ_i as

$$\begin{aligned} g_i(\lambda; \alpha, \beta, k, \theta_i) =& \frac{1}{2\Gamma(k)\theta_i^k} (\alpha\beta)^{-\frac{1}{2}k} \lambda^{\frac{1}{2}k-1} e^{-\frac{\sqrt{\lambda}}{\theta_i \sqrt{\alpha\beta}}} \\ & \lambda \geq 0; \alpha, \beta, k, \theta_i > 0. \end{aligned} \tag{3.18}$$

We can now obtain the compound density function for $f_i(x|\alpha, \beta, m, k, \theta_i)$ as (3.19) where the distribution parameters are $m = M_{\mathrm{PU}}$, $k = M$, $\theta_i = \frac{\|\Delta \boldsymbol{a}_i\|}{M}$, $\alpha = \sigma_i^2$ and $\beta = \sigma_G^2$. Finally, the probability density function of the total interference power observed at the PU can be obtained using (3.16) with $f_i(x)$ given by (3.19).

3.4.3 Proposed power control method

The drawback of the density function (3.19) is that it does not admit a simple closed form. The issue is further complicated when more than one spatial stream is used for the secondary transmission, i.e., $d \geq 2$ because of the d-fold convolution required for the composite distribution (3.16). Therefore we propose a sub-optimal, search-based method for obtaining the maximum allowable transmit power allocations for the SU that guarantee that the SU satisfies the PU protection constraint (3.2) and the transmit power constraint (3.3). An iterative search method for finding the maximal power allocations is proposed as follows:

1. Find the optimal $\boldsymbol{\Sigma}$ with respect to the maximum transmit power constraint. This can obtained by performing waterfilling over $\boldsymbol{H}_{\perp}$.

2. With the obtained transmit powers σ_i^2, numerically evaluate the integral $\text{Prob}(\bar{I}_P \leq \gamma) = \int_0^{\gamma} f_{\bar{I}_P}(x)dx$, the verify whether the solution satisfies the interference power constraint (up to desired precision) or not.

3. If the interference power constraint is not satisfied, decrease the maximum transmit power constraint P_{SU} and return to step 1; otherwise, end the search.

While the search method is computationally very intensive as it requires repeated numerical integration, it should be noted that when $d = 1$, online computation of the maximum allowable transmit power is not required as it does not depend on the instantaneous channel $\boldsymbol{H}_{\text{SU}}$. Therefore, the maximum transmit powers can computed beforehand and the SU can select the one corresponding to ρ_{est} and T_{est}.

3.5 Numerical results

In this section, we present numerical simulation results to show how the interference power constraint improves the protection of the PU in the presence of estimation error. For the simulations, we considered an SU with $M = N = 4$ antennas and PUs with $M_{\text{PU}} = 3$ antennas and, thus, $d = 1$ transmit streams for the secondary transmission. For each simulated transmission frame, channel matrices $\boldsymbol{H}_{\text{PU}}$, $\boldsymbol{H}_{\text{SU}}$ and $\boldsymbol{G}$ were randomly generated from the standard Rayleigh fading distribution. The estimation period was then simulated by having the SU transmitter to observe T_{est} signal vectors transmitted by the first PU over the reverse interference channel $\boldsymbol{G}^H$. Based on the received signal vectors, the SU then performed channel estimation and constructed the precoding matrix as well as obtained the power allocations. The power allocations were computed using a search based on the bisection method with

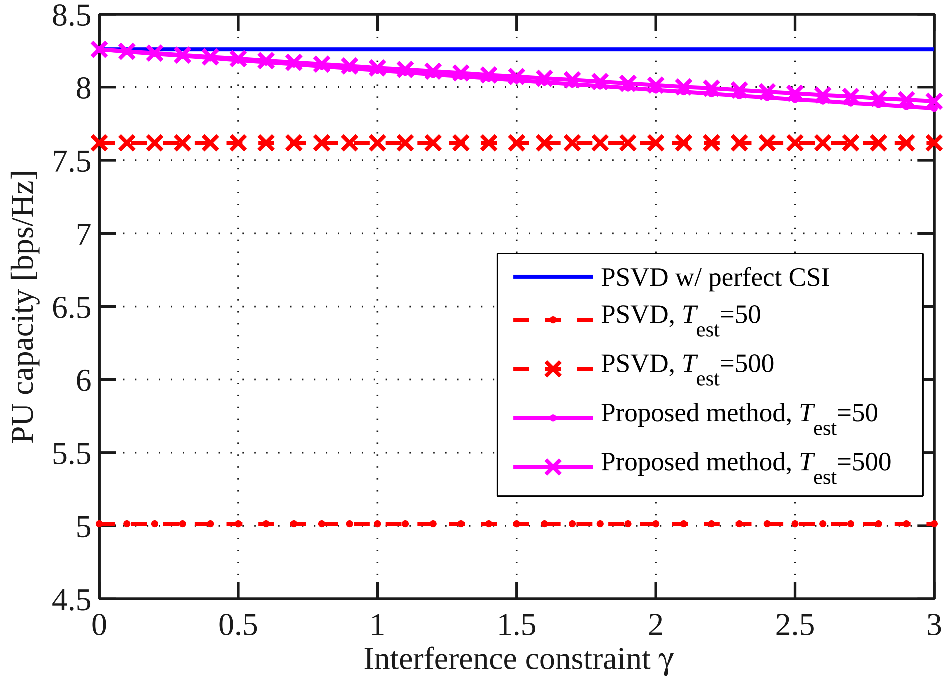

Figure 3.3: Capacity of the primary transmission at 10 dB as a function of γ with target probability $P_{\text{out}} = 0.01$.

the stopping criterion of 10^{-4}, i.e., the power allocations satisfy $\text{Prob}(\overline{I}_P \leq \gamma) \geq 1 - (P_{\text{out}} + 10^{-4})$. The interference power at the PU was then computed according to (3.9) using the obtained transmit covariance matrix.

First we demonstrate the performance of the system from the PU's point of view. Interference channel estimation was simulated and based on the estimate, the SU then computes the precoding matrix as described in Section 3.4.3. The resulting interference power was computed and the channel capacity for primary transmission was computed by taking the interference from the SU into account. The capacity of the primary channel $\boldsymbol{H}_{\text{PU}}$ with interference was computed as

$$C_{\text{PU}} = \log_2 \det \left(\boldsymbol{I}_{M_{\text{PU}}} + \frac{\rho_{\text{PU}}}{M_{\text{PU}}} \boldsymbol{H}_{\text{PU}} \boldsymbol{H}_{\text{PU}}^H \right) \tag{3.19}$$

where $\rho_{\text{PU}} = \frac{P_2}{I_P + \sigma_z^2}$ denotes the received signal to noise and interference ratio at PU #1 and P_2 is the transmit power of PU #2. Here we have assumed that PU #2 transmits with equal power allocation for simplicity. The transmit power was fixed to $P_2 = 10$ and the received SNR at PU #1 was fixed to $\frac{P_2}{\sigma_z^2} = 10$ dB. For the SU, the maximum transmit power was set to $P_{\text{SU}} = 100$ and the target probability for the interference constraint was set to $P_{\text{out}} = 0.01$. In addition, for the interference distribution (3.19), we used empirical values of $\overline{\|\Delta \boldsymbol{a}_1\|}$ obtained according to Section 3.4.2 which are assumed to be available a priori to the SU. The parameters used

