Optimization of cognitive radio systems with energy harvesting

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OPTIMIZATION OF COGNITIVE RADIO SYSTEMS WITH ENERGY HARVESTING

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in partial fulfillment of the requirement for the degree of

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*Dedicated to my beloved parents,
Mrs Bimla Rana and Dr Jagmohinder Singh Rana.*

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List of Abbreviations

ACK	Acknowledgement
AP	Access point
CC	Central controller
CMM	Combined metric maximization scheme
CoMP	Coordinated multipoint system
CR	Cognitive radio
CSI	Channel state information
CSS	Cooperative sensing scheduling
D2D	Device-to-device
DP	Dynamic programming
EC	Energy-causality constraint
ECM	Energy cost minimization scheme
EH	Energy harvester
ETM	Expected throughput maximization scheme
GSM	Global system for mobile communications
HMM	Hidden Markov model
HPPP	Homogeneous Poisson point process
IOT	Internet-of-things

LIST OF ABBREVIATIONS

IP	Incremental pruning algorithm
IR	Information receivers
KKT	Karush-Kuhn-Tucker
MIMO	Multiple-input-multiple-output
OFDM	Orthogonal frequency division multiplexing
PB	Power beacon
PC	Primary user collision constraint
PD	Primary user detection constraint
POMDP	Partially observable Markov decision process
PU	Primary user
PWLC	Piece-wise linear convex
QCQP	Quadratically constrained quadratic program
QoS	Quality of service
RF	Radio frequency
SINR	Signal-to-interference-plus-noise-ratio
SNR	Signal-to-noise ratio
SOM	Spectrum opportunity maximization scheme
SOS	Sum-of-squares
STM	Secondary user throughput maximization scheme
SU	Secondary user
SWIPT	Simultaneous wireless information and power transfer
TDMA	Time division multiple access
TV	Television

LIST OF ABBREVIATIONS

UCS	Uniform channel selection scheme
UMTS	Universal Mobile Telecommunications System
WP	Weighted proportional policy
WPT	Wireless power transfer

List of Notations

$\mathbb{P}(X)$	Probability of event X
$\mathbb{P}\{\mathcal{H}_i \mathcal{H}_j\}$	Probability of deciding $\mathcal{H}_i$ when we actually have $\mathcal{H}_j$
$\bar{x}$	Denotes $1 - x$
$\mathbf{x}$	Vector
$\mathbf{X}$	Matrix
$\mathbf{x}^T$	Transpose operation
$\succ$	Element-wise greater than
$f(x)$	Function of x
$\cup$	Union of sets
$\cap$	Intersection of sets
$X \setminus Y$	Set of values in X not present in Y
$\mathbf{x}^*$	Optimal value of $\mathbf{x}$
$\mathbb{E}$	Expectation operator
$\mathcal{Q}$	$\mathcal{Q}$ -function, given by $\mathcal{Q}(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp\left(-\frac{y^2}{2}\right) dy$
I_x	Indicator function which attains a unit value when x is true
$\mathbf{1}$	Unit vector given by $[1, 1, \dots, 1]^T$
$ x $	Number of possible values of x

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Abstract

Cognitive radio (CR) enables dynamic spectrum access and offers a promising solution to the impending spectrum scarcity problem. It senses the licensed spectrum and identifies spectrum opportunities which can be utilized by the secondary users (SUs) without disrupting the primary user (PU) transmission. Hence, it improves the spectrum efficiency by opportunistic spectrum access. Power is another critical resource. Recently, a lot of work has been focused on utilizing energy-harvesting techniques to achieve self-sustaining wireless networks. Adding energy-harvesting capability will further enhance the ability of CR systems. However, the random and sporadic nature of the energy arrival poses challenges in the realization of such self-reliant CR devices. We identify and address some new interesting research problems that arise in different types of energy-harvesting CR systems. Our research is focused on finding the optimal spectrum sensing and access policies to maximize the opportunistic spectrum utilization while considering the energy uncertainty at the CR users and preventing intolerable interference to the PUs.

We first consider an opportunistic energy-harvesting CR system. Low-power CRs are equipped with rechargeable batteries to harvest radio-frequency (RF) energy from the PU transmission. A stochastic geometry based multichannel CR system is considered where each PU channel has a different PU density offering varied opportunities for harvesting energy or transmission for the SU. At any time, SUs can access a PU channel to exploit either the spatiotemporal spectrum opportunities for transmission or the PU busy periods for RF energy harvesting. A decentralized channel-access strategy is pro-

ABSTRACT

posed for the multichannel energy-harvesting CR system. An optimal channel-selection probability vector is obtained to achieve the maximum SU throughput by finding sufficient spectrum-access and energy-harvesting opportunities while accounting for SU contention on the same channel. Numerical results show that the proposed channel-selection policy enables an energy-harvesting SU to achieve better expected throughput by utilizing greater spectrum-opportunities through an enhanced probability of having a charged battery as compared to the case when only the spectrum opportunities are optimized.

Furthermore, we investigate the opportunistic RF energy-harvesting CR system in the context of an unslotted PU system. We optimize the sensing intervals to balance between energy harvesting and spectrum access, considering the PU traffic statistics that affects both the energy arrival and consumption in addition to the opportunistic spectrum access. We propose that in such a scenario, different sensing intervals should be used if the CR user decides to transmit or harvest energy. The harvesting and transmission durations can be used to optimize the tradeoff between maximizing the utilization of PU spectrum opportunities and harvesting sufficient energy to transmit. Optimal transmission and harvesting durations have been found to maximize the CR throughput while protecting the PU. Furthermore, we enhance the system capability by considering that the SU can choose to purchase energy from the PU during the PU idle periods in addition to the energy harvested opportunistically. It can further exploit the disparity in the PU busy and idle periods as per its energy needs. The average energy cost spent in a time slot is minimized to achieve a given SU transmission rate while adhering to the PU collision constraint.

Next, we study the advantages of employing cooperation in an energy-harvesting CR system. We consider a CR system where each SU harvests energy to recharge its battery. Cooperative spectrum sensing is employed to enhance the sensing performance.

ABSTRACT

We propose that in this energy-constrained scenario, the SUs can be coordinated to achieve higher opportunistic spectrum utilization and improved PU detection. For a heterogeneous CR system with different sensing environment and energy-arrival process at each SU, the optimal probability of sensing is obtained for each SU to maximize the SU network throughput while satisfying the PU collision and energy-causality constraints. Moreover, under a homogeneous scenario, it is shown that with a minimum number of SUs cooperating, the CR throughput performance is no longer limited by the energy-causality and PU collision constraints.

Furthermore, we propose a dynamic sensing-access policy for the cooperative CR system. We employ centralized cooperative spectrum sensing, and the optimal sensors are chosen from among the SUs with varied received PU signal power levels and energy-arrival rates. We consider a discrete Markov chain based PU traffic and the proposed policy exploits the correlation in PU occupancy states to make decisions in each time slot based on the SU energy levels and the believed PU channel state. The finite-horizon partially observable Markov decision process (POMDP) framework is employed to optimally schedule the SUs for sensing and access to maximize throughput with the available energy while satisfying the PU detection constraint. The sensing-access policy decides whether to sense, the set of sensing SUs, the sensing detection threshold, and the SU that accesses the spectrum opportunities. The optimal policy achieves an optimum tradeoff between SU transmission, preventing energy shortage, and obtaining sensing information for the future gains.

Chapter 1

Introduction

1.1 Background

Radio frequency (RF) spectrum which facilitates wireless communication is a limited resource. Presently, with the proliferation of wireless services and users, we are heading towards a grave spectrum scarcity problem as almost all of the spectrum has been assigned to various applications which in turn is not enough to accommodate the increasing number of users. A report by the USA Federal Communications Commission states that a large part of the allocated spectrum is severely underutilized [1]. The licensed spectrum is largely vacant at different time or location which offers spatio-temporal spectrum opportunities. This suggests that dynamic spectrum access, instead of the present static spectrum allocation policy, should be adopted for enhanced spectrum efficiency. Cognitive radio (CR) is a promising avenue to enable dynamic spectrum access. It is an intelligent wireless communication system that can sense and learn from its environment, and can reconfigure its parameters accordingly [2]. Thus, it not only improves spectrum efficiency but with its ability to sense the radio environment and adapt accordingly, it can choose optimal resource allocation, for example, transmission

power, channel frequency, modulation scheme, etc., to enhance the overall usage of resources by achieving a greater performance in terms of energy efficiency, throughput, latency, outage probability, etc. The unlicensed CR users are called the secondary users (SUs), which dynamically access the licensed spectrum without causing unacceptable interference to the licensed users of the spectrum called the primary users (PUs). Depending on how they access the licensed band, there are two operational modes for the CR networks [3]:

1. In *overlay* systems, SUs opportunistically access the PU spectrum by exploiting the spatio-temporal spectrum holes without interfering with the PU transmission.
2. In *underlay* systems, SUs can transmit concurrently with PUs while maintaining the interference caused by the SUs at the PU receivers below an acceptable threshold.

In our work, we focus on the opportunistic CR access model. In order to enable the dynamic spectrum access and to achieve the optimal utilization of the available spectrum, a CR needs to perform the following functions [2,3]:

1. *Spectrum sensing*: The licensed users need to be guaranteed a specified quality of service (QoS) by preventing intolerable interference due to the dynamic spectrum access. The CR users sense the licensed spectrum periodically to detect the presence of the PUs and avoid collisions. They also sense the channel in order to discover the spectrum opportunities and acquire information about the available channels which can be used to optimize the channel access decisions.
2. *Spectrum management and mobility*: In order to optimally utilize the spectrum, the CR user needs to decide which channel or channels to sense. Based on the sensing information, it decides the best channel to access. Moreover, whenever

the PU returns to access the channel being used by the SU, it finds the optimal channel for switching in order to continue the SU transmission.

3. *Resource allocation and sharing*: The CR user should decide the optimal power allocation and channel access policies to utilize the available spectrum opportunities optimally and fairly while considering the other coexisting CR users.

1.2 Motivation

The CR paradigm can help to solve the spectrum underutilization problem by sensing and utilizing the vacant licensed spectrum bands. There is a rich literature exploring the optimal spectrum sensing and access strategies for efficient realization of this dynamic spectrum access tool [3–7]. Another crucial resource is the energy. We need power to sustain the communication services and the exploding number of user devices. A lot of work has been done on energy-efficient schemes for CR users [8–11]. A prominent research topic these days is to exploit energy-harvesting techniques to power wireless networks [12]. Being an effort towards green communication and its convenience of not having to replace the device batteries makes it an appealing technique. Many different sources of energy have been studied and utilized, for example, solar energy, wind energy, vibrational energy, ambient RF energy, etc. An output dc power density comparison was made between the ambient RF energy harvesting and the alternative energy-harvesting technologies in [13], which highlighted that ambient RF energy sources, specifically, digital TV, GSM 900, GSM 1800, and 3G, can be a competitive practical solution. The game-theory based approach was utilized to determine an optimal sleep-and-wake-up strategy to achieve energy-saving in a solar-powered wireless sensor relay network [14]. Optimal save-and-transmit policy and energy-transfer cooperation was obtained to maximize the communication throughput and minimize the outage probability in two

different scenarios for a pair of energy-harvesting transmitter and receiver [15].

Spectrum-efficient CR systems can further be made self-sustainable by employing the energy-harvesting techniques to power the SUs [16–20]. Introduction of the energy-harvesting concept imposes an important energy-causality constraint in the CR system, which mandates that the average energy consumed cannot be more than the average energy harvested in a time slot [16]. The detection threshold of spectrum sensor was optimized to maximize the CR throughput while satisfying the PU collision and energy-causality constraints [16]. Furthermore, a partially observable Markov decision process (POMDP) framework was employed to jointly design an optimal spectrum sensing policy and the detection threshold for a given energy-arrival rate and temporal correlation of the primary traffic [17]. In [18], the authors used stochastic geometry tool to analyze the performance of energy-harvesting CR based device-to-device (D2D) communication in a cellular network with different access policies. In this thesis, our research efforts are mainly concentrated on optimization of energy-harvesting CR system by managing the ambient RF energy harvested opportunistically from the PU transmissions and by utilizing cooperation among the energy-constrained SUs. Our research motivations are stated as follows:

- Recent work on ambient RF energy harvesting suggests that it can be utilized for low-power wireless networks [13, 21]. It is thus a good idea to employ it to achieve self-sustainable wireless networks. A novel opportunistic energy-harvesting scheme was proposed in [19], where CR users employed RF energy-harvesting technique and used PU transmissions as the RF energy source. In the first part of our work, we explore to enhance the SU spectrum utilization in such RF energy-harvesting CR systems.
 - We consider a multichannel PU system where the SU can only access one

channel in each time slot. In this opportunistic energy-harvesting system, this choice affects both energy harvesting and SU transmission. Choosing a low PU density channel more frequently avails more transmission opportunities for the SU, but a channel with higher PU density provides more energy-harvesting opportunities. In order to utilize the transmission opportunities, the SU battery should be charged, so the increased energy-harvesting opportunities, in turn, aid the SU transmission. We propose an optimal decentralized SU channel-selection strategy which provides greater spatio-temporal spectrum opportunities for the SUs while ensuring that the SUs do not miss the spectrum opportunities due to energy shortage.

- Different spectrum sensing and access policies have been studied for an unslotted PU system, where the PU can change states any number of times after it has been detected to be idle or busy at the beginning of the SU slot [22–24]. We further analyze the opportunistic RF energy-harvesting CR system by considering an unslotted PU system, which presents greater challenges due to the asynchronous PU behavior in addition to the existing uncertainty in the energy and spectrum availability. In this scenario, the sensing frequency affects the discovery of energy-harvesting and spectrum opportunities, and the average amount of energy harvested and consumed. Optimal sensing intervals are determined to balance between energy harvesting and spectrum access by considering the PU traffic statistics.
- Cooperative spectrum sensing is a robust sensing technique which utilizes cooperation among the sensing SUs to achieve better PU detection in harsh radio environments and hidden-node situations [25, 26]. In energy-harvesting CR systems, SUs may not possess energies to operate at all the times. Also, aiming for an energy-efficient system, all the SUs do not need to sense at all times; they can

be optimally scheduled for sensing to satisfy the performance goals.

- In this energy-constrained system, we propose that the SUs can cooperate both for sensing and access operations as per their energy-arrival rates to achieve greater PU detection and opportunistic spectrum utilization. We propose a decentralized probabilistic sensing policy for the cooperating SUs.
- Furthermore, we consider a discrete Markov chain based PU traffic and determine a dynamic sensing-access policy to maximize the expected SU throughput while sufficiently protecting the PU. It can be used to make decisions in each time slot, based on the expected PU channel and SU energy states, to achieve the optimal cooperation among the energy-harvesting SUs.

1.3 Major Thesis Contributions

The main objective of our work is to propose and investigate new frameworks and the associated research problems for efficient realization of energy-harvesting CR systems. We derive optimal spectrum sensing and access policies to maximize the opportunistic spectrum utilization while considering the energy-uncertainty at the CR users and preventing intolerable interference to the PUs. Our major contributions are as follows:

1. Firstly in Chapter 3, we investigate an opportunistic RF energy harvesting CR system by using homogeneous Poisson point processes to model SUs and PUs spatially. We study a multichannel low-power CR system with RF energy harvesting capability. Each SU is equipped with a rechargeable battery to harvest RF energy from the PU transmission. Hence, SUs exploit the spatio-temporal spectrum opportunities for transmission and the PU busy periods for RF energy harvesting. There is a guard zone associated with each PU to protect it from SU interference.

An SU lying outside the guard zones of all active PUs can utilize a spectrum opportunity provided that it has an adequate energy. Each PU has a harvesting zone where sufficient PU transmit power is received to meet the threshold requirement of the energy-harvesting circuit. Each SU lying in the harvesting zone of any active PU can harvest the PU transmitted power to charge its battery. An interference zone is introduced around each SU to account for the access contention with the neighboring SUs on the same PU channels. The different PU channels with varied PU density offer heterogeneous access and harvesting opportunities. In each time slot, the SU selects a sensing channel that may either offer a chance to harvest energy or to transmit. We propose a decentralized channel-access strategy for the multichannel low-power cognitive radio system. (This work has been published in *IEEE Trans. Veh. Technol.*, vol. 65, Jan. 2016)

- The SU battery power level is modeled as a 2-state Markov chain and an expression for the average probability that an SU battery is fully charged in any time slot is derived.
- At any time, SUs can exploit either the spatiotemporal spectrum opportunities for transmission or the PU busy periods for RF energy harvesting. An optimal channel-selection probability vector is determined to enable the SU to achieve maximum throughput by utilizing sufficient spectrum-access and energy-harvesting opportunities while accounting for contention among the co-channel SUs. We have a nonconvex optimization problem. It is decomposed to formulate a convex optimization subproblem, and an exhaustive search is performed to solve the master problem.
- Moreover, we propose an iterative algorithm wherein a combined metric is formulated by taking into consideration the spectrum-access and energy-harvesting opportunities, and access-contention on different PU channels. A

convex optimization problem is solved in each iteration for which we have obtained a closed-form solution.

- The proposed channel-selection policy achieves a higher expected throughput for an energy-harvesting SU through an enhanced probability of having adequate energy as compared to the schemes that do not consider the energy-harvesting opportunities.

2. Furthermore in Chapter 4, we consider an opportunistic energy-harvesting CR system coexisting with an unslotted PU system, i.e., the PU can return to access the channel at any time and can change states any number of times during the remaining slot duration after the channel was sensed to be idle or busy. The CR user can either harvest energy from the PU transmissions or transmit when the PU is sensed to be idle. The SU needs to sense frequently in order to discover greater transmission opportunities, energy-harvesting opportunities, and to protect PU from interference but this reduces the transmission and harvesting durations. Also, it consumes energy for the sensing and transmission operations which is supplied during the harvesting periods. A dual-sensing-interval policy is proposed in which different sensing intervals are used if the SU decides to transmit or harvest energy. The harvesting and transmission durations can be optimized to maximize the utilization of PU spectrum opportunities by harvesting sufficient energy to transmit. (This work will appear in *IEEE Trans. Veh. Technol.*)

- We adopt a 3-state Markov chain to model the SU energy and PU channel-availability status. It is utilized to find the stationary probabilities of the PU being found idle or busy by the SU while incorporating the SU energy uncertainty and sensing-interval policy. Moreover, we derive a closed-form expression for the probability of an SU having energy to transmit during a

discovered idle period as a function of the PU traffic statistics and CR user's access and harvesting durations.

- Optimal transmission and harvesting durations are found to maximize the CR throughput under the energy-causality constraint while protecting the PU.
- It is shown that the largest permitted value of the transmission duration can be bounded by analyzing the energy-causality and PU collision constraints.
- Furthermore, a power-purchasing option is introduced to enable the SU to further exploit the disparity in PU busy and idle periods to meet its energy requirements. In addition to the energy harvested opportunistically, the SU can choose to purchase energy from the PU during the discovered PU idle periods. Hence, a higher throughput can be attained by compromising on some of the spectrum opportunities to obtain the needed energy by paying an extra cost. Optimal energy-purchasing probability and sensing intervals are found to minimize the average energy cost for a time slot to achieve a given SU transmission rate while meeting the PU collision constraint.

3. Next in Chapter 5, we study cooperative policies for an energy-harvesting CR system. We consider a CR system where each SU harvests energy to recharge its battery. We have a heterogeneous CR system with different sensing environment and energy-arrival process at each SU. Cooperative spectrum sensing is employed for an improved sensing performance. Due to random energy arrival, the SUs may not have energies to operate in each time slot. Moreover, from energy efficiency point-of-view, fewer SUs with high probability of detection values should sense more frequently provided that their harvested energies are sufficient. Similarly, a lesser number of sensing SUs with smaller probabilities of false alarm achieve a

higher throughput for an OR-based fusion rule. (This work has been published in *Proc. IEEE GLOBECOM*, Dec. 2015)

- We propose that in this energy-constrained scenario, the SUs can cooperate to achieve a higher opportunistic spectrum utilization and PU detection reliability. In each time slot, only some of the SUs, based on the proposed decentralized sensing policy, perform sensing operations. We obtain the optimal probability of sensing for each SU to maximize the SU network throughput, subject to the PU collision and energy-causality constraints. SOSTOOLS is employed to solve the polynomial optimization problem. Moreover, an iterative suboptimal strategy is proposed which can be used to solve for larger systems.
 - We analyze a homogeneous scenario where all the SUs have the same sensing performance and energy-arrival processes. It is shown that by utilizing cooperation among a minimum number of SUs, the CR throughput performance can be made to overcome the energy-causality and PU collision constraints. An algorithm is provided to find the minimum number of cooperating SUs required to achieve the unconstrained CR system for a given energy-arrival rate and maximum tolerable probability of collision at the PU.
4. Furthermore in Chapter 6, we propose a dynamic cooperative sensing-access policy for energy-harvesting CR systems with finite batteries. The SUs are coordinated to enhance both the PU detection and the opportunistic utilization of the PU spectrum. Optimal sensors are chosen from the SUs with varied received PU signal power levels and energy-arrival rates for cooperative spectrum sensing. We consider a discrete Markov chain based PU traffic. The proposed sensing-access policy is used by the central controller to take the optimal decisions in each time

slot based on the belief about the PU channel state, available energy at the SUs and the remaining operation time to maximize the spectrum-access opportunities over a finite-time duration while sufficiently protecting the PU. (This work has been published in *IEEE Trans. Veh. Technol.*, vol. 65, Dec. 2016)

- Since the PU channel state is only partially known to the central controller through spectrum sensing, a finite-horizon POMDP framework is applied to obtain the optimal cooperation among the SUs for sensing and access to maximize the throughput while satisfying the PU detection constraint. The sensing-access policy is used to decide whether to sense, the set of sensing SUs, the sensing detection threshold, and the SU that accesses the idle spectrum. Using the optimal policy, an optimum tradeoff is achieved among SU transmission, energy management, and obtaining sensing information for the future gains. We also present a myopic policy, a low-complexity scheme, under which the actions are chosen in order to maximize the immediate gain only.
- Furthermore, we attempt to provide some insights into the tradeoffs involved in choosing the optimal action. It is shown that for a given belief about the PU channel state, the expected SU throughput for the remaining duration is non-decreasing in the present energy levels at the SUs. Also, it is proved to be non-decreasing in the belief value for the PU to be in idle state for a given energy state of the SUs provided that the PU is more likely to stay in the idle state than to switch from a busy to idle state.

1.4 Organization of Thesis

The thesis is organized as follows. In Chapter 1, we present a brief introduction on energy-harvesting CRs and summarize our main research contributions. Chapter 2 is devoted to an elaborate literature survey about spectrum sensing and access strategies for CR, and energy-harvesting techniques. In Chapter 3, we study a multichannel CR employing RF energy harvesting, using PUs as the RF energy sources. A decentralized channel-selection strategy is proposed to obtain a greater number of spectrum-access and energy-harvesting opportunities to maximize the CR throughput. A dual-sensing-interval policy and energy-trading options are explored for the opportunistic RF energy-harvesting CR in an unslotted PU system in Chapter 4. In Chapter 5, we investigate the gains for an energy-harvesting CR system by employing cooperation to enhance the spectrum utilization and PU detection. A dynamic sensing-access policy is developed for a cooperative energy-harvesting CR system to determine the optimal CR sensors, sensing threshold, and the SU for opportunistic transmission in Chapter 6. In Chapter 7, we conclude the research work and present potential future directions.

Chapter 2

Literature Survey

Cognitive radio (CR) [27] is a promising solution to the impending spectrum scarcity problem. It enhances spectrum efficiency by detecting and utilizing the vacant spectrum bands licensed to primary user (PU). The CR users being the secondary users (SUs) need to sense the spectrum periodically in order to prevent interference to the PU transmission and to detect the spectrum-access opportunities. Also, the CR users need to make access decisions to optimally utilize the discovered opportunities based on their channel quality information and the potential contention with other SUs. Owing to its dynamic nature and the super adaptability, there is a lot of scope to CR systems. Many new aspects are being identified and the work is still in progress. Some of the interesting research problems that have been investigated can be categorized under spectrum sensing, power allocation, channel-access policy, and spectrum handoff on return of the PU to the SU channel [3,28]. In the following, we present the existing work on different functionalities of the CR based communication systems.

2.1 Spectrum Sensing

In an opportunistic CR model, SUs identify and exploit the idle PU spectrum bands. Such an opportunistically accessing SU should vacate the spectrum band as soon as the PU returns to access the spectrum. Hence, the SUs need to perform spectrum sensing at proper intervals to detect the presence or absence of the PUs. The received signal $y(n)$ at the SU is given by

$$y(n) = x(n) + w(n) \quad (2.1)$$

where $x(n)$ denotes the received PU signal and $w(n)$ is the additive white Gaussian noise. Spectrum sensing at the SU involves deciding between the following two hypothesis [29]

$$\begin{aligned} \mathcal{H}_0 : y(n) &= w(n) \\ \mathcal{H}_1 : y(n) &= x(n) + w(n) \end{aligned} \quad (2.2)$$

where $\mathcal{H}_0$ and $\mathcal{H}_1$ correspond to the cases when PU signal is absent and present, respectively. There is a missed detection when the PU signal is present but is wrongly decided to be absent by the SU. When the SU decides the PU signal to be present while the PU is not transmitting, it is a false alarm. The performance of a spectrum sensing method is evaluated in terms of the probability of missed detection p_{md} and probability of false alarm p_f , which are defined as

$$\begin{aligned} p_{md} &= \mathbb{P}\{\mathcal{H}_0|\mathcal{H}_1\} \\ p_f &= \mathbb{P}\{\mathcal{H}_1|\mathcal{H}_0\} \end{aligned} \quad (2.3)$$

where $\mathbb{P}\{\mathcal{H}_i|\mathcal{H}_j\}$ denotes probability of deciding $\mathcal{H}_i$ when we actually have $\mathcal{H}_j$. It is desirable to have low probabilities of misdetection and false alarm. Various spectrum

sensing techniques have been proposed for CR systems [30, 31]. In the following, we discuss some of the basic sensing algorithms.

- Energy detection: Energy detection is a simple sensing method and requires no knowledge of the PU signal to be detected [32, 33]. The sensing decision is made by comparing the signal energy measured over a sequence of L received samples against a suitable threshold ϵ .

$$T_{ed} = \frac{1}{L} \sum_{n=1}^L |y(n)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\geq}} \epsilon \quad (2.4)$$

A perfect knowledge of the noise variance is needed in order to decide the appropriate detection threshold. Hence, this algorithm is highly susceptible to noise uncertainty, which introduces a signal-to-noise ratio (SNR) wall [34]. For optimum performance, we need to find an optimal L and detection threshold, which presents a tradeoff between SU throughput and sensing reliability [35]. In another work on energy detection, the sensing performance degradation due to uncertainty in the PU signal was analyzed [36].

- Cyclostationary feature detection: When the PU signal is not perfectly known but some of its features are known, it may be helpful in distinguishing it from noise. Generally, modulated signals exhibit periodicity in their statistical parameters, like symbol rate, sampling frequency, frame rate etc., called cyclostationarity [37]. Cyclostationary feature detection method detects the PU by exploiting the cyclostationarity feature of the received signals [38]. It analyzes the cyclic autocorrelation function of the received signals, which is periodic for the PU data signal and aperiodic for noise [39]. The cyclic autocorrelation function of received signal

$y(t)$ is given by

$$R^\alpha(\tau) = \lim_{T_0 \rightarrow \infty} \frac{1}{T_0} \int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} y\left(t + \frac{\tau}{2}\right) y^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi\alpha t} dt \quad (2.5)$$

where α is called the cyclic frequency. Unlike stationary signals, for cyclostationary signals, $R^\alpha(\tau) \neq 0$ for some nonzero values of α [39]. Cyclostationary feature detection is more complex but is robust to uncertainty in noise power and works well even for very low SNR. Thus, it overcomes the shortcomings of energy detection. In [40], the authors analyzed the degradation in detection performance due to cyclic frequency offset. A sequential detection method which uses both cyclic phase and magnitude information was proposed in order to reduce the long detection times in cyclostationary sensing which enhanced the cognitive spectrum utilization [41].

- Matched filtering: When perfect information is available about the PU signal *a priori*, matched filtering, which maximizes the received SNR, is the optimal detection method in a Gaussian additive noise channel [29]. The received signal is correlated with the already known PU signal to detect the presence of PU. It is more robust to noise uncertainty than the other two schemes but the number of samples required for detection increases as the received SNR decreases [42]. Also, its implementation complexity is high as a separate receiver is needed to detect each type of PU signal [28]. For the case, when PU pilot signal is known, the test statistic which is compared with threshold ϵ is given by [42]

$$T_{mf} = \frac{1}{L} \sum_{n=1}^L y(n) \hat{x}_p(n) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \epsilon \quad (2.6)$$

where $y(n)$ is the received signal and $\hat{x}_p(n)$ is a unit vector in the direction of the pilot signal which is assumed to be orthogonal to the desired PU signal. A novel hybrid detector was proposed based on a combination of energy detection and coherent detection which utilized both the pilot symbols and energy contained in the data symbols to enhance the detection performance over the individual methods [43].

