Proactive spectrum sensing and spectrum sharing for cognitive radio

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**PROACTIVE SPECTRUM SENSING AND SPECTRUM
SHARING FOR COGNITIVE RADIO**

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Proactive Spectrum Sensing and Spectrum Sharing for Cognitive Radio

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Table of Contents

1	Introduction	1
1.1	Motivation	1
1.2	Objectives	2
1.3	Major contribution of the Thesis	2
1.4	Organization of the Thesis	3
2	Literature Survey	4
2.1	Spectrum Sensing	7
2.2	Opportunistic Spectrum Access	11
2.3	Spectrum Sharing	14
2.4	Cooperative Communication	18
3	Proactive Spectrum Sensing with Probing Power Control	22
3.1	Introduction to Proactive Systems	22
3.2	Proactive Spectrum Sensing	23
3.3	System Model	24
3.4	Numerical Formulation With Power Control Description	25
3.5	Numerical Results	28
4	Cross-Channel Estimation With Supervised Probing	31
4.1	System Model	32
4.2	Design of System Parameters	34
4.2.1	Power Assignment and Primary Transmitter's Power Adaptation Values	34
4.2.2	Probing Power Increment	35
4.3	Cross-Channel Estimation	36
4.4	Optimization of Probing Power Increment and Simulation Results	37
4.4.1	Training Based Optimization	37
4.4.2	Simulation Results	39
5	Proactive Spectrum Sharing	42
5.1	Protocol Design	43
5.2	System Description	44
5.2.1	Cooperation Mode	46

5.2.2	Full Access Mode	48
5.2.3	Simultaneous Sharing Mode	48
5.3	Outage and Rate Calculation	48
5.4	Simulation Results	51
6	Conclusion and Future Work	59
6.1	Conclusion	59
6.2	Future Work	60
	Author's Publications	62
	Bibliography	63

List of Figures

2.1	Singapore Spectrum Allocation Chart	5
3.1	The concept of power feedback loop in the proactive system model.	24
3.2	CU data frame for the proactive sensing scheme.	25
3.3	Variation of $\mathcal{P}_f$ for change in probing power.	28
3.4	Probability of detection versus probing power.	29
3.5	Sensing-Throughput Tradeoff.	30
4.1	The supervised probing and sensing system model	32
4.2	(a) ST's slotted probing and sensing frame structure. (b) ST's data frame structure.	34
4.3	Distribution of ΔP_{pb} for channel success.	38
4.4	Rate of change of SME with ΔP_{pb}	39
4.5	Recorded SME values for the random cross-channels.	40
4.6	Primary user protection in terms of $P_{s_{max}} \cdot h_{cp} ^2$	40
5.1	Proactive Spectrum Sharing System Model.	43
5.2	Flowchart of Cooperative Handshaking.	45
5.3	CR Frame structure.	49
5.4	LU outage probability versus CU power.	51
5.5	LU outage probability versus LU power.	52
5.6	PU Power Saving versus CU power for $P_{out} = P_{out}^d = 10^{-2}$	52
5.7	Critical power regions for 10% outage rate ($C_{10\%}$) with PU target rate $R_t=1$ bps/Hz (a) Direct PU Transmission, (b) With our proposed protocol.	54
5.8	Average CU rate with CU transmit power.	55
5.9	Average CU rate versus LU target rate threshold.	55
5.10	Percentage of spectrum access opportunities versus LU target rate threshold.	56
5.11	Average CU rate with CU transmit power.	57
5.12	Average CU rate versus LU target rate threshold.	57

List of Tables

4.1	PT's power adaptation table.	33
4.2	Table of training results.	38

List of Abbreviations

ACK	Acknowledgement
AF	Amplify-and-Forward
AIP	Average Interference Power
ARQ	Automatic Repeat-Request
ATC	Acknowledgement To Cooperate
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
CCI	Co-channel Interference
CDMA	Code Division Multiple Access
CF	Compress-and-Forward
CR	Cognitive Radio
CR	Cognitive Radio
CRN	Cognitive Radio Network
CSD	Cyclostationary Detection
CSI	Channel State Information
CSIT	Channel State Information at the Transmitter
CT	Cognitive Transmitter
CTC	Confirm To Cooperate
CTS	Confirm To Share
CU	Cognitive User
DF	Decode-and-Forward
DFA	Distributed Frequency Assignment

DFH	Dynamic Frequency Hopping
DH	Double Hopping
DPC	Distributed Power Control
ED	Energy detection
FCC	Federal Communications Commission
FDD	Frequency Division Duplex
FDPC	Finite-Horizon Distributed Power Control
FTC	Fail To Cooperate
HARQ	Hybrid Automatic Repeat-Request
IR	Incremental Redundancy
ISM	Industrial, Scientific and Medical
ITC	Interference Temperature Constraint
JTRS	Joint Tactical Radio System
LR	Licensed Receiver
LR	Licensed Receiver
LRT	Likelihood ratio test
LT	Licensed Transmitter
LU	Licensed User
LU	Licensed User
MF	Matched Filtering
MIMO	Multiple-Input Multiple-Output
MSE	Mean Squared Error
NACK	No Acknowledgement
OSA	Opportunistic Spectrum Access
PA	Power Adaptation
PAM	Pulse Amplitude Modulation
PDF	Probability Density Function
PIP	Peak Interference Power

PR	Primary Receiver
PT	Primary Transmitter
PTS	Permit To Share
PU	Primary User
QOS	Quality of Service
ROI	Region of Interference
RTA	Request To Access
RTC	Request To Cooperate
RTD	Repetition Time Diversity
SCA	Software Communications Architecture
SINR	Signal-to-Interference-plus-Noise Ratio
SME	Square of the Magnitude of Channel Error
SNR	Signal-to-Noise Ratio
SR	Secondary Receiver
SSDT	Simultaneous Sensing and Data Transmission
ST	Secondary Transmitter
STF	Space-Time-Frequency
SU	Secondary User
TDMA	Time Division Multiple Access

Abstract

Cognitive radio (CR) is emerging as a field essential to the progress of wireless communications. With spectral efficiency at the forefront in protocol design, CR aims in combating the supposed spectrum crisis due to inefficiency in spectral utilization. Thus a lot more spectrum-hungry services can be supported by the limited frequency bands through opportunistic access or sharing of licensed spectrum. As spectrum sensing precedes any possible access or sharing of spectrum, it is crucial that the sensing result is accurate when the initial sensing decision is made. Most of the current sensing techniques are passive in nature (i.e. they do not involve any participation of the CR) and hence can incur sensing errors when eavesdropping in the midst of high-noise or fading environments. Thus we consider a novel proactive spectrum sensing scheme that increases the certainty in the spectrum decision while combating the hidden-node problem. This is achieved when the CR sends out a probing signal prior to the sensing process. We study the results of applying power constraints to the power available for probing, and see how this scheme proves beneficial to the licensed user (LU) in terms of greater protection while still maintaining the throughput needs of the CR.

After proactive sensing we focus our attention on the issues raised with spectrum sharing in the field of CR communication. As outlined by most work in literature, cross-channel estimation still remains an issue. Assumptions regarding cross-channel information are common amongst work that deals with a spectrum sharing protocol. In actuality this is impractical, and there is no way for the CR to ascertain the actual interference it deals to the LU. Thus we propose a supervised probing and sensing model that enables a CR to estimate the magnitude of the cross-channel link between itself and the LU, thus allowing for interference-shielding. With probing power playing an essential role in cross-channel estimation, we optimize the incremental probing step-size to allow for the highest estimation success and study its effect on cross-channel estimation error.

Finally we take the conventional spectrum sharing protocols one step further to design proactive spectrum sharing. With a protocol established with bandwidth efficiency in mind, we see how cooperation

between a proactive CR and a willing LU can prove doubly beneficial to both parties. Typically the LU would have to deal with the dynamic fading channel on its own, in meeting a target outage probability. But with a proactive scenario, the CR can take the initiative by sending out a cooperation request signal, to help relay the LU signal thus lowering the outage probability. For the CR, this opportunity means spectrum access, through superimposition of its own signal atop the forwarded LU signal. We also study the optimum power allocation strategy used by the CR for maximum LU power saving in maintaining the target outage probability at the licensed receiver (LR). Our results show that through innovations in spectrum sensing, sharing and cooperation, CR opens up many opportunities in the field of wireless communication that brings about significant improvements in the performance of wireless services.

Chapter 1

Introduction

“The desire of knowledge, like the thirst of riches, increases ever with the acquisition of it” – Laurence Sterne.

1.1 Motivation

The trend in wireless communication research towards energy and bandwidth efficient systems, has propelled the idea of cognitive radio (CR) to mainstream research. Significant work in the field of spectrum sensing, spectrum allocation and thereafter rate and power adaptation have been carried out for such cognitive communication systems, with spectrum efficiency in mind. Though efficient spectral utility was the reason for the introduction of cognitive systems that dynamically adapt to their wireless environment, the problem of inefficient spectrum allocation is still not dealt with. Efficiency in spectrum allocation can only be achieved through accurate detection of spectrum usage. For CRs, spectrum sensing is its way of accessing this utilization statistic. Though the field of spectrum sensing is well investigated, with techniques that range from energy detection to eigenvalue-based sensing, they do not fully utilize the cognition of such brain-empowered wireless systems to better the sensing performance. That is, they rely on CRs being passive players or eavesdroppers on primary link communication. However the idea of a proactive approach to spectrum sensing as introduced in [1] and [2], allows the CR to take an active approach to analyzing the spectrum utility and use this information for appropriate spectrum allocation. The protocol proposed in [1] is initiated by the CR sending out a probing signal, intended to foster a feedback response from the primary user (PU) system. For primary systems with a feedback link in place, the primary transmitter (PT) controls the corresponding variation in received signal-to-

noise ratio (SNR) (due to probing) by allocating more power to transmission. Thus by activating a hidden power-feedback loop between the PU pair to support the target SNR requirement at the primary receiver (PR), we see that probing can greatly affect the probability of detecting the PU even amidst noisy conditions.

Though the idea of a proactive sensing approach had been laid out, we were motivated to pursue this further to see how the power allocated to probing power is linked with sensing performance, with certain power constraints in place. The results of this experiment fueled our interest to then look at other possibilities where the probing signal could be used. With our focus on safe spectrum sharing, we designed a cross-channel estimation algorithm that is based on an active CR scenario. With probing power step-size as the key optimization criteria to minimize cross-channel estimation error, probing once again proved useful in safeguarding PU systems against cross-interference from spectrum sharing cognitive users. The freedom of protocol design with probing as the initiation signal was seen in our final idea of incorporating proactive CR systems into cooperative relaying scenarios. By interacting with the licensed user (LU), the cognitive user (CU) could act as a partial relay to licensed communication, while accessing spectrum itself. The culmination of our thesis with this cooperative protocol, clearly established the wide array of possibilities with probing, and the benefits seen for proactive CRs.

1.2 Objectives

- To study the nature of probing signal, and discover its use in different areas of communications research
- Develop suitable algorithms to incorporate the proactive component of probing into existing communication scenarios
- To simulate such proactive CR systems, and observe the benefits seen over their passive counterparts

1.3 Major contribution of the Thesis

Throughout the Thesis, we have aimed to convey the advantages seen for CUs who take an active approach to spectrum learning, sharing and thereafter transmission. The work we have conducted has followed the same systematic approach taken by a CR to establish communication, i.e. spectrum sensing, spectrum allocation, and finally transmission. When looking at spectrum sensing, we analyzed the simplest case of energy detection (ED) that suffers from common issues of deep fading and hidden

node problem due to high receiver noise. We then reworked the model to include probing power, to compare the effective difference that probing can bring to spectrum sensing. The improvements in terms of probability of detection and false alarm, enforced the idea for us to look into PU protection for CRs sharing spectrum. Therefore we focused our attention to cross-channel estimation, in our attempt to control the interference that the sharing CU does to the PR. With successful results for our blind cross-channel estimation, we then looked at how transmission for such a proactive system could be fashioned into different transmission modes based on the available spectrum opportunity. By still focusing on PU protection, we decided to design a cooperative relay scenario that could benefit both the PU and CU systems, thus resulting in a win-win situation. We considered all modes of operation, i.e. cooperation, sharing and full access, in our cooperative protocol with the CR system. As always this model was also fashioned around an active CU system, that initiates the hand-shaking protocol. Through our simulation results, and the ideas presented, we hoped to have presented a well-rounded picture for proactive users that respect PU interference boundaries while creating opportunities for themselves, to fare better in a competitive spectrum environment.

1.4 Organization of the Thesis

The report is structured as follows. In Chapter 2, we carry out a literature survey on the prominent and applicable areas of CR communication, highlighting the pressing issues in the field. The idea of proactive systems is introduced briefly in Chapter 3, with a glimpse of the opportunities that can be seen with such a protocol implementation. We then discuss how the proactive scheme can be applied to a spectrum sensing scenario to tackle the effects that deep fading and the hidden-node problem have on the sensing result particular to passive sensing systems. We also demonstrate through simulations, the comparative advantage seen through controlled probing, in terms of LU protection and greater detection probabilities. In Chapter 4, we consider the possibility of using probing in a cross-channel estimation scenario to ensure safe spectrum sharing for CRs, with numerical results showing the performance of this blind cross-channel estimation technique. The extension of the spectrum sharing scenario to include cooperative relaying is introduced in Chapter 5, where we highlight the significant gains to both the LU and CR involved in such a scheme. We finally conclude with Chapter 6, including a summary of the work done on proactive CRs and the possibilities that lie ahead. It is to be noted that the terms cognitive/secondary user and licensed/primary user with their respective transmitter and receiver pairs, are used interchangeably throughout the thesis based on the context.

Chapter 2

Literature Survey

In this chapter, we are going to discuss the origin of CR research, existing techniques implemented in the field of spectrum sharing, allocation and transmission, and also discuss pertinent issues that exists in literature.

