

Stable Throughput in Cognitive Radio Networks Using Perfect Sensing Technique

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ABSTRACT- In network layer perspective, the effect of an Ad-Hoc secondary network with N nodes accessing the spectrum licensed to a primary node. If the sensing is perfect, then the secondary nodes do not interfere with the primary node and thus do not affect its stable throughput. In case of imperfect sensing, it is shown that if the primary node's arrival rate is less than some calculated value, then the secondary transmissions do not affect its queuing stability; otherwise, the secondary nodes should regulate their transmission parameters to reduce their interference on the primary. It is also shown that in contrast with the primary user's maximum stable throughput rate which strictly decreases with increased sensing errors, the throughput of the secondary nodes might increase with sensing errors as more transmission opportunities become available to them. Finally, we explore the use of the secondary nodes as relays of the primary node's traffic to compensate for the interference they might cause. In this case, for appropriate modulation scheme and under perfect sensing, it is shown that the more secondary nodes in the system, the better for the primary user in terms of his stable throughput. Meanwhile, the secondary nodes might benefit from relaying by having access to a larger number of idle slots becoming available to them due to the increase of the service rate of the primary. For the case of a single secondary node, the proposed relaying protocol guarantees that either both the primary and the secondary benefit from relaying or none of them does.

KEYWORDS—Cognitive radio, queueing analysis, spectrum sensing, sensing errors, cooperative relaying.

I. INTRODUCTION

Cognitive radio (CR) is the enabling technology that allows unlicensed secondary users (SUs) to exploit idle licensed frequency bands, forming thus a cognitive radio network (CRN). CRs can autonomously adjust their transmission parameters and modify their behaviour based on the electromagnetic environment conditions. Spectrum sensing is a key phase in the operation cycle of a CR [1], leveraging the radio's ability to measure, sense and be aware of the channel characteristics. It can be performed either individually or cooperatively in order to detect idle frequencies, referred to as spectrum holes, and minimize interference to the licensed or primary user (PU) activities [2]. The accuracy on detecting spectrum holes determines the efficiency of exploiting the spectrum. Thus, either sensing errors related to hardware outages [3], [4] or susceptibility to specialized attacks on the sensing functionality can result in significant performance degradation. Existing works on security in CR mainly address concerns of designs for cryptography, intrusion detection system and authentication. However, these security measures are not sufficient to preserve the correctness of spectrum sensing results against attacks and intrusions [4]. Preventive security mechanisms, as cryptography, provide confidentiality, integrity and authentication, but they are inefficient against data injection overload, interception, manipulation or impersonation attacks, such as Denial of Services (DoS), PU emulation (PUE) attacks and jamming. Reactive security mechanisms, as intrusion detection systems (IDS), are based on network behaviour analysis, or previously known attack patterns, being inflexible to handle unpredictable misbehaviours. Furthermore, since new communication technologies are more dynamic and adaptive, attacks are also becoming smarter, often bypassing common security mechanisms [4]. This paper presents a cooperative spectrum sensing framework to effectively provide resilience against both faults and attacks. Applying a low-cost multi-criteria analysis technique, the framework is adaptable to radio environment and flexible to consider unpredictable behaviours that emerge from various practical deployment scenarios. Also, it is able to handle multi-dimensional (e.g. frequency, time, geographical space, security) data in order to effectively sense the spectrum, and detect or mitigate faults and attacks in an optimal way. In the framework, CRs share their initial estimation of the likelihood of an attack with neighbors to gather a collective perception of the network. Thus, they apply the non-parametric Bayesian inference technique to classify spectrum holes and indicate the ones that are least susceptible to failures and attacks, being then resilient in the sense that nodes do not simply rely on majority voting by a collection of nearby nodes. Our approach is evaluated under network disconnections and PUE attacks, considering different sets of physical layer features and their corresponding thresholds that indicate a deviation from the expected results. Simulation results, founded on real traces, show the benefit of the proposed framework in terms of attack detection and its adaptation to network conditions.