2.1.1 Cooperative Sensing

When there are multiple SUs distributed in an area, cooperative schemes may be employed to utilize the spatial diversity to achieve better detection performance in the presence of multipath fading, shadowing, and noise uncertainty [25, 26, 44, 45]. It overcomes the hidden node problem faced by single-user detection methods. Cooperative sensing can be centralized or distributed. In centralized cooperative sensing scheme, all the SUs send their observed local data to a single central controller (CC) which makes the final decision, whereas in distributed sensing scheme, they share information among each other and based on it all SUs make their individual decisions. Censoring of the collaborating SUs can be done to allow only the SUs with useful information to transmit their sensing data, which reduces data overhead, saves transmission energy, and prevents degradation of sensing reliability due to erroneous data [46]. Depending on the type of information shared by the cooperating SUs, the final decision can be made using two types of schemes, i.e., data fusion and decision fusion. In the first scheme, different SUs send all the collected data to the CC, which jointly processes the data reported by all SUs and makes a decision whereas in the latter scheme, the SUs process their collected data independently and send only the sensing decisions to the CC, which makes the final decision. The CC generally uses hard combination decision fusion rules with single decision bits like logical-OR, logical-AND or k -out-of- N rule [47–49]. It may also use

soft combination for multi-bit decisions, like maximal-ratio combining and equal-gain combining based fusion schemes, which have a higher complexity but better detection reliability [50, 51].

All the works mentioned so far consider only temporal spectrum sensing, i.e., they find the time periods when PU channel is idle. In [52], the authors addressed spatial spectrum sensing. A group of SUs collaboratively estimated the location and transmitted power of the PU, and calculated the maximum transmission power allowed for a given SU based on the acceptable interference to the PU. In order to realize full capability of opportunistic spectrum access, both temporal and spatial spectrum sensing should be considered [53, 54]. Based on the PU localization information provided by spatial spectrum sensing, an observation set was selected from the cooperating SUs to minimize correlations in the collected data, which improved the performance of temporal sensing [53]. A two-dimensional sensing was proposed to improve the spectrum sensing performance, which exploited correlations in time and space simultaneously during data fusion [54]. Furthermore, a two-dimensional sensing based distributed power control scheme was proposed to improve the spectrum utilization by exploiting both grey and white spectrum opportunities, which were classified based on the maximum transmission powers allowed by the PU interference constraints.

With an increasing stress on green communications, much recent research on cooperative spectrum sensing has been concentrated on enhancing the energy efficiency. In [47], the dependency of energy efficiency on fusion-rule threshold, SU detection threshold, number of cooperative SUs, and sensing time has been analyzed as they affect both the SU throughput and the average energy consumed at the SUs. Convex optimization tools were used to derive the optimal detection threshold and SU sensors in order to minimize the energy consumption while attaining the specified global probabilities of false alarm and detection [11]. The optimal censoring and sleeping parameters were

determined to achieve an energy-efficient distributed spectrum sensing with bounds on global probabilities of false alarm and PU detection [49]. In a multichannel CR network, energy-efficient cooperative sensing scheduling (CSS) with satisfactory PU protection was considered to determine which SUs should sense a channel and the sensing duration for each combination of the SU and PU channel [48]. In another work on CSS, discrete convex framework was employed to analyze the problem [55].

2.1.2 Sensing Throughput Tradeoff

As mentioned before, there are two performance metrics for spectrum sensing: probability of missed detection p_{md} and probability of false alarm p_f . Low p_{md} is desirable for better PU protection. However, from the SU's perspective, a lower p_f is needed to reduce the chances of missing a spectrum opportunity and achieve higher throughput for the SU network. An optimal tradeoff needs to be attained as p_f increases when p_{md} is decreased. In [35], the authors studied the sensing-throughput tradeoff for energy detection based sensing method. An optimal sensing duration was obtained to maximize the secondary network throughput while meeting the PU protection constraints. A similar problem was considered for the case where SUs employed cooperative sensing with k -out-of- N fusion rule [56]. The optimal sensing time and k value were obtained to maximize the SU throughput while attaining the specified PU protection level. In [57], the sensing-throughput tradeoff problem was investigated for a multichannel CR network. The optimal sensing time and power allocation schemes were designed to maximize the aggregate ergodic SU throughput while meeting the PU interference constraints and the SU average power constraint.

The sensing throughput tradeoff problem occurs because the SU cannot transmit data during the sensing time. A novel receiver and frame structure were proposed to overcome

this problem by performing spectrum sensing and data transmission at the same time [58]. The proposed CR system was shown to achieve higher throughput and improved sensing capabilities. Furthermore, the authors showed that the proposed CR system can achieve a higher average throughput under a high target detection probability constraint, as compared to the conventional CR systems [59]. The problem of maximizing the ergodic throughput under joint average transmit and interference power constraints was studied, and optimal target detection probability and power allocation strategy were obtained.

2.2 Resource Allocation

For a CR system, the aim is to identify good quality spectrum opportunities as soon as possible with reduced false alarm while meeting the PU interference constraints. The available spectrum, time, and energy resources should be optimally utilized to enhance the SU throughput in the presence of multiple SUs and multiple PU channels.

2.2.1 Sensing-Access Scheduling

Considering the hardware and energy limitations, the spectrum is partitioned into multiple channels in order to make spectrum sensing more feasible. The SU decides which spectrum bands to sense, their sensing order, and the channel to access in order to optimize the SU throughput. The SUs sequentially sense the channels until a spectrum hole is detected. In order to maximize the time available for SU transmission, the sensing policy should detect a vacant channel with acceptable quality as soon as possible. The SUs can learn from past PU activities on each channel and predict the next channel state. Modeling the CR system as a hidden Markov model (HMM), an SU estimated the channel parameters such as the sojourn times for the active and the inactive states

of the PU and the PU signal strength, on the basis of the sequence of the sensing results [60]. It was proposed that if channels were sensed in the decreasing order of the channel-availability likelihoods, there was a high probability that the SU got a channel upon its first sensing attempt [61]. In [5], it was shown that when adaptive modulation scheme is employed, it is not always optimal to sense the channels in the descending order of the channel-availability probabilities. A dynamic programming (DP) approach was presented to find an optimal sensing-channel sequence when using adaptive modulation. For the case when the SU has no knowledge of the PU traffic profile *a priori*, it was shown that adopting a sensing-channel sequence as the descending order of the achievable rates on the channels, it is optimal for the SU to stop at the first available channel to maximize the achievable throughput [62]. In [63], the authors further investigated the sensing order problem for multi-user CR networks in which multiple SUs sequentially sense and access the channels following their individual sensing orders. A novel metric was proposed, which considered the three important factors: channel availability, channel rate, and channel access collisions among SUs. A DP algorithm was used at each SU to determine its sensing order based on the metric, to achieve higher CR network throughput with reduced collisions among the SUs.

Using a partially observable Markov decision process (POMDP) framework, sensing and access policies were designed to select which channel to sense and the access decision, respectively, to maximize the SU throughput while considering sensing errors and constraints on probability of collision with PUs [4]. For statistically independent PUs, belief about the PU channel state was shown to be a sufficient statistic to reduce the computational complexity. Optimal spectrum sensor design, and spectrum sensing and access policies were obtained to maximize the throughput of SUs under the PU collision constraint [64]. The authors established a separation principle that the optimal joint design can be obtained by decoupling the selection of optimal spectrum sensor and

access policy from the sensing policy. Using the separation principle, a closed-form optimal sensor operating point and access policy were obtained. The constrained POMDP was reduced to an unconstrained one, leading to a deterministic optimal sensing policy. An optimal sensing channel-selection policy based on POMDP was proposed in [65], in which the SU made a decision on which channel to sense based on the previous observations of the channels. Optimal sensing channel and sensing time were obtained jointly to maximize the SU throughput. It was shown that the optimal sensing time achieved better channel efficiency as compared to the fixed sensing time approach.

2.2.2 SU Spectrum Handoff Strategies

Primary user is the licensed user. The SU which opportunistically accesses the PU spectrum should vacate it as soon as the return of the PU is detected. In order to minimize the disruption in SU services, we have spectrum handoff techniques. On return of the PU, the SU needs to find another channel to continue its transmission. The target switching channels can be predetermined to reduce SU service disruption. There are reactive handoff policies where the SU vacates the channel and switches to another channel on collision with the PU on the incumbent channel [23]. On the other hand, the SU can predict and vacate the spectrum before the PU arrival using proactive handoff techniques [7,66]. In [23], the authors proposed a novel wait-or-switch strategy to be used on the return of the PU to the SU channel in an unslotted PU system while considering the overheads incurred in channel switching. The performance of a CR system using a dedicated common control channel for spectrum handoff was analyzed in terms of delay, spectrum utilization, energy efficiency, and distributed event sensing distortion [67]. In [66], a proactive spectrum handoff protocol for CR ad hoc networks was proposed to prevent interference to the PU. It incorporated network coordination schemes without using a common control channel. Considering multiple CR pairs in the network, a

novel distributed channel-selection scheme was proposed for spectrum handoff to reduce the multiuser collisions and handoff delays. A prediction based optimal transmission strategy was determined for an SU to decide on whether to stay idle, transmit on current channel, or switch to a new transmission channel [7]. An MDP framework was utilized to find the optimal strategy to minimize the expected total energy cost for transmissions and handoff and the penalty for not completing the packet transmission within the predefined deadline. A preemptive resume priority M/G/1 queuing network paradigm was proposed to model the CR spectrum usage, which was used to analyze the extended data delivery time of a CR connection with multiple handoffs [68]. Furthermore, a traffic-adaptive switching-channel selection for spectrum handoff was proposed to improve the latency performance. To better support the multimedia applications in CR networks, a mixed queuing model was developed for spectrum handoff to cater to the heterogeneous quality-of-service (QoS) requirements of SUs and reduce the SU channel contentions [69]. It was used to design a spectrum handoff scheme to satisfy the heterogeneous multimedia users.

2.2.3 Power Allocation

For maximal utilization of the available spectrum, power allocation of the SUs should be optimized by considering the channel quality to maximize CR throughput while limiting the total interference at the PU and other CR users [2]. An optimal power-allocation strategy was obtained for an orthogonal frequency division multiplexing (OFDM) based opportunistic CR system to maximize the downlink capacity of the SU while maintaining the interference to the PU below the specified level [70]. Different from the classical water-filling algorithm, it considered both the channel fading gain and its spectral distance from the PU band. In a spectrum-sharing CR system, optimal power allocation was determined to maximize the ergodic and outage capacities for various channel fad-

ing models under different combinations of peak or average transmit and interference power constraints [71]. It was shown that the average power constraint allowed a higher SU capacity as compared to the peak power constraints. Also, fading of the channel between SU transmitter and PU receiver was found to be beneficial for the SU channel capacities. In a spectrum underlay CR system, when the PU channel state information was known, a constraint on the upper bound on the rate loss of the PU due to SU transmission was proposed instead of the conventional interference power constraint [72]. The optimal power allocation derived under the rate loss constraint was shown to achieve a significant rate gain over the interference power constraint solution. Using a two-user CR network over Rayleigh fading channels, the authors demonstrated the performance gains of network-coded cooperation with optimal power allocation in terms of energy efficiency and outage probability as compared to the non-cooperative and typical cooperative relaying CR systems [73]. Two schemes based on the statistical channel state information (CSI) and instantaneous CSI were investigated which obtained the minimum fixed power to achieve the predefined outage probability and dynamic transmit power to guarantee the required instantaneous signal-to-interference-plus-noise-ratio (SINR) at the receiver, respectively. A cooperative overlay CR scenario was considered where the CR users were allowed to transmit on a fraction of the PU spectrum while they helped to relay the PU transmission on the remaining bandwidth using multiple-input-multiple-output (MIMO) two-way relay schemes [6]. The transmit power per antenna and bandwidth allocated to the PU and CR user were optimized to maximize the CR sum rate while meeting the PU QoS target under bandwidth and power budget constraints. In [74], the authors investigated the power-allocation problem for a spectrum-sharing MIMO CR system with statistical CSI to maximize the ergodic capacity under interference power constraints at each of the primary receivers. The nonconvex ergodic capacity maximization problem was solved by using the Lagrangian

dual method to solve an equivalent problem to obtain the optimal precoding matrix and power allocation.

In a system managed by the primary base station, cooperative game theory was utilized to develop optimal power and subchannel allocation using periodic information received from the PUs and SUs about their CSI, QoS requirements, and power limitations [75]. Two alternative strategies were investigated, i.e., transmission power minimization to achieve power saving for the cellular uplink PUs and to reduce interference from the SU transmission to PU, and sum rate maximization to enhance the spectral efficiency. Nash bargaining solutions were used to develop a fair resource allocation. A distributed approach for power and subchannel allocation was studied for an underlay two-tier cognitive femtocell network [76]. An uplink sum-rate maximization problem was formulated with constraints on the intra-tier and inter-tier interferences while meeting the average delay target for the CR users. The NP hard optimization problem was simplified using a self-organizing framework for disjoint groups which was solved as a coalition game in partition form. In another work on cooperative transmission between PU and SU, joint interference pricing and power allocation were obtained for the PU and the cognitive relay by using the Stackelberg model [77]. PU benefited from CR relay in terms of enhanced battery life and outage performance while the SU was rewarded spectrum resource. A non-cooperative game was formulated to obtain the optimal power allocation for spatial spectrum sharing based multiuser CR networks where the SU obtained spectrum sharing by paying the PU and employed multihop relaying by paying the nearby SUs [78]. Two distributed algorithms were proposed, i.e., subgradient based power allocation and Q-learning based relay-selection scheme, to achieve the Nash equilibrium.

2.2.4 Energy Efficient Cognitive Radio Systems

In CR wireless networks, SUs are often battery-powered. This introduces an energy constraint in the system. The sensing-access strategies are focused on low power consumption to achieve maximum performance with the limited energy resource. For instance, if the present available channel is of poor quality, the SU may decide not to access the channel for transmission at low rate using a high power. Instead, it may choose to remain idle to save energy for a better channel expected in the next slot, which introduces delay and reduction in SU throughput. Such a scenario was studied in [79], where a reward was defined as a function of the delay and energy costs associated with the SU staying idle, and sensing and transmission, respectively, and the throughput gain on a successful transmission. A POMDP framework was utilized to find an optimal spectrum sensing duration and an optimal policy selecting between the idle and sensing modes, maximizing the expected reward. In a time-varying channel condition, sensing and access strategies with SU rate adaptation are needed for better performance [80]. It may be preferable to slow down the SU transmission rate and save transmit power under a deep fading channel. However, rate reduction leads to delay and additional energy consumption for sensing and idling in future slots. The problem was formulated as a discrete-time MDP, where the SU aimed at minimizing its average total cost, including the energy consumption and delay cost, to finish a target traffic payload through an appropriate rate allocation. It was solved as a stochastic shortest path problem using the value iteration algorithm.

Optimal distributed spectrum sensing and access policies to maximize the throughput of the SU during a finite duration before its battery depletes were obtained [10]. A sequential decision-making problem was formulated for the energy-constrained SU to decide whether to sense, which channel to sense, and whether to access. The problem

was casted into POMDP framework, and stationary spectrum sensing and access policies were obtained. An energy-efficient design was proposed, which found the channel sensing order, the sensing strategy specifying when to stop sensing and start transmission, and the access strategy determining the power level to be used upon transmission [8]. For a given sensing order, the problem was formulated as a stochastic sequential decision-making problem, which was casted into another parametric formulation and DP was applied to identify the optimal strategy. In [81], the authors addressed two fundamental tradeoffs involved in energy minimization: the sensing-transmission tradeoff and the wait-switch tradeoff. A convex optimization problem was solved to obtain the sensing slot duration and the channel-switching probability that minimized the average energy consumed in spectrum sensing, spectrum mobility, and data transmission, while satisfying the constraints on the sensing reliability, minimum throughput requirement, and delay in SU transmission. In [82], a joint design was studied for energy-efficient CR systems to obtain optimal sensing and transmission durations, simultaneously. The PU was protected by constraints on the detection probability and the PU's reoccupation probability, which considered the interference between PU and SU during SU transmission. A hybrid spectrum access scheme was proposed to minimize the total energy consumption while meeting the throughput requirement and the delay constraint in cognitive vehicular ad hoc networks [9]. In an underlay CR system, Stackleberg game was formulated to obtain the transmission powers and channels for the PU and SU to maximize their energy efficiency [83].

2.3 Energy Harvesting Cognitive Radio Systems

Energy harvesting is an attractive solution to power or enhance battery lives of wireless nodes and remotely located sensors for which it is inconvenient to periodically

replace the batteries. Some of the potential energy sources for practical self-powered devices are solar power, wind energy, vibration, thermal energy, ambient RF signals, etc. The existing resource management algorithms for the wireless networks need to be revised to consider the energy-arrival and consumption mechanisms [12,84]. Offline and online transmission policies were proposed for an energy-harvesting transmitter with a finite battery to maximize the achieved throughput and minimize the transmission completion time under the constraints of time deadline and number of bits to be transmitted, respectively, on a wireless fading channel [85]. For the offline throughput maximization problem, a novel directional water-filling algorithm was proposed to obtain the optimal power allocation while taking into account the energy causality and channel fading. For multiple energy-harvesting nodes sharing a common channel, a transmitting-node selection and discrete-rate adaptation rule was proposed to maximize the achievable throughput [86]. It was proved to be optimal for a general class of ergodic and stationary energy-arrival and channel fading processes. Cognitive radio, an important part of future wireless communication networks, has also been studied by considering the adaptability issues arising due to the random energy availability and new algorithms have been proposed for the same.

2.3.1 Ambient RF Energy Harvesting

Employing energy-harvesting techniques to power the wireless networks has been a topic of research for many years. Recently, ambient RF energy harvesting has become a hot topic. RF energy is available all the time unlike solar energy, which is not available during night. With rapid deployment of wireless services over a wide range of frequencies and power levels, we have a widely available source of RF energy everywhere. Research involves finding potential RF sources that can deliver significant energy. The effectiveness of RF energy harvesting was demonstrated based on the measurements of the

output of a rectenna by using TV broadcasts as an energy source for 7 days [87]. An RF energy harvesting prototype was developed for wireless sensor networks and an adaptive duty cycle determination method was implemented for the system. The prototype was shown to be capable of sensing and transmitting temperature data every 5 seconds by using RF energy harvesting. Based on the power density measurements obtained by field trials performed in two cities, it was found that GSM 900, GSM 1800, and UMTS provide good opportunities for RF energy harvesting [88]. An output dc power density comparison was made between the ambient RF energy harvesting and the alternative energy-harvesting technologies, which highlighted that it can be a competitive practical solution [13]. Digital TV, GSM 900, GSM 1800, and 3G were identified as potential ambient RF energy sources.

The RF energy harvesting process needs a rectenna which consists of an antenna and a rectifier [13]. It captures the RF energy and converts it into direct current power. Efforts are being made in designing better energy-harvesting circuits that can operate over a wide range of frequencies, can start to operate at very low input powers, and can achieve high RF-to-dc conversion efficiency. A dual-stage energy-harvesting circuit was proposed, which composed of one design that was more efficient in the low input power regions, while the other was more suitable for higher power range [89]. An optimization framework was designed to select the switching point between the two stages. As a whole the harvesting circuit delivered high efficiency in the input power range of -20 to 20 dBm. The proposed design was fabricated on a printed circuit board and was used to run a commercial Mica2 sensor mote. A high-gain antenna was designed for a 2.45 GHz rectenna to achieve a high-efficiency harvesting from low-power RF input [90]. The rectenna was shown to have a maximum conversion efficiency of 83% and an overall conversion efficiency of 50% for low input power level of -17.2 dBm. A novel rectenna was designed with high-gain broadband 1×4 quasi-Yagi antenna array to harvest the

ambient RF power of GSM 1800 and UMTS 2100 bands [91]. A dual-band rectifier was proposed for enhanced RF-to-dc power conversion efficiency at low ambient RF power level, and an output dc voltage varying between 300 to 400 mV was achieved. An ambient RF-powered sensor node prototype was developed which could measure and transmit the temperature and light level [92]. Based on the tests in a real-world RF harvesting scenario, minimum -18 dBm ($15.8\mu\text{W}$) RF input power was required for sensor node operation. Using a 6 dBi receive antenna, the most sensitive harvester was shown to operate at a distance of 10.4 km from a 1 MW TV broadcast transmitter, and at a distance of 200 m from a cellular base station. In another model exploiting ambient wireless digital-TV signals to power an embedded microcontroller for sensing operations, the wireless power was harvested at a distance of over 6.3 km from the TV broadcast source [93]. An improved RF-dc charge-pump circuit, with maximum sensitivities of -14.6 and -18.86 dBm, was presented to rectify and step-up lower levels of RF signals. Low-leakage capacitors were used to collect and use ambient wireless signals instead of batteries because the capacitors can have infinite charge-discharge cycles and are more environment friendly.

2.3.2 Sensing-Access Strategies

Unlike the battery-limited and energy-efficient scenarios where power consumption minimization was important, for the energy-harvesting case, the sensing-access policies need to be designed with the objective to sustain the CR system by taking into account the energy-arrival process. In this direction, an optimal spectrum sensor detection threshold was obtained by maximizing the CR throughput, subject to the PU collision constraint and the energy-causality constraint to keep the average energy consumption below the average energy harvested [16]. An optimal pairing of sensing duration and detection threshold was found [94]. Further, the authors investigated the

effect of temporal correlation of PU traffic and derived the upper bounds on the achievable throughput that can be drawn from any spectrum access policy as a function of the detection threshold of the spectrum sensor, energy-arrival rate, and the correlation in the PU traffic [95]. Additionally, optimal detection threshold was found to maximize the upper bound under the energy-causality and collision constraints. In [17], the authors designed optimal spectrum access policy that achieves the upper bound of the achievable throughput derived in [95]. The energy arrival and primary traffic were modeled as independent and identically distributed (i.i.d.) random process and discrete Markov process, respectively. Using POMDP framework, an optimal spectrum sensing policy and a detection threshold were jointly designed, under the energy-causality and collision constraints for a given energy-arrival rate and temporal correlation of the primary traffic. In [96], the author studied optimal sensing and access policies for an energy-harvesting CR user with a finite energy queue by formulating an MDP. At the beginning of each time slot, SU decides whether to remain idle or carry out spectrum sensing and also decides upon optimal sensing and transmission energies considering the throughput-reliability tradeoff. An optimal random access strategy was proposed for an energy-harvesting SU with multipacket reception capability [97]. The authors investigated the CR throughput maximization under the primary queuing delay constraints, while considering an energy queue with Bernoulli arrival model. A channel-selection strategy was proposed to maximize the SU throughput based on the PU belief state, channel fading conditions, and available energy with Bernoulli arrival model [98]. In [99], both SUs and PUs were assumed to operate using the energy harvested from same renewable source and possess no batteries. A novel 2-D sensing scheme was proposed based on a hidden input Markov model which enhanced the PU detection by exploiting the spatial correlation in the energy-harvesting process.

2.3.2.1 RF Energy-Harvesting Cognitive Radio

Recently, there has been much work on using opportunistic RF energy harvesting which is specific to the CR system [19, 100]. The SUs not only utilize the PU spectrum holes for transmission but also exploit the PU busy periods to harvest RF energy from PU transmission. In [19], the authors used the stochastic geometry paradigm to analyze the SU transmission probability in an opportunistic RF energy-harvesting CR system. Optimal SU density and transmission power level were obtained to maximize the throughput of the CR network while satisfying the outage probability constraints at the PUs and SUs. A decision-making problem was formulated as a POMDP to decide between the spectrum-access and energy-harvest modes for the SU in each time slot to maximize the SU throughput while harvesting energy for future slots [100]. In a multichannel system with RF energy-harvesting SU, an optimal channel-access policy was derived to maximize the SU throughput by using an MDP framework for the case when model parameters for the SU transmission and harvesting, and PU channel state occupancy were available [101]. An online learning algorithm was proposed for the case when no information was available. In a similar multichannel system with multiple SUs, optimal channel-access policies were obtained for the SUs cooperating in a round-robin and a decentralized manner [20]. In [102], the authors utilized both RF energy-harvesting and other ambient renewable sources of energy and a POMDP framework was employed to decide among different modes, i.e., overlay transmission, underlay transmission, energy harvesting, and sleeping. It was shown that a greater SU throughput can be achieved by considering the hybrid energy-harvesting and transmission modes as compared to that obtained by only operating in overlay mode using ambient energy sources. An RF energy-harvesting CR based device-to-device (D2D) communication was considered to access a predefined channel of a multichannel cellular network in an underlay mode [18]. Stochastic geometry was employed to analyze the outage performance of both the D2D

and cellular networks for two different access policies for cellular system, i.e., D2D channel can be selected randomly by the cellular user and the D2D channel can only be used when no other channel is available. In another work on RF energy harvesting underlay CR system, outage probability was derived for different types of power constraints at the PUs and the SU [103]. Additionally, throughput expressions were determined and analyzed for both delay-sensitive and delay-tolerant systems.

2.3.3 Wireless Power Transfer

A more efficient and reliable way to harvest significant power from RF signals is to use a dedicated wireless power transmission to the energy receiver called a wireless power transfer (WPT) [104]. Multi-antenna based energy beamforming can be utilized to achieve high energy-transfer efficiency in the presence of channel propagation losses which requires CSI of the transfer channel [105]. Optimal training design needed for the channel-reciprocity based CSI acquisition method was studied while satisfying the tradeoffs between the energy-beamforming gain, and the energy and time overheads. Optimal time allocation was obtained to maximize the sum-throughput achieved for a harvest-then-transmit protocol based WPT system where an access point (AP) first broadcasted power to multiple distributed users which later sent their data using a time division multiple access (TDMA) framework [106]. A new common-throughput metric which entailed equal transmission rates for all users despite of their varied distances from the AP was proposed to solve the doubly near-far problem encountered in such systems. In a similar model with CR functionality, PU channel was shared by the AP and CR users for wireless power and information transfer [107]. Optimal time and power allocations were obtained to maximize the CR throughput while satisfying the PU QoS constraints for overlay and underlay based CR systems. The overlay system, which cooperated with the PU using the information about the PU channel and data, was shown to

outperform the underlay design. Application of RF signals to transfer usable power introduces the area of simultaneous wireless information and power transfer (SWIPT) for communication systems [108–111]. A capacity region was defined to study the tradeoffs involved in maximizing the information rate while simultaneously transferring sufficient power for Gaussian and binary channel models [109]. In a MIMO broadcast SWIPT system, optimal transmission strategy was proposed to achieve different tradeoffs between maximizing the information and energy transfer [108]. Two receiver designs were proposed for a co-located energy harvester and information decoder, i.e., power splitting scheme under which the SU utilizes a fraction of the received power for information coding and rest for harvesting, and time switching to divide the time slot for energy and information transmission. In another work, a multi-antenna AP simultaneously transferred power and information to many nearby and distant energy and information receivers, respectively, by considering the input power requirements for the two operations [110]. A semidefinite relaxation is used to solve the quadratically constrained quadratic program (QCQP) to obtain the optimal beamforming and power allocation at the transmitter by maximizing the sum-power transferred to all energy harvesters (EHs) while meeting the SINR requirements at the information receivers (IRs).

2.3.3.1 Secure Communication

Most of the work on WPT in CR is concentrated on developing physical layer security. An underlay CR system was considered with SWIPT operation to a desired IR and multiple ERs, respectively, while limiting the interference at multiple PUs [112]. The ERs were assumed to be eavesdroppers which used a power-splitting method to decode the information. Closed-form expression was derived for the secrecy outage probability. In another work on SWIPT CR system, both the idle SUs receiving power and PU receivers were considered to be potential eavesdroppers [111]. An optimal resource

allocation was obtained using a semidefinite relaxation to achieve transmit power and interference-power-leakage-to-transmit-power ratio minimization with maximal energy-harvesting efficiency while guaranteeing the SU Communication secrecy. Stochastic geometry tools were employed to analyze an underlay CR D2D communication, where a battery-free D2D transmitter harvested energy from power beacons (PBs) [113]. In this regard, three WPT policies were proposed, namely, cooperative, best, and nearest PB power transfer. Using these policies, secrecy performance was studied for best and nearest receiver-selection schemes, and it was observed to be improving with an increase in PB and D2D receiver densities due to a larger multiuser diversity gain. A PU used SWIPT for an energy-constrained SU transmitter, which was granted spectrum to transmit both the PU and SU data [114]. Considering the SU receivers as potential eavesdroppers for PU data, optimal power-splitting and beamforming designs are studied to maximize the SU throughput while guaranteeing the secrecy of the PU system. In a similar scenario, secure communication was ensured for the SU where the relaying SU transmitter with continuous power supply performed concurrent information and power transfer to the SU and PU receivers and PU receivers were potential eavesdroppers [115].