The dynamic growth in the wireless communication industry has opened up many possibilities for wireless mobile access and on-the-go wireless services for the consumer of today. The explosion with 3G has led to a generation of new users being engaged with this dynamic connectivity, and instant communication through a host of applications that thrive on spectrum bandwidth. However with limited spectrum and the insatiable demand for more, the strain on available spectrum is ever so pressing. Moreover large chunks of the frequency spectrum are either licensed out for government purposes of military and national security, with telecommunication providers salvaging almost all of what is left. This presents a grim picture for the spectrum-heavy future of wireless communication. The frequency spectrum being a limited natural resource, requires constant management through spectrum regulatory bodies like the Federal Communications Commission (FCC) in the United States. However spectrum allocation, as has been followed over time, is typically inflexible; allocating a majority of the spectrum to exclusive licensee's, with minimal spectrum gaps or white spaces for public access. These sporadic frequency gaps are unviable as a means to support the dynamic growth in wireless communication services. FCC however did conduct spectrum surveys [3] in 2002 to measure the efficiency of spectrum utility in the U.S. with their current allocation scheme. What they noticed was that parts of the spectrum were being under-utilized, while 85% of it went unutilized for periods of time. This prompted researchers at the Institute for Infocomm Research in Singapore to carry out definitive experiments measuring the spectrum occupancy in the local environment and see how it compared to the global issue

Singapore Spectrum Allocation Chart

- *Frequency Spectrum is not drawn to scale.*

Figure 2.1: source: Infocomm Development Authority, Singapore <http://www.ida.gov.sg/doc/Policies_and_Regulation/Policies_and_Regulation_Level2/20060421164253/Spectrum_Chart.pdf>, retrieved: 22 July 2011.

with spectrum management. With their study of the 80 MHz-5850 MHz frequency band in [4], they noticed that apart from the broadcast and GSM900 bands, most of the allocated frequency spectrum is heavily underutilized. An average of 4.54% of spectrum occupancy was measured during their study of Singapore's radio spectrum (Fig 2.1). These spectrum reports meant that the spectrum crisis defined as a dearth of available radio spectrum had to be redefined to a spectrum utility problem. But with the fixed spectrum allocation system in place, the solution to this crisis could only rely on systems that access the statically allocated spectrum differently. This opened up possibilities for an emergence of radio systems that could dynamically access spectrum and wait upon freed up spectrum opportunities for their own spectral cause. This was the motivation to think of involving a cognitive reasoning side to the then already present software radios. In [5], Joseph Mitola III first hinted at how dependent, software radios were, on pre-existing rules with regard to radio communication etiquette, programmed

or defined in the software. But changing these defined parameters such as: usable radio frequency bands, protocols for transmission, and spatial and temporal configurations that affect spectrum utility, must be done manually in such systems and can be extremely labor-intensive. An example of software communications architecture (SCA) in place to specify and monitor the operations that can be carried out by the software-defined radios is the US military's Joint Tactical Radio System (JTRS). The JTRS project aims at providing flexible and interoperable communication between fixed or mobile radio terminals in battle, working within the endorsed open architecture framework, i.e. SCA. However, Mitola wished to highlight the need for an open to public, unlicensed, and commercial radio system that was capable of operating independently in the frequency spectrum while automatically adjusting its parameters to suit user needs. This dynamic spectrum management radio came to be known as CR. Mitola in [5], further discussed the openness of a new architecture representation of radio etiquette with its radio devices and networks as participants of a particular spectral scenario that was automatically controlled through automated reasoning based on the users needs. This gave form to the role of CR, and its functionality began to gain more clarity over time. Simon Haykin elaborated in [6], that the CR functioned as a brain-empowered wireless communication system, being aware of its changing environment while accordingly adapting its signal parameters to best utilize the available spectrum for reliable communication. He then classified the three distinct tasks of the CR as: sensing and analysis of the radio spectrum, estimation of channel state information, and finally dynamic spectrum management. As these tasks of the CR are sequential in searching for available spectrum and then deciding how to make use of it, each stage is wholly dependent on the accuracy of the previous stage result. Thus spectrum sensing forms a vital part of CR communication, wherein the CU locates white spaces or unused frequency bands for unlicensed spectrum access. If the frequency spectrum found as a result of spectrum sensing is licensed spectrum, then the CR has two options: Opportunistic Spectrum Access (OSA) or Spectrum Sharing. OSA as the name suggests allows the CR to access licensed spectrum in the absence or period of inactivity of the LU. However on return of the LU to its spectrum the CR must be vigilant and discontinue communication on the link. Spectrum sharing on the other hand is a more open protocol that allows the CU to share spectrum usage with a LU within a given interference margin. This interference constraint commonly referred to as the Interference Temperature Constraint (ITC), is the limit to the cross-interference that the licensed receiver (LR) can handle from a spectrum sharing CR. These spectrum opportunities definitely help the CR in transmitting his own data, while improving on the local spectral efficiency. However the work being carried out in CR research nowadays is both varied and extensive, ranging from distributed rate and power control for dynamic spectrum management to cooperative and competitive CR communication,

and stochastic games involving the Nash equilibrium for CR networks. But we wish to focus the crux of the literature review on the major areas of CR research that we have investigated, studied, and developed innovative protocols for, while conducting our research. We first discuss spectrum sensing and the existing techniques used in literature to carry out this all-important stage of communication.

2.1 Spectrum Sensing

Spectrum Sensing is a field well investigated in communications research. With the advent of CR, spectrum sensing has been reborn as an active research area, forming the core of CR spectrum access process. Spectrum sensing is seen as supplying the CR with localized information regarding channel usage and PU transmission characteristics. Over the years a number of techniques have been studied and improved on with respect to the sensing accuracy and statistical information needed for the process. Review papers such as [7] and [8] discuss the history of spectrum sensing, detailing the most common sensing techniques used, the challenges and issues faced during sensing, and the ongoing work to better improve the sensing results. In [7], we see the authors concerned with the issues common to the field of spectrum sensing, in particular LU signal detection problems due to deep fading, multipath fading, time dispersion, and noise uncertainty at the time of sensing. These are issues that can drastically affect the accuracy of CR sensing, and as a result CRs that use such spectrum allocations can cause intolerable interference to the PU systems. Deep fading is a very common issue with sensing owing to the nature of the wireless environment. Therefore it becomes very difficult for a CR to detect LU activity due to its relatively low received power. For example, wireless microphones operating over the TV band transmit with less than 50mW of power and for a CR a few hundred meters away, the received SNR can be much lower than -20dB. Multipath fading which can pose problems in terms of fluctuation of the received signal power, and time dispersion of the wireless channel which can complicate coherent detection are also problems to be dealt with. The determinants of successful sensing in the communication world are given by detection and false alarm probabilities. Detection probability is defined as the accurate detection of a LU in its band, and is commonly used as a threshold standard to determine the quality of the sensing result. False alarm probability on the other hand is the incorrect reading of the LU's presence in the band when in fact the band is vacant. This is primarily due to the surrounding noise power which can overshadow a weak signal or appear as LU activity, allowing for incorrect detection. They have been several sensing techniques discussed over the years that deal with trying to desensitize the CR to these surrounding influences.

Some sensing methods are more popular among others due to their ease of implementation and low order of complexity. Matched filtering (MF) detection, ED and likelihood ratio test (LRT) are a few of the common ones. MF detection has been considered as the optimum sensing technique with perfect PU signal knowledge [9] [10], i.e. knowledge about the LU operating frequency, modulation pattern and frame format to name a few. But given this statistical information, it allows the CR to achieve the target probability of false alarm within minimal sensing time [11]. However the number of samples required for sensing grows with reduction in PU SNR as $O(\frac{1}{SNR})$. Given the amount of pre-information regarding PU statistics that is required, this scheme is usually deemed impractical for a stand-alone CR. We see that the comparatively less complex ED technique senses for PU signal power and hence requires samples as a function of $O(\frac{1}{SNR^2})$ [11] to meet a target sensing quality. But as was with MF, the ED is also the optimal sensing scheme given the noise power information [12] required to warrant the presence of a LU. Because the ED senses only for signal power, most work involving the use of ED as a sensing technique use a detection threshold for the received signal energy over the duration of the sensing frame in order to make the sensing decision. Therefore the ED scheme does not perform well for low SNR scenarios, especially when the detection threshold is set with LU protection in mind. This detection threshold can be calculated [13] as a function of detection or false alarm probabilities, and the surrounding noise floor. Therefore in terms of simulation, we see a lot of work that makes assumptions of the use of white noise with zero mean and known variance. However it is impossible to control surrounding noise, as it might come from very distant source transmissions, or even thermal noise at the receiver itself, so its variance cannot be known precisely. Thus the results from simulations can be inconsistent with real-time implementation of the same technique. For example we see how a bound to detection probability is developed when the ED scheme is subjected to practical noise uncertainties in [14]. The performance results also show that increasing the sensing time does not affect a change in detection probability when the LU signal is weak.

Now the LRT is a test statistic to measure the probability of detection, when given a target false alarm probability of the LU, based off Neyman-Pearson's Theorem [10]. The LRT compares the ratio of probability density functions (PDF) of the LU signal distribution when present and absent from the frequency spectrum with a target threshold determining the result of the test. Therefore the limitations in implementing the LRT lie in its dependence on signal, channel and noise distribution statistics necessary to calculate their respective probability densities. Though some work go onto use this detection technique in their papers with estimates of the respective PDFs, this work cannot be optimal given limited sensing samples for detection, and the added knowledge of signal and noise statistics required.

Despite the impracticalities involved with these methods, the benefit in using these low complexity sensing techniques is the relatively small sensing time needed to achieve the target detection or false alarm probability. As one can imagine greater sensing time would improve sensing results in certain scenarios significantly, however there is also a tradeoff. As studied in [13], we introduce the popular sensing time-throughput tradeoff scenario. With secondary user (SU) transmission following the spectrum sensing process, the time available for data transmission will be the time left in the data frame after allocating the time it took to arrive at the sensing result. That is to say, the CU throughput is a function of $(1 - \tau_n)$, where τ_n is the normalized sensing time (with respect to total frame time). Therefore though the accuracy of the sensing result might be boosted through delayed spectrum decisions, the effective average throughput of the CU will be smaller. The tradeoff seen is due to the dependence of the CU throughput on both sensing time and probability of false alarm given a target detection probability, as shown in [13]. Given the dynamic noise and signal statistics, there will be only one optimal sensing time giving rise to maximum CU throughput. However the optimization parameter can be different. Like in [15], we see the formulation of an optimization problem to maximize the channel efficiency based on the sensing time. Channel efficiency as defined in this paper is the effective idle spectrum opportunities utilized out of all the available vacant spectral chances for opportunistic access. Though through their scheme we observe that a peak channel efficiency can be arrived at for an optimal number of sensing symbols, a higher target detection probability or lower LU SNR can significantly deteriorate this achievable channel efficiency limit. Thus we see that the effect of sensing time can have different results given the optimization criteria.

Another technique that has gained ground in spectrum sensing research is cyclostationary detection (CSD). This technique is particularly popular because it removes the ambiguity of signal detection in a noisy environment; a common problem in practical sensing scenarios. This is done by analyzing the periodicity of the received signal statistics and comparing it with that of noise. A cyclostationary signal is one whose spectral correlation density function has a non-zero value for non-zero cyclic frequencies. Noise as we know is random and has no cyclostationarity and can thus be easily distinguished from the LU signal. CSD can also be beneficial in distinguishing between different transmission signal types with different cyclic frequencies. However we see that CSD has its own implementation difficulties [7]. We see the high level of complexity involved in the CSD process and the fact that it requires large number of samples to carry out this computation, the effective time left for data transmission is cut down. As the process for spectral correlation depends on matching cyclic features, any offset in frequency or error in sampling can affect the frequencies being tested, and result in detection errors. Also the assumptions

on carrier and bandwidth frequencies by most work involving CSD given its computational complexity, does not make this sensing technique favorable for implementation. We must mention that there has been work carried out (like [16]) that aims at LU detection using CSD with no apriori knowledge of the transmission signal but a rough estimate of signal bandwidth. Moreover this work focuses on detecting and classifying signals in a low SNR regime, given the practical nature of communication channels. We see how cyclic spectral analysis can also be carried out in [17] to extract the cyclic frequency information from the signals, thus not requiring any knowledge of channel or signal, prior to sensing. The extension of this work to neural networks allows signal classification to be done offline, and thus not requiring the unusually long sensing time for typical CSD.

With the issues raised regarding signal, channel and noise pre-information required with most of the sensing techniques discussed thus far, practical approaches to spectrum sensing have been looked at, in particular, blind spectrum sensing. Eigenvalue-based sensing and covariance-based sensing drew much attention primarily due to complete independence of the sensing result from signal, channel and noise information. We see that eigenvalue-based sensing is carried out by finding the ratio of the minimum or average eigenvalue of the received signal covariance matrix to the maximum eigenvalue of the same matrix, and comparing it to a defined threshold. In doing so, the presence or absence of the LU can be confirmed. This threshold as calculated in [18], is based of a target probability of false alarm and can be calculated using random matrix theory (interested readers may refer to [19]). Similarly for covariance-based sensing, the cognitive transmitter (CT) must calculate the auto-correlations of the received signal in forming the sample covariance matrix. Following a transformation of the covariance matrix, two different techniques (covariance absolute value and covariance frobenius norm) are highlighted in [20] that demonstrate a threshold based decision to determine LU presence. Both these methods are shown to perform better for real-time implementation given the surrounding noise uncertainties as compared to the other techniques mentioned. Other work in [21], discusses how oversampling the received LU signal or simply using multiple receive antennas at the CT, can significantly eliminate the uncertainty of noise. For example, two different received signal components will result in high correlation of the transmitted signal statistics when compared to uncorrelated noise samples. Therefore this ratio of signal to noise statistics at the CT can significantly boost detection rates and as seen through simulations, outperforms the common energy detector. The practicality of these blind detection schemes in requiring no prior statistical information regarding signal, noise or of the multipath channel, makes these schemes viable for implementation.

However ED remains the most common sensing technique used in literature because of the ease with

which different protocols or algorithms can be designed around its simple architecture. The authors in [22] saw the potential that spatial diversity can bring to an ED based scenario. By using multiple antennas at the receiver, the CT can optimally combine the individual received samples to maximize the received SNR, and then carry out ED. But since the process of optimal combination revolves around the need for LU signal and channel information, the authors here introduced a technique called blindly combined energy detection (BCED) as a spectrum sensing technique. Through transformation of the received sample covariance matrix and on comparison with a threshold for LU detection, we see that the new BCED scheme outperforms the ED scheme. Moreover the BCED scheme does not need noise power information like its counterpart, and is unaffected by the uncertainties in the noisy environment. Though all these blind spectrum sensing techniques presented are truly exceptional, we see that the detection threshold as calculated in these schemes are a function of the number of sensing samples. Therefore to achieve a certain level of accuracy, greater amount of time would be needed to be spent in sensing, but being completely blind sensing techniques, one would expect that.

