

CHANNEL SELECTION AND ASSIGNMENT SCHEMES FOR EFFICIENT
SPECTRUM SHARING AND ENERGY EFFICIENCY IN COGNITIVE RADIO
NETWORKS

by

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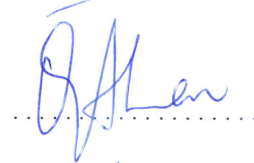
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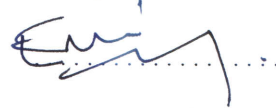
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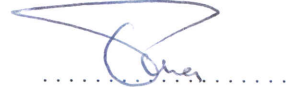
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ABSTRACT

CHANNEL SELECTION AND ASSIGNMENT SCHEMES FOR EFFICIENT SPECTRUM SHARING AND ENERGY EFFICIENCY IN COGNITIVE RADIO NETWORKS

In this thesis, we focus on distributed channel selection and centralized channel assignment in cognitive radio networks (CRN). For the former topic, we are concerned with the efficiency of spectrum sharing whereas in the latter, we also aim to improve energy efficiency of the CRN. First, we propose a non-selfish distributed channel selection scheme which improves the efficiency of spectrum sharing by mitigating the spectrum fragmentation. We also present an analytical model for our proposal using Continuous Time Markov Chains. In this thesis, we also devise various centralized channel assignment algorithms that outperform pure opportunistic schedulers in terms of energy efficiency and fairness notion without significantly trading off throughput efficiency. Initially, we consider a CRN which acquires channel occupancy information from a *white space database*. We develop heuristic algorithms considering transmission, idling and channel switching periods in both contiguous and fragmented spectrum. Finally, we consider a CRN in which CRs apply a listen-before-talk access approach. Different from our previous proposal, this scheduler ensures that interference caused by CRs does not exceed the tolerable limits in any of the primary user (PU) channels. In addition, it considers the differences among the PU channels in terms of probability of being idle as well as the control messaging overhead in downlink and uplink. Considering the tradeoff between the scheduling overhead and PU interference probability, we identify the frame length achieving high throughput. Simulation results show that our proposal achieves high throughput performance comparable to a throughput maximizing scheduler but it consumes lower energy than the latter.

ÖZET

BİLİŞSEL RADYO AĞLARINDA VERİMLİ SPEKTRUM PAYLAŞIMI ve ENERJİ VERİMLİLİĞİ İÇİN KANAL SEÇME VE ATAMA ALGORİTMALARI

Bu tezde dağıtık kanal seçme ve merkezi kanal atama problemlerine odaklanıyoruz. İlk konu için spektrum paylaşım verimliliği ile ilgilenirken ikinci kısımda ayrıca enerji verimliliğini de dikkate alıyoruz. Öncelikle, spektrum parçalanmasını azaltarak spektrum paylaşım verimliliğini arttıran bencil olmayan bir dağıtık kanal seçim algoritması öneriyoruz. Ayrıca, önerimiz için Sürekli Zaman Markov Zincirleri kullanarak bir analitik model sunuyoruz. Bu tezde ayrıca iş oranı açısından ciddi bir şekilde ödün vermeden, sadece fırsatçı olan çizelgeleyicilerden enerji verimliliği ve adalet nosyonu açısından daha iyi başarımlar gösteren çeşitli merkezi kanal atama algoritmaları geliştiriyoruz. Öncelikle, spektrum doluluk bilgisini *beyaz spektrum veritabanından* alan bir BR Ağı'na (BRA) odaklanıyoruz. İletim, boşa bekleme ve hem sürekli hem parçalı spektrum organizasyonunda kanal değiştirme sürelerini dikkate alarak buluşsal algoritmalar geliştiriyoruz. Son olarak, BRlerin konuşmadan-önce-dinle erişim yaklaşımını uyguladıkları bir BRA'na odaklanıyoruz. Önceki önerimizden farklı olarak, bu çizelgeleyici, BRlerin oluşturduğu karışımın herhangi bir Birincil Kullanıcı (BK) kanalında tolere edilebilir limitleri aşmamasını garanti eder. Bununla birlikte, bu çizelgeleyici birincil kanallar arasında boş olma ihtimallerine göre ayırım yaptığı gibi merkeze giden ve merkezden gelen hattaki kontrol için harcanan süreyi dikkate alır. Çizelgeleme kontrol yükü ve BK karışım ihtimali arasındaki ödünleşimi dikkate alarak yüksek iş oranını sağlayan çerçeve süresini belirliyoruz. Başarım çalışmaları önerdiğimiz yöntemin iş oranını en iyileyen çizelgeleyiciye benzer iş oranı başarımı gösterdiğini ancak ondan daha az enerji harcadığını göstermektedir.

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LIST OF SYMBOLS

$B_{i,f}$	Shannon capacity of link between CR_i and the CBS at frequency f
$\mathcal{C}_{busy}$	Set of busy channels
$\mathcal{C}_{idle}$	Set of idle channels
C_{idle}	Number of idle channels
$\mathcal{C}_{PU}$	Set of channels occupied by PUs
$\mathcal{C}_{CR}$	Set of channels occupied by CRs
CR	Vector showing the CR identities of traffic activities
E_c	Energy consumption due to circuitry
E_{max}	Maximum allowed energy consumption in a time slot
E_{sw}	Energy consumption due to channel switching
E_{tx}	Energy consumption due to transmission
F	Number of frequencies
F_{Gini}	Gini index related to a scheduling scheme
g	Antenna gain
G_{start}	Gap start time
G_{end}	Gap end time
L	Vector showing the length of spectrum opportunities
$L_{i,f}$	Number of bits that can be sent by CR_i at frequency f in a frame
$L^{\bar{opp}}$	Estimated opportunity size
L^{opp}	Actual opportunity size
N	Number of CRs
$N_{CR}(t)$	Number of CRs transmitting in the system at time t
$\mathcal{N}_{idle}$	Set of idle CRs
N_{tx}	Number of CRs in transmission/transmission request
$N_{PU}(t)$	Number of PUs transmitting in the system at time t
$\mathcal{N}_{tx}$	Set of CRs in transmission
N_0	Background noise

P_c	Circuit power
$P_{cs}^B(i, j)$	Probability of success in channel selection for BFC at state $S_{i,j}$
$P_{cs}^L(i, j)$	Probability of success in channel selection for LITC at state $S_{i,j}$
P_d	Probability of detection
P_{id}	Idling power
$P_{(i,j k,l)}$	Probability of transition from state $S_{i,j}$ to state $S_{k,l}$
P_{idle}^f	Probability that PU channel f is idle at a time
P_{fa}	Probability of false alarm
P_{max}	Maximum transmission power
P_{sw}	Channel switching power
P_{tx}	Transmission power
PU	Vector showing the PU channel identities of opportunities
Q_i	Number of bits in CR_i 's buffer
$Q_{(i,j k,l)}$	Rate of transition from state $S_{i,j}$ to state $S_{k,l}$
R	Shannon capacity of an Additive White Gaussian Channel
$R_{i,f}$	Achievable rate of frequency f if used by CR_i in bits
R_{min}	Minimum throughput to be achieved in a time slot
$\mathcal{S}$	The state space
$\mathcal{S}_{empty}$	Idle system in which all channels are unoccupied
$\mathcal{S}_f$	Set of <i>full-states</i>
$\mathcal{S}_{fail}$	Set of <i>fail-states</i>
$\mathcal{S}_{full}$	Set of states in which all channels are occupied
S_i	Channel state i of a FSMC
$S_{i,j}$	State representing the case i PUs and j CRs are transmitting
T_c	Channel search time
T_{on}^{CR}	CR average transmission duration
t_{sw}	Time needed to switch to a unit bandwidth (ms/MHz)
T_{sw}	Total time spent on channel switching
T_{frame}	Frame duration
T^{off}	Vector showing the starting times of spectrum opportunities

$\mathbf{T}^{\text{on}}$	Vector showing the starting times of CR traffic
T_s	Sensing duration
T_P	Sensing period
W	Channel bandwidth
$X_{i,f}$	Binary decision variable showing CR_i is assigned to frequency f or not
α	Average number of channel switching
α_{CR}	Parameter of exponential distribution of cognitive radio on duration
α_{PU}	Parameter of exponential distribution of primary user busy duration
α_f	Mean activity duration of primary user channel f
β	Energy-throughput tradeoff parameter
β_{CR}	Parameter of exponential distribution of cognitive radio off duration
β_{PU}	Parameter of exponential distribution of primary user idle duration
η_{EE}	Energy efficiency
$\gamma_{i,f}$	SNR of CR_i at channel f
Γ_{thresh}^f	Maximum tolerable interference ratio of PU channel f
λ	Average number of packets generated by a CR in a time slot
λ_G^B	Gap size parameter for BFC
λ_G^L	Gap size parameter for LITC
λ_{on}^{CR}	Parameter of CR on duration
ω_i	Satisfaction ratio of a CR_i
θ_f	Spectrum opportunity at frequency f
θ	Total spectrum opportunity through all frequencies
Θ	Spectrum opportunity utilization

LIST OF ACRONYMS/ABBREVIATIONS

BFC	Best-Fit Channel Selection
CH	Cluster Head
CO ₂ e	CO ₂ Equivalent
CR	Cognitive Radio
CRN	Cognitive Radio Network
CRSN	Cognitive Radio Sensor Network
CSS	Cooperative Sensing Scheduling
DTMC	Discrete Time Markov Chain
EEHS	Energy-Efficient Heuristic Scheduler
EMTG	Energy Consumption Minimizing Scheduler With Minimum Throughput Guarantees
GHG	Greenhouse Gas
IT	Interference Temperature
LITC	Longest Idle Time Channel Selection
LL	Traffic Type With Long On And Off Durations
LONG I	Long And Low Error In Estimations
LONG II	Long And Medium Error In Estimations
LONG III	Long And High Error In Estimations
MRHS	Maximum Rate Heuristic Scheduler
NC-OFDM	Noncontiguous Orthogonal Frequency Division Multiplexing
NFHS	Nearest Frequency Heuristic Scheduler
NLP	Nonlinear Programming
OFDM	Orthogonal Frequency Division Multiplexing
POMDP	Partially Observable Markov Decision Process
PU	Primary User
RAND I	Random And Low Error In Estimations
RAND II	Random And Medium Error In Estimations
RAND III	Random And High Error In Estimations
RF	Radio Front-end

RS	Random Scheduling
SHORT I	Short And High Error In Estimations
SHORT II	Short And Medium Error In Estimations
SHORT III	Short And Low Error In Estimations
SNR	Signal-to-noise Ratio
SS	Traffic Type With Short On And Off Durations
SU	Secondary User
TMER	Throughput Maximizing Scheduler With A Restriction On Energy Consumption

1. INTRODUCTION

It is of no doubt that wireless communications have permeated into almost every sphere of daily life. However, spectrum allocation and management is still based on the classical techniques from the very early days of wireless communications. In this so called *static spectrum access*, a significant portion of the radio spectrum is allocated to the parties via auctions for long terms (e.g. tens of years) and for large geographical areas (e.g. the whole country) whereas a small portion is dedicated to unlicensed access (e.g. ISM at 2.4 GHz). However, this approach which is more than a century old, falls short of effective spectrum management. It is widely debated that this approach is cumbersome since it restricts a wireless device to operate only in the bands for which it has a license to access.

In addition, measurement campaigns in various parts of the world [1] have corroborated that static spectrum access leads to some portions of the spectrum to be overcrowded while some other to be underutilized, which results into a questionable perception that *spectrum is scarce*. In order to tackle with this inefficiency, a more agile spectrum access paradigm is proposed. Dynamic spectrum access (DSA) allows wireless devices to operate opportunistically in *spectrum holes*, i.e., frequency bands not being used at a time by the actual licensed users, until these license holders (a.k.a. *primary users*, PUs) begin to use the band. In such a DSA network, a PU has the right to access the spectrum any time. Therefore, the DSA users (a.k.a. *secondary users*, SUs) should make sure that their operation does not compromise the operation of PUs. To support this spectrum reuse functionality, SUs analyze radio frequency environment via spectrum sensing. In case there exist no active PU communications in the band, SU can keep on utilizing the spectrum. On the other hand, upon detection of a PU, SU vacates the band and looks for alternate bands for communication.

Cognitive radio (CR) is mostly coupled with DSA philosophy and defined as a wireless device that enables DSA. When it was first defined in 1999 by Joseph Mitola III (and Gerald Q. Maguire, Jr.) in the scope of his dissertation, it was a more general

and probably *futuristic* concept which defined CR as “radio-domain-aware intelligent agents that search out ways to deliver the services the user wants even if that user does not know how to obtain them” [2]. After the initial works in the literature on the architecture and basic concepts of CR, current research extensively focuses on how to realize DSA and more “cognitive” devices via artificial intelligence. Spectrum sensing, medium access and resource allocation, spectrum sharing among operators, and security are some of the fundamental topics that have attracted interest in the CR domain. However, there still remains many challenges to be tackled for making CRs viable as operational networks.

Broadly speaking, the major challenge of CR networks (CRNs) is to provide efficient spectrum sharing among the CRs as in conventional wireless networks with the increased complexity due to dynamic nature of spectrum resources depending on time, space and frequency. CRs have to comply with the PU interference constraints and ensure sufficient protection of PUs. This thesis concerns with the basic problems of (i) how a CR should select a channel for transmission in a distributed CRN for providing efficient spectrum sharing and (ii) how a centralized entity should make channel assignment in an infrastructure-based CRN attaining both high throughput and energy efficiency. Distributed channel selection is paramount as it determines the efficiency of spectrum sharing in a multi-user CR ad hoc network (CRAHN). How should a CR select a channel for transmission in a CRAHN is the basic question in the first part of this thesis. In the second part, we are concerned with how a central authority makes channel assignment given that it has some information collected from the CRs in the network. Our objective is to increase energy efficiency of the CRN. We focus on a centralized network as the currently emerging realizations of CR are of this type. Moreover, our emphasis is on uplink scheduling since CRs, as battery-operated devices, are more energy-constrained compared to the cognitive base station (CBS).

1.1. Key Contributions

The solutions presented in this thesis cover both channel¹ selection in ad hoc CRNs, and channel assignment in infrastructure-based CRNs. For the first, we consider a CRN with random access approach whereas in the second we consider a time-slotted network.

Main contributions of this thesis can be grouped into four as:

- (i) *Distributed channel selection*: We propose a generalized channel access scheme by arguing the performance of a scheme that intuitively seemed to be a good solution in the literature. We argue that CRs should select the channel with sufficiently long opportunity duration rather than the one with the longest duration. The second approach, to which we refer as *longest idle time channel selection* (LITC), results in the spectrum to be fragmented in the time domain which consequently may decrease the efficiency of spectrum sharing. Our solution, *best-fit channel selection* (BFC), is inspired from 0-1 multiple knapsack problems (0-1 MNP) in which there are multiple knapsacks (frequencies) and items (CR transmission requests) cannot be divided. Further with this analogy, we use a well-known algorithm for on-line bin-packing, *best-fit* algorithm as a channel selection scheme. Our algorithm can be modeled as a variant of a best-fit algorithm and has $O(F \log F)$ complexity where F is the number of PU channels. We introduce BFC in Chapter 3 and provide a Continuous Time Markov Chain model for it in Chapter 4.
- (ii) *Analysis of spectrum fragmentation*: Spectrum can be fragmented in two domains: time and frequency domains. Fragmentation is not desirable as in memory allocation schemes since it is challenging to manage increasingly small pieces of the spectrum resources. Moreover, it may not be feasible to use such small portions of the spectrum. Fragmentation in time domain occurs due to the dynamic arrival and departure of both CRs and PUs, while fragmentation in frequency domain may be experienced both due to adaptive bandwidth allocation in CRNs

¹Throughout this thesis, we use the terms frequency and channel interchangeably.

and due to some portions of the spectrum being closed for the use of CRNs. For fragmentation in time domain, we introduced BFC in Chapter 3 and Chapter 4. For fragmentation in frequency domain, in Chapter 6 and Chapter 7, we propose scheduling schemes that take the channel switching cost into account between different fragments of the spectrum and make frequency assignment accordingly.

- (iii) *Energy efficiency in CRNs*: Despite the recent efforts for improving the energy efficiency of CRNs, the problem of energy-efficient scheduling has not been explored before. In this thesis, we aim to fill this gap by providing efficient solutions for the scheduling problem that can simultaneously attain high throughput and energy efficiency. Moreover, we incorporate the past transmission history of each CR as a satisfaction parameter in order to provide some degree of fairness among the CRs. Chapter 5 surveys the related work while Chapter 6 and Chapter 7 formulate energy-efficient scheduling and provide sub-optimal yet efficient heuristic algorithms.
- (iv) *Scheduling in CRNs*: Many aspects of centralized channel assignment has been explored in CRNs. However, energy efficiency has not gained much interest till recently. We introduce various schedulers in Chapter 6 and Chapter 7 for improving energy efficiency of the CRN and show that they can provide high throughput performance with lower energy consumption compared to a pure throughput-maximizing scheduler.

In a nutshell, in this thesis we are concerned with the problem of channel selection in a CRN with no infrastructure and channel assignment in an infrastructure-based CRN. In the first case, we are only concerned with the efficiency of spectrum sharing, i.e. throughput efficiency, whereas in the second we also aim to improve energy efficiency of the CRN.

1.2. Thesis Outline

First, in Chapter 2 we review the related works in order to clearly identify our main contributions in the literature. In this chapter, we summarize the outstanding works related to our contributions listed in Section 1.1.

The next chapters can be grouped into two as chapters concerned with distributed channel selection in CRNs (Chapter 3 and Chapter 4) and chapters concerned with energy efficiency in CRNs (Chapter 5, Chapter 6 and Chapter 7).

Chapter 3 presents an algorithm for distributed channel selection in CRNs. The proposed solution can easily be applied to the existing channel selection schemes in which CRs know their traffic activity durations owing to their self-awareness property, and know the availability durations of PU channels as well as their occupancy states owing to their environment-awareness property. CRs operate in a random access manner as time synchronization is one of the key challenges in ad hoc networks. Chapter 3 provides the performance evaluation of the proposed solution under increasing number of CRs, different traffic activity types, and estimation accuracy by simulations. Simulation studies indicate the performance improvement attained by our proposal compared to the scheme that is referred to as an efficient scheme in the literature. Chapter 4 develops an analytical model based on a Continuous Time Markov Chain model for the introduced scheme.

Chapter 5 first highlights the basic issues in spectrum sensing and access from an energy efficiency perspective. Next, it lists the outstanding works in the literature on energy efficiency in CRNs. Providing the key challenges of this topic in Chapter 5, we propose energy-efficient solutions for centralized channel assignment in CRNs. First, we consider a CRN that acquires spectrum occupancy information from a *white space database* (WSDB) at the beginning of each frame. Chapter 6 formulates an energy efficiency maximizing scheduler as a nonlinear optimization problem, and next presents a polynomial time heuristic algorithm for the formulated problem. In addition, two scheduling schemes with a fairness notion are introduced considering the channel assignment problem from both throughput and energy consumption perspectives.

Chapter 7 presents a scheduling scheme similar to Chapter 6 but considers what is neglected in that chapter: (i) as opposed to the WSDB architecture, CRs carry out spectrum sensing, and sensing outcomes are subject to errors, (ii) burden of control messaging period is not neglected and length of this period is incorporated into the

calculations. Both Chapter 6 and Chapter 7 compare the performance of our proposal to that of throughput maximizing scheduler and show that our solutions in general can perform as good as throughput maximizing scheduler but consume less energy.

Finally, Chapter 8 concludes this thesis by summarizing our key contributions in addition to a discussion on possible future directions.

2. RELATED WORK

2.1. Distributed Channel Selection in CR Ad Hoc Networks (CRAHNs)

Due to the peculiarities of the CRAHNs, channel selection raises fundamental challenges concerning the implementation of efficient distributed schemes. Since each CR decides on its own, it is difficult to provide a network-wide optimal resource allocation. Therefore, nodes usually consider their own performances and each CR tries to maximize its own benefit. This approach is optimal from the perspective of a single CR. However, it may not be optimal in a network-wide context.

Game theory with the ability to model single agents acting as an independent decision maker and whose actions potentially affect all other decision makers, is particularly attractive for ad hoc wireless networks [3]. In this framework, CRs are the players and their actions are the selection of a transmission channel and related transmission parameters (e.g. transmission power) for operation in the selected channel. Channel selection can be formulated as a potential game played by various selfish and cooperative players, i.e. CRs. In addition to the network properties, objective of each user determines the rules of the game and the strategy of each CR. The objective function is another representation of the profit a CR expects from its actions and is quantified by assigning numbers to different outcomes, e.g., SINR, BER, and latency [4]. Games can be cooperative or non-cooperative. In [5], each CR accesses the channels with the aim of maximizing its own throughput playing two sub-games; the first game is the channel selection game whereas the second game is medium access control game. Detailed information on game-theoretical approaches can be found in [3, 4] and references therein.

Apart from game theoretical approaches, graph theory based protocol design has also been at the interest of the researchers working on CRAHNs. In graph coloring based approaches [6–10], the CRN is considered as a bidirectional graph that is defined as $\mathcal{G} = (\mathcal{V}, \mathcal{L}, \mathcal{E})$. In this model, CRs and spectrum opportunities are represented by

the set of vertices $\mathcal{V}$ and color list $\mathcal{L}$, respectively. $\mathcal{E}$ refers to the set of edges between vertices. The spectrum allocation problem is equivalent to coloring each vertex with one color while conforming to the restrictions of the primary network [11]. After defining an objective function that may consider bandwidth, network coverage or fairness, different channel assignment policies can be defined. Once the spectrum holes are discovered, CR nodes within the interference range of each other are colored with different colors so that their transmissions do not provide harmful interference to each other. Graph-coloring based channel assignment is analogous to partitioning of the set of vertices to k disjoint partitions, termed color partitions $C = C_1, C_2, \dots, C_k$ [10]. In [9], authors define the centralized allocation approach as an NP-hard problem and propose a color-sensitive graph coloring algorithm for decentralized channel assignment. In [12], the trade-off between spectrum sensing and transmission is considered in the CR throughput maximization problem using improper list-coloring. Minimum number of channels that are required to be sensed for maximal throughput is formulated as a linear function of the CR network density.

There are also works that propose joint channel and route allocation schemes [13–15]. In CRAHNS, since nodes may have multi-hop communications between the two ends of the communication, the route formation with low complexity is an issue. It is similar to the routing in ad hoc networks with the additional issue of location and time-dependent frequency availability. Hence, route and channel selection should be managed concurrently while taking the burden of channel switching delay into consideration. In [13], route and channel selection is accomplished in a joint manner. The proposed routing scheme considers the geographical locations of PU activities and avoids those regions while routing with the objective of minimization of end-to-end delay.

Previous works [16–19] have shown that CRs should utilize information about the PU channels such as PU busy and idle durations and probability of a PU channel's being idle. Otherwise, a CR may blindly select the channel that is heavily used by PUs. This will certainly result in waste of CR's time and energy. Hence, most of the channel access schemes apply some estimation based channel access scheme. Chapter 3 of this

thesis considers this fact and devises a channel access scheme that is independent of the underlying estimation or problem formulation approach, e.g. either game theory or not. Our proposal is a general one which can be adapted to channel selection schemes that can estimate the busy and idle duration of PU channels. Chapter 4 provides an analytical model using Continuous Time Markov Chains for the proposed channel selection scheme in Chapter 3.

2.2. Spectrum Fragmentation in CRNs

Spectrum fragmentation means a portion of the spectrum is unusable although being free due to inefficient resource allocation [20]. This is experienced in CRNs due to various reasons, the most significant one being the adaptive bandwidth allocation. In conventional wireless networks, fixed bandwidth allocation is applied in which channels have predefined fixed bandwidth. As CRs occupy the spectrum opportunities and release them upon completion of their transmission, available spectrum becomes increasingly divided into discrete fragments. Although being free, the fragmented spectrum may be effectively unusable due to the cost of using such small chunks of the spectrum [20]. Figure 2.1 depicts this phenomenon in a network consisting of five frequencies $F = \{f_1, f_2, f_3, f_4, f_5\}$. The left figure depicts the change in occupancy of each frequency with time whereas the right figure is a snapshot of the former at a specific time t . As the figures show, spectrum opportunities are distributed over various frequencies with various sizes. Moreover, the left figure also depicts the *fragmentation in time domain* whereas the right figure shows how the spectrum is fragmented in *frequency domain*. At t , non-adjacent f_2 and f_4 are idle. In such a case, if a CR does not possess the hardware to utilize these two frequencies simultaneously, it will transmit through only either f_2 or f_4 . However, if they were adjacent, CR would be able to tune its hardware to transmit over the contiguous wider block formed by these bands. If not tackled seriously, spectrum fragmentation leads to inefficient use of the spectrum opportunities and thereby results in significant detrimental effects on CRN performance. Hence, resource allocation schemes should define precautions in order to overcome fragmentation. Various mechanisms in physical layer (PHY) and medium

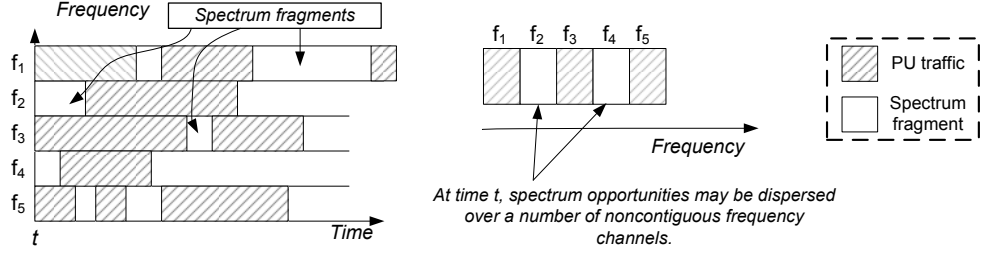


Figure 2.1. Spectrum may be fragmented in CRNs in time (left) and frequency (right) domains.

access control (MAC) layer exist in the literature [20, 21].

Providing a physical layer solution to fragmentation, current OFDMA based CRs can utilize these noncontiguous fragments by defragmenting via spectrum aggregation at the expense of increased complexity and spectrum overhead. Channel aggregation requires implementation of guard bands at the boundaries in order to prevent interference between these adjacent channels. [22] proposes two solutions, one at the PHY and one at the MAC layer. At the PHY, CRs transmit combining noncontiguous multiple frequencies to a single higher bandwidth block by using OFDMA. At the MAC, the receiving and transmitting CR pairs synchronously adjust their frequency. In other words, they periodically perform online defragmentation by moving their communication to other bands. Various methods in selection of these new bands are examined. Similar to our work, authors also conclude that best-fit spectrum allocation outperforms all other heuristic approaches, namely *worst-fit* and *first-fit*. Defragmentation process proposed in that work may result in disrupting CR communications while migrating communications to alternate bands. Work in [20] presents another PHY layer solution and analyzes two kinds of radios, namely *1-agile* and *k-agile* radios. The former can only use single frequency channel with adaptable bandwidth hence faces the spectrum fragmentation challenge, whereas the latter can combine up to k noncontiguous channels thus tackles the fragmentation issue. However, there is a trade-off between reduced fragmentation and increased overhead that is linear with k . Hence, it is crucial to identify the impact of the parameter k on network performance. Work in [21] introduces the *time-spectrum block* concept to represent the time during which a CR uses a specific frequency band, and formalizes the spectrum allocation problem. Authors show

that finding a *feasible* schedule, i.e. allocation with non-overlapping time-spectrum blocks, is NP-hard. Hence, heuristics are proposed. However, the introduced approach can better fit to delay-tolerant traffic since lower bandwidth blocks spanning a longer time duration are preferred [20]. For an elaborate analysis of spectrum fragmentation, we refer the readers to [23] on theoretical analysis of channel fragmentation process utilizing the fundamentals of analysis of disk allocation algorithms.

Different from the previous works, in Chapter 3, we provide a channel selection scheme that mitigates spectrum fragmentation in time domain at medium access control layer. Moreover, none of the works in the literature focus on how spectrum opportunities are located; all works consider the spectrum as a contiguous block of frequencies whereas it is expected to be fragmented covering a range of frequencies from low frequency bands to higher frequencies. Spectrum organization accounts principally for the channel switching cost among frequencies. Channel switching cost is almost neglected in all works in channel assignment except [24]. Work in [24] formulates a scheduling scheme considering the cost of channel switching as a linear function of the frequency separation between two frequencies. However, they also assume the spectrum is contiguous. Different from [24], we explore how spectrum fragmentation in frequency domain affects the operation of our scheduling schemes that is introduced in Chapter 6.

2.3. Energy Efficiency in CRNs

Energy efficiency has been an issue for wireless networks in which nodes have size and weight constraints for the ease of mobility. However, it has recently become more critical with the wide penetration of large screen mobile devices which offer ubiquitous connectivity as well as a multitude of applications. Research on wireless sensor networks (WSN), has principally considered energy efficiency performance as it lies at the very core of network operation. However, limited work has been done to address energy efficiency in CRNs.

Energy efficiency in CRN context has gained more interest in the domain of spec-

trum sensing and spectrum access [25–32]. Since CRs generally pause transmission during sensing, mostly this sensing period is desired to be minimized for both throughput efficiency and energy consumption concerns. However, as the throughput attained in transmission duration is a function of the total discovered spectrum opportunities and collision rate with the PU traffic, achieved throughput is affected by the sensing duration. Therefore, most of the research considered this tradeoff between sensing and transmission to design throughput-efficient CR systems with low energy consumption. Works in [29, 33] focus on energy efficiency of CR sensor networks (CRSNs [34]) which consist of energy limited nodes as in conventional WSNs. Works in [35, 36] propose cooperation schemes for attaining energy efficiency in cooperative sensing which can also attain favorable PU detection performance. Chapter 5 first summarizes the basics of spectrum sensing and access, and next reviews the related work in CRNs in the scope of energy efficiency of spectrum sensing and access.

To the best of our knowledge, energy efficiency is neglected as a design criteria in CRN scheduling. As CRs are expected to possess operation capability within a wide range of spectrum owing to power-intensive spectrum sensing tasks, they are expected to operate with high energy efficiency. Furthermore, with the emerging green communications paradigm, CRs as other next generation networks are desired to be greener. Hence, cognitive protocols must also be designed with an energy efficiency perspective in order to have longer battery lifetime and for being more environment-friendly. In this sense, a cognitive scheduler located at the base station (BS) should consider the energy efficiency while determining a schedule. Different from conventional wireless scheduling problem, the scheduler in CRN has to take channel switching cost, spectrum organization, and PU interference regulations. Our schedulers developed in Chapter 6 and Chapter 7 are different from the existing work in the literature at least one of the following aspects: (1) we consider not only the throughput efficiency of the CRN but also the energy consumption perspective and energy efficiency as well, (2) we model the spectrum as a collection of discontinuous bands, (3) we consider the antenna orientation of each CR to decide on the frequency to assign as channel switching incurs a cost, (4) we quantify the effect of control messaging on the CRN performance. Our schedulers in Chapter 6 and Chapter 7 can maintain higher energy efficiency in

a CRN while they can also provide similar throughput efficiency compared to a pure throughput maximizing scheduler.

2.4. Scheduling in CRNs

Centralized resource allocation, also known as *scheduling*, is a well-investigated problem in CRNs. Specific to CRNs, medium access rules are not defined for a single resource (medium) but a set of channels so called multi-channels. There is a plethora of cognitive frequency assignment schemes, each having an objective. Basically, these objectives can be listed in three groups as follows: (i) energy-cost minimization [37] (ii) throughput maximization [38–42] and (iii) delay minimization [38], all subject to PU interference restrictions. Depending on the CRN properties, objective function considers various parameters some of which can be listed as CR queue states, application requirements of CRs, channel conditions between each CR and the scheduler.

When throughput-optimality is considered, max-weight scheduling is proposed as an efficient solution. Simply, the scheduler maximizes the sum of the product of queue length and channel rate of all users. Hence, generally the user with maximum product is assigned the corresponding resource (e.g. time-slot, frequency) [43]. While throughput-optimality of max-weight scheduling is proved in [44], it is shown in [45] that it holds for only networks with backlogged users which continually generate traffic. In networks with dynamic population of flows (including both long-lived and short-lived flows [43]), max-weight based schedulers may fail to guarantee maximum throughput. Furthermore, it may lack the *stability condition*, e.g. the number of flows active in the network may grow unbounded in case the maximum queue-capacity product flows are served and other flows wait unserved. As a solution to this issue, [43] devises a scheduling algorithm which can utilize the flow-level dynamics in scheduling.

CR queue-awareness is vital for efficient resource allocation since size of the CR traffic queues has direct implications on the quality-of-service (QoS) parameters, eg. packet delay and packet dropping probability due to buffer overflow. Some of the works addressing this issue are [41, 46–48]. [41] and [46] consider the queue status in

order to evade waste of spectrum resources in case time slots are allocated to those CRs with empty queues but with good channel conditions. Furthermore, an efficient scheduler should exploit the multi-user diversity, in particular wireless channel diversity. Channel-aware scheduling can significantly improve the network capacity since it favors the users with higher capacity links [49, 50]. However, this approach can lead to unfairness among users. For instance, transmission slots are allocated to the CRs that are geographically closest to the BS and hence have higher channel capacity meanwhile farther-away CRs suffer from lack of service. Scheduler in [47] considers the multi-class users in the scheduling decisions and achieves QoS satisfaction, fairness among users while conforming to the limitations of harmful interference.

Performance of centralized scheduling is strongly dependent on the CR-state and environment-awareness of the scheduler. Hence, schedulers usually collect information from CRs (e.g. channel conditions, queue sizes etc.). However, information exchange may become a burden on the network in terms of energy consumption. Therefore, instead of intensive information exchange between the CRs and CBS, CBS can rely on less frequently collected information and estimate the subsequent states. Consequently, the scheduler can apply frame-by-frame scheduling instead of slot-by-slot allocation. Authors in [41] propose a frame-by-frame based scheduling instead of slot-based assignment due to the overhead incurred by control messaging for each slot. In [41], CRs observe the channels and estimate the throughput for the first time slot of the frame while throughput in the rest of the slots are estimated using the probabilistic models, e.g. PU activity transition matrix and primary channel SNR change matrix. Each frame as a whole is allocated to the user with the maximum transmission capability. Performance evaluations show that this scheme achieves higher aggregate throughput. However, as the authors note, this scheme may lead to the challenge of excessive delay for those CRs who are not allocated a frequency in a frame. [48] provides a good overview of the CR scheduling schemes with various goals: maximizing capacity, providing fairness, and considering the delay requirements of various CRs. Each scheme with a combination of these goals proposed in [48] is restricted with the crucial concern of operation without destructing the PU communications. Energy efficiency is not taken into account in any of these proposed schedulers.