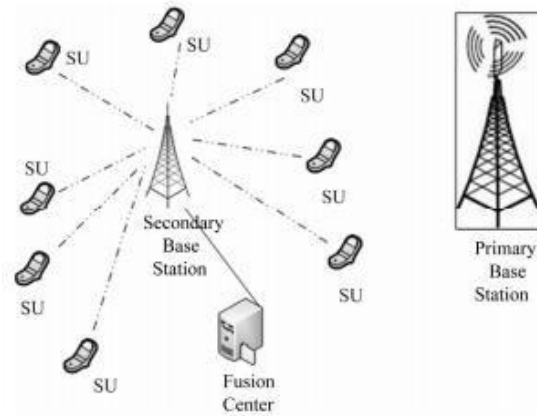


Fig.1.1 A typical collaborate spectrum sensing in cognitive radio network.

One of the most important challenges in cognitive radio is reliable spectrum sensing. It has attracted far-reaching attention recently. Spectrum sensing procedure can be accomplished individually or cooperatively. If spectrum sensing procedure is used by cooperative decision, it could be more reliable because there might happen something to several users and they couldn't sense the spectrum well and their local decisions don't be true. virtual queue concept and introduce its distributed implementation.

A. Energy Detector Based Sensing

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities. In addition, it is more generic (as compared to methods given in this section) as receivers do not need any knowledge on the primary users' signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor [64]. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values [48]. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [26], [59]. Let us assume that the received signal has the following simple form

$$y(n) = s(n) + w(n) \quad (1)$$

where,

$s(n)$ is the signal to be detected,

$w(n)$ is the additive white Gaussian noise (AWGN) sample, and

n is the sample index.

Note that $s(n)=0$ when there is no transmission by primary user. The decision metric for the energy detector can be written as

$$M = \sum_{n=0}^{N-1} |y(n)|^2, \quad (2)$$

II. SYSTEM MODEL

The present literature for spectrum sensing is still in its early stages of development. A number of different methods are proposed for identifying the presence of signal transmissions. In some approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the signal type. In this section, some of the most common spectrum sensing techniques in the cognitive radio literature are explained. The CRN from the perspective of individual SUs and their requirements of sensing quality. Accordingly, we develop a provably arbitrarily close to optimal sensing scheduling algorithm through a novel sensing deficiency

where N is the size of the observation vector. The decision on the occupancy of a band can be obtained by comparing the decision metric M against a fixed threshold λE . This is equivalent to distinguishing between the following two hypotheses:

$$H_0 : y(n) = w(n), \quad (3)$$

$$H_1 : y(n) = s(n) + w(n). \quad (4)$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection PD and probability of false alarm PF . PD is the probability of detecting signal on the considered frequency when it truly is present. Thus, a large detection probability is desired. It can be formulated as

$$PD = \Pr (M > \lambda E | H1). \quad (5)$$

PF is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$PF = \Pr (M > \lambda E | H0). \quad (6)$$

PF should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λE can be selected for finding an optimum balance between PD and PF . However, this requires knowledge of noise and detected signal powers. The noise power can be estimated, but the signal power is difficult to estimate as it changes depending on going transmission characteristics and the distance between the cognitive radio and primary user. In practice, the threshold is chosen to obtain a certain false alarm rate [65]. Hence, knowledge of noise variance is sufficient for selection of a threshold. The white noise can be modeled as a zero-mean Gaussian random variable with variance σ^2_w , i.e. $w(n) = N(0, \sigma^2_w)$. For a simplified analysis, let us model the signal term as a zero-mean Gaussian variable as well, i.e. $s(n) = N(0, \sigma^2_s)$. The model for $s(n)$ is more complicated as fading should also be considered. Because of these assumptions, the decision metric (2) follows chi-square distribution with $2N$ degrees of freedom χ^2_{2N} and hence, it can be modelled as

$$M = \sigma^2_w \chi^2_{2N} | H0, \sigma^2_w + \sigma^2_s \chi^2_{2N} | H1. \quad (7)$$

B. Waveform-Based Sensing

Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc. A preamble is a known sequence transmitted before each burst and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [48], [58], [63]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent sensing. In [48], it is shown that waveform based sensing outperforms energy detector based sensing in reliability and convergence time. Furthermore, it is shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases. Using the same model given in (1), the waveform-based sensing metric can be obtained.