Overview

The idea of CR is fashioned around LUs that are oblivious to CR transmission and spectrum access, and therefore the pre-information necessary for spectrum sensing to be carried out is usually assumed or based on a cooperative exchange of information between the LU and the CR. However in actuality, implementation of such idealistic approaches may be difficult. Therefore when working incognito, it is important to understand that many sensing techniques that demand for PU information other than that which is publicly available might fail in implementation. It is here that the CU must rely on either blind sensing estimates [18] [20]-[23] which may not be fully reliable given a high-noise environment, or allow a longer sensing duration to average out the effect of additive noise on the received signal. As we have also discussed the effect of longer sensing durations, also imply smaller performance gains for the CR, and hence the most common technique used in literature is still the basic ED technique. As seen later in Chapter 3, we demonstrate how the traditional ED can be remodeled to incorporate probing, resulting in significant performance gains for the CU.

2.2 Opportunistic Spectrum Access

As highlighted in the previous section, spectrum sensing is critical to establishing the presence of spectrum holes or vacant pockets of unused frequency spectrum. However once an idle or inactive

frequency band is found, it then relies on the CR's dynamic spectrum management skills to be able to best utilize the spectrum opportunity. OSA is a form of spectrum access that is non-intrusive. The CR here does not wish to invade the privacy of a licensee's communication, but only transmits in the absence of the LU. This interference-free access makes this process of spectrum efficiency management simple and uncomplicated. But we realize that as OSA actually involves complete access of licensed spectrum, the dependence on the initial process of sensing is even more crucial. We see the authors in [24] highlight that importance, in optimizing the sensing technique to guarantee interference-free spectrum access.

Research in OSA has also extended to more practical cognitive radio networks (CRNs). With multiple SUs vying for spectrum opportunities, the process can get quite chaotic in the absence of any spectrum pooling architecture in place. However with CRNs, we see a self-organizing network of CUs that do not depend on an infrastructure backbone. We see the implementation of OSA in such a self-aware CRN in [23]. Here a system of time division multiple access (TDMA) is used in allocating specific timeslots for each individual CU in the network. Moreover each CU has a probability p of transmitting in one of the other $N - 1$ available timeslots. In maximizing the overall network throughput, we see how by appropriately choosing this p , can allow for complete spectral usage thus utilizing every possibility for CR transmission.

But after accessing the spectrum, the CR must be vigil in sensing the return of the LU to its band. For wireless regional access networks, IEEE 802.22 standards state that the CR must interrupt transmission every two seconds to sense for licensed activity. That is on sensing the LU, the CR must show a sense of urgency in vacating the current spectrum, to avoid any interference to LU communication. This intermittent transmission and instant channel departure can cause the CR transmission to be extremely choppy, and significantly impair the quality of service (QOS). In mitigating this problem, dynamic frequency hopping (DFH) was suggested [25]. Here the process coined as simultaneous sensing and data transmissions (SSDT) involves the CU simultaneously transmitting while sensing the frequency spectrum for available spectrum holes to jump to, prior to the return of the LU to the in-use frequency band. This is possible with two antennas equipped at the receiver for SSDT with the sensing and transmitting frequencies different. When a new spectrum opportunity is found, the channel switching must be fast, but given the switching capabilities of today's hardware, this does not pose a problem for the CR. In comparing the performance of dynamic hopping systems to the traditional non-hopping systems, we can look at work done in [26], which highlights the comparative advantages seen in simultaneously scanning the frequency spectrum for channel occupancy. Here, DFH systems show a comparative reduction in LU collisions given the dynamic hop nature, in exchange for greater number of frequency bands occupied as

a result. Even with significantly more channel usage, we see that DFH systems achieve a greater overall channel utilization efficiency for the networked CUs. An interesting study is the throughput for such SSDT systems. With simultaneous sensing, the throughput of the CUs no longer depend on a tradeoff between sensing time to the total frame time, and is in fact completely independent of sensing time. The throughput as represented in [25] [26] is always equal to the bit rate of the transmitting party, and as seen is greater than that achieved by non-hopping systems. Therefore DFH seems promising for CR OSA, but in implementing it for CRNs we see there are more problems to be addressed [25]. Primarily when CRs wish to hop to dynamically available spectrum opportunities, they must ensure that no two CUs access the same frequency band, resulting in co-channel interference (CCI). To effectively access the spectrum while avoiding this mutual interference between DFH users, Double Hopping (DH) is proposed as an approach in [27]. With DH, each CU has two specific frequencies it can access, its dedicated and vacant working frequency, and a common sensing frequency. As this approach is based on a time-slotted spectrum access, each CU decides on a spectrum access time opportunity. After the allocated data transmission time for the CU, it then switches to the common sensing frequency to continue to support transmission. This sensing frequency is also appropriately slotted, thus supporting only one CU at a time. This CU is then given a time-period of t_{quiet} , to sense another free frequency spectrum opportunity and to switch back to that working frequency. The time-period of t_{quiet} will depend on the number of networked users willing to participate and the available sensing slots in that data frame. The paper also suggests a distributed frequency assignment (DFA), where network users learn of the frequency allocation and patterns of their neighborhood nodes. Any new node must learn of the data transmission and sensing times of the current participating nodes, before appropriately choosing its frequency and sensing timeslots. In such a scheme, every node must broadcast the latest utilized frequency when switching from the common sensing frequency back to the working frequency. On comparing this DFA against previous dynamic hopping schemes, we see that DFA results in fewer frequencies being used, which in turn allows for greater number of CUs to be supported, and minimizes the possibility of interference with LUs. With sufficient distance between the networked users, we also see this scheme approaches optimality in frequency assignment, while remaining practical and simple in implementation.

Overview

The field of OSA has allowed for simple and unintrusive access of licensed spectrum based on sensed spectrum opportunities for CR communication. This greatly minimized any issues that would arise,

as a result of interaction through cooperation or interference with LUs. But as we see, there were still research issues brought up with this opportunistic access scheme. Of primary concern, was the transmission quality of the CUs transmitting on this licensed band. Given the fleeting nature of these spectrum holes, the CU is responsible to maintain vigilance in sensing for any licensed activity on its band. This intermittent spectral scan, meant discontinuous CU transmission. Moreover on sensing the presence of a LU, immediate spectrum vacancy results in signal drops and lower QOS at the receiver. Work on DFH [25] [26] was as a result particularly important, given the ability for a CU to achieve seamless data transmission over opportunistic spectrum. An extension to cognitive networks also allowed for DH [27], where CU nodes had two operating frequencies, one for transmission, and other for spectrum sensing. However the time allocated for spectrum sensing as calculated in this approach is dependent on the number of network users, and can be significantly small given a congested network. As a result CCI could be a problem, with multiple users attempting to access the same spectrum opportunities simultaneously. Also the need for a dedicated sensing frequency for operation is not as easy commodity to come by.

2.3 Spectrum Sharing

Spectrum sharing has evolved as one of the options of efficient spectrum use, particularly addressing the issues of underutilized spectrum bands presented in [3] [4]. But unlike the non-intrusive nature of OSA, the process of sharing spectrum involves the coexistence of both cognitive and licensed users on licensed frequency. In doing so, the sharing CR must be aware of the interference it deals to the LU with ongoing communication on the link. As a measure of protection, a wide range of work in literature in spectrum sharing [28] [29], depend on an interference constraint to limit the cross-interference felt from the CR. This publicly available threshold, commonly known as the ITC [6], serves as the sole condition governing spectrum sharing rights for a CU. However with no cooperation between licensed and cognitive users, it is purely based on the good faith of the LU that the CU would be vigil in maintaining its interference below the predefined ITC. We see that work in [30] highlights that the ITC can be specified as either a peak or average interference power constraint for the sharing CU. With peak interference power (PIP), the CU must ensure that its cross-interference remains below a peak limit, fixed for every fading state of the channel. On the other hand, the average interference power (AIP) constraint, allows the CR more flexibility in power assignment, stressing only that the average interference felt over many fading states must adhere to this constraint. With AIP, we see that the CU

can adaptively increase or decrease its power as it seems fit, given the dynamic nature of the channel. It is obvious here that AIP would outperform PIP in terms of CU channel capacities. However one would assume that the PIP scheme would serve better protection to the PU, owing to the inflexible and restrictive nature of this constraint. But as pointed out in [30], it is quite contrary. For the same power threshold value, AIP provides better interference shielding for the PU as well. This is due to an interesting study of how interference diversity over the fading states allows for smaller capacity losses for the PU over the fading channel. Therefore in all instances, the AIP outperforms the restrictive PIP, giving utmost flexibility to CU power control, as well as maximizing both CUs and LUs ergodic capacity.

But however restrictive the scheme may be, outages are imminent in the field of spectrum sharing. Though it is the CR's responsibility to ensure no leakage interference is seen at the LU end, it is practically impossible to do so without cross-channel knowledge. And given the fading nature of the channels, knowledge of the cross-channel gain for each individual fading state must be known, to implement either PIP or AIP as an ITC. Most work involved in a spectrum sharing scenario overlook this issue, with assumptions of full or partial cross-channel knowledge, in ensuring its cross-interference respects the ITC as set by the LR. Though substantial work on blind channel estimation [31]-[33] has been carried out and been around long before the concept of CR was birthed, estimation techniques particular to the CR system setup have not been touched upon. These techniques implement techniques ranging from the most common constant modulus adaptive algorithm, to using blind trellis search and maximization of the average likelihood function, in gaining a blind estimate to cross-channel knowledge. However all of these channel estimation techniques refer to gaining knowledge of the communication channel on which data transmission occurs (i.e. established between a transmitter and receiver pair) and usually relies on the feedback received from the receiver, or a property of the modulation technique used between the transmitter and receiver pair ([34] [35] uses the cross-correlation property of Orthogonal Frequency Division Multiplexing systems), to calculate the channel estimate. But with the CR scenario, the CT wishes to gain knowledge of a channel between itself and another receiver, who is unaware of the very existence of the CR. We see that the beamforming has also been suggested as a technique [36]-[38]. However this technique also relies on full knowledge of the interference channel between the cognitive and licensed user, or otherwise cooperation with the LU to ensure optimization of the transmit beamforming weights to help the CU remain subject to the set ITC. Therefore we are still brought back to the issue of cross-channel knowledge. Authors in [36] attempted to solve this issue with the proposal of a new effective interference channel that aims at making cognitive beamforming practical. In calculating the effective interference channel, the sample covariance matrices of the PT and PR transmissions are used and

noise power at the CR estimated. The paper studies the leakage interference seen due to the imperfect channel estimation, and introduces a learning-throughput tradeoff, similar to the sensing-throughput tradeoff discussed and seen earlier in [13]. This work optimizes the time allocation to efficiently balance maximization of CR throughput while adhering to the CR transmit power constraints and interference power constraints at the PR. This work definitely opens up the research in cross-channel estimation in CR, but with timing synchronicity being a necessity for the scheme to work, there is still a lot of work in this area of CR research.

When we consider systems operating in frequency division duplex mode, all assumptions regarding time reciprocity of the communication channels do not hold. Hence channel estimation techniques based off this assumption cannot work. Under such circumstances the CU can only rely on feedback information sent from the PR to gauge licensed activity and use this statistical information for LU interference shielding. Usually in feedback based PU systems, the response to dynamic channel variations can be conveyed through information bits to the intended PT. This feedback is a low rate data stream on the reverse link that usually contains information regarding the channel state, received power or interference levels at the receiver. However due to the restricted bandwidth on the reverse link, this feedback information has to be limited and is usually quantized to bits corresponding to specific information in the codebook established between the primary pair. The work presented in [39] gives us an overview of limited feedback techniques used for both single antenna and multiple-input multiple-output wireless communication systems. The most common form of feedback is 1-bit outage reporting, where the receiver informs the transmitter when a certain frame is received in outage or not. Other forms of feedback limited to one bit can be seen for threshold constrained SNR scenarios, when the received SNR falls below a predefined QOS level. These 1-bit schemes are definitely bandwidth efficient, and in terms of throughput sustenance, can measure up to the throughput that is achievable with full received SNR knowledge at the PT. The study was first made by Floren et al. in [40], where optimum 1-bit quantized SNR can deliver 90% throughput sustenance if the average received SNR is known at the PT. In the absence of this knowledge, quantization to two bits of information can result in the same throughput performance. But in reality, the feedback received would be noisy and erroneous, so work with adaptive systems operating on noisy quantized feedback over slow fading channels, was studied in [41]. This work aimed at rate maximization through the design of a transmission scheme impervious to feedback errors. In providing channel state information at the transmitter, this feedback approach allowed for appropriate rate and power adaptations resulting in throughput gains approaching the bound of that seen in noiseless scenarios when the feedback link quality was good, and converging to a transmission scenario void of

feedback, as the feedback link quality degraded. Another example of adaptive closed-loop power control can be seen in [42], where authors focused on optimized quantization to reduce the information loss due to feedback errors, and the corresponding power control error as a result. This induced error brings about a power change at the transmitter, different from the power adaptation requested at the receiver through feedback. The uncertainties that this noisy and delayed feedback bring to the system can be solved by loop filtering at the transmitter, as seen in [42]. A loop filter functions as a variable power control step size that utilizes an adaptive control to correct feedback errors based on memory of previous feedbacks. In simulating the performance for uplink in code division multiple access (CDMA) system, the filter is designed to minimize signal-to-interference-plus-noise ratio (SINR) quantization error while maintaining loop stability. The proposed closed-loop adaptive scheme is shown to outperform more traditional fixed power control systems by exploiting feedback history.

But all these feedback schemes describe the throughput benefits to self, when either a primary or secondary user adopts these power control strategies. Our aim of investigating the feedback link, however, was to see if the CU can gain any localized knowledge regarding PU activity through eavesdropping on the PU feedback link. In assisting the process of interference estimation, we see how a CR can monitor its own transmission power to reflect the SNR situation at the PR end through this feedback, while sharing its licensed spectrum. Work in [43] discusses this very scenario of CU power control based on primary link control feedback. The framework is proposed for practical PU systems that depend on feedback control for power management and as a quality indicator of the channel, such as CDMA cellular networks and WiFi networks. The SU system proposed here follows a decentralized approach to power control, thus making it viable for most general applications.

Though there exists other feedback schemes employed in literature and facets of spectrum sharing research like power and rate adaptation for CR capacity maximization, we will not discuss these topics, in lieu of staying consistent with the areas of spectrum sharing we have worked on and applied.