In Chapter 6 and Chapter 7, we employ a similar network model as in [41, 48]. But different from [41, 48], we consider energy efficiency of the CRN and *satisfaction* of the CRs while trying to achieve high CRN throughput. Our emphasis is on uplink scheduling as it is a key concern for battery-operated devices. The proposed solutions take advantage of multi-user diversity in terms of channel quality, queue backlogs, and transmission frequency for improving the energy efficiency of the CRN.

3. A NON-SELFISH DISTRIBUTED CHANNEL SELECTION SCHEME FOR MITIGATING SPECTRUM FRAGMENTATION

3.1. Contributions

In this chapter, we propose a distributed channel selection scheme in which each CR behaves in a non-selfish way and improves the efficiency of the spectrum sharing. The proposed approach, *best-fit channel selection* (BFC) [51], differs from the selfish approaches in that each CR selects the channel for transmission which satisfies its transmission requirement, not the *best channel* with the longest opportunity duration. In BFC, each CR estimates the primary channel availability times, and selects the channel that has sufficiently long channel idle time to meet its transmission time. BFC improves efficiency of spectrum sharing and thereby increases total transmission time (i.e. throughput) compared to the selfish scheme in which each CR selects the *longest idle time channel* (LITC). By a set of simulations, we analyze BFC under various settings and highlight the cases where it improves the CRN performance. In this chapter, we also shed light on the spectrum fragmentation phenomena by analyzing the distribution of unused opportunities (fragments) under various channel selection schemes.

Best-fit algorithm is a kind of bin-packing algorithm which is applied to many resource allocation problems in various networking domains. Work in [52] utilizes this algorithm in assigning time slots in the uplink channel to the satellite terminals (RCST in particular). Skorin-Kapov [53] utilizes it for routing and wavelength assignment in optical networks. Similarly, Cohen and Katzir [54] study the OFDMA scheduling using best-fit and other types of bin-packing algorithms. Our work can also be considered a special case of best-fit bin-packing algorithm for CRN domain.

The rest of the chapter is organized as follows. In the next section, we first intro-

duce the system model and formulate the channel selection problem as a throughput maximizing optimization problem as if there exists a central spectrum manager with resource allocation functionalities. Since the complexity of this problem is NP-hard, we present our sub-optimal performing proposal that operates in a distributed manner. We provide performance analysis of our proposal by simulations and present the simulation results in Section 3.3. This section presents detailed performance evaluation of BFC while comparing it with LITC. Finally, we conclude in Section 3.4.

3.2. Best-Fit Channel Selection

3.2.1. System Model

We consider a system composed of a primary network (PN) and a decentralized CRN with N CRs. The PN is abstracted as a system consisting of F PU channels. Hence, rather than modeling the PUs explicitly, we model their effect on the primary channels, i.e. the primary channel traffic patterns. The set of channels is represented by $\mathcal{C} = \{C_1, C_2, \dots, C_F\}$, C_i standing for the primary channel i . The CRN consists of a number of CRs that is in the interference range of each other. This assumption is for eliminating the challenge of modeling the dynamics of the spectrum opportunities due to the spatial variations.

Traffic of each PU channel is modeled as two-state Markov process: one state representing the activity times and the other for inactivity times. These states are referred to as *busy* and *idle* states. CR model composes of three states: *Off* (O), *Channel sense and search* (CSS) and *Transmit* (T). The states O and T correspond to the idle and busy states in the primary channel model, respectively. The duration of these states depends on the traffic generation dynamics of the CR, and thereby it is mostly modeled as an exponential random variable. We assume that time consumed in the CSS state is negligible. As the idle time in the off state expires, the CR searches for an idle channel (the CSS state). The channel search sequence is constructed by the rules of the channel search policy. Due to the single transceiver restriction in the hardware, the CR senses the channels one by one in the order that is determined by the

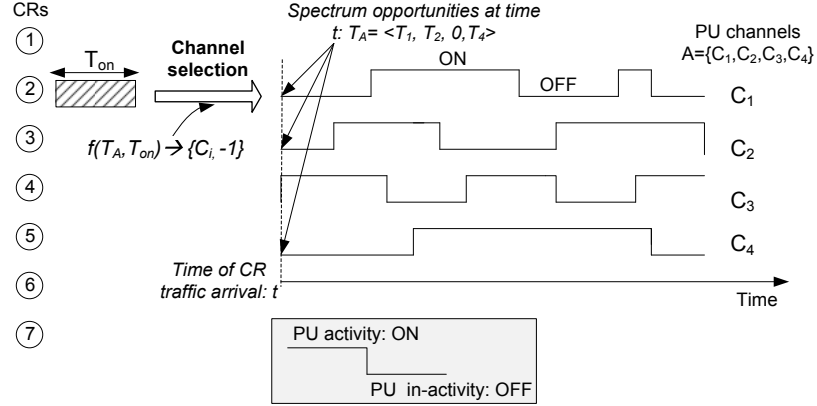


Figure 3.1. An example with $N=7$, $F=4$. T_A is the vector showing the spectrum opportunity duration of each PU channel whereas T_{on} is the CR traffic duration.

channel search sequence. If the sensed channel is available, it transmits at that band which drives its state from the CSS state to the state T . If not available, it continues channel searching. After completion of the packet transmission, the CR switches to the state O , which is the starting state of its life-cycle.

The state sojourn times are exponentially distributed with mean values α_* and β_* , $* \in \{PU, CR\}$. Both PUs and CRs apply a random access scheme in which PUs access the band whenever they have packets to transmit, whereas the CRs follow the rules of channel selection policy. Figure 3.1 illustrates the system under consideration for $N = 7$ and $F = 4$. As the figure depicts, channel selection can be considered as a function of spectrum opportunities and CR traffic attempt duration, that maps to a PU channel (C_i), or -1 (failure).

3.2.2. Optimal Channel Assignment

Assume that for a time period of T , all the PU channel and CR activities are known by a central node called *spectrum manager*. In this duration, all PU channel activities are represented by the following three vectors: $\mathbf{T}^{\text{off}}$, $\mathbf{L}^{\text{opp}}$ and $\mathbf{PU}$. $\mathbf{T}^{\text{off}}$ is the vector of the starting time of spectrum opportunities listed in increasing order. That is, $\mathbf{T}^{\text{off}} = [t_1^{\text{off}}, \dots, t_i^{\text{off}}, \dots, t_G^{\text{off}}]$ where t_i^{off} represents the time that the i^{th} spectrum opportunity starts and $t_i^{\text{off}} \leq t_j^{\text{off}}$ for each $i \leq j$. This is also the time when PU channel whose

identification is stored in the PU_i becomes off. $\mathbf{L}^{\text{opp}} = [L_1^{\text{opp}}, \dots, L_i^{\text{opp}}, \dots, L_G^{\text{opp}}]$ is the vector of length of spectrum opportunities; the length of i^{th} opportunity is L_i^{opp} . Similarly, CR activities are represented by three vectors: $\mathbf{T}^{\text{on}}$, $\mathbf{L}$ and $\mathbf{CR}$. $\mathbf{T}^{\text{on}}$ is the vector of the time instants that a CR packet generation starts. $\mathbf{L}$ is the vector of the length of the generated packets. $\mathbf{CR}$ is the vector of CR identities yielding the packet generations stored in $\mathbf{L}$ and $\mathbf{T}^{\text{on}}$. Packet generation times t^{on} in $\mathbf{T}^{\text{on}}$ are also sorted in increasing order.

Given $\mathbf{T}^{\text{off}}$, $\mathbf{L}^{\text{opp}}$, $\mathbf{PU}$, $\mathbf{T}^{\text{on}}$, $\mathbf{L}$ and $\mathbf{CR}$, our aim is to find an allocation vector $\mathbf{X} = [X_{if}]$ that maximizes the CR throughput. In this allocation if $X_{if} = 1$ then i^{th} CR activity is assigned to the f^{th} spectrum opportunity, $X_{if} = 0$ otherwise. This optimization problem is formulated as follows:

$$\max \sum_{f=1}^G \sum_{i=1}^K X_{if} L_i \quad (3.1)$$

$$\text{s.t.} \sum_{f=1}^G X_{if} \leq 1, \quad i \in \{1, \dots, K\} \quad (3.2)$$

$$\sum_{i=1}^K (X_{if} L_i) \leq L_f^{\text{opp}}, \quad f \in \{1, \dots, G\} \quad (3.3)$$

$$X_{if} t_f^{\text{off}} \leq X_{if} t_i^{\text{on}} \leq X_{if} (t_f^{\text{off}} + L_f^{\text{opp}}), \quad i \in \{1, \dots, K\}, f \in \{1, \dots, G\} \quad (3.4)$$

where L_i is the i^{th} transmission duration, $K = \|\mathbf{T}^{\text{on}}\|$ is the number of CR on periods and $G = \|\mathbf{T}^{\text{off}}\|$ is the number of spectrum opportunities. Equation 3.2 imposes that a CR transmission is assigned to only one spectrum opportunity whereas Equation 3.3 ensures that the transmission durations assigned to a spectrum opportunity cannot be greater than the size of that opportunity. Equation 3.4 is necessary for ensuring the allocation of spectrum opportunities to CR transmissions that emerge between the start and the end time of the spectrum opportunity.

The above formulation is a binary integer programming problem, which is known to be NP-hard [9]. Solving this problem requires global knowledge of all channel and CR traffic activities. Moreover, it is centralized, and therefore impractical for CRAHNs.

Due to its complexity and requirements, distributed solutions with lower complexity are more appropriate for CRAHNs. Hence, we define three access schemes; BFC, LITC and p-selfish scheme that all determine the channel access list depending on the CR's knowledge of its own traffic activity duration and availability time of PU channels. In these schemes, we assume that the CR is capable of estimating the channel availability times. BFC and p-selfish scheme are our proposals, the former being the special case of the latter, whereas LITC is one of the proposals that is accepted as an effective scheme in the literature [19, 55]. We use LITC as a benchmark and evaluate the performance of our proposals.

3.2.3. Best-fit Channel Selection (BFC)

Before presenting our proposal, let us list our basic assumptions and provide a brief discussion on each of them:

- (i) Each CR can estimate the primary channel occupancy times (idle and busy durations) accurately. This estimation can be formed via various modeling approaches [16–19]. Any estimation algorithm can be incorporated into our proposal.
- (ii) Both PUs and CRs use a CSMA/CA based medium access protocol. Contention among CRs are resolved as done in CSMA protocols via carrier sensing and backoff mechanism.
- (iii) Each CR has single radio transceiver that can be tuned to various frequencies licensed to the PN. Due to the single radio restriction, sensing and transmission are performed sequentially. Additionally, CRs can perfectly detect the state of the channel.
- (iv) A single-hop transmission area is assumed as the network in operation. Hence, route selection and related issues are ignored. Moreover, we consider a small coverage area such that no frequency reuse pattern can be applied due to the spatial proximity of the CR nodes.
- (v) For the sake of brevity, we do not consider the control messaging transmission and assume all the control and signaling messages are transferred via a dedicated

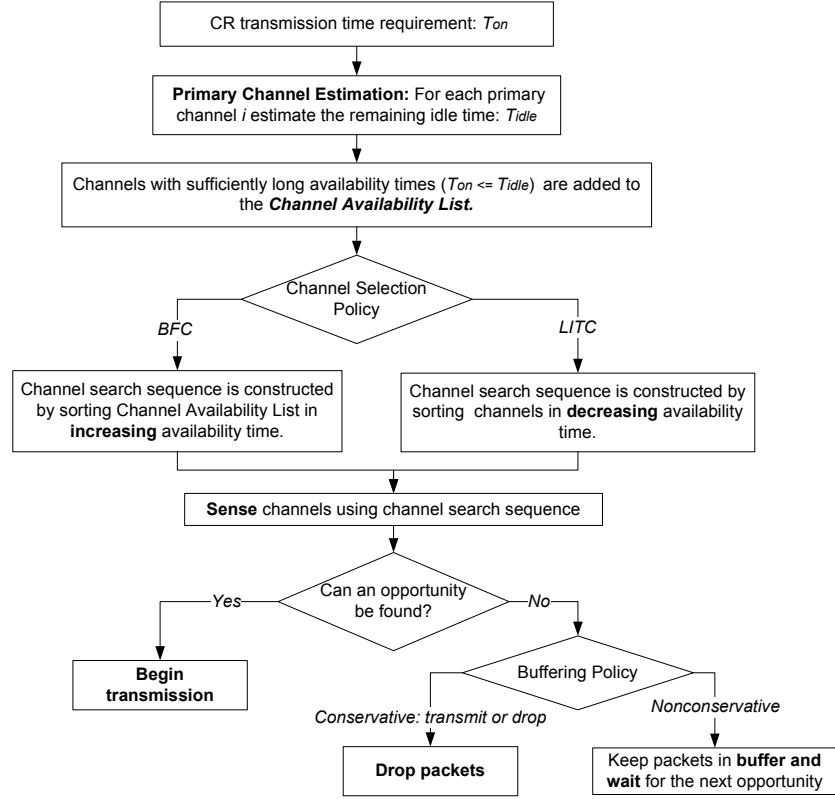


Figure 3.2. Flowchart of channel selection schemes.

control channel.

In this access scheme, when a CR has any packet to transmit, it considers its transmission time (T_{on}). Next, it estimates the availability time of each primary channel which is denoted by T_{idle} . Channels meeting the minimum time availability requirement ($T_{idle} \geq T_{on}$) are added to the available channel list $\mathcal{C}_{idle}$. $\mathcal{C}_{idle}$ is also the list of candidate channels for CR transmission. Depending on the channel selection policy, elements of $\mathcal{C}_{idle}$ are sorted either in increasing or decreasing order of spectrum opportunity time for BFC and LITC, respectively. The sorted list is the channel search sequence. If no channel meets CR transmission requirement (i.e. $\mathcal{C}_{idle} = \emptyset$), then the transmission attempt fails in case of *conservative access* policy. In this case, the CR does not have buffering capability and applies a *transmit or drop* policy. It is similar to 0-1 knapsack problems in which fractional assignment of an item to a bag is not possible. In *non-conservative case*, the CR performs partial transmission during the longest spectrum opportunity, buffers the rest of the request and waits for the next opportunity.

3.2.4. Longest Idle Time Channel Selection (LITC)

In this scheme, CR simply selects the channel with the longest idle time from $\mathcal{C}_{idle}$. This approach is considered as *selfish* since CR selects the best available channel in terms of availability time even if it does not need the entire spectrum opportunity. Figure 3.2 provides the control flow of BFC and LITC schemes.

3.2.5. p-selfish Channel Selection

Let p denote the probability of each CR acting in a selfish way. In other words, at each channel access attempt CR selects its strategy probabilistically between BFC and LITC according to the value of p . Note that $p = 0$ corresponds to BFC whereas $p = 1$ is LITC.

3.2.6. Algorithm Complexity Analysis

Complexity of each algorithm depends on the complexity of the channel availability time estimation algorithm and the sorting algorithm applied for sorting the channels according to their spectrum opportunity durations. Since our emphasis is on the second part independent of the channel estimation algorithm, we consider only the sorting step. Hence, complexity of each scheme is $O(F \log F)$ as sorting can be done by an algorithm with $O(F \log F)$ complexity. Therefore, our algorithms are computationally efficient as they are solvable in polynomial time.

3.3. Results and Discussions

In this section, we present simulation results. A discrete-event simulator is developed in MATLAB to mimic the considered model and operation of channel selection schemes. Simulation runs are collected from ten independent runs for ensuring the statistical validity. First, we analyze the access schemes under conservative access policy. Finally, effect of selfishness for CRs with buffering capability is examined.

3.3.1. Definitions

Before presenting our results, we first provide the basic definitions that will be used in the following sections.

- *Spectrum opportunity* (θ) represents the total spectrum opportunities in all PU channels. Spectrum opportunity of a PU channel f , denoted by θ_f , is calculated as the total time duration for the PU channel f during which there is no ongoing PU transmission, that is, expected value of the channel's idle duration ($E[T_{idle}^f]$).

$$\theta_f = E[T_{idle}^f] = P_{idle}^f T_{sim} \quad (3.5)$$

$$P_{idle}^f = \frac{\alpha_{PU}}{\alpha_{PU} + \beta_{PU}} \quad (3.6)$$

In Equation 3.5 and 3.6, P_{idle}^f , α_{PU} and β_{PU} stand for the channel's probability of being idle and PU channel's traffic generation on and off duration parameters, respectively. T_{sim} is the simulation duration. Total spectrum opportunities is the sum of spectrum holes through all PU channels, i.e. $\theta = \sum_{f=1}^F \theta_f$.

- *CR traffic load* (δ_{CR}) is the ratio of total generated CR traffic by N CRs to the total spectrum opportunities through all F primary channels: $\delta = \frac{E[P]}{\theta}$ where $E[P]$ is the expected value of the total CR traffic. It is calculated as follows:

$$E[P] = \sum_{i=1}^N E[T_{on}^i] = \sum_{i=1}^N p_{on}^i T_{sim} \quad (3.7)$$

$$p_{on}^i = \frac{\beta_{CR}}{\alpha_{CR} + \beta_{CR}} \quad (3.8)$$

In the above equations, p_{on}^i is the probability that CR_i generates traffic at a time and $E[T_{on}^i]$ is the expected total activity time of this CR.

- *Probability of successful transmission* (p_s) represents the probability that a CR with a transmission request will find an available channel for transmission. It is used as a performance metric and calculated as the ratio of total CR successful transmission time to the total generated CR traffic.

- *Spectrum opportunity utilization* (Θ) represents how much of the actual spectrum opportunities is utilized by the CRs. It is simply the ratio of CR total successful transmission time to the total PU idle times, and calculated as follows:

$$\Theta = \frac{\sum_{i=1}^N E[T_{\text{success}}^i]}{\sum_{f=1}^F E[T_{\text{idle}}^f]} \quad (3.9)$$

In the following, we consider identical PU channels and identical CRs in terms of PU and CR activities. Hence, we drop the index values in p_{on}^i and P_{idle}^f . We use them as p_{on} and P_{idle} . In addition, when not used with subscripts, α and β stand for on and off duration parameters in general, respectively.

3.3.2. Effect of Primary Channel and CR Traffic Activities

In this set of simulations, we analyze how CR and primary channel traffic affect the performance of each scheme in terms of probability of successful transmission (p_s) and spectrum opportunity utilization (Θ). Expected value of the system throughput $E[T]$ is $p_s E[P]$ where $E[P]$ is the total generated CR traffic. Since $E[P]$ is the same for the BFC and LITC, the determining factor in $E[T]$ is p_s . Via simulations, we derive values for p_s under various settings for these two access schemes using the approach in [56] to model the PU and CR traffic. We classify each traffic activity into four groups as long-term activity (LL), high activity (LS), low activity (SL) and intermittent activity (SS). L and S stand for long (L) and short (S) durations, respectively. What we mean by long and short is listed in Table 3.1 [56]. Each scenario is represented with a tuple of four elements as follows: $\langle \text{CR}_{on} \text{CR}_{off} \text{PU}_{busy} \text{PU}_{idle} \rangle$. For instance, the scenario denoted by LSSL has long on times and short off times for the CR traffic whereas it has short busy and long opportunity times for the primary channels. Primary channel traffic and CR traffic can be in one of these activity types that makes 16 combinations in total. We test all these cases in the simulations using the following mean on/busy (α^{-1}) and off/idle (β^{-1}) duration values: $\alpha^{-1} = \{0.75, 1.5\}$ and $\beta^{-1} = \{0.75, 1.5\}$.

Table 3.2 summarizes and Figure 3.3 depicts the simulation results. Traffic cases

in the rows stand for the CR activity whereas the traffic types in the columns represent the PU activity type. In the table, p_s for each scheme, percentage performance improvement (Δ) of BFC over LITC for all traffic activity cases and the corresponding CR traffic load (δ_{CR}) are listed. As expected, in some of the scenarios (e.g. LSSL) there is not a significant performance difference. When CRs have long traffic (L) durations and primary channels have short idle (S) durations, both schemes perform similarly. This is expected since there are not enough (sufficiently long) spectrum opportunities in either case, and p_s is quite low around 0.16. The simulation results are consistent with the expected value of system throughput derived from Equation 3.7. For instance, the throughput achieved in BFC is 15% higher than LITC for LSLS traffic activity. In order to perform well, evidently CR total transmission demand must be less than the available resources satisfying the following inequality: $CR_{demand} \leq PU_{resource}$. Total CR demand and available PU resources are calculated as follows:

$$CR_{demand} = N \times p_{on} \times T_{sim} \quad (3.10)$$

$$PU_{resource} = F \times P_{idle} \times T_{sim} \quad (3.11)$$

where p_{on} and P_{idle} are calculated as in Eqn. 3.8 and Eqn. 3.6, respectively. The cases where BFC and LITC perform similarly and have low p_s are the ones that cannot satisfy the above inequality. In the simulations, we set $N = 8, F = 10$. Under these parameters, BFC outperforms LITC with an increase in p_s ranging from 7% to 14%. The lowest improvement is achieved for LSLS and LLLS cases whereas the largest is in SSLS, LSSL and LLSL cases. Although these values might seem marginal, it does not imply an inefficiency in the proposed approach. Since the maximum efficiency that can be achieved by these two schemes is bounded by various parameters, e.g. P_{idle} of the PU channels and the CR traffic load, the low values for p_s are expected in some traffic activities such as LSLS. In general, for scenarios with short CR on durations (SS and SL) both schemes have better performance compared to the scenarios with long CR on durations (LL and LS).

Next, we set α_{CR} and β_{CR} values to 1 and evaluate p_s for the two schemes under

Table 3.1. Traffic activity type and related parameters of primary channels and CRs.

Traffic activity type	ON/BUSY parameter	OFF/IDLE parameter
Long-Term Activity (LL)	$\alpha \leq 1$	$\beta \leq 1$
High Activity (LS)	$\alpha \leq 1$	$\beta > 1$
Low Activity (SL)	$\alpha > 1$	$\beta \leq 1$
Intermittent Activity (SS)	$\alpha > 1$	$\beta > 1$

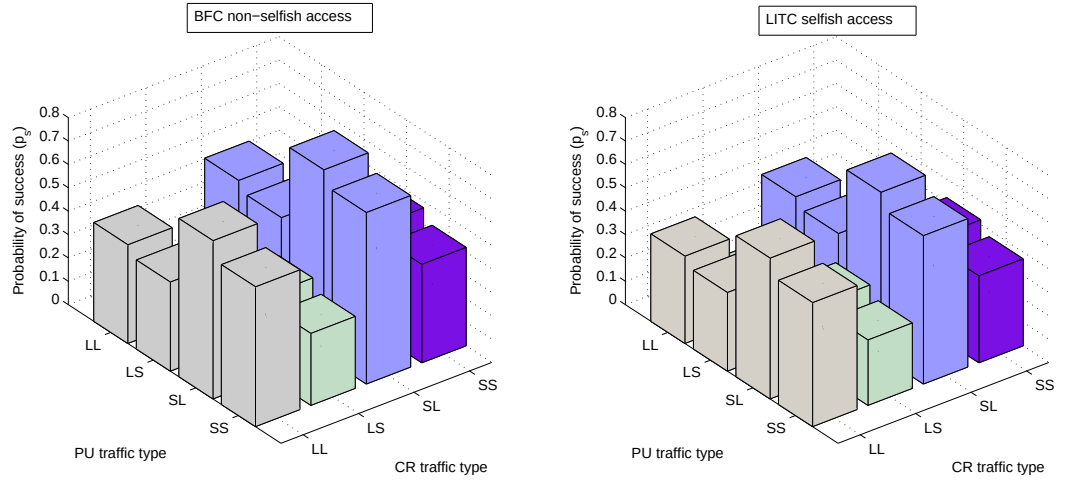


Figure 3.3. Performance of BFC and LITC under sixteen traffic activity cases.

$$N = 8, F = 10.$$

Table 3.2. Summary of results on performance of BFC and LITC under sixteen traffic activity cases.

	LL				LS				SL				SS			
	BFC	LITC	δ_{CR}	Δ	BFC	LITC	δ_{CR}	Δ	BFC	LITC	δ_{CR}	Δ	BFC	LITC	δ_{CR}	Δ
LL	0.42	0.37	0.80	13	0.18	0.16	1.20	7	0.52	0.45	0.45	14	0.24	0.21	0.80	10
LS	0.38	0.34	1.07	13	0.16	0.15	1.59	7	0.48	0.41	0.41	14	0.22	0.20	1.06	12
SL	0.68	0.60	0.54	12	0.35	0.32	0.80	8	0.80	0.70	0.70	12	0.47	0.42	0.53	12
SS	0.60	0.53	0.80	13	0.31	0.28	1.20	9	0.73	0.63	0.63	14	0.42	0.37	0.80	13

Table 3.3. Effect of traffic parameters on probability of successful transmission.

	$\beta^{-1} = 0.1$		$\beta^{-1} = 0.5$		$\beta^{-1} = 1$		$\beta^{-1} = 1.5$		$\beta^{-1} = 20$	
	BFC	LITC	BFC	LITC	BFC	LITC	BFC	LITC	BFC	LITC
$\alpha^{-1} = 0.1$	0.03	0.02	0.32	0.29	0.61	0.52	0.78	0.66	1.00	1.00
$\alpha^{-1} = 0.5$	0.01	0.01	0.24	0.22	0.52	0.45	0.71	0.60	1.00	1.00
$\alpha^{-1} = 1$	0.01	0.01	0.18	0.16	0.42	0.37	0.60	0.52	1.00	0.99
$\alpha^{-1} = 1.5$	0.00	0.00	0.14	0.13	0.36	0.32	0.53	0.47	1.00	0.99

varying PU channel parameters that are selected from the following sets $\alpha_{PU}^{-1} = \{0.1, 0.5, 1, 1.5\}$ and $\beta_{PU}^{-1} = \{0.1, 0.5, 1, 1.5, 20\}$. Note that $\alpha_{PU}^{-1}=20$ is missing in the first set. It is omitted since such a PU channel is practically of no use for the CRs due to its very long busy times. Table 3.3 presents the change in p_s for BFC and LITC with the change in mean primary channel on (α_{PU}^{-1}) and off (β_{PU}^{-1}) durations. BFC and LITC behave similarly in the same regions, with BFC having higher p_s values than that of LITC. The results are as expected: very long PU opportunity times ($\beta_{PU}^{-1}=20$) result in the highest success probabilities and CR throughput whereas short idle times ($\beta_{PU}^{-1}=0.1$) result in poor performance. However, please note that other than the abstract values of α_{PU} and β_{PU} , their relative values compared to the CR activity parameters (α_{CR} and β_{CR}) are the actual parameters affecting the system performance.

Since primary network is already settled and cannot be changed, the CRN can adapt its traffic parameters according to the PU channel characteristics and thus operates efficiently. For instance, if the PU channel availabilities are exponential with mean value β_{PU}^{-1} then CRN must have transmission in units shorter than these spectrum opportunities by setting CR packet size significantly smaller than the mean PU channel opportunity times, i.e. $\alpha_{CR}^{-1} \ll \beta_{PU}^{-1}$. Otherwise, it operates either in an intrusive way or it needs to fragment the transmission in units shorter than mean PU opportunity durations. Our results are also consistent with the results of various works in the literature, such as [57]. In [57], with increasing PU duty cycle, quality of the CR transmission degrades. The duty cycle stands for the percentage of time PU is *on* which is another representation of probability of a PU channel's being busy ($1-P_{idle}$) used in our model.

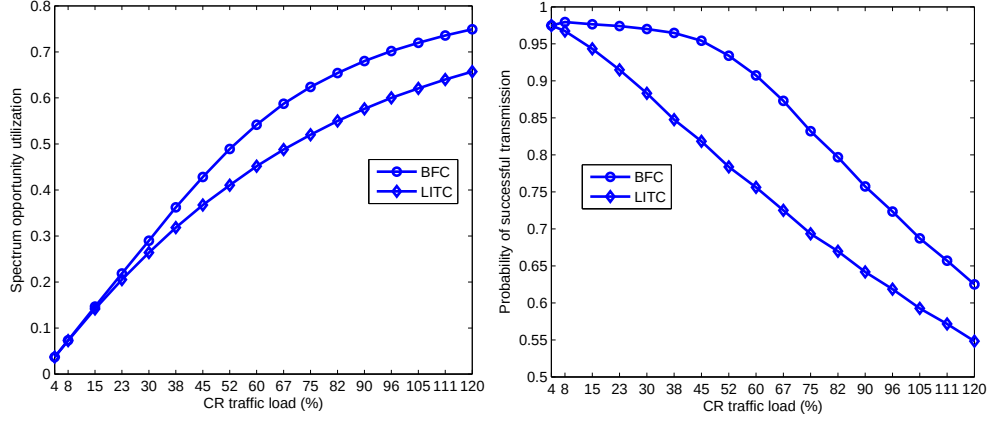


Figure 3.4. Spectrum opportunity utilization and probability of successful transmission for BFC and LITC under increasing number of CRs in the network.

$$F = 16, \alpha_{PU}^{-1} = 0.4, \beta_{PU}^{-1} = 20, \alpha_{CR} = 1 \text{ and } \beta_{CR} = 1.$$

3.3.3. Effect of Number of CRs

In this set of simulations, we analyze how each scheme reacts to the increasing CR traffic demand. Hence, we test the scenarios with sufficient spectrum opportunities, i.e., satisfying $CR_{demand} \leq PU_{resource}$, so that the performances of BFC and LITC are not restricted due to the natural scarcity of resources. We set the number of PU channels $F = 16$. Considering the analysis in the previous section, we set $\alpha_{PU}^{-1} = 0.4$ and $\beta_{PU}^{-1} = 20$ for the PU channels and $\alpha_{CR} = 1$ and $\beta_{CR} = 1$ for each CR user traffic. Θ and p_s performances are illustrated in Figure 3.4. Figure 3.5 depicts the distribution of spectrum fragment sizes that result in the channels after applying the BFC and LITC access schemes. The word *fragment* refers to the unused spectrum opportunities.

With the increase in number of CRs in the network (CR traffic load changing from 4% to 120%), the competition for the spectrum holes becomes more intense. As a natural consequence of this competition, the average throughput per CR and p_s decrease in both schemes. However, as the Figure 3.4 demonstrates, BFC always outperforms LITC. The x-axis represents the CR traffic load (δ_{CR}) corresponding to the increasing number of CRs in the network from a single CR ($N = 1$) to $N = 32$. In light load ($\delta_{CR} = 0.04$) when $N = 1$, p_s is 0.97 and Θ is 0.04. This is a single CR case,

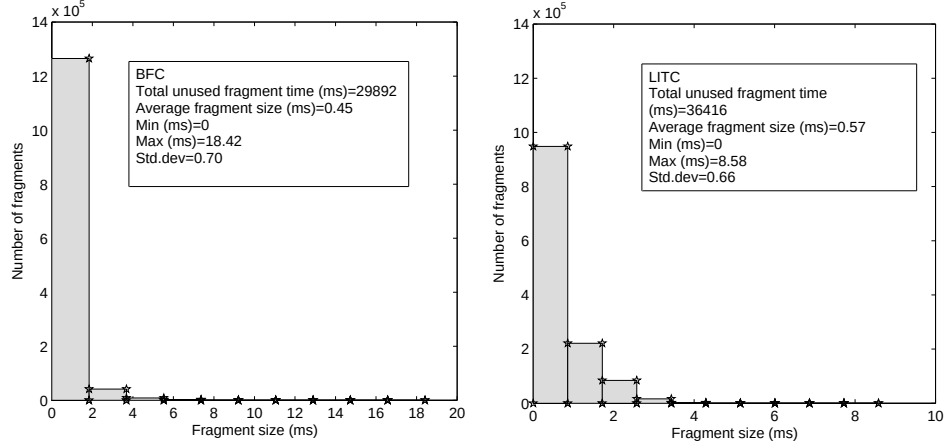


Figure 3.5. Distribution of spectrum fragment sizes after the BFC and LITC schemes. $N = 20$, $\delta_{CR} = 0.60$.

and thereby there is no competition. Nonetheless, the transmission is not guaranteed ($p_s < 1$). That is caused by the size of the spectrum opportunities and *transmit or drop* policy of the CR. Similarly, the increase in the CR traffic results in increase in Θ . However, it is not a linear function of number of CRs. Although not all the spectrum voids are utilized ($\Theta < 1$), p_s is around 0.87 (BFC) and 0.72 (LITC) when $\delta_{CR} = 0.67$. This is also caused by the conservative operation principle of the CRs. In all scenarios, BFC outperforms LITC in terms of average throughput per CR, Θ and p_s .

Figure 3.5 depicts the fragment size distribution under BFC and LITC, and summarizes the fragment characteristics of the PU channels after all the CR communications are processed. BFC results in less total spectrum fragments since it improves the CR throughput by better sharing the spectrum opportunities. In the figure (left), most of the fragments are short whereas there are very few number of long spectrum fragments. Compared to the BFC, LITC (figure on the right) results in lower number of fragments with long duration since a CR applying LITC prefers spectrum opportunity with the longest idle duration in the first place for channel access. Hence, maximum fragment size in BFC is larger than that of LITC. These long duration fragments can be used if more CR traffic is generated in the CRN whereas short fragments may not be preferred due to the inefficiency and cost of using them.

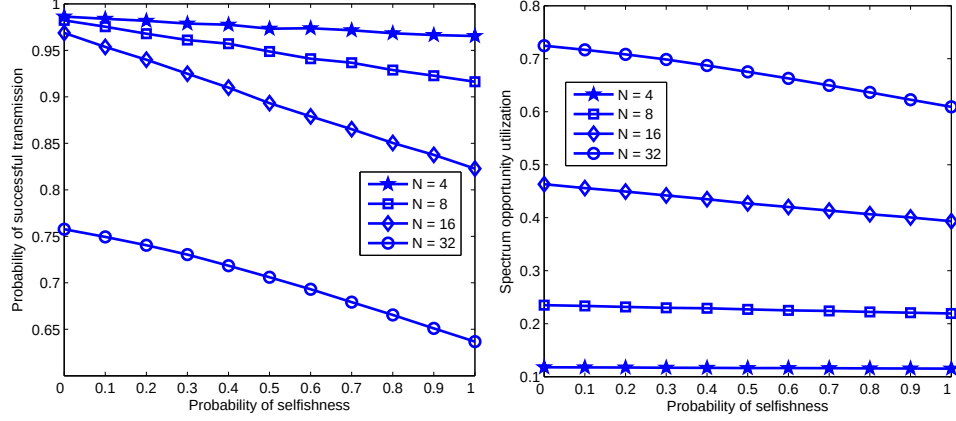


Figure 3.6. Probability of successful transmission and spectrum opportunity utilization with increasing selfishness for $N = \{4, 8, 16, 32\}$, $F = 20$, $\alpha_{PU}^{-1} = 0.4$,

$$\beta_{PU}^{-1} = 20 \text{ and } \alpha_{CR} = \beta_{CR} = 1.$$

3.3.4. Effect of Selfishness: Analysis of p-selfish Access Scheme

We analyze the effect of selfishness under varying number of CRs. In the simulations, CRs generate traffic with $\alpha_{CR} = \beta_{CR} = 1$ while α_{PU}^{-1} is set to 0.4 and β_{PU}^{-1} is 20. We set $F = 20$, $N = \{4, 8, 16, 32\}$ corresponding to the traffic load of $\delta_{CR} = \{0.12, 0.24, 0.48, 0.96\}$. Note that with these scenarios, we test how our proposed scheme behaves under various CR traffic loads. Figure 3.6 depicts the change in p_s and Θ with increasing selfishness under four traffic loads. With the increase in selfishness of the CRs, p_s decreases. This indicates that non-selfish BFC performs better than selfish LITC. In other words, *0-selfish* access scheme outperforms the *1-selfish* access scheme. Although this conclusion is valid for all the above scenarios, the performance difference is more significant under heavier loads (e.g. $N = 16$ and $N = 32$).