The decision on the presence of a primary user signal can be made by comparing the decision metric M against a fixed threshold λW . For analyzing the WLAN channel usage characteristics, packet preambles of IEEE 802.11b [71] signals are exploited in [55], [56]. Measurement results presented in [25] show that waveform-based sensing requires short measurement time; however, it is susceptible to synchronization errors. Uplink packet preambles are exploited for detecting Worldwide Interoperability for Microwave Access (WiMAX) signals.

C. Cyclostationarity-Based Sensing Cyclostationarity feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation [80] or they can be intentionally induced to assist spectrum sensing. Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [74]. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users.

D. Radio Identification Based Sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such an identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [59]. For example, assume that a primary user's technology is identified as a Bluetooth signal. Cognitive radio can use this information for extracting some useful information in space dimension as the range of Bluetooth signal is known to be around 10 meters. Furthermore, cognitive radio may want to communicate with the identified communication systems in some

applications. For radio identification, feature extraction and classification techniques are used in the context of European transparent ubiquitous terminal (TRUST) project [86]. The goal is to identify the presence of some known transmission technologies and achieve communication through them. The two main tasks are initial mode identification (IMI) and alternative mode monitoring (AMM). In IMI, the cognitive device searches for a possible transmission mode (network) following the power on. AMM is the task of monitoring other modes while the cognitive device is communicating in a certain mode.

E. Matched-Filtering

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [91]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of miss detection [92] as compared to other methods that are discussed in this section. In fact, the required number of samples grows as $O(1/SNR)$ for a target probability of false alarm at low SNRs for matched- filtering [92]. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signalling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format.

F. Other Sensing Methods

Other alternative spectrum sensing methods include multitaper spectral estimation, wavelet transform based estimation, Hough transform, and time-frequency analysis. Multitaper spectrum estimation is proposed in [93]. The proposed algorithm is shown to be an approximation to maximum likelihood PSD estimator, and for wideband signals, it is nearly optimal. Although the complexity of this method is smaller than the maximum likelihood estimator, it is still computationally demanding. Random Hough transform of received signal is used in [94] for identifying the presence of radar pulses in the operating channels of IEEE 802.11 systems.

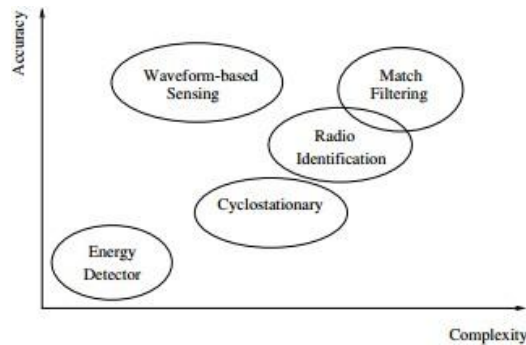


Fig.1.2 Main sensing methods in terms of their sensing accuracies and complexities.

This method can be used to detect any type of signal with a periodic pattern as well. Statistical covariance of noise and signal are known to be different. This fact is used in [95] to develop algorithms for identifying the existence of a communication signal. Proposed methods are shown to be effective to detect digital television (DTV) signals.

III. COGNITIVE RADIONETWORKS

Cognitive radio is an intelligent radio that can be programmed and configured dynamically. Its transceiver is designed to use the best wireless channels in its vicinity. Such a radio automatically detects available channels in wireless spectrum, then accordingly changes its transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band at one location. This process is a form of dynamic spectrum management.

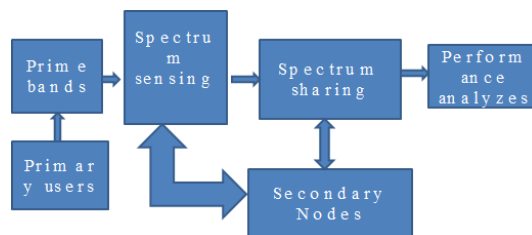


Fig.1.3 CR Network

The main functions of cognitive radios are:

Power Control: Power control is used for both opportunistic spectrum access and spectrum sharing CR systems for finding the cut-off level in SNR supporting the channel allocation and imposing interference power constraints for the primary user's protection respectively.