2.3.3.2 Spectrum-Energy Cooperation

The introduction of RF energy-harvesting capability to the CR systems has led to a new line of research for analyzing and optimizing the potential gains of spectrum-energy cooperation among SUs and PUs. An RF energy-harvesting SU operating on a save-then-transmit protocol was considered, which either acted as relay to help PU finish its transmission earlier or waited for the PU to finish its transmission [116]. A cooperative strategy was proposed for the SU to decide whether or not to cooperate with the PU, and the optimal time for energy harvesting and power for cooperative relaying were found. An optimal beamforming was designed for a multi-antenna SU transmitter in a cooper-

ative system where the PU allowed the opportunistic use of its spectrum and transferred energy to the SU using power or time splitting techniques; in exchange the SU helped in relaying the PU signal [117]. For a similar cooperative system with a single-antenna SU, simultaneous transmission of PU and SU data was achieved by using Alamouti coding at the transmitters, and joint decoding and interference cancellation techniques at the receivers [118]. An RF energy-harvesting multi-antenna SU can either transmit while suffering from PU interference at its receiver or it may relay the PU data using power-splitting technique while the PU remained silent and provided monetary benefits [119]. A Stackelberg game was formulated to choose between the non-cooperative and cooperative modes and the corresponding optimal parameters, i.e., time ratio, and price, time ratio, and power ratio, respectively. Stochastic geometry was used to model a cooperative system where SUs with dedicated power supply transferred energy and relayed the data of a PU that operated on the RF energy transferred by an AP to obtain a part of the PU spectrum in return [120]. Optimal bandwidth allocated to the SU and time allocation for PU energy transfer were determined to maximize the SU throughput while satisfying the PU performance constraints. In another work on energy-deficit PU system, the PU receiver used time-splitting technique to harvest energy from the SU transmitter which was given spectrum access for a fraction of time [121]. Multiple antennas were used at both the SU transmitter and PU receiver while using optimal precoding to maximize the SU transmission and enhance the energy harvesting at PU.

Chapter 3

Channel Selection in RF Energy Harvesting Cognitive Radios

In this chapter, we study channel-access policy for a multichannel RF energy harvesting cognitive radio (CR) system. At any time, a secondary user (SU) can only sense one of the primary user (PU) channels. Depending on the sensing outcome, it can either transmit on an idle PU channel provided that it has sufficient energy or it can harvest RF energy from the PU transmission. The channel-selection decision involves a tradeoff between the spectrum and harvesting opportunities offered by the different PU channels. We propose an optimal decentralized channel-access strategy to maximize the SU throughput by obtaining greater spectrum opportunities and the energy-harvesting opportunities required to sustain the SU transmission.

3.1 Introduction

In the fast few years, there has been a lot of work on the ambient RF energy-harvesting technique. Based on the field trials performed in two cities, it was found that

GSM 900, GSM 1800, and UMTS can provide significant energy to be used as potential RF energy sources. In [21], a Powercast harvester was used to obtain 1.93 mW of harvested power at a distance of 0.6 m and 1 μ W at a distance of 11 m from an RF source transmitting at 915 MHz. A novel wireless energy-harvesting prototype was developed to power embedded sensors without batteries using a digital-TV broadcast source at a distance of 6.3 km [93]. Hence, the ambient RF energy harvesting can be used as a practical solution for low-power wireless networks. For CR sensor networks powered by RF energy harvesting, an optimal policy was determined to achieve an optimal balance between the immediate throughput gain obtained by using the available energy and harvesting energy for future use [100]. For a CR system that utilized the PU transmissions for RF energy harvesting, optimal transmit power and SU density were obtained to maximize the SU throughput subject to outage probability constraints [19]. Markov decision process (MDP) formulation was employed to obtain an optimal channel-selection policy for an RF-powered CR network, which considered the data queue and energy levels of the SU [122]. In this chapter, we aim to find a decentralized channel-access strategy for a multichannel RF energy-harvesting CR system, using which the SUs can choose the optimal PU channel to sense in each time slot to maximize the expected CR throughput. Different from other works on energy-harvesting CR networks [16, 17, 96, 98], we consider a scenario where energy arrival depends on PU traffic profile. For RF energy-harvesting CRs, in [19, 100], the authors investigated a single-channel case whereas in [122], the contention among multiple SUs was not considered.

In this chapter, we study a multichannel energy-harvesting CR scenario under stochastic geometry paradigm. Poisson point process has been widely used to analyze the aggregate interference in CR networks [19, 123, 124]. We employ homogeneous Poisson point processes (HPPPs) [125] to model the spatially distributed PUs and SUs. The energy-harvesting SUs recharge their batteries using RF energy harvested from PU

transmissions. Depending on the PU state and SU energy level, it can either transmit, harvest, or remain idle in a time slot. There is a harvesting zone associated with each active PU, and any SU within it can harvest the PU transmitted power [19]. In order to protect it from SU interference, a guard zone is allocated around each PU transmitter. Hence, any SU which does not lie in the guard zone of any active PU on a channel can utilize the available spectrum band [19]. The PU channels with different average PU densities exhibit heterogeneity in terms of the spectrum and harvesting opportunities. In order to harvest more energy, the SU should sense a PU channel with a high PU density more frequently. Alternatively, on selecting a less occupied channel, it gets more chances to transmit but cannot harvest enough energy. Hence, channel selection involves a tradeoff between maximizing the SU transmission and obtaining sufficient energy-harvesting opportunities. We formulate a non-convex optimization problem that yields an optimal channel-selection probability vector to maximize the SU throughput while taking into account the contention due to the nearby SUs accessing the same PU channels. Two approaches have been used to solve the optimization problem. In the first scheme, primal decomposition [126] is applied to obtain a convex optimization subproblem and exhaustive search is performed to solve the master problem. In the second approach, we propose an iterative algorithm wherein a convex optimization problem with a closed-form solution is solved in each iteration.

3.2 System Model

The system consists of wireless PUs and SUs coexisting in a geographical area, and their locations are modeled using independent HPPPs [125]. We consider a circular network area of radius R . There are $N = \pi R^2 \lambda^s$ SUs in the network, where λ^s is the average SU density. The spectrum is partitioned into K channels. Each channel

Figure 3.1: A geographical model of RF energy-harvesting CR system with two PU channels.

is occupied by a different group of PUs. The PU density vector is denoted by $\lambda^{\mathbf{P}} = [\lambda_1^p, \lambda_2^p, \dots, \lambda_K^p]^T$, where λ_k^p is the PU density on the k -th channel and the superscript T represents the transpose operation. In a time slot, a PU transmitting on a channel is called an active PU. The active PU density on the k -th channel is given by $\lambda_k'^p = p_0 \lambda_k^p$, where p_0 is the probability of a PU being active. Using independent thinning [125], the active PUs on the k -th channel form an HPPP of rate $\pi R^2 \lambda_k'^p$. The PUs and SUs are assumed to have slotted transmissions. Each transmitter has a receiver associated with it, which is located close to it. The PU transmitters, PU receivers, and SU receivers have a continuous power supply whereas the SU transmitters rely on energy-harvesting process. Each SU transmitter is equipped with a rechargeable battery. Ambient RF energy-harvesting technique is employed to charge the battery using PU transmitted power. We will study the PU transmitter and the energy-harvesting SU transmitter, referring them as the PU and the SU, respectively. Each PU and SU operate on fixed

power levels of P_t^p and P_t^s , respectively. In this study, both the temporal and spatial spectrum opportunities are considered. As shown in Fig. 3.1, there is a guard zone of radius r_g and a small harvesting zone of radius r_h around each active PU. The guard zone and harvesting zone radii can be chosen according to the tolerable interference at the PU and the threshold requirements of the energy-harvesting circuit, respectively. Also, the guard zone is assumed to be large enough to prevent SU interference at the PU receiver [19]. An interference zone of radius R_I is associated with each SU. All other co-channel SUs with charged batteries that lie within the interference zone of the SU are denoted to be its interfering neighbors.

There is a channel-selection probability vector $\mathbf{p} = [p_1, p_2, \dots, p_K]^T$. In each time slot, every SU randomly chooses the k -th channel for spectrum sensing with probability p_k . Based on the spectrum-sensing result, the SU can either decide to harvest energy or transmit on the channel. An SU lying outside the guard zones of all active PUs on a channel, with a charged battery, gets a spectrum opportunity for transmission. If the SU lies inside the guard zone of any active PU, it cannot transmit on that channel as it can interfere with the high-priority PU transmission. However, an SU lying inside the harvesting zone of any active PU can harvest the PU transmitted energy to recharge its battery. In Fig. 3.1, say an SU lies in the harvesting zone of a PU on channel 1. Taking into consideration channel 2, the SU lies outside the guard zones of all active PUs transmitting on channel 2. If it has a charged battery, it can get an opportunity to transmit in that time slot by choosing channel 2. On the other hand, if it decides to sense channel 1, it cannot transmit because it is inside the guard zone of an active PU. However, it also lies in the harvesting zone of the active PU and can harvest the PU transmitted energy to recharge its battery.

In the following, we consider the opportunistic transmission and the opportunistic energy-harvesting probabilities on each channel of the multichannel system. The prob-

ability that a typical SU does not lie in the guard zone of any active PU is equal to the probability that there is no active PU within a region of radius r_g around the SU [19]. On the k -th channel, the number of active PUs within the radius r_g region around an SU, denoted by W_k , is Poisson distributed with mean $\pi r_g^2 \lambda_k'^p$ and its probability mass function is given by

$$\mathbb{P}(W_k = w) = e^{-\pi r_g^2 \lambda_k'^p} \frac{(\pi r_g^2 \lambda_k'^p)^w}{w!}. \quad (3.1)$$

Hence, the probability that an SU finds a spectrum opportunity on the k -th channel or the probability that a typical SU on the k -th channel does not lie in the guard zone of any active PU is given by [19]

$$\begin{aligned} p_k^g &= \mathbb{P}(W_k = 0) \\ &= e^{-\pi r_g^2 \lambda_k'^p}. \end{aligned} \quad (3.2)$$

Similarly, the probability that a typical SU on the k -th channel lies in the harvesting zone of any active PU, which is the same as the probability of finding an energy-harvesting opportunity, is given by

$$\begin{aligned} p_k^h &= \mathbb{P}(U_k \geq 1) \\ &= 1 - e^{-\pi r_h^2 \lambda_k'^p} \end{aligned} \quad (3.3)$$

where U_k , a Poisson random variable with mean $\pi r_h^2 \lambda_k'^p$, denotes the number of active PUs within the radius r_h region around an SU on the k -th channel. When a high p_k is assigned to a PU channel with a high or low PU density, the SU can obtain a greater number of energy-harvesting or spectrum-access opportunities, respectively.

3.3 Average Probability of SU Battery Being Fully Charged

We adopt the opportunistic energy-harvesting CR model in [19]. Each SU is assumed to possess a battery with capacity equal to the energy required for transmission in one time slot. The SU can utilize the spectrum opportunity on the k -th channel only if its battery is fully charged. Hence, the probability of transmission for an SU on the k -th channel is $p_k^t = p_a p_k^g$, where p_a is the average probability that an SU battery is fully charged in any time slot. The average power harvested in a time slot, from a PU transmitter at a distance $d \leq r_h$ from the SU, is $\eta P_t^p d^{-\alpha}$, where η denotes the energy-harvesting efficiency of the circuit and α is the path-loss exponent. In this work, we consider low-power SUs with $P_t^s \leq \eta P_t^p r_h^{-\alpha}$ so that the SU battery can be fully charged within one time slot. In [19], a 2-state Markov chain model was presented for a single-slot charging SU battery with states 0 and 1 corresponding to the power levels of 0 and P_t^s , respectively, and p_a for a single-channel system was derived. Unlike the single-channel case, in the multichannel system, an SU can decide to sense any one of the PU channels to harvest energy or to transmit in a time slot. The 2-state Markov chain state transition probability matrix $\mathbf{Q}$ for the SU battery in the multichannel RF energy-harvesting CR system is given by

$$\mathbf{Q} = \begin{bmatrix} 1 - p_h & p_h \\ p_g & 1 - p_g \end{bmatrix} \quad (3.4)$$

where the terms $p_h(\mathbf{p}) = \sum_{k=1}^K p_k p_k^h$ and $p_g(\mathbf{p}) = \sum_{k=1}^K p_k p_k^g$ denote the average probabilities that an SU obtains an energy-harvesting and spectrum-access opportunity in a time slot, respectively. They are obtained by averaging over all the channels as the SU can access any of the channels with probability p_k for harvesting energy or transmission. The steady state probability vector of an SU battery power level is given

Figure 3.2: The plots of average probability that an SU battery is charged versus probability of a PU being active. $\lambda^s = 0.3$, $\lambda^p = [0.005, 0.01, 0.02, 0.03, 0.06]^T$.

by $\mathbf{s} = [s_0 \ s_1]$, where s_0 and s_1 are the steady state probabilities of being in states 0 and 1, respectively. $\mathbf{s}$ is the left eigenvector of $\mathbf{Q}$ corresponding to the unit eigenvalue, which is found by solving $\mathbf{s}\mathbf{Q} = \mathbf{s}$. By obtaining s_1 , we get the expression of p_a for the multichannel case as

$$p_a = \frac{p_h}{(p_h + p_g)} \quad (3.5)$$

In Fig. 3.2, we validate the expression for p_a by plotting the simulation results. The plots are generated using the optimal channel-selection probability vector obtained using the proposed scheme in Section 3.4.

3.4 Optimal Decentralized Channel Access Policy

Each SU is assumed to know p_0 , average SU density, and average PU density on each channel [127]. We propose a decentralized channel-selection policy. It is assumed that all SUs independently follow the same channel-selection policy. An SU has a charged

battery in the beginning of a time slot with the stationary probability p_a , which does not affect its location in the present time slot. Hence, to model the contention among the SUs sharing a spectrum opportunity, we assume the SUs with charged batteries to form an HPPP with density $p_a \lambda^s$, which may not be true in general. In fact, the simulation plot in Fig. 3.5 of Section 3.5 supports our assumption. Using independent thinning, the SUs with charged batteries on the k -th channel form an HPPP with density $p_k p_a \lambda^s$. There are a total of $N p_k p_a$ SUs contending for transmission on the k -th channel. The conditional probability for an SU on the k -th channel to have m interfering SUs follows a binomial distribution with probability of interfering, $p_I = \pi R_I^2 / \pi R^2$ (THEOREM 2.9 in [125]). By taking into account the SU battery power level, and the spatio-temporal spectrum opportunities and access contention among multiple SUs on different PU channels, the expected throughput [127] of an SU can be expressed as

$$\begin{aligned}
 R_s(\mathbf{p}) &= \sum_{k=1}^K p_k \sum_{m=0}^{N p_k p_a - 1} \frac{p_a p_k^g}{m+1} \binom{N p_k p_a - 1}{m} p_I^m \bar{p}_I^{N p_k p_a - 1 - m} \\
 &= \sum_{k=1}^K p_k^g \frac{(1 - \bar{p}_I^{N p_k p_a})}{N p_I}
 \end{aligned} \tag{3.6}$$

where $\bar{x} = (1 - x)$. Each SU can only access one channel at a time. In the case of multiple channels, the SU selects a channel to sense which affects both energy harvesting and SU transmission. A channel with low active PU density provides more spectrum opportunities to the SU, whereas a higher PU density channel promises a greater number of energy-harvesting opportunities in the long term. The optimal channel-access strategy should allow the SUs to achieve greater spatio-temporal spectrum opportunities, equipping it with sufficient energy to utilize those spectrum opportunities. We formulate the expected throughput maximization (ETM) problem to obtain an optimal channel-selection probability vector which maximizes the expected throughput of an SU

as follows:

$$\begin{aligned} \min_{\mathbf{p}} \quad & -R_s(\mathbf{p}) \\ \text{s.t.} \quad & \sum_{k=1}^K p_k = 1 \text{ and } \mathbf{p} \succeq 0. \end{aligned} \quad (3.7)$$

The above problem has a non-convex objective due to the dependency of p_a on $\mathbf{p}$ as shown in Section 3.3. Hence, it is reformulated as

$$\begin{aligned} \min_{\mathbf{p}, p_a} \quad & -R_s(\mathbf{p}, p_a) \\ \text{s.t.} \quad & \sum_{k=1}^K p_k \left(p_k^h - p_a (p_k^h + p_k^g) \right) = 0 \\ & \sum_{k=1}^K p_k = 1 \text{ and } \mathbf{p} \succeq 0. \end{aligned} \quad (3.8)$$

Furthermore, by using the primal decomposition method [126], we obtain a sub-problem for a fixed p_a , which is given by

$$\begin{aligned} P2 : \min_{\mathbf{p}} \quad & -R_s(\mathbf{p}, p_a) \\ \text{s.t.} \quad & \sum_{k=1}^K p_k \left(p_k^h - p_a (p_k^h + p_k^g) \right) = 0 \\ & \sum_{k=1}^K p_k = 1 \text{ and } \mathbf{p} \succeq 0. \end{aligned} \quad (3.9)$$

The second derivative of the objective function is given by

$$\frac{-\partial^2 R_s(\mathbf{p}, p_a)}{\partial p_k^2} = p_k^g \frac{\bar{p}_I^{N p_k p_a}}{N p_I} \left(\ln(\bar{p}_I^{N p_a}) \right)^2 > 0. \quad (3.10)$$

Hence, with the convex objective function and affine constraints, the obtained subproblem is a convex optimization problem [128], which can be solved using a CVX solver. The master problem, which obtains the optimal p_a to maximize the throughput term

obtained after maximizing over $\mathbf{p}$, is given as follows:

$$\begin{aligned} P1 : \min_{p_a} & -R_s(\mathbf{p}^*, p_a) \\ \text{s.t. } & p_a^{\min} \leq p_a \leq p_a^{\max} \end{aligned} \quad (3.11)$$

where $p_a^{\min} = p_{k \min}^h / (p_{k \min}^h + p_{k \max}^g)$ and $p_a^{\max} = p_{k \max}^h / (p_{k \max}^h + p_{k \min}^g)$ are found to ensure the feasibility of the sub-problem, and $p_{k \min / \max}^h = \min / \max(p_1^h, p_2^h, \dots, p_K^h)$ and $p_{k \min / \max}^g = \min / \max(p_1^g, p_2^g, \dots, p_K^g)$. In order to achieve the optimal $\mathbf{p}$, an exhaustive search is performed in p_a over the interval $[p_a^{\min}, p_a^{\max}]$, and CVX is used to solve the sub-problem $P2$ for each p_a . For the ETM scheme, an analytical expression for the optimal $\mathbf{p}$ of the convex sub-problem $P2$ cannot be obtained. Hence, we propose the combined metric maximization (CMM) scheme in which an iterative algorithm is used to obtain the optimal $\mathbf{p}$ to maximize the SU throughput. We attempt to obtain a closed-form solution for the optimization problem solved in each iteration.

3.4.1 Combined Metric Maximization Scheme

As mentioned in the previous section, the SU throughput $R_s(\mathbf{p})$ is a non-convex function due to the dependency of p_a on $\mathbf{p}$. In the following, we propose an alternative solution to our non-convex throughput optimization problem. We attempt to formulate a convex optimization problem by fixing p_a . An iterative algorithm is employed to handle the interdependence between p_a and $\mathbf{p}$. Since the optimization problem in each iteration is solved for a fixed p_a , we introduce an additional term in the objective function in order to optimize p_a . A combined metric is defined to consider both the transmission and energy-harvesting probabilities of the SU, given by

$$\Lambda(\mathbf{p}, p_a) = \bar{\gamma} R_s(\mathbf{p}, p_a) + \gamma (1 - p_a) \sum_{k=1}^K p_k p_k^h \quad (3.12)$$

where $\gamma \in [0, 1)$ is a weighting factor. The first term corresponds to the average SU throughput and the second term is the average probability of finding an energy-harvesting opportunity when the SU battery runs out of charge. The second term is introduced to emphasize the energy-harvesting opportunities, which in turn enhances p_a through our iterative approach that is described later in Algorithm 1. A high p_a further improves the SU throughput as it reduces the chance of missing a spectrum opportunity due to an energy shortage. However, by increasing the harvesting opportunities, we compromise on the spectrum holes available for the SU. Moreover, a high p_a leads to a greater number of SUs contending for channel access on each channel. A suitable value of γ is chosen to attain an optimal tradeoff between the spectrum-access and energy-harvesting opportunities to achieve the maximum expected SU throughput. The CMM problem that finds the optimal $\mathbf{p}$, for a given value of γ and fixed p_a , is as follows:

$$\begin{aligned} \min_{\mathbf{p}} \quad & -\Lambda(\mathbf{p}, p_a) \\ \text{s.t.} \quad & \sum_{k=1}^K p_k = 1 \text{ and } \mathbf{p} \succeq 0. \end{aligned} \quad (3.13)$$

The second derivative of the objective function is given by

$$\frac{-\partial^2 \Lambda(\mathbf{p}, p_a)}{\partial p_k^2} = \bar{\gamma} p_k^g \frac{\bar{p}_I^{N p_k p_a}}{N p_I} (\ln(\bar{p}_I^{N p_a}))^2 > 0. \quad (3.14)$$

We observe that with convex objective function and affine constraints, the problem in (3.13) is a convex optimization problem. The Lagrangian can be formulated as

$$L(\mathbf{p}, \lambda, \mathbf{v}) = -\Lambda(\mathbf{p}, p_a) + \lambda \left(\sum_{k=1}^K p_k - 1 \right) - \sum_{k=1}^K v_k p_k \quad (3.15)$$

where the dual variables λ and $\mathbf{v}$ are Lagrange multipliers. The primal and dual optimal points can be obtained by solving the Karush-Kuhn-Tucker (KKT) conditions [128],

given as

$$\mathbf{p} \succeq 0, \sum_{k=1}^K p_k = 1, \mathbf{v} \succeq 0, \quad (3.16)$$

$$-b_k \bar{p}_I^{N p_k p_a} + a_k + \lambda - v_k = 0, \quad \text{and} \quad v_k p_k = 0 \forall k.$$

where $b_k = -\bar{\gamma} p_a p_k^g \frac{\ln \bar{p}_I}{p_I}$ and $a_k = -\gamma (1 - p_a) p_k^h$. After eliminating $\mathbf{v}$, we get

$$\mathbf{p} \succeq 0, \sum_{k=1}^K p_k = 1, \quad (3.17)$$

$$p_k (\lambda - b_k \bar{p}_I^{N p_k p_a} + a_k) = 0 \forall k, \quad (3.18)$$

$$\lambda - b_k \bar{p}_I^{N p_k p_a} + a_k \geq 0 \forall k. \quad (3.19)$$

For $\lambda < b_k - a_k$, (3.19) holds true only if $p_k > 0$. Using (3.18), it implies that $\lambda - b_k \bar{p}_I^{N p_k p_a} + a_k = 0$, which yields $p_k = \frac{\ln(\lambda + a_k) - \ln(b_k)}{N p_a \ln(\bar{p}_I)}$. For $\lambda \geq b_k - a_k$, we get $p_k = 0$, as $p_k > 0$ violates (3.18). The optimal channel-selection probability satisfying the KKT conditions is given by

$$p_k = \max \left(\frac{\ln(\lambda + a_k) - \ln(b_k)}{N p_a \ln(\bar{p}_I)}, 0 \right) \quad (3.20)$$

where the constant λ can be derived by solving $\sum_{k=1}^K p_k = 1$. It is shown in Appendix A that a unique solution exists. Hence, p_k depends on p_a , which in turn depends on $\mathbf{p}$. We propose Algorithm 1, an iterative solving approach used in [127], to obtain the optimal $\mathbf{p}$. The convergence in p_a is equivalent to convergence in $\mathbf{p}$. The partial derivative of p_a is given by

$$\frac{\partial p_a(\mathbf{p})}{\partial p_k} = \frac{p_k^h (1 - p_a) - p_k^g p_a}{\sum_{j=1}^K p_j (p_j^h + p_j^g)}. \quad (3.21)$$

Algorithm 1 Iterative Algorithm for CMM scheme

1. Initialize $\mathbf{p} = [\frac{1}{K}, \dots, \frac{1}{K}]^T$, $\mathbf{p}_{prev} = \mathbf{p}$
 2. Update p_a using $\mathbf{p}_{prev}$
 3. Find $\mathbf{p}$ using (3.20)
 4. $\mathbf{p}_{prev} = (1 - \beta) \mathbf{p}_{prev} + \beta \mathbf{p}$
 5. Repeat steps 2 – 4 until $\mathbf{p} - \mathbf{p}_{prev} \leq \varepsilon$
-

It is observed that the change in p_a depends on the value of p_a in the previous iteration. If p_a in the present iteration is large, $\mathbf{p}$ obtained in the next iteration favors the channels with greater spectrum opportunities, which will decrease p_a . On the other hand, when p_a is small, the channels offering more harvesting opportunities are chosen with a higher probability to improve p_a . Hence, with each iteration, it thrives towards an appropriate balance, given by γ , between the spectrum-access and energy-harvesting opportunities for the SU. The iterative algorithm may either achieve a monotonic convergence or there may be an oscillatory behavior. We use under-relaxation [129] to slow down the variable changes and aid convergence, using a suitable $\beta \in (0, 1]$. Using Algorithm 1, we can achieve the optimal $\mathbf{p}$ for a given value of γ . In order to determine γ_{opt} , we do an exhaustive search in $\gamma \in [0, 1)$ and the value corresponding to the maximum R_s is the optimal γ .

3.5 Numerical Results and Discussions

The licensed spectrum is partitioned into $K = 5$ channels. The SUs and PUs follow HPPP distribution in a network area of radius $R = 50$ m. The PU and SU power levels are taken to be $P_t^p = 100$ units and $P_t^s = 10$ units, respectively. The efficiency of the energy-harvesting circuit is $\eta = 0.1$ and the path-loss exponent is taken to be $\alpha = 4$. The guard zone, harvesting zone, and SU interference zone radii are $r_g =$

Figure 3.3: The plots of expected SU throughput versus probability of a PU being active. $\lambda^s = 0.3$, $\lambda_k^p \in [0.001, 0.2]$.

3 m, $r_h = 1$ m, and $R_I = 2$ m, respectively. The unit for λ^s and λ_k^p is m^{-2} . The performance achieved by adopting the proposed CMM scheme with γ_{opt} is compared to that of two other schemes, namely, uniform channel selection (UCS) and spectrum opportunity maximization (SOM). In the UCS scheme, the SU assigns equal probabilities to all the channels. In SOM, with $\gamma = 0$, the channel-selection probability vector is obtained to maximize the expected SU throughput by considering only the spectrum opportunities.

The expected throughput plots and the corresponding p_a plots in Figs. 3.3 and 3.4, respectively are obtained by averaging over 1000 simulations, and λ_k^p is randomly selected from the interval $[0.001, 0.2]$. In Fig. 3.3, we observe that the proposed CMM scheme, which optimizes both the transmission and energy-harvesting opportunities, outperforms others over a wide range of PU densities on each channel. In Fig. 3.4, for a high active PU density, the p_a obtained for the CMM scheme is lower as compared to that for the UCS scheme. Thus, in order to achieve maximum throughput, our scheme obtains

Figure 3.4: The plots of average probability that an SU battery is charged versus probability of a PU being active. $\lambda^s = 0.3$, $\lambda_k^p \in [0.001, 0.2]$.

Figure 3.5: The plots of expected SU throughput versus probability of a PU being active. $\lambda^s = 0.3$, $\lambda^p = [0.005, 0.01, 0.02, 0.03, 0.06]^T$.

maximal transmission opportunities and adequate harvesting opportunities to utilize them. In a conventional CR paradigm, the SU throughput should decrease as the PU density is increased. However, in the considered scenario, where CR is powered by the RF energy harvested from PU transmission, it is observed that the throughput first increases but later decreases. This is because as the active PU density on all the channels is increased, initially, the increase in p_a improves the transmission probability, but later the decrease in spectrum opportunities dominates and throughput starts to fall. A similar observation was made for a single-channel case in [19].

An instance with multiple low and high PU density channels is considered to depict how the proposed scheme can be used to exploit the diversity in the PU channels to achieve higher gains. In Fig. 3.5, we show that by adopting the proposed CMM scheme, we can achieve a higher expected SU throughput with significant performance gain because the SU optimally chooses the low and high PU density channels to obtain a greater number of transmission and harvesting opportunities, respectively, in the long term. Even for a high p_0 , the low PU density channels can provide good spectrum opportunities while the high PU density channels offer greater harvesting opportunities. Also, in Fig. 3.5, the expected throughput plot obtained by performing simulations using the optimal channel-selection probability vector supports that the SUs with charged batteries can be assumed to form an HPPP to account for the interfering SU neighbors. The results for the proposed ETM scheme have been provided to show that the CMM scheme is a good approximation of the optimal scheme. In Fig. 3.6, we observe that for CMM, p_a is considerably higher than the others. This is because, by maximizing the combined metric, we are also enhancing p_a by choosing the channels with higher energy-harvesting opportunities more often, which in turn allows the SUs to utilize more spectrum opportunities. The performance of the UCS scheme is still better than SOM as all the channels are denoted equal probabilities. The SOM scheme is observed to perform

Figure 3.6: The plots of average probability that an SU battery is charged versus probability of a PU being active. $\lambda^s = 0.3$, $\lambda^p = [0.005, 0.01, 0.02, 0.03, 0.06]^T$.

the worst because in it the throughput is maximized by concentrating only on the low active PU density channels which provide greater spectrum opportunities. It is not possible to find many harvesting opportunities, resulting in a lower p_a . In our proposed scenario, especially with the limitations of RF energy-harvesting circuit, maximizing the energy-harvesting opportunities is very important. Since these are not taken into account in the SOM scheme, the obtained p_a is low. The throughput performance also suffers, as shown in Fig. 3.5, because the SU cannot utilize the more spectrum opportunities that it obtains.