Overview

Spectrum sharing was first suggested to further improve spectrum utility, given the high rate of underutilized spectrum. Unlike OSA, spectrum sharing involves deliberate interference with LU through sharing of spectrum. But the CR must be well aware of the cross-interference it deals to the LR so as to prevent any deterioration to the ongoing LU communication. In respecting this interference barrier, the CR can safely share licensed spectrum. However it is impossible to ascertain the exact interference felt at the LU, without knowledge of the cross-channel between them. Most work in spectrum sharing

have been conveniently based on the assumption of full cross-channel knowledge in respecting the ITC [6] [30] set at the LR. Though blind channel estimation techniques have been suggested [31]-[35] even before the very concept of CR, its implementation in a CR scenario has not been considered. Most of the existing channel estimation techniques refer to gaining knowledge over the transmission channel, through pilot training symbols from the transmitter and corresponding feedback from the receiver, or a dedicated control channel for the purpose of communication channel statistics. However CRs are faced with the task of estimating the cross-channel to a LR, who in most cases is unaware of the very existence of the CR. Thus the issue of gaining cross-channel knowledge in a CR atmosphere is still difficult to resolve. In our attempt to solve this issue, we have proposed a blind cross-channel estimation scheme that accesses the limited feedback information from the PR to the PT, in order to maintain the PIP limit set at the PR for CU spectrum sharing, as detailed in Chapter 4.

2.4 Cooperative Communication

Cooperative communication is an extension of wireless communication protocols to include spatially distributed collaboration between users with a common spectrum goal. Cooperative techniques are most commonly applied to spectrum sensing and dynamic spectrum access scenarios. The benefit introduced by cooperation between individual networked users is a form of space diversity, which can help combat the detrimental effects of the wireless fading channels. Spectrum sensing as seen can derive the most benefits from this spatially distributed cooperation, especially given the geographic limitations of an individual CU sensing spectrum. Multipath fading common for a dense city environment, like Singapore, can lead to severely faded received PU signals. The resulting shadowed CU often referred to as a hidden terminal node, can have completely inaccurate sensing results as a consequence. Cooperative spectrum sensing takes advantage of the multiple receptions of the primary signal at different cooperative nodes through different paths, thus eliminating the effects of the geographic environment. The general approach to cooperative sensing is discussed in detail in [44] [45]. Another significant benefit to cooperative spectrum sensing is the reduced sensing time. The spectrum sensing-tradeoff picture described earlier in [13], also considers distributed sensing results with multiple CUs in calculating the optimal sensing time required, which reduces with the number of CU terminals. Correspondingly, the achievable throughput is seen to increase with greater number of CUs. Work on agility improvement using cooperative diversity is seen again in [47], which helps quantify the sensing time improvement seen. In their simulations a 35% reduction in detection time is seen for a simple two-user CU network, and the agility rate increases for

greater number of sensing users. But however significant the improvement is, uncontrollable increase in the number of networked CUs for cooperation is ill-advised. This is because the reporting time for CUs local decisions will be significantly large, given timeslot-based reporting, as seen in TDMA based protocols for exchange and management of spectrum sensing data [48].

The extension of cooperative networks can also be seen in OSA and spectrum sharing scenarios as well. We see that the work in [45] discusses maximizing spectral efficiency through collaborative sensing, with performance results showing that ten cooperative users can alone locate 99% of the white spaces in the frequency spectrum. However cooperative OSA involves more than just sensing for unoccupied frequency spectrum. In accessing spectrum, what spectrum rights do individual CUs have? Is there a pooling priority for access? Can multiple CUs access the spectrum opportunities simultaneously, or do they follow a slotted based approach to spectrum access? These questions are all be answered in [50]. The paper discusses and presents two approaches to spectrum assignment: a centralized strategy and a distributed approach, that aim at maximizing the spectrum utilization and fairness for open access systems. In the centralized strategy, the central controller makes channel allocation decisions based on an informed global knowledge of received channel statistics. These statistics are location, power, sensing and interference information that is forwarded to the central controller by the respective CU nodes. On passing these parameters through an assignment algorithm, the central controller then broadcasts the channel assignments to the CUs for transmission. Though a central controller seems to bring order to a network strewn with individual CUs all looking for spectrum access, the complexity of such a system increases with larger networks. The strain on the dedicated control channel and the computational complexity required at the central controller for large number of users could well result in large delays and system overload. This motivated researchers to look at non-centralized techniques for channel assignment, and thus distributed architectures came to be. A distributed approach, on the other hand, allowed CUs to determine their own spectrum allocation, through shared locally available information. The CUs first sense the spectrum for channel occupancy, and then based off certain labeling policies [50] or spectrum rules [51], assigns itself an access priority, which it then broadcasts to the neighboring CUs. The CU with the highest priority is then given first right in channel assignment. Each of the surrounding clusters of neighbors also broadcast their own assignment patterns, thus making these local cooperative decisions function similarly to a global optimized strategy. The comparison of both approaches to channel allocation in [50], shows greater spectrum efficiency, and fairness in channel assignment with the centralized approach over the distributed strategy. However the iterations required in computing channel assignment, and the time taken for channel labeling, is significantly smaller for

distributed systems. Also greater the number of channels and cooperative CUs, the complexity for the centralized approach significantly increases, while the distributed approach still maintains a small computation time.

Cooperative communication nodes have also been seen to function as relay systems, where individual users invest their resources of time and power, in forwarding signals from a source node to the destination receiver. There are three main relaying protocols: amplify-and-forward (AF), decode-and-forward (DF) and compress-and-forward (CF). In the AF protocol, the received signal is amplified at the relay and forwarded to the destination. This scheme is popular as a relaying option primarily for its straightforward and low cost implementation. However in boosting the received signal, the added noise due to the wireless channel also gets amplified at the relay. A simple example of AF protocol is data fusion, where each user forwards the received signal statistics to the common central controller. In the DF scheme, the relay is responsible to decode the received signal, re-encode it and retransmit the signal to the receiver. On the other hand, CF based relays focus on helping the destination node decode the received signal, through a compressed and encoded estimate of the signal, as seen at the relay. Both DF and CF based approaches are studied in detail in [52] for wireless channels. It has been shown that DF protocols perform best when the relay node is close to the source, whereas the CF protocol has the upper hand when it is closer to the receiver. The application of relay networks can be seen particularly when cooperative users wish to access spectrum opportunistically. As discussed earlier, OSA can result in users facing choppy transmission habitually due to unexpected returns of the LU to the spectrum, causing them to vacate the band instantly. These regular interruptions not only affect the continuous transmission quality but also result in unpredictable delays. Work in [44] attempts to solve this issue through sharing of frequency bands by CUs in a cognitive relay network for seamless data transmission. The benefit of large number of cognitive relays is seen here, where return of PUs to the band do not necessarily imply a complete halt to CU communication, as there will always be at least one vacant band for cognitive relay opportunities. The approach suggested here is a time-slotted approach, where only one intermediary relay node is allowed to communicate to the destination in a given timeslot. The network access opportunity as calculated by this approach is maximized for greater number of cognitive relays to support seamless transmission. The research in cooperative communication is actively growing and given its wide application to practical communication scenarios, the infusion of cooperative diversity in other areas of research can be expected.

Overview

Though cooperative communications is seen more as an extension of research in CR communication, the active research in this field is always coming across new issues and corresponding techniques to better the existing wireless communication techniques. Cooperation was first seen as an opportunity for collaborative advantages of spatial diversity by canceling out the local bias seen in individual spectrum decisions. Cooperative CUs [45] could now achieve greater sensing accuracy in a smaller sensing time and with lesser sensitivity to noise. Collaborative sensing was first looked at in a centralized manner [44], requiring a collaborator or access point coordinator to make a global network decision. With multiple users communicating spectrum sensing statistics to a specific node, many issues can arise. For a time-slotted approach we see that a large cooperative network could result in significantly long delays and can be computationally taxing on the central controller. Also the need for a dedicated control channel for collaboration alone is questionable. On the other hand simultaneous transmissions can be possible only through dynamic spectrum access techniques that require high bandwidth, which can be very expensive to license, or difficult to sense vacant licensed bands, given the current sporadic spectrum allocation tendencies. As an alternative distributed approaches to cooperative spectrum sensing for CUs was discussed. However for a distributed approach, specified rules and policies for spectrum assignment and access must be in place [50] [51]. We see that though this distributed access allows for an independent non-centralized approach, yet achieving a form of global diversity through shared network rules, measures for non-cooperative users or the coexistence of such users with cooperative parties in a collaborative environment have not been laid out. Considering the nature of our work on cognitive systems, we found it helpful to incorporate AF relaying to allow the CUs to enter into a cooperative agreement with LUs who wish primary link support for fading channels. The culmination of our Thesis work in Chapter 5, incorporates all the spectrum access opportunities thus presented for a complete cooperative network scenario.

Chapter 3

Proactive Spectrum Sensing with Probing Power Control

3.1 Introduction to Proactive Systems

CRs have the functionality to operate independently and have the processing capabilities to acquire dynamic real-time information from the environment, to better its chances for spectral utility. However the functionality of the CR is underplayed when such brain-empowered systems remain dependent on the condition of the surrounding environment and the nature of the fading channel in order to gain spectral access. For example, with protocols designed around opportunistic transmission during LU outage, the performance that is achievable for the CR is still dependent on the probability of LU outage, and in-turn on the physical nature of the wireless channels.

With the development of newer techniques to enhance the spectrum sensing and sharing results, even in the midst of a harsh environment, the process still relies on statistical information necessary to carry out these techniques. As most of this pre-information is unavailable publicly, the CR can only depend on LU cooperation in order to benefit its own performance. All these external conditions and criteria shackle the possibilities that could be seen with a fully cognitive and independent radio system.

The idea behind proactive CRs was to free these systems from operating in a passive and restricted manner given the surrounding environment and circumstances. Proactive behavior involves the CR taking charge of its spectrum duties in ensuring greater spectral utilization through efficient and reliable spectrum sensing and sharing. Though forward in approach, the proactive CR is designed with LU

protection as first priority. This act of self-initiation opens up many more opportunities for spectrum use, thus resulting in significant performance breakthroughs in core aspects like spectrum sensing accuracy and utilization efficiency.

The proactive component of the CR can in most cases be embedded within a probing signal as designed by the cognitive user. This probing signal initiates the proactive scenario, and triggers a response from the LU that serves as additional localized information for the CR. With this sort of feedback, different protocols can be designed around the respective problem statement at hand. We now illustrate how a self-initiated probing signal can be used to enhance spectrum sensing and sharing for CR scenarios.

3.2 Proactive Spectrum Sensing

As part of the CR's primary function, spectrum sensing is given its due importance in the field of communications research. Effectively assessing the spectrum usage and locating spectrum holes with no licensed activity is the prime purpose of spectrum sensing. However with issues that arise given a heavy fading environment or noisy conditions, the performance of the sensing result is often degraded. Hence we see a wide variety of spectrum sensing techniques that have been developed for greater accuracy in spectrum decision making. With LU detection being the easiest method to detect spectrum occupancy, techniques like matched filter, energy and cyclostationary detection became quite popular [7][8]. Cooperative communications also found its way into CR spectrum sensing [44]-[46] by allowing an extra degree of location diversity to enhance spectrum sensing results. This essentially implies that geographically separated secondary transmitters (ST) with a common sensing result would ensure greater certainty of the sensing decision. But the drawback of most of the existing sensing techniques was a dependence on critical noise information or channel statistics necessary for each approach. Therefore the idea of a completely uninformed CR seeking out spectral utility statistics and guaranteeing with a certain degree of accuracy the presence or absence of licensed activity was researched on, and has resulted in a number of blind spectrum sensing techniques [18] [20]-[22].

Now with all these methods to sense spectrum, proactive sensing may seem like it does not have a place. However we wish to point out that this novel concept of actively involving the CR in the spectrum sensing process is independent of the method used to sense spectrum. It however guarantees greater performance for CR systems that wish to incorporate a proactive approach to sensing. For the purpose of comparison, we choose a simple sensing technique like energy detection to measure the

significant improvement as a result of proactive sensing. As mentioned earlier, this technique considers PU systems that already have a feedback loop in place to monitor and maintain SNR variations at their respective receivers, such as CDMA or ACK/NACK based cellular networks. The PU feedback loop is then triggered by a probing signal sent out by the ST prior to sensing.

3.3 System Model

For the proactive sensing scenario, we consider a system model that consists of a PT-PR pair and a CU as shown in Fig. 3.1, where the CU acts as a ST. We label the channel gains from PT to PR as h_p , from PT to ST as h_1^{cp} , from PT to the secondary receiver (SR) as h_2^{cp} , from ST to PR as h_3^{cp} , and from ST to SR as h_c . We consider that all the channels are Rayleigh slow-fading channels, with the corresponding power gains given by $\gamma_p = |h_p|^2$, $\gamma_c = |h_c|^2$, $\gamma_1^{cp} = |h_1^{cp}|^2$, $\gamma_2^{cp} = |h_2^{cp}|^2$, and $\gamma_3^{cp} = |h_3^{cp}|^2$ respectively.

Figure 3.1: The concept of power feedback loop in the proactive system model.

The SNR measured at the PR denoted as $SNR_{PR} = P_t \cdot \gamma_p / N_0$ can be maintained at a target SNR, SNR_T , with the help of the power-feedback loop. P_t here represents the transmit power of the PT, and N_0 , the additive white Gaussian noise (AWGN) power observed at the PR. However when the ST sends out a probing signal with adequate power, the resultant SNR at the PR drops, and the power-feedback loop is activated. To maintain the QOS standard, the PR communicates this need to the PT via the feedback loop and asks it to increase its transmission power, to compensate for the increased interference. After compensation we see that the target SNR can still be met given an increment in PT's transmission power,

$$SNR_T = \frac{\dot{P}_t \cdot \gamma_p}{P_{pb} \cdot \gamma_3^{cp} + N_0} \quad (3.1)$$

where P_{pb} is the probing power of the ST, and $\dot{P}_t$, the incremented PT transmission power. It is clear that this boost in primary transmission power, increases the chances of the ST detecting the presence of the PU with higher certainty.

3.4 Numerical Formulation With Power Control Description

Unlike passive spectrum sensing, proactive sensing involves a probing section before sensing and transmission, as part of the entire CU data frame. This probing frame is primarily to aid in sensing the PU, and is represented as shown in Fig. 3.2.

Figure 3.2: CU data frame for the proactive sensing scheme.

After sending the probing signal, the CU waits for a response by the PU in the next time instant. In response to probing, if the PU's transmit power spikes then the channel is deemed busy, and the CU can choose to vacate the spectrum immediately or share the spectrum resources under the ITC. However, when there is no reaction from the PU to probing, the channel is deemed idle, and free for unlicensed traffic.