We also analyze the probability that a transmission attempt succeeds or fails. Let the probability of success in channel selection (P_{cs}) be defined as the probability that a CR transmission attempt can find an appropriate spectrum opportunity and transmits on that channel. P_{cs} and probability of blocking (P_b) are calculated as follows:

$$P_{cs} = \frac{\text{Number of successful CR transmission attempts}}{\text{Total number of CR transmission attempts}}$$

$$P_b = 1 - P_{cs} \quad (3.12)$$

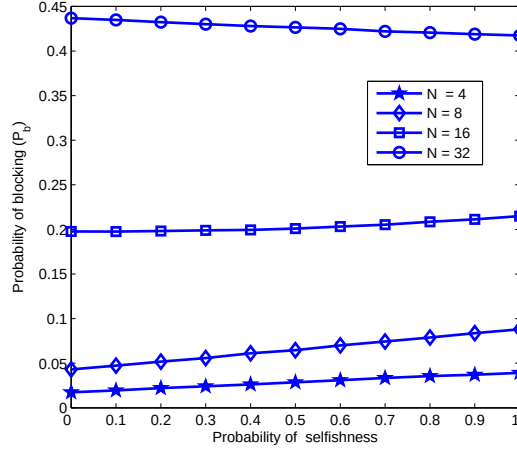


Figure 3.7. Probability of selfishness vs. probability of blocking for $N = \{4, 8, 16, 32\}$.

Figure 3.7 depicts the effect of selfishness on P_b under increasing number of CRs. As expected, P_b increases with the increase in selfishness for $N = \{4, 8, 16\}$. However, contrary to what is expected, increase in selfishness leads to a decrease in P_b for $N = 32$ (heavy load). At first, this situation seems to be in contradiction with our previous findings. However, further analysis on the distribution of the failed transmission attempts leads to the following explanation: since BFC enables better spectrum allocation and less fragmented spectrum, long transmission requests can find appropriate channels for transmission. Hence, long requests begin transmission in the channels. The arriving short requests cannot get channels since longer requests have already begun transmission. This results in higher P_b . On the other hand, LITC results in spectrum to be heavily fragmented in time domain, and thus cannot handle long transmission requests. Those long transmission requests are blocked, which enables shorter requests to access to the idle channels. Hence, LITC has lower P_b but still has lower throughput compared to BFC under heavy traffic load.

3.3.5. Analysis of Fragmentation with the Change in Selfishness

We examine the distribution of spectrum fragments (gaps) in two ways: (i) at the time that a CR arrival occurs and observe the spectrum for potential transmission opportunities (during the simulation) and (ii) after all the spectrum allocation is completed (at the end of the simulation). Figure 3.8 depicts the view of the spectrum

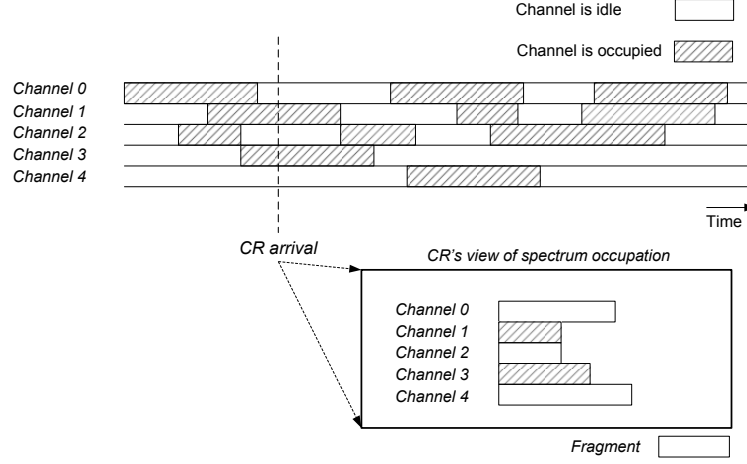
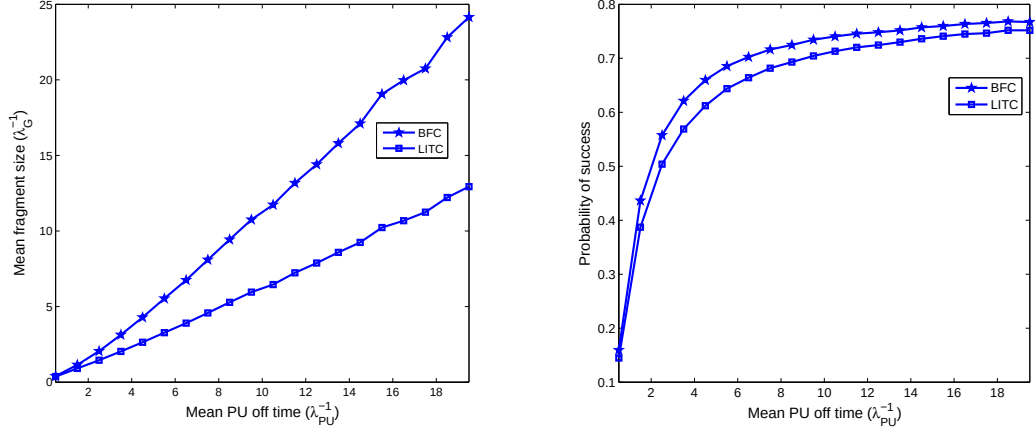


Figure 3.8. CR's view of spectrum occupation.

observed by an arriving CR. The channels which are already occupied are ignored in the channel selection process whereas the idle channels are evaluated according to their *fragment sizes*.

Fragment size in this first analysis is the size of the spectrum gap (in time units) that is observed by an arriving CR. We record the fragment sizes during the simulations (simulation time=10 seconds, and number of runs with different seeds is 20). The collected data consists of around 300000 samples. On this sample, we use distribution fitting software to determine the possible distribution functions for the fragment size. EasyFit [58] is such a tool which consists of 56 distributions and advanced fitting analysis tools. EasyFit provides also goodness of fit tests (i.e. Kolmogorov-Smirnov, Anderson-Darling and Chi-Square tests). Our data shows good matching to an exponential distribution. Although there are a number of other distribution functions (e.g., Phased Bi-Weibull, Wakeby, Weibull etc.) that provide a better matching to our data, goodness of fit tests show that exponential function is still a good choice. After discovering that fragment sizes in both channel selection schemes follow an exponential distribution, we fit the recorded fragment sizes to exponential distributions and find the related parameters.

Figure 3.9a shows the mean fragment size for both BFC and LITC with increasing mean PU off time (spectrum opportunity duration). These values are acquired by fitting the fragment record data to the exponential distribution, hence are the inverse



(a) BFC and LITC mean fragment size

(b) Probability of success.

Figure 3.9. Effect of mean PU off time on mean fragment size and probability of success.

of parameters (λ_G^{-1}) of corresponding exponential functions. As Figure 3.9a illustrates BFC has always longer mean fragment size compared to the selfish scheme LITC. This is expected since we already intuitively concluded that BFC decreases fragmentation. Figure 3.9b shows the related performance increase in terms of probability of success in channel selection for BFC and LITC with increasing spectrum opportunity duration.

As the second analysis, we examine total unused spectrum fragment duration in BFC and LITC. Additionally, the maximum, the minimum and average size of fragments are analyzed. Finally, the CR transmission attempts that failed and succeeded are recorded. Figure 3.10a summarizes the change in total unused spectrum opportunity duration with the increasing selfishness parameter for various number of CRs in the network. Since selfishness decreases performance in terms of spectrum allocation, less spectrum can be utilized in more selfish approaches. This results in more unused spectrum opportunities. Related to this fact, average gap size is also shorter for BFC compared to LITC.

Maximum fragment size with increasing selfishness parameter is depicted in Figure 3.10b. Since BFC allocates CR traffic requests to the best-fitting spectrum opportunities, it results in less fragmentation. This can be seen from the figure as higher maximum fragment size values for BFC compared to LITC and more selfish schemes.

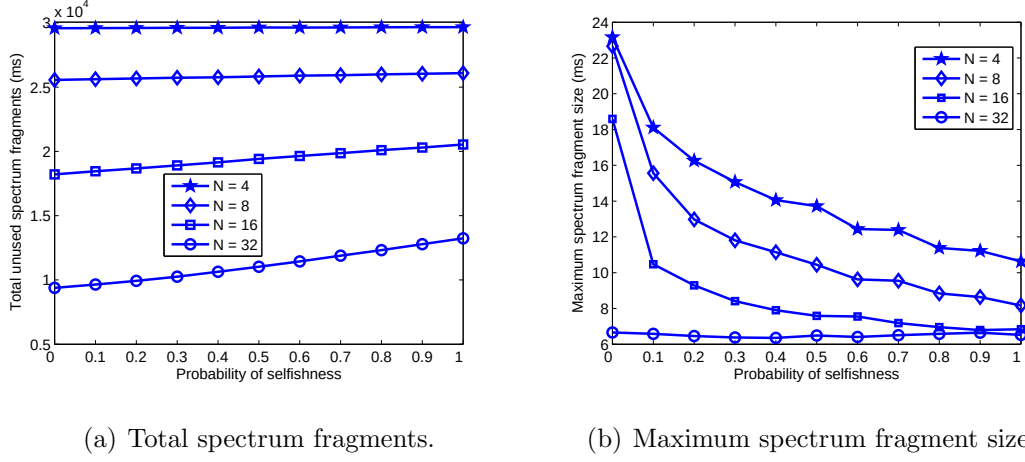


Figure 3.10. Total spectrum gaps and maximum fragment size with increasing selfishness $N = \{4, 8, 16, 32\}$, $F = 20$, $\alpha_{PU}^{-1} = 0.4$, $\beta_{PU}^{-1} = 20$ and $\alpha_{CR} = \beta_{CR} = 1$.

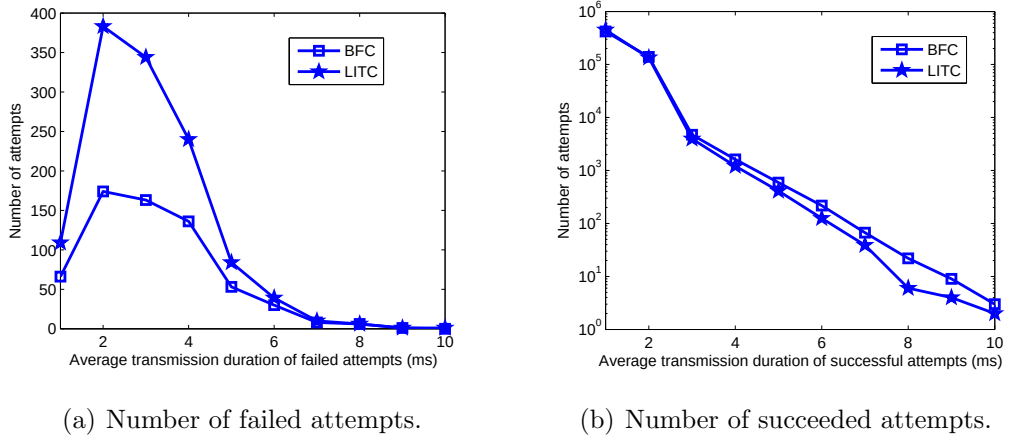


Figure 3.11. Number of CR transmission attempts in channel selection with increasing transmission duration.

On the other hand, average fragment size for BFC is lower than LITC. These two results show that BFC improves spectrum opportunity utilization (less total spectrum fragments, Figure 3.10a) without fragmenting the spectrum as much as that of LITC. For the high load scenario ($N = 32$), there is a slight difference among the access schemes, whereas it is more noticeable for lower load scenarios, e.g. $N = \{4, 8, 16\}$. This is predictable since under high load almost all spectrum opportunities are allocated to the CR traffic, thereby leading to less distinction in fragment sizes. However, under low load scenarios, the access scheme has a more significant impact on the final fragment size distribution.

Finally, Figure 3.11, derived from the histogram of failed and successful CR transmission durations, shows the number of attempts that failed and succeeded. Minimum fragment size does not significantly change depending on the selfishness parameter and there is not a consistent trend in the change of minimum fragment size.

3.3.6. Effect of Estimation Errors

In the previous sections, we assumed that all CRs have the capability to perfectly estimate (know) the primary channel idle time durations. However, this is infeasible in practice. In this set of simulations, we analyze the performance of the channel access schemes under various estimation errors. Errors are classified into three as follows:

- (i) Estimated idle durations are always shorter than the actual durations (scenarios denoted by SHORT I, SHORT II and SHORT III),
- (ii) Estimated idle durations are always longer than the actual durations (scenarios denoted by LONG I, LONG II and LONG III),
- (iii) Random errors in which estimations may be either longer or shorter (scenarios denoted by RAND I, RAND II and RAND III)

Each of the three scenarios (I, II and III) represents the low, medium and high error cases in the related groups. Scenario denoted by EXACT represents the previously studied scenarios where estimations are exact. Figure 3.12 depicts a simple example of how the CR acts under SHORT, EXACT and LONG estimation error cases. In the SHORT scenarios, a CR due to its inaccurate short estimations thinks that the spectrum opportunity will not meet its demand. Thereby, it does not access the channel and the transmission is not attempted. This leads to poor spectrum utilization and low CR throughput. In the LONG scenarios, a CR with its inaccurate long estimations, presumes that the spectrum opportunity is sufficiently long for its transmission. CR transmits in the selected opportunity, which may lead to interference to the arriving PU traffic in the transmission channel. In the EXACT scenarios, CR perfectly fits into the spectrum opportunity without disturbing the PUs. The estimated durations ($\overline{L^{opp}}$)

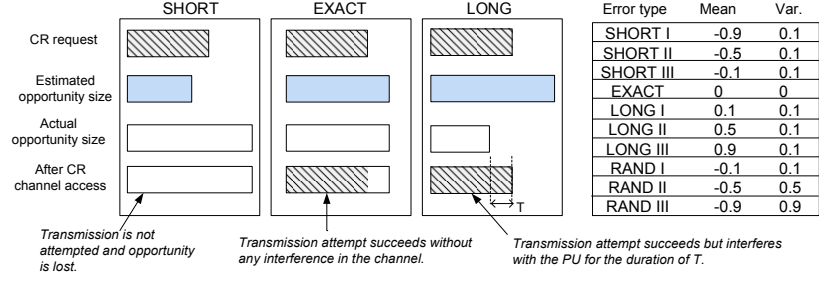


Figure 3.12. Effect of three types of estimation errors on the CR channel access.

Estimation error parameters of respective scenarios are listed in the table.

are calculated as follows:

$$\overline{L^{opp}} = L^{opp} + F(L^{opp} \times v, L^{opp} \times \rho) \quad (3.13)$$

where L^{opp} is the actual opportunity size and $F(L^{opp} \times v, L^{opp} \times \rho)$ is the error function with mean parameter v and variance parameter ρ . For the RAND scenarios, F is uniform (i.e. error values are uniformly distributed on $[L^{opp} \times v, L^{opp} \times \rho]$) whereas for the LONG and SHORT scenarios it follows normal distribution. These v and ρ values for each scenario are presented in Figure 3.12.

Figure 3.13 and 3.14 depict the change in spectrum utilization success (Θ) and the spectrum utilization attempt. We also analyze CR/PU traffic corruption rate due to collisions among CRs and PUs, respectively. Traffic corruption ratio is the ratio of failed transmission time due to collision, to the total CR traffic. We assume that if the interfered ratio ($\xi = \frac{\text{interference time}}{\text{transmission duration}}$) for a transmission attempt is above a threshold value (ϖ_{corr}), then that transmission is recorded as corrupted. In the simulations, we set $\varpi_{\text{corr}}=0.1$. As opposed to Θ which only records successful transmission attempts, spectrum utilization attempt considers all transmission attempts. It is a measure of the opportunities that are accessed by CRs during which the attempt results in success or failure since $\xi \geq \varpi_{\text{corr}}$.

As the figures show, for SHORT I scenario, since the estimated idle durations are significantly shorter than actual values and the CRs apply a conservative approach, CRs almost never attempt to transmit. That leads to wasted spectrum, i.e. the

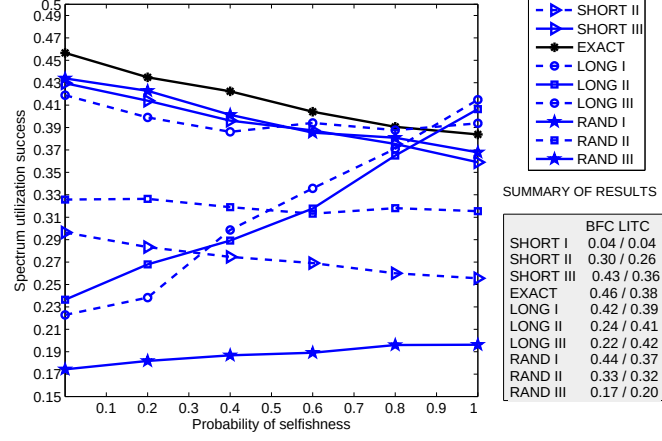


Figure 3.13. Probability of selfishness vs. spectrum utilization (only successful attempts) under various estimation error types.

spectrum available but cannot be used since it is not discovered by the CRs. Hence, spectrum access attempt and success are very low ($\Theta = 0.04$ while $\Theta = 0.46$ for BFC EXACT scenario). In these scenarios, increase in selfishness still decreases the network performance.

Unlike SHORT scenarios, selfishness improves the performance for LONG scenarios. In these latter cases, CRs are optimistic about the channel idle durations (e.g. they expect the channels stay idle longer than they will) and hence begin transmission even if their transmission will not fit into the actual gap. This access policy may result in interference with the PUs. However, some of the transmissions will not noticeably affect the PU transmissions or will not lead to corruption in CR traffic. That is the rationale behind the fact that performance in LONG III scenario is the highest (Figure 3.14), even better than the EXACT estimation case. In BFC and less selfish access schemes, shorter gaps are selected which results in longer interference time with the PUs. Some of the collisions result in packet corruption while those with corruption ratio under the threshold are successfully completed. As a result, selfishness in LONG scenarios (II and III) improves the spectrum opportunity utilization, CR throughput and probability of successful transmission. The most probable scenario, i.e. RAND I, has better efficiency in BFC ($\Theta = 0.44$) compared to LITC ($\Theta = 0.37$). In this case, with the increase in selfishness, spectrum utilization decreases. With regard to random errors, LITC outperforms BFC under high error RAND III scenario while BFC and

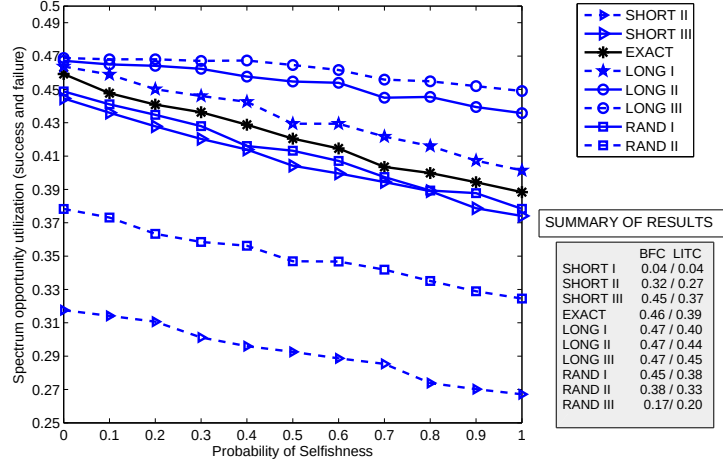


Figure 3.14. Probability of selfishness vs. spectrum utilization attempt (both successful and failed attempts) under various estimation error types.

LITC have similar performances for RAND II.

Since the same CR transmission may collide with a number of PU transmissions in a channel (e.g. three PU transmission interferes with the same CR transmission), the aggregate interference time drastically affects the CR performance as opposed to the PU traffic. For instance, for LONG III scenario CR corruption ratio is around 0.5 whereas it is 0.03 for PU traffic which may be tolerable. In SHORT and EXACT scenarios, selfishness does not affect the corruption ratio since they are all collision-free. However, for LONG and RAND error cases, corruption ratio for both the PU and CR traffic increases with increasing selfishness. For example, for RAND III scenario PU corruption ratio is 0.007 and 0.001 whilst CR corruption ratio is 0.20 and 0.08 for BFC and LITC, respectively. Hence, it is crucial to consider both the corruption ratio and the desired spectrum utilization success in determining the ideal access scheme.

To sum up, the best access strategy strongly depends on the accuracy of estimations. Hence, an adaptive access scheme can be applied depending on the estimation capability of CRs. For instance, if the CRs have not acquired sufficient information on the system yet, then a selfish strategy is more appropriate. However, as the CRs learn the communication environment and thereby estimations become more precise, they can apply *non-selfish* (BFC) or *p-selfish* approach with smaller p values.

3.3.7. Effect of Selfishness Under Buffering Capability

In the previous parts, we considered a *conservative* access scheme in which the CR does not start transmission if its transmission time requirement is not satisfied by the spectrum opportunities and thus drops the packets. Now, we relax this scheme to a *non-conservative* one in which the CR transmits through the discovered opportunities even if none of the expected estimated availability times of the channels is sufficiently long. Briefly, if there exist no sufficient opportunities ($T_{\text{idle}}^i \leq T_{\text{on}}, \forall i$) the CR selects the channel with the longest availability and it achieves only a part of its transmission. The remaining part is kept in the CR buffer till the next availability. With the assumption that each CR estimates how long a PU channel is going to be busy, it waits till the start of the nearest opportunity (i.e., the first spectrum hole in time domain). Since more than one CR may attempt to access the spectrum opportunity as soon as the channel becomes idle, collisions among the attempting CRs may occur. To tackle with this potential issue, each node waits for a random duration that is inversely proportional to its instantaneous buffer size before accessing the channel. Hence, the CRs with more loaded buffers have higher probability of winning the contention for the channel compared to those with less loaded buffers. Differentiation among CRs depending on their traffic types can be enabled by assigning different contention windows. Since we focus on the channel access and do not consider a complete MAC protocol, we do not study the optimal length of this waiting duration or related issues. In this scheme, if there are sufficiently long spectrum holes and if there is sufficient capacity, CR acts as it does in the conservative schemes (e.g. BFC and LITC) depending on the value of p . For $F = 10$, $\alpha_{PU}^{-1} = 0.4$ and $\beta_{PU}^{-1} = 20$, Figure 3.15 shows the change in the average medium access delay of the CRs with increasing degree of selfishness. As the figure shows, less selfish schemes (e.g. BFC with $p = 0$) outperform the more selfish schemes (e.g. LITC with $p = 1$) in terms of medium access delay. To sum up, BFC is more efficient not only in terms of throughput and fragmentation but also in terms of average channel access delay.

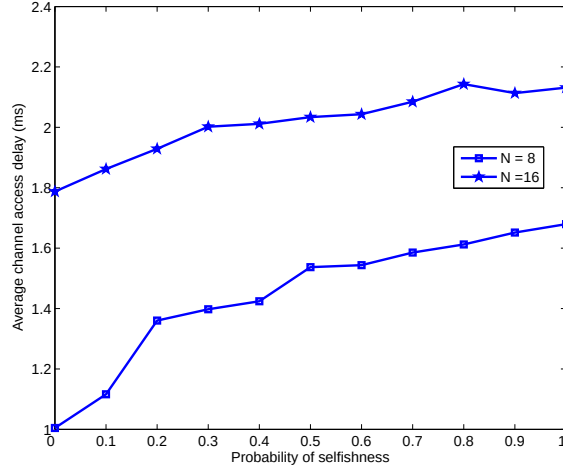


Figure 3.15. Average medium access delay of the CRs with increasing p . $F = 20$, $\alpha_{PU}^{-1}=0.4$, $\beta_{PU}^{-1} = 20$ and $\alpha_{CR} = \beta_{CR} = 1$.

3.3.8. Discussions

BFC and LITC both depend on the assumption that PU channel traffic pattern can be estimated by each CR accurately. There are various methods for forecasting the PU traffic characteristics [16–19]. Kim and Shin [18] utilize the theory of alternating renewal processes to model the primary traffic and to estimate the PU channels' idle and busy times in a IEEE 802.22-like single hop CRN. Given the average idle and busy times of a channel, a CR can estimate the state of the channel (busy or idle) and how long the channel state will stay in the current state (i.e. residual idle time and residual busy time). Similar to [18], authors in [16] propose an alternating renewal theory based modeling and prediction. In [18], channel usage pattern estimation is based on the estimation of on and off durations of the 2-state renewal process using the maximum likelihood estimators whereas in [16], CRs are assumed to have a priori information on these parameters. In [19], authors first propose a PU traffic pattern classification scheme that determines if the PU traffic is periodic or stochastic based on collected information. The proposed algorithm classifies the channel traffic activities using the sampling data collected during the spectrum sensing durations. Next, an algorithm for predicting the future availability times of PU channels considering the traffic class determined at the first stage is designed. Using these two algorithms, CRs

apply an intelligent channel selection scheme.

Considering the outcomes of these works, it is possible to predict the channel availabilities and to apply our proposal for distributed channel selection. Since local information may be inadequate in providing accurate estimation, collaboration among CRs can improve the estimation accuracy. In the literature, it is shown that cooperative behavior at various tasks (from spectrum sensing to spectrum sharing) can improve the CRN performance [59, 60]. Hence, the prediction algorithm can incorporate this feature, as well.

3.4. Chapter Summary

In this chapter, we introduced *best-fit channel selection* (BFC) for distributed channel selection that facilitates efficient spectrum sharing in addition to suppressing the effects of spectrum fragmentation.

We assumed that each CR has the precise information on the state of the channel. Each CR, with the knowledge of the transmission time needed to send its packets, considers only the channels with longer availability time than this time requirement as the candidate transmission channels. In BFC, it selects the channel with the shortest idle time from these candidates. We compared the performance of BFC to that of a widely-accepted scheme which we refer to as *longest idle time channel selection* (LITC). Via simulations, we showed that BFC outperforms LITC in terms of CR throughput, probability of successful transmission (p_s) and spectrum utilization (Θ). BFC and LITC correspond to two special cases of *p-selfish channel selection* scheme in which $p = 0$ and $p = 1$ for BFC and LITC, respectively. With increasing selfishness, the overall network performance decreases, i.e. lower p_s and Θ values. Our analysis on the size of fragments (opportunities that are not used), demonstrates that while total fragment size in LITC is longer (due to lower efficiency in spectrum utilization), the maximum fragment size is shorter compared to BFC. This analysis corroborates our assertion that BFC tackles the spectrum fragmentation issue by efficient sharing of the spectrum opportunities better than LITC.

We also evaluated these access schemes under various estimation error types. Simulation results show that the performance depends on the estimation accuracy, therefore the best strategy should be selected based on the performance of CRs in estimating the PU channel idle durations. For low random error scenarios, less selfish schemes outperform the more selfish ones. Finally, medium access delay performance in a system where CRs can buffer the packets till they find an opportunity is analyzed. BFC with better spectrum sharing leads to lower medium access delay compared to LITC. In conclusion, our experimental analysis demonstrates that for network-wide efficiency rather than node level efficiency, a non-selfish operation is more appropriate.

4. A MARKOVIAN MODEL FOR BEST-FIT CHANNEL SELECTION

In Chapter 3, we have evaluated the performance of BFC via simulations and showed that increase in selfishness degrades CRN performance in terms of CR throughput, probability of blocking, and channel access delay. In other words, BFC ($p = 0$) outperforms LITC ($p = 1$). This performance improvement of BFC over LITC is due to the fact that BFC facilitates the spectrum access in such a way that spectrum fragmentation is reduced.

In this chapter, we present a Markovian model of the proposed channel selection scheme [61]. BFC is proposed for distributed networks in which time synchronization is very challenging. Hence, BFC operates in a random access manner lacking the discrete time-slot operation. Therefore, it has a continuous time nature. Moreover, spectrum opportunities are not discrete. Considering these two aspects, continuous time continuous state space models seem to be more appropriate to the nature of our proposal. However, this approach may lead to state space explosion. Therefore, in this work we prefer a simplified continuous time discrete state space model as described in the following sections.

The rest of this chapter is organized as follows. Section 4.1 presents the details of the proposed Continuous Time Markov Chain (CTMC) model while Section 4.2 evaluates this model comparing it with the results obtained from simulations in Chapter 3. Section 4.3 summarizes the outcomes of our work presented in this chapter.

4.1. Analytical Modeling of BFC by Markov Chains

4.1.1. State Space Definition

In a system with F primary channels and N CR users, let $N_{PU}(t)$ and $N_{CR}(t)$ stand for the stochastic processes representing the number of PUs and CRs actively transmitting in the system at time t , respectively. Let $X(t) = S_{i,j} = \{N_{PU}(t) = i, N_{CR}(t) = j\}$ denote the state of the system at time t . Number of channels that are occupied by PUs is i , and total number of CRs transmitting in any of the channels is j . The set of primary channels that are occupied by PUs and CRs are denoted by $\mathcal{C}_{PU}$ and $\mathcal{C}_{CR}$, respectively. $\mathcal{C}_{idle}$ ($\mathcal{C}_{busy}$) is the set of idle (busy) channels. The set of all primary channels is $\mathcal{C}$ where $\mathcal{C} = \mathcal{C}_{busy} \cup \mathcal{C}_{idle}$ and $\mathcal{C}_{busy} = \mathcal{C}_{PU} \cup \mathcal{C}_{CR}$. Note that $\mathcal{C}_{PU} \cap \mathcal{C}_{CR} = \emptyset$. The set of CRs that are in transmission is denoted by $\mathcal{N}_{CR}$ whereas the set of CRs not transmitting is $\mathcal{N}_{idle}$. The set of CRs is $\mathcal{N}$ where $\mathcal{N} = \mathcal{N}_{CR} \cup \mathcal{N}_{idle}$ and $\mathcal{N}_{CR} \cap \mathcal{N}_{idle} = \emptyset$.

The state space $\mathcal{S} = \{S_{0,0}, S_{0,1}, \dots, S_{i,j}, \dots, S_{F,0}\}$ consists of the states $S_{i,j}$ with $0 \leq i, j$, and $(i+j) \leq F$, and $j \leq \min(N, F)$. Since simultaneous transmission in a channel is not permitted (i.e. $\mathcal{C}_{PU} \cap \mathcal{C}_{CR} = \emptyset$), maximum number of transmitting users in the system (CRs and PUs) is restricted to the number of primary channels, F . The idle system is represented by $S_{0,0}$ in which all channels are idle whereas $S_{i,F-i}$ represents the cases all channels are occupied. All channels can be occupied either by only CRs ($S_{0,F}$ if $F \leq N$) or by only PUs ($S_{F,0}$) or both types of users exist in the system. Let the set of these states in which all channels are occupied be $\mathcal{S}_{full} = \{S_{i,F-i}\}$, and the set in which all channels are idle be $\mathcal{S}_{empty} = \{S_{0,0}\}$. Since we assume that CRs are aware of the PU traffic, they do not collide with the PUs. Besides, number of CRs in the network is N , therefore maximum number of CRs in transmission is bounded by $\min(N, F)$. Hence, total number of states $|\mathcal{S}|$ is:

$$|\mathcal{S}| = \sum_{i=0}^F (\min(F-i, N) + 1) \quad (4.1)$$

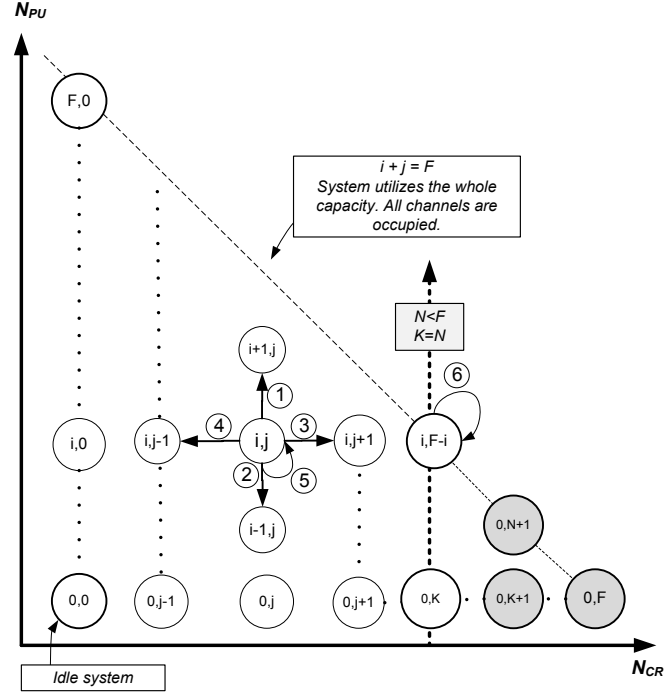


Figure 4.1. State space $\mathcal{S}$ for F primary channels ($F \leq N$). In case of $N < F$, the state space reduces to the one that only includes the states on the left of the line marked, and the shaded states are missing in CRNs.