Plots in Figs. 3.7, 3.8, 3.9, and 3.10 are obtained by averaging over 1000 simulations, choosing λ_k^p randomly over an interval $[0.001, 0.04]$. In Fig. 3.7, it is observed that the SU throughput decreases as the SU density is increased due to a growing number of the interfering SU neighbors contending for the same channel. We observe a sharper fall in the plot corresponding to the proposed CMM scheme than the others. The reason is that using the CMM scheme, the SU achieves a higher p_a , as shown in Fig. 3.8. Hence, as

Figure 3.7: The plots of expected SU throughput versus SU density. $p_0 = 0.4$, $\lambda_k^p \in [0.001, 0.04]$.

Figure 3.8: The plots of average probability that an SU battery is charged versus SU density. $p_0 = 0.4$, $\lambda_k^p \in [0.001, 0.04]$.

Figure 3.9: The plots of expected SU throughput versus guard zone. $p_0 = 0.4$, $\lambda^s = 0.3$, $\lambda_k^p \in [0.001, 0.04]$.

the SU density is increased, the rise in the number of interfering neighbors is greater as compared to the other schemes. When the SUs are using the SOM scheme, the increasing interference due to an increased SU density causes the SUs to disperse to other higher PU density channels. Due to the increase in p_a as observed in Fig. 3.8, initially, the expected throughput for SOM increases, but later the increase in SU contention results in the falling SU throughput. For a larger SU interference zone, $R_I = 3$ m, the increasing SU density has a greater effect and the throughput plots for all three schemes fall faster than those obtained for a smaller $R_I = 2$ m. For a very high SU density, the throughput performance for both the CMM and SOM scheme is close to the UCS scheme due to very high contention.

In Figs. 3.9 and 3.10, we compare the performance with an increasing guard zone. In Fig. 3.9, we depict that a higher SU throughput is achieved using the CMM scheme than by the UCS and SOM schemes. We observe that in general, for all three schemes, the throughput decreases and p_a increases as r_g is increased. This is because, as the guard

Figure 3.10: The plots of average probability that an SU battery is charged versus guard zone. $p_0 = 0.4$, $\lambda^s = 0.3$, $\lambda_k^p \in [0.001, 0.04]$.

zone is increased, an SU gets lesser opportunities to transmit therefore its throughput falls. The SU gets to transmit less often therefore there is a higher probability that its battery is charged. Hence, p_a increases with increasing r_g , as observed in Fig. 3.10.

In Tables 3.1 and 3.2, we depict the optimal channel-selection probability vector and the expected throughput of an SU for varying SU density and active PU density values, for $r_g = 3$ m and $r_g = 5$ m, respectively. In Table 3.1, it is observed that for a low active PU density, $p_0 = 0.4$, since all the channels have abundant spectrum opportunities, a higher p_k is allocated to higher PU density channels, which offer greater energy-harvesting opportunities. For a higher active PU density, $p_0 = 0.6, 0.9$, high probabilities are assigned to the lowest and highest PU density channels which provide greater opportunities to the SU to transmit and harvest energy, respectively. Hence, when the active PU density on all the channels is low, finding greater harvesting opportunities is emphasized to enhance the performance. On the other hand, when the active PU density is high, it is also important to find better spectrum opportunities. Moreover,

Table 3.1: Optimal channel-selection probability vector. $\lambda^{\mathbf{p}} = [0.005, 0.02, 0.03, 0.06, 0.08]^T$, $r_g = 3$.

p_0	λ^s	$\mathbf{p}^T = [p_1, p_2, \dots, p_K]$	R_s
0.4	0.1	[0, 0, 0, 0.15, 0.85]	0.07
0.4	0.5	[0.05, 0.05, 0.06, 0.24, 0.6]	0.059
0.4	1	[0.08, 0.08, 0.09, 0.24, 0.51]	0.052
0.6	0.1	[0.14, 0, 0, 0, 0.86]	0.083
0.6	1	[0.13, 0.11, 0.1, 0.18, 0.48]	0.064
0.9	0.1	[0.25, 0, 0, 0, 0.75]	0.098
0.9	0.5	[0.19, 0.11, 0.06, 0.08, 0.56]	0.083

 Table 3.2: Optimal channel-selection probability vector. $\lambda^{\mathbf{p}} = [0.005, 0.02, 0.03, 0.06, 0.08]^T$, $r_g = 5$.

p_0	λ^s	$\mathbf{p}^T = [p_1, p_2, \dots, p_K]$	R_s
0.4	0.1	[0.3, 0, 0, 0, 0.7]	0.056
0.4	0.5	[0.22, 0.04, 0, 0, 0.74]	0.047
0.4	1	[0.18, 0.09, 0.04, 0.01, 0.68]	0.043
0.6	0.1	[0.28, 0, 0, 0, 0.72]	0.068
0.6	1	[0.24, 0.1, 0.03, 0, 0.63]	0.048
0.9	0.1	[0.39, 0, 0, 0, 0.61]	0.081
0.9	0.5	[0.34, 0, 0, 0, 0.66]	0.061

owing to the limitations of RF energy-harvesting circuit, very high probabilities are allocated to the high PU density channels as compared to those assigned to the lower PU density channels. It is observed that the SU throughput decreases with an increase in the SU density, and the SUs get distributed to all the channels to cope with the increasing contention. In Table 3.2, we show the optimal channel-selection probability vector and the expected SU throughput for a larger guard zone with $r_g = 5$ m. Here, for a low active PU density, $p_0 = 0.4$, unlike the case for a smaller r_g in Table 3.1, the channel with the lowest PU density is allocated a high probability p_k . This is because, with the increased value of r_g , the spectrum opportunities on all the channels have reduced. Also, for high active PU density cases, p_k values assigned to the low density channel are higher as compared to those in Table 3.1. The corresponding throughput values are also reduced as compared to those in Table 3.1 due to the decreased spectrum opportunities.

3.6 Conclusion

An interesting scenario of RF energy-harvesting CR system has been considered where the SUs can either harvest RF energy from PU transmission or transmit on a vacant spectrum band. With varying PU densities, the PU channels are heterogeneous in terms of the spectrum-access and energy-harvesting opportunities. If an SU senses a channel with a high PU density more often, it can harvest more energy in the long term, whereas the lower PU density channels provide higher chances to transmit. We have proposed a decentralized channel-selection policy for the SUs to attain an optimum tradeoff between the spectrum and harvesting opportunities. Using the proposed ETM and CMM schemes, the optimal channel-selection probability vector is obtained which enables the SU to achieve the appropriate tradeoff to maximize its expected throughput amid access contention with other co-channel SUs. We have shown that the performance of the CMM scheme is significantly better than the SOM scheme, which concentrates only on the spectrum opportunities to maximize the expected throughput. It highlights the importance of optimizing both the spatio-temporal spectrum opportunities and the energy-harvesting opportunities, which facilitates the SU to utilize the more spectrum opportunities discovered.

Chapter 4

Optimal Sensing Policy for RF Energy Harvesting Cognitive Radio

In the previous chapter, we studied an RF energy harvesting multichannel cognitive radio (CR) system. An optimal channel-selection policy was derived to provide sufficient energy-harvesting and spectrum-access opportunities amid the secondary user (SU) contention on the same primary user (PU) channels. In this chapter, we further investigate the opportunistic RF energy-harvesting CR system in the context of an unslotted PU system. We consider an ambient RF energy-harvesting CR user that coexists with an unslotted PU system. The SU switches to energy-harvesting mode when the PU is observed to be busy and transmits using the stored energy during the discovered idle periods. We propose that in such a scenario, different sensing intervals should be used if the CR user decides to transmit or harvest energy. The harvesting and transmission durations can be used to optimize the tradeoff between maximizing the utilization of

spectrum opportunities and harvesting sufficient energy to transmit. We attempt to find the optimal sensing intervals to maximize the SU throughput while satisfying the energy-causality (EC) and PU collision (PC) constraints.

To further even out the disparity in the amount of energy harvested and that required for transmission, we introduce energy-trading concept in our system. Instead of transmitting during the PU idle slots, the SU can decide to purchase energy from the PU which is received by wireless power transfer. We obtain the optimal sensing intervals and the energy-harvesting probability to minimize the average energy cost to attain a given SU throughput while guaranteeing the PU protection.

4.1 Introduction

In a related work on RF energy harvesting CR system, a partially observable Markov decision process (POMDP) was used to find an optimal policy to decide between the harvest or access actions for each time slot in a slotted PU system [100]. In [130], the authors used the alternate renewal theory to derive expressions for spectrum opportunities in an unslotted PU system and found the optimal sensing duration and sensing channel sequence. In an unslotted multichannel PU system, a new optimal wait-or-switch concept was proposed for the SU on return of the PU to the incumbent channel, and an adaptive sensing policy was developed for keeping track of the out-of-band channels [23]. In another work, the authors found sensing-outcome-dependent inter-sensing times to maximize the SU throughput while keeping the interference to PU under the tolerable limits [22]. The game-theoretic approach was used to jointly analyze the sensing and spectrum-access performance for both the cases of slotted and non-slotted PU [24]. Different from these existing works, we consider an energy-harvesting CR system which opportunistically harvests energy from and accesses the spectrum of an unslotted PU.

It introduces newer tradeoffs while choosing the optimal time slots for the SU due to the uncertainty in energy availability and the asynchronous PU behavior. The SUs need to sense the spectrum periodically in order to discover the spectrum opportunities and to prevent interference to the PU transmission, which reduces its transmission time. In addition to this inherent sensing-throughput tradeoff [23,35], there is a need to manage the energy inflow and outflow in the considered energy-harvesting CR system. Frequent sensing helps the SU to discover more opportunities to transmit and harvest energy, and prevents interference with PU. However, the transmission and harvesting durations are compromised as more time is spent on sensing. The SU consumes energy for the sensing and transmission operations and it is replenished during the harvesting periods. In this scenario, the PU traffic pattern affects both the energy arrival and consumption. Thus, the sensing intervals can be optimized to attain an optimum balance between energy harvesting and spectrum access.

Apart from energy harvesting, there is recently much work being done on energy transfer and energy trading [106,131,132]. In [106], the authors considered users powered by the wireless energy received from a hybrid access point. Optimal time allocations were obtained for wireless power transfer and information transmission using a harvest-then-transmit protocol to maximize the sum-throughput of all the users. Coordinated multipoint (CoMP) systems powered by smart grids with different prices for trading energy were studied [131]. The energy-harvesting base stations with varied energy supply and demand cooperatively optimize their energy trading with the grid and energy consumption for communication to minimize the total energy cost. In this work, we introduce an additional energy-purchasing option for the SU to fulfill its energy demands by paying the PU for an energy transfer during its idle periods. Optimal energy-purchasing policy is found to attain the required SU rate while paying a minimum energy cost.

We consider an unslotted PU system, where the PU idle and busy periods are ex-

ponentially distributed and form an alternate on-off process. For an opportunistic RF energy-harvesting CR system, we optimize the SU sensing intervals while considering the PU traffic pattern. We propose a dual-sensing-interval policy where the SU adopts different sensing intervals for the cases when the PU is found idle and when the PU is found busy or when the SU does not have energy. The sensing interval after the PU is detected to be idle is also the transmission duration. It is desirable to have a greater transmission duration to maximize the SU throughput, but the available energy and the PU protection requirement limit the slot length. Also, the transmit duration should be chosen considering the PU traffic profile as the SU transmission is not successful whenever the PU returns to the channel during transmission. The sensing interval after the PU is detected to be busy is the harvesting duration. A greater harvesting duration can be used to garner more energy but the SU may miss the spectrum opportunities while it is harvesting energy. It should be chosen in accordance with the PU traffic behavior as the SU cannot harvest any energy when the PU goes idle during the harvesting period. Based on the pattern of PU busy and idle periods, the SU can have different sensing intervals, i.e., the transmission and harvesting slot durations, which can be chosen to optimize the energy consumption and harvesting to maximize the SU spectrum utilization. Also, due to the uncertainty in the energy availability, the SU may not always have enough energy to operate. The chosen durations decide the SU activation probability through the EC constraint.

The objective is to find the optimal sensing interval so as to maximize the discovery of spectrum opportunities while causing acceptable interference to PU and to be able to harvest sufficient energy to utilize them. It depends on the PU traffic pattern, the average energy harvested, and the energy needed for transmission and sensing. We derive a closed-form expression for the probability of having sufficient energy for an RF energy harvesting SU in an unslotted PU channel. The optimal transmission and harvesting

durations are found to maximize the SU spectrum utilization while protecting the PU using the energy harvested from PU transmissions. We also show that the maximum allowable value of the transmit duration can be bounded by analyzing the EC and PC constraints.

Furthermore, if the energy arrival is low due to shorter or infrequent PU busy periods or low harvesting efficiency, the SU cannot utilize the available spectrum opportunities due to a lack of energy to transmit. We propose that it is beneficial for the SU to compromise some of the spectrum opportunities and use those PU idle periods to harvest energy from PU. The PU can do a wireless power transfer to the SU whenever it is idle during that SU slot which incurs an additional cost to the SU. We find the optimal probability that an SU decides to purchase energy instead of transmitting in an idle duration and the optimal sensing intervals with an aim to minimize the average energy cost while meeting the quality of service constraints for the SU and PU transmissions.

4.2 System Model

We consider an on-off PU channel model [130]. The PU alternates between the busy and idle states with independent and identically distributed idle and busy durations which follow exponential distributions with means $1/\lambda_1$ and $1/\lambda_0$, respectively. The corresponding PU idle and busy states are denoted by 1 and 0. The SU is assumed to always have packets to transmit. It accesses the PU spectrum opportunistically when it is sensed to be idle. We assume perfect spectrum sensing. The SU is powered by the energy harvested from the PU transmission. It possesses an infinite-capacity battery to store the energy harvested during PU busy periods. The uncertainty in the energy available at the SU is captured by the SU active probability p_a , i.e., the probability that an SU has sufficient energy to transmit in a time slot when the PU channel is found

Figure 4.1: Time framework for energy-harvesting CR system.

idle. In the beginning of each time slot, if the SU has energy, it senses the PU spectrum for a duration of τ_s units or otherwise remains idle. Based on the sensing result, the SU can transmit when the PU is found to be idle or may switch to harvest mode if it is found busy. Also, when it runs out of energy, the SU enters the harvest mode. Note that here the PU's guard zone and harvesting zone have been assumed to be touching which is not true practically considering the current RF energy-harvesting capabilities [19, 122].

In Fig. 4.1, we depict two different sequences of PU on-off periods and the corresponding SU operations in the bars below the PU activity bars. As shown in the first instance, the SU time slot consists of the sensing time τ_s followed by a transmission slot of $T_a - \tau_s$ when an active SU detects an idle PU spectrum. However, in the unslotted PU model, the PU can return to the channel anytime during the SU transmission resulting in a collision between the two transmissions. In the case, when either the SU is not active or if the PU channel is found busy as shown in the second instance, a harvesting slot of duration $T_h - \tau_s$ is allocated. However, the SU cannot harvest energy in the

Figure 4.2: Markov chain model for SU states.

periods when the PU gets idle during the SU harvesting period. In order to transmit during the i -th time slot, the SU needs energy $E_i \geq P_s \tau_s + P_t^s (T_a - \tau_s)$ where P_s and P_t^s are the power levels needed for sensing and transmission, respectively. The sensing intervals affect the SU's probability of being active, and the probability of PU being found idle and busy by the SU which in turn determines the SU throughput. An increase in T_a , i.e., a greater time to transmit, increases the SU throughput but depending on the average PU idle period, a longer T_a may not be effective. Additionally, a smaller T_a is needed for a quick detection of the PU's return to diminish interference to the PU and to prevent missing the energy-harvesting opportunities. Similarly, a greater T_h provides more harvested energy. However, a smaller T_h is desirable to discover greater spectrum opportunities. When the SU does not have sufficient energy, it enters the harvesting mode and the PU state is not known.

As shown in Fig. 4.2, the CR system can be in one of the three possible states:

- SU is active and senses the PU to be idle.
- PU channel is busy and SU may or may not have energy.

- PU channel is idle and SU does not have energy so the channel state is unknown.

In different states, the SU chooses different sensing intervals which affect the state transition probability. When the PU is busy, regardless of whether the SU has energy to sense or not, it enters the harvest mode and the sensing interval is T_h , therefore we do not consider the SU energy state for that case. In this unslotted system, the PU can change its state during the SU sensing period. It is assumed that the final PU state observed before the end of the sensing period is taken to be the sensing decision. Additionally, for the simplification of expressions, it is assumed that when the SU does not have energy, it remains idle during the sensing period, and later switches to harvest mode for $T_h - \tau_s$ duration. We have a stationary probability vector $\mathbf{s} = [p_a p_1 \quad p_0 \quad (1 - p_a) p_1]$ for the SU states where p_1 and p_0 are the probabilities that the PU is found to be idle and busy by the SU, respectively. The SU state transition matrix is as follows:

$$\mathbf{Q} = \begin{bmatrix} p_a p_{11}(T_a) & \bar{p}_{11}(T_a) & \bar{p}_a p_{11}(T_a) \\ p_a p_{01}(T_h) & \bar{p}_{01}(T_h) & \bar{p}_a p_{01}(T_h) \\ p_a p_{11}(T_h) & \bar{p}_{11}(T_h) & \bar{p}_a p_{11}(T_h) \end{bmatrix} \quad (4.1)$$

where p_{11} and p_{01} are the PU state transition probabilities to switch from PU states 1 to 1 and 0 to 1, respectively, whose expressions can be found in [22, 130], and $\bar{x} = 1 - x$. We find the stationary probabilities, the left eigenvector of $\mathbf{Q}$ corresponding to the unit eigenvalue obtained by solving $\mathbf{s}\mathbf{Q} = \mathbf{s}$, and obtain the observed PU state probabilities given by

$$p_1(\mathbf{T}) = p_{01}(T_h) / D \quad (4.2)$$

$$p_0(\mathbf{T}) = (1 - p_a p_{11}(T_a) - (1 - p_a) p_{11}(T_h)) / D \quad (4.3)$$

where $D = (1 - p_a p_{11}(T_a) - (1 - p_a) p_{11}(T_h) + p_{01}(T_h))$ and $\mathbf{T} = [T_a \ T_h]$.

We consider an unslotted PU system, i.e., the PU can return to access the channel any time and can change states any number of times while the SU is transmitting after the channel was found to be idle during the sensing period or while it is harvesting energy. Using the renewal process theory [133], the average duration D_{11} for which the PU channel is idle during a transmission slot of the SU once it is sensed to be idle at the beginning of the slot is given by [22, 130]

$$D_{11}(T_a) = T_a - \tau_s - u \left(T_a - \tau_s - \frac{(1 - e^{-(\lambda_0 + \lambda_1)(T_a - \tau_s)})}{\lambda_0 + \lambda_1} \right) \quad (4.4)$$

where $u = \lambda_1 / (\lambda_0 + \lambda_1)$ is the PU channel utility. Using the average idle time available in a transmit slot, the maximum achievable normalized throughput for the SU is given by

$$R_s = p_a p_1(\mathbf{T}) \frac{D_{11}(T_a)}{T_N} \quad (4.5)$$

where $T_N = p_1(\mathbf{T}) (p_a T_a + (1 - p_a) T_h) + p_0(\mathbf{T}) T_h$. Based on the aforementioned expression, the probability of collision with the PU can be expressed as

$$P_c = p_a p_1(\mathbf{T}) \frac{(T_a - \tau_s - D_{11}(T_a))}{T_N}. \quad (4.6)$$

Similar to D_{11} , the expression for D_{00} , the average duration for which the PU channel is busy during the harvesting slot of the SU once it is sensed to be busy at the beginning of the slot, is given by

$$D_{00}(T_h) = T_h - \tau_s - \bar{u} \left(T_h - \tau_s - \frac{(1 - e^{-(\lambda_0 + \lambda_1)(T_h - \tau_s)})}{\lambda_0 + \lambda_1} \right) \quad (4.7)$$

and D_{10} , the average duration for which the PU channel is busy during a harvesting

time slot of the SU if the PU channel was idle at the beginning of the slot, is given as

$$D_{10}(T_h) = u \left(T_h - \tau_s - \frac{(1 - e^{-(\lambda_0 + \lambda_1)(T_h - \tau_s)})}{\lambda_0 + \lambda_1} \right). \quad (4.8)$$

Using the aforementioned expressions, the average energy harvested in a time slot, can be expressed as

$$e_h = \eta_h P_t^p (p_0(\mathbf{T}) D_{00}(T_h) + \bar{p}_a p_1(\mathbf{T}) D_{10}(T_h)) \quad (4.9)$$

where η_h and P_t^p are the energy-harvesting efficiency and the PU transmission power, respectively. The average energy consumed in a slot can be expressed as

$$e_c = p_a (P_s \tau_s + P_t^s (T_a - \tau_s) p_1(\mathbf{T})). \quad (4.10)$$

In the above equation, we have substituted the conditional probability of the SU being active when PU is found idle i.e., p_a , for the SU activation probability when PU is busy. It causes negligible effect on the value of p_a because when the PU is busy, the SU only consumes the energy to sense and we assume that $P_s \ll P_t^s$. Additionally, when the PU is busy, regardless of whether the SU has energy or not, it subsequently enters the harvesting mode. The energy consumed by the energy-harvesting circuit has been assumed to be negligible.

4.2.1 Probability of the SU Being Active

In the following, we derive the expression for $p_a(\mathbf{T}) \in [0, 1]$, the probability of the SU being active when the spectrum is found to be idle. The energy-harvesting CR is under the EC constraint which mandates that the average energy consumed in a time slot cannot be greater than the average energy harvested, i.e., $e_h \geq e_c$ [16]. The maximum probability of an SU being active is determined by solving the EC constraint for equality.

Figure 4.3: The plots of probability of SU being active when the channel is found idle versus its transmission duration. $1/\lambda_1 = 800$ and $1/\lambda_0 = 500$.

The dependency of the probability of observing the PU to be busy and idle on p_a results in a quadratic EC equation of the form $f = ap_a^2 + bp_a + c = 0$, where

$$a = P_s \tau_s (p_{11}(T_a) - p_{11}(T_h))$$

$$b = -(\eta_h P_t^p D_{00}(T_h) (p_{11}(T_a) - p_{11}(T_h)) + \eta_h P_t^p D_{10}(T_h) p_{01}(T_h) + P_s \tau_s (1 - p_{11}(T_h) + p_{01}(T_h)) + p_{01}(T_h) P_t^s (T_a - \tau_s))$$

$$c = \eta_h P_t^p D_{00}(T_h) (1 - p_{11}(T_h)) + \eta_h P_t^p D_{10}(T_h) p_{01}(T_h).$$

We have, $\frac{df}{dp_a} = 0$ at $p_a = p_a^1 = -b/2a$. There can be three cases:

- For $T_h = T_a$, we have $a = 0$ and $p_a = \min(-c/b, 1)$.
- For $T_h > T_a$ or $a > 0$, f is an upward parabola. For practical utility of this model, it is reasonable to assume that the average energy harvested in a time slot is greater than the energy needed for a sensing duration, i.e., $\eta_h P_t^p D_{00}(T_h) \gg P_s \tau_s$. Based on this assumption, we observe that $p_a^1 > 1$; hence, there can only be a maximum

one root $\in [0, 1]$. Here $-b > 0$, $a > 0$, and $c > 0$, thus we obtain

$$p_a = \begin{cases} \min\left(\frac{-b - \sqrt{b^2 - 4ac}}{2a}, 1\right) & b^2 - 4ac \geq 0, \\ 1 & \text{otherwise.} \end{cases} \quad (4.11)$$

- For $T_h < T_a$ or $a < 0$, f is an inverted parabola. It can be seen that $f(0) > 0$ so there can be only one real root $\in [0, 1]$. With $a < 0$ and $c > 0$, we get

$$p_a = \min\left(\frac{-b - \sqrt{b^2 - 4ac}}{2a}, 1\right). \quad (4.12)$$

Considering all the possible cases, the closed-form expression for the SU activation probability is given by

$$p_a = \begin{cases} \min\left(-\frac{c}{b}, 1\right) & T_a = T_h \\ \min\left(\frac{-b - \sqrt{b^2 - 4ac}}{2a}, 1\right) & T_a \neq T_h, \quad b^2 - 4ac \geq 0 \\ 1 & \text{otherwise.} \end{cases} \quad (4.13)$$

In Fig. 4.3, we observe that the plots for the derived p_a expression matches quite well with the corresponding simulation results. For a given value of T_h , p_a decreases as T_a is increased due to an increase in the energy consumption. Also, a higher p_a is achieved for a greater value of T_h as the SU can harvest more energy.

4.3 Optimal Sensing Policy

We aim to find the optimal sensing intervals to maximize the SU throughput by obtaining greater spectrum opportunities with adequate energy-harvesting opportunities while maintaining the PU collision probability below the maximum tolerable value $\bar{P}_c$.

For the case of a very large battery, T_h can be made longer to harvest and store more energy but it is not practical. The SU service is disrupted for this period T_h due to energy harvesting or energy shortage. Based on the application scenario, there should be a maximum delay or inactive period that can be tolerated. We introduce constraints on the minimum acceptable probability of SU being active, $p_{a \min}$, and the maximum harvesting duration allowed, $D_{\max}$. The optimization problem of SU throughput maximization (STM) is as follows:

$$\begin{aligned}
 & \max_{\mathbf{T}} R_s(\mathbf{T}) & (4.14) \\
 & \text{s.t. } P_c(\mathbf{T}) \leq \bar{P}_c \\
 & T_h \leq D_{\max} \\
 & p_{a \min} \leq p_a(\mathbf{T}) \leq 1 \\
 & T_a, T_h > \tau_s.
 \end{aligned}$$

The objective and constraint functions are non-convex in $\mathbf{T}$. By considering T_a and T_h to be integers, an exhaustive search is performed to find their optimal values [22]. For that we need an upper bound on the maximum possible T_a value for a given T_h .

Proposition 1 *For a fixed value of T_h , the probability of the SU being active p_a is decreasing in T_a for $T_a > T'_a$, for some $T'_a > T_h$.*

Proof: For $T_a > T_h$, we have $a < 0$ and $p_a = \frac{-b - \sqrt{b^2 - 4ac}}{2a}$ for $\frac{-b - \sqrt{b^2 - 4ac}}{2a} \leq 1$, which gives the condition

$$b + \sqrt{b^2 - 4ac} + 2a < 0 \quad (4.15)$$

The first derivative of p_a is given by

$$\begin{aligned} \frac{dp_a}{dT_a} = & \frac{2P_s\tau_s}{4a^2\sqrt{b^2-4ac}} \left(\left(-b - \sqrt{b^2-4ac} \right) \left(\eta_h P_t^p D_{00}(T_h) (p_{11}(T_h) - p_{11}(T_a)) \frac{dp_{11}(T_a)}{dT_a} \right. \right. \\ & \left. \left. + p_{01}(T_h) P_t^s (p_{11}(T_h) - p_{11}(T_a)) - b \frac{dp_{11}(T_a)}{dT_a} \right) - 2ac \frac{dp_{11}(T_a)}{dT_a} \right). \end{aligned} \quad (4.16)$$

It can be observed that $\frac{dp_{11}(T_a)}{dT_a} < 0$, which implies that $\frac{dp_a}{dT_a} < 0$ for

$$\begin{aligned} y = & \left(-b - \sqrt{b^2-4ac} \right) (\eta_h P_t^p D_{00}(T_h) (p_{11}(T_h) - p_{11}(T_a)) \\ & + \frac{p_{01}(T_h) P_t^s}{\frac{dp_{11}(T_a)}{dT_a}} (p_{11}(T_h) - p_{11}(T_a)) - b) - 2ac > 0. \end{aligned} \quad (4.17)$$

The condition (4.17) can be achieved if $x = (p_{11}(T_h) - p_{11}(T_a))$

$\times \left(\eta_h P_t^p D_{00}(T_h) + \frac{p_{01}(T_h) P_t^s}{\frac{dp_{11}(T_a)}{dT_a}} \right) - b < 0$, otherwise if $0 < x < c$, we get

$$y \geq \left(-b - \sqrt{b^2-4ac} \right) c - 2ac > 0 \quad (4.18)$$

where the second inequality is obtained using (4.15). We have c , a constant w.r.t T_a , and $\frac{dx}{dT_a} = -(p_{11}(T_h) - p_{11}(T_a)) P_t^s p_{01}(T_h) < 0$. Hence, for some $T'_a > T_h$, we have $c > x$ and p_a will be decreasing in $T_a \geq T'_a$. Thus, T_a cannot be greater than a finite value after which $p_a < p_{a \min}$. ■

Proposition 2 For a fixed value of T_h , $P_c(p_{a \min}, T_a) = \bar{P}_c$ gives the maximum value of T_a ($> 1/(\lambda_0 + \lambda_1)$) allowed by the PC constraint.