Spectrum sensing: Detecting unused spectrum and sharing it, without harmful interference to other users; an important requirement of the cognitive- radio network to sense empty spectrum. Detecting primary users is the most efficient way to detect empty spectrum. Spectrum-sensing techniques may be grouped into three categories:

Transmitter detection: Cognitive radios must have the capability to determine if a signal from a primary transmitter is locally present in a certain spectrum. There are several proposed approaches to transmitter detection:

Energy detection: Energy detection is a spectrum sensing method that detects the presence/absence of a signal just by measuring the received signal power. This signal detection approach is quite easy and convenient for practical implementation. To implement energy detector, however, perfect noise variance information is required. And surprisingly when there is noise uncertainty, there is an SNR wall below which the energy detector cannot reliably detect any transmitted signal. In a new energy based spectrum sensing algorithm with noise variance uncertainty is proposed. This algorithm does not suffer from SNR wall and outperforms the existing signal detectors (see for example and its USRP implementation). And most importantly, the relationship between the energy detector of and that of is quantified analytically. Also when the noise variance is known perfectly these two energy detectors achieve the same probability of detection and false alarm rates.

Cooperative detection: Refers to spectrum-sensing methods where information from multiple cognitive-radio users is incorporated for primary- user detection.

Null-space based CR: With the aid of multiple antennas, CR detects the null-space of the primary- user and then transmit within this null-space, such that its subsequent transmission causes less interference to the primary-user

Spectrum management: Capturing the best available spectrum to meet user communication requirements, while not creating undue interference to other (primary) users. Cognitive radios should decide on the best spectrum band (of all bands available) to meet quality of service requirements; therefore, spectrum-management functions are required for cognitive radios. Spectrum- management functions are classified as:

- Spectrum analysis
- Spectrum decision

IV. PERFECT SENSING CASE - NORELAYING

In this case, the secondary nodes are able to perfectly identify the primary idle slots where they can access the channel from the busy slots where they must remain silent to avoid interfering with the primary. In this case, the primary gets its maximum possible service rate. Clearly, this is an ideal situation serving as an upper bound on the performance of the primary node. We focus on the case of no-relaying while the relaying case is considered in section V.

V. IMPERFECT SENSING CASE - NORELAYING

Due to fading and other channel impairments, secondary Nodes can encounter errors while sensing the channel and hence there is some possibility that they interfere with the primary node leading to a possible drastic reduction of its stable throughput. In this section, we quantify the effect of sensing errors on the throughputs of the primary and the secondary nodes. Two errors may occur at the secondary nodes while sensing the channel, namely, false alarm and misdetection errors. False alarm occurs when the primary node is idle but is sensed to be busy. Clearly, false alarm error does not affect the primary's stable throughput but degrades the throughput of the secondary nodes. Misdetection occurs when the primary node is busy but is sensed by some secondary nodes to be idle. Those secondary nodes will simultaneously transmit with the primary leading to some interference at the primary destination. If the interference is strong enough, it may lead to instability of the primary queue. All subsequent throughput results are applicable from any sensing method as they are given in terms of general false alarm P_f and misdetection P_e probabilities. It

should be noted that by the independence of the fading processes between nodes, the misdetection and false alarm events are independent between secondary nodes, and by symmetry the probabilities P_e and P_f are the same for all the secondary nodes.

VI. RELAYING IN THE PERFECT SENSING CASE

Primary users would be willing to share their channel resources with secondary users if they can benefit from such sharing. Forcing the secondary nodes to relay the primary node's unsuccessful packets may lead to a higher maximum stable throughput at the primary compared with the nonrelaying case. Moreover, by relaying the primary's packets, secondary nodes might benefit from the increase of the primary's stable throughput by increasing the number of idle slots available for secondary transmissions. The analysis of the relaying protocol proposed in this section is restricted to the perfect sensing case but the imperfect sensing case can be handled similarly. The case of perfect sensing serves as an upper bound for the imperfect sensing case as well as a good approximation for systems employing cooperative and sophisticated sensing techniques.