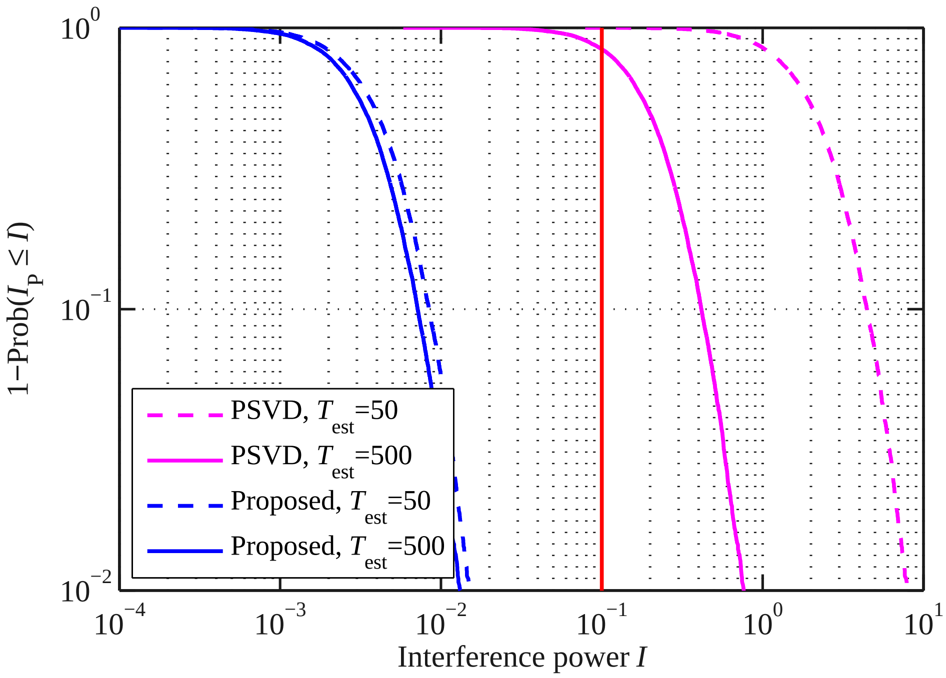

Figure 3.4: Probability of satisfying the interference constraint $\gamma = 0.1$ at $\rho_{\text{est}} = 10$ dB with target probability $P_{\text{out}} = 0.01$.

for the estimation period were $\rho_{\text{est}} = 10$ dB and $T_{\text{est}} = \{50, 500\}$ symbols. The simulation was performed by generating 10 000 channel realizations and the average PU capacity was obtained. We have evaluated the performance of our proposed method with varying γ and compared it to the PSVD which uses the estimated CSI without compensation for the estimation error and the results can be seen in Fig. 3.3.

For the conventional PSVD, the amount of capacity loss depends on the magnitude of the precoding matrix error and therefore on the estimation parameters ρ_{est} and T_{est}. It can be seen that for short estimation period such as $T_{\text{est}} = 50$, a significant capacity loss is observed at the PU whereas for $T_{\text{est}} = 500$ it will be considerably smaller. For the proposed method, however, the capacity loss at the PU can be made arbitrarily small regardless of T_{est} by adjusting the interference threshold γ. However, when $\gamma \to 0$, it eventually results in no secondary transmission due to the limiting of the SU's transmit power.

In addition to the PU capacity, the probability of the interference power satisfying the threshold γ was evaluated and the result can be found in Fig. 3.4 where the complement probability of satisfying the interference power constraint is shown for $\rho_{\text{est}} = 10$ dB. It can be seen that for the simulated T_{est}, proposed method can satisfy interference threshold $\gamma = 0.1$ with probability $P_{\text{out}} \leq 0.01$ as required. In fact, there is even some overcompensation which is due to the fact we have approximated the precoding error distribution. If one could obtain the exact distribution for the precoding error, it would be possible to allocate even more transmit power for the SU while satisfying the constraint, therefore leading to increased SU capacity. As a comparison, it can be noted that PSVD without the interference constraint can not satisfy the interference constraint even when $T_{\text{est}} = 500$ at $\rho_{\text{est}} = 10$ dB resulting in reduced PU capacity. In fact, it is always possible for PSVD to satisfy the protection constraint given large enough T_{est} for given ρ_{est} but the proposed method can satisfy it regardless of the estimation period length.

3.6 Conclusion

In this chapter, we have considered a SS technique for MIMO-based CR networks. It was shown that the existing SS techniques fail to sufficiently protect the PU terminals when only estimates of the CSI is available. In order to reduce the harmful interference towards the PU, a method for compensating the effects of the imperfect CSI by regulating the SU's transmit power was proposed. In our work, we considered a practical scenario where the SU obtains the necessary CSI by estimating the interference channel. We then obtained a statistical model for the estimation error and by considering the error statistics, derived the distribution for the interference power. Based on the interference statistics, we set a probabilistic interference power constraint and in order to satisfy it, proposed a search-based method for obtaining the maximum allowable transmit power. The validity of our model and the performance of the proposed method were verified by analysis and computer simulations and it was shown that it is possible to negate the effects of the channel estimation error in terms of interference power. The drawback of the proposed method is that limiting the SU's maximum transmit power will also reduce the maximum achievable capacity for the secondary transmission, however this is unavoidable when we want to improve the primary user protection using transmit power control.

Chapter 4

Joint interference avoidance for spatial spectrum sharing

In order to achieve efficient spectrum utilization, it is possible to employ beamforming based spectrum sharing methods in multiantenna equipped cognitive radio systems. To realize this in a manner that will only result in tolerable amount of interference for the primary users, the secondary users must be able to accurately allocate the transmissions in the available signal space. In this chapter, we study the issue of avoiding interference to the primary users when the secondary users incorrectly allocate too many spatial streams for the secondary transmissions. We provide analysis for the interference power statistics in the case of error in order to satisfy the interference constraint in terms of primary user outage probability. We also show that protecting the primary user from the stream allocation errors, we can at the same time take into account the possible channel estimation errors. We take advantage of the moment matching method to obtain an approximated expression for the interference power that is tractable for practical analysis. Furthermore, we provide a method that can find the maximum allowable transmit power for the secondary user which can satisfy the interference constraint.

4.1 Introduction

Cognitive radio (CR) techniques have attracted significant amount of interest in the recent years as a possible solution to the impending spectrum scarcity problem. Especially interesting are the methods that employ multiantenna techniques such as beamforming to spatially interleave the secondary transmissions so that interference to the primary user (PU) can be avoided. Ideally, when the secondary system (SU) is equipped with multiple transmit antennas, it is possible to transmit concurrently with the PU while negating all interference that would otherwise be caused to the PU.

In practical systems, however, there are two important sources that can result in harmful interference. First is the use of imperfect channel state information (CSI) and the second one is when the SU incorrectly allocates too many streams for the secondary transmission. While the former is a major issue and it has been studied in the literature, the latter has not been studied deeply.

In this chapter, we investigate the issue of avoiding interference in CR network with incorrect allocation of secondary transmit streams. We carry out analysis of the interference power statistics so that it is possible to satisfy an outage-based protection constraint by regulating the transmit power at the SU terminal. We take advantage of moment matching technique to obtain tractable expression for the interference power distribution. We also provide a method that can obtain the maximum allowable transmit power for SU which can guarantee the desired outage probability for the primary system.