The energy detector used in this experiment is to facilitate sensing of the PU, by calculating the energy of the transmitted signal in the sensing slot as

$$\theta = \frac{1}{M} \sum_{m=1}^M |y[m]|^2 \quad (3.2)$$

where M is the number of samples and $y[m]$ denotes the received signal at the sensing detector, i.e.,

$$y[m] = \begin{cases} p[m] \cdot h_1^{cp} + z[m] & H_B \\ z[m] & H_I \end{cases} \quad (3.3)$$

where $p[m]$, the primary transmitted signal and $z[m]$, the gaussian noise are both modeled as circularly symmetric complex Gaussian variables. H_B here represents a busy channel or an active LU in the spectrum, where H_I on the other hand denotes the absence of a LU, or an idle channel. From central limit theorem it can be proved [53], that θ follows a Gaussian distribution with mean μ and variance σ^2

as shown.

$$\mu = \begin{cases} (1 + \rho) \cdot N_0 & H_B \\ N_0 & H_I \end{cases} \quad (3.4)$$

$$\sigma^2 = \begin{cases} \frac{1}{M}(1 + \rho)^2 \cdot N_0^2 & H_B \\ \frac{1}{M} \cdot N_0^2 & H_I \end{cases} \quad (3.5)$$

where for a busy channel, ρ denotes the SNR measured at the ST, following the increment in PT's transmission power as compensation for the SNR drop due to probing.

$$\rho = \frac{\dot{P}_t \cdot \gamma_1^{cp}}{N_0} \quad (3.6)$$

From (3.1), we can substitute for $\dot{P}_t$ in (3.6) to get,

$$\rho = \frac{SNR_T(P_{pb} \cdot \gamma_3^{cp} + N_0) \cdot \gamma_1^{cp}}{\gamma_p \cdot N_0} \quad (3.7)$$

Contrary to the work in [1], we consider probing and sensing as disparate operations, where the response of the PT to probing is measured subsequently during sensing, after sending out the probing signal. Thus the observation at the energy detector as a result of probing can be modeled as a Gaussian random variable with the following distribution,

$$\theta \sim \begin{cases} N[(1 + \rho) \cdot N_0, \frac{1}{M}(1 + \rho)^2 \cdot N_0^2] & H_B \\ N[N_0, \frac{1}{M} \cdot N_0^2] & H_I \end{cases} \quad (3.8)$$

where $N[\mu_\theta, \sigma_\theta^2]$ represents the real gaussian distribution with mean μ_θ and variance σ_θ^2 . The final sensing decision is then made by comparing θ to a detection threshold λ .

We define the probability of detection, $\mathcal{P}_d$, as the probability of correctly detecting the presence of the PU when it is active in its spectrum, while the probability of false alarm, $\mathcal{P}_f$, represents the probability of incorrectly detecting the presence of a PU in an idle channel. A higher λ in this case helps in reducing the false alarms in a high noise environment. The probabilities $\mathcal{P}_d$ and $\mathcal{P}_f$ can be represented as,

$$\mathcal{P}_d = P_r(\theta > \lambda | H_B) = \int_\lambda^\infty \frac{1}{\sqrt{2\pi\sigma_\theta^2}} e^{-\frac{(y-\mu_\theta)^2}{2\sigma_\theta^2}} dy = Q\left(\frac{\lambda - \mu_\theta}{\sigma_\theta}\right) \quad (3.9)$$

and similarly,

$$\mathcal{P}_f = P_r(\theta > \lambda | H_I) = Q\left(\frac{\lambda - \mu_\theta}{\sigma_\theta}\right) \quad (3.10)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{u^2}{2}} du$ is the Q-function. From (3.8) we then get,

$$\mathcal{P}_d = Q\left(\frac{\lambda - (1 + \rho) \cdot N_0}{\sqrt{\frac{1}{M}(1 + \rho)^2 \cdot N_0^2}}\right) \quad (3.11)$$

and

$$\mathcal{P}_f = Q\left(\frac{\lambda - N_0}{\sqrt{\frac{1}{M} \cdot N_0^2}}\right) \quad (3.12)$$

respectively. We eliminate λ from (3.12) by substituting for it from (3.11) to get

$$\mathcal{P}_f = Q\left(Q^{-1}(\mathcal{P}_d) \cdot (1 + \rho) + \rho \cdot \sqrt{M}\right) \quad (3.13)$$

where $Q^{-1}(\cdot)$ represents the inverse Q-function.

With expressions for both $\mathcal{P}_f$ and $\mathcal{P}_d$, we can now observe the role they play in determining the channel throughput. The achievable throughput for the cognitive channel given a sensing time is [13]

$$R(\tau) = \left(1 - \frac{\tau_{pb} + \tau_s}{T}\right) [p_1 C_1 (1 - \mathcal{P}_d) + p_0 C_0 (1 - \mathcal{P}_f)] \quad (3.14)$$

where τ_{pb} is the probing time, τ_s the sensing time, T the total frame time, and p_0/p_1 the probability of off/on activity of the PU. We define C_0 as the throughput of the cognitive channel in the absence of a PU and C_1 as the throughput measured in the presence of a PU. It follows that

$$C_0 = \log_2 \left(1 + \frac{P_s \cdot \gamma_c}{N_0}\right) \quad (3.15)$$

and

$$C_1 = \log_2 \left(1 + \frac{P_s \cdot \gamma_c}{\hat{P}_t \cdot \gamma_2^{cp} + N_0}\right) \quad (3.16)$$

where P_s is the ST's transmit power.

The benefits of proactive sensing can clearly be seen by analyzing (3.11)-(3.14). We can see that if λ is fixed in (3.11), the probability of detecting the PU in the spectrum greatly increases, with subsequent

increase in probing power. On the other hand if we have a fixed $\mathcal{P}_d$, the drop in probability of false alarm with increase in probing power is evident from (3.13). These results imply that proactive sensing is doubly beneficial in its role of protecting the PU against unwarranted missed detections, and ensuring fewer noise impairments in the ST's sensing decision. Also we notice that as a result of fewer false alarms, the CU can enjoy greater throughput as seen in (3.14). Therefore proactive sensing is seen as being favorable to both cognitive and licensed user.

In applying proactive sensing for practical CR networks, we consider an average secondary power constraint over one CU data frame, which is established as

$$P_{ave} = P_{pb} \cdot \frac{\tau_{pb}}{T} + P_s \cdot \left(1 - \frac{\tau_{pb} + \tau_s}{T}\right) \quad (3.17)$$

Figure 3.3: Variation of $\mathcal{P}_f$ for change in probing power.

3.5 Numerical Results

In this section we simulate the proactive sensing scheme for the system model described in Section 3.3. We assume that the power feedback loop in the primary channel is both delay and error free. We consider a noise variance of 1, P_{ave} of 30 dB, and a normalized probing time of 0.05. The variance of each of the Rayleigh fading channels depends on the distance of the respective communicating links. We consider a path-loss exponent of 3 and define d_i as the distance for each channel h_i , with $d_p=1, d_c=$

Figure 3.4: Probability of detection versus probing power.

1, $d_1^{cp}=2$, $d_2^{cp}=d_3^{cp}=\sqrt{5}$. It is also to be noted that, M , the number of samples per data frame is a function of the sensing time given by, $M = \tau_s \cdot f_s$, where f_s is the sampling frequency.

In the first experiment, we fix the probability of detection at 0.9 (as we consider a case of low interference to the PU) by varying the detection threshold with increase in probing power, to notice the effect probing has on $\mathcal{P}_f$. We know that the greater the number of samples in the sensing frame, the lower the probability of false alarm is. For a $SNR_T=7$ dB, we can see how the the probability of false alarm drops with increase in the number of samples per frame, but more importantly how it varies with probing power from Fig. 3.3. For the same number of samples, we see that with probing we can achieve a smaller $\mathcal{P}_f$ with higher levels of probing power. These reduced levels of $\mathcal{P}_f$ means that the ST has greater chance of filtering out the random noise in the absence of a PU, and thus maximizing its throughput.

In the next experiment, we consider $M=30$, $SNR_T=15$ dB, and a PU on-activity of 20%, therefore $p_1 = 0.2$ and $p_0 = 1 - p_1 = 0.8$. We then set λ at 10 dB and measure the increase in $\mathcal{P}_d$ with probing power, as shown in Fig. 3.4. The detection curve for the case of passive sensing given the same simulation parameters is shown for mere comparison and is independent of the probing power (as it does not involve probing). The performance boost that can be achieved with the proactive sensing scheme with probing power control is made clear by the steady increment in $\mathcal{P}_d$ with increased probing power levels. From (3.11) we see, that by setting a lower threshold, detection would be easier and we can observe a greater

Figure 3.5: Sensing-Throughput Tradeoff.

improvement in $\mathcal{P}_d$, but too low a threshold would only reduce the certainty of signal detection in a high noise environment. The increased detection probability also means that the CU throughput would drop as seen in (3.14).

For a fixed number of samples (i.e., $M=30$) we see that our throughput-sensing tradeoff scenario turns into a linear relationship, as shown in Fig. 3.5, where we can rely on a shorter τ to achieve the required CU channel throughput. Here we notice that the throughput curve for the case of passive sensing and with probing power of -5 dB overlap, because of the negligible effect that probing at -5 dB has on both $\mathcal{P}_f$ and $\mathcal{P}_d$. However the throughput drop is significant as we increase the probing power. We also notice that after a certain probing power level, the throughput decrement is smaller due to the saturation in $\mathcal{P}_d$ beyond 15 dB of probing power as seen in Fig. 3.4. This throughput reduction as a result of the substantial boost in $\mathcal{P}_d$ can be compensated with a shorter τ . Therefore this tradeoff in transmission rate versus sensing performance must be balanced accordingly. Overall we believe that this proactive sensing technique ensures greater protection to the PU, by preventing missed detection transmissions, that contribute to some of the CUs erroneous throughput opportunities. With probing power available at hand, our results guarantee that missed detections can be completely eliminated, thus making this scheme a truly safe and opportunistic spectrum access scheme.

Chapter 4

Cross-Channel Estimation With Supervised Probing

As seen in the previous chapter, the benefits of probing are two fold, in safeguarding the LU and promoting both throughput and detection rates for a CU. Probing is essentially a technique to facilitate easier detection of the PU in its licensed spectrum, while still respecting the interference constraints set at its receiver. PR interference shielding is the peak and primary concern when a CU wants to share licensed spectrum. Therefore by isolating the PR from the system model and focusing on the aspect of cross-interference felt at the PR as a result of probing, many exciting areas open up.

A general concern for CUs that wish to share spectrum, is how to gain cross-channel knowledge (i.e. between a ST and PR) without any cooperation with the PU. Most work currently relies on an assumption of cross-channel information being made available to the ST. This information is essential in allowing the ST to monitor the cross-interference felt at the PR, due to its concurrent transmission or probing signals. Therefore by respecting the interference constraints set at the PR [30], the CU is free to share licensed spectrum, which is independent of the fact whether the PU is active or idle in the band. Like before, the ST first sends out a probing signal, dealing an additional interference to the PR and forcing it to trigger the power-feedback loop. This experiment focuses on gaining control of this feedback link, by prying on the bits fed back in response to a certain level of interference. By sequentially increasing the power of probing, the ST pushes the SNR envelope at the PR, until it senses a change in the feedback pattern. With this knowledge available to the ST, the magnitude of the cross-channel gain between itself and the PR, can be estimated. With this estimate and publicly available

Figure 4.1: The supervised probing and sensing system model

ITC [6] set at the PR to protect licensed communication, the ST can then calculate the maximum transmission power allowable for spectrum sharing. Depending on its throughput requirement the CU can then decide on sharing the licensed spectrum with this maximum transmission power, or opting for interference free-access at lower powers.

4.1 System Model

In this section, we describe the system design for a CR carrying out the supervised probing and sensing experiment in its attempt to gain knowledge of the cross-channel information between itself and a PR, in its region of interference (ROI).

As seen in Fig. 4.1 we consider a PT-PR pair and a ST-SR pair, with focus on the link between the ST and PR. All the channels are unit variance Rayleigh block fading channels where the fading depends on the distances between the associated parties (the channel gains also vary over each frame of data due to the block fading nature of the channels). We denote the primary channel (PT-PR link) as h_p , the cognitive/secondary channel (ST-SR link) as h_c , and the cross channel of interest (ST-PR link) as h_{cp} . It is assumed that time reciprocity holds for the cross-channel, such that the forward and reverse link have the same channel characteristics (i.e. h_{cp} , the cross-channel from ST to PR, is equivalent to h_{pc} , the channel from PR to ST).

To convey change in instantaneous channel SNR, a feedback loop is in place on the primary link is

considered, whose codebook is a 2-bit representation of the power change required at the PT to counter the additional interference felt at the PR. When the ST sends out a probing signal of power P_{pb} , the SNR at the PR drops to

$$SNR_{PR} = \frac{P_p \cdot |h_p|^2}{P_{pb} \cdot |h_{cp}|^2 + N_0} \quad (4.1)$$

where P_p is the transmit power of the PT and N_0 is the AWGN power observed at the PR. This instantaneous SNR is then compared to the target SNR for the channel, denoted by m in Table 4.1. To compensate for the change in SNR at PR, α is calculated as the percentage transmit power change required at the PT (shown in Table 4.1), and the corresponding power adaptation (PA) is quantized to a bit pattern to be fed back. For practicality we have assumed a 10% SNR tolerance at the PR, as reflected in Table 4.1. (The PA values α_x , α_y and the threshold range of transmit power change, r_{th} , are discussed in greater detail in Section 4.2.1).

The 2-bit information is then pulse amplitude modulated (PAM) and sent back on the primary feedback link. Here we assume that the ST is aware of the 4-level PAM feedback system in place at the PU end, but oblivious to the exact power levels being used, which is only known to and decided upon by the PT-PR pair. Therefore, the ST aims at prying on these instantaneous feedback responses while increasing the probing power in steps, to seek out 4 different PAM levels corresponding to the bit patterns fed back. The probing power levels that force a change in the bit patterns are recorded and are used to estimate the magnitude of the cross-channel gain.

The supervised probing and sensing experiment relies heavily on the probing behavior of the ST, and how its designed power levels can affect the PR's response to what may seem like harmless interference. The ST follows a slotted probing and sensing approach, where the ST remains silent for two timeslots after a probing instant, in order to:

- give the PR time to stabilize its channel SNR
- pry on the bits fed back during the silent period while the PR requests for an increase in PT's transmission power

$m = \frac{SNR_{Target}}{SNR_{PR}}$	$\alpha = m - 1 $ (in %)	PA	Bit Pattern
> 1	$10\% \sim r_{th}\%$	$\alpha_x\% \uparrow$	10
	$> r_{th}\%$	$\alpha_y\% \uparrow$	11
< 1	$10\% \sim (\frac{r_{th}}{1+r_{th}})\%$	$(\frac{\alpha_x}{1+\alpha_x})\% \downarrow$	01
	$> (\frac{r_{th}}{1+r_{th}})\%$	$(\frac{\alpha_y}{1+\alpha_y})\% \downarrow$	00

Table 4.1: PT's power adaptation table.