VII. NUMERICAL RESULTS

In this section, we provide numerical results to illustrate the conclusions drawn analytically. The values of the parameters are chosen based on practical values but also for sake of clarity of presentation.

Figures 1 and 2 illustrate the effect of erroneous sensing on the normalized maximum stable throughput of the primary node.

Figure 1 plots the normalized maximum stable throughput of the primary node versus the secondary nodes' transmission power. It shows that μP can severely drop from its perfect sensing value $\mu_{max} P$ even for small number of secondary nodes and small values of qP_e and shows that secondary nodes can effectively limit their interference on the primary by controlling their transmission power P_0 , their channel access probability q or by enhancing the sensing performance to reduce P_e by using better detectors or using cooperative sensing techniques. Figure 2 plots the normalized maximum stable throughput rate at the primary node versus the number of secondary nodes N showing a similar effect.

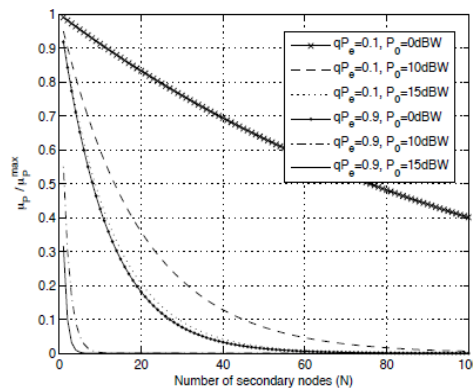


Fig. 2. Effect of number of secondary nodes on primary maximum stable throughput rate.

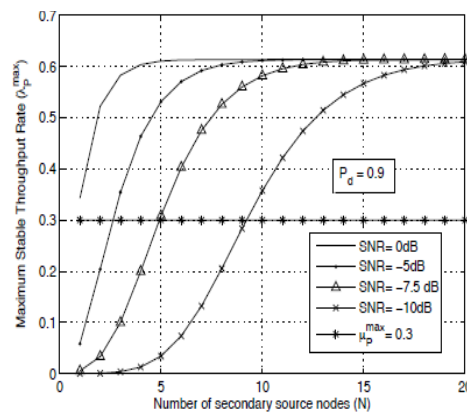


Fig. 4. Effect of relaying on maximum stable throughput rate (λ_p^{\max}) for detection probability $P_d = 0.9$.

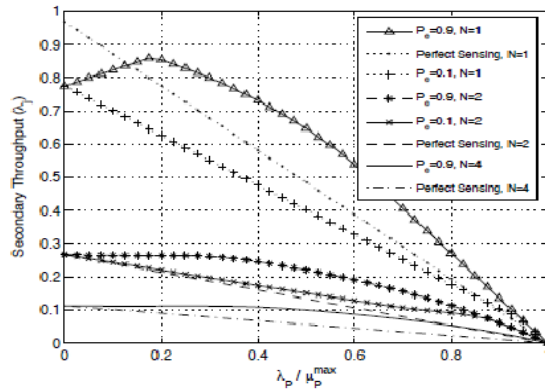


Fig. 6. Secondary throughput versus primary normalized arrival rate for various values of P_e and N . $I = 0.1$ (Case of very low interference from the primary).

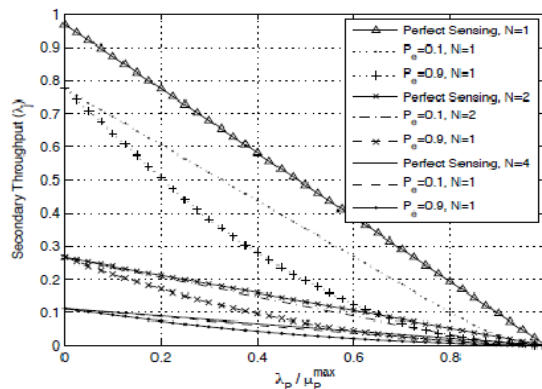


Fig. 5. Secondary throughput versus primary normalized arrival rate for various values of P_e and N . $I = 100$ (Case of high primary interference).