In practical systems, number of CRs is greater than the number of primary channels, i.e. $N \geq F$, leading to $\min(F - i, N) = F - i$. Hence, $|\mathcal{S}|$ becomes:

$$|\mathcal{S}| = \sum_{i=0}^F (F - i + 1) = \frac{(F + 1)(F + 2)}{2}. \quad (4.2)$$

In this model (as in [62–64]), instead of the state of each channel (whether *occupied by a CR*, *occupied by a PU*, or *unoccupied*), total number of CRs and PUs transmitting in the system are represented. Hence, channel-based analysis is not possible. If the state of each channel were to be modeled individually, the state space $\mathcal{R}$ would consist of the following F -tuples: $R(t) = (R_1, R_2, \dots, R_i, \dots, R_F)$ where the state of C_i can be $R_i = \{\text{occupied by PU (0), occupied by CR (1), idle (2)}\}$. $\mathcal{S}$ can be considered as a compact set that represents a group of states in $\mathcal{R}$ such that $S_{i,j}$ corresponds to $\binom{F}{i} \binom{F-i}{j}$ different states in $\mathcal{R}$, i and j being subject to the same restrictions as

before. In this alternate model, the number of states is calculated as follows:

$$|\mathcal{R}| = \begin{cases} (|R_i|)^M = 3^F & \text{for } F \leq N \\ \sum_{i=0}^F \sum_{j=0}^{\min(F-i, N)} \binom{F}{i} \binom{F-i}{j} & \text{for } F > N \end{cases} \quad (4.3)$$

However, the comparison of the state space sizes of $\mathcal{R}$ and $\mathcal{S}$ shows that $|\mathcal{R}|$, compared to $|\mathcal{S}|$, grows significantly faster with increasing N and F . For instance, $|\mathcal{R}|$ is 3^{10} whereas $|\mathcal{S}|$ is 66 for $N = 20$ and $F = 10$. Rather than this model which preserves state information on the individual channels, in order to keep the system analytically tractable, we prefer the former simplified but compact model. In this work, we assume that all PU channels are identical, e.g. have the same traffic occupancy distributions. Thus, this simplification does not make a significant difference in our analysis as it would in case of non-identical PU channels. For the more general case, our model can be extended doing the necessary modifications.

4.1.2. PU Channel and CR Model

Let U define the duration that a PU channel is occupied until the PU completes its transmission. The channel remains idle for a period of D . The first period is referred to as *on state* whilst the second period is the *off state*. Figure 4.2 depicts the state of a single channel changing with time. Successive on state durations U are iid. exponentially distributed with μ . Similarly, successive off state durations D are iid. exponentially distributed with λ . Moreover, U and D are independent. Let $X(t)$ be the random variable denoting the number of primary channels that are occupied by PUs (in on state) at time t . $\{X(t), t \geq 0\}$ is a CTMC with the following state space $S = \{0, 1, 2, \dots, F\}$ [65]. Figure 4.3 depicts the states of S and the transition among these states. Given $U \sim \exp(\mu)$ and $D \sim \exp(\lambda)$, transition rate matrix $Q \triangleq \{q_{i,j}\}$ is defined in (4.4) where $q_{i,j}$ denotes the transition rate from state i to state j .

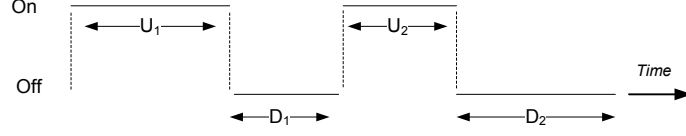


Figure 4.2. A PU channel with two states: on (occupied by PU) and off (idle). U and D are iid. exponential random variables with rate μ and λ , respectively.

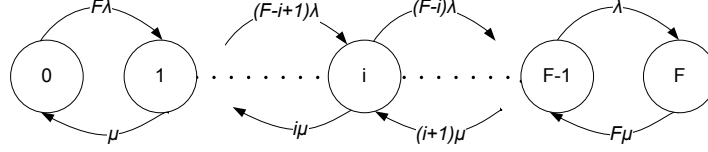


Figure 4.3. In a CRN with F channels, number of channels that are occupied by PUs can be modeled by a CTMC.

$$Q \triangleq \{q_{i,j}\} \begin{cases} (F-i)\lambda & \text{for } j = i+1, i < F \\ i\mu & \text{for } j = i-1, i \geq 1 \\ 0 & \text{ow.} \end{cases} \quad (4.4)$$

CRs operating in on-off manner are modeled similarly. In the following section, we validate our model is a CTMC using these process models. We use λ_{CR} and μ_{CR} for denoting the parameters related to CRs, and λ_{PU} and μ_{PU} for PU parameters.

4.1.3. CTMC Model Validation

Recall that a CTMC must possess two fundamental properties: state sojourn time in any state is exponentially distributed (*memoryless property*) and time to transition to other states are mutually independent [66]. We check if our model exhibits these properties.

Let the system be in state $S_{i,j}$ at time t and e denote the event occurring at time $t + \Delta t$. With the effect of the event e the system changes state to $S_{k,l}$. The event e can be one of the following:

- (i) PU arrival,
- (ii) PU departure,
- (iii) CR arrival,
- (iv) CR departure.

Arrows in Figure 4.1 mark transitions caused by these events for the state $S_{i,j}$. The following defines the state transitions from $S_{i,j}$.

- $S_{i,j}$ to $S_{i+1,j}$: State transition to $S_{i+1,j}$ happens in case of a PU arrival. Since there are $(F - i)$ primary channels not being used by the PUs, there can be an arrival in any of these channels. Hence the first arrival results in $S_{i+1,j}$. Say the earliest arrival is in channel k at time $t + T_k$. Let $T_{i,j|i+1,j}$ denote the duration of stay in $S_{i,j}$ till this transition to $S_{i+1,j}$ occurs. $T_{i,j|i+1,j}$ can be defined as follows:

$$T_{i,j|i+1,j} = \min(T_k : k \in \mathcal{C} \setminus \mathcal{C}_{\mathcal{PU}}) \quad (4.5)$$

Since all T_k are exponentially distributed and mutually independent, $T_{i,j|i+1,j} \sim \exp(\sum_{k=1}^{F-i} \lambda_k)$. Therefore $T_{i,j|i+1,j} \sim \exp((F - i)\lambda_{PU})$ given that all channels are identical. This derivation can also be directly accessed from Figure 4.3 and through formula in (4.4).

- $S_{i,j}$ to $S_{i-1,j}$: Similarly, state transition to $S_{i-1,j}$ happens at $t + T_{i,j|i-1,j}$ if one of the PUs in service completes its service. The first PU completing its service in channel k releases the channel. Service time T_k is $\exp(\mu_k)$, and it is the minimum of i PU channels ($|\mathcal{C}_{\mathcal{PU}}| = i$). The state transition time to $S_{i-1,j}$ is defined as follows:

$$T_{i,j|i-1,j} = \min(T_k : k \in \mathcal{C}_{\mathcal{PU}}) \quad (4.6)$$

Hence, $T_{i,j|i-1,j} \sim \exp(i\mu_{PU})$.

- $S_{i,j}$ to $S_{i,j+1}$: In case of a CR arrival, system may enter the state $S_{i,j+1}$. Since there are N CRs in the network and j are already in transmission, an arrival can

happen due to the remaining $(N - j)$ CRs. However, in order to move to $S_{i,j+1}$, the arriving CR must find an idle channel that is longer than its transmission time. For now, assume that CR can find such a channel with probability P_{cs} . Hence, the first arrival is the event that triggers this state change.

$$T_{i,j|i,j+1} = \min(T_k : k \in \mathcal{N}_{idle}) \quad (4.7)$$

$T_{i,j|i,j+1}$ is exponential with rate parameter $(N - j)\lambda_{CR}P_{cs}$.

- $S_{i,j}$ to $S_{i,j-1}$: The first CR completing its transmission at $t + T_k$ releases the channel k and results in a new state $S_{i,j-1}$. Duration of stay in $S_{i,j}$ until this transition is $T_{i,j|i,j-1}$ and it is defined as follows:

$$T_{i,j|i,j-1} = \min(T_k : k \in \mathcal{C}_{CR}) \quad (4.8)$$

From above, it is derived that $T_{i,j|i,j-1} \sim \exp(j\mu_{CR})$.

- $S_{i,j}$ to $S_{i,j}$: The system does not change state in two cases: (i) A CR arrival occurs but the CR cannot find an opportunity that is sufficiently long for its transmission although there are some idle channels (*arrow 5* in Figure 4.1) or (ii) A CR arrival occurs but all channels are occupied (*arrow 6* in Figure 4.1). For the first case, the transition rate is the total CR arrival rate $((N - j)\lambda_{CR})$ multiplied by probability of failure in channel selection $(1 - P_{cs})$. Probability of success (and failure) in channel selection (P_{cs}) depends on the channel selection scheme and the state of the system $X(t) = S_{i,j}$. For the second case, rate of transition equals to the total CR arrival rate.

Since self transitions are not allowed in CTMCs by definition (i.e. $q_{ii} = 0, \forall i$), such transitions must be represented in a different way. Hence, we revised our model (*arrow 5* and *arrow 6* in Figure 4.1) as in Figure 4.4. In this new model, we represent the failure in channel selection attempt of an arriving CR by the transition *arrow 5*. For the cases corresponding to transitions shown by *arrow 5*, derivation of $T_{i,j|i,j_{fail}}$ is similar to $T_{i,j|i,j+1}$. $T_{i,j|i,j_{fail}}$ is exponential with rate parameter $(N - j)\lambda_{CR}(1 - P_{cs})$.

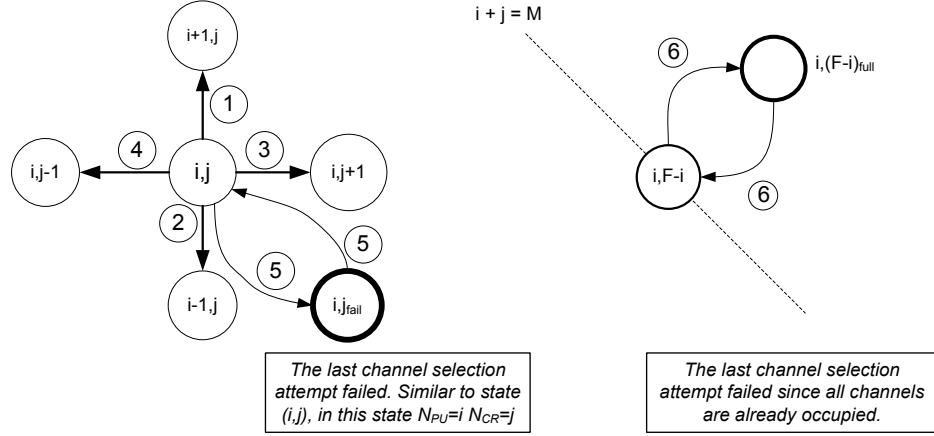


Figure 4.4. State transitions with self transition (arrow 5 and arrow 6) in Figure 4.1 is removed.

For the remaining cases (*arrow 6*), we also extend the state space with $S_{i,(F-i)_{full}}$ states. Similar to the previous extension, this state represents the cases where the previous CR transmission attempt has failed. However, as opposed to the previous case where there are idle but unsatisfactory channels, it has failed since all channels in the system are already occupied (full). In these states, $N_{PU} = i$ and $N_{CR} = F - i$. Such transitions are experienced when a CR arrival event occurs but finds the system full. We represent time to this transition as $T_{i,F-i|i,(F-i)_{full}}$, and it is also exponential with rate parameter $((N - j)\lambda_{CR})$.

Let $\mathcal{S}_{fail}$ and $\mathcal{S}_f$ stand for the set of all these added *fail-states* and *full-states*, respectively. With the addition of these two types of states, the new state space can be represented as a two-layered system. One layer stands for the ordinary states whereas the other consists of states in $\mathcal{S}_{fail} \cup \mathcal{S}_f$ as depicted in Figure 4.5. State transitions are illustrated for a fail-state, however it applies to the full-states by replacing the transition marked as 5 with transitions marked as 6. Rate of transition k' depicted in the figure equals to that of k where $k \in 1, \dots, 6$. Expanding our model with $S_{i,j_{fail}}$ for each state in $\mathcal{S} \setminus \mathcal{S}_{full}$ and $S_{i,(F-i)_{full}}$ for each state in $\mathcal{S}_{full}$, now the state space $\mathcal{S}$ has two-fold states resulting in $|\mathcal{S}| = (F + 1)(F + 2)$.

As discussed above, for all $S, S' \in \mathcal{S}$, $T_{S|S'}$ is an exponential random variable and independent of all others. Let $\lambda_{T_{S,S'}}$ denote the rate parameter for $T_{S,S'}$. State sojourn

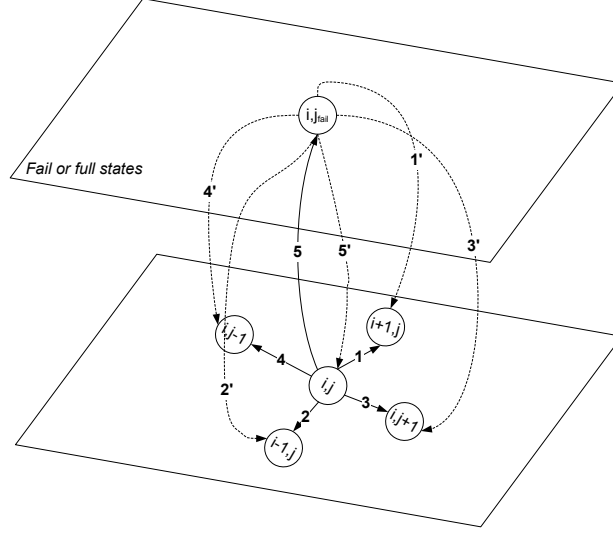


Figure 4.5. Two-layered representation of the state space, one layer has elements from $S_{fail} \cup S_f$ whereas the other is composed of the states in $\mathcal{S} \setminus (S_{fail} \cup S_f)$.

time $T_S \sim \exp(\sum_{\forall S' \in \mathcal{S}} \lambda_{T_{S,S'}})$ since it is the minimum of all $T_{S,S'}$. This completes the verification that our model is a CTMC.

4.1.4. Transition Rate Matrix

The transition probability matrix P defines the probability of change from $S_{i,j}$ to $S_{k,l}$. The steady state probability vector $\pi = [\pi_s]$ ($\forall s \in \mathcal{S}$) is obtained by solving the following system:

$$\pi P = \pi \quad (4.9)$$

$$\sum_{s \in \mathcal{S}} \pi_s = 1 \quad (4.10)$$

In the CTMC model validation section, we define all transitions from state $S_{i,j}$ and corresponding transition rates. Before obtaining $P = [P_{(i,j|k,l)}]$ from these rates, we need to define the probability of success in channel selection (P_{cs}). P_{cs} is the probability that a CR with a transmission request at a time can find an appropriate opportunity. As explained before, if CR can find an appropriate opportunity, the channel selection is completed with a success, or completed with a failure otherwise. P_{cs} depends on the

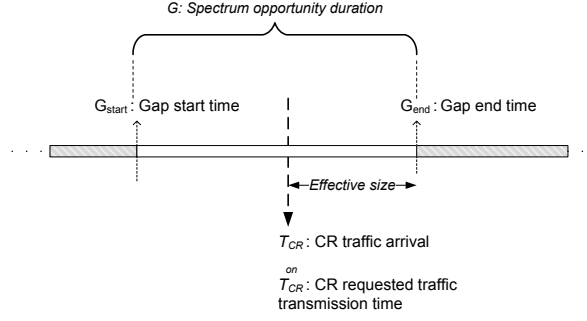


Figure 4.6. Probability of finding an appropriate channel depends on the CR traffic request size, PU spectrum opportunity sizes, and the state of the system, $S_{i,j}$.

channel selection scheme, i.e. BFC, LITC or p -selfish.

Theorem 4.1. *The conditional channel selection success probabilities for BFC ($P_{cs}^B(i, j)$) and LITC ($P_{cs}^L(i, j)$) at state $S_{i,j}$ are given by*

$$P_{cs}^B(i, j) = 1 - \left(\frac{\lambda_G^B}{\lambda_G^B + 2\lambda_{on}^{CR}} \right)^{F-(i+j)} \quad (4.11)$$

$$P_{cs}^L(i, j) = 1 - \left(\frac{\lambda_G^L}{\lambda_G^L + 2\lambda_{on}^{CR}} \right)^{F-(i+j)} \quad (4.12)$$

where λ_{on}^{CR} , λ_G^B and λ_G^L stand for the parameter of CR on-time distribution, parameter of gap size if BFC is applied as the channel selection scheme and gap size parameter for LITC, respectively.

Proof. Let T_{on}^{CR} and G denote the random variables representing the CR transmission time duration and PU channel idle times, respectively where $T_{on}^{CR} \sim \exp(\lambda_{on}^{CR})$. *Effective size* of PU channel idle duration is the duration that a PU channel is going to be idle observed by a CR at the CR arrival instant. Figure 4.6 depicts the single channel case. We refer the spectrum opportunity starting at G_{start} and ending at G_{end} as a *gap* or *fragment*. The CR arrives at T_{CR} and remaining idle time of the channel is $G_{end} - T_{CR}$. The channel opportunity has started at G_{start} and ends at G_{end} . For this CR to be satisfied with the channel, the effective size must be longer than the requested transmission time (T_{on}^{CR}). Assuming that the arrival probability of the CR during a spectrum opportunity is uniform, the CR arrival occurs at the middle of the spectrum gap on average. If spectrum opportunity size is $G = G_{end} - G_{start}$, T_{CR} equals

to $G_{start} + (G_{end} - G_{start})/2$. Therefore, expected effective size is $G - G/2 = \frac{G}{2}$. Hence, probability of success in channel selection is simply interpreted as follows:

$$P_{cs} = Pr\{T_{on}^{CR} \leq \frac{G}{2}\}. \quad (4.13)$$

We can generalize this finding to the F channel case as in Eqn. (4.14). $P_{cs}(i, j)$ denoting the success probability at state $S_{i,j}$ is the probability that at least one of the channels in $\mathcal{C}_{idle}$ with $|\mathcal{C}_{idle}| = F - (i + j)$ has sufficiently long opportunity.

If spectrum gap duration at each channel is iid. exponentially distributed with mean λ_G^{-1} , P_{cs} equals to the following:

$$P_{cs}(i, j) = 1 - \left(\frac{\lambda_G}{\lambda_G + 2\lambda_{on}^{CR}} \right)^{F-(i+j)} \quad (4.14)$$

$P_{cs}^B(i, j)$ and $P_{cs}^L(i, j)$ are derived by replacing the gap size parameter (λ_G) with λ_G^B for BFC and with λ_G^L for LITC as follows:

$$P_{cs}^B(i, j) = 1 - \left(\frac{\lambda_G^B}{\lambda_G^B + 2\lambda_{on}^{CR}} \right)^{F-(i+j)} \quad (4.15)$$

$$P_{cs}^L(i, j) = 1 - \left(\frac{\lambda_G^L}{\lambda_G^L + 2\lambda_{on}^{CR}} \right)^{F-(i+j)} \quad (4.16)$$

□

Initially, spectrum opportunity (gap) at each channel is exponentially distributed with parameter λ_{PU} . However, as the CRs access the bands, gap size distribution changes. Our analysis with a distribution fitting tool [58] on the spectrum gap size collected from simulations shows that effective size of gaps observed by CRs at the CR arrival instant is exponential with parameter λ_G . Moreover, BFC results in longer gaps

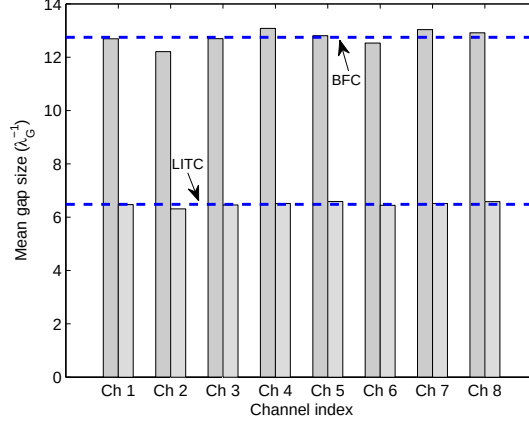


Figure 4.7. Channel based fragmentation analysis for BFC and LITC, $\lambda_{PU}^{-1} = 10$,
 $F = 8$, $N = 10$.

(thereby larger effective size) compared to LITC resulting in $\lambda_G^B < \lambda_G^L$ as we depicted in Figure 3.9a in Chapter 3. Since we do not make any differentiation among channels, we make this analysis considering gaps from all channels as a single source. On the other hand, as the Figure 4.7 depicts, the mean fragment size caused by the fragmentation process for each channel may yield different fragment sizes. However, this variance is marginal and it is ignored for the sake of simplicity.

Please note that P_{cs} depends on the λ_G parameters. However, these values can be derived by analysis of the simulation results and are computed offline after the completion of simulations. Figure 4.8 illustrates the state dependent P_{cs} values for BFC and LITC under two λ_{PU}^{-1} parameters for $F = 8$ and $N = 10$. In the figure, only the states in the first layer (in Figure 4.5) are depicted since states in the second layer have the same P_{cs} values as their counterparts in the first layer. States are enumerated based on their (i, j) values from left to right and down to up according to their location in Figure 4.1, starting with $S_{0,0}, S_{0,1}, \dots, S_{0,8}, S_{1,0} \dots S_{8,0}$. Note that change in P_{cs} follows a pattern and repeats it. Each single pattern corresponds to a row of $\mathcal{S}$ in Figure 4.1. Remember that in each row, the left to right move represents an increase in N_{CR} , number of active CRs, resulting in decrease in P_{cs} . Similarly, move to next pattern in Figure 4.8 corresponds to a move in up direction in $\mathcal{S}$ in Figure 4.1. In words, N_{PU} , number of active PUs increases by 1. Regarding the spectrum opportunity duration lengths, success probabilities in the first case where $\lambda_{PU}^{-1} = 2.5$, are lower than that of

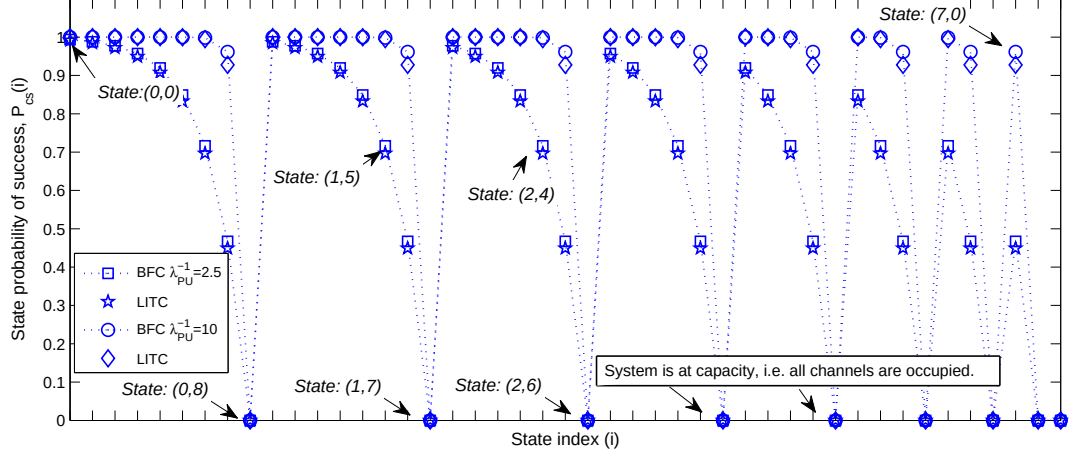


Figure 4.8. State dependent P_{cs} values. $F = 8$, $N = 10$ and $\lambda_{PU}^{-1} = 2.5$ and $\lambda_{PU}^{-1} = 10$.

the second case with $\lambda_{PU}^{-1} = 10$. Regarding the access schemes, BFC and LITC seem to have very similar P_{cs} . However, BFC has always higher values, which leads it to outperform the latter in general. The data points on the x-axis stand for the states in $\mathcal{S}_{full}$, hence P_{cs} are zero.

P_{cs} values are critical in determining the steady states. In our model, we use $P_{cs}(i, j)$ values collected from the simulations. We compute these values by averaging P_{cs} derived in various ways such as probability in terms of number of attempts and analytic values calculated through Eqn.4.14 by setting $\lambda_G > \lambda_{PU}$. Inserting P_{cs} values in Eqn. 4.17 to the transition rate matrix and setting main diagonal elements $Q_{(i,j|i,j)} = -\sum_{(k,l),(k,l) \neq (i,j)} Q_{(i,j|k,l)}$, we derive $Q = [Q_{(i,j|k,l)}]$. Next, we derive $P = [P_{(i,j|k,l)}]$ by normalizing each row and setting the main diagonal entries to 0. Using the state transitions defined in Section 4.1.3 and P_{cs} , we can define the rate of transition from $S_{i,j}$ to $S_{k,l}$ (denoted by $Q_{(i,j|k,l)}$) as follows:

$$Q_{(i,j|k,l)} = \begin{cases} (F-i)\lambda_{PU} & \text{for } k = i+1, i < F, l = j \\ i\mu_{PU} & \text{for } k = i-1, i \geq 1, l = j \\ (N-j)\lambda_{CR}P_{cs} & \text{for } k = i, l = j+1, l < F \\ j\mu_{CR} & \text{for } k = i, l = j-1, j \geq 1 \\ (N-j)\lambda_{CR}(1-P_{cs}) & \text{for } k = i, l = j_{fail}, i+j < F \\ (N-j)\lambda_{CR} & \text{for } k = i, l = j_{full}, i+j = F \\ 0 & \text{ow.} \end{cases}$$

Now, since the constructed Markov chain is *irreducible*, we can solve the linear system of equations in Equation 4.9 and 4.10, and find the steady state probability distributions. A Markov chain's irreducibility can be tested using basic graph algorithms. Simply, Markov chain is represented as a directed graph, so testing the irreducibility is possible via finding the strongly connected components of this graph. If there is a single component, then the Markov chain is irreducible [67].

4.1.5. Performance Parameters

In the following equations, $\pi_{i,j}$ denotes the stationary probability of state $S_{i,j}$.

- *Average number of CRs transmitting in the network*

$$E[N_{CR}] = \sum_{\forall S_{i,j} \in \mathcal{S}} (j\pi_{i,j}) \quad (4.17)$$

- *Average number of PUs transmitting in the network*

$$E[N_{PU}] = \sum_{\forall S_{i,j} \in \mathcal{S}} (i\pi_{i,j}) \quad (4.18)$$

- *Average number of channels occupied*

$$E[C_{busy}] = \sum_{\forall S_{i,j} \in \mathcal{S}} (i + j) \pi_{i,j} \quad (4.19)$$

- *Average CR throughput* is the total CR throughput divided by the number of CRs measured in seconds (e.g. airtime or successful transmission duration). Simply, it is throughput for each CR over F channels for the simulated time duration (T_{sim}).

$$R_{CR} = \frac{E[N_{CR}]T_{sim}}{N} \quad (4.20)$$

- *Average probability of successful transmission* (p_s) is the probability that a CR's traffic request can find an appropriate spectrum opportunity and this CR can achieve transmission in the selected opportunity. D_{CR} is the CR duty cycle.

$$p_s = \frac{E[N_{CR}]}{ND_{CR}} \quad (4.21)$$

- *Spectrum opportunity utilization* (Θ) is the ratio of spectrum opportunities that CRs used for transmission, to the total spectrum opportunities through all F channels. D_{PU} is the PU duty cycle.

$$\Theta = \frac{E[N_{CR}]}{F(1 - D_{PU})} \quad (4.22)$$

4.2. Evaluation of the Analytical Model

In order to measure how good the introduced model matches to the real system, we compare our analytical model with the results obtained from our system-level simulator developed in Chapter 3. Since we simplified our continuous time continuous space model into a compact model that only considers the number of PUs and CRs in the network, we expect some deviation between the performance results of these two models. However, if the presented analytical model has the power to present the

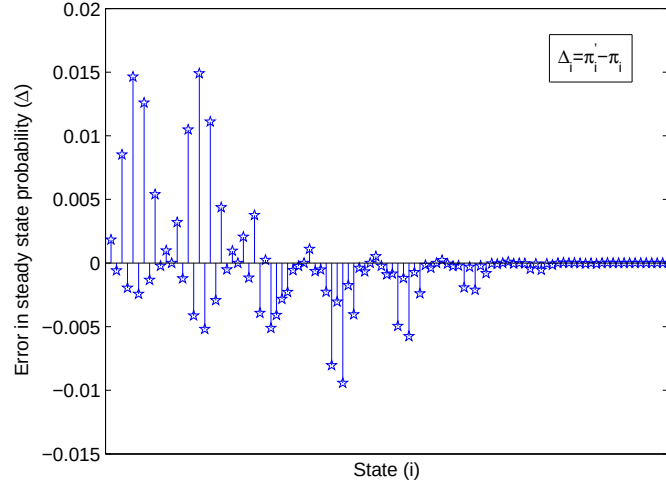


Figure 4.9. Error in steady state probability distribution for $N = 5$. $\Delta_i = \pi'_i - \pi_i$

real world (simulated) case, the performance evaluation of analytical model will match that of the simulated model. To this aim, we analyze three cases: low, moderate and heavy load CR traffic cases. In all cases, we set number of channels $F = 10$, $\lambda_{CR} = 1$, $\mu_{CR} = 1$, $\lambda_{PU} = 0.4$, and $\mu_{PU} = 2$. Under these parameters, setting $N = 5$ leads to low load case with 0.30 CR traffic load. We represent the moderate and heavy load cases by setting $N = 10$ and $N = 15$ corresponding to the CR traffic load 0.6 and 0.9, respectively.

As the derivations in Section 4.1.5 show, performance metrics are directly computed from steady state probability vector. Hence, as a first step, we compare the steady state probabilities derived from analysis ($\pi_{i,j}$) with the ones derived from the simulations ($\pi'_{i,j}$) [62]. In order to ensure that the system is in steady state, simulation time is set to sufficiently long duration. Figure 4.9 plots the error in steady state distribution where $\Delta_{i,j} = \pi'_{i,j} - \pi_{i,j}$. The zero-line (values exactly on x-axis) shows the perfect match between π and π' whereas points much above/below this line show high deviation between the analytical and simulated model. These deviations result into errors in computation of performance values. The errors lie in interval $[-0.010, 0.015]$. In this case $|S| = 102$ while for $N = 10$ and $N = 15$, $|S| = 132$.

Figure 4.10 depicts the change in average number of transmitting CRs in the

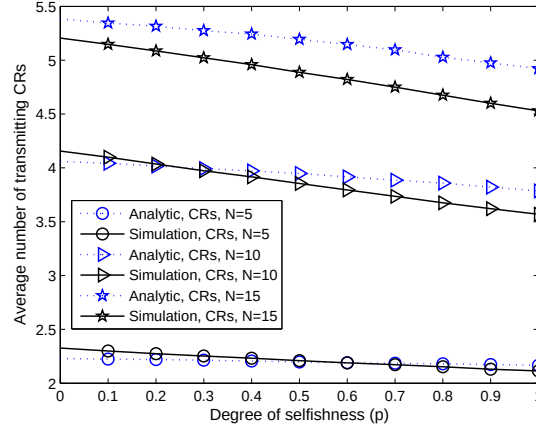
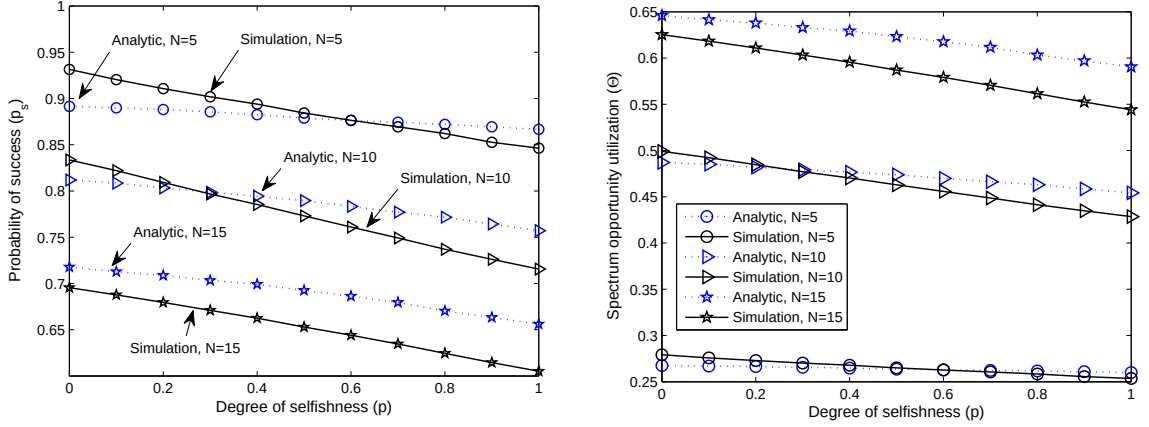


Figure 4.10. Number of transmitting CRs: comparison of analytical model and simulations.



(a) Probability of success (p_s).

(b) Spectrum opportunity utilization (Θ).

Figure 4.11. Comparison of analytical model and simulations in terms of p_s and Θ .

system. At a first glance, it can be seen that selfishness degrades the CRN performance leading less CRs to be able to capture a channel for transmission. Figure 4.10 shows that there is almost a perfect match for low load case in average number of transmitting CRs. The error is around 0.7%-4% depending on the degree of selfishness. For moderate and high load cases, analytical results deviate from the simulations with an error rate between 0.5%-6% and 3%-8%, respectively. Regarding PUs, as expected, number of PUs does not change with p . PUs are independent of the CRN and their performance is not affected by the access mechanism.

Figure 4.11a and Figure 4.11b depict the corresponding p_s and Θ values for each load case. As the derivations in Section 4.1.5 show, p_s and Θ are linear functions of

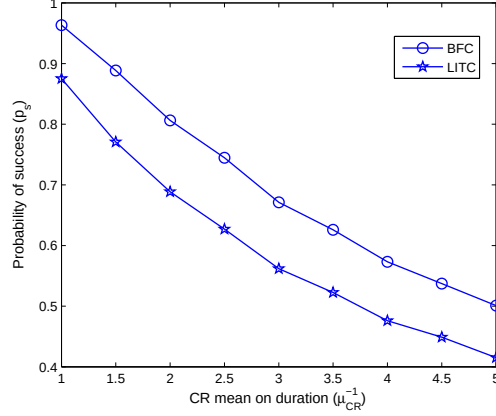


Figure 4.12. Probability of success with increasing CR on duration for $\lambda_{PU}^{-1} = 5$.

N_{CR} . Hence, the error in computation of N_{CR} is carried to these metrics. Therefore, these two metrics follow the same trend as N_{CR} depicted in Figure 4.10. Examining the results, we see that there is a better match between analytical model and simulations under low load while the error increases in moderate and heavy load scenarios. In low load case, the error is around 0.1%-3% whereas it is 0.7%-6% in moderate and 3%-8% in heavy load case. These results also apply to the analysis of Θ . The increase in deviation between the two models is due to the increased state space size. With larger state space, the error depicted in Figure 4.9 increases on the average. This may be mitigated with much longer simulations.

Figure 4.12 depicts the performance of BFC and LITC for increasing CR mean on duration ($1/\lambda_{CR}^{on}$ or μ_{CR}^{-1}). As the CR packets get longer (increasing CR on duration), the success probability decreases. This is expected since fractional transmission is not enabled in the system under consideration. Therefore, transmission requests exceeding the spectrum opportunities at the time of transmission attempt fail. Hence, CR packet durations should be kept significantly lower than the mean PU spectrum opportunity duration. However, note that smaller packet size results in higher overhead. This overhead should also be considered in the design of practical communication systems.