The rest of chapter is organized as follows. In Section 4.2 we present the system model considered herein. In Section 4.3, we analyze the interference power in the case of stream allocation error and describe the method which can be used to obtain the maximum transmit power. The method is verified by numerical simulations in 4.4, and in Section 4.5 we conclude this chapter.

4.2 System model

We consider a system model where the SU attempts to access spectrum reserved for the primary system. The SU consists of a transmitter-receiver pair and both terminals are equipped with M_{SU} antennas. The PU has a single terminal with M_{PU} antennas and it is assumed to operate in receiving mode. We denote the interference channel between the SU transmitter and the PU receiver by $\boldsymbol{G} \in \mathbb{C}^{M_{\mathrm{PU}} \times M_{\mathrm{SU}}}$ and the secondary transmission channel by $\boldsymbol{H} \in \mathbb{C}^{M_{\mathrm{SU}} \times M_{\mathrm{SU}}}$.

Under the CR principle, the SU is allowed to access the reserved spectrum as long as it will not cause harmful interference to the PU. In multiple-input multiple-output (MIMO) based spectrum sharing, this can be realized by having the SU map its signal onto the null space of $\boldsymbol{G}$. Note that for concurrent transmissions $M_{\mathrm{SU}} > M_{\mathrm{PU}}$ is required so that the dimension of the available signal space is larger than zero. In practice, the SU has to estimate the null space of the interference channel before engaging transmission. For reciprocal channel, this can be done by having the SU probe the channel while the PU is transmitting and compute the covariance matrix of the PU signal. Then, the null space of the interference channel can be obtained as the eigenvectors of the covariance matrix that correspond to the noise subspace. The dimension of the null space dictates the number of spatial streams that can support orthogonal secondary transmission. In order to maximize the capacity of the secondary transmission, the goal is to use all of the available streams which is equal to $d = M_{\text{SU}} - M_{\text{PU}}$.

In order to orthogonalize the secondary transmit signals with the interference channel, the SU has to design a beamforming matrix $\boldsymbol{A}$ that satisfies $\boldsymbol{GA} = 0$. The beamforming matrix can be further decomposed into $\boldsymbol{A} = \boldsymbol{G}_0\boldsymbol{B}$ where $\boldsymbol{G}_0$ is the basis of the null space of $\boldsymbol{G}$, and in this case, the optimal beamforming matrix $\boldsymbol{A}$ can be obtained by finding $\boldsymbol{B}$ using singular value decomposition based precoder design for the auxiliary channel $\boldsymbol{HG}_0$ and the transmit power allocations can be correspondingly obtained with waterfilling [61].

In a CR system where the PU parameters are not known at the SU and no cooperation is provided by the primary system, the SU has to estimate d to determine the available spatial transmit resources. This can be done by estimating the number of PU transmit streams during the channel learning. Because the SU does not have perfect knowledge of d, it is possible that an erroneous estimate will result in interference towards the PU. If the SU underestimates the null space dimension, i.e. $\hat{d} < d$, the secondary transmission will not use all the available spatial dimensions. While this results in suboptimal capacity for the SU, it will not cause any interference to the PU. However, in the case $\hat{d} > d$ the SU's transmit space will overlap with primary signal space and this will cause significant amount of interference.

In the optimal case where the SU knows d, the beamforming matrix is obtained as a product of $\boldsymbol{G}_0$ and the right singular vectors of the matrix $\boldsymbol{HG}_0 \in \mathbb{C}^{M_{\text{SU}} \times d}$. When the signal space dimension is overestimated, additional column vectors are chosen to be included in $\boldsymbol{G}_0$ which has the effect of increasing the rank of the auxiliary channel used for the precoder design. Furthermore, this completely changes the corresponding singular vectors as well as the resulting beamforming matrix and thus will cause interference to the PU.

In this chapter, we study the effects of the stream allocation error in the case $\hat{d} > d$ and the resulting interference. We attempt to limit the interference so that a desired quality of service can be guaranteed for the PU. Therefore, we define a protection constraint that the SU must satisfy in order for the secondary transmission to be allowed. This is done in terms of outage probability, i.e., we want to constrain the probability of the interference power exceeding a predefined interference threshold. Therefore, our protection constraint is expressed as

$$\text{Prob}(I_P \le \gamma) = 1 - P_{\text{out}} \tag{4.1}$$

where I_P denotes the interference power, γ is the interference threshold, and P_{out} is the desired outage probability

4.3 Interference with stream allocation error

After the channel learning, the SU has obtained an estimate for the available transmit streams, $\hat{d}$, and the corresponding beamforming matrix $\boldsymbol{A} \in \mathbb{C}^{M_{\mathrm{SU}} \times \hat{d}}$. Now, the interference power at the PU due to the secondary transmission can be expressed as

$$I_P = \mathcal{E}\{\|\boldsymbol{G}\boldsymbol{A}\boldsymbol{x}_{\mathrm{SU}}[n]\|_2^2\} = \mathcal{E}\{\mathrm{trace}(\boldsymbol{G}\boldsymbol{A}\boldsymbol{x}_{\mathrm{SU}}[n]\boldsymbol{x}_{\mathrm{SU}}^H[n]\boldsymbol{A}^H\boldsymbol{G}^H)\}. \tag{4.2}$$

Here we assume block fading scenario where the channel is considered constant during a single transmission frame. For the transmitted secondary signals we have $\mathcal{E}\{\|\boldsymbol{x}_{\mathrm{SU}}\|_2^2\} = \boldsymbol{\Sigma}$, where $\boldsymbol{\Sigma} = \mathrm{diag}(\sigma_1^2 \ldots \sigma_{\hat{d}}^2)$ and $\mathrm{trace}(\boldsymbol{\Sigma}) = P_{\mathrm{t}}$, where σ_i^2 denote the transmit power allocated for the ith stream and P_{t} is the transmit power constraint. Therefore, the average interference during the SU transmission can be rewritten as

$$I_P = \mathrm{trace}(\boldsymbol{\Sigma}\boldsymbol{A}^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{A}). \tag{4.3}$$

In order to satisfy the protection constraint (4.1), the distribution of I_P is required. Looking at (4.3) it can be seen that the product $\boldsymbol{G}^H\boldsymbol{G}$ is Wishart matrix with the distribution $\mathcal{W}_{M_{\mathrm{SU}}}(M_{\mathrm{SU}}, \boldsymbol{I}_{M_{\mathrm{PU}}})$. Due to the matrix trace, I_P can also be written as a sum

$$I_P = \sigma_1^2\boldsymbol{a}_1^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{a}_1 + \ldots + \boldsymbol{a}_{\hat{d}}^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{a}_{\hat{d}} \tag{4.4}$$

where $\boldsymbol{a}_i$ is the ith column vector of the beamforming matrix. From the property of Wishart matrices it follows that $\boldsymbol{a}_i^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{a}_i$ follow the Gamma distribution as $\Gamma(M_{\mathrm{PU}}, \boldsymbol{a}_i^H\boldsymbol{a}_i = 1)$ and due to the scaling property of the Gamma distribution we also have $\sigma_i^2\boldsymbol{a}_i^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{a}_i \sim \Gamma(M_{\mathrm{PU}}, \sigma_i^2)$. Therefore the interference power can be viewed as a sum of $\hat{d}$ Gamma distributed random variables. It should be noted that by setting $\boldsymbol{a}_i^H\boldsymbol{a}_i = 1$ we at the same time protect the PU from the possible errors in the precoding matrix that are caused by the channel estimation errors, calibration errors, delayed channel state information, and so forth. This is due to the fact that that for a unit-length precoding vector, if a part of it would lie in the orthogonal complement space of $\boldsymbol{G}$, the component that would lie in the space spanned by $\boldsymbol{G}$ would be less than one, and therefore also $\boldsymbol{a}_i^H\boldsymbol{a}_i < 1$.