(a)

(b)

Figure 4.2: (a) ST's slotted probing and sensing frame structure. (b) ST's data frame structure.

In subsequent timeslots the ST increases the probing power by a predefined step-size (explained in Section 4.2.2). Simultaneously the ST listens to the feedback response and scans through the incremental probing power levels, till it records a different power level. This training is continued till the ST has confirmed four different feedback responses that correlate with the ST probing behavior shown in Fig. 4.2(a). During the sensing slot following a probing timeslot, the ST looks to gain knowledge of the responses corresponding to an increase in PR SNR relative to the target SNR, with the idea that a bigger increment usually follows a bigger SNR drop (i.e. 01 follows 10 and 00 follows 11). Once the training is completed, the ST uses the remainder of the data frame for transmission as seen in Fig. 4.2(b) (The typical training time is 10% of the frame time for a 500 symbol data frame).

4.2 Design of System Parameters

In a block-fading scenario, where the channel changes with every frame of data, the ST has to re-engage the PR in each frame to estimate the new cross-channel gain. But in order for the ST to be competent given any channel setting, the probing power increment used and the PT's PA pattern must be carefully studied and designed prior to the supervised probing and sensing experiment.

4.2.1 Power Assignment and Primary Transmitter's Power Adaptation Values

As seen in Table 4.1, the PT's PA table is carefully mapped to include all possible power adjustments necessary for SNR stability at the PR. When the PR sees an additional interference, it categorizes it into one of two interference ranges, assigns an appropriate PA value and quantizes it for feedback. The

threshold value r_{th} which characterizes interference as mild or strong is entirely dependent on the decision made between the primary pair (PT-PR). The single PA values chosen (here α_x and α_y) to represent the range of interference is also preset at the PR. However with α representing the transmission power change in PT, knowing r_{th} can help in analyzing the threshold limit for the case with surplus SNR being seen at the PR (i.e. $m < 1$). For example (as in Section 4.4.2), r_{th} can be set to 50% which represents the percentage increment in primary transmission power, when interference felt at the PR falls in that respective range. However in the absence of probing or interference, this surplus of power causes a surge in the PR SNR beyond what is required and the corresponding drop in power needed to stabilize the SNR, can easily be calculated as $\frac{r_{th}}{1+r_{th}}\%$ of the current PT's transmission power.

Though the ROI is bounded only by a threshold, the limitation of the feedback channel forces a confinement to 2 bits of information statistic. Therefore the appropriate PA value suitable to the range of interference must be chosen by the PU prior to the start of communication. For simulation PA values for α_x as 25% and α_y as 75% have been chosen. Though these values of PA are set at the PU end, with training the ST can estimate these values based on the probability of successfully probing all 4 feedback responses, and which over a large sample size converge to the true PA values set at the PU. For the sake of conciseness we have excluded the training results that show this convergence and instead drawn focus to the probing power increment, a design parameter set at the CU end and essential to the whole supervised probing and sensing scheme.

4.2.2 Probing Power Increment

Probing is seen as a way for the ST to test the surrounding area, by incrementing the power in steps and listening for a feedback. Once the first feedback is heard, the ST is given two choices. It can use the last interference-free probing power to access the spectrum without causing interference to any PRs in its ROI, or probe further and learn of the maximum tolerable interference in order to share the spectrum with the PR by initializing the supervised probing and sensing experiment.

In incrementing the probing power, the ST has to be careful in choosing a step-size appropriate to the varying channel conditions. If the step-size chosen is too small, the ST would meticulously scan through all probing power levels, till all 4 levels of feedback information are sensed, and would require a much longer training time. Although a smaller step-size would also mean greater accuracy in the recorded probing power levels, effective transmission time plays a key role in the CU throughput. The optimization of this system parameter is discussed further in Section 4.4.1.

4.3 Cross-Channel Estimation

In the estimation process the ST relies on correlating 2 feedback responses to different probing power levels within the same frame, thus arriving at an analytical representation for the magnitude of the cross-channel gain. As seen from (4.1), the instantaneous SNR at the PR for two different probing powers can be represented as

$$SNR_1 = \frac{P_p \cdot |h_p|^2}{P_{pb_1} \cdot |h_{cp}|^2 + N_0} \quad (4.2)$$

$$SNR_2 = \frac{P_p \cdot |h_p|^2}{P_{pb_2} \cdot |h_{cp}|^2 + N_0} \quad (4.3)$$

where P_{pb_1} and P_{pb_2} are the higher and lower probing power levels that forced a feedback of bits 11 and 10, and resulted in PT power adaptations of α_y and α_x respectively. By introducing SNR_{Target} to both equations, dividing (4.2) by (4.3) and assuming a noise power of unity (i.e. $N_0 = 1$) we get

$$\frac{m_y}{m_x} = \frac{P_{pb_1} \cdot |h_{cp}|^2 + 1}{P_{pb_2} \cdot |h_{cp}|^2 + 1} \quad (4.4)$$

where $m_y \triangleq \frac{SNR_{Target}}{SNR_1}$ and $m_x \triangleq \frac{SNR_{Target}}{SNR_2}$. P_{pb_1} can also be represented as a function of P_{pb_2} and the probing power increment, ΔP_{pb} as

$$P_{pb_1} = P_{pb_2} + \Delta P_{pb} \cdot n \quad (4.5)$$

where n represents the number of symbols required to make the jump to a higher probing power level, P_{pb_1} corresponding to a different feedback response. Then from Table 4.1, (4.4) becomes

$$\frac{\alpha_y + 1}{\alpha_x + 1} = \frac{(P_{pb_2} + \Delta P_{pb} \cdot n) \cdot |h_{cp}|^2 + 1}{P_{pb_2} \cdot |h_{cp}|^2 + 1} \quad (4.6)$$

As there is a unique value of ΔP_{pb} for each new channel, that will optimize the performance of the probing experiment, we will label ΔP_{pb}^* as its optimized value (discussed later in Section 4.4.1). Then $|h_{cp}|$ in (4.6) becomes $|\hat{h}_{cp}|$, the estimate of the magnitude of the cross-channel gain and can be written as

$$|\hat{h}_{cp}| = \sqrt{\frac{\alpha_y - \alpha_x}{|(\alpha_x - \alpha_y) \cdot P_{pb_2} + (\alpha_x + 1) \cdot \Delta P_{pb}^* \cdot n|}} \quad (4.7)$$

With the interference threshold at the PR (i.e. ITC) being made known to public, the maximum

allowable ST transmission power for a spectrum sharing scenario is

$$P_{s_{max}} = \frac{P_{peak}}{|\hat{h}_{cp}|^2} \quad (4.8)$$

where P_{peak} is the instantaneous peak interference power threshold set at the PR as an ITC.

4.4 Optimization of Probing Power Increment and Simulation Results

Before the ST can begin to share or access the randomly changing spectrum, an initial system training is required, which involves optimizing the probing power increment parameter discussed in Section 4.2.2.

4.4.1 Training Based Optimization

It is vital that the CU makes full use of the available spectrum, when sharing it with the PU. Therefore maximizing the probability of channel success (i.e., the ability of the ST being able to sense all 4 feedback responses within the supervised frame time such that a cross-channel estimate can be arrived at) is key when optimizing the probing power increment parameter. To accomplish this we pass the ST through a series of varying channels where the ΔP_{pb} 's resilience to this set of randomly changing channels is measured. Here we vary the value of ΔP_{pb} from 0.01 to 5 in steps of 0.01, and record the corresponding channel success probability. The optimum ΔP_{pb} is chosen as the one that records the highest channel success probability. This training is run for a set of 500 rayleigh fading channels with variance 1, and the corresponding table of training results is shown in Table 4.2. The corresponding probability density function of the ΔP_{pb} that results in channel success is obtained from this training and plotted in Fig. 4.3.

Though we optimize ΔP_{pb} with respect to channel success, we see that the probing power increment can play a dominant role in influencing the cross-channel gain estimation mean squared error (MSE). The square of the magnitude of cross-channel gain estimation error (SME) for one given frame is given by

$$SME = (|h_{cp}| - |\hat{h}_{cp}|)^2 \quad (4.9)$$

If we let the constant A represent $|h_{cp}|$ for this frame, while $|\hat{h}_{cp}|$ takes the analytical form as in (4.7), with ΔP_{pb}^* being replaced by ΔP_{pb} , the variable in this formulation, we can see that on differentiating

Mean Values	Optimal Value
$\bar{P}_{pb_2} = 0.3366, \bar{n} = 10.28$	$\Delta P_{pb}^* = 0.1$

Table 4.2: Table of training results.

Figure 4.3: Distribution of ΔP_{pb} for channel success.

(4.9) with respect to ΔP_{pb} we have

$$\frac{dSME}{d\Delta P_{pb}} = \left[\bar{n} \cdot \text{sign}(F)(\alpha_x + 1)(\sqrt{\alpha_y - \alpha_x})(A \cdot \sqrt{|F|} - \sqrt{\alpha_y - \alpha_x}) \right] \cdot \frac{1}{|F|^2} \quad (4.10)$$

where $F = [(\alpha_x - \alpha_y) \cdot \bar{P}_{pb_2} + (\alpha_x + 1) \cdot \Delta P_{pb} \cdot \bar{n}]$ is used for convenience in representation, and $\bar{P}_{pb_2}$ and $\bar{n}$ are the average values of P_{pb_2} and n recorded during the initial training phase, respectively. By substituting for these 2 parameters with the training results from Table 4.2, we can plot the SME differential with the probing power increment as shown in Fig. 4.4 for a channel realization with magnitude $A = 0.6$. We notice that the rate of change of SME is negative upto an optimal point of ΔP_{pb} unique to a given channel, and increases beyond this point with negligible rate of change. As MSE can be represented as an average of SMEs over N frames, then the dependence SME has on ΔP_{pb} can be extended to say that the probing power increment also plays a major role in the resultant cross-channel MSE. From Fig. 4.4, we can see that it is critical to choose an appropriate value for ΔP_{pb} , in minimizing the cross-channel gain estimation MSE.

Figure 4.4: Rate of change of SME with ΔP_{pb} .

4.4.2 Simulation Results

As ST's channel success probability determines the effective spectrum usage, we ensure that the optimized probing parameter set during the initial system training, is robust given any set of varying channels. With ΔP_{pb} of 0.1 (from Table 4.2), the ST carries out probing and sensing followed by data transmission for each frame (as in Fig. 4.2(b)) to estimate the underlying cross-channel. The recorded SME levels for a set of 100 random cross-channels is plotted in Fig. 4.5. Here we notice that though the system was trained with preference given to channel success, we still achieve a relatively low cross-channel MSE. Through simulations, we also observe that the channel success rate for our optimization methodology averages to 90% over a series of varying channels. Therefore when comparing the CU throughput achievable through our estimation technique, with that of an ideal scenario where the ST has full cross-channel knowledge, we realize that the channel success rate alone will determine the percentage difference in the result. With a channel success rate of 90% (as achievable through our model, shown in Fig. 4.5), we can expect a maximum drop of only 10% in throughput when comparing our scheme against the case for full channel knowledge being made available, for the same system parameters. This tradeoff comes at the cost of practicality.

The significance of the supervised probing and sensing method is seen in the negligible tradeoff in CU throughput with PU protection given top priority. Before sharing the spectrum with the PU, the ST must make sure that the interference dealt by its own transmission must be below an interference threshold

Figure 4.5: Recorded SME values for the random cross-channels.

Figure 4.6: Primary user protection in terms of $P_{s_{max}} \cdot |h_{cp}|^2$.

set at the PR. From (4.8), we know that the maximum ST transmission power is calculated with respect to a peak interference constraint based on the instantaneous cross-channel estimate, however due to the error in estimation, there will be a deviation from the ideal $P_{s_{max}}$. Therefore the actual interference felt at the PR (calculated as $P_{s_{max}} \cdot |h_{cp}|^2$) may differ with respect to P_{peak} set at the PR. As seen in Fig.

4.6, the percentage of error events ($P_{s_{max}} \cdot |h_{cp}|^2 > P_{peak}$) is less than 10%, which shows the high degree of PU protection, during concurrent ST transmissions.

Therefore the supervised probing and sensing model discussed thus far, aims at maximizing the probability of channel success for estimating the cross-channel gain without knowledge or cooperation with the PR (i.e., a blind estimation), and with the performance results achieved, it can be seen as a viable option for future work related to cross-channel estimation.

Chapter 5

Proactive Spectrum Sharing

Proactive CRs can be seen in almost any practical communication setup, given the benefits that can be seen for both the LU and the CR system. With common issues with regard to passive spectrum sensing and cross-channel estimation dealt with, we now wish to extend the proactive scene to cooperative systems involved in a spectrum sharing setup.

The problem that CR was envisioned to solve, was the spectrum crisis, in particular the inefficient spectral utilization. Spectrum sharing is a viable option in tackling this problem. The work carried out in spectrum sharing [54]-[56] however seems to be self-indulgent, where the CR has all to gain while the LU's spectrum is being used. The ITC [6] used in most spectrum sharing scenarios, only ensures a tolerable margin of cross-interference from CR's simultaneous transmissions, and does not guarantee constant LU protection.

In the world of cooperative communications [44], we see a major concentration of work focused on collaboration between individual CR pairs, to improve on spectrum sensing [46]-[49] and to establish fair spectrum pooling [50][51] for a network of CRs. Cooperative relaying by itself is used extensively to enhance the throughput of the respective source nodes that implement dedicated or adaptive relay nodes [52]. This is also commonly implemented for LU systems that require relay support for licensed transmission.

What we see in literature is that most cooperative communication or spectrum sharing system setups are modeled around the performance gain achievable at the CR end, while not harming the LU. Such a protocol would only appeal to a LU that willfully participates for the good of global spectral efficiency. Inspired by the work in [57] that discusses a cooperative protocol between a LU and a CU, we wish to investigate the further interactions between these cooperative users by considering various scenarios

that could arise when the CU attempts to gain opportunistic spectrum access. Through our work, we propose a protocol design centered around spectral management with the combined effort of the CR and LU, bringing mutual benefit to both parties involved, through proactive and opportunistic spectrum sharing.