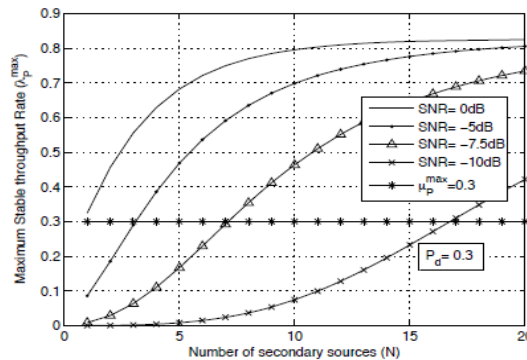


Fig. 3. Effect of relaying on maximum stable throughput rate (λ_p^{\max}) for detection probability $P_d = 0.3$.

VIII. CONCLUSION

The number of secondary nodes and their transmission parameters on the stable throughput of the primary user as well as on the secondary's throughput in both perfect and imperfect sensing cases. It was shown that if the primary user's arrival rate is less than some calculated value, there is no need for controlling secondary nodes' transmission parameters; otherwise, secondary nodes have to control them to limit their interference on the primary and avoid affecting its stability. In contrast with the primary's stable throughput which always decreases if sensing is erroneous, secondary nodes might benefit from incorrect sensing by having more opportunities to access the channel. It is shown that, if the secondary nodes do not relay the primary's unsuccessful packets, their presence reduces his maximum stable throughput. However, if the secondary nodes are forced to relay the primary's packets, then the primary always benefits from having many nodes relaying its packets and secondary nodes might benefit by having access to a larger number of primary user's idle slots.

This observation reveals that with relaying protocols, cognitive radio technology is appealing for licensed users to share their resources with other unlicensed users.

REFERENCES

- [1]. FCC, "Et docket no. 03-108," [Online] Available: <http://www.fcc.gov/oet/cognitiveradio/>.
- [2]. D. Chen, S. Yin, Q. Zhang, and S. Li, "Mining spectrum usage data: a large-scale spectrum measurement study," in Proc. of international conference on Mobile computing and networking. ACM Mobicom 2009, Beijing, China, September 2009.
- [3]. Y. C. Liang, K. C. Chen, G. Y. Li, and P. Mahonen, "Cognitive radio networking and communications: An overview," IEEE Trans. Veh. Commun., vol. 60, no. 7, pp. 3386–3407, September 2011.
- [4]. I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey," Computer Networks (Elsevier) J., vol. 50, no. 4, pp. 2127–2159, September 2006.
- [5]. J. N. Laneman, D. N. C. Tse, and G. W. Wornell, "Cooperative diversity in wireless networks: Efficient protocols and outage behavior," IEEE Trans. Inf. Theory, vol. 50, no. 12, pp. 3062–3080, December 2004.
- [6]. J. N. Laneman and G. W. Wornell, "Distributed space-time-coded protocols for exploiting cooperative diversity in wireless networks," IEEE Trans. Inf. Theory, vol. 49, no. 10, pp. 2415–2425, October 2003.
- [7]. A. K. Sadek, K. J. R. Liu, and Ephremides, "Cognitive multiple access via cooperation: Protocol design and performance analysis," IEEE Trans. Inf. Theory, vol. 53, no. 10, pp. 3677–3696, October 2007.
- [8]. N. Devroye, P. Mitran, and V. Tarokh, "Achievable Rates in Cognitive Radio Channels," IEEE Trans. Inf. Theory, vol. 52, no. 5, pp. 1813–1827, May 2006.
- [9]. A. Jovicic and P. Viswanath, "Cognitive radio: An information-theoretic perspective," IEEE Trans. Inf. Theory, vol. 55, no. 9, pp. 3945–3958, September 2009.