4.3. Chapter Summary

In Chapter 3, we strictly relied on the simulation results and showed that BFC enhances the CRN performance by effectively sharing the spectrum among CRs. In this chapter, we introduced a Markovian approach for theoretical analysis of BFC. We introduced our Markov based model, defined the derivations and performance metrics. Finally, we evaluated our model by comparing it with the outcomes of simulations presented in Chapter 3. Our model is a simplified one that models a continuous time continuous state space model with a continuous time discrete state space model. Despite this simplification, our results show that it captures the operation of BFC.

As an extension to our work, PU detection impairments, e.g., nonzero false alarm values, as well as errors in spectrum opportunity time estimation can be incorporated in the model. Such a model is more appropriate for a realistic CRN. Moreover, a more elaborate model with continuous state space model can better capture the operation principles of the proposed channel selection scheme without requiring simulation-based P_{cs} values to be utilized. However, it is quite challenging to discover such a scheme with low-complexity that overcomes the exponential state space explosion.

5. ENERGY-EFFICIENT SPECTRUM SENSING AND ACCESS IN CRNs

In contrast to the plethora of studies in basic cognitive protocols in CRNs, energy efficiency of CRNs has yet to be explored. Energy efficiency, although it has been established for a long time for conventional wireless networks, has once again become a hot topic with the increasing concerns on ecological crisis and increasing energy costs. In this chapter, we aim to provide an elaborate review of the energy efficiency concerns in CRNs with a focus on spectrum sensing and spectrum access in CRNs. Section 5.1 overviews the basics of wireless communications in terms of relations among throughput, energy and delay. Section 5.2 summarizes the tasks related to physical layer (PHY) and examines how they can be more energy-efficient with an overview of current proposals mostly on spectrum sensing. Similarly, Section 5.3 provides information on MAC layer tasks and their energy consumption performance. Finally, Section 5.4 derives the conclusions.

5.1. Fundamentals of Energy-Efficient Wireless Communications

Performance of a wireless network is measured by various metrics, the commonly agreed ones being the *spectral efficiency* and *deployment efficiency*. Generally, *spectral efficiency* is taken as the primary indicator of a network's performance. It is formally defined as the number of bits that can be transmitted per unit bandwidth (*bits/Hz*). If efficiency is considered from an economical point of view, then deployment efficiency [68] becomes the primary performance measure. *Deployment efficiency*, mostly measured in *bits/capital expenditure*, is defined as the number of bits that can be transmitted per unit bandwidth and per unit capital spent for the network deployment and operation of the network for a defined time period. In addition to these two metrics, considering the performance from energy viewpoint, energy efficiency (*bits/Joule*) measures the transmission capacity of a network per unit energy consumption for a given time period. While all these metrics are valuable indicators of how well a network op-

erates, they reflect the concept of efficiency mostly from the network service provider's perspective. As the performance is perceived by the users (agents) communicating in the network, major QoS parameters such as throughput and delay become the main indicators of the network performance.

An intelligent energy management scheme constantly searches for ways of keeping a balance between QoS and energy consumption in line with the user requirements and changes in the operation environment [69]. In this section, we aim to recall basic relations among throughput, delay and energy consumption. In order to design and develop efficient wireless protocols, capturing these relations and having a general insight on them are essential. For instance, a protocol designed with throughput concerns may be optimal in terms of throughput whilst it is not in terms of delay or energy.

5.1.1. Energy-Delay Tradeoff

Energy efficiency (η_{EE}) is mostly defined as the number of successfully transmitted information bits per unit of consumed energy, and it is measured in terms of bits/Joule. In general, energy consumption of a wireless device transmitting for a time period T can be formulated as follows:

$$E = P_{tx}T + P_cT \quad (5.1)$$

where P_{tx} and P_c denote the transmission power and average circuit power, respectively. Circuit power represents all power consumption due to device electronics: digital-to-analog converter, mixer, frequency synthesizer and filter [70]. As opposed to transmission power, circuit power is considered to be independent of the transmission rate. According to Shannon's capacity formula, achievable rate of an Additive White Gaussian Noise (AWGN) channel with bandwidth W is calculated as follows:

$$R = W \log_2 \left(1 + \frac{P_{tx}g}{N_0W} \right) \text{ (bits/second)} \quad (5.2)$$

where N_0 is the noise power and g is the channel gain. From (5.2), P_{tx} can be written as follows:

$$P_{tx} = (2^{\frac{R}{W}} - 1) \frac{N_0 W}{g} \quad (5.3)$$

As (5.3) shows, transmission power is an exponential function of the transmission rate. Hence, even a small decrease in the transmission rate leads to remarkable exponential decrease in transmission power, and thereby in energy consumption. However, decrease in R (bits/second) results in longer transmission time (T) of a single bit as $T = \frac{1}{R}$ seconds [70, 71]. When the circuit power is not taken into account, then (5.1), which now denotes the energy consumption per transmission of a bit, becomes:

$$E = P_{tx} T = (2^{\frac{1}{WT}} - 1) \frac{N_0 W}{g} T \quad (5.4)$$

and energy efficiency is calculated as follows:

$$\eta_{EE} = \frac{RT}{E} = \frac{1}{(2^{\frac{1}{WT}} - 1) \frac{N_0 W}{g} T} \quad (5.5)$$

Since η_{EE} is a monotonic increasing function of T , theoretically it is optimal in terms of energy efficiency to transmit a bit over an infinite duration hence with infinitely low rate (as $T \rightarrow \infty$, $R \rightarrow 0$). As only energy efficiency is concerned, some fixed amount of information should be sent in longer time instead of transmissions in bursts with high energy consumption. This can also be derived from (5.5).

In practical systems, timing constraints restrict the design of networks. Delay should be kept at acceptable levels depending on the application type (e.g. multimedia or urgent data). In addition, in a multiuser system, capturing the shared medium by a user for an infinitely long time is not desired at all. Thus, energy-delay tradeoff (Figure 5.1a from [72]) should be considered in designing efficient transmission schemes and

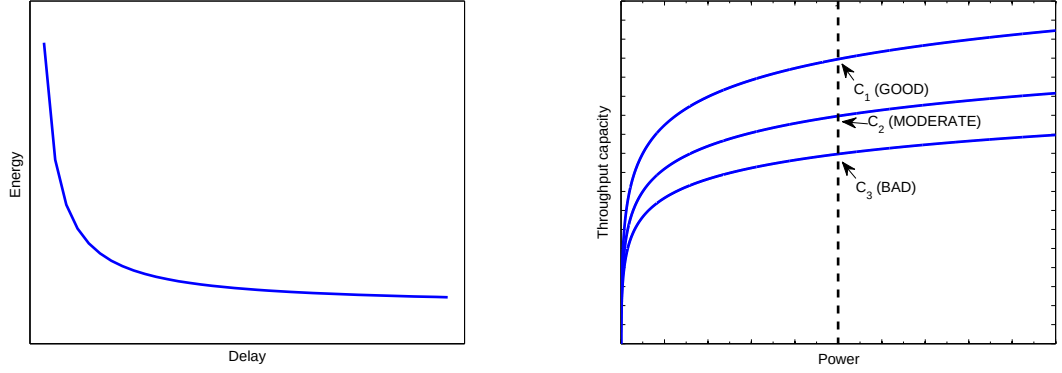
selecting the most appropriate rate (thereby corresponding PHY parameters).

On the other hand, energy consumption due to circuit power, $E_c = P_c T$ in (5.1), cannot be ignored especially in short range communications where it is the dominating component in overall energy dissipation [70]. If E_c is not neglected, such an operation results in relatively large energy consumption due to circuitry. To sum up, total transmission energy (E_{tx}) decreases with transmission time meanwhile circuit energy increases. Thus, optimal operation point should be selected taking both E_{tx} and E_c into consideration.

5.1.2. Energy-Throughput Tradeoff

Regarding energy-throughput relationship, as stated in [73], *every bit has a cost*. Naturally, energy consumption is proportional to the volume of transmitted data (throughput). However, exact nature of this relationship is not so trivial. Energy cost of transmitting a bit is referred to as *energy-per-bit* and measured in *Joule/bit*. How much energy is required for transmission of some amount of data depends on several factors. Under constant power and modulation schemes, wireless channel condition determines the rate of the channel, and therefore total energy required for transmission. Simply, the better is the channel quality, the lower is the energy consumption. Figure 5.1b illustrates capacity of a channel versus transmission power under three channel conditions. As the figure shows, for a constant power level, channel capacity increases as the channel quality gets better. Therefore, degrading channel quality decreases energy efficiency in general. Furthermore, energy consumption is not only related to the total amount of transmitted data, but also intimately related to the characteristics of the workload [74]. Please refer to [71] and [75] for an overview of fundamental concerns in energy efficiency of wireless networks.

Henceforth, we turn our attention to CRNs. CRs are expected to perform intense information processing functions for realizing the environment-awareness and intelligence capabilities. However, it is reported that wireless interfaces are the dominant factor in overall energy consumption [77], and the information processing on modern



(a) Energy-delay relationship (adapted from [72]). (b) Power-channel rate relationship (adapted from [76]).

Figure 5.1. Energy vs. delay and channel-rate vs. power profiles for wireless transmission.

processors can be neglected in energy consumption compared to communication tasks. Therefore, we mainly concentrate on tasks related to wireless interfaces and their energy consumption profiles. For the sake of presentation, we stick to the layer-wise approach and focus on the related layers separately from energy efficiency viewpoint. However, since some topics need to be analyzed using a cross-layer approach, we review them under the most relevant section.

5.2. Energy Efficiency at Physical Layer

5.2.1. Spectrum Sensing

Consider the cognitive cycle in Figure 5.2. The fundamental step of CR operation that provides environment-awareness is the spectrum sensing task. Spectrum sensing is the act of observing RF environment divided into frequency channels, and determining the occupancy state of the observed channel. Via spectrum sensing, CR becomes aware of its wireless environment; the existence of PUs in a geographical area and spectrum usage information across various dimensions such as time, space and frequency [78]. A channel can be either occupied by a PU or by a CR, or it can be unoccupied. Therefore, a CR via spectrum sensing can detect PUs (or CR signals) in the band and

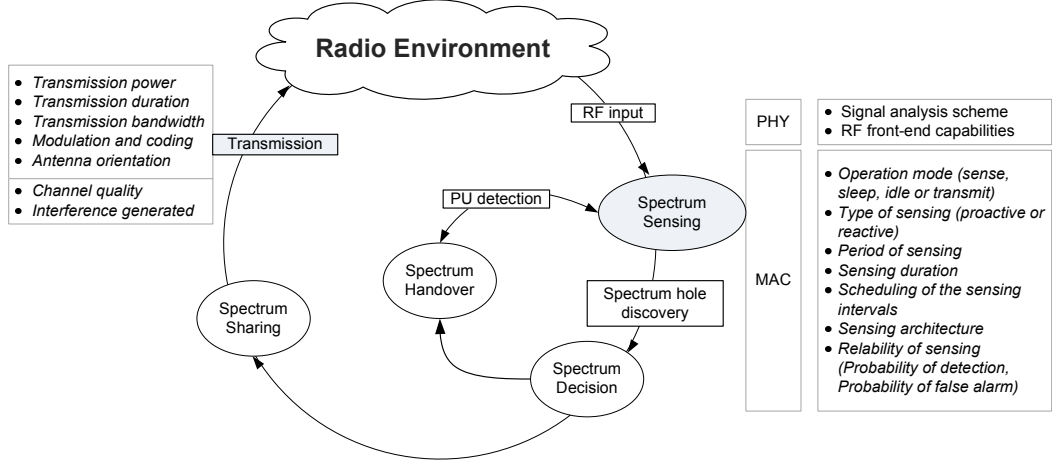


Figure 5.2. CR cognitive cycle [79] and related energy efficiency issues.

discover spectrum opportunities for its use. CR decisions on channel states may be subject to errors due to internal (e.g. faulty sensors) or external factors (e.g. noisy channels). However, CRs must meet a certain degree of reliability in these decisions in order to prevent harming PU communications. Sensing reliability is mostly measured by *probability of detection* (P_d), the probability that the existence of a PU signal is successfully detected, and *probability of false alarm* (P_{fa}), the probability that a PU signal is incorrectly detected although there exists no PU signal.

Previous works [80] have shown that sensing duration determines the sensing accuracy. The more time consumed on sensing, the more reliable is the sensing scheme. However, long sensing duration is not preferred since it consumes time that can be utilized for transmission leading to lower throughput [80]. Hence, spectrum sensing schemes try to provide a balance between these two conflicting objectives. Mostly, schemes that ensure $P_d \geq 0.9$ and $P_{fa} \geq 0.1$ (e.g. IEEE 802.22 standard [81]) can meet the fundamental criteria of incumbent protection. Considering the CRN performance objectives, spectrum sensing performance is mostly evaluated in terms of throughput efficiency or time utilization.

Spectrum sensing is a process involving both PHY and MAC layers. While signal analysis is realized by the hardware, deciding on various parameters as answers to *when*, *where* and *how to perform sensing and make final decision on PU existence* is related

to the MAC. Regarding the pure signal analysis process at PHY, there are various sensing algorithms for signal detection: energy detector, waveform, cyclostationary, matched filter and radio identification based sensing, to name a few. Basically, radio environment is analyzed using one of these methods and final decision is made on the existence or absence of the primary signal. Implementation complexity, robustness to noise uncertainty, requirements (e.g. a priori knowledge on PU signal characteristics) and spectrum sensing time overhead must all be considered to determine the most appropriate PU detection scheme for a CRN [78].

For effective CR operation, a spectrum sensing scheme must be designed with the aim of attaining CR performance goals while the restrictions commanded by the PU network are met properly and CR network properties are carefully analyzed. Figure 5.3 depicts a general sensing framework. As illustrated in the figure, CRN properties ranging from CR hardware properties to network architecture and CRN performance goals determine the sensing scheme and thereby the access scheme. For instance, if energy efficiency is the main performance criteria, then the sensing scheme avoids tasks that would not significantly improve sensing accuracy but leads to high energy consumption. Primary network may require various operation restrictions on the CRN via defining its restrictions in terms of various measures such as maximum tolerable interference ratio or probability of detection.

Regarding the MAC sensing, existing spectrum sensing schemes can be classified into various ways as depicted in Figure 5.4. *Proactive sensing* is the sensing in which a CR regularly collects information on the channels and processes that information in order to find a channel efficiently. Since CR carries out spectrum sensing even if it does not need an immediate channel for transmission, this scheme can be energy-inefficient. However, utilizing the outcomes of the past sensing observations, CR can decide on the best channel easier compared to the reactive scheme. *Reactive sensing*, also called *on-demand sensing*, is the sensing in which CR senses the spectrum only if it has an outgoing or incoming transmission. In this scheme, CR may be in lack of information on channels' states, thereby it results in more channel search time or inefficient channel switchings. Depending on the CR properties such as energy restrictions, one of the

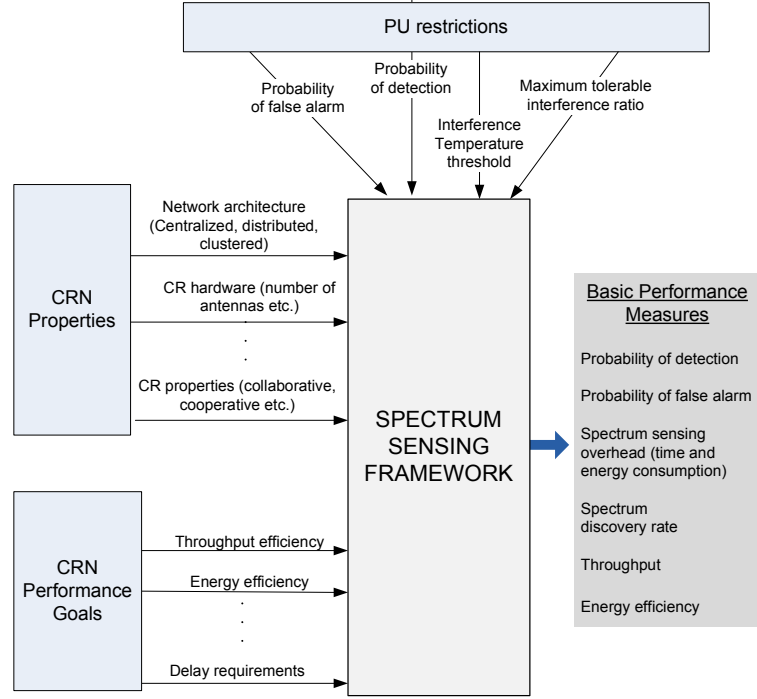


Figure 5.3. Spectrum sensing framework.

schemes may be more preferable than the other. When a channel is discovered to be idle and a secondary transmission is initiated at the channel, the state of the channel needs to be checked regularly in order not to collide with a reappearing primary transmission. Otherwise, a CR continues its transmission till all packets are transmitted in the channel, which will evidently result in primary traffic to be blocked. This sensing scheme is called *periodic sensing*. The period of sensing (T_p), time duration between two sensing actions, is dependent on the channel characteristics and maximum duration that a PU can tolerate simultaneous transmission with a CR. Periodic sensing is an example of proactive sensing.

If a CR has a single transmitter antenna, then it has to sense channels sequentially, in other words one-by-one. This scheme is called *sequential* or *single-channel sensing*. Conversely, if a group of channels are sensed in parallel with the CR's multiple antenna hardware, then it is *multi-channel sensing* or *parallel sensing*. Evidently, parallel sensing is more efficient in terms of spectrum discovery success. In multi-channel sensing, an idle channel is located faster. However, this scheme requires multiple antennas in the CR, which may not be the case for most of the wireless network nodes.

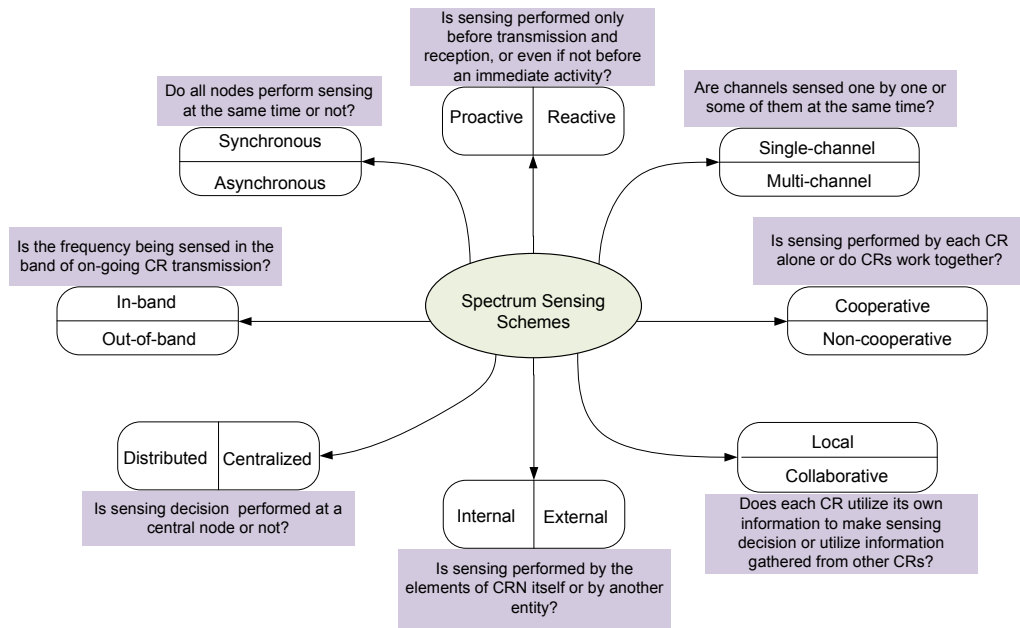


Figure 5.4. Classification of MAC spectrum sensing schemes.

Spectrum sensing is necessary for both locating the idle bands for transmission (*out-of-band sensing*) and for ensuring that CR does not interfere with a reappearing PU (*in-band sensing*). Obviously, in-band sensing is crucial for obeying the basic operation principle of CRs; operation without any noticeable effect on the PUs, while CRs can discover alternate opportunities by out-of-band sensing.

Decision on the existence of spectrum holes can be determined either at a central node or each CR decides on its own. Central node, also called *decision fusion center*, collects information from CRs and fuses the collected data to make a decision. Consequently, it broadcasts the decision to all CRs or it can manage allocation of identified opportunities. This scheme is referred to as *centralized sensing scheme*. Decision fusion can be done in various ways such as applying AND, OR or K-out-of-N operation [82] on the one-bit sensing information received from CRs. Instead of sending lightweight one-bit sensing data (*hard* decision data), CRs may also send individual measurements (dubbed *soft* decision data) such as sensed interference power in the environment. However, especially in case of networks with large number of users, soft decision sharing may result in using of the available bandwidth for sharing purposes only [78]. Thus, decision fusion scheme depends on the data sent by CRs. As opposed to centralized sensing scheme, in *distributed sensing* each CR makes independent sensing decision

and therefore does not necessarily require exchange of information among CRs. If all CRs carry out sensing at the same time, it is *synchronous sensing*. If each device has a diverse schedule for sensing, it is *asynchronous sensing*. Synchronous sensing has the challenge of providing synchronicity of the network whereas asynchronous sensing may not be as accurate as synchronous sensing would be.

In *local sensing* a CR utilizes only its own sensing data. However, this scheme may result in missed detection of PU signals especially in case of noise uncertainty, hidden-terminals or fading channels. Hence, using multiuser diversity can be a good choice to empower the sensing scheme by processing sensing outcomes collected at various locations. Communicating the outcomes of the sensing operation to nodes in the neighborhood or to the central node certainly contributes to more reliable sensing decision. This kind of sensing is called *collaborative sensing*. Collaborative sensing comes at the cost of communication overhead among the collaborating nodes. Sharing of sensing data is done through a *common control channel* (CCC) which might also create a potential issue in collaboration. Conceptually, control channel must be available at all times, must not be saturated with high traffic load, and it must be scalable with the network size [83,84]. One step further from collaborative sensing is *cooperative sensing*. In collaborative sensing, information is shared but final decision can still be made by each CR individually. In *cooperative sensing*, CRs decide together [85].

Although there is a multitude of efficient sensing schemes, sensing planning is non-trivial. Due to challenges in the design, sensing information can be acquired from an external entity such as a sensor network or a geolocation database storing the spectrum usage information [78]. Although, *external sensing* overcomes sensing challenges which the CRN experiences in case of *internal sensing*, it is not widely accepted due to the reason that it requires other infrastructure located in the same coverage region as the CRN (e.g. sensor network [86]). Moreover, in a way it contradicts with the basic promise of CRs; the autonomous operation with its environment-awareness property. In external sensing, CRN is dependent on another entity for performing the most critical step in DSA.

Depending on the CR network properties, one or a combination of the above-mentioned sensing schemes can be applied in the CRN.

5.2.2. Energy-efficient Spectrum Sensing

The aim of spectrum sensing is to provide a decision on the state of the primary channel with a sufficient accuracy (e.g. it does not have to be 100% accurate since PUs have some tolerance) and detect the spectrum holes effectively. Hence, the interplay between detection accuracy and opportunity discovery rate is the key concern of spectrum sensing. Moreover, with the rising issue of power consumption, this interplay has a third factor of energy efficiency.

When and by which nodes spectrum sensing should be carried out and how final sensing decision should be made with sufficient accuracy are the fundamental questions. Related to these two questions, more detailed ones can be listed as follows:

- (i) Should a CR sense or not? If sensing is decided, which part of the spectrum should the CR sense?
- (ii) What is the optimal sensing duration?
- (iii) Should all CRs or a subset of them sense the spectrum? How to determine these groupings?
- (iv) Should proactive or reactive sensing be applied?
- (v) If periodic sensing is preferred as a kind of proactive sensing, what should be the period of sensing? Should periods be fixed for all channels and for all times, or should it be adaptive?
- (vi) How should the final decision be made? Should it be centralized or decentralized? If centralized, what kind of information (e.g. soft decision vs. hard decision) should be propagated to the decision fusion center?
- (vii) If CRs are clustered in sensing, how should the information be propagated intra-cluster or inter-cluster? How to form the clusters, select the cluster heads and the head of all cluster heads are the related questions.

After a careful analysis of these questions, sensing scheme must be determined in accordance with the specific performance goals of the CRN. In the following, we will overview the literature with the goal of constituting insights on answers to the above questions from energy efficiency point of view.

5.2.2.1. Proactive vs. reactive sensing. At a first glance, proactive scheme seems to be more energy-efficient. However, this expectation may not always hold. Proactive sensing locates an idle channel faster at the expense of regular spectrum analysis which means higher energy consumption, meanwhile on-demand sensing spends energy on sensing only when transmission is required but is subject to very long channel search time due to random searching. Since energy efficiency is defined by both throughput and energy consumption, it is not straightforward to generalize that one scheme is more energy-efficient than the other. CRN dynamics determine the energy efficiency performance of each scheme. Work in [87] investigates whether proactive or reactive sensing is more energy-efficient, defining energy efficiency as the ratio of time spent for spectrum sensing per unit time over the time for locating an idle channel per packet arrival/departure. Authors in [87] formulate energy efficiency of each scheme using the tradeoff between periodic sensing overhead and on-demand channel search overhead. Best operation mode can be selected dynamically based on the solution of the formulated problem.

5.2.2.2. Periodic sensing: adaptive periods vs. fixed periods. If a proactive approach is preferred as the sensing mechanism, scheduling the regular sensing periods becomes the main concern in sensing planning. Mostly, CRs perform sensing with a predetermined periodicity that avoids PU interference. For instance, in a time slotted CRN, each CR carries out spectrum analysis at the beginning of each time slot. As mentioned earlier, periodic sensing is mostly applied as a PU protection mechanism. However, the period of sensing determines the performance of spectrum opportunity discovery rate and PU interference. Due to differences in the primary traffic characteristics, each channel exposes a different opportunities distribution throughout time. Further, if not sensed at the appropriate time, some of the white spaces will not be discovered. For

instance, if a channel is sensed when it is busy, then it will be marked as busy till the next sensing event, although just after sensing it becomes idle. Those white spaces that are not discovered are called *undiscovered opportunities* or *lost spectrum opportunities* [18]. In order to increase the efficiency of opportunity discovery, sensing period T_P^i as well as special sensing duration T_S^i should be determined for each channel i rather than the same parameters T_P and T_S for all channels, depending on the primary traffic characteristics of i^{th} channel [18].

Kim and Shin [18] propose sensing-period adaptation that maximizes the discovered spectrum opportunity ratio for a single hop CRN. Total undiscovered opportunities and spectrum sensing overhead (since each CR has to keep silent and performs sensing) are formulated as a function of sensing period. Performance evaluation studies show that this adaptive scheme outperforms the fixed period scheme in terms of discovered spectrum opportunity ratio. Although not discussed in [18], [26] corroborates that period adaptation can achieve significantly higher energy efficiency. [26] with a similar approach to [18] models the amount of undiscovered spectrum opportunities, and next discovers the maximum period that keeps total lost spectrum opportunity below a given level. Since sensing period is maximized (with some restrictions), less time and energy is consumed for periodic sensing. Energy efficiency ratio, defined as the ratio of discovered spectrum opportunities to the energy consumption, is higher in adaptive periodic sensing scheme compared to the fixed period scheme.

5.2.2.3. Cooperative sensing: how to cooperate and make decision combining. Previous works [88,89] have shown that wireless networks benefit from user cooperation. In the CRN domain, cooperation can be incorporated into the cognitive cycle at various steps, mostly in spectrum sensing [25, 35, 90] and transmission relaying. For energy-efficient operation, benefits of cooperative sensing must be analyzed against cost of cooperation, e.g. number and size of cooperation messages, number of cooperating nodes.

Cooperation overhead can be reduced with proper design of cooperation schemes.

Additionally, cooperation may sometimes become a burden on some CRs in the network. For instance, if a CR does not have any packets in its buffer, it may be unwilling to perform sensing for other CRs in transmission. Work in [91] devises a selective spectrum analysis for those *idle* CRs who are not in search for spectrum but still participate in sensing process as a cooperation with the *busy* CRs who use the spectrum. Energy consumption of these idle CRs is decreased by letting them apply partial spectrum sensing, i.e., CRs sense not the whole bandwidth but a proportion of the spectrum, and transmit only outcomes related to this portion to the fusion center. However, this partial sensing may result in some parts of the spectrum to be unexplored. In order to overcome this issue, authors propose a *detection result prediction* (DRP) scheme for those unexplored portions. Furthermore, *decision result modification* (DRM) post-processes the gathered information based on the fact that PU signals span mostly continuous bands making the occupancy of a band highly correlated with its adjacent bands. DRM improves the detection performance meanwhile DRP decreases energy consumption of idle CRs.

As an alternative strategy for reducing the cooperation overhead, not all the CRs but a subset of them are scheduled to sense. Since sensing accuracy is closely related to the number of CRs carrying out spectrum sensing, number of collaborators cannot be decreased directly down to a single CR. Therefore, [92] finds the optimal number of cooperating CRs for attaining both the best energy efficiency and the throughput performance subject to PU detection performance requirements.

The choice of cooperating nodes directly affects the performance of the sensing decision. Basically, uncorrelated data will be more beneficial for the decision scheme compared to correlated information from CRs. Furthermore, faulty nodes giving erroneous decisions (intentionally or non-intentionally) may affect the decision resulting in lower P_d or higher P_{fa} values. Therefore, credibility of CRs is also taken into account in some of the works [25, 90] and censoring mechanisms are applied [33, 93]. Distinguishing unreliable CRs at the decision fusion center (e.g. CBS) and discarding the received data from them certainly mitigates this challenge. However, a scheme that prevents CRs to send unreliable decision data is a better solution in terms of energy

efficiency. Such a scheme does not allow waste of energy by avoiding transmission of unreliable (also useless) information. In this scheme, a CR with low reliability refrains itself from sending its decision [90]. Reference [33] applies a censoring algorithm which prohibits a CR report its sensing result if the observed energy is in the *censoring region*, the region between two detection thresholds. Censoring improves energy efficiency due to reduced transmission of uncertain decision data, however the width of this region requires attention in order not to degrade the PU detection performance.

Cooperative sensing is generally proposed to improve the spectrum sensing accuracy (or reduce detection time) on a single channel [94]. However, in practical cases, networks operate with multiple channels. Then, deciding on which channels to sense (especially when number of CRs is lower than number of primary channels), how many users should sense each channel, and how long to sense become the main concern of cooperative sensing. *Cooperative sensing scheduling* (CSS) [35, 36, 94] determines the parameters accounting the above questions in consideration of a utility function. The more CRs sense a channel, the higher is the detection accuracy for the sensed channel, which would ultimately result in all CRs sense a single channel and other primary channels being unexplored. However, this policy contradicts with the goal of maximizing the discovered spectrum opportunities. Therefore, [35] shows that CRs should be distributed equally among channels to attain a balance between detection accuracy and exploited spectrum opportunities. [35] investigates optimal policy for CSS and defines the utility as a function of energy consumption (cost) and throughput (reward). Authors utilize a Partially Observable Markov Decision Process (POMDP) framework to design an energy-efficient scheduler which penalizes the CRs colliding with PUs, and rewards them on successful transmissions. Penalizing is applied for discouraging undesired actions while rewarding motivates desirable actions. In [35], these mechanisms are applied to attain high energy efficiency via appropriate tuning of the penalty parameter.

Another work addressing CSS problem is [36]. Hao *et al.* [36] model multi-channel energy-efficient CSS as a coalition formation game. In this game, some of the CRs form a group, also called *coalition*, and act in agreement as a single entity [95]. Each CR

performs spectrum sensing in the sensing slot on a channel randomly picked by the CR. Decision fusion center, the CR with the maximum SNR link selected among the CRs sensing the same channel, decides on the channel state and one of the CRs in the coalition is randomly selected for transmission. Authors propose an algorithm for forming groups properly of all F^N possible coalitions. The coalition formation is done in a way that the resulting coalitions can achieve maximum aggregate utility for each coalition. The proposed utility function is an interpretation of energy efficiency accounting both the expected throughput (thereby sensing reliability) and energy consumption for a frame. The proposed iterative algorithm is proved to be stable using the fact that set of all possible partitions is finite, i.e., exactly F^N . CRN applying this algorithm for multiple channel sensing and access benefits from it in terms of throughput and energy efficiency compared to the noncooperative scheme.

Other concerns for energy-efficient cooperative sensing are number of message exchanges and length of these messages. Network architecture and form of cooperation information determine the energy consumption related to these concerns. Clustering, combining the related information and evading the transmission of useless or redundant information decrease the number of messages while compact data with sufficient information reduces message sizes.

5.2.2.4. Clustering based sensing. Node clustering is a well-known approach in mobile ad hoc networks [96] and WSNs [97], [98]. In WSNs, energy efficiency is a fundamental concern. Since sensors report their sensing results to a sink via other nodes, the more the decision data to be transmitted, the higher is the energy consumption. Most of the cases, data is correlated, i.e. redundant. Hence, correlated data can be reduced to a smaller data set and less data is communicated to the sink resulting in a decrease of energy consumption. Due to this fact, clusters are formed to alleviate communication burden, thereby the energy consumption. Nodes that are located close to each other are grouped into the same cluster, and all data by the cluster members are sent to *cluster-head* (CH), that is responsible to process the collected data and transmit it to the sink. Thus, with the assumption that data by sensors in the same cluster are

correlated with a high probability, data is reduced to an effective data. Spatial statistics based approaches can also be applied to determine the correlation of sensing outcomes of the nodes in a CRN.

In a distributed CRN, clustering as a way of organizing a distributed network into a centralized network architecture is accepted as an efficient way of managing a network. Furthermore, multi-hop transmission in a clustered CRN as opposed to broadcasting in single-tier distributed CRN, has energy conserving potential at the expense of cluster formation and communication overhead.