Figure 5.1: Proactive Spectrum Sharing System Model.

5.1 Protocol Design

Let us consider a system design that involves one LU and one CU transmitter-receiver pair, with the channels between the respective nodes following slow Rayleigh fading. The corresponding system setup is shown in Fig. 5.1, with the channel gains of the respective LU channel, CU channel and cooperative channels given by h_p , h_c , h_1^{cp} , h_2^{cp} , and h_3^{cp} respectively. The corresponding power gains can be given by $\gamma_p = |h_p|^2$, $\gamma_c = |h_c|^2$, $\gamma_1^{cp} = |h_1^{cp}|^2$, $\gamma_2^{cp} = |h_2^{cp}|^2$, and $\gamma_3^{cp} = |h_3^{cp}|^2$ respectively. The LU we propose here is self-sufficient in terms of its own outage management. With adaptive power control, the licensed transmitter (LT) can deal with outage as indicated by the LR through feedback. Therefore the cooperative sharing model we are going to propose is not entirely dependent on cooperation, and the LU in question can function independent of any other user.

We now bring in a proactive CR into the scenario that wishes to gain spectral access by approaching the LU with a proposal for cooperation. The CR initially sends out a probing signal designed as a Request To Access (RTA) message to the LU. It is to the discretion of the LU whether or not to accept this message. But if the LU wishes to cooperate, then the LR, can respond to this request with either of two messages: Request To Cooperate (RTC) or Permit To Share (PTS). If the LR has surpassed the

instantaneous target rate for that given fading channel, and can accommodate additional interference from simultaneous CR transmissions, it uses this opportunity to improve the spectral efficiency and informs the CR through an PTS message. This initiative to share licensed spectrum is then acknowledged by the LT through a Confirm To Share (CTS) message sent out to the CU. We define this scenario as the Simultaneous Sharing Mode, as the primary link can support both simultaneous LU and CU transmissions.

On the other hand if the LU is in outage, and needs CU's relay support, the LR sends out the RTC message. This request for cooperation is backed up by an Acknowledgement To Cooperate (ATC) message sent by the LT to the CU. On receiving the RTC and ATC messages, the CU can determine if it can support the LU transmission, in preventing outage for the current channel realization. If so, the CU broadcasts a Confirm To Cooperate (CTC) message, indicating its support in acting as a relay to LU communication. This scenario is defined as the Cooperation Mode and the LT and LR switch to accommodate a two-phase relaying scheme (discussed in Section 5.2) to prevent outage at the LR. If however, the CU cannot support the LU given its limited transmission power, it broadcasts a Fail To Cooperate (FTC) message, which informs the licensed transmitter and receiver to stop transmission, and to preserve its power for a better channel. This on the other hand implies full spectrum access for the CU. This mode is appropriately named the Full Access Mode, as the CU can have interference-free access to licensed spectrum.

This protocol is defined such that there is confirmation from each party through acknowledgement messages of either cooperation, access or sharing. The LT and LR embed training symbols in each of these outgoing handshake messages, which the CU uses to estimate the respective channel gains through training-aided channel estimation processes [58] for calculation and confirmation of the mode of operation. For illustrative purposes this entire protocol is demonstrated in Fig. 5.2. Therefore for a willing LU and a proactive CR, this cooperation can result in significant boost to spectral utilization efficiency, and joint benefits to LU outage and CR rate as seen later.

5.2 System Description

The process as discussed above is initiated by a proactive CU with the aim of rate and spectral maximization. In general spectrum sharing scenarios, both of these criteria can be fulfilled, however, the LU may or may not be completely protected against CR's cross-interference due to simultaneous transmission. The model design here is for the LU to get a fair bargain and to derive some gain out

of leasing out spectrum. Therefore the CR proposes cooperative relaying as a solution to both these problems. In the cooperative relaying scenario, after the CT has confirmed cooperation with the CTC message, the CU works as a partial relay, accessing spectrum while forwarding the LU signal to the LR to help out the LU in outage. The CT here receives the LU data in the first phase, which it superimposes with its own signal and then broadcasts this over the next transmission phase. The cognitive receiver can then decode this signal by isolating the CT's message from the LU data, by eavesdropping on the initially broadcasted LU message.

If however the CT's power is insufficient to support the requested target rate at the LR, the CT sends out a FTC message, thus entering into the Full Access Mode. Here the CU can transmit with maximum power, as the LU ceases to operate, and as seen through our simulation results in Section 5.4

Figure 5.2: Flowchart of Cooperative Handshaking.

this results in a significant boost to the average CU rate.

We also consider the scenario where, the LU has no problem with data transmission, but still wishes to cooperate as the LU rate is way above the target rate necessary to meet an outage probability. The LU here, can allow the CR to share spectrum with interference within the acceptable margin of the rate gain. The CR can acquire the corresponding channel knowledge as needed to maintain its interference, through training symbols sent in the form of the PTS and CTS messages from the LR and LT, respectively. For the purpose of simplicity, we assume that all these handshaking messages are low-powered to avoid interference with surrounding users and can be publicly decoded by the users in the surrounding area. Therefore the cooperative spectrum sharing and relaying model just described allows three modes of operation based on the current channel condition on the licensed link: simultaneous spectrum sharing to improve spectral utilization, cooperation to benefit the LU in outage, and full access mode that allows complete access to LU spectrum for CU data transmission.

5.2.1 Cooperation Mode

Under this scenario, the CU has already calculated the power necessary to devote to LU transmission in meeting the LU's instantaneous target rate, R_t through two-phase cooperative relaying. If we denote the LU power as P_p , then the LU rate in the absence of cooperation would be given by,

$$R_d = \log_2 \left(1 + \frac{P_p \cdot \gamma_p}{N_0} \right) \quad (5.1)$$

where N_0 is the noise variance. From here on out, we assume unity noise variance (i.e. $N_0 = 1$) for all the noise terms involved.

For this two-phase relaying, the LU broadcasts its signal, x_p with power P_p in the first transmission phase. The signal received at the CT and the LR in this first transmission phase can be given by y_{ct} and y_{lr_1} respectively,

$$y_{ct} = \sqrt{P_p} \cdot h_1^{cp} \cdot x_p + n_1^{ct} \quad (5.2)$$

$$y_{lr_1} = \sqrt{P_p} \cdot h_p \cdot x_p + n_1^{lr} \quad (5.3)$$

where n_1^{ct} and n_1^{lr} represent the AWGN at the CT and LR respectively, during the first transmission phase.

Here we propose to use AF relaying that requires the CT to boost the received signal before forwarding it. The CT first normalizes the power of the received LU signal, y_{ct} and then amplifies it with a percentage

of its own power given by α . This signal is further superimposed with the CT's own signal, x_s of power P_s , and then broadcasted in the second transmission phase. This composite signal is given by,

$$x_{ct} = \sqrt{\alpha \cdot z} \cdot y_{ct} + \sqrt{P_s \cdot (1 - \alpha)} \cdot x_s \quad (5.4)$$

where $z = \frac{P_s}{P_p \cdot \gamma_1^{cp} + 1}$ is the normalization factor. Thus the signal received at the LR in the second transmission phase then becomes,

$$\begin{aligned} y_{lr2} &= x_{ct} \cdot \gamma_3^{cp} + n_2^{lr} \\ &= (\sqrt{P_p \cdot \alpha \cdot z} \cdot h_1^{cp} \cdot h_3^{cp})x_p + (\sqrt{P_s(1 - \alpha)} \cdot h_3^{cp})x_s + \sqrt{\alpha \cdot z} \cdot h_3^{cp} \cdot n_1^{ct} + n_2^{lr} \end{aligned} \quad (5.5)$$

where n_2^{lr} represents the AWGN at the LR in phase two of transmission.

Therefore from (5.3) and (5.5), the LU rate under cooperation for a 2-phase relay system can be written as,

$$R_p^c = \frac{1}{2} \log_2 \left(1 + P_p \cdot \gamma_p + \frac{P_p \cdot \gamma_1^{cp} \cdot \gamma_3^{cp} \cdot z \cdot \alpha}{P_s \cdot (1 - \alpha) \cdot \gamma_3^{cp} + \alpha \cdot z \cdot \gamma_3^{cp} + 1} \right). \quad (5.6)$$

The decision made by the CR before accepting cooperative based relaying is to ensure that it can support the instantaneous LU rate as given by (5.6) to be no less than the target R_t . However for this, the CR can at most assign 100% (i.e. $\alpha = 1$) of its transmission power acting as a pure relay to help the LU in outage. With dynamic channel information made available through training symbols in the received handshake messages, the CR makes the cognitive decision of whether it can help the LU or not, based on the calculation of α . On equating the RHS of (5.6) to R_t , we get,

$$\alpha = \frac{(P_p \cdot \gamma_1^{cp} + 1)(P_s \cdot \gamma_3^{cp} + 1)(P_p \cdot \gamma_p - 4^{R_t} + 1)}{P_p \cdot P_s \cdot \gamma_1^{cp} \cdot \gamma_3^{cp} \cdot (P_p \cdot \gamma_p - 4^{R_t})}. \quad (5.7)$$

Here it is obvious to see that α is always positive. But with $\alpha < 1$, the CR can cooperate and affect a change in the LU's outage probability. We see that this value of α is dynamic given the random channel realizations and is found to be optimal in maintaining or lowering outage at the LU, while maximizing CR's average rate. With a static value of α , the corresponding gains for the LU and the CR might be affected and can be verified through our simulations.

5.2.2 Full Access Mode

Under the scenario where the value of α is greater than 1, it implies that the CU cannot support LU transmission even as a pure relay. The LU here cannot gain from carrying on transmission, and must preserve its power for better spectrum opportunities. We term this opportunity for the CU as the full access mode. In this window of opportunity, the CU can maximize its rate through interference-free access of licensed spectrum. The respective rate calculations for the CU will be detailed later in Section 5.3.

5.2.3 Simultaneous Sharing Mode

With systems that work together to better the spectrum utility issue, spectrum sharing is a natural solution. When the instantaneous LU rate is significantly greater than the target rate, R_t , then it can use this surplus rate margin to extend a spectrum sharing opportunity to the CR, as gratitude for its relay help during the outage frame. The CU in this case receives the PTS and CTS messages with the encoded channel information, necessary to guarantee a cross-interference lower than the acceptable margin for an outage-free LU. The spectrum sharing rate of the LU in this case would be

$$R_p^s = \log_2 \left(1 + \frac{P_p \cdot \gamma_p}{P_s \cdot \gamma_3^{cp} + 1} \right) \quad (5.8)$$

which cannot be lower than R_t . Thus the maximum instantaneous transmission power of the CT can be found by equating the RHS of (5.8) to R_t , and is

$$P_{s_{max}} = \frac{1}{\gamma_3^{cp}} \cdot \left(\frac{P_p \cdot \gamma_p}{2^{R_t} - 1} - 1 \right). \quad (5.9)$$

5.3 Outage and Rate Calculation

LU Outage Probability:

- For direct PU transmission - $\mathcal{P}_{out}^d = \mathcal{P}(R_d < R_t) = 1 - \exp\left(-\frac{R_t}{P_p \cdot \bar{\gamma}_p}\right)$
- With our protocol - $\mathcal{P}_{out} = \mathcal{P}(R_d < R_t) \cdot (1 - \mathcal{P}(\alpha < 1))$

where $\mathcal{P}(\cdot)$ represents the probability of an event, and $\bar{\gamma}_p$ is the average channel power gain for the licensed link.

Probing (RTA)	Sensing (RTC)	Sensing (ATC)	$\mu < 1$ (CTC)	Cooperation Mode
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(a)

Probing (RTA)	Sensing (RTC)	Sensing (ATC)	$\mu \geq 1$ (FTC)	Full Access Mode
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(b)

Probing (RTA)	Sensing (PTS)	Sensing (CTS)	Simultaneous Sharing Mode
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(c)

Figure 5.3: CR Frame structure.

CR Rate:

When the LU broadcasts its message to the CT, the cognitive receiver also eavesdrops and receives the transmitted signal, x_p . The signal received at the cognitive receiver is given by,

$$y_{cr_1} = \sqrt{P_p} \cdot h_2^{cp} \cdot x_p + n_1^{cr} \quad (5.10)$$

where n_1^{cr} is the AWGN at the cognitive receiver for the first transmission phase. With the received signal, y_{cr_1} , the cognitive receiver has an estimate of x_p given by,

$$\tilde{x}_p = x_p + \frac{n_1^{cr}}{\sqrt{P_p} \cdot h_2^{cp}}. \quad (5.11)$$

With the broadcast of the composite relayed signal from CT in the second transmission phase, the received signal at the cognitive receiver for this phase is

$$\begin{aligned} y_{cr_2} &= x_{ct} \cdot h_c + n_2^{cr} \\ &= (\sqrt{P_p} \cdot \alpha \cdot z \cdot h_1^{cp} \cdot h_c) x_p + (\sqrt{P_s} \cdot (1 - \alpha) \cdot h_c) x_s + \sqrt{\alpha \cdot z} \cdot h_c \cdot n_1^{ct} + n_2^{cr} \end{aligned} \quad (5.12)$$

where n_2^{cr} is the AWGN at the cognitive receiver for the second transmission phase. Now with the estimate of x_p from (5.11), the cognitive receiver can cancel out the interference from the LU from the

received signal to get,

$$\begin{aligned}\tilde{y}_{cr_2} &= y_{cr_2} - (\sqrt{P_p \cdot \alpha \cdot z} \cdot h_1^{cp} \cdot h_c) \tilde{x}_p \\ &= (\sqrt{P_s \cdot (1 - \alpha)} \cdot h_c) x_s - \frac{\sqrt{\alpha \cdot z} \cdot h_1^{cp} \cdot h_c \cdot n_1^{cr}}{h_2^{cp}} + \sqrt{\alpha \cdot z} \cdot h_c \cdot n_1^{ct} + n_2^{cr}.\end{aligned}\quad (5.13)$$

In calculating the instantaneous CR rate, there are 3 scenarios that our protocol is designed to handle. From Fig. 5.3, we see the data frame structure for a CR implementing our protocol. A proactive CR sends out the initial access request embedded within the probing signal used in all our previous proactive scenario models as a protocol initiation signal. This is followed by two sensing slots for the CU to gain channel knowledge through handshaking messages from the PU. Finally based on the various dynamic parameters, the appropriate transmission scenario is chosen, which can be one of these three:

- Cooperation Mode - When the LU is in outage and $0 < \alpha < 1$

From (5.13), we can calculate the instantaneous CU rate for cooperation mode as

$$R_s^c = \frac{1}{2} \log_2 \left(1 + \frac{P_s(1 - \alpha) \cdot \gamma_2^{cp} \cdot \gamma_c}{\alpha \cdot z(\gamma_1^{cp} + \gamma_2^{cp})\gamma_c + \gamma_2^{cp}} \right). \quad (5.14)$$

- Full Access Mode - When the α needed to meet LU target rate is greater than 1, the CU cannot support the LU in outage. Here the LU ceases to transmit, with only pure spectrum access for the CU. The resulting instantaneous CU rate is given by,

$$R_s^a = \log_2 (1 + P_s \cdot \gamma_c). \quad (5.15)$$

- Simultaneous Sharing Mode - When $R_d > R_t$, the CR can share the spectrum with an instantaneous rate given by,

$$R_s^s = \log_2 \left(1 + \frac{P_s \cdot \gamma_c}{P_p \cdot \gamma_2^{cp} + 1} \right) \quad (5.16)$$

s.t. $P_s \leq P_{s_{max}}$ as calculate in (5.9).