While exact expressions are available for a sum of Gamma distributed variables [72], they are usually expressed as infinite sums or in terms of hypergeometric functions and thus are not tractable for practical analysis. This issue can be circumvented by approximating the distribution with another Gamma distribution by matching its moments to the sum of the corresponding moments of the coefficients [73]. If we denote the r.v. used to approximate I_P by $X \approx \sum_{i=1}^{\hat{d}} \sigma_i^2\boldsymbol{a}_i^H\boldsymbol{G}^H\boldsymbol{G}\boldsymbol{a}_i$, then for the two first moments of X we have

$$\mu_X = \sum_{i=1}^{\hat{d}} M_{\mathrm{PU}} \sigma_i^2 = M_{\mathrm{PU}} \sum_{i=1}^{\hat{d}} \sigma_i^2 = M_{\mathrm{PU}} P_{\mathrm{t}} \tag{4.5}$$

and

$$\sigma_X^2 = \sum_{i=1}^{\hat{d}} M_{\mathrm{PU}} (\sigma_i^2)^2 = M_{\mathrm{PU}} \sum_{i=1}^{\hat{d}} (\sigma_i^2)^2 \tag{4.6}$$

which follows from the fact that the two first moments of a r.v. having the distribution $\Gamma(k, \theta)$ are $k\theta$ and $k\theta^2$, respectively. Furthermore, we get the distribution for the approximation as $\Gamma(k_X = \frac{\mu_X^2}{\sigma_X^2}, \theta_X = \frac{\sigma_X^2}{\mu_X})$. The validity of the approximation can be seen in Fig. 4.1, where it is compared with empirical distribution obtained for fixed $\boldsymbol{A}$ and $\boldsymbol{\Sigma}$ over 10 000 realizations of $\boldsymbol{G}$ with $M_{\mathrm{SU}} = 5$, $M_{\mathrm{PU}} = 3$, and $\hat{d} = 3$.

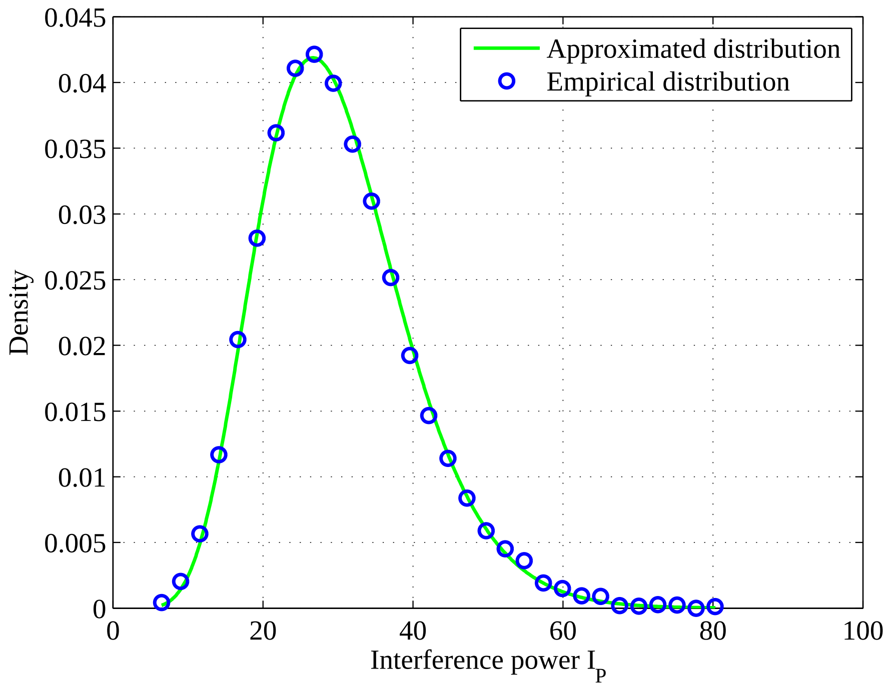

Figure 4.1: Interference power distribution with $M_{\mathrm{SU}} = 5$, $M_{\mathrm{PU}} = 3$, and $\hat{d} = 3$.

In order to determine the maximum transmit power P_{t} that the SU can allocate for the secondary transmission while satisfying the protection constraint, we need the cumulative distribution function for X which is

$$F_X(x; k_X, \theta_X) = \frac{1}{\Gamma(k_X)} \int_0^{\frac{x}{\theta_X}} t^{k_X - 1} e^{-t} dt. \tag{4.7}$$

To satisfy the protection constraint (4.1) for given interference threshold γ we get

$$\mathrm{Prob}(X \leq \gamma) = F_X(\gamma) = \frac{1}{\Gamma(k)} \int^{\frac{\gamma}{\theta_X}} t^{k_X - 1} e^{-t} dt = 1 - P_{\mathrm{out}} \tag{4.8}$$

from where we can solve for P_{t} by finding the upper limit $x_0 = \frac{\gamma}{\theta_X}$ for the integral which results the in integrand being equal to $1 - P_{\mathrm{out}}$.

Consider the shape and scale parameters for the approximated distribution

$$k_X = \frac{\mu_X^2}{\sigma_X^2} = \frac{(M_{\mathrm{PU}} P_{\mathrm{t}})^2}{M_{\mathrm{PU}} \sum_{i=1}^{\hat{d}} (\sigma^2)^2} = \frac{M_{\mathrm{PU}} P_{\mathrm{t}}^2}{\sum_{i=1}^{\hat{d}} (\sigma_i^2)^2} \tag{4.9}$$

and

$$\theta_X = \frac{M_{\mathrm{PU}} \sum_{i=1}^{\hat{d}} (\sigma_i^2)^2}{M_{\mathrm{PU}} P_{\mathrm{t}}} = \frac{\sum_{i=1}^{\hat{d}} (\sigma_i^2)^2}{P_{\mathrm{t}}}. \tag{4.10}$$

We can notice two issues that further complicate the problem of solving for maximal P_{t}. First, both parameters depend on the M_{PU} for which only an incorrect estimate (in the case of stream allocation error) is available at the SU. In addition, the parameters also depend on the power allocations for the individual streams which in turn depend on P_{t}. In practice, the SU can instead use the value M_{SU} which is a worst case approximation of M_{PU}. While this serves as a safeguard against the interference towards the PU, it will result in suboptimal SU capacity. However, let us ignore this issue for now so that we can attempt to evaluate the theoretically achievable maximum transmit power. For the second issue, we can consider two different cases. The term $\sum_{i=1}^{\hat{d}} (\sigma_i^2)^2$ achieves its maximum P_{t}^2 when all the transmit power is allocated for a single stream which in practice occurs when P_{t} is relatively small compared to the singular values of the auxiliary channel $\boldsymbol{HG}_0$. On the other hand, the sum achieves its minimum $\frac{P_{\mathrm{t}}^2}{\hat{d}}$ when equal powers are allocated for each stream. It is intuitive that when higher transmit power P_{t} is used, more interference will be caused to the PU. Therefore, the single stream power allocation can also be used as a worst case approximation. However, we will also evaluate the maximum transmit powers for the uniform power allocation which can be useful for the cases where the SU does not have CSI at the transmitter. Now, the resulting shape and scale parameters for the interference power distribution are $k_X^{\max} = M_{\mathrm{PU}}$ and $\theta_X^{\max} = P_{\mathrm{t}}$ for the single stream power allocation, and $k_X^{\min} = M_{\mathrm{PU}} \hat{d}$ and $\theta_X^{\min} = \frac{P_{\mathrm{t}}}{\hat{d}}$ for the uniform power allocation. In both cases, only the scale parameter θ_X depends on P_{t} so after finding x_0 that satisfies (4.8) we can solve the maximum transmit power as $P_{\mathrm{t}} = \frac{\gamma}{x_0}$ and $P_{\mathrm{t}} = \frac{\gamma \hat{d}}{x_0}$ for the single stream and uniform power allocation cases, respectively.