Clustering eases cooperative sensing. However, there still remains to be done in a clustered CRN to minimize the cost of sensing and information flow for energy efficiency. To this goal, spectrum sensing scheme must avoid the flow of redundant and unreliable data by employing reliability-based collaboration schemes. Work in [90] proposes a cooperative sensing scheme dubbed *confidence voting* and a clustered sensing scheme dubbed *cluster-collect-forward* (CCF). In this *confidence voting*, a CR does not transmit its sensing data until it becomes confident of its sensing reliability. *Sensing reliability* of a CR is computed by comparing CR's own sensing decision with the majority decision of all CRs, and it is updated regularly after each sensing decision. As the node reliability exceeds a pre-defined threshold, CR transmits its sensing decision to the corresponding CH. This selective sensing transmission scheme saves significant energy (up to over 40% depending on the number of CRs and initial confidence parameter) while resulting in a slightly higher probability of sensing errors. In CCF, nodes are arranged in a hierarchy of clusters. Sensing decision of each CR is transmitted through this hierarchy instead of widely adopted less-efficient broadcasting. Broadcasting requires each CR to align its transmission power to be received with sufficient quality (e.g. above a threshold SNR) at the farthest CR. Moreover, it takes longer compared to the CCF for propagation of information. For instance, in a network of N CRs, N time slots are needed for each CR to broadcast its sensing data. Authors show that CCF is significantly more energy-efficient compared to the broadcasting scheme. Results in [25] support these conclusions. *Contribution-based decision scheme* in [25] selects the CR with the highest reliability as CH for each cluster. Moreover, as in [90],

each CH in turn acts as the fusion center in order not to drain the power of a specific CR. Effect of number of clusters on energy saving and detection accuracy are also investigated. Larger number of clusters leads to lower delay and better parallelism at the cost of higher clustering overhead [25]. Naturally, number of CRs contributing to the decision process accounts for the sensing reliability. If there are very few number of CRs then probability of detection error increases. Therefore, tradeoff among energy-saving potential and detection accuracy must be captured properly in order to determine the optimal cluster size and threshold for determining the reliability of a CR.

5.2.2.5. Hard vs. soft decision. In general, soft decision has performance gains over hard decision scheme while it is shown in [99] that hard decision combining is almost as reliable as the soft decision combining in case there are sufficiently large number of collaborators. Average number of sensing bits in hard decision is obviously less than that of soft decision. Therefore, hard decision combining consumes less energy due to decreased communication overhead. However, though being small in some cases, throughput performance loss due to hard decision should also be taken into account.

5.2.2.6. Single stage vs. multi-stage sensing. Due to imperfection in spectrum sensing, sensing schemes sometimes give false alarms which lead to time and energy consumption in channel searching and channel switching, in addition to waste of opportunities. Therefore, keeping false alarm rate as low as possible is desired for energy efficiency, while keeping detection probability over a threshold P_d is sufficient. In order to alleviate the adverse effects of false alarm and to develop robustness against it, a CR does not immediately search for opportunities or switch spectrum upon an alarm. In this *multi-stage sensing*, a CR becomes certain that PU exists in the band after S consecutive occurrences [100]. S is the number of stages which equals 1 in conventional schemes. Performance improvement facilitated by multi-stage sensing is due to its robustness to false alarms. In contrast to single stage sensing, a CR in multi-stage sensing goes on transmission and sensing cycles at the risk of creating interference to the in-band PU. However, proper design of the multi-stage sensing can ensure that this interference is in tolerable limits. Because multi-stage sensing avoids unnecessary

spectrum switchings and sensing, it consumes less energy.

The first CR standard, IEEE 802.22 [101], also applies a type of multi-stage sensing. In this two-stage sensing, IEEE 802.22 BS schedules either *fast* or *fine sensing* in a *quiet period* during which all CR communications are suspended. Fast sensing takes shorter time owing to the energy detection while fine sensing yields better performance due to applying feature detection [102]. Luo *et al.* [103] show that two-stage sensing can locate an idle channel faster than single stage random sensing while [100] introduces a more general analytical model for S -stage sensing and explores energy efficiency of multi-stage sensing. In [103], a CR senses a wide contiguous spectrum block in the first stage so called *coarse resolution sensing*. If it considers this block as an opportunity, it performs *fine resolution sensing* by dividing this block into narrower bands. In [100], a CR performs in-band sensing for T_s in each stage and transmits for the rest of the time slot ($T - T_s$) even if a PU alarm is received. If the band is detected to be free, it resets the multi-stage sensing and starts from the first stage. Otherwise, CR goes on to the next stage. In case all stages trigger a PU alarm, CR explores another band by entering the quiet period and carrying out spectrum sensing for the whole time slot in order to increase its sensing reliability on this new channel. Through analytical derivations and extensive simulations, authors show that throughput and energy efficiency performance improve with the increase in number of stages for slow PU traffic (low PU arrival/departure probabilities in a time slot). In summary, multi-stage sensing is generally beneficial for CRNs in terms of both throughput efficiency and energy efficiency.

5.2.3. Energy-efficient Transmission Power Allocation

Cognitive cycle in Figure 5.2 starts with radio-scene analysis of the surrounding wireless environment and completes the cycle with transmission. Transmission is performed with parameters (e.g. transmission power and modulation) determined by the cognitive protocols utilizing the outcomes of radio-scene analysis. Transmission power as a fundamental factor in energy consumption is worth attention for improving energy efficiency. Reducing the transmission power has been one of the apparent

solutions for reducing energy consumption. However, as summarized in Section 5.1.2, capacity of a channel degrades monotonically with decreasing power. Thus, transmission power determines the network throughput. This tradeoff must be captured in a utility function which is defined depending on the specialities of a CRN and the targeted performance criteria. Optimum trading-off capacity for achieving higher energy efficiency has been studied widely in the domain of wireless networks [104]. However, CRNs have peculiarities owing to the DSA philosophy. Different from conventional wireless networks, transmission power of a CR has direct impact on the white spaces and primary signal detection reliability. [105] sheds light on the interplay between power, PU detection performance and spectrum opportunity discovery efficiency, and elaborates on power control in CRNs. Power control in CRNs has not been positioned except a few works [32, 106–110] from the perspective of energy efficiency.

In CRNs, power control is mostly considered in the scope of capacity improvement while resulting interference is kept within a tolerable range [111]. CRs via power control restrict the interference to each other as well as to the PUs and thereby improve spectrum sharing in the CRN. For eliminating the excessive interference in a network, wireless nodes have maximum transmission power (P_{max}) constraints determined by the regulatory guidelines. Such a limit also bounds transmission energy consumption. If throughput efficiency is of principal concern, maximum transmit power may be the choice for transmission power which may not always be optimal from energy efficiency perspective [107]. It is vital to manage power resources effectively for keeping an optimal balance among energy efficiency, throughput efficiency and PU interference. Throughput and energy performance can be balanced by defining a utility function which tunes itself via a design parameter. That parameter puts more emphasis on either throughput or power efficiency, and next favors it. For instance, work in [108] seeks the transmission power for optimal operation point under varying values of the design parameter while [107] similarly formulates expected net reward of a sensing-access scheme as a function of this energy efficiency design parameter.

For CRs capable of transmission through multiple channels, power allocation remains to be explored for higher energy efficiency. Each channel may experience different

channel fading conditions, and a CR should exploit this diversity among channels. For instance, a channel in deep fading should not be selected for transmission (zero power allocation) as it requires higher transmission power for attaining the same channel rate (refer to Figure 5.1b). As in opportunistic scheduling, better channel realizations should be waited instead of immediate access to a channel in bad propagation conditions [28]. In energy-constrained CRNs, CR should estimate the channel statistics and make power allocations accordingly. It is shown in [112] that truncated power control reduces energy consumption of a CR at the cost of random delays. In this approach, a CR suspends its transmission whenever the channel condition is below a prescribed threshold and continues again when it gets better. However, it introduces random delays which is not desirable in case of delay-intolerant applications. Work in [32] formulates the energy-efficient power allocation problem considering the rate of each channel, and associated circuit and transmission power consumption. A CR with the capability of parallel sensing and transmission through K channels, makes power allocation for each channel subject to PU interference restriction and its power budget. Coupled with sensing duration optimization, proposed optimal power allocation improves energy efficiency.

OFDM which is recognized as an efficient modulation scheme for next generation wireless technologies, fits to the operation dynamics of CRNs due to its flexibility in resource allocation [111]. Conventional power loading algorithms make subcarrier allocations in static spectrum networks considering the channel dynamics. However, in CRNs, discovered idle subcarriers must be allocated to CRs with great attention to the created interference to the subcarriers used by the PUs. Allocated power to the CR subcarrier and its frequency distance to the PU subcarriers determine the level of interference experienced in the victim subcarrier. For instance, interference to a neighbor PU in terms of frequency would be higher compared to the PU using a subcarrier which is spectrally more distant. However, setting the power of the subcarriers in the immediate vicinity of PU carriers to zero, also called *subcarrier nulling*, has a throughput tradeoff since even these subcarriers have very favorable channel conditions, they are not allocated for transmission [111]. Moreover, classical waterfilling algorithm falls short of meeting interference criteria in CRNs, since it favors the subcarrier with the

highest channel gain with no concerns on the PU interference [106]. Therefore, CR-compatible power allocation schemes are to be devised. [106] deals with energy-efficient subcarrier power allocation for a single user OFDM CR system. Authors define a linear rate loss function that represents the risk of an allocated subcarrier to cause rate loss due to imperfect spectrum sensing and PU reappearance. Those risky channels are avoided in subcarrier power allocation so that energy waste due to these assignments is decreased. Simulations show that proposed optimal and suboptimal solutions outperform classical waterfilling scheme in terms of CR capacity and generated interference. Gao *et al.* [113] and [114] propose an *energy-efficient waterfilling* algorithm for distributed energy-efficient power control in CRAHNs and CRSNs, respectively.

Transmission power control in a CRN can be considered as a (noncooperative) game [109, 110] as a CR's transmission is perceived at other CR receivers as interference. [110] forms a noncooperative game in which each CR wants to maximize its long term valuation that is a function of energy efficiency. In this game, CRs predict the expected future rewards considering the stochastic environment in terms of expected power noise, and select transmission power from the interval $[0, P_{max}]$. As opposed to myopic adaptation which lacks estimating the dynamics of the environment, the proposed online power adaptation algorithm owing to the dynamic learning process estimates the environment. Hence, it results in the highest accumulated energy efficiency. Work in [109] explores how to control transmission power of a CR in a decentralized manner in order to provide maximum energy efficiency in a CRN. Primary network cooperates with the CRN by informing the tolerable interference levels of PUs. CRs are located at different distances from the AP, and if identical P_{max} is defined for each CR, received signal strength at the AP due to distant CRs are lower while close CRs have higher signal strength. Therefore, in order to eliminate the disadvantage of far away CRs, P_{max} of each CR is adapted such that received signal strengths at the AP are equal. Under this CRN setting, noncooperative power control game for maximum energy efficiency is shown to have a unique Nash equilibrium and CRs benefit from such power allocation at a slight adverse impact on PU communications.

According to the Shannon's formula in (Equation 5.2), channel bandwidth is also

a determining factor in channel capacity. Therefore, we can also interpret that there is a tradeoff between channel bandwidth and power consumption. That is, in order to attain the target channel capacity under various bandwidth, transmission power must be adjusted. The narrower is the bandwidth, the higher is the transmission power. Besides, while bandwidth linearly affects the capacity, the effect of power is in logarithmic scale [115]. Hence, wider bandwidth channels can be exploited at lower transmission power levels for better energy efficiency. CRs as nodes capable of transmitting over flexible bandwidth can take advantage of bandwidth and power adaptation for higher energy efficiency.

5.3. Energy Efficiency at MAC Layer

5.3.1. Energy-efficient Sensing Scheduling

Determining how long sensing and transmission should be carried out is of great importance for both spectrum efficiency and energy efficiency. Previous research [80] has revealed that sensing duration determines the sensing accuracy leading to a tradeoff between sensing and throughput. Consider a frame-based CR network in which each frame is divided into two parts: spectrum sensing period (t_s) and transmission period (t_{tx}). Energy efficiency for such an orientation can be defined as a function of t_s and t_{tx} . Since no data is transmitted during sensing (assuming single antennas), achieved throughput is due to t_{tx} . At a first glance, we can conclude that the longer the transmission duration, the better is the energy efficiency. However, it is not so trivial. In the extreme case, such conclusion leads to transmission without performing any sensing. It is obvious that this kind of operation is neither efficient nor legal (due to the violation of the CRs' promise for non-harmful PU operation). Actually, throughput obtained in t_{tx} depends on the accuracy of the sensing outcomes which is determined by the spectrum sensing scheme and t_s . Most of the works in the literature focusing on energy efficiency in CRNs consider this interplay between sensing and transmission, and devise solutions to strike a balance among energy efficiency, throughput efficiency and PU protection.

In addition to scheduling sensing and transmission periods, a cognitive MAC protocol can schedule sleeping periods for energy-saving purposes as *duty-cycling* is known to improve energy efficiency [69]. *Duty cycling*, which enables a node to sleep periodically, is an effective way of reducing energy dissipation since an *active* (non-sleeping) wireless node consumes energy even if it does not transmit/receive but keeps its circuitry active [116, 117]. This idle state is mostly considered as a pure overhead since it does not contribute to throughput but consumes considerable energy. As a solution to this issue, sleeping mode is proposed. Sleeping is the act of putting the various hardware components into low-power states by switching them off so that they consume noticeably lower energy. By activating this mode, percentage of time a node is in active state, also called *duty cycle*, decreases. However, switching from sleep mode to active mode has a cost in terms of latency and *wake-up cost* owing to state transition time. Besides, if sleeping is blindly applied, it may lead to higher energy consumption than it would if no sleeping is applied [118]. Therefore, MAC should pay careful attention to strike a balance between duty cycling for reducing power dissipation and the latency it exposes. If no energy constraints were inserted, MAC would make sensing continuously, and transmit whenever a spectrum opportunity is discovered. However, in practical CRNs with energy constraints, a CR may sleep even if it has packets in its buffer and sensed channel is idle. CR's policy is strongly affected by its remaining energy level and cost of sensing. It should be more aggressive if little energy is left and sensing is costly, while it would prefer idling if it has enough energy and sensing consumes very low energy [28]. MAC can schedule various sleeping periods (e.g. *deep sleep* or *light sleep*) with different wake-up costs considering the CR traffic dynamics such as CR buffer state and traffic requirements (e.g. delay tolerance).

References [30, 119, 120] and [121] investigate the best operation mode for a CR in terms of energy efficiency under various scenarios. Hoang *et al.* [119] model operation of a CR that dynamically decides on its action between carrying out sensing (if so, how long) and staying idle for a time slot, while [30] decides to transmit or not transmit in the discovered holes depending on its power budget, and [120] considers additionally the sleeping option. In [119], a listen-before-talk approach is applied in which sensing is performed before each transmission attempt for the sake of PU protection, while

staying idle is preferred for energy-saving purposes. The optimal policy is derived from a reward maximization problem utilizing a POMDP framework. Reward function takes both costs into account: delay cost due to idling and energy consumption due to sensing. It is revealed via analysis of the reward function that optimal control policy is threshold-based such that CR prefers sensing if its belief state is above a threshold value, and stays idle otherwise [119].

Decision maker in [120] decides on the operation mode of the CR for a time slot: transmission, idle and sleep among various sleeping modes with different wake-up latency and power consumption values, depending on the state of the system. System state is interpreted by a tuple consisting of number of packets in CR buffer, latest operational mode of the CR, channel occupancy status, and timer showing the remaining time to next periodic sensing slot. Defined cost function aims to minimize energy consumption while it applies a penalty for buffer overflows. This penalty ensures the CR will perform transmission rather than staying in low energy consuming sleep modes. Authors show that so called *drowsy transmission* results in lower energy-per-bit compared to the two baseline scenarios in which CR always performs periodic sensing even if its buffer is empty, and a sleeping CR always wakes up upon a packet arrival, respectively. Since in drowsy transmission CR may decide to rest in one of the sleeping states even if a packet arrival occurs, delay associated with drowsy transmission is expected to be higher than baseline scenarios. However, delay value is still acceptable due to the penalty applied for buffer overflows.

Work in [121] finds out jointly the optimal transmission duration and power at each of the channels for a CR with multiple antennas to ensure the maximum energy efficiency while the generated interference is below the PU's tolerable interference ratio. Depending on the states of the channels acquired by parallel spectrum sensing at the beginning of each frame, CR either keeps silent in case of PU detection, or decides on the transmission duration and the power allocated to transmission on this channel. The experimental analysis shows that the proposed optimal allocation scheme and a sub-optimal solution with much lower complexity perform better than the equal power allocation scheme.

5.3.2. Energy-efficient Scheduling

In centralized CRNs, as in cellular networks, a scheduler located at the CBS is in charge of resource allocation. In order to provide the optimal operation, the scheduler should exploit the diversity across CRs and also across frequencies. It is a fact that different frequency channels have different channel conditions, e.g. channel fading in each channel differs. Moreover, the quality of a channel with the same central frequency varies from user to user. Hence, all these dimensions should be taken into consideration. The scheduler should apply opportunistic scheduling. For instance, CRs with better channel conditions at a specific frequency channel and with more transmission capacity can be favored in scheduling. Similarly, the scheduler can consider the buffer states of the CRs in resource allocation and schedule sleep periods for them. As in conventional scheduling schemes in wireless networks, scheduler aims to provide a balance among various conflicting objectives: ensuring some degree of fairness, maximizing throughput and minimizing delay. Furthermore, a scheduler designed with energy efficiency concerns should perform resource allocation such that energy consumption is kept at minimum without a significant sacrifice of the QoS.

Works in [122] and [123] investigate scheduling in a CRN in an underlay scenario. [122] derives mean capacity of an opportunistic scheduler in a network of N CRs and a PU. In each time slot, the CBS selects the CR for transmission with the minimum channel gain. Given that all CRs transmit with equal power, generated PU interference is minimum at the CR with minimum channel gain. Since an underlay scenario is considered, the PU must be protected from the CR transmitting simultaneously. This is ensured by the CR's operation with maximum possible transmission power such that resulting outage probability is below the outage probability threshold. [123] analytically shows that round-robin scheduling achieves the same mean capacity and bit rate as opportunistic scheduler but with lower energy consumption. Round-robin scheduler simply assigns one time slot to each CR in a time frame without keeping track of channel gains as done in opportunistic scheduler. Assigning one time slot per time frame to each of N CRs, round-robin scheduler simply has power consumption as $1/N^{th}$ of that of opportunistic scheduler. Therefore, it yields lower energy consump-

tion. Statistics-based scheduler that also exploits channel variations as in opportunistic scheduler further improves the energy efficiency by attaining the same mean capacity at lower power values. However, traffic dynamics are not considered in neither of these works. As indicated earlier, a scheduler must exploit the channel variations as well as variations in queue backlogs. For instance, a CR assigned its turn in round-robin scheduling might have no packets to transmit which leads to waste of resources.

Conventionally, capacity of a CRN is evaluated with achievable throughput capacity. However, we also need alternative measures to assess the network capacity with the change in communications paradigms and emergence of new approaches (e.g. green communications concept). In this regard, [31] defines a capacity metric, *achievable average capacity normalized by energy consumption* (bps/Hz/Joule) which is an interpretation of bits-per-Joule capacity. Authors evaluate the capacity of a CRN by incorporating the effect of energy consumption due to spectrum sensing and transmission. In the examined system, CR transmitters ensure via transmit power regulation that interference temperature (IT) at each PU receiver is guaranteed to be below the IT limit. The tradeoff between spectrum sensing and throughput capacity is due to the opportunistic selection of a CR transmitter only from the set of CRs performing spectrum sensing. The CR receiver (i.e., BS in an uplink communication scenario) selects the CR transmitter with the best channel gain among the ones performing spectrum sensing, estimating the interference channel and not violating the IT limits. Next, optimal selection of the number of sensing CRs is formulated as a capacity maximization problem. Determining the best set of CRs for spectrum sensing is non-trivial. There are 2^{N_s} alternatives, N_s denoting the number of CRs. Hence, a sub-optimal scheme, *best-n* scheme, operating with near-optimal performance is also developed. Experimental and simulation analysis outline how the throughput capacity (bits/s/Hz) and the achievable average capacity normalized by the energy consumption differ under various operation parameters.

Centralized scheduling requires a considerable amount of information to be transmitted to the CBS from the CRs. Motivated by this overhead both in time and energy consumption of control messaging, preventing frequent message exchanges is desirable

for more energy-aware protocols. [41] argues the burden of *slot-by-slot scheduling* and instead proposes a *frame-by-frame scheduling* scheme. The frame-by-frame scheduling can be seen as a generalized version of the former in which scheduling is performed once in K time slots, K standing for the number of slots in a frame. At the first time slot of each frame, CRs report their status, e.g. channel capacities based on channel SNRs and queue status, to the CBS. Status of CRs in the subsequent time slots are predicted using stochastic modeling, more particularly utilizing the PU activity model and channel model. Applying such a scheduling scheme decreases both the uplink and downlink scheduling overheads in terms of bits transmitted, and accordingly increases throughput. On the other hand, this scheme may experience performance loss in case of estimation errors. If the CBS fails to predict the CR status approximately, some of the resources will be wasted. For instance, if a CR with deep fading or empty queue is assigned a frequency instead of other CRs with better channel conditions and longer queues, then the assigned frequency will not be effectively utilized during the whole frame. The longer is the frame duration, the lower is the estimation accuracy. On the other hand, the shorter is the frame size, the higher is the overhead as in the case of slot-by-slot sensing for $K = 1$. As a solution to this issue, optimal frame size is determined by analysis of simulation and analytical results.

Energy efficiency is generally considered as a network-wide performance parameter in previous works while CR-centric energy efficiency is more practical considering fairness and individual QoS. Besides, individual energy consumption becomes the major concern in some constrained and energy-limited networks such as WSNs, where network becomes non-functional if some portion of nodes cannot operate due to energy outages. In this regard, [124] proposes residual energy aware channel assignment that exploits user-diversity in terms of energy potential of each CR for a CR sensor network (CRSN). A CRSN [34] is a special type of WSN in which sensor nodes are equipped with CR capabilities and DSA is applied for transmission in a multi-channel environment. CR functionalities are beneficial for WSNs since they usually operate at unlicensed bands (e.g. ISM) which is already overcrowded. WSNs can tackle this issue of spectrum scarcity via DSA at the expense of increased energy consumption due to CR-inherent operations for PU protection and opportunity discovery [29]. Energy-

efficient cognitive operation is obviously more crucial for energy-constrained CRSNs. Works in [29,33,114,124,125] analyze the CRSN energy efficiency. [33] show that censoring as well as sleeping reduces total energy consumption of a CRSN while meeting the targeted performance level. If no censoring and sleeping is forced, energy consumption scales linearly with the number of CR sensor nodes. In contrast, energy consumption in sleeping and censoring scheme saturates to a level which is significantly lower.

In [124], CRSN is organized in clusters and each CH manages channel assignment just like CBSs in CRNs. Since CRSN lifetime is constrained by the residual energy of CR sensors, channel assignment algorithm aims to keep a balance in the energy consumption of the nodes, e.g. a node with higher energy is assigned the channel which is expected to require higher communication energy. Sensor energy consumption differs among nodes and channels due to primary channel dynamics and the distance of the CR sensors from the CH. Proposed algorithms which allocate resources using the predicted residual energy of each CR sensor have lower energy consumption and longer lifetime compared to *random pairing* in which available channels and CR sensors with channel request are randomly paired. It is also shown that residual energy distribution of CR sensors has low standard deviation in both approaches since both of them pay attention to balance the energy consumption of each node. Residual energy metric is useful for channel assignment with network lifetime concerns, however it lacks throughput-efficiency perspective. In this CRSN, burden of event detection is charged on CR sensors with high residual energy which is not applicable to CRNs. Therefore, these approaches cannot be extended to conventional CRNs in which throughput efficiency must also be attained. Reference [125] considers this concern by naming sensing for data collection as *application-oriented source sensing* (AppOS) and sensing for opportunity discovery as *ambient-oriented channel sensing* (AmOS). These two sensing is interrelated in that the event information must be collected effectively while its delivery success depends on the quality (and occupancy state) of delivery channel that is discovered by AmOS. The relationship between the two sensing is exploited. Subsequently, optimal power allocation scheme for minimum power consumption that ensures operation at a predefined quality metric is described in a time slotted CRSN.

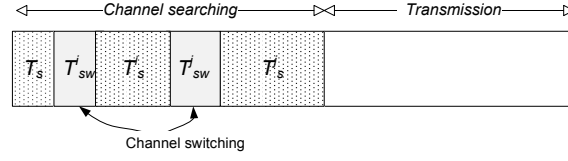


Figure 5.5. Before performing a channel sensing, CR tunes its RF front-end to the channel to be sensed which results in channel switching latency (e.g., T_{cs}^i for channel i).

5.3.3. Intelligent Channel Selection and Energy-efficient Channel Switching

In contrast to centralized networks, in a distributed CRN, each CR makes sensing and access decisions by itself. In case a CR needs to find a transmission opportunity, it initiates channel searching that is determined by the channel search algorithm. Searching should utilize the primary network statistics acquired by the secondary network via previous sensing observations. More precisely, if a CR predicts which channels are probably vacant, it starts probing the channel with the highest probability of being idle. However, this operation mode requires some processing for accurate estimation of channel occupancy characteristics. It is shown in previous works [115], [126] that rather than a blind channel search (also known as random search) intelligent channel selection can locate an opportunity faster which results in higher throughput and energy efficiency performance.

Figure 5.5 illustrates the composition of time for a CR in a channel search. In the considered scenario, sensing outcomes show the existence of an incumbent in the band. Therefore, CR constructs its search sequence as $(i, j, \dots)$, channel i being the first channel to be sensed, channel j be the next in case the prior is occupied. This CR tunes its hardware to channel i . T_{sw}^i denotes the time that is spent for configuring the hardware from current transmission frequency (f) to the center frequency of channel i (f^i). CR senses the channel for a given sensing accuracy for a duration of T_s^i , and moves to the channel j since this channel is occupied. Same sensing operations are performed this time in channel j . It is observed to be idle, and in sequel, CR begins transmission in channel j .

Based on the spectrum measurement devices in the market [127], previous works [24, 128, 129] have considered channel switching delay as a linear function of the frequency separation between f and f^i . If switching to an adjacent frequency takes t_{sw} units in time, then total time spent for switching from f to f^i is calculated as $T_{sw}^i = t_{sw}|f - f^i|$. Similarly, we can model total energy consumption due to channel switching (E_{sw}) as follows:

$$E_{sw} = P_{sw}T_{sw}^i \text{ and } T_{sw}^i = t_{sw}|f - f^i| \quad (5.6)$$

where P_{sw} is the power dissipation for switching to an adjacent frequency.

Channel switching depends on the hardware capabilities of the CR and the bandwidth of the frequency distance. In [128], 1 ms delay is assumed for tuning to a frequency 10 MHz further, i.e. $t_{sw} = 1ms/10MHz$, while [129] takes it as $10ms/10MHz$, both works referencing to different members of the same product family [127]. [55] uses $5ms$ and $10ms$ t_{sw} values based on a IEEE 802.11 wireless interface driver [130]. As this simple example gives insights, channel search sequence affects energy consumption and moreover energy efficiency performance of a CR. Therefore, design of intelligent channel selection utilizing the CR knowledge base and observations is vital for energy-efficient CRNs. In addition, effect of channel switching must also be taken into account in the design of CR channel selection or resource allocation schemes since CRs promise to operate in a wide and presumably discontinuous spectrum range.

Table 5.1 summarizes the works in the literature which consider energy/power consumption or energy efficiency of CRNs. References are grouped according to their design approach: optimization, game theory, POMDP/dynamic programming, and analytical modeling are commonly used tools. We broadly classify the literature as works focusing on sensing scheduling (SS), transmission duration decision (t_{tx}), sensing duration decision (t_s) and power allocation (P_{tx}), and mark the corresponding column if the reference explores that issue.

Table 5.1. Summary of related works on energy efficiency in CRNs (SS:Sensing scheduling, Game: Game theoretical approaches, DP: Dynamic Programming).

Tool	Ref.	SS	t_{tx}	t_s	P_{tx}	Comments
Optimization	[31]	+	+		+	CR receiver selects N CR transmitters with maximum received SNR for energy-efficient sensing.
	[30]	+	+	+		Optimal sensing, transmission and idling durations.
	[131]		+			Energy-efficient uplink scheduling
	[108]	+	+	+	+	Parametric utility function for balancing throughput-power efficiency tradeoff.
	[121]		+		+	Joint P_{tx} and T_t optimization
	[106]				+	Power allocation to underutilized subcarriers.
	[32]		+		+	Transmission duration and power allocation over multiple channels.
	[124]		+			Channel assignment considering the residual energy of sensor nodes prolongs CRSN network lifetime.
	[92]	+				Optimal number of cooperating CRs for energy efficiency.
	[114]				+	Energy-efficient waterfilling for CRSNs.
Game	[109]		+		+	Noncooperative power control game for maximum energy efficiency.
	[36]				+	Coalition formation game for CSS.
POMDP/DP	[35, 94]	+		+		Number of CRs for sensing various channels and sensing duration for energy-efficient CSS.
	[29]	+	+			Operation mode selection for energy-efficient CRSN.
	[37]	+		+		Operation mode selection for energy-efficient CR.
	[28]	+	+		+	Operation mode (sleeping or sensing/access) selection based on residual energy.
	[107]	+	+	+	+	Joint design of sensing sequence, access and power allocation.
	[120]	+				Operation mode (transmission, idle and various sleeping modes) selection for maximum energy efficiency.
Analytical Modeling	[90]		+			Confidence based participation of CRs in cooperative sensing decreases energy consumption.
	[100]	+				Multi-stage sensing improves energy efficiency.
	[103]	+				Two-stage sensing consumes less power.
	[132]					Network selection based on network's energy cost.
	[26]	+				Period adaptation reduces energy consumption. Two threshold based sensing decreases false alarm rate and therefore improves energy efficiency.

5.4. Chapter Summary

Vast majority of prior research on CRNs have focused on how to access the spectrum effectively and to improve the CRN throughput performance subject to some restrictions imposed by either PUs or CRN itself. Energy efficiency has not been taken into account in most of the works. However, as CRs promise to provide intelligent spectrum access by the help of spectrum analysis which is power-intensive, power consumption and energy efficiency in CRNs is worth further attention. Moreover, green communications concept due to the recent environmental concerns necessitate improved energy efficiency in CRNs. In this chapter, we provided a literature survey on energy efficiency in CRNs. Our focus was basically on spectrum sensing and access. However, most of the works in the literature is also in this scope. There is little work on energy efficiency dimension of routing, transport protocols or higher level protocols.

Energy efficiency, defined as number of useful bits excluding control data transmitted per unit energy consumption, is a function of throughput and energy consumption. Therefore, for operation with high energy efficiency, keeping throughput high and energy consumption low is desired. However, as *every bit has a cost*, facilitating transmission at lower energy expenditure requires CR protocols to be designed that prevents waste of energy and spectrum resources. As achievable throughput depends on the sensing performance, spectrum sensing and access have to be balanced such that a certain degree of PU protection and sensing reliability is achieved while CRN throughput is maximized. Therefore, as is the case for throughput efficiency, energy efficiency has to consider this tradeoff between sensing and access.

We first summarized the basics of spectrum sensing and next, evaluated each sensing scheme according to their energy efficiency perspective. Cooperative sensing, cluster based sensing, periodic or reactive sensing, hard or soft sensing are all discussed from an energy efficiency perspective. Second, we surveyed the current literature on energy efficiency of spectrum access. As mentioned before, most of the research is on striking a balance between spectrum sensing and access. Besides, some of the works consider sleeping as a low energy consuming state and tries to find the best mode of

operation for the maximum energy efficiency of a CR. As energy consumption is directly related to the power consumption, some of the works examines power allocation issue in CRNs. In traditional wireless networks, waterfilling based power allocation methods are commonly applied. However, for energy efficiency in CRNs, these methods are not directly applicable. There are various proposals, also called *energy-efficient waterfilling*, for energy-efficient power allocation in CRNs.

In this chapter, we focused particularly on spectrum sensing and transmission for energy efficiency. However, in order to move CR concept into practical systems by applying green communications approach, there is a need to extend the CR design to a level that is inclusive of all aspects such as from network routing, application layer requirements to security. In the literature, there exist very few works on routing, hardware design and network selection for attaining higher energy efficiency in CRNs. Each of these research topics is crucial for realizing CRNs that are environment-friendly, cost-effective and have longer battery lifetime. Energy efficiency research certainly needs to be in the agenda of CR research if CR is recognized as the one of the major components of next generation smart networks.

6. ENERGY-EFFICIENT SCHEDULING IN CRNs ENABLED VIA WHITE SPACE DATABASE

In this chapter, we focus on scheduling in CRNs in which cognitive base station (CBS) makes frequency allocations to the CRs with a transmission request at the beginning of each frame, depending on the reports collected from the CRs. We consider a CRN that acquires spectrum availability information from an external entity, namely a *white space database* (WSDB). Hence, we ignore the PU protection and sensing mechanisms in our work. We outline the components of energy dissipation in a CRN: *transmission, circuitry, idling* and *channel switching*. The first three components are common to all wireless networks while channel switching is specific to multi-channel networks. Different from conventional scheduling problems in wireless networks, the schedulers in CRNs have to cope with the spatiotemporal changes in spectrum resources and PU protection requirements. Since, we assume that spectrum occupancy related information is already available at the CRN via WSDB, we only consider the first issue. Moreover, we account for the cost of frequency switching between channels.

We formulate centralized channel assignment problem as an energy-efficiency maximization problem [131]. The formulated problem is a nonlinear integer programming (NLP) problem which is mostly known to be computationally hard to solve. Therefore, we seek for computationally easier solutions. To this goal, we propose a polynomial time heuristic algorithm, *energy-efficient heuristic scheduler* dubbed EEHS, that aims to provide maximum energy efficiency in a frame. Next, we revise our problem formulation and present two approaches: (1) maximization of throughput in a frame while meeting energy consumption restrictions (referred to as TMER), and (2) minimization of energy consumption in a frame while ensuring a desirable throughput performance (referred to as EMTG). In addition, TMER and EMTG schedulers incorporate the past transmission history of each CR into the objective function to maintain a degree of fairness in channel allocation. We evaluate performance of these schedulers

under both contiguous and fragmented spectrum organization, and compare them with our previous proposal EEHS.

The rest of this chapter is organized as follows. Section 6.1 presents the system model and Section 6.2 consequently formulates the energy-efficient scheduling in CRNs. Next, Section 6.3 introduces EEHS while Section 6.4 and Section 6.5 introduce the revised problem formulations, TMER and EMTG, respectively. Section 6.6 provides performance evaluation of the designed schedulers. Finally, Section 6.7 discusses the proposed schedulers and possible enhancements that can be applied to them while Section 6.8 concludes the chapter with a summary.

6.1. System Model

We consider a centralized CRN as in Figure 6.1 which has N CRs and F frequencies licensed to the primary network. Occupancy state of each primary channel is modeled as a two-state Markov chain and the probability of a channel's being idle is P_{idle} . Each CR is equipped with only one antenna, hence transmission through multiple frequencies is not possible. CRs and CBS are all synchronized in time.

CBS makes channel allocation at the beginning of a frame. A frame spans a time duration of T_{frame} ms. Let assume that at the beginning of each frame, CBS queries the WSDB for the spectrum occupancy information and acquires the occupancy states of the primary channels from WSDB. As a result, CRs do not perform spectrum sensing. At first sight, this assumption seems to be contradictory with the main thought of CRs, however it is not unrealistic. For instance, in September 2010 Federal Communications Commission (FCC), the regulatory institution in the US, made sensing optional in TV white spectrum devices, and instead, CRs are mandated to consult a centralized entity called *geolocation database* to query the idle frequencies. SenseLess [133] is an example of a geolocation database that maintains an up-to-date information on active users and generates a map of the spectrum use, also known as *interference cartography*, via sophisticated signal processing and terrain modeling tools.