Proof: For fixed values of T_h and T_a , the probability of collision with the PU is increasing in p_a .

$$\begin{aligned} \frac{\partial P_c}{\partial p_a} &= \frac{T_h p_{10}(T_h)}{D^2 T_N^2} (T_a - t_s - D_{00}(T_a)) \left(1 - e^{-(\lambda_0 + \lambda_1)T_h}\right) \\ &\geq 0 \end{aligned} \quad (4.19)$$

For a fixed T_h and p_a , we have $\frac{\partial P_c}{\partial T_a} > \frac{u p_a p_{10}(T_h)}{(D T_N)^2} (k_1 x(T_a) - k_2 y(T_a))$, where

$$k_1 = (1 - p_a \bar{u} - \bar{p}_a (p_{00}(T_h) - p_{10}(T_h))) T_h + \frac{p_{10}(T_h) p_a}{\lambda_0 + \lambda_1} \quad (4.20)$$

$$k_2 = p_{10}(T_h) p_a + p_a u T_h (\lambda_0 + \lambda_1) \quad (4.21)$$

$$x(T_a) = \left(1 - e^{-(\lambda_0 + \lambda_1)(T_a - t_s)}\right) \quad (4.22)$$

$$y(T_a) = T_a e^{-(\lambda_0 + \lambda_1)(T_a - t_s)} \quad (4.23)$$

Here, $k_1 > 0$, $k_2 > 0$, $\frac{dx}{dT_a} > 0$, and $\frac{dy}{dT_a} < 0$ for $T_a > 1/(\lambda_0 + \lambda_1)$, which implies that P_c is decreasing-increasing or increasing in $T_a (> 1/(\lambda_0 + \lambda_1))$.

In the following, we show that for a fixed T_h , $P_c(p_a \min, T_a) = \bar{P}_c$ can give the maximum T_a allowed. Using the aforementioned derivative information, it can be seen that if $P_c(p_a \min, T_a) = \bar{P}_c$ this implies that $P_c(p_a, T_a) \geq \bar{P}_c$ and $P_c(p_a \min, T_a^{\max}) = \bar{P}_c$ implies that in the increasing region for $T_a > 1/(\lambda_0 + \lambda_1)$, for any $T_a < T_a^{\max}$, $P_c(p_a \min, T_a) \leq \bar{P}_c$. Hence, $P_c(p_a \min, T_a \max) = \bar{P}_c$ can be solved to find $T_a^{\max}$. ■

For a fixed T_h , T_a is limited by the EC constraint as the energy consumption increases with an increase in T_a . Using Proposition 1, we can find an upper bound $T_{1 \max} > T_h$ on permissible values of T_a by solving $p_a = p_a \min$. The solution can be found using Lambert function [134, p. 337]. Similarly, T_a is limited by the PC constraint because a greater T_a reduces the sensing frequency which increases potential collisions with the PU. According to Proposition 2, we use PC constraint to find the maximum value of

T_a permitted which is denoted by $T_{2\max}$. As shown in the proofs for Propositions 1 and 2, $p_a(T_a)$ and $P_c(p_{a\min}, T_a)$ are increasing-decreasing in $T_a(> T_h)$ and decreasing-increasing in $T_a(> 1/(\lambda_0 + \lambda_1))$, respectively. We may get at most two values for each of the parameters $T_{1\max}$ and $T_{2\max}$. The greater ones give us the corresponding upper bounds on T_a . For each T_h , we perform an exhaustive search in T_a upto $T_{a\max} = \min(T_{1\max}, T_{2\max})$. To find the maximum SU throughput, a line search is performed in $\tau_s < T_h \leq D_{\max}$ and for each T_h , we search $\tau_s < T_a \leq T_{a\max}(T_h)$ while satisfying the following constraints:

$$P_c(\mathbf{T}) \leq \bar{P}_c \quad (4.24)$$

$$p_{a\min} \leq p_a(\mathbf{T}) \leq 1.$$

4.3.1 Suboptimal Uniform Slot Scheme

In this suboptimal scheme, the SU uses the same sensing interval T in all the three states. The energy uncertainty is expressed in p_a but the heterogeneity in the PU busy and idle periods is not optimally utilized. Therefore, the performance is lower than the proposed optimal scheme. With $T_h = T_a = T$, an exhaustive search is performed in $\tau_s < T \leq D_{\max}$ to find the optimal T that maximizes the SU throughput while satisfying the constraints in (4.24).

4.4 Energy Trading during PU Idle Periods

We propose an additional feature of energy trading where the PU can wirelessly transfer power during its idle duration and make some profit. The SU can decide to purchase power from the PU when it is sensed to be idle to harvest more energy in addition to the RF energy harvested during the busy periods. The energy-trading

decision can be optimally chosen for the SU to further enhance the energy availability while compromising on some of the spectrum opportunities and paying an extra cost in order to achieve a given transmission rate. Depending on the disparity in the spectrum-access and energy-harvesting opportunities for the SU as per the PU traffic pattern, the SU may decide not to access but to purchase energy from the PU for an additional cost, say c_e per unit time. The PU can perform wireless energy transfer to the SU only during those time intervals when it is actually idle during the remaining duration of the SU slot. In each time slot, when the SU has energy to sense and the spectrum is found to be idle, the SU can decide to purchase energy with a probability p_p or transmit with probability $1 - p_p$. The average energy cost $C(\mathbf{T}, p_p)$ incurred by the SU in a time slot can be expressed as

$$C = p_1 p'_a p_p D_{11}(T_a) c_e \quad (4.25)$$

where p'_a is the probability of the SU being active when the PU channel is found to be idle. The modified expressions for SU throughput R'_s , PU collision probability P'_c , average energy harvested e'_h , and average energy consumed e'_c by an SU are given by

$$R'_s = (1 - p_p) p'_a p_1 \frac{D_{11}(T_a)}{T_N}, \quad (4.26)$$

$$P'_c = (1 - p_p) p'_a p_1 \frac{(T_a - \tau_s - D_{11}(T_a))}{T_N}, \quad (4.27)$$

$$e'_h = \eta_h P_t^p (p_0 D_{00}(T_h) + \bar{p}'_a p_1 D_{10}(T_h)) + \eta_t P_t^p p'_a p_p p_1 D_{11}(T_a), \quad (4.28)$$

$$e'_c = p'_a (P_s \tau_s + P_t^s (T_a - \tau_s) p_1 (1 - p_p)), \quad (4.29)$$

respectively, where η_t is the energy-transfer efficiency.

Proposition 3 The expression for $p'_a(\mathbf{T}, p_p)$ is given by

$$p'_a = \begin{cases} \min\left(-\frac{c}{b'}, 1\right) & T_a = T_h, \quad b' < 0 \\ \min\left(\frac{-b' - \sqrt{b'^2 - 4ac}}{2a}, 1\right) & T_a > T_h \quad \text{or} \quad (T_a < T_h, \\ & b'^2 - 4ac \geq 0 \quad \text{and} \quad b' < 0) \\ 1 & \text{otherwise} \end{cases} \quad (4.30)$$

where

$$b' = -(\eta_h P_t^p D_{00}(T_h)(p_{11}(T_a) - p_{11}(T_h)) + \eta_h P_t^p D_{10}(T_h)p_{01}(T_h) + P_s \tau_s(1 - p_{11}(T_h) \\ + p_{01}(T_h)) + p_{01}(T_h)(1 - p_p)P_t^s(T_a - \tau_s) - p_p \eta_t P_t^p D_{11}(T_a)p_{01}(T_h)).$$

Proof: The EC constraint is expressed as $f' = ap_a'^2 + b'p_a' + c = 0$. We get $\frac{df'}{dp_a'} = 0$ at $p_a' = p_a^{11} = -b'/2a$. The expression for p_a' , for the cases of $T_a = T_h$ and $T_a > T_h$, can be obtained by following a similar analysis as in Section 4.2.1. For $T_h > T_a$ or $a > 0$, there are following two possibilities,

1. If $b' \geq 0$ then both the roots of f' are negative and $p_a' = 1$.
2. For $b' < 0$, if $b'^2 - 4ac \geq 0$, it implies $b'^2 - 4a^2 \geq 0$ as based on our assumption of $\eta_h P_t^p D_{00}(T_h) \gg P_s \tau_s$, we have $a < c$. Thus, we obtain that $-b' > 2a$ or $p_a^{11} > 1$.

Hence, for the case of $T_h > T_a$, we get

$$p'_a = \begin{cases} \min\left(\frac{-b' - \sqrt{b'^2 - 4ac}}{2a}, 1\right) & b'^2 - 4ac \geq 0, b' < 0 \\ 1 & \text{otherwise.} \end{cases} \quad (4.31)$$

■

Proposition 4 *For a fixed value of $\mathbf{T}$, the average cost of energy C is increasing in p_p , the probability of the SU purchasing energy from PU, in the two disjoint feasible sets of p_p values obtained for $p'_a < 1$ and $p'_a = 1$.*

Proof: For $T_a = T_h$ and $b' < 0$, we have

$$\frac{dp'_a}{dp_p} = \frac{c}{b'^2} \frac{db'}{dp_p} > 0 \quad (4.32)$$

where $\frac{db'}{dp_p} = p_{01}(T_h)(\eta_t P_t^p D_{11}(T_a) + P_t^s(T_a - \tau_s)) > 0$. For $T_a > T_h$, we have $b'^2 - 4ac \geq 0 \forall p_p$. For $T_h > T_a$, we have $p'_a = 1$ for values of p_p such that $-b' < \sqrt{4ac}$, the region where the roots of EC constraint are either complex or negative real values, and $p'_a \leq 1$ for p_p such that $-b' \geq \sqrt{4ac}$. Moreover, $-b'$ is an increasing linear function of p_p . Therefore, we consider two disjoint feasible sets of p_p for $b'^2 - 4ac \geq 0$ and $p'_a < 1$, and $b'^2 - 4ac < 0$ and/or $p'_a = 1$. In the following, we show that C is a increasing function of p_p in both these regions. Firstly, for $-b' \geq \sqrt{4ac}$,

$$\frac{dp'_a}{dp_p} = \frac{-1}{2a} \left(1 + \frac{b'}{\sqrt{b'^2 - 4ac}} \right) \frac{db'}{dp_p} \quad (4.33)$$

where $\frac{db'}{dp_p} > 0$. For $T_a > T_h$, we have $a < 0$ and $|b'/\sqrt{b'^2 - 4ac}| < 1$, which obtains $\frac{dp'_a}{dp_p} > 0$. For $T_h > T_a$ or $a > 0$, with $-b' > 0$ we get $|b'/\sqrt{b'^2 - 4ac}| > 1$. Hence, $\frac{dp'_a}{dp_p} > 0$.

We have,

$$\frac{dC}{dp_p} = D_{11}(T_a)c_e \left(\frac{dp_1}{dp_p} p'_a p_p + \frac{dp'_a}{dp_p} p_1 p_p + p'_a p_1 \right) \quad (4.34)$$

$$= D_{11}(T_a)c_e \left(\frac{dp'_a}{dp_p} \left(\frac{dp_1}{dp'_a} p'_a + p_1 \right) + p'_a p_1 \right) \quad (4.35)$$

where $\left(\frac{dp_1}{dp'_a} p'_a + p_1 \right) = \frac{p_{01}(T_h)(1-p_{11}(T_h)+p_{01}(T_h))}{(1-p_{11}(T_h)+p'_a(p_{11}(T_h)-p_{11}(T_a))+p_{01}(T_h))^2} > 0$, which implies that $\frac{dC}{dp_p} > 0$. For the case when $-b' < \sqrt{4ac}$ or $p'_a = 1$, it can be clearly seen that C is

increasing in p_p . ■

In this scenario, it is more logical to minimize the average energy cost given that the SU can achieve a required throughput R_0 with sufficient spectrum opportunities and energy to utilize them while keeping the probability of PU collision under the threshold $\bar{P}_c$. The energy cost minimization (ECM) optimization problem to obtain optimal sensing and harvesting slot durations, and probability of purchasing energy is as follows:

$$\begin{aligned}
 & \min_{\mathbf{T}, p_p} C(\mathbf{T}, p_p) & (4.36) \\
 & \text{s.t. } R'_s(\mathbf{T}, p_p) \geq R_0 \\
 & P'_c(\mathbf{T}, p_p) \leq \bar{P}_c \\
 & T_h \leq D_{\max} \\
 & p_{a \min} \leq p'_a(\mathbf{T}, p_p) \leq 1 \\
 & T_a, T_h > \tau_s \\
 & 0 \leq p_p \leq 1.
 \end{aligned}$$

In the following, we solve the constraints to obtain the feasible set of p_p values for a given $\mathbf{T}$. Firstly, we consider the PC constraint. For the case of $T_a \neq T_h$, we can express the PC constraint as $p'_a(p_p)x_1(p_p) - y_1 \leq 0$, where

$$\begin{aligned}
 x_1 &= (1 - p_p) p_{01}(T_h) (T_a - \tau_s - D_{11}(T_a)) \\
 &\quad - \bar{P}_c (p_{01}(T_h) T_a + T_h (p_{11}(T_h) - p_{11}(T_a) - p_{01}(T_h))), \\
 y_1 &= \bar{P}_c T_h (1 - p_{11}(T_h) + p_{01}(T_h)),
 \end{aligned}$$

and $y_1 > 0$. The feasible set of p_p is given by $(P_1^c \cup P_2^c \cup P_3^c \cup P_4^c) \cap [0, 1]$ which are defined as follows:

1. $p_p \in P_1^c$ s.t.

$$x_1 \leq 0, b'^2 - 4ac > 0, \quad (4.37)$$

$$\text{and } p_{a \min} \leq \frac{-b' - \sqrt{b'^2 - 4ac}}{2a} \leq 1. \quad (4.38)$$

2. $p_p \in P_2^c$ s.t.

$$x_1 \leq 0 \text{ and } I = 1. \quad (4.39)$$

where $I = 1$ when $b'^2 - 4ac < 0$ or $(-b' \leq 0 \text{ and } a > 0)$ or $(-b' - \sqrt{b'^2 - 4ac})/2a \geq 1$.

3. $p_p \in P_3^c$ s.t.

$$x_1 > 0, b'^2 - 4ac > 0, \quad (4.40)$$

$$\text{and } p_{a \min} \leq \frac{-b' - \sqrt{b'^2 - 4ac}}{2a} \leq \min\left(\frac{y_1}{x_1}, 1\right). \quad (4.41)$$

4. $p_p \in P_4^c$ s.t.

$$x_1 > 0, I = 1, \quad (4.42)$$

$$p'_a = 1, \text{ and } x_1 \leq y_1. \quad (4.43)$$

The rate constraint can be expressed as $p'_a(p_p)x_2(p_p) - y_2 \geq 0$, where

$$x_2 = (1 - p_p)p_{01}(T_h)D_{11}(T_a) - R_0(p_{01}(T_h)T_a + T_h(p_{11}(T_h) - p_{11}(T_a) - p_{01}(T_h))),$$

$$y_2 = R_0T_h(1 - p_{11}(T_h) + p_{01}(T_h)),$$

and $y_2 > 0$. The feasible set of p_p is given by $(P_1^r \cup P_2^r) \cap [0, 1]$ which are defined as follows:

1. $p_p \in P_1^r$ s.t.

$$x_2 > 0, b'^2 - 4ac > 0, \quad (4.44)$$

$$\text{and } \max\left(\frac{y_2}{x_2}, p_{a \min}\right) \leq \frac{-b' - \sqrt{b'^2 - 4ac}}{2a} \leq 1. \quad (4.45)$$

2. $p_p \in P_2^r$ s.t.

$$x_2 > 0, I = 1, \quad (4.46)$$

$$p'_a = 1, \text{ and } x_2 \geq y_2. \quad (4.47)$$

All the above equations are either linear or quadratic functions in p_p . Hence, they can be solved accordingly for $a < 0$ and $a > 0$ for the cases of $T_a > T_h$ and $T_a < T_h$, respectively, to obtain the feasible set of values for p_p . Similarly, we can obtain the feasible set for the case of $T_a = T_h$. Unlike the previous problem in Section 4.3, here we cannot find an upper bound for T_a as there is no closed-form solution for p_p . We choose a big value for $T_{a \max}$. An exhaustive search is performed in $\tau_s < T_h < D_{\max}$ and $\tau_s < T_a < T_{a \max}$. The optimal p_p for each $\mathbf{T}$ is the value obtaining the minimum C among the smallest values in the two exclusive sets $(P_1^c \cup P_3^c) \cap P_1^r \cap [0, 1]$ and $(P_2^c \cup P_4^c) \cap P_2^r \cap [0, 1]$ obtained for $p'_a < 1$ and $p'_a = 1$, respectively, using Proposition 4. Finally, the feasible $\mathbf{T}$ obtaining the minimum C and the corresponding p_p is the optimal solution.

Figure 4.4: The plots of expected SU throughput versus mean PU idle duration.

4.5 Numerical Results and Discussions

The results are generated for a CR system which requires $p_{a \min} = 0.2$ and $T_{h \max} = 100$ units. The PU allows a maximum probability of collision $\bar{P}_c = 0.1$. Other parameter values are taken to be $\eta_h = 0.1$, $P_t^p = 100$ units, $P_t^s = 20$ units, $P_s = 2$ units, and $\tau_s = 3$ units. For the ECM scheme, we take $c_e = 10$ per time unit, $T_{a \max} = 100$ units, and $\eta_t = 0.25$ unless otherwise specified. The simulation results, which have been calculated after reaching the steady state, validate the expressions used.

In Fig. 4.4, we depict the performance of the STM scheme for varying PU mean idle duration $1/\lambda_1$. It is observed that as $1/\lambda_1$ is increased, the SU throughput first increases but later starts to fall. It is because as $1/\lambda_1$ increases, more spectrum opportunities are available for the SU. By using the optimal transmit and harvesting durations obtained using the proposed STM scheme, the SU enhances the discovery and utilization of the spectrum opportunities with sufficient energy. For a fixed value of $1/\lambda_0$, as $1/\lambda_1$ is increased, the probability of PU being busy given by $\lambda_1/(\lambda_0 + \lambda_1)$ decreases, reducing

Figure 4.5: The plots of expected SU throughput versus mean PU busy duration.

the energy-harvesting opportunities for the SU. As $1/\lambda_1$ is further increased, the harvested energy is not enough to exploit the increasing spectrum opportunities and the SU throughput starts to decrease. On comparing the throughput plots obtained for different fixed values of $1/\lambda_0$, we observe that for a larger value of $1/\lambda_0$, which provides more chances to harvest energy, the throughput peak shifts to the right. For higher values of $1/\lambda_0$, throughput starts to fall for greater values of $1/\lambda_1$ as compared to the case with a lower value of $1/\lambda_0$.

In Fig. 4.5, we observe that as the PU mean busy duration $1/\lambda_0$ is increased, initially, the SU throughput increases but later starts to decrease. The reason is that with an increase in $1/\lambda_0$, the SU gets more harvesting opportunities; it can harvest more energy to be able to utilize a greater number of spectrum opportunities resulting in the increasing throughput curve. For a fixed $1/\lambda_1$, the probability of PU being idle decreases as $1/\lambda_0$ is increased thus diminishing the available spectrum opportunities. As $1/\lambda_0$ is further increased, the effect of the decreasing spectrum opportunities starts to dominate and the corresponding increase in harvested energy does not enhance the

Figure 4.6: The plots of expected SU throughput versus mean PU idle duration. $1/\lambda_0 \in [100, 1000]$.

Figure 4.7: The plots of expected SU throughput versus mean PU busy duration. $1/\lambda_1 \in [100, 1000]$.

Figure 4.8: The plots of expected SU throughput versus SU transmission power.

throughput which starts to fall. For larger values of $1/\lambda_1$, the SU obtains a greater number of spectrum opportunities. Hence, the throughput peak shifts to the right. In Fig. 4.6, we plot the SU throughput obtained by using the sensing intervals determined by the optimal and suboptimal policies for varying PU mean idle duration, choosing $1/\lambda_0$ randomly over an interval $[100, 1000]$. It is observed that by using the proposed STM policy that optimally utilizes the heterogeneity in PU idle and busy durations, the SU can achieve higher throughput performance than that of the suboptimal scheme. The performance gain increases as $1/\lambda_1$ is increased which provides the SU a greater number of spectrum opportunities to exploit. Similarly, in Fig. 4.7, the performance gain is higher for lower values of $1/\lambda_0$, which highlights that when the SU has a smaller number of harvesting opportunities, their optimal utilization becomes even more critical.

In Fig. 4.8, we observe that as the SU transmission power is increased, the SU throughput also decreases. The reason is the falling probability of the SU being active due to an increase in the energy consumption. It needs greater harvesting durations to garner more energy which compromises on the transmission durations. For a fixed

Figure 4.9: The plots of average energy cost in a time slot versus mean PU idle duration.

value of $1/\lambda_0$, initially, the SU throughput for a greater $1/\lambda_1$ is higher due to a greater number of spectrum opportunities. As P_t^s is increased, the fall in the throughput will also be sharper due to a faster increase in the energy consumption as compared to that for smaller values of $1/\lambda_1$. For larger values of P_t^s , the lesser number of harvesting opportunities offered by a greater $1/\lambda_1$ becomes more critical and a smaller SU throughput is obtained. Similarly, for a fixed value of $1/\lambda_1$, a smaller $1/\lambda_0$ provides a greater probability of PU being idle. Thus, the fall in SU throughput is sharper.

In Figs. 4.9 and 4.10, we plot the average energy cost incurred by the SU in a time slot obtained by using the ECM scheme for varying PU traffic parameters. A negative value is used to denote an infeasible case where the required SU rate cannot be achieved due to insufficient spectrum-access or energy-harvesting opportunities. Firstly, the plots demonstrate that a higher SU throughput can be achieved by using some of the spectrum opportunities for harvesting energy and paying an extra cost to the PU as we observe that $R_0 = 0.3, 0.4$ can be achieved by using the ECM scheme which is greater than the maximum throughput achieved by the SU by applying the STM scheme for the

same parameter values in Figs. 4.4 and 4.5. In Fig. 4.9, we observe that as $1/\lambda_1$ is increased, the available spectrum opportunities increase, the problem becomes feasible. For the cases corresponding to a greater value of $1/\lambda_0$ which provides lesser spectrum opportunities and a greater R_0 , a greater value of $1/\lambda_1$ is required for the problem to become feasible. In the feasible region, as $1/\lambda_1$ is further increased, the average energy cost also increases. This is because as $1/\lambda_1$ is increased the probability of PU being busy decreases which reduces the opportunistically harvested energy and the SU needs to purchase more energy to achieve the required rate. For a greater fixed value of $1/\lambda_0$, more energy-harvesting opportunities are available to the SU, therefore the average energy cost values are lower. For the curve corresponding to a greater value of R_0 , the average energy cost is higher due to a rise in the energy needs. The curve for $R_0 = 0.35$ depicts a varied behavior as compared to those corresponding to a lower R_0 value, i.e., the average energy cost decreases as $1/\lambda_1$ is increased. The energy cost depends on the probability of PU to be found idle, the SU transmit duration, and p_p as expressed in (4.25). For high R_0 values, the rate constraint is more dominating for smaller values of $1/\lambda_1$, and the optimal parameter values are chosen to acquire the maximum possible spectrum opportunities to achieve the required rate. As $1/\lambda_1$ is further increased, we have a greater number of spectrum opportunities available and the rate constraint starts to relax. Thus, the observed channel idle probability and duration can be decreased and the average energy cost in a time slot starts to fall. On comparing the plots obtained for different values of η_t , it is observed that the average cost for a lower value of energy-transfer efficiency is higher. Also, the increase in cost with increasing $1/\lambda_1$ is lesser for a larger η_t because greater energy can be transferred per time slot as compared to that needed to utilize the increasing spectrum opportunities.

In Fig. 4.10, it is observed that as $1/\lambda_0$ is increased, with a greater number of energy-harvesting opportunities, the average energy cost decreases. The problem becomes in-

Figure 4.10: The plots of average energy cost in a time slot versus mean PU busy duration.

Figure 4.11: The plots of average energy cost in a time slot versus SU transmission power. $R_0 = 0.3$.

Figure 4.12: The plots of average energy cost in a time slot versus minimum required SU throughput.

feasible for larger values of $1/\lambda_0$ as the spectrum opportunities are not enough to meet the SU rate constraint. The average cost values obtained for a greater fixed value of $1/\lambda_1$ are higher because the PU busy probability or the energy-harvesting opportunities are reduced. Similar to Fig. 4.9, for a greater R_0 value, the rate constraint is active and we observe that the energy cost increases rather than decreasing as $1/\lambda_0$ is increased. As $1/\lambda_0$ is increased, the SU gets a lesser number of spectrum opportunities and the rate constraint starts to dominate more; the observed channel idle probability and transmit duration are increased to grab maximum possible transmission opportunities. Thus, the average energy cost in a time slot increases unless it can no longer achieve the required rate and the problem becomes infeasible.

In Fig. 4.11, we observe that the average energy cost increases as the SU transmission power is increased. For a fixed value of $1/\lambda_1$, the energy cost for a larger $1/\lambda_0$ is lower due to a greater number of harvesting opportunities. For $1/\lambda_1 = 700$, for a larger P_t^s value, the rate constraint is active and we observe that the energy cost is slightly higher for a

larger $1/\lambda_0$. As P_t^s is increased, the SU does not have enough spectrum opportunities to trade for purchasing more energy and to meet the required R_0 . Hence, the problem becomes infeasible. In Fig. 4.12, similar behavior is observed for the average energy cost as the minimum required SU throughput is increased.

4.6 Conclusion

For an opportunistic RF energy harvesting CR system, optimal sensing intervals, i.e., the transmission and harvesting durations have been determined to maximize the SU throughput by taking into account the traffic pattern in an unslotted PU system. The aim is to achieve an optimum utilization of the spectrum and harvesting opportunities while considering the energy-arrival rate and the energy needs for SU transmission and sensing. Numerical results depict the dependence of SU on PU busy and idle pattern for energy and transmission opportunities and the performance gain over the suboptimal scheme achieved by exploiting the knowledge about the PU traffic behavior. Furthermore, having the option to purchase energy enhances the SU ability to get more energy from PU when it is needed to achieve the required quality of service. Numerical results have shown that a higher throughput can be attained by paying an extra cost using the ECM scheme as compared to that achieved by using the STM scheme for the case without energy trading.

Chapter 5

Cooperative Energy-Harvesting Cognitive Radio Systems

In an energy-harvesting cognitive radio (CR) system, the secondary users (SUs) may not have adequate energy levels to operate at all the times. Moreover, energy is not evenly distributed among the SUs. Some of the SUs with better sensing performance or transmission channel conditions may have lower or greater energy-arrival rates than the others. Hence, it is only natural to utilize cooperative schemes to enhance the overall performance of such energy-constrained systems. In this chapter, we study the performance gains obtained by employing cooperation among the energy-harvesting SUs for spectrum sensing and utilization. An optimal sensing-scheduling policy has been proposed for heterogeneous SUs to maximize the SU throughput while limiting the primary user (PU) collision probability based on the mean energy-arrival rate.

5.1 Introduction

In order to utilize the opportunistic spectrum access method, the SUs need to sense the licensed spectrum periodically to discover spectrum holes and to prevent interference to the PUs. Performance of single-user spectrum sensing is limited due to multi-path fading and shadowing which causes hidden-node problem [26]. Cooperative spectrum sensing has been suggested to enhance the PU detection reliability in such adverse channel conditions [25]. Aiming for green communications, much recent research on cooperative spectrum sensing has been concentrated on energy efficiency. In [47], the fusion-rule threshold and detector threshold at SUs were optimized to maximize the energy efficiency of a cooperative sensing based CR system. Optimal detection threshold and SU sensors were found to minimize the energy consumed under constraints on the SU sensing performance [11]. For a multichannel case, energy-efficient cooperative sensing scheduling (CSS) was studied to determine the SU sensors for a channel and the corresponding sensing durations [48]. In [55], the authors utilized discrete convex framework to analyze the CSS problem. Moreover, optimal spectrum sensing and access policies have been studied for energy-harvesting CR systems [16, 94, 96, 98]. We study the optimization of cooperative spectrum sensing in the context of energy-harvesting CR systems and propose the potential benefits of cooperating for both sensing and spectrum utilization.