4.4 Simulation results

We have evaluated the maximum achievable transmit powers for $M_{\text{SU}} = 5$ and $M_{\text{PU}} = 3$ antenna configuration. In this case, $d = 5 - 3 = 2$ and for the erroneous stream number we have used $\hat{d} = 3$. The maximum transmit powers were solved from (4.8) by using numerical integration and a bisection based search for x_0 with a stopping criterion of 10^{-6}, i.e., the interference power satisfies $|\,\text{Prob}(I_P \leq \gamma) - (1 - P_{\text{out}})| \leq 10^{-6}$. The results for the maximum transmit power can be seen in Fig. 4.2 where the achievable P_{t} is plotted as a function of the target outage probability for different values of the interference threshold γ.

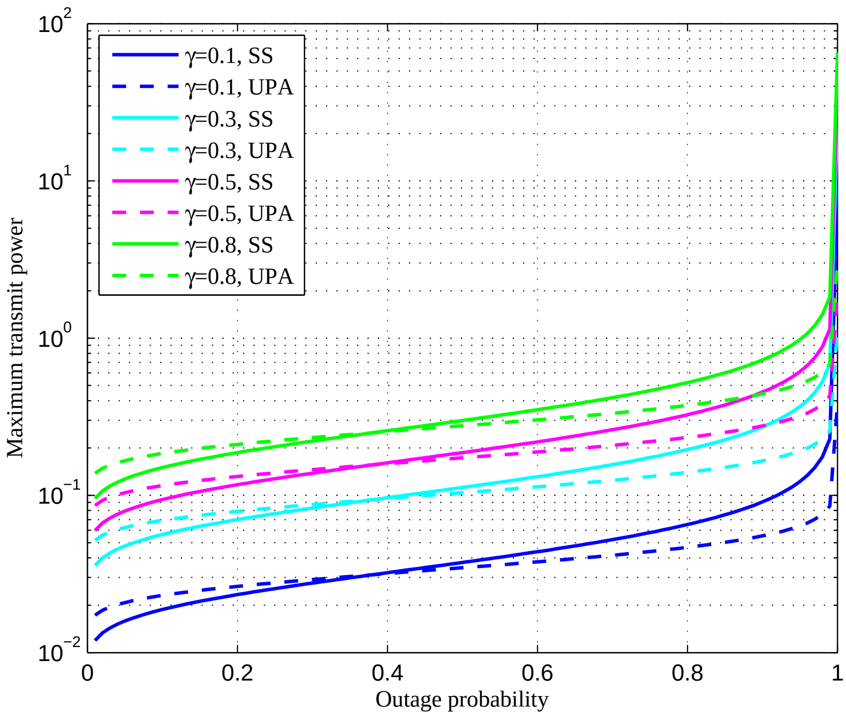

Figure 4.2: Maximum achievable transmit powers as function of outage probability for $M_{\text{SU}} = 5$, $M_{\text{PU}} = 3$ and $\hat{d} = 3$.

It can be seen that for small outage probabilities, the single stream power allocation results in smaller allowable transmit powers. On the other hand, with higher outage probabilities the single stream power allocation will result in higher transmit power than the uniform power allocation. This is due to the fact that the minimum and maximum approximations have different shape parameters for the interference power distribution and its effect is more pronounced at smaller probabilities.

While the results are somewhat discouraging as the resulting maximum transmit powers are fairly small, there are some additional considerations that should be taken into account for more practical transmit power control. First, the probability of erroneous stream allocation was not considered here. If the probability of SU correctly estimating the number of available streams is 0.9 for example, the protection constraint can be further relaxed to achieve the desired outage probability. Moreover, it has been shown that very high estimation probability for the number of streams can be achieved even at quite low signal-to-noise ratio (SNR) region [74]. In practice the low SNR scenario usually occurs when the PU is located far away from the SU terminal. Therefore in the SNR region where stream allocation errors are likely to occur, it would be possible to allocate more transmit power for the secondary transmission if we also take into account the path loss attenuation which was not considered here. The contribution of this chapter is to provide a framework for the interference power analysis and some preliminary results in terms of the achievable transmit power. Future work will include more realistic interference model as well as incorporation of the stream allocation error probabilities.

4.5 Conclusion

In this chapter, we have investigated the issue where a multiantenna enabled SU of a CR network incorrectly allocates more spatial streams for the secondary transmission than actually available. We have analyzed the interference power caused to the PU resulting from such scenario and obtained an approximation for the interference power distribution. This distribution can be used to obtain the maximum transmit power for the SU which can satisfy the PU protection constraint with desired probability. Our results show that while it is possible to protect the PU from the stream allocation error, it will cause severe degradation for the SU transmission capacity. Therefore, we can conclude that accurate estimation of the available spatial transmit resources is essential in MIMO-based spectrum sharing in order to achieve proper performance.

Chapter 5

Conclusions and future work

The aim of this thesis was to study methods for primary user protection in MIMO-based cognitive radio systems with channel estimation and spatial resource allocation errors. The investigation was motivated by the fact that in order to resolve the problem of spectrum scarcity, there is demand for dynamic spectrum access methods which can achieve efficient spectrum utilization. MIMO-based spectrum sharing methods enable the reuse of licensed spectrum by unlicensed secondary systems. In order to achieve coexistence, the secondary systems must ensure that no harmful interference will be caused to the primary system. However, the fact the secondary spectrum use must be done without cooperation from the primary users leads to the problem that the secondary system must estimate the primary system parameters, often by relying blind methods which can result in significant estimation errors. Therefore, it is important that the secondary system can somehow compensate the interference caused by these errors in order to access the licensed spectrum. In Chapter 1, a look into the problem background was provided and the preliminaries of dynamic spectrum access and cognitive radio techniques were presented with a review of the current state of developments.

Chapter 2 focused on the problem of estimating the estimation of available spatial degrees of freedom that can be used for the secondary transmission. A cooperative secondary network with decision fusion was considered. It was shown that with cooperative estimation, it is possible to improve the estimation accuracy by taking advantage of the increased spatial diversity. The estimation accuracy was further improved by employing a decision fusion rule which takes advantage of the estimation bias of the considered MDL estimation algorithm. The proposed decision fusion rule was also shown to be able to avoid the error event which results in the harmful interference to the primary user due to allocating too many spatial streams for the secondary transmission. While the work in Chapter 2 showed that it is possible to improve the estimation accuracy in the low signal-to-noise region, more elaborate system model should be considered in the future work. Instead of a heterogenous model where all the secondary users receive a signal with equal strength, distributing the secondary terminals within the cell at different distances from the primary terminal would provide more realistic scenario. Furthermore, taking into account the path loss attenuation will have implications on the distribution of the candidate estimates and therefore other decision fusion rules might be able to provide better estimation accuracy in different scenarios.