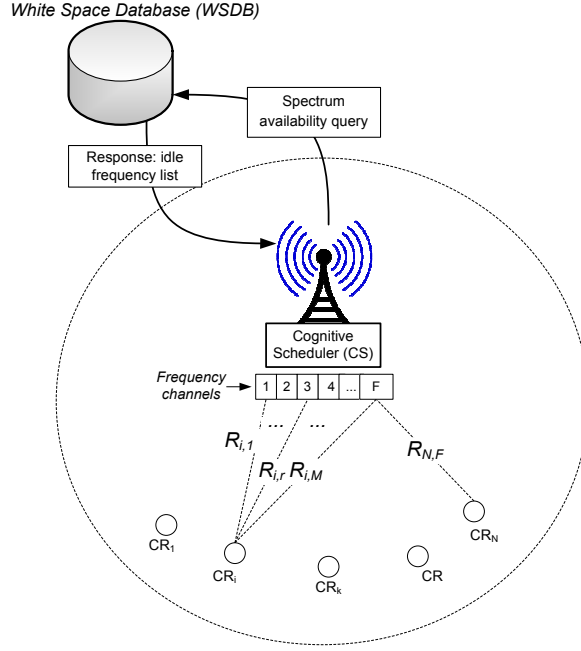


Figure 6.1. Each CR_i maintains a link with the CBS for each frequency f denoted by

$$R_{i,f}, i \in \{1, \dots, N\} \text{ and } f \in \{1, \dots, F\}.$$

In order to prevent ambiguity between frequency channels ($f \in \{1, \dots, F\}$) and the wireless channels between the CRs and the CBS ($l_{i,f}$, $i \in \{1, \dots, N\}$ and $f \in \{1, \dots, F\}$), we refer to the former as *channels* and the latter as *links*. At the beginning of a frame, each CR sends its state to the CBS. The state of a CR is represented as a vector showing the *effective rate* ($L_{i,f}$, will be defined in the next section) of each link $l_{i,f}$. As all information is gathered at CBS, it determines a transmission schedule applying its scheduling policy, and broadcasts it to the CRs. All these transactions are completed in control messaging period which takes t_{ctrl} units of time. Set of CRs that are assigned a frequency is denoted by $\mathcal{N}_{tx}$. CRs in $\mathcal{N}_{tx}$ tune their antennas to the assigned frequency and begin transmission while others stay in idling state till the end of frame. CRs switch to idling state after completion of transmission.

Please note that in the following, we use f to refer to both the frequency index of channels in the system as well as the center frequency of this channel (in units of MHz).

6.1.1. Link Capacity Calculation with Channel Switching Cost

Obviously, channel switching introduces additional cost of time and energy consumption due to necessary RF front-end hardware configurations. In the literature, total time spent during all these configurations is referred to as *channel switching latency* (delay) and it is considered as a linear function of total frequency distance between the former (f') and the latter frequencies (f) as explained in Chapter 5. Accordingly, channel switching latency denoted by T_{sw} is calculated as follows:

$$T_{sw} = t_{sw}|f - f'| \quad (6.1)$$

where t_{sw} represents the delay for switching unit bandwidth (ms/MHz).

Capacity of $l_{i,f}$ can be derived using Shannon's formula as follows:

$$B_{i,f} = W \log_2(1 + \gamma_{i,f}) \text{ bits/second} \quad (6.2)$$

where W is the channel bandwidth in Hz , $\gamma_{i,f}$ is the signal-to-noise ratio of $l_{i,f}$. Consequently, we can calculate the throughput that will be obtained if CR_i transmits at $l_{i,f}$ given that CR_i 's antenna is tuned to f' :

$$R_{i,f} = B_{i,f}(T_{frame} - T_{sw}^{i,f}) \text{ bits/frame} \quad (6.3)$$

where $T_{sw}^{i,f}$ is the channel switching time for CR_i to switch to frequency f . However, $R_{i,f}$ can exceed the number of bits in CR's buffer (Q_i). Hence, effective rate of $l_{i,f}$, denoted by $L_{i,f}$, is restricted by:

$$L_{i,f} = \min(R_{i,f}, Q_i) \quad (6.4)$$

since a CR cannot transmit more than its channel capacity lets or the number of bits

in its buffer. Next, we calculate total CRN throughput as follows:

$$R = \sum_{i=1}^N \sum_{f=1}^F X_{i,f} L_{i,f} \text{ bits/frame} \quad (6.5)$$

$X_{i,f}$ standing for the binary decision variable that represents the allocation state of CR_i at frequency f , i.e. $X_{i,f} = 1$ if f is assigned to CR_i , and $X_{i,f} = 0$ otherwise.

6.1.2. Energy Consumption Modeling

We model energy consumption of a CRN considering the frame organization. If CR_i is assigned a frequency ($i \in \mathcal{N}_{tx}$), first it tunes its antenna to the assigned frequency which takes T_{sw} time units. Next, CR begins transmission. As the transmission is completed (after t_{tx} ms), it switches to the idling state, and keeps idle till the end of the frame. If $i \notin \mathcal{N}_{tx}$, CR_i waits idle in this frame. Since every CR participates in control messaging, we do not consider this period in our calculations. Hence, for the sake of simplicity, we treat it as $t_{ctrl} = 0$.

Since wireless interfaces are the dominant sources of energy consumption in a wireless device especially for long range communications [120], we ignore energy consumption due to information processing. Energy consumption of a CR in such a CRN setting is due to various tasks and components:

- (i) Transmission (E_{tx}): The CRs in $\mathcal{N}_{tx}$ consume transmission energy while those that are not assigned any frequencies stay in *idling* state. The transmission power (P_{tx}) is assumed to be constant. Energy consumption during transmission equals to $E_{tx} = P_{tx} t_{tx}^{i,f}$ where $t_{tx}^{i,f}$ is the transmission duration of CR_i at frequency f and calculated as follows:

$$t_{tx}^{i,f} = \frac{L_{i,f}}{B_{i,f}} \text{ seconds.} \quad (6.6)$$

- (ii) Circuitry (E_c): Power consumed by electronic circuits (e.g. digital-to-analog

converters, mixers, filters, etc.) of a mobile device during transmission is referred to as *circuit power* (P_c). It is almost constant and assumed to be independent of the transmission rate. Energy consumption due to circuitry equals to $P_c t_{tx}^{i,f}$ [70].

- (iii) Channel switching (E_{sw}): E_{sw} represents the energy consumed for configuring the hardware from current transmission frequency (f') to the assigned transmission frequency (f). Using Equation 6.1, we model total energy consumption due to channel switching (E_{sw}) as follows:

$$E_{sw} = P_{sw} T_{sw} \text{ and } T_{sw} = t_{sw} |f - f'| \quad (6.7)$$

where P_{sw} is the power dissipation for switching to an adjacent frequency. Due to channel switching, actual transmission duration of a frame is decreased to $T_{frame} - T_{sw}$.

- (iv) Idling (E_{id}): As mentioned above, CRs that are not selected for transmission stay idle. Hence, they consume idling power (P_{id}) for a duration of T_{frame} which results in energy consumption $E_{id} = P_{id} T_{frame}$. Moreover, the transmitting CRs switch to idling state till the end of the frame once they complete transmission of all the bits in their buffers. In this case idling time is $T_{frame} - T_{sw}^{i,f} - t_{tx}^{i,f}$.

Taking the above components into consideration, energy consumption of CR_i at frequency f can be formulated as follows:

$$E_{i,f} = (P_{tx} + P_c) t_{tx}^{i,f} + P_{sw} T_{sw}^{i,f} + P_{id} (T_{frame} - T_{sw}^{i,f} - t_{tx}^{i,f}) \quad (6.8)$$

In the above formulation, the first term is due to transmission whereas the second is due to idling, and the third due to the channel switching. Total CRN energy consumption for a frame is calculated as follows:

$$E = \sum_{i \in \mathcal{N}_{tx}} \sum_{f=1}^F E_{i,f} X_{i,f} + \sum_{i \notin \mathcal{N}_{tx}} P_{id} T_{frame} \quad (6.9)$$

6.2. Problem Formulation

Using Equation (6.5) and (6.9) to compute total CRN throughput (R) and total CRN energy consumption (E) respectively, we can formulate the energy efficiency maximization problem as follows:

$$\mathbf{P1}: \max_{\vec{x}} \eta = \frac{R}{E} \quad (6.10)$$

$$s.t. \sum_{f=1}^F X_{i,f} \leq 1, i \in \{1, \dots, N\} \quad (6.11)$$

$$\sum_{i=1}^N X_{i,f} \leq 1, f \in \{1, \dots, F\} \quad (6.12)$$

where

$$X_{i,f} = \begin{cases} 1 & \text{if channel } f \text{ is assigned to } CR_i \\ 0 & \text{otherwise} \end{cases} \quad (6.13)$$

In the above formulation, Equation 6.11 ensures that each CR is assigned to at most one frequency due to our assumption that CRs all have a single antenna. Equation 6.12 is necessary for preventing simultaneous transmissions in a frequency band. In other words, at most one CR can be assigned to a frequency. As shown in Equation 6.13, $X_{i,f}$ are binary variables.

The scheduler solves **P1** (6.10) at the beginning of each frame and broadcasts the scheduling decision $\vec{x}$ consisting of tuples as (f, CR_i) standing for the assignment of CR_i at frequency f . In sequel, CRs tune their antennas to the assigned frequencies if they are selected for transmission. However, this problem is computationally difficult to solve since it is in the family of NLP problems. Scheduling should be both efficient and computationally easy. Therefore, we propose maximum energy efficiency heuristic scheduler (EEHS) which is a polynomial time heuristic algorithm for **P1**.

6.3. Maximum Energy Efficiency Heuristic Scheduler (EEHS)

Let $\mathcal{C}_{idle}$ denote the set of idle frequencies, $\mathcal{N}_{tx}$ the set of CRs with nonempty buffers, $\mathcal{R} = \{L_{i,f}\}$ the set of effective rates of $l_{i,f}$. $\mathcal{E} = \{E_{i,f}\}$ is the set of energy consumption if CR_i is assigned to frequency f and transmits at this frequency. The cardinality of $\mathcal{C}_{idle}$ denoted by $|\mathcal{C}_{idle}|$ equals to the number of idle frequencies. Number of CRs with a transmission request is $N_{tx} = |\mathcal{N}_{tx}|$.

EEHS operates applying the steps listed in Figure 6.2. Briefly, if there are more CRs than the number of idle frequencies (Line 1), then the *best CR* for each idle frequency is selected in channel assignment. We call the CR achieving the highest energy efficiency (Line 4) at a frequency the best CR for f . In case of ties, CR with higher effective rate, i.e., larger $L_{i,f}$, is selected for this frequency. If there are plenty of frequencies (Line 8), then the *best frequency* is selected for each CR in $\mathcal{N}_{tx}$. The frequency at which CR_i maintains the highest energy efficiency is the best frequency for this CR. After a frequency is assigned to a CR, it is removed from the set of idle frequencies (Line 13). Likewise, if CR_i is assigned a frequency, it is removed from $\mathcal{N}_{tx}$ (Line 6).

Algorithm in Figure 6.2 terminates after assigning all frequencies/CRs in $\mathcal{C}_{idle}/\mathcal{N}_{tx}$. This algorithm operates in polynomial time. More particularly, it is in the order of $O(FP_{idle}N_{tx})$ complexity where FP_{idle} is the expected number of idle channels and P_{idle} is the probability that a channel is idle.

6.4. Maximizing Throughput with Maximum Total Energy-Consumption Constraint (TMER)

Instead of formulating the centralized resource allocation problem as an energy efficiency maximization problem, we can formulate it as a throughput maximizing

Require: List of idle channels ($\mathcal{C}_{idle}$) are acquired from the WSDB, Q_i , $\mathcal{R}$, $\mathcal{E}$.

Ensure: Assignment vector $\vec{x} : [(f, CR_i)], f \in \mathcal{C}_{idle}$ and $CR_i \in \mathcal{N}_{tx}$.

```

1: if  $|\mathcal{C}_{idle}| < N_{tx}$  then
2:   for all  $f \in \mathcal{C}_{idle}$  do
3:      $\eta_{i,f} = \frac{L_{i,f}}{E_{i,f}}, \forall CR_i \in \mathcal{N}_{tx}$ 
4:      $i^* \leftarrow \arg \max_i \eta_{i,f}$ 
5:     Add  $(f, CR_{i^*})$  to the assignment vector
6:      $\mathcal{N}_{tx} \leftarrow \mathcal{N}_{tx} \setminus CR_{i^*}$ 
7:   end for
8: else
9:   for all  $CR_i \in \mathcal{N}_{tx}$  do
10:     $\eta_{i,f} = \frac{L_{i,f}}{E_{i,f}}, \forall f \in \mathcal{C}_{idle}$ 
11:     $f^* \leftarrow \arg \max_f \eta_{i,f}$ 
12:    Add  $(f^*, CR_i)$  to the assignment vector
13:     $\mathcal{C}_{idle} \leftarrow \mathcal{C}_{idle} \setminus f^*$ 
14:   end for
15: end if

```

Figure 6.2. Proposed energy efficiency maximizing heuristic scheduler: EEHS

scheduler with a restriction on energy consumption (TMER) as below:

$$\mathbf{P2:} \quad \max_{\vec{x}} \sum_{i=1}^N \sum_{f=1}^F (1 - \omega_i) X_{i,f} L_{i,f} \quad (6.14)$$

$$\text{s.t.} \quad \sum_{i=1}^N \sum_{f=1}^F X_{i,f} E_{i,f} \leq E_{max} \quad (6.15)$$

$$\sum_{f=1}^F X_{i,f} \leq 1, \quad i \in \{1, \dots, N\} \quad (6.16)$$

$$\sum_{i=1}^N X_{i,f} \leq 1, \quad f \in \{1, \dots, F\} \quad (6.17)$$

$$X_{i,f} \in \{0, 1\} \quad (6.18)$$

where E_{max} is the maximum allowed energy consumption for a frame, ω_i is the *satisfaction ratio* of CR_i up to this frame. We use satisfaction ratio as a kind of fairness criteria in our scheduler. Satisfaction ratio (ω_i) is simply the ratio of CR_i 's transmitted traffic to its total generated traffic up to now. Therefore, $(1 - \omega_i)$ in the objective serves to ensure a notion of fairness and favor the CRs with lower ω_i .

E_{max} is calculated by the scheduler depending on the reports collected from CRs. It represents the expected energy consumption in a frame. Let K be the number of CRs in transmission, α the average number of channel switchings per user, and T_{id} be the average idling time of CRs after transmission. Accordingly, E_{max} is calculated as follows:

$$E_{max} = \beta (K[(P_{tx} + P_c)(T_{frame} - \alpha t_{sw} - T_{id}) + P_{id}T_{id} + P_{sw}\alpha t_{sw}] + (N - K)P_{id}T_{frame}) \quad (6.19)$$

In the above formula, $\beta \in (0, 1]$ is the energy-throughput tradeoff parameter. Number of CRs in transmission is simply the minimum of number of CRs with a transmission request (N_{tx}) and number of idle channels ($|\mathcal{C}_{idle}|$):

$$K = \min(N_{tx}, |\mathcal{C}_{idle}|) \quad (6.20)$$

Next, average idling time of CRs after transmission (T_{id}) is computed as follows:

$$T_{id} = T_{frame} - \alpha t_{sw} - T_{avg} \quad (6.21)$$

where T_{avg} is the average transmission time of a CR. T_{avg} is the time required for transmitting all bits in the CR's buffer. However, as this time may be greater than the effective time available for transmission, i.e., $T_{frame} - \alpha t_{sw}$, we take the minimum of these values as below:

$$T_{avg} = \min\left(\frac{Q_{avg}}{R_{avg}}, T_{frame} - \alpha t_{sw}\right) \quad (6.22)$$

$$Q_{avg} = \frac{\sum_i Q_i}{N_{tx}} \quad \forall CR_i, Q_i > 0 \quad (6.23)$$

$$R_{avg} = \frac{\sum_i \sum_j B_{i,j}}{|\mathcal{C}_{idle}| N_{tx}} \quad \forall j \in \mathcal{C}_{idle} \quad (6.24)$$

Q_{avg} in (6.23) and R_{avg} in (6.24) denote the average queue size of CRs with transmission request and average rate of idle channels, respectively.

P2 is a variant of **P1** which is a linear integer programming (LP) problem, and can be solved using an optimization software such as CPLEX [134].

6.5. Minimizing Energy Consumption With Minimum Sum-Rate Guarantee Constraint (EMTG)

Similar to **P2**, we can formulate an energy consumption minimization problem with minimum throughput guarantees (EMTG) as follows:

$$\mathbf{P3:} \quad \min_{\vec{x}} \sum_{i=1}^N \sum_{f=1}^F \omega_i X_{i,f} E_{i,f} \quad (6.25)$$

$$\text{s.t.} \quad R_{min} \leq \sum_{i=1}^N \sum_{f=1}^F X_{i,f} L_{i,f} \quad (6.26)$$

$$\sum_{i=1}^N \sum_{f=1}^F X_{i,f} = K \quad (6.27)$$

$$\sum_{f=1}^F X_{i,f} \leq 1, \quad i \in \{1, \dots, N\} \quad (6.28)$$

$$\sum_{i=1}^N X_{i,f} \leq 1, \quad f \in \{1, \dots, F\} \quad (6.29)$$

$$X_{i,f} \in \{0, 1\} \quad (6.30)$$

Equation 6.27 ensures that all idle channels are allocated to CRs, or all CRs with a transmission request are assigned a frequency if $N_{tx} < |\mathcal{C}_{idle}|$. Recall $K = \min(N_{tx}, |\mathcal{C}_{idle}|)$. Otherwise, this scheduler may leave some channels unused although being idle. Equation 6.26 ensures at least R_{min} sum-rate is attained in a frame while energy consumption is minimized. Similar to E_{max} , R_{min} is a constant value determined by the scheduler. It stands for the expected throughput in a frame. R_{min} is calculated as follows:

$$R_{min} = \beta K T_{avg} R_{avg} \quad (6.31)$$

$\beta \in (0, 1]$ is the energy-throughput tradeoff parameter.

Both TMER and EMTG schedulers can be changed into schedulers ignoring fairness by setting $\omega_i = 0$ for TMER, and $\omega_i = 1$ for EMTG. Regarding computational complexity of TMER and EMTG, both solve an LP problem. If we model the frequency

assignment problem using bipartite graphs (CRs as vertices in V_1 and frequencies in the other vertex group V_2 , $V_1 \cap V_2 = \emptyset$), throughput maximization corresponds to *maximum weighted matching* in this bipartite graph. In this model, $(1 - \omega_i)L_{i,f}$ is the weight of the edge between vertex i and vertex f . Likewise, frequency assignment in EMTG can be modeled using *minimum weighted bipartite matching*. However, we have additional energy consumption (Equation 6.15) and minimum throughput constraints (Equation 6.26). In the literature, there are various algorithms running in polynomial time for maximum/minimum weighted bipartite matching, e.g. $O(|F|^3)$ as in Hungarian algorithm [135]. Using the solutions in the literature and dealing with the additional constraints, EMTG and TMER optimization problems can be solved efficiently.

6.6. Performance Evaluation

Basic performance metrics are probability of success, energy consumption, and energy efficiency. Probability of success represents the percentage of CR traffic that is delivered successfully. We use it as a means to evaluate throughput performance. First, we deactivate fairness in TMER and EMTG schedulers by appropriately setting ω values. In the last set of scenarios, we evaluate the fairness of each scheduler.

As benchmark, we also present performance of *maximum rate heuristic scheduler* (MRHS) in the following scenarios. MRHS is a well-known and commonly applied heuristic scheduler that aims to maximize sum-rate of a CRN in a frame. Simply, MRHS assigns each idle frequency f to the CR with maximum effective rate ($L_{i,f}$) as opposed to EEHS which assigns frequency f to the CR which will attain maximum energy efficiency at frequency f . Similar to EEHS, MRHS has polynomial time complexity, i.e. linear in N and F .

The amount of energy saving per bit achieved by a scheme S over the reference scheme (i.e., MRHS) can be computed as energy saving ratio (ESR). It is calculated

Table 6.1. Summary of symbols and basic simulation parameters.

Symbol	Description	Value/metric
$X_{i,f}$	CR_i assigned to frequency f or not.	$\{0, 1\}$
$B_{i,f}$	Shannon capacity of frequency f if used by CR_i	bits/second
$R_{i,f}$	Number of bits that can be sent in a frame through frequency f if used by CR_i	bits/frame
$L_{i,f}$	Maximum number of bits CR_i can transmit at frequency f	bits
Q_i	Number of bits in CR_i 's buffer	bits
F	Number of frequencies	$[5, 50]$
N	Number of CRs	$[5, 45]$
P_{tx}	Transmission power	90 mW
P_{id}	Idling power	50 mW
P_c	Circuit power	10 mW
P_{sw}	Channel switching power	55 mW
t_{sw}	Channel switching latency for unit bandwidth	0.1 ms/MHz
T_{frame}	Frame duration	100 ms
W	Channel bandwidth	5 MHz
λ_{CR}	Average number of packets generated by a CR in a frame	4.7 packets
α	Average number of channel switching	$F/10$
β	Energy-throughput tradeoff parameter	$(0, 1]$
E_{max}	Maximum allowed energy consumption in a frame	mJ
R_{min}	Minimum throughput to be achieved in a frame	bits

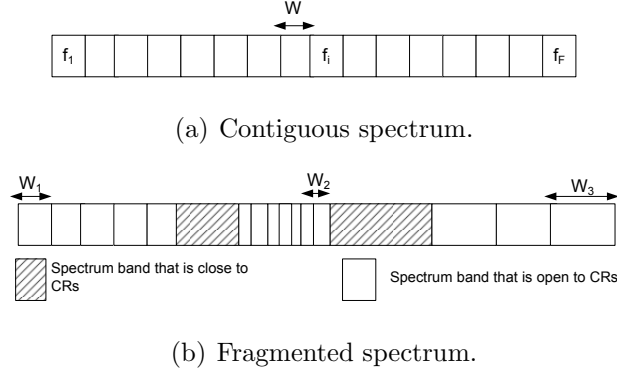


Figure 6.3. Spectrum organization .

as follows:

$$ESR_S = (1 - \frac{E_S^b}{E_{MRHS}^b})100 \% \quad (6.32)$$

where E_S^b is the energy-per-bit cost of scheme S .

Two spectrum occupancy scenarios are analyzed. In the first (Figure 6.3a), CRN operates on a contiguous spectrum of F bands all with equal bandwidth, whereas in the second (Figure 6.3b) frequency bands are discontinuous. The second scenario is more realistic, since some of the spectrum is for the exclusive use of PUs such as military bands, that part of the spectrum is closed for CR access. Moreover, spectrum is divided into bands with various bandwidths, e.g. GSM has 200 kHz bands while WLAN has 22 MHz channels. Thus, spectrum for CRN's use becomes collection of various frequency bands with non-identical bandwidth and spectrally separated from each other. Actual location of an opportunity is important since channel switching is a function of spectral separation of two frequencies. In our analysis, we only consider fragmented spectrum of identical bandwidth channels for analyzing the effect of spectral distance in the fragmented scenario and ignore any other factors.

In the following, results are collected from ten independent runs for scheduling performed over 100 consecutive frames. In our runs, we set $\lambda = 4.7$ packets/CR, and average channel capacity is 55 packets/frame. We set $\alpha = F/10$. In all scenarios, channel switching latency t_{sw} is set to $0.1ms/1MHz$ and $T_{frame} = 100$ ms. SNR of

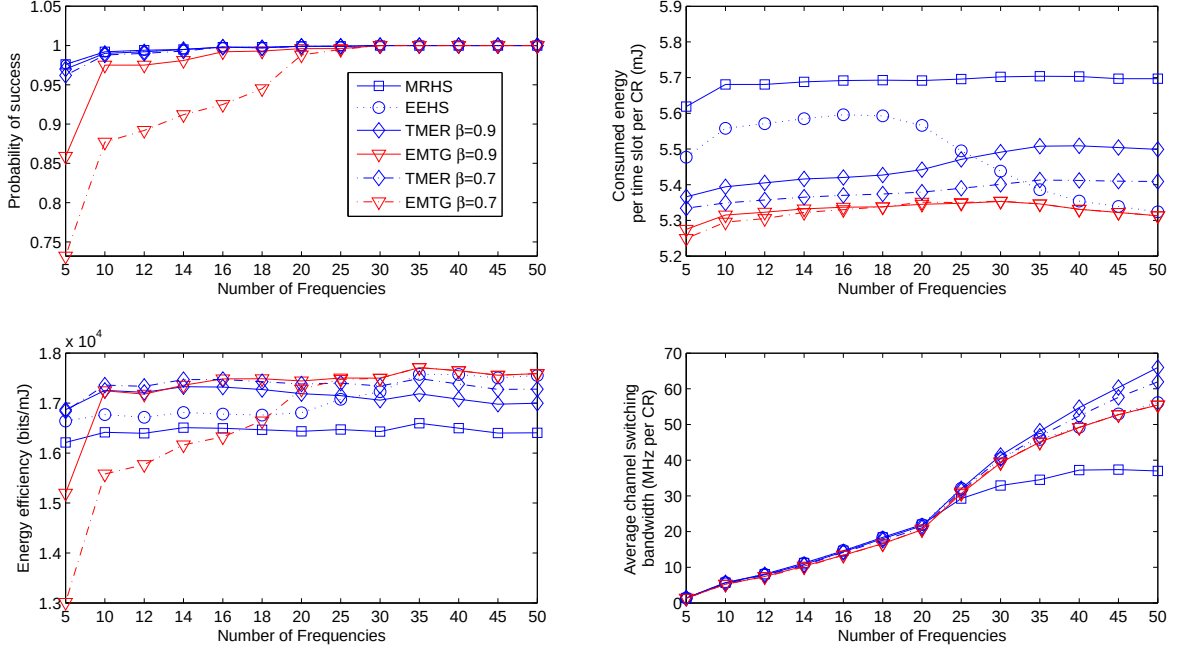


Figure 6.4. Contiguous frequency bands with lightly loaded CR traffic scenario. We set packet size 20 Kb in these runs.

a link is assumed to follow an exponential process with mean SNR=2.5 dB. Table 6.1 summarizes the symbols and basic simulation parameters.

6.6.1. Contiguous Spectrum

We test both light and heavy CR traffic scenarios. In the first scenario, traffic load varies from 0.73 ($F = 5$) and 0.07 ($F = 50$) while in the second scenario it is between 2.95 ($F = 5$) and 0.30 ($F = 50$). In the former, we set packet size 20 Kb and 80 Kb in the latter.

Figure 6.4 illustrates the change in successful transmission probability of a CR with increasing number of frequencies for light load. As expected, increase in F also leads to an increase in success rate. TMER and EEHS perform almost as good as MRHS for all F values while EMTG schedulers are close to MRHS in throughput performance only for high F . For $F > 20$, almost all schedulers have the same throughput performance while they differ in total energy consumption. As Figure 6.4 (up right) depicts, EMTGs have the lowest energy consumption while MRHS always consume the

highest energy. Energy efficiency of MRHS is always the lowest among all schedulers while efficiency of others change with increasing load. For high load (low F), EMTGs have low throughput performance leading to low energy efficiency. However, for high F , energy efficiency of EMTGs and EEHS increase. ESR of EEHS increases from 3-7% with increasing F while it changes from -5% (higher energy-per-bit) to 7% for EMTG with $\beta = 0.7$. For MRHS, energy consumption does not change significantly. On the other hand, energy consumption of EEHS decreases with increasing F since there exists a huge amount of available resources, scheduler assigns the frequency which will lead to the highest energy efficiency. Moreover, since more frequencies are available, CRs' queues are shorter in general. That is, CRs can transmit quickly and switch to low energy consuming idling state.

Time and energy spent on channel switching depends on the number of frequencies in the CRN. For $F = 50$, average channel switching distance is around 60 MHz for TMERs, 37 MHz for MRHS, 55 MHz for EMTGs and EEHS. Given that $t_{sw} = 0.1ms/MHz$, total channel switching time is around 6 ms ($T_{sw} = 60MHz \times 0.1ms/MHz$) for TMERs and shorter for the others. For $T_{frame} = 100$ ms, 94% of the frame is effectively useable. Since spectrum is contiguous and P_{sw} is small, channel switching does not noticeably affect the performance of the schedulers. Performance figures for heavy traffic follow the same trend with low CR traffic. Hence, we omit the figures here.

Given the fact that CR operators ensure a certain degree of success rate by various admission control techniques, a typical operation scenario is that CR load is kept at reasonable values. Therefore, in such scenarios, e.g. $F > 20$, success rates attained by EEHS, EMTG and TMERs are the same as that of MRHS and energy efficiencies are higher. Hence, any of EEHS, TMER or EMTG should be the choice for energy-efficient CRN scheduling. For small F , in case a slight throughput sacrifice is tolerable, EEHS and TMER schedulers can be the choice since they consume lower energy compared to MRHS.

Figure 6.5 demonstrates the performance of schedulers with increasing number

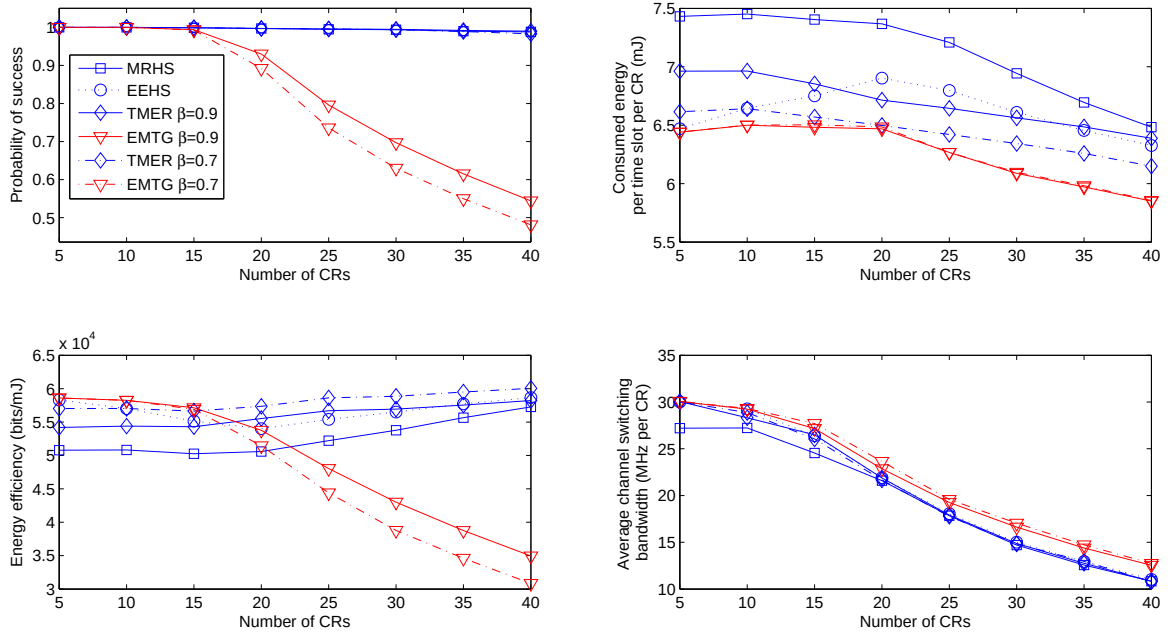


Figure 6.5. Performance with increasing number of CRs in the network under contiguous frequency bands, packet size is 80 Kb.

of CRs for $F = 20$ and heavy load. This scenario is similar to the previous scenario in a way that increase in N represents the increase in CR traffic load (and corresponds to decrease in F). For low number of CRs (as in high F), all schedulers have higher energy efficiency performance than that of MRHS while EMTGs consume the lowest energy. Throughput and energy efficiency performance of EMTG drastically decrease with increasing N . This is caused by the inability of R_{min} capturing the throughput performance of the CRN. It is an estimate of the average throughput of the CRN in a frame. However, as schedulers can assign channels to the CRs with high effective rate, attained throughput can be higher than R_{min} . For low number of CRs, this estimate does not deviate from the throughput attained in other schedulers. Hence, it does not degrade the performance of EMTG. However, note that for $N = 40$ traffic load is 1.66 which is much more higher than would be allowed in operational networks. A typical operation point would be $N = 15$ for $F = 20$ corresponding to load of 0.54. At this point, EMTGs are more energy-efficient and have the same throughput performance as MRHS. In all schemes, average channel switching bandwidth decreases with increasing N . This is not surprising since there are many CRs requesting frequency, and the ones which will require lower channel switching are more favorable in terms of throughput and energy efficiency. ESR of EEHS changes from 13% to 3% while it changes from

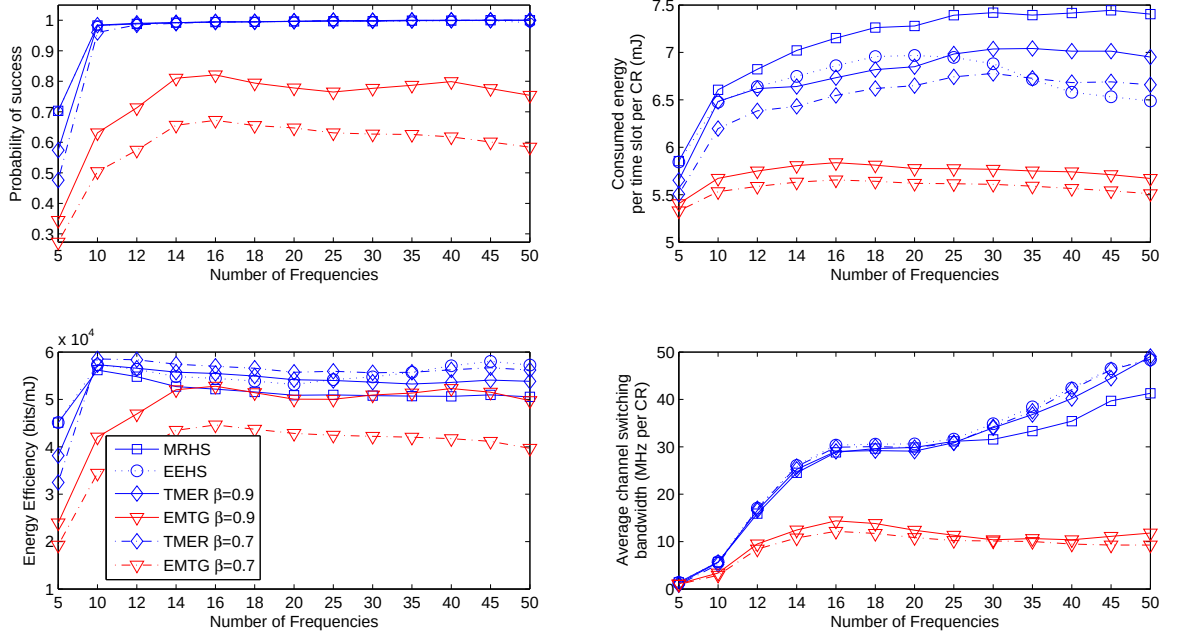


Figure 6.6. Performance of scheduling schemes with increasing F under fragmented spectrum and heavy load.