In this study on energy-harvesting CR systems, we explore new aspects to cooperative spectrum sensing. We investigate energy-harvesting CR systems where the robust cooperative spectrum sensing approach with OR fusion-rule is employed for an improved spectrum sensing. Introducing the energy-harvesting concept results in an energy-limited scenario, which makes the cooperative system even more desirable besides its sensing-enhancing property. The SUs not only cooperate for sensing but also

collectively utilize their harvested energies to enhance the SU spectrum utilization and PU detection reliability. We consider a heterogeneous CR scenario where the SUs have different sensing performances and diverse energy-arrival processes. A probabilistic sensing policy is proposed to optimally employ the cooperative SUs to maximize the SU transmission while attaining the required PU protection with the available energy. In order to save energy, the SUs with higher probabilities of detection should sense more often so that the PU detection constraint can be met with a lesser number of SUs sensing in a time slot. Using the OR fusion-rule, a higher expected throughput can be achieved with fewer sensing SUs, having those with lower probabilities of false alarm sense more often. However, the SUs may not have sufficient harvested energies to operate. We formulate a polynomial optimization problem and use SOSTOOLS [135] to determine the optimal probability of sensing for each SU to achieve the maximum SU throughput while ensuring the PU protection under the energy-causality (EC) constraints at the SUs. Moreover, we propose a suboptimal scheme which uses an iterative algorithm to maximize the SU throughput. For a homogeneous case, it is shown that using a minimum number of SUs to cooperate, the PU detection can be enhanced and the energy limitations can be overcome.

5.2 System Model

The CR system consists of N SUs that opportunistically access a licensed channel occupied by a PU transmitter. We consider a slotted PU transmission. In each time slot, the PU occupies the spectrum with a probability p_0 and it is idle with probability $p_1 = 1 - p_0$. The PU is assumed to have a continuous supply of power. The SUs harvest energy to carry out the sensing and transmission operations. In the previous chapters, we considered opportunistic RF energy-harvesting SUs which harvested energy from

Figure 5.1: Framework for energy-harvesting CR system with cooperative sensing.

the PU transmissions. In this Chapter, the energy-arrival process at the n -th SU is assumed to be a sequence of independent and identically distributed random variables $E_{n,i}^h$, corresponding to the i -th time slot, with mean value e_{hn} . The mean energy-arrival rate vector is denoted by $\mathbf{e}_h = [e_{h1}, e_{h2}, \dots, e_{hN}]$. Each SU is assumed to have a battery with an infinite capacity to store the harvested energy. It is assumed that they can harvest energy and sense or access simultaneously. We employ cooperative spectrum sensing and each SU uses the energy-detection method to carry out sensing. As shown in Fig. 5.1, a time slot of duration T consists of sensing time τ_s , sub-slots of time r for the SUs to report their sensing decisions to a central controller (CC) in a time division multiple access (TDMA) framework, and the time for SU transmission [47].

As depicted in Fig. 5.2, in any time slot, only some of the SUs, according to the sensing policy, perform sensing while other SUs remain idle to save energy or due to an energy shortage. We will refer to the sensing SUs as the active SUs. At the end of the sensing period, all the active SUs report their sensing decisions to the CC in their respective time slots. The CC uses a logical-OR based fusion rule to combine the decisions to make a final decision on the PU channel state. In the i -th time slot, the probability of false alarm (Q_{fi}) and probability of detection (Q_{di}) for the cooperative system are given by [48]

$$Q_{fi} = 1 - \prod_{n \in S_i^a} (1 - p_{fn}) \quad (5.1)$$

Figure 5.2: Energy-harvesting CR system with cooperative spectrum sensing.

and

$$Q_{di} = 1 - \prod_{n \in S_i^a} (1 - p_{dn}), \quad (5.2)$$

respectively, where S_i^a denotes the set of active SUs sensing the spectrum in the i -th time slot, and p_{fn} and p_{dn} are the probabilities of false alarm and PU detection of the n -th SU, respectively. It is assumed that all SUs have the same transmission channel conditions. The SUs are assumed to have heterogeneous sensing performances depending on the received PU signal power and their individual detection threshold values, which is given by $\mathbf{p}_f = [p_{f1}, p_{f2} \cdots, p_{fN}]$ and $\mathbf{p}_d = [p_{d1}, p_{d2} \cdots, p_{dN}]$. The energies consumed by an SU for sensing and transmission in a time slot are denoted by e_s and e_t , respectively. It is assumed that the energy needed to report the decision bit is included in e_s . Taking into account the SU battery power level, SU action, and the amount of energy harvested in the previous time slot, the energy available with the n -th SU at the beginning of the $(i + 1)$ -st slot is given by

$$e_{n,i+1} = e_{n,i} - e_{n,i}^c + E_{n,i}^h \quad (5.3)$$

where $e_{n,i}^c$ is the energy consumed by the n -th SU in the i -th time slot, which is given by

$$e_{n,i}^c = \begin{cases} 0 & \text{SU not active,} \\ e_s & \text{active SU senses PU channel,} \\ e_s + e_t & \text{active SU selected to access idle PU channel.} \end{cases} \quad (5.4)$$

There is a sensing-probability vector denoted by $\mathbf{p}_s = [p_{s1}, p_{s2}, \dots, p_{sN}]$. In the beginning of a time slot, the n -th SU decides to sense the PU spectrum with probability p_{sn} . The active SUs sense the spectrum and report their sensing decisions to the CC in the respective sub-slots allocated to them. If it is decided to be vacant, for fairness, we assume that the CC chooses an SU uniformly at random among the active SUs to transmit. Otherwise, some SUs may always be sensing whereas others may be chosen for transmission on the idle spectrum more often. Given that the n -th SU is active, the probability that a set of other SUs A is sensing the spectrum can be expressed as [136, 137]

$$q(A, n) = \prod_{j \in A} p_{sj} \prod_{k \in S \setminus A, k \neq n} \bar{p}_{sk} \quad (5.5)$$

where $\bar{x} = (1 - x)$ and S is the set of N cooperative SUs. The average throughput of the SU network $R_s(\mathbf{p}_s)$ can be expressed as

$$R_s(\mathbf{p}_s) = \sum_{n=1}^N \sum_{m=0}^{N-1} \frac{p_{sn}}{m+1} \sum_{l=1}^{\binom{N-1}{m}} \prod_{i \in \{c_l^m, n\}} \bar{p}_{fi} q(c_l^m, n) p_1 \quad (5.6)$$

where c_l^m denotes the set of SUs in the l -th combination of size m [136]. An SU is chosen for transmission among the active SUs therefore $\mathbf{p}_s$ affects the probability of CR transmission. In order to enhance the SU throughput, $\mathbf{p}_s$ should achieve an optimal balance between maximizing the probability of having an active SU to transmit and minimizing the average probability of false alarm for the cooperative system (Q_f).

For opportunistic access to PU spectrum, the CR system should satisfy the PU Collision (PC) constraint, i.e., the probability of an SU transmission interfering with the PU transmission should be lower than the specified value. In our cooperative energy-harvesting CR paradigm, the probability of collision with PU is given by

$$P_c(\mathbf{p}_s) = \sum_{n=1}^N \sum_{m=0}^{N-1} \frac{p_{sn}}{m+1} \sum_{l=1}^{\binom{N-1}{m}} \prod_{i \in \{c_l^m, n\}} \bar{p}_{di} q(c_l^m, n) p_0. \quad (5.7)$$

A sufficient number of active SUs with high p_{dn} values is required to attain a high average probability of detection for the cooperative system (Q_d) to achieve a low P_c . However, if a high Q_d cannot be obtained then the required P_c is achieved by reducing the probability of SU transmission. The EC constraint mandates that the average energy consumed by an SU cannot be more than the average energy harvested in a time slot [16]. The average energy consumed by the n -th SU in a time slot $e_{cn}(\mathbf{p}_s)$ can be expressed as

$$e_{cn}(\mathbf{p}_s) = e_s p_{sn} + e_t \sum_{m=0}^{N-1} \frac{p_{sn}}{m+1} \sum_{l=1}^{\binom{N-1}{m}} \left(\prod_{i \in \{c_l^m, n\}} \bar{p}_{fi} p_1 + \prod_{j \in \{c_l^m, n\}} \bar{p}_{dj} p_0 \right) q(c_l^m, n). \quad (5.8)$$

The above expression for energy consumption presents the complex dependency of e_{cn} on $\mathbf{p}_s$. As p_{sn} is increased, e_{cn} increases because on average more energy is spent on spectrum sensing. The probability that the n -th SU obtains a transmission opportunity depends on N and the probabilities of sensing of other SUs [136]. Additionally, as $\mathbf{p}_s$ is varied, Q_d and Q_f also change which affects the energy consumption of the n -th SU.

5.3 Optimal Spectrum Sensing Policy

In this cooperative energy-harvesting CR scenario, the sensing policy should optimally exploit the diversity in p_{dn} , p_{fn} , and e_{hn} values at the heterogeneous SUs to

maximize the discovery and utilization of the spectrum opportunities while protecting the PU. We aim to find the optimal sensing-probability vector $\mathbf{p}_s$ to maximize the SU network throughput and maintain P_c below the maximum tolerable value $\bar{P}_c$ with the energies harvested at the cooperative SUs. The optimization problem to obtain the optimal $\mathbf{p}_s$ is as follows:

$$\max_{\mathbf{p}_s} R_s(\mathbf{p}_s) \quad (5.9)$$

$$\text{s.t. } P_c(\mathbf{p}_s) \leq \bar{P}_c \quad (5.10)$$

$$e_{cn}(\mathbf{p}_s) \leq e_{hn} \quad \forall n \quad (5.11)$$

$$0 \leq p_{sn} \leq 1 \quad \forall n. \quad (5.12)$$

It is a non-convex optimization problem, specifically, a polynomial optimization problem. Based on the sum-of-squares (SOS) relaxation of the dual problem, any polynomial optimization problem can be solved using semidefinite programming problems [137,138]. We employ SOSTOOLS [135] to obtain a bound on the maximum achievable throughput which gets tighter as the even degree of the polynomials in SOS problem is increased. Further details about using SOS relaxations to obtain the optimal solution can be found in [138] and the references therein. For the above optimization problem, it is feasible to use this method to obtain the optimal solution only for small values of N . As the number of variables is increased, a higher degree is required to achieve a tight bound and the problem gets very large.

In Table 5.1, we depict the optimal $\mathbf{p}_s$ that achieves the maximum R_s for different examples of heterogeneous SUs. The obtained $\mathbf{p}_s$ values are analyzed to understand the deciding factors for the optimal policy. Based on it, we will propose a suboptimal policy with reduced complexity. In Table 5.1, in entry 1, we observe that SU 2 with a low e_{h2} and high p_{f2} is allocated very low p_{s2} . In entry 2, SU 3 with high e_{h3} and p_{d3} is

Table 5.1: Optimal sensing-probability vector $\mathbf{p}_s$. $\bar{P}_c = 0.1$.

No.	$\mathbf{p}_f$	$\mathbf{p}_d$	$\mathbf{e}_h/(e_s + e_t)$	$\mathbf{p}_s$
1	[0.08, 0.24, 0.1]	[0.7, 0.8, 0.6]	[0.3, 0.2, 0.6]	[0.56, 0.01, 0.92]
2	[0.1, 0.08, 0.24]	[0.6, 0.7, 0.8]	[0.3, 0.2, 0.6]	[0.09, 0.43, 1]
3	[0.1, 0.08, 0.24]	[0.6, 0.7, 0.8]	[0.3, 0.3, 0.3]	[0.6, 0.6, 0.62]
4	[0.1, 0.08, 0.24]	[0.6, 0.7, 0.8]	[0.6, 0.6, 0.6]	[0.73, 1, 0]
5	[0.1, 0.1, 0.1]	[0.7, 0.7, 0.7]	[0.1, 0.3, 0.5]	[0.21, 0.57, 0.83]
6	[0.2, 0.2, 0.2]	[0.8, 0.8, 0.8]	[0.1, 0.3, 0.5]	[0, 0.62, 0.89]

allocated very high p_{s3} though it has a greater p_{f3} too. To counter this, SU 2 with low p_{f2} is allocated a high p_{s2} though it has a lower energy-arrival rate than SU 1. In entry 3, due to low e_{hn} values, EC constraint dominates the system and all SUs cooperate equally. However, in entry 4, when they possess higher e_{hn} values, in order to achieve low Q_f and an acceptable Q_d , SU 2 is assigned a very high p_{s2} whereas SU 3 is mostly inactive. On comparing entries 5 and 6, we find that for higher values of p_{fn} and p_{dn} , it is optimal to have a smaller number of sensing SUs.

5.3.1 Suboptimal Weighted Proportional Policy

Based on the above observations, we propose a suboptimal scheme, namely, weighted proportional (WP) policy which can be used to find the optimal $\mathbf{p}_s$ for greater values of N too. In this energy-harvesting CR scenario, energy-arrival rate is the most dominant deciding factor. It is assumed that p_{sn} is directly proportional to the mean energy-harvesting rate e_{hn} with a proportionality constant γ . Using a common γ reduces the complexity but it limits the performance because the SUs cannot attain very low or high p_{sn} values as compared to others. Hence, a weighting-factor vector $\mathbf{w} = [w_1 \dots w_N]$ is attached to γ . Considering OR fusion-rule, in order to achieve a higher throughput, it is optimal to have lower average number of active SUs with low p_{fn} values to reduce Q_f and high p_{dn} values to satisfy the PC constraint. Also, a greater R_s is achieved by allocating higher p_{sn} values to fewer SUs and very low to others as compared to allocating low

Algorithm 2 Weighted Proportional Policy

- Initialize $\mathbf{w}=[1,1,\dots,1]$ and $p_{sn} = \gamma w_n e_{hn} \forall n$.
 - In ascending order of $(p_{dn} - p_{fn})$, perform the following set of operations for each SU:
 1. $[R_s, \mathbf{p}_s] = \text{OptimizeGamma}(\mathbf{w})$.
 2. $w_n = \beta w_n$, where $\beta < 1$.
 3. Repeat 1) and 2) until either R_s starts to fall or $w_n < \varepsilon$.
 - Finally, we obtain the maximum R_s and $\mathbf{p}_s^*$.
-

Algorithm 3 Function OptimizeGamma($\mathbf{w}$)

- Obtain the feasibility region F for the polynomial optimization problem (5.9) as follows:
 1. Solve PC constraint (5.10) for equality. The feasible region is where the expression is negative, i.e., the odd intervals formed by the roots on the real line representing $\gamma \in [0, 1/\max_j (w_j e_{hj})]$.
 2. Similarly, solve the EC constraint (5.11) for each SU for equality to obtain the feasible region.
 - The γ^* that maximizes $R_s(\mathbf{w}, \gamma)$ is searched among the stationary points $\gamma_s \in F$ obtained by setting its first-derivative to zero and the end points of the feasible intervals in F [139].
 - Return updated $R_s(\mathbf{p}_s)$ and $\mathbf{p}_s$ with $p_{sj} = \gamma^* w_j e_{hj} \forall j$.
-

p_{sn} values to many SUs provided that the constraints allow it. The former allocation results in higher probabilities for low Q_f values, reducing the average Q_f . Thus, the weighting factor is computed for each SU in the ascending order of $p_{dn} - p_{fn}$ as shown in Algorithm 2. An iterative method is used to compute the optimal $\mathbf{w}$ and γ to maximize the CR throughput.

The proposed WP policy is suboptimal in the sense that it does not optimally utilize the heterogeneity in the $\mathbf{p}_f$ and $\mathbf{p}_d$ values. It takes into account the energy available at each SU and attempts to optimize the probability of transmission and the average number of active SUs. Hence, it performs optimally for the homogeneous scenario. The

numerical results for the heterogeneous CR system in Section 5.5 show that it performs close to the optimal scheme.

5.4 Minimum Number of Cooperative SUs for Unconstrained CR System

We attempt to show that depending on the energy-arrival process at each SU and the PU protection requirement, there is a minimum number of SUs $N_{\min}$, which can achieve an energy-unconstrained CR system with the required PU detection by cooperatively sensing and utilizing the PU spectrum. Considering the reporting time r to be very small as compared to T , it is assumed to have a negligible effect on throughput and transmission energy as N is varied. In this section, we consider a homogeneous system where all SUs are assumed to have the same sensing performance, i.e., $p_{fn} = p_f$ and $p_{dn} = p_d$, and the same energy-arrival processes with mean $\mathbb{E}[E_{n,i}^h] = e_h$. For particular values of e_h and $\bar{P}_c$, if $N < N_{\min}$, the CR system performance will be limited by EC or PC constraint. Based on the above assumptions, in this homogeneous scenario, for the case when $N < N_{\min}$, i.e., when the system is under constraint, it is optimal to assume that the probability of sensing is the same for all SUs. Thus, we can obtain closed-form expressions for the expected SU throughput, PU collision probability, and average energy consumed by an SU. In each time slot, the n -th SU is active with probability $p_{sn} = p_s$. The average throughput of the SU network for the homogeneous case $R'_s(p_s)$ can be expressed as

$$\begin{aligned} R'_s(p_s) &= \sum_{n=1}^N \sum_{m=0}^{N-1} \frac{p_s}{m+1} p_m^{N-1}(p_s) \bar{p}_f^{m+1} p_1 \\ &= (\bar{p}_f p_s^N - \bar{p}_s^N) p_1 \end{aligned} \quad (5.13)$$

where $p_m^{N-1}(p_s) = \binom{N-1}{m} p_s^m \bar{p}_s^{N-1-m}$ is the probability that there are m other active SUs. Similarly, the probability of collision with PU $P'_c(p_s)$ is given by

$$P'_c(p_s) = (\bar{p}_d \bar{p}_s^N - \bar{p}_s^N) p_0. \quad (5.14)$$

The average energy consumed by an SU in a time slot $e'_c(p_s)$ can be expressed as

$$e'_c(p_s) = p_s e_s + \frac{e_t}{N} (\bar{p}_f \bar{p}_s^N p_1 + \bar{p}_d \bar{p}_s^N p_0 - \bar{p}_s^N). \quad (5.15)$$

We find the $N_{\min}$ needed to achieve an unconstrained SU performance by solving the optimization problem in (5.9) for the homogeneous case. Before we present the procedures to find $N_{\min}$, we first discuss some properties of the objective and constraint functions.

Property 1 *For an energy-constrained CR system, maximum $R'_s(p_s)$ is achieved at $p_s^r = \left(1 - p_f^{1/N-1}\right) / \left(1 - p_f^{N/N-1}\right)$ and p_s^r decreases with N .*

Proof: For a fixed $N < N_{\min}$, the first-order differentiation of the objective function $R'_s(p_s)$ in (5.13) is given by

$$\frac{dR'_s}{dp_s} = N \left(-p_f \bar{p}_f \bar{p}_s^{N-1} + \bar{p}_s^{N-1} \right) p_1. \quad (5.16)$$

For $0 \leq p_s \leq 1$, $\frac{dR'_s}{dp_s} \geq 0$ for $p_s \leq p_s^r$, which is given by

$$p_s^r = \frac{1 - (p_f)^{1/N-1}}{1 - (p_f)^{N/N-1}}. \quad (5.17)$$

The SU throughput is a monotonically increasing function for $p_s \leq p_s^r$ and monotonically decreasing for $p_s \geq p_s^r$. Hence, the objective function is a unimodal function and its maximum value is achieved at $p_s = p_s^r$. This is because, initially as p_s is increased, the

effect of increase in the probability of having an active SU to transmit dominates the SU throughput whereas later, for $p_s \geq p_s^r$, the increase in Q_f overtakes and degrades the throughput. The first-order differentiation of p_s^r shows that it is decreasing in N , which is given by

$$\frac{dp_s^r}{dN} = \frac{(p_f)^{1/(N-1)} \ln(p_f) (1 - p_f)}{(N-1)^2 \left(1 - p_f^{N/(N-1)}\right)^2} \leq 0. \quad (5.18)$$

■

Property 2 For a fixed $N < N_{\min}$, $P'_c(p_s)$ is a unimodal function for $0 \leq p_s \leq 1$.

Proof: Similar to Property 1, using first-order differentiation of P'_c given in (5.14), it can be shown that P'_c is a unimodal function with maxima at $p_s = p_s^c$, which is given by,

$$p_s^c = \frac{1 - p_d^{1/N-1}}{1 - p_d^{N/(N-1)}}. \quad (5.19)$$

When p_s is increased, initially, the enhancing effect of the increase in transmission probability directs the P'_c curve. As p_s is increased further, the increase in Q_d starts to dominate and it starts to fall. ■

We can obtain the infeasible region F^c for the PC constraint by solving it for equality. Since P'_c is a unimodal function, it can have at most two real roots: b_1 and b_2 and $F^c = \{p_s | b_1 < p_s < b_2\}$. It is not possible to mathematically analyze the effect of N on $P'_c(p_s, N)$ and $e'_c(p_s, N)$ because the optimal p_s depends on N and there is no closed-form expression for p_s . In the following, it is proved that the maximum value of the unimodal function $P'_c(p_s)$ is decreasing in N . For this analysis, N is treated as a continuous variable.

Property 3 $P'_c(p_s^c)$ is a decreasing function of N .

Proof: Differentiating $P'_c(p_s^c)$ in (5.14), we get

$$\begin{aligned} \frac{dP'_c}{dN} &= (1 - p_d p_s^c)^N \ln(1 - p_d p_s^c) - (1 - p_s^c)^N \ln(1 - p_s^c) \\ &\quad - N \frac{dp_s^c}{dN} \left(p_d (1 - p_d p_s^c)^{N-1} - (1 - p_s^c)^{N-1} \right). \end{aligned} \quad (5.20)$$

On substituting the expression for p_s^c , the later terms add up to zero and we are left with the following:

$$\frac{dP'_c}{dN} = \left(\frac{1 - p_d}{1 - p_d^{N/N-1}} \right)^N \left(\left(1 - p_d^{N/N-1} \right) \ln \left(\frac{1 - p_d}{1 - p_d^{N/N-1}} \right) - \frac{p_d^{N/N-1}}{N-1} \ln p_d \right). \quad (5.21)$$

In order to prove that $P'_c(p_s^c)$ is a decreasing function of N , we show that $\frac{dP'_c}{dN} \leq 0$ or equivalently

$$f(N) = p_d^{\frac{1}{(N-1)(p_d^{N/N-1}-1)}} \left(\frac{1 - p_d^{N/N-1}}{1 - p_d} \right) \geq 1. \quad (5.22)$$

Here, $\lim_{N \rightarrow \infty} f(N) = 1$. Next, we attempt to prove that $f(N)$ is a decreasing function of N , which implies that $f(N) \geq 1 \forall N < \infty$; hence, $P'_c(p_s^c)$ is a decreasing function of N . The first-order differentiation of $f(N)$ is given by

$$\frac{df}{dN} = - \frac{p_d^{\frac{1}{(N-1)(p_d^{N/N-1}-1)}} p_d^{N/N-1}}{(N-1)^3 (1 - p_d^{N/N-1})} \frac{(\ln p_d)^2}{(1 - p_d)} \leq 0. \quad (5.23)$$

■

Furthermore, by finding the first-derivative, it can be shown that p_s^c decreases in N . Hence, as N is increased, the peak of $P'_c(p_s)$ decreases and shifts to the left, and it can be observed that the infeasible region F^c shifts to the left. The reason is that for larger values of N , the PC constraint becomes active and then is satisfied too for relatively

Algorithm 4 $N_{\min}$ for Unconstrained CR System

1. Initialize $N = 1$.
 2. Find the infeasible region F^c by solving the polynomial equation $P'_c(p_s, N) = \bar{P}_c$.
 3. If $p_s^r \notin F^c$ then $p_s^* = p_s^r$.
 Elseif the polynomial equation has two real roots $p_s^* = \arg \max (R'_s(b_1, N), R'_s(b_2, N))$.
 Else increase N by 1 and go to step 2).
 4. If $e'_c(p_s^*, N) \leq e_h$ then $N_{\min} = N$.
 Else increase N by 1 and go to step 2).
-

lower values of p_s . This is because for a larger N , even a small p_s results in a greater SU transmission probability and a higher Q_d , respectively. When the PC constraint equation has only one real root, we have $F^c = \{p_s | b_1 < p_s \leq 1\}$. It happens when N is not sufficient for the CR system to achieve the required Q_d even with $p_s = 1$. In that case, the PC constraint is satisfied by decreasing the probability of transmission which severely limits the SU throughput. N should be increased to attain the required Q_d , i.e., until it has two roots. With the knowledge of F^c , the optimal p_s^* can be determined to achieve the optimal sensing-throughput tradeoff by using Property 1.

The energy-unconstrained system is attained when the SUs can provide the required p_s^* with the available e_h . Next, we study the effect of N on e'_c given in (5.15). As discussed before, the possible values of p_s^* , i.e., b_1 , b_2 , and p_s^r decrease with N . Therefore, on average, an SU spends less energy on sensing. Additionally, since there are more SUs to transmit, the probability of transmission for each SU decreases. An increase in N and the corresponding decrease in p_s may decrease or increase Q_f but the maximum value of probability of CR transmission with no false alarm $R'_s(p_s^r)$ decreases in N (Proof is the same as that for Property 3). Similarly, the probability of CR transmission in the missed detection case is bounded by $\bar{P}_c$. Ultimately, the diminishing effect of the decrease in sensing and transmission probability for each SU dominates and e'_c decreases as N is

Figure 5.3: The plots of expected SU throughput versus normalized mean energy arrival at SU 1. $p_1 = 0.8$, $\mathbf{p}_f = [0.1, 0.06, 0.08, 0.24]$, and $\mathbf{p}_d = [0.6, 0.65, 0.7, 0.8]$.

increased. We increase N until p_s^* can be achieved by all the SUs with e_h . In a different scenario of energy-harvesting relays, the relay nodes were shown to achieve energy-unconstrained operation under certain conditions [136]. In our model, Algorithm 4 is used to obtain the $N_{\min}$ for given values of e_h and $\bar{P}_c$, which can achieve an unconstrained CR system.

5.5 Numerical Results and Discussions

The CR system consists of N SUs. The energy requirement for each SU is taken to be $e_s = 1$ unit and $e_t = 3$ units. In Fig. 5.3, we observe that as e_{h1} is increased, the CR throughput first increases but becomes constant after a certain value of e_{h1} . This is because initially, when the system is under the EC constraint, increasing e_{h1} means there is more energy arriving at the first SU. Therefore, it can be active more often to enhance the CR throughput. As e_{h1} is increased further, it is no longer under

the EC constraint and a constant value of R_s is attained which is determined by the optimal tradeoff between the probability of SU transmission, Q_f and Q_d . In the plot corresponding to a lower value of $\bar{P}_c = 0.05$ a lower constant value of R_s is attained because the CR system performance is limited by the PC constraint. For a stricter PC constraint, a higher Q_d is required which implies a higher Q_f too. On comparing the optimal R_s obtained for different $\mathbf{e}_h$, we observe that the one which has higher values of e_{hn} for other SUs achieves a greater R_s . The R_s obtained for the case of lower e_{hn} values increases faster with an increase in e_{h1} . For the case with higher e_{hn} values, for lower values of $e_{h1} \leq 0.2 e$, there is a minimal increase in R_s because the CR system already has high-energy SUs to perform sensing. Once SU 1 has greater e_{h1} than others, R_s starts to increase with increase in e_{h1} . We observe that the throughput performance achieved by using the proposed suboptimal WP policy is close to that of the optimal scheme for most of the parameter values. For simulation results in Fig. 5.3, we adopt a Bernoulli energy-arrival model [96, 98]. In each time slot, the SUs harvest energy $e = (e_s + e_t)$ with a harvesting-probability vector $\mathbf{p}_h = [p_{h1}, p_{h2} \cdots, p_{hN}]$, resulting in $\mathbf{e}_h = e \mathbf{p}_h$. The simulation results obtained using the optimal $\mathbf{p}_s$ validate the expressions used.

In Fig. 5.4, we plot the SU throughput versus the mean energy-arrival at the first SU for a smaller probability of the PU being idle. It is observed that the maximum constant value of R_s attained is lower than that in Fig. 5.3 because in this case the SU gets a smaller number of spectrum opportunities due to a lower p_1 . Also, the PC constraint becomes more stringent due to a greater p_0 . Here, we adopt a Poisson energy-arrival model for the simulation results [140, 141]. In each time slot, an SU harvests k packets each carrying one unit of energy with an arrival-rate vector $\lambda_h = [\lambda_{h1}, \lambda_{h2} \cdots, \lambda_{hN}]$, hence $\mathbf{e}_h = \lambda_h$.

In Fig. 5.5, we show the $N_{\min}$ that attains an energy-unconstrained CR system with a

Figure 5.4: The plots of expected SU throughput versus normalized mean energy arrival at SU 1. $p_1 = 0.7$, $\mathbf{p}_f = [0.08, 0.06, 0.1, 0.24]$ and $\mathbf{p}_d = [0.7, 0.65, 0.6, 0.8]$.

Figure 5.5: The plots of $N_{\min}$ versus normalized mean energy arrival at each SU. $p_f = 0.1$, $p_d = 0.6$, and $p_1 = 0.8$.