In Chapter 3 a spectrum sharing scenario with channel estimation errors was considered. As opposed to conventional interference temperature based methods, a probabilistic protection constraint was formulated where desired interference outage probability for the primary user can be guaranteed. While this method results in lower capacity for the secondary user due to stricter transmit power constraint, the primary user can be protected at all times with the desired probability. Furthermore, the proposed approach is tolerant to possible channel variations during the secondary transmission since the constraint is satisfied over all channel realizations. The difficulty in compensating for the estimation errors is due to the fact that the estimation errors propagate to the beamforming matrix via non-linear transformations such as singular value decomposition. While some results are available in the literature for the perturbation of singular vectors they can be difficult to apply to the problem at hand due to dependence on the relative gap between singular values. In Chapter 3, the errors were modeled as a random variables and the corresponding distributions were obtained by a somewhat crude approach based on first order statistics and empirical distributions. Investigating the distribution of the estimation error in more detail can lead to more accurate interference models. Especially, if it is possible to establish a dependence between the estimation parameters and the error distribution.

Chapter 4 dealt with the interference due to spatial resource allocation errors. By the means of interference analysis, it was shown that in order to protect the primary user from the stream allocation errors due to the inability of lower bounding the precoding matrix error, the proposed constraint is also tolerant to channel estimation errors. As in Chapter 3, a probabilistic protection constraint was considered in order to be able to exert more control over the resulting interference and therefore being able to enable more flexible spectrum utilization. The analysis of the interference power showed that optimal interference cancellation is not possible due to the dependence on the unknown parameters. However, the analysis revealed the achievable maximum transmission powers for the optimal case which provides some insight into the maximum achievable performance. In practical applications, one way to circumvent this problem is to use worst case approximations which however leads to sub-optimal capacity for the secondary users. While the results of the Chapter 4 provide preliminary results in terms of achievable capacity in the case of a stream allocation error, in future work the connection between the spatial resource estimation and primary user protection should be established. By considering the estimation error probalities in conjuction with the interference distribution, it is possible to achieve more relaxed protection constraint which allows higher transmit power for the secondary user while satisfying the protection constraint. Furthermore, the stream allocation errors are unlikely even at relatively low signal-to-noise ratio region. Therefore, a simple approach would be to consider an adaptive method which switches between the joint interference mitigation and the imperfect CSI method based on the received primary signal strength.

In this work, it was shown that it is possible to protect the primary user in the presence of estimation errors. By employing statistical models for the interference, it is possible to control the resulting interference and to provide required quality of service for the primary user based on the interference outage probability. While the methods provided here are not conclusive and they tend to result in suboptimal performance for the secondary user, they provide a framework for future research. By considering more realistic system models by taking into account the geographical location of the terminals, path loss attenuation due to distance, and possibly correlated channel models will result in more detailed interference power characterization, and therefore would demonstrate more practical performance bounds for spatial spectrum sharing based cognitive radio systems.

Appendix A

List of papers by author

A.1 Journal papers with review

1. Samuli Tiiro, Kenta Umebayashi and Yasuo Suzuki, "Study on MIMO-Based Spectrum Sharing With Stream Allocation and Channel Estimation Errors," IEICE Communications Express, review underway.

2. Samuli Tiiro, Kenta Umebayashi, Janne Lehtomäki and Yasuo Suzuki, "Spectrum Sharing in MIMO Cognitive Radio Systems With Imperfect Channel State Information," IEICE Transactions on Communications, Vol. E97-B, no. 4, April 2014, to be published.

3. Samuli Tiiro, Kenta Umebayashi, Janne Lehtomäki and Yasuo Suzuki, "Decision Fusion for Cooperative Source Number Estimation in Cognitive Radio Networks," IEICE Communications Express, Vol. 2, No. 11, November 2013.

A.2 International conferences

1. Samuli Tiiro, Kenta Umebayashi and Yasuo Suzuki, "Cooperative Source Number Estimation for Cognitive Radio Networks," Proceedings of International Conference on Information Networking (ICOIN 2014), Phuket, Thailand, 2014, to be published.

2. Samuli Tiiro, Kenta Umebayashi and Yasuo Suzuki, "Power Control Method for MIMO-Based Cognitive Radio With Imperfect Channel State Information," Proceedings of IEEE Wireless Communications and Networking Conference (WCNC 2013), Shanghai, China, April 2013.

A.3 Technical reports

1. Samuli Tiiro, Kenta Umebayashi and Yasuo Suzuki, "Study on Spatial Spectrum Sharing With Imperfect Channel State Information," IEICE Technical Report, Vol. 113, No. 57, Hiroshima, Japan, May 2013.

2. Samuli Tiiro, Kenta Umebayashi and Yasuo Suzuki, "A Study on MIMO-Based Spectrum Sharing," IEICE Technical Report, Vol. 112, No. 153, Yakushima, Japan, July 2012.

Acknowledgements

First of all, I would like to express my gratitude to my thesis supervisor Professor Yasuo Suzuki for accepting me to join Suzuki laboratory as a doctoral student. Furthermore, I would like to thank him for his guidance and for all the advice I have received during my stay. I am also forever grateful for my advisor Professor Kenta Umebayashi who helped me to pursue postgraduate studies in Japan. I would also like to thank Professor Umebayashi for his guidance during my doctoral studies. It has been an honor and pleasure to study in Suzuki laboratory.

I owe my gratitude also to the rest of the members of the evaluation committee, Professor Takuji Arima, Professor Toshihisa Tanaka and Professor Toru Uno for reviewing my dissertation. I also appreciate the comments I received during my final defense which helped greatly improve this work.

I also want to thank all the members of Suzuki laboratory who I have met during my stay. Some of you have already graduated and moved on, some of you have just joined the laboratory as new students. It has been a lot of fun to study alongside you. I want to especially mention Dr. Masashi Tsuji who sacrificed a lot of his own time to help me get familiar with Japanese lifestyle as well as support me with my studies. I also want to thank Mr. Ryota Takagi for assisting me with various paper work on several occasions. I am grateful to Mr. Takagi and Mr. Tokihito Watanabe who helped me to prepare for my final defense.

Last but not least, I want to thank my family for their support from overseas, you have been an invaluable asset during my studies.

Bibliography

[1] J. Maxwell, "A dynamical theory of the electromagnetic field," *Philosophical Transactions of the Royal Society of London*, vol. 155, pp. 459–512, 1865.

[2] R. W. Lucky, "The precious radio spectrum," *IEEE Spectr.*, vol. 38, no. 9, pp. 90–90, Sep. 2001.

[3] FCC, "Report of the spectrum efficiency working group," Federal Communications Commission (FCC) Spectrum Policy Task Force, Report, Nov. 2002. [Online]. Available: http://transition.fcc.gov/sptf/reports.html

[4] J. A. Hoffmeyer, "Regulatory and standardization aspects of DSA technologies - global requirements and perspective," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE Internation Symposium on*, Nov. 2005, pp. 700–705.