Thus the total effective average CR rate, after taking into account all these scenarios, can be written as,

$$\overline{R}_s = \overline{R}_s^c \cdot \mathcal{P}_{out}^d \cdot \mathcal{P}(\alpha < 1) + \overline{R}_s^a \cdot \mathcal{P}_{out}^d \cdot \mathcal{P}(\alpha \geq 1) + \overline{R}_s^s \cdot (1 - \mathcal{P}_{out}^d) \quad (5.17)$$

where $\overline{R}_s^c$, $\overline{R}_s^a$, and $\overline{R}_s^s$ are the effective averages of the individual scenario CR rates.

5.4 Simulation Results

In this section, we plot the simulation results for the different performance parameters in the cooperative sharing model. For analysis, we have fixed the transmission powers of the LU and CU at 10 dB and 20 dB respectively (i.e. $P_p=10$ dB, $P_s=20$ dB), and the instantaneous target rate, R_t , for the LU at 1 bps/Hz, unless otherwise specified. This target rate is used in calculating if the CU can engage in cooperative relaying or exclusive access scenarios, and in maintaining the acceptable interference margin for a spectrum sharing scenario.

Figure 5.4: LU outage probability versus CU power.

The LU system considered here is adaptive and in the absence of cooperative CR's is designed to meet the instantaneous target rate, R_t by varying its transmit power. But we see that with cooperation the outage probability of the LU system can be greatly reduced for the same R_t . In Fig. 5.4, we see how an increase in the CU transmit power can facilitate a greater level of cooperation and significantly reduce the outage probability of the LU. Moreover one can notice the considerable difference in outage probabilities, between dedicated power allocations of 75%, 85%, and 95% of the CU's total available transmit power, as opposed to the optimal α , as calculated by (5.7). With dynamic channel realizations, the optimal value of α can provide the lowest outage probability, while conserving CR power for its own transmission and rate requirements. We see a similar comparison being made with LU power in Fig. 5.5. As seen again, the CR's real-time calculation of the optimal α , serves the least outage probability given the dynamic nature of the fading channel. Another improvement one can observe is that for the same

Figure 5.5: LU outage probability versus LU power.

Figure 5.6: PU Power Saving versus CU power for $P_{out} = P_{out}^d = 10^{-2}$.

outage probability, our protocol results in substantial power conservation. This can be verified in our plot in Fig. 5.6. For a target outage probability of 10^{-2} , we see that the PU can conserve more power when operating under our designed protocol. This power saving is observed to increase significantly with higher CU transmission powers, as more LU outage scenarios can be supported through cooperation.

We also study the typical 10% outage rate used as a target QOS for LU communication. We see that in Fig. 5.7(a), that the LU void of cooperation can adjust its transmission power such that this outage rate is met. But when the PT power falls below this threshold, there is nothing that the PU can do, resulting in certain transmission outage for the LU. With our proposed protocol however (Fig. 5.7(b)), we see that increased CU transmission powers can significantly reduce the number of outage events, while also reducing the strain on the required P_p to meet this 10% outage rate. With smaller transmission powers available however, the CU may not be able to effect much change, due to the fewer cooperation opportunities it can support and participate in.

Next we discuss the performance gain that the CR derives from cooperation with the LU. Primarily through cooperative relaying, the CR sets up virtually a 100% spectral access opportunity as long as the LU is willing to participate in the protocol. Through our discussion of the three different scenarios for CR rate, in Section 5.3, (5.17) shows us that the CR can enjoy a transmission rate that increases with the signal power of the CR. This can be verified through our plot in Fig. 5.8. Here we also notice an initial CU rate gain for small values of PU transmit power, P_p . This is because under our protocol, there would be more chances for cooperation or pure spectrum access for a weak PU signal, and is reflected in the increase in transmission opportunities. Thus on combining all the respective scenario rates in Section 5.3, we see a confluence of spectrum opportunities that vary significantly in performance with change in target rate and CR transmit power as seen in Fig. 5.9. We observe three regions of CU rate change, that can be attributed to the dominance of three scenario modes in our protocol for different ranges of R_t . First we notice the spectrum sharing bit of the protocol (as a result of R_s^s), in effect at lower target rates. Here when the LU experiences a rate much greater than the target rate, R_t , it leases its spectrum to the CR for transmission within the acceptable margin of interference. However such opportunities reduce as the required target rate increases and the CR misses out on such spectrum sharing opportunities. But with this increase in target rate, the dominance of cooperation and full access modes on the effective average rate of the CU can be seen. It is interesting to notice that for lower CU powers, we see no significant change in average CU rate with the target rate. But with higher power available to the CR, we see rate gains evident from cooperation opportunities with the LU. Moreover this point of trend shift (i.e. when $\bar{R}_s$ begins to increase) is unique given a particular pair of power and target rate values. This is primarily due to the dependence of α on both these parameters as seen in (5.7), and thus influences the effective rate in (5.17). With further increase in R_t , the LU in outage cannot be supported any longer by CR cooperation (i.e. the required α is greater than 1) and full access opportunities take dominance. The saturation in CU rate seen beyond a unique threshold of R_t (for

Figure 5.7: Critical power regions for 10% outage rate ($C_{10\%}$) with PU target rate $R_t = 1$ bps/Hz
 (a) Direct PU Transmission, (b) With our proposed protocol.

example an $R_t > 6$ bps/Hz for $P_p = 10$ dB) is seen because no cooperation exists between the PU and CU, and only full spectrum access is in play. With a constant CU transmission power, the CU rate cannot further increase in this mode.

With this innovative protocol, we demonstrate the possibilities for cooperation between willing LUs and proactive CRs that are mutually benefited from their collaboration in achieving a greater level of

Figure 5.8: Average CU rate with CU transmit power.

Figure 5.9: Average CU rate versus LU target rate threshold.

spectral efficiency. Though many cooperative protocols have been implemented in literature, we believe that our proposed scheme is comprehensive, covering all opportunities for spectrum assignment for a CR in a cooperative environment. A lot of work in cooperative communications has focused on more-than-able LUs who have strong primary links with affluent received rates [28] [29]. The surplus rate margin in this case (above the target rate required by the receiver) is then justification for the CUs

Figure 5.10: Percentage of spectrum access opportunities versus LU target rate threshold.

to share this spectrum, with interference constraints to control the interference dealt by the CU due to simultaneous sharing of the spectrum. Therefore cooperative spectrum sharing as seen here is only possible when there exists good LU channel conditions. But in our protocol, we try to include the possibilities of incapable LUs that cannot support their own target link rate. Under such conditions, there also exists the possibility for cooperative relaying, as described by our protocol. Therefore in comparing our proposed protocol against the common spectrum sharing approach [28] [29] in cooperative communication, we see that our scheme can result in significant improvements in the achievable CU rate, while ensuring 100% spectrum access opportunities for the CU. The graphs that follow are compared against the basic spectrum sharing model in [29], based on the target LU rate.

The proposed proactive scheme is well justified by its ability to guarantee 100% spectral access, for any given communication scenario, as long as the LU in question is part of this cooperative protocol. The common spectrum sharing approach as highlighted earlier allows the CU to gain spectrum transmission rights only as long as the LU can exceed its own rate requirements. Therefore as seen in Fig. 5.10, the opportunity for transmission for these common sharing protocols reduces for higher target rates. However our proposed protocol still ensures complete spectrum access, as cooperative relay and access scenarios have been incorporated in this protocol to allow all spectrum opportunities to be utilized. As a result of this spectral access, the CU can experience rate gains over the existing spectrum sharing models used in cooperative communication scenarios, that depend entirely on the quality of the LU

Figure 5.11: Average CU rate with CU transmit power.

Figure 5.12: Average CU rate versus LU target rate threshold.

channel. Fig. 5.11 illustrates the achievable rate gap that can be seen in comparing these two schemes against available CU transmission power. With the basic spectrum sharing model in [29], we see that when the CU transmission power exceeds a particular limit, the LU cannot tolerate the interference due to spectrum sharing (as it needs to meet its target rate R_t), and the CU loses the opportunity for transmission, resulting in a drop in CU rate. But with our proposed protocol, the dynamic channel can

result in opportunities for cooperation, access and sharing thereby allowing a significant rate increase with increase in available CU transmission power (as highlighted by (5.14)-(5.17)). These rate gains are evident through our plot in Fig. 5.11.

Finally in Fig. 5.12, we see the rate improvement presented against the target rate of the LU system. The trend of the rate curve for our proposed scheme has been discussed earlier in Fig. 5.9, and as seen corresponds to the result plotted for $P_s=20$ dB. In the case for the basic spectrum sharing model in [29], we see that for lower rates, the LU can support spectrum sharing interference from the CU, but such opportunities deplete with higher requested LU target rates.

Through all the results presented, we believe that this protocol has been validated in its approach, and can also be implemented for different relaying strategies (like DF) for proactive CRs involved in a cooperative setting.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

Though the field of spectrum sensing is well investigated, the methods are either dependent on additional information regarding the LU signal or noise statistics, or are susceptible to fading and high-noise environments. But unlike conventional passive sensing techniques, proactive sensing ensures reliable detection of the LU, which safeguards the LU against missed detections and imprudent CU transmissions. In our work, we also extended the concept of proactive sensing to probing power control and studied its effect on the cognitive receiver statistics.

With power constraints on the CU's total available power and PU's interference limits, we see that probing power control is a step forward in this field. Simulations also show that for a fixed probability of detection, the ST can achieve good sensing performance even for a small number of samples in the sensing frame, owing to the drop in probability of false alarm with probing. On the other hand, by establishing a detection threshold, a gradual but pronounced increment in detection probability is observed. The increased detection levels mean greater security to the PU system and lesser chance of detrimental cross-interference due to missed detections. It is also established that the CU throughput decreases with increase in probing power beyond a certain level, because of the boost in detection probability. However with the concept of sensing time compensation, we see that the throughput can be sustained for even greater increments in the probing power. With proactive sensing with probing power control, we see a scheme that is both beneficial to the cognitive and licensed users.

Though a lot of research has gone into solving issues that the CR faces, a topic that has been brushed by has been the issue of cross-channel information for the CR. Most of the work in the field

of CR focuses on innovation in spectrum utilization, but the practicality of their methods lose sight with common assumptions like full cross-channel knowledge. With a proactive sensing approach, the supervised probing scheme proposed earlier can allow for estimation of the cross-channel with a high rate of success. Even in the absence of any cross-channel information, with this scheme, the difference in the CU throughput is marginal. Therefore the supervised probing approach for the CU seems complete in it being able to share the spectrum while respecting the interference thresholds set for PR security, and meeting the CU's spectrum needs with minimal probing time.

We further extend the work of spectrum sharing to a novel cooperative relaying scenario that aims at maximizing the global spectral efficiency. Here we propose the possibility of spectrum access for a proactive CR that is willing to relay LU data in a deeply faded channel. By superimposing its own signal atop the received LU signal, we see how the CR can gain spectral access through this partial relaying. In meeting an instantaneous target licensed rate, the CR must allocate its power accordingly to participate as a trusted relay node. By optimizing this power distribution between relaying and CR transmission, we see a significant improvement over a static allocation of CU power. We also discuss multiple scenarios that the CR might encounter and how it can manage 100% spectral access when operating under this cooperative protocol. Through our simulations we observe an overall boost to the average CR rate and a significant reduction in LU outage probability for the cooperative spectrum sharing scenario proposed. Through these results we see the viability of such an approach for future implementations of cooperative communications involving CRs.

6.2 Future Work

The field of proactive spectrum sensing gives rise to many possibilities, for both the cognitive and licensed user. A few possible areas of interest could include:

1. PU centric view on power management - With the scenario of proactive sensing, the PU is subject to probing signals, demanding a boost in transmission power for power adaptive feedback-based PU systems. However if the LU system is bound by a total power limit set for a frame, a tradeoff in terms of LU response/ CU sensing accuracy with probing power can be formulated. The PU can also be designed to allocate its transmit power on a knowledge based estimate of the average interference seen at the PR over past data frames. In this way the PU can map out CR's probing behavior/frequency while still oblivious to the presence of a CU, thus allowing for efficient power management at the LT.

2. Greater bandwidth feedback channel - With cross-channel estimation we see that the performance of the proposed supervised probing model is limited by the 2-bit feedback used in our setup. With a 3-bit feedback channel, the interference felt at a PR can be mapped to 4 different levels for both power increment and decrement, thus improving the sensitivity of the SNR compensation process for the primary link. This also means that a CU has a finer response to probing interference, when eavesdropping on the fed-back bits. This shows that the concept of supervised probing and sensing can clearly be extended to a higher bit feedback channel, however the added utility for a CU in terms of cross-channel estimation error, derived from this additional spectrum resource may be minimal.

3. Cooperative spectrum sharing networks - With the idea of cooperative spectrum sharing already detailed in Chapter 5, we wish to see if this idea can be extended to an array of cooperative cognitive radios. As with a practical radio environment, multiple users are involved in sensing for spectrum and prying for spectrum access or sharing opportunities. With the cooperative scheme in place, we see greater priority for relaying going to the CU that is geographically closest to the LU. This CU can decide on how he wishes to send the signal to the licensed recipient. By involving other nearby CRs in a multiple phase relay network, the global spectral efficiency can be increased by many fold, while still maintaining the LU rate. With a low bandwidth control channel in place, the respective CRs can have access to the critical channel statistics necessary to successfully relay the LU signal. Through this approach we can also optimize the global throughput/ rate of the CR network involved in cooperative spectrum sharing.

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