Figure 5.6: The plots of expected SU throughput versus normalized mean energy arrival at each SU. $p_f = 0.1$, $p_d = 0.6$, $p_1 = 0.8$, and $\bar{P}_c = 0.05$.

sufficient number of SUs to provide the required Q_d for a homogeneous case for any given e_h and $\bar{P}_c$ values. We observe that for a smaller value of e_h of each SU, a larger number of cooperative SUs is needed to achieve an unconstrained system. As e_h is increased, an SU can afford a higher p_s . Thus, a smaller N is sufficient. Also, for smaller values of $\bar{P}_c$, a higher $N_{\min}$ is required to satisfy the stricter PC constraint. In Fig. 5.7, we observe that with a greater probability of the PU being busy, the requisite $N_{\min}$ values are greater or equal to that in Fig. 5.5 to meet the higher Q_d requirement.

In Fig. 5.6, we plot the maximum R'_s achieved by using the suboptimal WP scheme for a homogeneous system. It depicts that for lower values of e_h , a cooperative CR system with a greater N obtains a higher throughput. As e_h is increased, the SUs are no longer under the EC constraint and even with smaller values of N it can achieve the optimum R'_s . Figure 5.5 shows $N_{\min} = 2$ for $\bar{P}_c = 0.05$. Hence, we can observe in Fig. 5.6 that for $N = 1$, R'_s is severely limited by the PC constraint even for higher e_h values. Also, for $e_h = 0.2e$, all plots for $N < 5$ are under the EC constraint. We

Figure 5.7: The plots of $N_{\min}$ versus normalized mean energy arrival at each SU. $p_f = 0.1$, $p_d = 0.6$, and $p_1 = 0.7$.

observe that for lower values of e_h , even for an unconstrained system, the achieved R'_s is slightly less and it increases as e_h is increased. This is because for a low e_h , a greater number of SUs cooperate to achieve an unconstrained system which increases Q_f . As e_h is increased, the SUs can afford higher p_s values. Thus, fewer SUs can sense with higher probabilities to achieve greater R'_s with a reduced Q_f .

In Fig. 5.8, we observe that initially, R'_s increases as p_d is increased and attains a constant value later. This is because initially, when the SUs cannot provide the required Q_d , PC constraint is satisfied by diminishing SU transmission probability. Hence, the system throughput is limited by the PC constraint. As p_d is increased, the SUs can provide greater Q_d values and PC constraint gets more relaxed. As it is further increased, the homogeneous CR system is no longer under the PC constraint and attains a constant throughput value. It can be observed in Fig. 5.7 that for $\bar{P}_c = 0.05$ and $e_h = 0.2e$, $N_{\min} > 5$. Therefore, as p_d is increased, though the system is no longer under the PC constraint, it is still limited by the EC constraint and the constant throughput value is

Figure 5.8: The plots of expected SU throughput versus probability of detection at each SU. $p_f = 0.1$, $e_h = 0.2e$, and $p_1 = 0.7$.

determined to achieve the tradeoff among the SU activation probability, Q_f and Q_d . For a stricter PC constraint with $\bar{P}_c = 0.02$, the SUs need a greater p_d to achieve the required Q_d to overcome the PC constraint. Similarly, for $N = 3$, a greater p_d is needed to obtain the required Q_d with a smaller number of cooperative SUs. Also, the CR system, which has a smaller number of SUs to pool in their energies, will be more energy-constrained. Hence, the constant throughput value attained by the CR system for $N = 3$ is lesser than that obtained for $N = 5$ case.

5.6 Conclusion

In this chapter, we have studied an energy-harvesting CR system which employs cooperation to enhance PU detection and SU throughput. An optimal sensing policy has been determined which optimally exploits the diversity in the cooperative SUs to maximize the SU throughput while satisfying the PC constraint and the EC constraints at the SUs. An optimum balance is found among average Q_d , Q_f , and the probability

of having an active SU to transmit with the available harvested energy. Numerical results have been provided to depict the improvement in both the PU detection and the spectrum utilization of the CR system achieved by the optimal and cooperative use of the energy available at each SU by employing the proposed optimal policy. In fact, for a homogeneous scenario, we obtained the minimum number of cooperative SUs required to achieve an unconstrained CR system for a given energy-arrival rate and PU protection level.

Chapter 6

Dynamic Cooperative Sensing-Access Policy

In the previous chapter, we studied a cooperative energy-harvesting cognitive radio (CR) system. An optimal probabilistic sensing policy was obtained for the secondary users (SUs) to maximally utilize the spectrum opportunities in an independent and identically distributed primary user (PU) channel. Moreover, the benefit of SU cooperation in overcoming the energy-causality and PU collision constraints was demonstrated. In this chapter, we adopt a Markovian PU traffic model to consider the temporal correlation in the PU channel occupancy states. We present a dynamic policy for the SUs which utilizes the information about available energy levels at the SUs and the possible PU channel occupancy state to optimally schedule the sensing and access actions for each time slot.

6.1 Introduction

For a successful deployment of CR systems, the SUs, which enhance spectrum efficiency by opportunistically accessing the licensed spectrum, must monitor and protect the PUs from SU interference. Cooperative spectrum sensing utilizes the spatially distributed SUs to achieve robust PU detection in adverse channel conditions [25]. For energy-efficient CR networks employing cooperative sensing, the SU detection thresholds, fusion-rule threshold, and censoring and sleeping parameters were optimized for a single-channel case [11, 47, 49]. In [48], cooperative sensing scheduling (CSS) policy was obtained for a multichannel system to choose which SUs should sense a channel and their sensing durations. Moreover, the CSS problem was studied using a partially observable Markov decision process (POMDP) and discrete convex framework in [142] and [143], respectively. In a multichannel system, where SUs harvest RF energy from PU transmissions, optimal channel-access policies were obtained for the SUs cooperating in a round-robin and a decentralized manner [20]. In a similar RF energy harvesting CR system, SU detection thresholds were optimized for cooperative sensing [144]. Different from these related works, we study the optimal sensing and access policies for a cooperative energy-harvesting CR system considering the diversity and uncertainty in the energy available at the SUs.

We have a heterogeneous CR system with varied received PU signal-to-noise ratio (SNR) and energy-arrival processes at the SUs. In an energy-harvesting CR system, an SU may not always be able to sense and access the spectrum due to lack of energy. We propose a cooperative sensing-access policy for an energy-harvesting CR system. Under this energy-uncertainty, cooperation among the SUs to sense and access the PU channel can improve both the PU detection and opportunistic spectrum utilization. We employ centralized cooperative spectrum sensing with OR fusion rule. A dynamic

sensing-access policy is determined to optimally employ the heterogeneous SUs with finite batteries to maximize the spectrum-access opportunities over a finite-time duration while guaranteeing the necessary protection level for the PU. In each time slot, the optimal policy is used to make a decision on whether to sense the spectrum, the set of sensing SUs, sensing detection threshold, and which SU gets to access the idle spectrum. We employ the finite-horizon POMDP model to derive the optimal policy to obtain the maximum expected SU throughput achieved over a finite duration while satisfying the PU detection (PD) and the energy causality (EC) constraints. It is used to decide the optimal action based on the belief about the PU channel state, energy available at each SU, and the remaining duration. Furthermore, we attempt to provide some insights into the tradeoff involved in choosing the optimal action. It is more energy efficient to select fewer SUs with higher probabilities of detection, either due to a higher received PU SNR or by choosing a lower sensing threshold, in order to achieve the required PU detection but they may not always possess sufficient energy to operate. Also, for an enhanced throughput, it is optimal to choose a smaller number of SUs to sense with lower probabilities of false alarm by selecting a higher sensor-detection threshold. The greater overall probabilities of false alarm and detection diminish the SU transmission but reduces the energy consumption. Hence, the sensing decision involves finding an optimal combination of SU sensors and the sensing threshold to achieve the optimal overall probabilities of false alarm and detection to obtain the maximum expected SU throughput with the available energy. For the access decision, it may not be optimal to transmit in a time slot in order to save the possible energy wastage due to the occurrence of a PU collision. The decision depends on the probability of channel being busy, the energy-arrival rate at the SUs, and the energy consumed in sensing and access operations. We also present a myopic policy, a low complexity scheme which maximizes only the immediate gain. Simulation results have been provided to illustrate the effect

of the energy-arrival rates, battery size, and PD constraint on the expected throughput of the CR system.

6.2 System Model

The system consists of a licensed channel occupied by a PU transmitter. For the i -th time slot, the PU channel occupancy state is denoted by $c_i \in C = \{0, 1\}$, where 0 and 1 represent busy and idle channels, respectively. The PU traffic is assumed to be a discrete-time Markov chain [10, 17, 98, 142], and the state transition probability $\Pr(c_i = c' | c_{i-1} = c)$ is denoted as $P_{cc'}$. The stationary probability of channel being occupied is $p_0 = P_{10} / (P_{10} + P_{01})$ and it is idle with the probability $p_1 = 1 - p_0$. The Markovian model enables us to exploit the temporal correlation in the PU traffic for improving the SU performance [17]. There are N SUs that cooperate in spectrum sensing and access. The SUs do not have a dedicated power supply and use energy-harvesting technique to recharge their batteries. Each SU has a battery with a capacity of B units. The energy-arrival process at the n -th SU is assumed to be a sequence of independent random variables $E_{n,i}^h$, which follow the Bernoulli distribution model [96, 98]. In each time slot, the SUs can harvest energy $\bar{e} = (e_s + e_t)$ with harvesting-probabilities $\mathbf{p}_h = [p_{h1}, p_{h2}, \dots, p_{hN}]$, where e_s and e_t denote the energy levels consumed by an SU for sensing and transmission in a time slot, respectively.

A time slot of total length T consists of sensing time τ_s , time r for each SU to report to a central controller (CC) in a time division multiple access (TDMA) framework, and the remaining time for transmission [47]. As shown in Fig. 6.1, in the beginning of each time slot, CC broadcasts the information about the chosen SU sensors and the detection threshold. The selected SUs perform sensing by energy detection while others remain idle. It is assumed that the SUs can simultaneously harvest energy whether in

Figure 6.1: Framework for each time slot of a cooperative energy-harvesting CR system.

the sensing or idle state, and the energy arrival at any SU always starts at the beginning of the time slot. After sensing, in the reporting phase, there is a 2-bit transmission to the CC; the sensing SUs send their 1-bit sensing decisions and all the SUs that are receiving energy send 1 bit in their respective TDMA slots. The time to transmit the control information is assumed to be negligible. Also, it is assumed that the e_s and $\bar{e}$ values are obtained after including and deducting the energies consumed in reporting the sensing and energy information, respectively.

The system state is given by $(c_i, \mathbf{e}_i)$. The energy available at the SUs in the i -th time slot $\mathbf{e}_i = [e_{1,i}, \dots, e_{N,i}]$ is known to the CC but the PU channel state is only partially observable through spectrum sensing so we employ a POMDP framework to determine the optimal decision making policy. In the i -th time slot, the CC takes sensing decision $\mathbf{x}_i$: whether to sense the spectrum and the set of sensing SUs; sensing detection threshold ε_{th} ; and access decision ϕ_i : which SU accesses the vacant spectrum. All the SUs are assumed to have the same ε_{th} . Detection-threshold optimization is realized by selecting a common probability of false alarm p_{fi} from a set of discrete values P_f [142]. The action vector for the i -th time slot is given by $\mathbf{a}_i = (\mathbf{x}_i, \phi_i, p_{fi})$. The channel between an SU and the PU transmitter is affected by additive white Gaussian noise. We adopt a scenario with a complex-valued phase-shift keying PU signal with average received SNR γ_n^p at the n -th SU and circularly symmetric complex Gaussian noise. In the i -th time

slot, the probability of detection for the n -th SU $p_{dn,i}$ for a given value of p_{fi} is given by [35]

$$p_{dn,i} = \mathcal{Q} \left(\left(\mathcal{Q}^{-1}(p_{fi}) - \gamma_n^p \sqrt{\tau_s f_s} \right) \frac{1}{\sqrt{2\gamma_n^p + 1}} \right) \quad (6.1)$$

where f_s is the sampling rate. All the SUs are assumed to have the same channel gain for transmission. For sensing action $\mathbf{x}_i = [x_{1,i}, x_{2,i}, \dots, x_{N,i}]$, the permissible sensing action for the n -th SU $x_{n,i} \in X_{n,i}(e_{n,i})$ depends on its energy state.

$$X_{n,i}(e_{n,i}) = \begin{cases} \{0, 1\} & e_{n,i} \geq e_s \\ \{0\} & \text{otherwise.} \end{cases} \quad (6.2)$$

The set of admissible sensing actions for the CC is given by $X_{1,i}(e_{1,i}) \times \dots \times X_{N,i}(e_{N,i})$, which takes care that only the SUs that have sufficient energy levels to sense can be chosen for sensing [10]. All the SUs with $x_{n,i} = 1$ are selected to perform sensing in the i -th time slot. The sensing SUs send their decisions to the CC. It makes the final decision on the channel state using the OR fusion rule, i.e., the channel is decided to be busy if one or more SUs detect the PU signal. The sensing outcome for the i -th time slot is denoted by $\theta_i \in \{-1, 0, 1\}$ where -1 , 0 , and 1 represent no sensing, busy channel, and idle channel, respectively. Based on the sensing decision, the overall probability of false alarm (Q_{fi}) and probability of detection (Q_{di}) for the cooperative CR system are given by [11]

$$Q_{fi}(\mathbf{a}_i) = 1 - \prod_{n=1}^N (1 - p_{fi} x_{n,i}) \quad (6.3)$$

and

$$Q_{di}(\mathbf{a}_i) = 1 - \prod_{n=1}^N (1 - p_{dn,i} x_{n,i}), \quad (6.4)$$

respectively. A low Q_{fi} is desirable to discover greater spectrum opportunities whereas a high Q_{di} is required to prevent misdetection of the PU, which causes interference to

the PU transmission and wastage of the SU transmission energy. The SUs cannot access the spectrum if it is detected to be occupied by the PU. When the spectrum is decided to be vacant, the CC chooses an SU among the sensing SUs to transmit which is given by the access decision $\phi_i \in \Phi_i(\theta_i, \mathbf{e}_i)$, and

$$\Phi_i(\theta_i, \mathbf{e}_i) = \begin{cases} \{0\} & \theta_i \in \{-1, 0\} \\ \{0, \{nI_{e_{n,i} \geq e_s + e_t} | x_{n,i} = 1\}\} & \theta_i = 1 \end{cases} \quad (6.5)$$

where I_y is the indicator function which attains a unit value when y is true. Thus, the action vectors take care of the EC constraint, which mandates that the SU cannot consume more energy than the available energy level [17]. The energy available with the n -th SU at the beginning of the $(i + 1)$ -st slot is given by

$$e_{n,i+1} = \min(e_{n,i} - e_{n,i}^c(\mathbf{a}_i) + E_{n,i}^h, B) \quad (6.6)$$

where $e_{n,i}^c(\mathbf{a}_i) = e_s x_{n,i} + I_{\phi_i=n} e_t$ is the energy consumed by the n -th SU in the i -th time slot. The energy state transition probability $\Pr(\mathbf{e}_{i+1} = \mathbf{e}' | \mathbf{e}_i = \mathbf{e}, \mathbf{a}_i)$ of the SUs is given by

$$P_{\mathbf{e}\mathbf{e}'} = \prod_{n=1}^N P_{e_n e'_n}, \quad (6.7)$$

where $P_{e_n e'_n}$ is the probability of energy-state change for the n -th SU, given by [98]

$$P_{e_n e'_n} = \begin{cases} p_{hn} & e'_n = \min(e_n - e_{n,i}^c(\mathbf{a}_i) + \bar{e}, B), \\ 1 - p_{hn} & e'_n = e_n - e_{n,i}^c(\mathbf{a}_i). \end{cases} \quad (6.8)$$

When the PU channel is found to be vacant, the SU chosen by the CC using the optimal policy transmits during that time slot. On successful transmission, the receiver broadcasts an acknowledgment (ACK) on the common control channel which is denoted

by ψ_i and is assumed to be always received without error. The observation in the i -th time slot, $Z_i : (\theta_i, \psi_i)$, can be explained by the following four cases [17, 142]:

- $Z_i = 1 : (\theta_i = -1, \psi_i = 0)$. CC decides not to sense due to energy shortage or otherwise.
- $Z_i = 2 : (\theta_i = 1, \psi_i = 1)$. When the channel is decided to be idle and an ACK is received indicating a successful transmission.
- $Z_i = 3 : (\theta_i = 1, \psi_i = 0)$. The channel is decided to be idle but no ACK is received. It may happen either due to a missed detection or if the CC decides not to access the spectrum due to energy shortage or otherwise.
- $Z_i = 4 : (\theta_i = 0, \psi_i = 0)$. When the channel is decided to be busy and there is no spectrum access.

The probability of observation at the CC $\Pr(Z_i = z | c_i = c, \mathbf{e}_i = \mathbf{e}, \mathbf{a}_i)$ is given by

$$P_z(c, \mathbf{e}, \mathbf{a}_i) = \begin{cases} I_{\mathbf{1}, \mathbf{x}_i=0} & z = 1 \\ I_{\mathbf{1}, \mathbf{x}_i \neq 0} I_{\phi_i \neq 0} \bar{Q}_{fi}(\mathbf{a}_i) c & z = 2 \\ I_{\mathbf{1}, \mathbf{x}_i \neq 0} (\bar{Q}_{di}(\mathbf{a}_i) \bar{c} + I_{\phi_i=0} \bar{Q}_{fi}(\mathbf{a}_i) c) & z = 3 \\ I_{\mathbf{1}, \mathbf{x}_i \neq 0} (Q_{fi}(\mathbf{a}_i) c + Q_{di}(\mathbf{a}_i) \bar{c}) & z = 4 \end{cases} \quad (6.9)$$

where $\bar{y} = (1 - y)$ and $\mathbf{1}$ is a unit vector. The observation obtained in each time slot is used to decide about the instantaneous reward and belief state update. For $Z_i = z$, the immediate throughput reward $R_i(z)$ for the i -th time slot is given by

$$R_i(z) = \begin{cases} k_\tau = \frac{T - \tau_s - Nr}{T} & z = 2, \\ 0 & \text{otherwise.} \end{cases} \quad (6.10)$$

The PU channel state is not known to the CC. It maintains a belief state vector denoted by $\mathbf{b}_i = [b_{0,i} b_{1,i}]$ [145]. The probability that the PU is in state c given all the action and observation history is given by $b_{c,i} = \Pr(c | \mathbf{a}_j, Z_j, \forall j \in [1, i])$. At the end of the i -th slot, the Bayes' rule is used to obtain the updated belief state $\mathbf{b}_i = \mathcal{T}(\mathbf{b}_{i-1}, Z_i = z, \mathbf{a}_i)$ at the CC, which is given by

$$b_{1,i} = \begin{cases} \sum_{c \in C} b_{c,i-1} P_{c1} & z = 1 \\ 1 & z = 2 \\ \frac{\sum_{c \in C} b_{c,i-1} P_{c1} \bar{Q}_{fi}(\mathbf{a}_i) I_{\phi_i=0}}{\sum_{c \in C} b_{c,i-1} (P_{c1} \bar{Q}_{fi}(\mathbf{a}_i) + P_{c0} \bar{Q}_{di}(\mathbf{a}_i))} & z = 3 \\ \frac{\sum_{c \in C} b_{c,i-1} P_{c1} Q_{fi}(\mathbf{a}_i)}{\sum_{c \in C} b_{c,i-1} (P_{c1} Q_{fi}(\mathbf{a}_i) + P_{c0} Q_{di}(\mathbf{a}_i))} & z = 4. \end{cases} \quad (6.11)$$

6.3 Optimal Sensing-Access Policy

The aim is to achieve an optimal sensing-access scheduling of the cooperating SUs to maximize the opportunistic spectrum utilization. The optimization problem that obtains the optimal policy to maximize the expected SU throughput over a finite duration H while satisfying the EC and PD constraints is as follows:

$$\max_{\{\pi_i\}} R_s = \mathbb{E} \left[\sum_{i=1}^H R_i(z) \mid \hat{\mathbf{b}} \right] \quad (6.12)$$

$$\text{s.t. } (1 - Q_{di}(\mathbf{a}_i)) I_{1.\mathbf{x}_i \neq 0} \leq P_{md} \quad \forall i \quad (6.13)$$

where π_i is the sensing-access policy to be used when $H - i$ time slots are remaining, P_{md} is the maximum probability of PU misdetection allowed, and $\hat{\mathbf{b}}$ is the initial belief vector which can be set to be the stationary distribution of the PU channel if not known.

The value function which is used to evaluate the optimal policy is given by [96, 98, 146]

$$\begin{aligned}
 V_i(\mathbf{b}_{i-1}, \mathbf{e}_i) = & \max_{\mathbf{a}_i} \sum_{c \in C} b_{c,i-1} \sum_{c' \in C} P_{cc'} \sum_{z=1}^4 P_z \left(R_i(z) \right. \\
 & \left. + \sum_{\mathbf{e}'} P_{\mathbf{e}\mathbf{e}'} V_{i+1}(\mathcal{T}(\mathbf{b}_{i-1}, z, \mathbf{a}_i), \mathbf{e}') \right)
 \end{aligned} \tag{6.14}$$

where $\mathbf{e}'$ denotes the updated $\mathbf{e}_{i+1}$ based on $E_{n,i}^h$ and $\mathbf{a}_i$ as per (6.6). The above value function maximizes the expected reward for the i -th time slot and the remaining $H - i$ time slots starting with the belief $\mathbf{b}_{i-1}$ and energy $\mathbf{e}_i$.

We employ a dynamic-programming approach using the incremental pruning (IP) algorithm [147] to obtain the optimal policy. The value function for a finite-horizon case is proved to be a piece-wise linear convex (PWLC) function of the belief state vector [145]. The value function that maximizes the expected throughput starting from the i -th time slot can be represented as

$$V_i(\mathbf{b}_{i-1}, \mathbf{e}_i = \mathbf{e}) = \max_{\mathbf{a}_i} \mathbf{b}_{i-1} \cdot \alpha_{i,\mathbf{e}}^{\mathbf{a}}, \tag{6.15}$$

where $\alpha_{i,\mathbf{e}}^{\mathbf{a}}$ is a policy vector of size $1 \times |c|$ corresponding to an action $\mathbf{a}$ and available energy $\mathbf{e}$, and $|y|$ denotes the number of possible values of y . We need to obtain the set of optimal policy vectors $\alpha_{i,\mathbf{e}}^{\mathbf{a}}$ for each possible energy vector and the number of remaining time slots. The optimal sensing-access decision $\mathbf{a}_i$ is the action corresponding to the policy vector that maximizes the value function for the current belief state $\mathbf{b}_{i-1}$. Based on the IP algorithm, the new $\alpha_{i,\mathbf{e}}^{\mathbf{a}}$ vectors are obtained using the optimal $\alpha_{i+1,\mathbf{e}'}^{\mathbf{a}}$. The updated policy vector for time i , action $\mathbf{a}$, observation z , and next energy state $\mathbf{e}'$ from $\mathbf{e}$ is given by

$$u_{\mathbf{a},z,\mathbf{e}'}(c) = \sum_{c'} P_{cc'} P_z(c', \mathbf{e}, \mathbf{a}) \left(\frac{R_i(z)}{|\mathbf{e}'|} + P_{\mathbf{e}\mathbf{e}'} \alpha_{i+1,\mathbf{e}'}^{\mathbf{a}}(c') \right) \tag{6.16}$$

We use the IP algorithm to obtain the minimum-size set of optimal policy vectors that maximizes the value function over the entire belief space. The averaging over next-slot energy states introduces an additional cross-sum of the set of optimal vectors $\mathbf{u}_{\mathbf{a},z,\mathbf{e}'}$ obtained for all possible next energy states to get the policy vectors for each $(\mathbf{a}, z)$, which is followed by the general steps in [147]. The optimal policy vectors and their corresponding actions are saved as the optimal policy for the i -th time slot and energy $\mathbf{e}$.

Next, we propose a myopic policy, which is aimed at maximizing the immediate reward and does not consider the throughput performance in the future time slots. The value function for the myopic policy can be expressed as:

$$V_i^m(\mathbf{b}_{i-1}, \mathbf{e}_i) = \max_{\mathbf{a}_i} (1 - Q_{fi}(\mathbf{a}_i)) k_\tau \sum_{c \in C} b_{c,i-1} P_{c1}. \quad (6.17)$$

The optimal action is found by maximizing the above value function while satisfying the constraints in (6.13). Hence, the myopic action is the sensing action $\{\mathbf{x}_i, p_{f,i}\}$ which achieves the minimum Q_{fi} among the finite set of possible actions allowed by the EC and PD constraints. If the PU channel is found idle, the CC chooses an SU at random from among the sensing SUs that have sufficient energy to access the spectrum.

6.3.1 Insights Into Optimal Policy

The CC can take three types of actions: 1) No sensing, 2) Sense and access the spectrum if it is observed to be idle, and 3) Sense but not to access the spectrum.

Lemma 1 *The updated belief about idle state, corresponding to different observations z in the i -th slot, in the descending order is given as: $b_{1,i|z=2} \geq b_{1,i|z=3,\phi_i=0} \geq b_{1,i|z=1} \geq b_{1,i|z=4} \geq b_{1,i|z=3,\phi_i \neq 0}$.*

Figure 6.2: Optimal policy versus $e_{1,i}$ and $b_{1,i-1}$. $\mathbf{e}_i = [e_{1,i}, 3, 4]$, $\mathbf{p}_h = [0.05, 0.2, 0.5]$, $i = 1$. Unshaded region represents action 1. Dark and gray regions represent action 2 with the minimum $Q_{f,i}$ achievable under the constraints and a greater $Q_{f,i}$, respectively.

Proof: It can be observed from (6.11) that the above statement is true for $Q_{di} > Q_{fi}$ which is a reasonable assumption for a functional CR system. ■

Proposition 5 For a given belief state $\mathbf{b}$, the value function $V_i(\mathbf{b}, \mathbf{e}_i)$ is non-decreasing in $\mathbf{e}_i$, i.e., for $\tilde{\mathbf{e}} \geq \mathbf{e}$ (component-wise), we have $V_i(\mathbf{b}, \tilde{\mathbf{e}}) \geq V_i(\mathbf{b}, \mathbf{e})$.

Proof: An SU with a greater energy can always pretend to have a lower energy [10]. Hence, the CR system with a greater $\mathbf{e}_i$ can never perform lower than a smaller $\mathbf{e}_i$ case. ■

Proposition 6 For a given $\mathbf{e}$, the value function $V_i(\mathbf{b}_i, \mathbf{e})$ is non-decreasing in $b_{1,i}$ for $P_{11} \geq P_{01}$, i.e., for $\tilde{b}_1 \geq b_1$, we have $V_i(\tilde{\mathbf{b}}, \mathbf{e}) \geq V_i(\mathbf{b}, \mathbf{e})$.

Proof: Please refer to the Appendix B. ■

The choice among the three actions presents a tradeoff among immediate throughput gain, acquiring more sensing information, and managing the harvested energy [10, 17].

Action 2 presents an opportunity for the SU for a throughput gain. On receiving an ACK, the PU idle state is confirmed, which promises better expected future rewards due to a higher $b_{1,i}$, using Lemma 1 and Proposition 6. However, energy is consumed for sensing and transmission which may result in lower future rewards as compared to other actions using Proposition 5. By adopting action 3, the SU can acquire sensing information but it consumes energy for sensing. Additionally, it saves the SU energy used for transmission and energy wastage due to a possible misdetection. Under action 1, the SU does not spend any energy but it obtains no throughput or sensing information gains. An optimal action is chosen for each time slot based on the available energy levels at the SUs and the current belief state information. It is favorable to choose to sense and access when there is a higher belief of being in the idle state as observed in Fig. 6.2 [10, 96]. In [142], the value function for the cooperative sensing case was shown to be decreasing in Q_{fi} , but with the additional energy-harvesting consideration, it may not be true as greater $Q_{f,i}$ and $Q_{d,i}$ save some transmission energy too. Also, depending on the energy-arrival rates, the SUs with higher PU SNR cannot always sense to attain the minimum Q_{fi} . Optimal scheduling is done considering the EC constraints as shown in Fig. 6.2.

6.4 Simulation Results and Discussions

The parameter values given in Table 6.1 are used to generate the simulation results unless otherwise specified. In Fig. 6.3, the throughput performance of the cooperative CR system achieved by using the optimal dynamic policy is compared with the other schemes, namely, myopic policy and random policy. The proposed policy that optimally utilizes the heterogeneous SUs is found to obtain a greater throughput than the others. In myopic policy, only the immediate reward is considered while the future performance

Table 6.1: Parameter values for simulation results.