[5] R. Ercole, "Innovation, spectrum regulation, and DySPAN technologies access to markets," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN. 2005 First IEEE International Symposium on*, Nov. 2005, pp. 494–511.

[6] C. Ting, S. Wildman, and J. Bauer, "Government policy and the comparative merits of alternative governance regimes for wireless services," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 IEEE International Symposium on*, Nov. 2005, pp. 401–419.

[7] N. Jesuale, "Overvief of state and local government interests in spectrum policy issues," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov. 2005, pp. 476–485.

[8] A. Gad and F. Digham, "Impact of DSA on current regulatory regimes," in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, Oct. 2008, pp. 1–6.

[9] M. J. Marcus, “Cognitive radio under conservative regulatory environments: lessons learned and near term options,” in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, Apr. 2010, pp. 1–5.

[10] H. Karimi, M. Fenton, G. Lapierre, and E. Fournier, “European harmonized technical conditions and band plans for broadband wireless access in the 790-862 MHz digital dividend spectrum,” in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, Apr. 2010, pp. 1–9.

[11] M. Cooper, “The economics of collaborative production in the spectrum commons,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. First IEEE International Symposium on*, Nov. 2005, pp. 379–400.

[12] C. Jackson, “Dynamic sharing of radio spectrum: a brief history,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov. 2005, pp. 445–466.

[13] Q. Zhao and B. Sadler, “A survey of dynamic spectrum access,” *IEEE Signal Process. Mag.*, vol. 24, no. 3, pp. 79–89, May 2007.

[14] D. Hatfield and P. Weiser, “Property rights in spectrum: taking the next step,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov. 2005, pp. 43–45.

[15] P. Leaves, K. Moessner, R. Tafazolli, D. Grandblaise, D. Bourse, R. Tönjes, and M. Breveglieri, “Dynamic spectrum allocation in composite reconfigurable wireless networks,” *IEEE Commun. Mag.*, vol. 42, no. 5, pp. 72–81, May 2004.

[16] W. Lehr and J. Crowcroft, “Managing shared access to a spectrum commons,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 420–444.

[17] A. Goldsmith, S. Jafar, I. Maric, and S. Srinivasa, “Breaking spectrum gridlock with cognitive radios: An information theoretic perspective,” *Proceedings of the IEEE*, vol. 97, no. 5, pp. 894–914, May 2009.

[18] S. Ball and A. Ferguson, “Consumer applications of cognitive radio defined networks,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 518–525.

[19] J. Stine, “Spectrum management: the killer application of ad hoc and mesh networking,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 184–193.

[20] P. Pawelczak, R. Venkatesha Prasad, L. Xia, and I. G. M. M. Niemegeers, "Cognitive radio emergency networks - requirements and design," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 601–606.

[21] A. Gorcin and H. Arslan, "Public safety and emergency case communications: Opportunities from the aspect of cognitive radio," in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, Oct 2008, pp. 1–10.

[22] J. Mitola, "Software radios-survey, critical evaluation and future directions," in *Telesystems Conference, 1992. NTC-92., National*, May 1992, pp. 13/15–13/23.

[23] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Pers. Commun.*, vol. 6, pp. 13–18, 1999.

[24] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey," *Computer Networks*, vol. 50, no. 13, pp. 2127 – 2159, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128606001009

[25] M. Buddhikot, P. Kolodzy, S. Miller, K. Ryan, and J. Evans, "DIMSUMnet: new directions in wireless networking using coordinated dynamic spectrum," in *World of Wireless Mobile and Multimedia Networks, 2005. WoWMoM 2005. Sixth IEEE International Symposium on a*, June 2005, pp. 78–85.

[26] O. Ileri, D. Samardzija, and N. Mandayam, "Demand responsive pricing and competitive spectrum allocation via a spectrum server," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 194–202.

[27] S. A. (Reza) Zekavat and X. Li, "User-central wireless system: ultimate dynamic channel allocation," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 82–87.

[28] M. J. Marcus, "CR: Cooperative radio or confrontational radio," in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, April 2007, pp. 208–211.

[29] O. Sallent, J. Perez-Romero, R. Agusti, and P. Cordier, "Cognitive pilot channel enabling spectrum awareness," in *Communications Workshops, 2009. ICC Workshops 2009. IEEE International Conference on*, June 2009, pp. 1–6.

[30] J. Perez-Romero, O. Sallent, R. Agusti, and L. Giupponi, “A novel on-demand cognitive pilot channel enabling dynamic spectrum allocation,” in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, April 2007, pp. 46–54.

[31] M. Filo, A. Hossain, A. Biswas, and R. Piesiewicz, “Cognitive pilot channel: Enabler for radio systems coexistence,” in *Cognitive Radio and Advanced Spectrum Management, 2009. CogART 2009. Second International Workshop on*, May 2009, pp. 17–23.

[32] S. Mishra, A. Sahai, and R. Brodersen, “Cooperative sensing among cognitive radios,” in *Communications, 2006. ICC ’06. IEEE International Conference on*, vol. 4, June 2006, pp. 1658–1663.

[33] A. Ghasemi and E. Sousa, “Collaborative spectrum sensing for opportunistic access in fading environments,” in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 131–136.

[34] G. Ganesan and Y. Li, “Cooperative spectrum sensing in cognitive radio, part I: Two user networks,” *Wireless Communications, IEEE Transactions on*, vol. 6, no. 6, pp. 2204–2213, June 2007.

[35] ——, “Cooperative spectrum sensing in cognitive radio, part II: Multiuser networks,” *Wireless Communications, IEEE Transactions on*, vol. 6, no. 6, pp. 2214–2222, June 2007.

[36] C. Cormio and K. R. Chowdhury, “A survey on MAC protocols for cognitive radio networks,” *Ad Hoc Netw.*, vol. 7, no. 7, pp. 1315–1329, Sep. 2009. [Online]. Available: http://dx.doi.org/10.1016/j.adhoc.2009.01.002

[37] Y. Zeng, Y.-C. Liang, Z. Lei, S. W. Oh, F. Chin, and S. Sun, “Worldwide regulatory and standardization activities on cognitive radio,” in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, April 2010, pp. 1–9.

[38] R. Venkatesha Prasad, P. Pawelczak, J. Hoffmeyer, and H. Berger, “Cognitive functionality in next generation wireless networks: standardization efforts,” *Communications Magazine, IEEE*, vol. 46, no. 4, pp. 72–78, April 2008.

[39] M. Sherman, A. Mody, R. Martinez, C. Rodriguez, and R. Reddy, “IEEE standards supporting cognitive radio and networks, dynamic spectrum access, and coexistence,” *Communications Magazine, IEEE*, vol. 46, no. 7, pp. 72–79, July 2008.

[40] C. Cordeiro, K. Challapali, D. Birru, and N. Sai Shankar, "IEEE 802.22: the first worldwide wireless standard based on cognitive radios," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 328–337.

[41] C. Stevenson, G. Chouinard, Z. Lei, W. Hu, S. Shellhammer, and W. Caldwell, "IEEE 802.22: The first cognitive radio wireless regional area network standard," *Communications Magazine, IEEE*, vol. 47, no. 1, pp. 130–138, January 2009.

[42] C. Cordeiro, K. Challapali, and M. Ghosh, "Cognitive PHY and MAC layers for dynamic spectrum access and sharing of TV bands," in *Proceedings of the First International Workshop on Technology and Policy for Accessing Spectrum*, ser. TAPAS '06. New York, NY, USA: ACM, 2006. [Online]. Available: http://doi.acm.org/10.1145/1234388.1234391

[43] K. Challapali, C. Cordeiro, and D. Birru, "Evolution of spectrum-agile cognitive radios: First wireless internet standard and beyond," in *Proceedings of the 2Nd Annual International Workshop on Wireless Internet*, ser. WICON '06. New York, NY, USA: ACM, 2006. [Online]. Available: http://doi.acm.org/10.1145/1234161.1234188

[44] M. Nekovee, "Quantifying the availability of TV white spaces for cognitive radio operation in the UK," in *Communications Workshops, 2009. ICC Workshops 2009. IEEE International Conference on*, June 2009, pp. 1–5.

[45] S. Deb, V. Srinivasan, and R. Maheshwari, "Dynamic spectrum access in DTV whitespaces: Design rules, architecture and algorithms," in *Proceedings of the 15th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '09. New York, NY, USA: ACM, 2009, pp. 1–12. [Online]. Available: http://doi.acm.org/10.1145/1614320.1614322

[46] P. Piggin and K. Stanwood, "Standardizing WiMAX solutions for coexistence in the 3.65 GHz band," in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, Oct 2008, pp. 1–7.

[47] ITU, "Software defined radio in IMT-2000, the future development of imt-2000 and systems beyond imt-2000," International Telecommunication Union, Technical Report ITU-R M.2063, 2005.

[48] ——, "Software-defined radio in the land mobile service," International Telecommunication Union, Technical Report ITU-R M.2064, 2005.

[49] ETSI, "Reconfigurable radio systems (RSS); summary of feasibility studies and potential standardization topics," European Telecommunications Standards Institute, Technical Report ETSI TR 102 838 v1.1.1, Oct. 2009.

[50] J. Wang, M.-S. Song, S. Santhiveeran, K. Lim, G. Ko, K. Kim, S.-H. Hwang, M. Ghosh, V. Gaddam, and K. Challapali, "First cognitive radio networking standard for personal/portable devices in TV white spaces," in *New Frontiers in Dynamic Spectrum, 2010 IEEE Symposium on*, April 2010, pp. 1–12.

[51] S. Seidel and R. Breinig, "Autonomous dynamic spectrum access system behavior and performance," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 180–183.

[52] H. Harada, "Software defined radio prototype toward cognitive radio communication systems," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 539–547.

[53] Y. Yuan, P. Bahl, R. Chandra, P. Chou, J. Ferrell, T. Moscibroda, S. Narlanka, and Y. Wu, "KNOWS: Cognitive radio networks over white spaces," in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, April 2007, pp. 416–427.

[54] R. Ahuja, R. Corke, and A. Bok, "Cognitive radio system using IEEE 802.11a over UHF TVWS," in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, Oct 2008, pp. 1–9.

[55] H. Harada, "A feasibility study on software defined cognitive radio equipment," in *New Frontiers in Dynamic Spectrum Access Networks, 2008. DySPAN 2008. 3rd IEEE Symposium on*, Oct 2008, pp. 1–12.

[56] R. DeGroot, D. Gurney, K. Hutchinson, M. Johnson, S. Kuffner, A. Schooler, S. Silk, and E. Visotsky, "A cognitive-enabled experimental system," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, Nov 2005, pp. 556–561.

[57] F. Seelig, "A description of the august 2006 XG demonstrations at Fort A.P. Hill," in *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on*, April 2007, pp. 1–12.

[58] M. McHenry, E. Livsics, T. Nguyen, and N. Majumdar, "XG dynamic spectrum access field test results [topics in radio communications]," *Communications Magazine, IEEE*, vol. 45, no. 6, pp. 51–57, June 2007.

[59] A. J. Paulraj, D. A. Gore, R. U. Nabar, and H. Bölcskei, “An overview of MIMO communications - a key to gigabit wireless,” *Proc. IEEE*, vol. 92, pp. 198–218, Feb. 2004.

[60] R. Zhang and Y.-C. Liang, “Exploiting multi-antennas for opportunistic spectrum sharing in cognitive radio networks,” *IEEE J. Sel. Topics Signal Process.*, vol. 2, pp. 88–102, Feb. 2008.

[61] R. Zhang, F. Gao, and Y.-C. Liang, “Cognitive beamforming made practical: Effective interference channel and learning-throughput tradeoff,” *IEEE Trans. Commun.*, vol. 58, pp. 706–718, Feb. 2010.

[62] F. Gao, R. Zhang, Y.-C. Liang, and X. Wang, “Design of learning-based MIMO cognitive radio systems,” *IEEE Trans. Veh. Technol.*, vol. 59, pp. 1707–1720, May 2010.

[63] G. Zheng, K.-K. Wong, and B. Ottersten, “Robust cognitive beamforming with bounded channel uncertainties,” *IEEE Trans. Signal Process.*, vol. 57, pp. 4871–4881, Dec. 2009.

[64] R. Zhang, Y. C. Liang, and S. Cui, “Dynamic resource allocation in cognitive radio networks,” *IEEE Signal Process. Mag.*, vol. 27, pp. 102–114, May 2010.

[65] M. Wax and T. Kailath, “Detection of signals by information theoretic criteria,” *IEEE Trans. Acoust., Speech, Signal Process.*, vol. 33, pp. 387–392, Apr. 1985.

[66] U. G. Mangai, S. Samanta, S. Das, and P. R. Chowdhury, “A survey of decision fusion and feature fusion strategies for pattern classification,” *IETE Technical Review*, vol. 27, pp. 293–307, Jun. 2010.

[67] W. Xu and M. Kaveh, “Analysis of the performance and sensitivity of eigendecomposition-based detectors,” *IEEE Trans. Signal Process.*, vol. 43, pp. 1413–1426, Jun. 1995.

[68] I. E. Telatar, “Capacity of multi-antenna gaussian channels,” Bell Laboratories, Lucent Technologies, Technical Memorandum, Oct. 1995. [Online]. Available: http://mars.bell-labs.com/papers/proof/

[69] G. Strang, *Linear Algebra and Its Applications.* USA: Brooks/Cole Publishing Company, 1988.

[70] T. J. Lim, R. Zhang, Y. C. Liang, and Y. Zeng, “GLRT-based spectrum sensing for cognitive radio,” in *Proc. IEEE Global Commun. Conf. (Globecom)*, New Orleans, LO, Nov./Dec. 2008.

[71] R. J. Muirhead, *Aspects of Multivariate Statistical Theory.* Hoboken, NJ: John Wiley & Sons, 2005.

[72] P. G. Moschopoulos, "The distribution of the sum of independent gamma random variables," *Annals of the Institute of Statistical Mathematics (Part A)*, vol. 37, no. 3, pp. 541–544, 1985.

[73] R. W. Heath, T. Wu, Y. H. Kwon, and A. C. Soong, "Multiuser MIMO in distributed antenna systems with out-of-cell interference," *IEEE Trans. Signal Process.*, vol. 59, no. 10, pp. 4885–4899, Oct. 2011.

[74] S. Tiiro, K. Umebayashi, J. Lehtomäki, and Y. Suzuki, "Decision fusion for cooperative source number estimation in cognitive radio networks," *IEICE Communications Express*, vol. 2, no. 11, pp. 484–489, 2013.