Parameter	Value	Description
N	3	Number of SUs
H	10 time slots	Time horizon
B	10 units	SU battery capacity
P_{11}, P_{01}	0.8, 0.4	PU state transition probabilities
T	100 ms	Slot length
τ_s, r	4 ms, 1 μ s	Sensing period, and reporting time
e_s, e_t	1 unit, 3 units	SU sensing and transmission energies
γ^p	$[-19\text{dB}, -18\text{dB}, -20\text{dB}]$	Received PU SNR
$\mathbf{p}_h$	$[0.05, 0.2, 0.5]$	Energy-harvesting probability vector
P_f	$\{0.07, 0.11, 0.15\}$	Set of probability of false alarm values
f_s	6 MHz	Sampling frequency
P_{md}	0.1	Probability of PU misdetection limit

 Figure 6.3: The plots of expected SU throughput versus time horizon: (solid-line) $\mathbf{p}_h = [0.05, 0.2, 0.5]$, and (dashed-line) $\mathbf{p}_h = [0.05, 0.2]$ and $\gamma^p = [-19\text{dB}, -18\text{dB}]$.

is disregarded. Hence, a lower SU throughput is achieved. The SU performance for the myopic policy is close to that for the optimal scheme and it can be used as a low-complexity suboptimal policy. The SUs perform the worst by using the random policy, where an action is chosen randomly among the permissible actions that satisfy the PD and EC constraints. On comparing with the dashed-line plot for $N = 2$, it is demonstrated that the cooperation of a greater number of SUs though may reduce the transmission time but enhances the spectrum utilization in this energy-limited system. It is observed that the SU throughput decreases as the PD constraint becomes stricter for smaller P_{md} values. This is because a higher Q_{di} value is required to satisfy the PD constraint. It can be achieved either by increasing the number of sensing SUs and/or by increasing the sensing detection threshold which may result in a greater energy consumption for sensing and/or higher Q_{fi} . Moreover, if the available SUs cannot achieve the required PU protection then the SUs are not allowed to sense the spectrum for that time slot. With an enhanced PU protection requirement such instances also occur more often degrading the expected SU throughput.

In Fig. 6.4, we observe that the SU throughput increases as p_{h1} is increased. This is because with more energy arriving, there is a lesser need for the SUs to sleep and save energy. Also, the instances of energy shortage at the SUs decrease and they are capable of operating more often. The dashed-line plots correspond to a homogeneous case where the performance gain of the optimal policy over the myopic policy is because of the optimal sleeping strategy for the SUs. As p_{h1} is increased, initially, the performance improvement increases since the proposed dynamic policy can be used to optimally utilize the greater energy supply to achieve a higher throughput. However, with increasing p_{h1} , the energy shortage is reduced and there is a lesser need to sleep and save energy. Hence, the incremental performance gain starts to decrease. In heterogeneous systems, the performance gain is contributed by two factors, i.e., the optimal exploitation of the

Figure 6.4: The plots of expected SU throughput versus the probability of harvesting energy for SU 1. (dashed-line) homogeneous system with $p_{hn} = p_{h1}$ and $\gamma_n^p = -19\text{dB}$, (solid-line) $\mathbf{p}_h = [p_{h1}, 0.2, 0.5]$, and (dashed-dotted-line) $\mathbf{p}_h = [p_{h1}, 0.3, 0.1]$.

diversity and the optimal sleeping strategy. The proposed policy exploits the diversity in γ_n^p and p_{hn} values and optimally utilizes the available energy to maximize the expected SU throughput. As p_{h1} is increased, the performance gain between the two policies may decrease, since there is a lesser need to sleep, but it may increase if the increased p_{h1} enhances the diversity of the energy-constrained CR system. For the solid-line plots, for $p_{h1} < 0.5$, the gain decreases with p_{h1} due to the decrease in energy shortage. As it is further increased, i.e., for $p_{h1} > 0.6$, the performance gain starts to increase because SU 1, which has a better PU SNR than SU 3, can operate more often. Thus, a higher throughput performance due to lower Q_{fi} values adds to the observed performance improvement. The dashed-dotted-line plots correspond to a case where other SUs have low p_{hn} values therefore the diversity gain increases as p_{h1} is increased.

In Fig. 6.5, it is depicted that the SU throughput increases as B is increased because the SUs can store more energy which can be used for future sensing and transmission operations. We observe that unlike the battery-limited scenario, in an energy-harvesting

Figure 6.5: The plots of expected SU throughput versus SU battery capacity: (dashed-line) $\mathbf{p}_h = [0.8, 0.2, 0.5]$, (solid-line) $\mathbf{p}_h = [0.05, 0.2, 0.5]$, and (dashed-dotted-line) $\mathbf{p}_h = [0.05, 0.08, 0.12]$.

system, the SUs do not require very large batteries as there is a minimal increase in the throughput performance from $B = 10$ to $B = 12$ for solid-line plots. Different instances with lower and higher energy-arrival rates have been provided to show that the sufficient battery capacity required and the gain achieved in the SU throughput with an increase in B are affected by the energy-arrival rates of the SUs. For the dashed-line plots, corresponding to a higher $p_{h,1}$, a lesser throughput improvement is observed from $B = 6$ to $B = 8$ as compared to that in solid-line plots. Hence, for higher energy-arrival rates at the SUs, a smaller battery is good enough because with more frequent energy-arrivals the SUs do not need to store a lot of energy. For the dashed-dotted-line plots, which correspond to the case with very low $p_{h,n}$ values, it is shown that even for small energy-arrival rates, the SUs do not benefit much from a larger battery. There is not much energy to be stored as the energy supply is already quite low as compared to the demand.

6.5 Conclusion

A dynamic sensing-access policy has been proposed for an energy-harvesting CR system. The diversity in the received PU SNR and the energy-arrival rates at the SUs has been exploited to schedule the SUs for cooperative sensing and access to obtain the optimal Q_{fi} and Q_{di} values by maximizing the expected SU throughput over a finite duration while meeting the PD and EC constraints. Simulation results have been presented to depict that the proposed policy can be used to achieve better performance than the myopic and random policies. Moreover, it has been shown that the SUs do not always need to possess large batteries. The sufficient battery capacity depends on the energy-arrival rates relative to the energy consumption at the SUs.

Chapter 7

Conclusion and Future Work

This thesis is focused on the optimization of energy-harvesting cognitive radio (CR) systems. Energy-harvesting CR is a wonderful tool that promises an enhanced spectrum efficiency and the much desirable self-sustainability for the proliferating wireless devices. We have addressed some of the challenges offered by the random nature of the energy-arrival process in the absence of a dedicated power source. Optimal sensing and access policies have been proposed for different scenarios of CR systems by considering the uncertainty in the energy availability and preventing unwanted secondary user (SU) interference at the the primary users (PUs). Specifically, we have explored the optimization of SU performance in the opportunistic RF energy-harvesting paradigm. Moreover, cooperative policies for general energy-harvesting CR systems have been proposed. In the following, we summarize the major contributions and inferences from our study on energy-harvesting CR systems.

1. Firstly, an opportunistic RF energy harvesting CR system has been investigated in a multichannel PU system using stochastic geometry. The SUs harvested RF energy from PU transmissions to recharge their batteries. At any time, SUs either

exploited the spatio-temporal spectrum opportunities for transmission or the PU active periods for harvesting energy. The PU channels, with different PU densities, were heterogeneous in terms of the spectrum-access and harvesting opportunities. The channels with high PU density should be sensed more often in order to harvest more energy. Sensing the low PU density channels provided the SUs with greater chances to transmit in the long term. We have analyzed the tradeoff between the spectrum-access and energy-harvesting opportunities. A decentralized channel-access strategy has been proposed for this interesting scenario. Optimal channel-selection probability vector has been obtained that achieved greater spectrum-access opportunities and adequate energy supply to maximize the SU throughput while accounting for SU contention. We have proposed the expected throughput maximization (ETM) scheme where the nonconvex optimization problem was decomposed to obtain a convex optimization subproblem, and an exhaustive search was required to solve the master problem. Alternatively, an iterative algorithm based combined metric maximization (CMM) scheme was proposed wherein we defined a combined metric to consider the spectrum-access and energy-harvesting opportunities on different PU channels. A convex optimization problem was solved with a closed-form solution in each iteration. Numerical results have been provided to show that the proposed ETM and CMM schemes can be used to achieve the optimal channel-selection probability vector that enabled the SUs to attain an appropriate tradeoff to maximize the SU throughput through an enhanced battery recharging probability. The performance achieved by using the proposed schemes was significantly higher than the spectrum opportunity maximization and uniform channel selection schemes. It has been highlighted that it is important to optimize both the spatio-temporal spectrum opportunities and the energy-harvesting opportunities to enable the SU to utilize the greater spectrum opportunities.

2. Secondly, the opportunistic RF energy-harvesting CR system has been studied by considering an unslotted PU system. The SU either harvested energy from the PU transmission or transmitted when the PU channel was found idle. Different sensing intervals have been proposed for the cases when SU decides to transmit or harvest energy in order to balance between energy harvesting and spectrum access. The harvesting and transmission durations have been optimized to attain the tradeoff between maximizing the spectrum utilization and harvesting adequate energy at the SUs. A closed-form expression has been determined for the probability of CR user being active. Optimal transmission and harvesting durations have been found to maximize the SU throughput while satisfying the PU collision constraint by considering the energy-arrival rate and the PU traffic pattern. Numerical results have been presented to depict the significant effect of mean PU busy and idle durations on the SU throughput and the performance gain achieved over the suboptimal scheme by exploiting the information on the PU traffic profile. Furthermore, the CR system capability has been enhanced by providing the SU an option to purchase energy from the PU during its idle periods apart from the energy harvested opportunistically. Optimal energy-trading and sensing-interval policies have been found to minimize the average energy cost spent in a time slot to achieve a given SU transmission rate while limiting the SU interference at the PU. Numerical results have been provided to demonstrate that a higher CR throughput can be attained by compromising on some of the spectrum opportunities to receive the needed energy by paying an extra cost as compared to that achieved for the case without considering energy trading.
3. Next, the SU spectrum-access and PU detection performance has been investigated by employing cooperation in an energy-harvesting CR system. We have considered a CR system where each SU can harvest energy and possesses a battery of infinite

capacity. Cooperative spectrum sensing with OR-fusion rule has been employed to enhance the sensing performance. The energy-constrained SUs operated cooperatively to enhance the SU spectrum utilization and PU detection performance. For SUs with different sensing environment and energy-arrival rates, an optimal sensing policy has been determined to optimally exploit the heterogeneous SUs to cooperate for maximizing the SU throughput while satisfying the energy-causality and PU collision constraints. SOSTOOLS has been employed to solve the polynomial optimization problem. Additionally, a suboptimal scheme has been proposed for larger systems. An optimum balance has been reached among the average overall probabilities of false alarm and PU detection, and the probability of having an active SU to transmit with the available harvested energy. Numerical results have been provided to show that the optimal policy, which obtains an optimal and cooperative scheduling of diverse SUs, can be used to improve both the PU detection and the spectrum utilization of the CR system. Moreover, under a homogeneous scenario, it has been shown that with a minimum number of SUs cooperating, the throughput performance of the SU system can overcome the energy-causality and PU collision constraints. We have obtained the minimum number of cooperative SUs required to attain an unconstrained CR system for a given energy-arrival rate and maximum tolerable PU interference, and its effect on the SU throughput and PU detection performance have been depicted using the numerical results.

4. Furthermore, a dynamic sensing-access policy has been proposed for the cooperative CR system by considering a discrete Markov chain based PU traffic model. Under the finite-horizon partially observable Markov decision process framework, the optimal cooperation has been obtained among the SUs for spectrum sensing and access to maximize the throughput while satisfying the PU detection constraint with the available energy. The diversity in the received PU power levels

and the energy-arrival rates has been exploited in scheduling the SUs for cooperative sensing and access to obtain the optimal overall probabilities of false alarm and PU detection in order to maximize the expected SU throughput over a finite duration. The central controller applied the sensing-access policy to decide whether to sense, the set of sensing SUs, the sensing detection threshold, and the SU that accessed the spectrum opportunities. The optimal policy achieved an optimum tradeoff among enhancing SU transmission, preventing energy shortage, and acquiring sensing information for the future gains. Simulation results have been provided to depict that the SUs can achieve a higher system performance by adopting the proposed policy, which uses an optimal sleeping strategy for the SUs and optimal exploitation of their diversity, than that obtained by using the myopic and random policies. It was shown that the SUs do not benefit from very large batteries when the energy supply is very low or high as compared to the energy consumed. Furthermore, we have analyzed the dependency of the expected SU throughput on the PU belief state and the available energy levels at the SUs at any time, providing insights into the tradeoff involved in choosing the optimal actions.

Some of the potential future research directions are as follows:

1. The opportunistic RF energy-harvesting scenario studied in Chapter 3 can be applied to an Internet-of-things (IOT) system. Cognitive radio is an important tool to satisfy the spectrum demands for a large number of connected devices and users in IOT paradigm [148, 149]. Employing energy-harvesting is indispensable to meet their increasing power needs [150, 151]. Low-power CR devices can be employed for sensing the desired information in an IoT system. They can opportunistically access the spectrum used by other network devices to transmit the sensed informa-

tion and can be made to operate only by harvesting the RF energy received from other communication devices transmitting nearby. In this IOT scenario, apart from the heterogeneity in the spectrum-access and energy-harvesting opportunities offered by the different PU channels, the energy-harvesting CR sensors also have diverse energy, channel bandwidth, and service quality requirements [152].

2. In Chapter 4, we have proposed a dual-sensing-interval policy for an energy-harvesting CR system in which the SU could either opportunistically access or harvest energy from an unslotted PU. In [23], an optimal wait-or-switch spectrum handoff policy was proposed for a multichannel unslotted PU network. Also, an adaptive sensing policy was studied to monitor the availability of out-of-band channels for a possible handoff. An optimal sensing frequency was determined for a sensor with a finite battery to optimize the long-term sensing performance [140]. A dynamic spectrum-sensing policy can be determined to choose the optimal sensing interval after each sensing epoch to further enhance the SU spectrum utilization and grab more harvesting opportunities based on the PU traffic pattern. The system model can further be expanded to a multichannel unslotted PU system to study the optimal handoff policy. It will significantly enhance the system complexity as in this opportunistic energy-harvesting CR system, the energy needs of the SU also need to be considered while making a decision on whether to stay on the current channel or switch to another channel when the PU returns. Also, during the channel-selection for handoff, both the spectrum-access and energy-harvesting opportunities and requirements need to be taken into account.
3. Recently, there has been much work on employing cooperation among SUs and PUs for mutual spectrum and energy assistance [116, 117, 119]. Most of them consider a slotted PU system. In Chapter 4, we optimized the energy-trading decision for

an opportunistic energy-harvesting SU coexisting in an unslotted PU system. At any time, when the PU channel was found idle, the SU could decide to purchase energy from the PU, instead of using it for transmission, by paying a cost for it. It will be interesting to analyze if cooperation between PU and SU can reduce the SU performance loss due to unslotted nature of the PU traffic. Game-theory approach can be utilized to analyze a scenario where the PU transmitter may either ask a nearby SU to relay its data to a faraway PU receiver and can transfer energy to the SU in the idle duration without charging any cost or if the receiver is closer and it has a better channel, it may not need a relay and can choose to charge the SU instead. On the other hand, the SU can decide to compromise on the energy that it could have harvested opportunistically during the PU busy period and spend its stored energy to relay the PU data. It can get a large energy for free in the next idle slot. Alternatively, it may be more interested to pay for the energy transfer if acting as a relay turns out to be more expensive in terms of the energy expenditure. However, it may experience collisions with PU during transmission and absence of PU during harvesting periods. For our single-antenna CR system, time-splitting technique can be utilized to receive and relay the PU data during the busy period and to receive energy transfer and transmit SU data during the idle period. In this regard, for an underlay CR multi-antenna system, a Stackelberg game was formulated to choose a non-cooperative mode to transmit while maintaining the interference at the PU or to cooperate to relay the PU data while receiving spectrum access and monetary benefits [119]. A dynamic energy-trading game was proposed to exploit the disparity in supply and consumption of energy among different energy-harvesting devices [132].

Appendix A

Derivation of Lagrange Multiplier

In this Appendix, based on the p_a expression in (3.20), we show that there exists a unique $\lambda \in (\lambda_{\min}, \lambda_{\max})$ which satisfies $f(\lambda) = \sum_{p_k > 0} p_k - 1 = 0$, where $\lambda_{\min} = \max(-a_k)$ and $\lambda_{\max} = \min(b_k - a_k)$. On substituting for p_k using (3.20), we get

$$f(\lambda) = \lambda^K + \sum_{i=1}^K a_i \lambda^{K-1} + \sum_{i < j}^K a_i a_j \lambda^{K-2} \dots + \prod_{i=1}^K a_i - c = 0$$

where $c = \bar{p}_I^{N p_a} \prod_{i=1}^K b_i$. For the polynomial $f(\lambda)$, we get

$$\lim_{\lambda \rightarrow \lambda_{\min}} f(\lambda) = +\infty. \quad (\text{A.1})$$

On substituting $\lambda_{\max}$, it can be expressed as

$$f(\lambda_{\max}) = \frac{1}{N p_a \ln(\bar{p}_I)} \sum_{k=1}^K \ln(x) - 1 \quad (\text{A.2})$$

where $x \leq 1$. Hence, $f(\lambda_{\max}) < 0$ for large N . Moreover, it can be observed that

$$\frac{df(\lambda)}{d\lambda} = \frac{1}{N p_a \ln(\bar{p}_I)} \sum_{i=1}^K \frac{1}{\lambda + a_i} < 0. \quad (\text{A.3})$$

Hence, $f(\lambda)$ is a strictly decreasing function with $f(\lambda_{\min}) > 0$ and $f(\lambda_{\max}) < 0$ which guarantees a unique root $\lambda \in (\lambda_{\min}, \lambda_{\max})$.

Appendix B

Proof of Proposition 6

The proof is by induction [10, 142]. It can be shown to be true for $i = H$, $\forall \mathbf{e}$. Let us assume that $\forall i + 1 < H$, $\forall \mathbf{e}$, for any $\tilde{b}_1 \geq b_1$, we have $V_{i+1}(\tilde{\mathbf{b}}, \mathbf{e}) \geq V_{i+1}(\mathbf{b}, \mathbf{e})$. In the following, it is shown to be true for $V_i(\mathbf{b}_{i-1}, \mathbf{e})$.

Let $V_i^n(\mathbf{b}, \mathbf{e})$ denote the value function for type- n action, i.e., it is only maximized over all feasible type- n actions, which are given by set A_n .

Lemma 2 *For a given $\mathbf{e}$, the value functions for type-1 and type-3 actions are non-decreasing in $b_{1,i}$ for $P_{11} \geq P_{01}$.*

Proof: For $\tilde{b}_1 \geq b_1$, we have

$$\begin{aligned} V_i^3(\tilde{\mathbf{b}}, \mathbf{e}) &\geq \max_{\mathbf{a}_i \in A_3} \sum_{c' \in C} P_{0c'} \sum_{\mathbf{e}'} P_{\mathbf{e}\mathbf{e}'} \left(\sum_{z=3}^4 P_z (V_{i+1}(\mathbf{b}'_z, \mathbf{e}') + R_i(z)) \right. \\ &\quad \left. + \tilde{b}_1 (P_{11} - P_{01}) (Q_{di}(\mathbf{a}_i) - Q_{fi}(\mathbf{a}_i)) (V_{i+1}(\mathbf{b}'_{z=3, \phi=0}, \mathbf{e}'^1) - V_{i+1}(\mathbf{b}'_{z=4}, \mathbf{e}'^1)) \right) \\ &\geq V_i^3(\mathbf{b}, \mathbf{e}). \end{aligned}$$

where $\mathbf{b}'_z = \mathcal{T}(\mathbf{b}, z)$, and $\mathbf{e}'^1$ denotes the updated energy for the $(i + 1)$ -st time slot corresponding to $z = 4$ and $(z = 3, \phi = 0)$. It can be proved using (6.11) that the

updated belief about idle state for each z is increasing in $b_{1,i-1}$. The first inequality is due to the assumed monotonicity for the $(i+1)$ -st time slot. For $P_{11} \geq P_{01}$ and $Q_{di} > Q_{fi}$, the second inequality follows using Lemma 1. Similarly, it can be shown to be true for $V_i^1(\mathbf{b}, \mathbf{e})$. $\blacksquare$

In the following, we consider the case when the optimal $\mathbf{a}_i$ that maximizes $V_i(\tilde{\mathbf{b}}, \mathbf{e})$ is an action of type 2. The optimal $\mathbf{a}_i$ obtains a greater value function than any type-1 action or

$$\begin{aligned} & \max_{\mathbf{a}_i} \sum_{c \in C} b_c \sum_{\mathbf{e}'} P_{\mathbf{e}\mathbf{e}'} \left(P_{c1} \bar{Q}_{fi}(\mathbf{a}_i) \left(k_\tau + V_{i+1}(1, \mathbf{e}'^2) - V_{i+1}(\tilde{\mathbf{b}}'_1, \mathbf{e}'^0) \right) \right. \\ & \quad + P_{c0} \bar{Q}_{di}(\mathbf{a}_i) \left(V_{i+1}(0, \mathbf{e}'^2) - V_{i+1}(\tilde{\mathbf{b}}'_1, \mathbf{e}'^0) \right) + (P_{c1} Q_{fi}(\mathbf{a}_i) + P_{c0} Q_{di}(\mathbf{a}_i)) \\ & \quad \left. \times \left(V_{i+1}(\tilde{\mathbf{b}}'_4, \mathbf{e}'^1) - V_{i+1}(\tilde{\mathbf{b}}'_1, \mathbf{e}'^0) \right) \right) > 0 \end{aligned} \quad (\text{B.1})$$

where $\mathbf{e}'^0$, $\mathbf{e}'^1$ and $\mathbf{e}'^2$ denote the updated energy for the $(i+1)$ -st time slot corresponding to $z = 1$, $z = 4$ and $(z = 2 \text{ or } (z = 3, \phi \neq 0))$, respectively. Using Lemma 1, Proposition 5 and the monotonicity for the $(i+1)$ -st time slot, for any $\mathbf{b}$

$$V_{i+1}(\mathbf{b}'_1, \mathbf{e}'^0) \geq V_{i+1}(\mathbf{b}'_4, \mathbf{e}'^1) \geq V_{i+1}(0, \mathbf{e}'^2). \quad (\text{B.2})$$

Therefore, (B.1) gives

$$k_\tau + V_{i+1}(1, \mathbf{e}'^2) \geq V_{i+1}(\tilde{\mathbf{b}}'_1, \mathbf{e}'^0) \geq V_{i+1}(\mathbf{b}'_1, \mathbf{e}'^0). \quad (\text{B.3})$$

For $\tilde{b}_1 \geq b_1$, we have

$$\begin{aligned}
 V_i^2(\tilde{\mathbf{b}}, \mathbf{e}) &\geq \max_{\mathbf{a}_i \in A_2} \sum_{c' \in C} P_{0c'} \sum_{\mathbf{e}'} P_{\mathbf{e}\mathbf{e}'} \left(\sum_{z=2}^4 P_z(V_{i+1}(\mathbf{b}'_z, \mathbf{e}') + R_i(z)) \right. \\
 &\quad + \tilde{b}_1 (P_{11} - P_{01}) \left(\overline{Q}_{fi}(\mathbf{a}_i)(k_\tau + V_{i+1}(1, \mathbf{e}'^2)) - \overline{Q}_{di}(\mathbf{a}_i)V_{i+1}(0, \mathbf{e}'^2) \right. \\
 &\quad \left. \left. - (Q_{di}(\mathbf{a}_i) - Q_{fi}(\mathbf{a}_i))V_{i+1}(\mathbf{b}'_{z=4}, \mathbf{e}'^1) \right) \right) \\
 &\geq V_i^2(\mathbf{b}, \mathbf{e}).
 \end{aligned}$$

The first inequality follows from the assumed monotonicity for the $(i+1)$ -st time slot.

Using (B.2) and (B.3), the coefficient of $\tilde{b}_1$ can be shown to be positive for $P_{11} \geq P_{01}$ and $Q_{di} > Q_{fi}$. Hence, using Lemma 2, we obtain

$$\begin{aligned}
 V_i(\tilde{\mathbf{b}}, \mathbf{e}) &= \max_{\mathbf{a}_i} \left(V_i^1(\tilde{\mathbf{b}}, \mathbf{e}), V_i^2(\tilde{\mathbf{b}}, \mathbf{e}), V_i^3(\tilde{\mathbf{b}}, \mathbf{e}) \right) \\
 &\geq \max_{\mathbf{a}_i} \left(V_i^1(\mathbf{b}, \mathbf{e}), V_i^2(\mathbf{b}, \mathbf{e}), V_i^3(\mathbf{b}, \mathbf{e}) \right) = V_i(\mathbf{b}, \mathbf{e}).
 \end{aligned}$$

Next, we consider the case when the optimal $\mathbf{a}_i$ that maximizes $V_i(\tilde{\mathbf{b}}, \mathbf{e})$ is an action of type 3. We have the following two possibilities:

1. If $(k_\tau + V_{i+1}(1, \mathbf{e}'^2)) \geq V_{i+1}(\mathbf{b}'_{z=4}, \mathbf{e}'^1)$, $V_i(\mathbf{b}_{i-1}, \mathbf{e})$ can be proved to be non-decreasing in $b_{1,i-1}$ as for the previous case.
2. For $(k_\tau + V_{i+1}(1, \mathbf{e}'^2)) < V_{i+1}(\mathbf{b}'_{z=4}, \mathbf{e}'^1)$, which, using Lemma 1, implies that

$$(k_\tau + V_{i+1}(1, \mathbf{e}'^2)) < V_{i+1}(\mathbf{b}'_{z=3, \phi=0}, \mathbf{e}'^1) \tag{B.4}$$

Any optimal sensing action for the optimal action $\mathbf{a}_i^* \in A_2$ that maximizes the value function of type-2 actions is also an action of type 3 with $\phi_i = 0$. Hence,

using (B.4), for any $\mathbf{b}$, we get

$$\begin{aligned}
 V_i^2(\mathbf{b}, \mathbf{e}) - V_i^3(\mathbf{b}, \mathbf{e}) &\leq \sum_{c \in C} b_c \sum_{\mathbf{e}'} P_{\mathbf{e}\mathbf{e}'} \left(P_{c1} \overline{Q}_{fi}(\mathbf{a}_i^*) (k_\tau + V_{i+1}(1, \mathbf{e}'^2)) \right. \\
 &\quad \left. - V_{i+1}(\mathbf{b}'_{z=3, \phi=0}, \mathbf{e}'^1) \right) + P_{c0} \overline{Q}_{di}(\mathbf{a}_i^*) (V_{i+1}(0, \mathbf{e}'^2) \\
 &\quad \left. - V_{i+1}(\mathbf{b}'_{z=3, \phi=0}, \mathbf{e}'^1) \right) \\
 &< 0
 \end{aligned} \tag{B.5}$$

Hence, using Lemma 2, we obtain

$$\begin{aligned}
 V_i(\tilde{\mathbf{b}}, \mathbf{e}) &= \max_{\mathbf{a}_i} \left(V_i^1(\tilde{\mathbf{b}}, \mathbf{e}), V_i^2(\tilde{\mathbf{b}}, \mathbf{e}), V_i^3(\tilde{\mathbf{b}}, \mathbf{e}) \right) \\
 &= \max_{\mathbf{a}_i} \left(V_i^1(\tilde{\mathbf{b}}, \mathbf{e}), V_i^3(\tilde{\mathbf{b}}, \mathbf{e}), V_i^3(\tilde{\mathbf{b}}, \mathbf{e}) \right) \\
 &\geq \max_{\mathbf{a}_i} \left(V_i^1(\mathbf{b}, \mathbf{e}), V_i^3(\mathbf{b}, \mathbf{e}), V_i^3(\mathbf{b}, \mathbf{e}) \right) = V_i(\mathbf{b}, \mathbf{e}).
 \end{aligned}$$

Similarly, it can be shown to be true for the case when the optimal action is of type

1.

List of Publications

- [1] Pratibha, Li Kwok Hung, and Teh Kah Chan, "Channel selection in multichannel cognitive radio systems employing RF energy harvesting," *IEEE Trans. Veh. Technol.*, vol. 65, no. 1, pp. 457-462, Jan. 2016.
- [2] Pratibha, Li Kwok Hung, and Teh Kah Chan, "Dynamic cooperative sensing-access policy for energy-harvesting cognitive radio systems," *IEEE Trans. Veh. Technol.*, vol. 65, no. 12, pp. 10137-10141, Dec. 2016.
- [3] Pratibha, Li Kwok Hung, and Teh Kah Chan, "Optimal spectrum access and energy supply for cognitive radio systems with opportunistic RF energy harvesting," to appear in *IEEE Trans. Veh. Technol.*
- [4] Pratibha, Li Kwok Hung, and Teh Kah Chan, "Energy-harvesting cognitive radio systems cooperating for spectrum sensing and utilization," in *Proc. IEEE GLOBE-COM*, Dec. 2015, pp.1-6.

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