10% to 5% for TMERs.

6.6.2. Fragmented Spectrum

In the last scenario of the previous section, we set $F = 20$ and $W = 5$ MHz. Hence, there is totally 100 MHz bandwidth as spectrum resource for CRN. In this scenario, let us have the same total bandwidth but in a fragmented way. Let us assume CRN can use ten channels at 470-520 MHz, five channels at 600-625 MHz and five channels at 2400-2425 MHz bands. We refer each block of channels as *spectrum fragment* in the following. More realistic scenario would be using the spectrum in TVWS bands, GSM, UMTS bands, ISM bands and amateur radio bands spread in different frequency bands with various bandwidths. However, for the sake of comparability we use identical bandwidth channels with 5 MHz bandwidth. Moreover, all channels have exactly the same two-state occupancy model leading to identical probability of being idle values ($P_{idle}=0.7$).

Figure 6.6 summarizes the performance figures of schedulers under fragmented spectrum for increasing F . The results agree with the previous runs for EEHS, MRHS

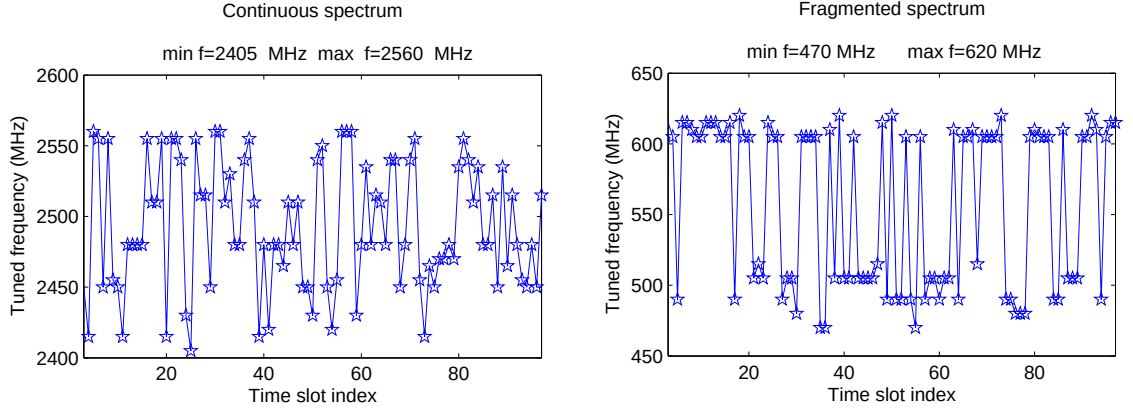


Figure 6.7. Antenna configuration of a CR for EEHS scheme with $F = 50$ and heavy CR traffic.

and TMERs where contiguous spectrum is considered. MRHS has lower energy efficiency than that of EEHS and TMERs. On the other hand, it is seen that EMTGs have low throughput performance with increasing F . In this case, we removed the Equation 6.27 as EMTG may not be able to allocate all channels due to infeasibility of switching to a distant channel. EMTGs allocate the frequencies in a way that not very distant frequencies are used by a CR in consecutive frames. Therefore, average channel switching bandwidth is around 10 MHz for EMTGs whereas it is around 40-50 MHz for MRHS, TMERs and EEHS, lower than the contiguous case. Comparing these results with the contiguous spectrum case, we conclude that each scheduler tries to allocate the CRs to its close frequency bands in the same/closer fragment. Therefore, despite the spectrum being fragmented, average channel switching bandwidth is lower than that of the contiguous spectrum case. Figure 6.7 corroborates this explanation.

We randomly select a CR and record its antenna configuration, i.e., the frequency it is tuned to, through the simulation duration for each frame for $F = 50$ and under heavy CR traffic and EEHS. Figure 6.7 depicts the frequencies for both contiguous and fragmented spectrum. Minimum and maximum operation frequencies are also written on the figures. The scheduler behaves as if CRs are partitioned in three classes, and each CR in a class is assigned a frequency in the corresponding spectrum fragment. As the figures show, for the fragmented spectrum scenario, it operates in the first and second fragment, does not hop to the 2400 MHz fragment. This CR mostly switches

to the frequencies in the same fragment which are only tens of MHz distant. As we set $t_{sw} = 0.1ms/MHz$ and CRs perform channel switching only before transmission, they may not be able to switch between different fragments of the spectrum due to *infeasibility* of switching. For $F = 50$, spectrum consists of 470-520 MHz (ten channels), 600-625 MHz (5 channels) and 2400-2575 MHz (35 channels) bands. Switching from the first fragment to the second is feasible whereas it is not to switch to the 2400 MHz bands. Frequency separation between the first and the third fragment is in the following interval: [2400-520 MHz, 2575-470 MHz]. It requires channel switching time in the interval [188 ms, 210.5 ms] which is much longer than the frame duration. Hence, such assignments are accepted as *infeasible* and are avoided by the scheduler.

With the developments in the hardware technologies, channel switching cost may become negligible. However, current systems incur channel switching cost that may sometimes be comparable to other energy consumption costs. Therefore, it is vital to implement scheduling schemes, especially for operation in the fragmented spectrum, that combats this cost. Our schedulers try to avoid switching and assign channels accordingly. On the other hand, switching to farther frequencies may be more favorable than operating in the close frequencies due to the diversity of channels. Hence, this trade-off should be taken into account in scheduling. With regard to time overhead of channel switching, switching delay can be hidden with careful scheduling and subsequently operation in all parts of the spectrum becomes possible. For instance, if CRs have the ability to tune their antennas in an intelligent way during their idling periods, channel switching does not lead to a decrease in the transmission time of a frame.

To sum up, spectrum fragmentation in frequency domain does not noticeably affect the CRN performance if considered from a network-wide perspective since scheduling schemes tackle fragmentation via careful frequency allocation. If considered from the viewpoint of a single CR, spectrum resources a CR can use is decreased to a smaller portion, which may deteriorate the performance of this CR. On the other hand, the set of CRs competing with this CR may be reduced to a smaller set as some CRs are restricted to another portion of the spectrum. Considering these two points, we can conclude that fragmentation, on the average, does not affect the individual CR

performance.

6.6.3. Fairness in Scheduling

In this section, we analyze each scheduling scheme in terms of fairness criteria. Ensuring a degree of fairness is desirable even if fairness objective may conflict with the objective of throughput maximization. Otherwise, some users starve while others may be over allocated. As in opportunistic scheduling, MRHS and EEHS favor CRs leading to higher throughput and higher energy efficiency, respectively. However, ω_i in TMER and EMTG schedulers enable fairness in resource allocation. We interpret fairness in our system in terms of mean satisfaction ratio. In an informal way, we can say that a scheme is more fair than the other if it can keep satisfaction ratios of CRs close to each other. Formally, we evaluate fairness in terms of Gini index. Gini index computes how much resource allocation deviates from the ideal fair allocation [136]. Hence, it can be considered as a measure of inequality. A perfectly fair allocation scheme has Gini index 0 whereas a highly unfair allocation has high Gini index. Let F_{Gini} denote this index, and it is calculated as follows:

$$F_{Gini} = \frac{1}{2N^2\bar{\omega}} \sum_i^N \sum_k^N |\omega_i - \omega_k| \quad (6.33)$$

$$\bar{\omega} = \frac{\sum_i^N \omega_i}{N} \quad (6.34)$$

where $\bar{\omega}$ is the mean satisfaction ratio of CRs.

For a clear understanding of the behavior of our schedulers, we focus on a scenario where CRs have non-homogenous traffic density and non-uniform SNR conditions [136]. Consider a network as in Figure 6.8 where half of the users (referred to as Group 1 in Region 1) are located closer to the CBS and have favorable channel conditions. We reflect this by setting mean SNR = 5 dB for these CRs. In addition, these CRs generate high traffic. The other half (say CRs with identities $\lfloor N/2 \rfloor, \lfloor N/2 \rfloor + 1, \dots, N$) have lower SNR (SNR=0 dB) and generate low traffic. We assume CRs in the first group generates four-fold traffic that of the second group. There are 40 CRs and 20 frequencies in this

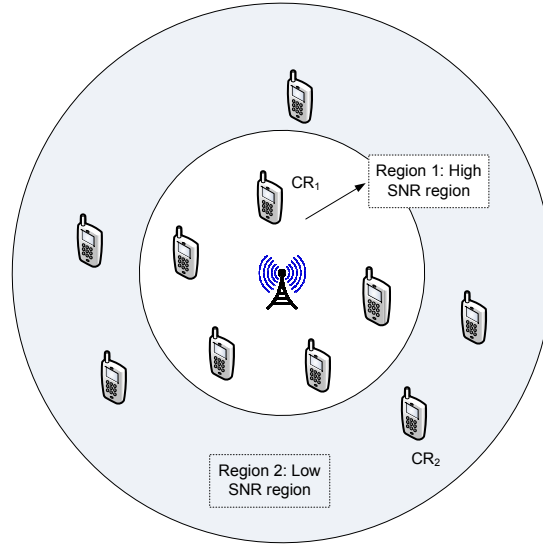


Figure 6.8. CRs have different link SNRs owing to their locations.

setting. For low traffic, each scheme can satisfy a certain degree of fairness since non-served CRs have longer queues (i.e. Q_i) leading to higher $L_{i,f}$ values. Therefore, these CRs are also served. However, for high, non-identical traffic, and non-identical link conditions, scheduling schemes may fall short of providing fairness.

Figure 6.9 illustrates the change of satisfaction ratios of two CRs, CR_1 from the first group and CR_2 from the second group. Since CR_2 has bad channel conditions, MRHS and EEHS never allocate frequency to this CR. On the other hand, TMER and EEHS assign a frequency to the CR when its satisfaction ratio decreases for a while. Therefore, satisfaction ratios of CRs are close to each other in TMER and EMTG.

The unfairness of MRHS and EEHS can also be seen in Figure 6.10. Dashed red line in each figure shows the mean satisfaction ratio of the CRN. For EEHS and MRHS, deviation from this line is larger compared to the TMERs and EMTGs. This variation shows the unfairness in channel assignment in opportunistic schedulers. CRs in the first group are always favored in MRHS and EEHS whereas TMER and EMTG distribute resources more fairly. Table 6.2 presents the basic performance results for this scenario. Since MRHS and EEHS cannot serve CRs in a fair way, F_{Gini} is very high for these schemes. However, for TMERs with fairness enabled it is almost a perfect system. For TMERs, F_{Gini} is very close to 0. For EMTGs, F_{Gini} is higher than TMER,

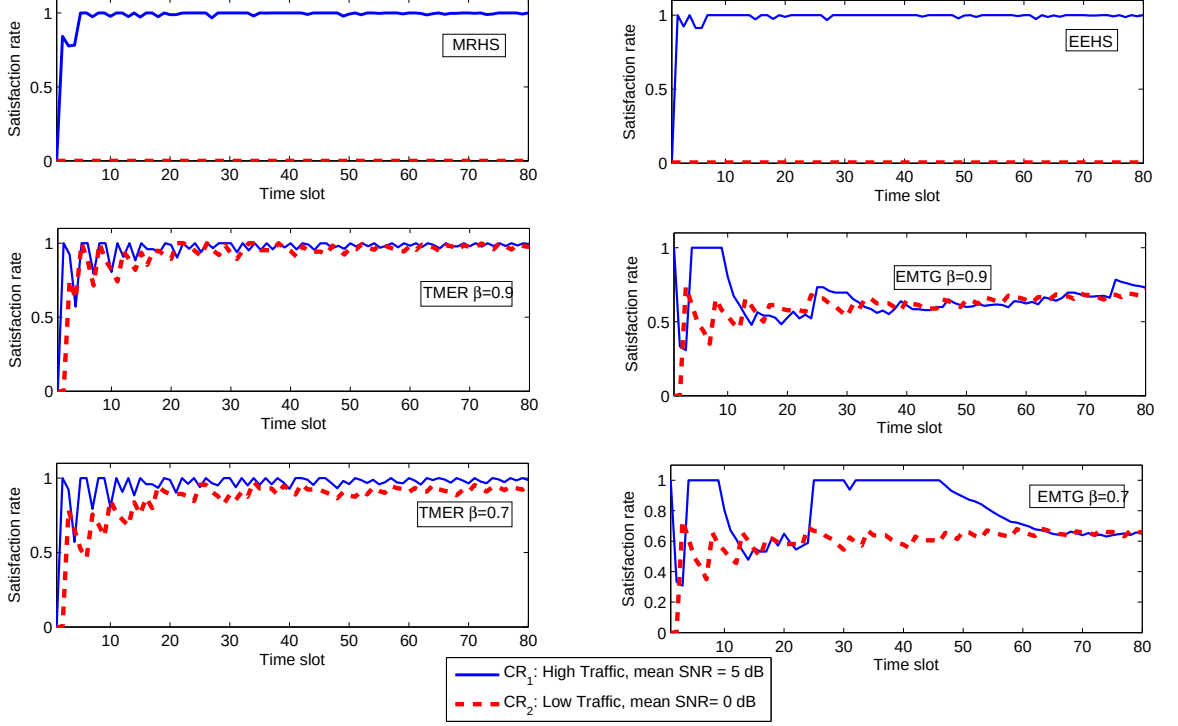


Figure 6.9. Change of satisfaction ratios versus time. CR_1 has almost four-fold traffic compared to CR_2 . Additionally, mean SNR of the links associated with CR_1 is 5 dB whereas it is 0 dB for CR_2 .

but still it is around 0.072. Regarding the probability of success results, it can be seen that enabling fairness in TMERs and EMTGs also has a positive effect on throughput performance. Fair schemes compared to the unfair counterparts have higher probability of success and energy efficiency performance for this particular setting.

6.7. Discussions

Our schedulers rely on acquiring the channel state information at the beginning of each frame. However, we neglect the cost of probing the channels and acquiring this information. In practical systems, this cost may be nonzero in terms of time and power consumption. Hence, our schedulers can be extended to the ones that also consider this cost and can define channel probing policies (e.g. probe a channel probabilistically) depending on the expected channel state and CR queue sizes. This will increase the control dimensions of the scheduling schemes leading to more sophisticated algorithms. However, there are some works showing the non-optimality of the completely channel-

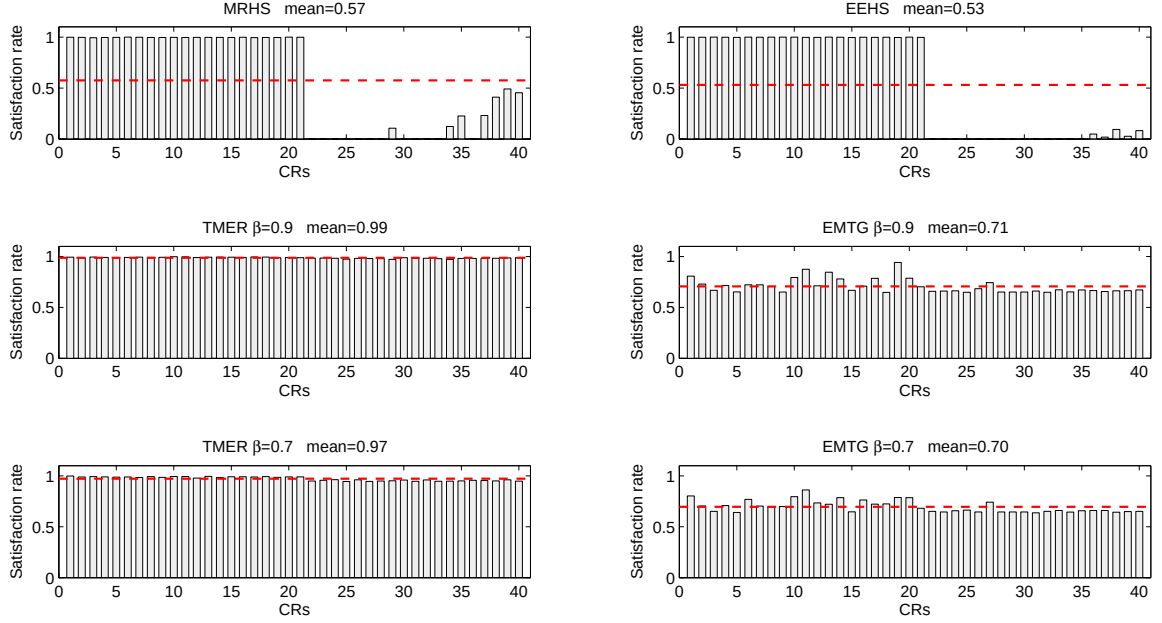


Figure 6.10. Satisfaction ratios of CRs under various scheduling schemes.

Table 6.2. Summary of simulation results for $N = 40$, $F = 20$, contiguous spectrum, heterogenous CR traffic and non-uniform link SNRs.

	Satisfaction	Prob.success	Energy efficiency	F_{Gini}
MRHS	0.57	0.85	48149	0.422
EEHS	0.53	0.83	49997	0.468
TMER $\beta = 0.9$, fair	0.99	0.99	56638	0.007
TMER $\beta = 0.9$	0.62	0.86	50271	0.372
EMTG $\beta = 0.9$, fair	0.71	0.73	42911	0.072
EMTG $\beta = 0.9$	0.48	0.59	37494	0.438
TMER $\beta = 0.7$, fair	0.97	0.98	57129	0.013
TMER $\beta = 0.7$	0.62	0.86	51012	0.371
EMTG $\beta = 0.7$, fair	0.70	0.72	41969	0.072
EMTG $\beta = 0.7$	0.47	0.53	33921	0.465

aware scheduling schemes if this channel acquisition cost is considered [137].

Control messaging overhead is also ignored in our analysis. However, for a more complete system this period should be analyzed. Several mechanisms to decrease this control overhead is possible. For instance, exploiting the clustering in case of the fragmented spectrum can help to decrease this cost. We showed that schedulers under fragmented spectrum lead to clustering of the CRs and this clustering results in CRs to be assigned to only a restricted channel set. Briefly, the CRs can compete for the related spectrum fragment (e.g. only L channels out of F channels) and send state information related to this portion of the spectrum instead of sensing the whole state information. Likewise, if a channel quality is observed to be under a threshold SNR value, then this CR can refrain itself from sending information about this channel. CBS can conclude that the states of the channels with missing information are not sufficiently good for transmission. Several mechanisms decreasing the control messaging overhead can also be added to our design.

6.8. Chapter Summary

In this work, we focused on energy efficiency in scheduling and formulated an energy efficiency maximizing scheduler. First, we presented EEHS, a heuristic algorithm running in polynomial time, for energy-efficient channel allocation. As EEHS does not directly aim to provide high throughput performance, it may fall short of throughput efficiency. Therefore, we reformulated frequency assignment problem as a throughput maximization problem subject to energy consumption restrictions (TMER) and as an energy consumption minimization problem subject to throughput guarantees (EMTG). TMER and EMTG also have the power to provide fairness among the CRs owing to the satisfaction parameter in their objective functions. Satisfaction ratio of a CR represents the portion of the traffic generated by a particular CR transmitted up to that point in time. CRs with lower satisfaction are favored in frequency allocation resulting in their satisfaction ratios to increase, and in turn facilitating less satisfied CRs to be favored in the subsequent frames.

We evaluated the performance of these schedulers and compared them with the commonly-known throughput maximizing heuristic scheduler (MRHS). MRHS has always lower energy efficiency performance compared to EEHS, TMER and EMTG whereas its throughput performance is similar to the proposed schedulers in general. Therefore, we conclude that schedulers with energy efficiency or energy consumption concerns should be the preferred scheduling scheme for more energy-efficient CRNs. Considering fairness, for low traffic load and homogeneous conditions, all schemes serve CRs almost equally as expected. On the other hand, under non-homogeneous traffic and link quality conditions, EEHS and MRHS as opportunistic schedulers cannot provide fairness among CRs. EMTG and TMER provide a good balance in resource allocation among CRs.

Moreover, we focused our attention on the spectrum organization. Spectrum available for CRN's use may consist of either contiguous bands or it may be a collection of spectrally distant frequency bands (also called fragments). Frequency separation in the second case determines the range of frequencies that can be assigned to a CR since channel switching time and energy consumption is a function of frequency separation between the two frequency bands. We showed that spectrum fragmentation in frequency domain on the average does not significantly affect the overall CRN throughput as each scheduler avoids assignments to very far away frequencies. In addition, set of CRs competing for a fragment is reduced to a smaller set. As hardware technology advances, switching delay and energy consumption cost may become less significant. However, for current devices, this can be combated at the software level by creating interface switching times during idling periods via intelligent scheduling schemes.

7. ENERGY-EFFICIENT SCHEDULING CONSIDERING PRIMARY USER INTERFERENCE CONSTRAINTS

In this chapter, we extend our previous work in Chapter 6 to a CRN that discovers the spectrum opportunities internally (e.g. CRs sense the spectrum before accessing the band) and ensures operation without interfering with the PUs more than allowed. We quantize the interference as the ratio of time a CR simultaneously transmits with a PU in the band to the mean PU busy duration. Our scheduler assigns frequencies to the CRs in a way that expected interference time in any of the channels is below the *tolerable interference ratio* of that band. Different from the previous chapter, we also account for the control messaging overhead in this chapter.

First, we analyze the effect of frame length on the CRN throughput performance. After tuning the frame length for maximum throughput efficiency, we then analyze the energy efficiency of the proposed scheduler under various parameters. Experimental results indicate that our proposal consumes lower energy than throughput maximizing scheduler to provide the same throughput performance.

The rest of this chapter is organized as follows. Section 7.1 defines the network model in consideration. Section 7.2 introduces the problem formulation which serves as a utility maximization framework with satisfaction of PU protection requirements. Calculation of utility of a CR at a frequency and its expected interference on the PU channel are also presented in Section 7.2. Next, Section 7.3 evaluates the performance of our proposed scheduler under various frame lengths, number of PU channels, and various channel occupancy conditions. Finally, Section 7.4 summarizes the chapter with a brief discussion on possible future research directions.

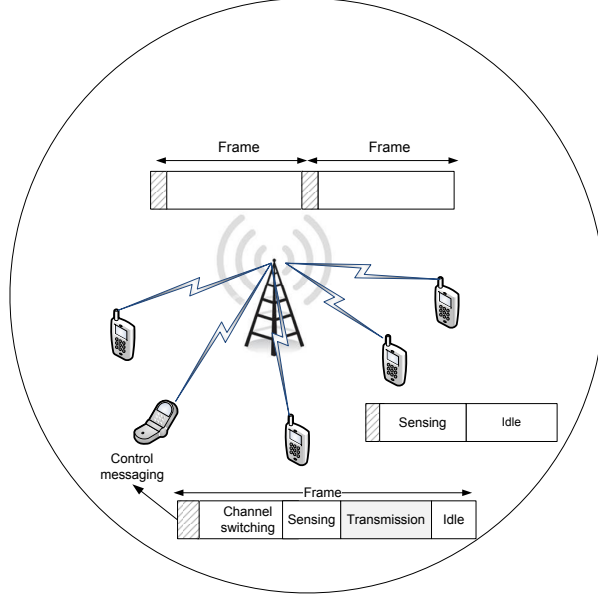


Figure 7.1. Network model and frame organization.

7.1. Network Model

We focus on a CRN as depicted in Figure 7.1. Denote the number of CRs in the network by N and frequency bands licensed to primary network by F . Primary channel traffic is modeled as an on-off process. Duration of each state follows exponential distribution with mean values α and β , respectively. Probability density functions related to the duration of these states are expressed as:

$$p_{on}(t) = \frac{1}{\alpha} \exp\left(-\frac{t}{\alpha}\right) \quad (7.1)$$

$$p_{off}(t) = \frac{1}{\beta} \exp\left(-\frac{t}{\beta}\right) \quad (7.2)$$

The channel is expected to be idle with probability P_{idle} which is calculated as follows:

$$P_{idle} = \frac{\beta}{\alpha + \beta} \quad (7.3)$$

CBS is assumed to have perfect knowledge of α and β values for each channel.

Scheduler at CBS makes frequency assignment at the beginning of each frame based on the reports collected from the CRs in control messaging period. A CR's

report consists of number of packets that can be sent through each frequency band. Simply, it is a function of CR's queue state information (Q_i) and channel quality of CR_i at frequency f ($\gamma_{i,f}$). CRs generate traffic at the beginning of each frame with rate λ_{CR} . Scheduler assigns frequencies to the CRs with transmission request with the objective defined by the scheduling scheme. Consequently, this frequency assignment is transmitted to the CRs. A CR, if assigned a frequency, tunes to the assigned frequency (*channel switching period* in Figure 7.1) and senses the channel. In case the channel is discovered to be idle, CR starts transmitting in the channel. Otherwise, it stays idle. If transmission is completed before the frame ends, CR switches to the idle state till the beginning of the next frame. In a system operating as described here, we will formulate the scheduling problem in the next section. Before presenting our solution, let us give some definitions that will be used in what follows:

- PU interference ratio ($I_{i,f}$): It is the ratio of expected duration that CR_i will unwittingly transmit in the frequency band f through which a PU communication is active to the mean PU activity duration in this band.
- CR satisfaction ratio (ω_i): It is a metric of how much of the traffic generated by a CR is transmitted up to the current time. It is simply ratio of the transmitted traffic to the generated traffic by a specific CR.

7.2. Problem Formulation

Given the idle probability of each frequency P_{idle}^f , our objective is to maximize the total utility of the CRN considering the individual utilities ($U_{i,f}$) of each CR_i at each frequency f . Our scheduler executes the scheduling algorithm at the beginning of each frame. It ensures that CRs do not create harmful interference to any of the PU channels. We deem a CR transmission harmful if its transmission collides with a PU transmission more than the tolerable ratio defined by the corresponding PU channel. Tolerable interference ratio is determined and announced by the regulator. This value may change from one frequency to another depending on the urgency of the PU communications in the band of interest or restrictions of the primary network. For

instance, it can be very low for public safety bands whereas it can be set to higher for TV bands.

We formulate our utility maximizing scheduler as follows:

$$\max \sum_{i=1}^N \sum_{f=1}^F P_{idle}^f X_{i,f} U_{i,f} \quad (7.4)$$

$$\text{s.t. } I_{i,f} X_{i,f} \leq \Gamma_{thresh}^f \quad \forall i \in \{1, \dots, N\} \quad (7.5)$$

$$\sum_{\forall f} X_{i,f} \leq 1 \quad \forall i \in \{1, \dots, N\} \quad (7.6)$$

$$\sum_{\forall i} X_{i,f} \leq 1 \quad \forall f \in \{1, \dots, F\} \quad (7.7)$$

where

$$X_{i,f} = \begin{cases} 1 & \text{if channel } f \text{ is assigned to } CR_i \\ 0 & \text{otherwise} \end{cases} \quad (7.8)$$

and $I_{i,f}$ denotes the interference ratio caused by interference of CR_i at f if this frequency is to be accessed by CR_i . Γ_{thresh}^f is the tolerable interference ratio for frequency f . Equation 7.6 and 7.7 ensure CRs transmit at most at one frequency (i.e. single antenna) and at a frequency only one CR can transmit, respectively. Equation 7.5 assures that PU interference constraints are not violated. Our scheduler avoids the primary channels with lower probability of being idle due to the term P_{idle}^f in the objective function in (7.4). In what follows, we give details on how utilities and interference ratios are calculated. Notations used in this formulation and throughout the chapter are summarized in Table 7.2.

7.2.1. Calculation of Utilities ($U_{i,f}$)

Let a frame be composed of five periods as in Figure 7.1: control messaging (t_{ctrl}), frequency switching (t_{sw}), spectrum sensing (t_s), transmission (t_{tx}) and idling (t_{id}). If

a CR_i is assigned frequency f , we formulate the throughput and energy consumption of this CR at frequency f proportional to the time spent in each state. As t_{ctrl} is the same for all CRs, it is not considered in the utility calculation.

- Frequency switching: Let t_{sw} and P_{sw} denote the total time and power spent on switching from frequency f to f' . Energy consumed for switching denoted by E_{sw} is calculated as follows:

$$E_{sw} = P_{sw}T_{sw} \text{ and } T_{sw} = |f - f'|t_{sw} \quad (7.9)$$

where t_{sw} is the time needed for tuning to a frequency unit bandwidth away.

- Spectrum sensing: Minimum sensing duration t_s using energy detection under the given target probability of detection and false alarm values (P_d, P_{fa}) is shown to be a function of channel SNR (γ) in [80]. For a constant sampling rate f_s , minimum sensing duration is formulated as below:

$$t_s = \frac{\frac{1}{\gamma^2}[\mathcal{Q}^{-1}(P_{fa}) - \mathcal{Q}^{-1}(P_d)\sqrt{2\gamma + 1}]^2}{f_s} \quad (7.10)$$

$\mathcal{Q}(\cdot)$ is the complementary distribution function of the standard Gaussian [80]. Energy consumed during sensing is:

$$E_s = P_s t_s \quad (7.11)$$

where P_s is the power consumption during sensing.

- Transmission and idling: Sensing outcome determines the duration of transmission (t_{tx}) and idling (t_{id}) states. There are four possible outcomes of the sensing process: (i) channel opportunity is detected, (ii) channel opportunity is lost due to a false alarm, (iii) PU in the channel is detected, and (iv) active PU could not be detected.

(i) *Case 1: PU channel is idle and it is sensed as idle.*

In this case, CR successfully detects the opportunity and can begin trans-

Table 7.1. Four outcomes of spectrum sensing.

Case	Probability (P_{S_k})	Throughput (R_{S_k})	Energy Consumption (E_{S_k})
1) Opportunity detected	$P_{idle}^f(1 - P_{fa})$	$(1 - q)t_{tx}C_{i,f}$	$P_{tx}t_{tx} + P_{id}(t_r - t_{tx})$
2) False alarm	$P_{idle}^f P_{fa}$	0	$P_{id}t_r$
3) PU detected	$(1 - P_{idle}^f)P_d$	0	$P_{id}t_r$
4) PU missed	$(1 - P_{idle}^f)(1 - P_d)$	0	$P_{id}t_{tx} + P_{id}(t_r - t_{tx})$

mission. However, if a PU reappears in the band, CR collides with this PU transmission and transmission fails. If no such arrival occurs, CR goes on transmission, and switches to idling state after completing its transmission. Let β_f denote the mean idle duration of channel f , probability that a PU reappears during t_{tx} is calculated as follows [32]:

$$\begin{aligned}
\Pr(\text{Collision}) &= \Pr(\text{PU off time is shorter than } t_{tx}) \\
q &= \int_0^{t_{tx}} p_{off}(t) dt \\
&= 1 - \exp\left(\frac{-t_{tx}}{\beta_f}\right)
\end{aligned} \tag{7.12}$$

Let T_{frame} be the frame duration, and t_r denote the remaining time for transmission after control messaging, frequency switching and channel sensing:

$$t_r = T_{frame} - t_{ctrl} - t_{sw} - t_s \tag{7.13}$$

Required transmission time for transmitting all bits in the CR queue (Q_i) depends on the channel capacity ($C_{i,f}$). Data transmission rate of CR_i at frequency f is bounded by the achievable capacity of the channel f :

$$C_{i,f} = W_f \log_2(1 + \gamma_{i,f}) \tag{7.14}$$

where W_f is the channel bandwidth (Hz) and $\gamma_{i,f}$ is the channel SNR.

Required transmission time may be longer than t_r . Hence, transmission time

(t_{tx}) must be the minimum of these durations as below:

$$t_{tx} = \min\left(\frac{Q_i}{C_{i,f}}, t_r\right) \quad (7.15)$$

The resultant throughput (R) and energy consumption (E) in this case are calculated as follows:

$$R = (1 - q)t_{tx}C_{i,f} \quad (7.16)$$

$$E = P_{tx}t_{tx} + P_{id}(t_r - t_{tx}) \quad (7.17)$$

where P_{tx} and P_{id} stand for transmission power and idling power, respectively.

(ii) *Case 2: PU channel is idle, but it is sensed as busy.*

In this case, due to false alarm, spectrum opportunity cannot be detected. Thus, CR stays idle.

$$R = 0 \quad (7.18)$$

$$E = P_{id}t_r \quad (7.19)$$

(iii) *Case 3: PU channel is busy and it is sensed as busy.*

The sensed channel is successfully detected to be busy leading to CR stay in idling state.

$$R = 0 \quad (7.20)$$

$$E = P_{id}t_r \quad (7.21)$$

(iv) *Case 4: PU channel is busy, but it is sensed as idle.*

The channel is busy but CR falsely reports that it is idle. This case results in CR to begin transmission on the channel that has already an ongoing PU transmission, thereby leads to a collision. Assuming that no collision

detection mechanism is activated, R and E are:

$$R = 0 \quad (7.22)$$

$$E = t_{tx}P_{tx} + P_{id}(t_r - t_{tx}) \quad (7.23)$$

Considering the four cases listed above, total energy consumption $E_{i,f}$ and total throughput $R_{i,f}$ are computed as follows:

$$E_{i,f} = E_{sw} + E_s + \sum_{\forall S_k} P_{S_k} E_{S_k} \quad (7.24)$$

$$R_{i,f} = \sum_{\forall S_k} P_{S_k} R_{S_k} \quad (7.25)$$

where S_k represents the Case k with probability of occurrence P_{S_k} . P_{S_k} is given as follows:

$$P_{S_k} = \begin{cases} P_{idle}^f(1 - P_{fa}) & \text{for } k = 1 \\ P_{idle}^f P_{fa} & \text{for } k = 2 \\ (1 - P_{idle}^f)P_d & \text{for } k = 3 \\ (1 - P_{idle}^f)(1 - P_d) & \text{for } k = 4 \end{cases} \quad (7.26)$$

From (7.24) and (7.25), we calculate the utility of CR_i if assigned to frequency f for various scheduling objectives. Let EE_{max} and Thr_{max} stand for energy-efficiency maximizing and throughput maximizing objectives, respectively. We incorporate satisfaction of CRs (ω_i) into the formulations for fair schedulers in order to prevent the suffering of some disadvantageous CRs. $EE_{max} - fair$ and $Thr_{max} - fair$ denote the energy-efficiency maximizing scheduler with fairness notion and throughput maximizing scheduler with fairness notion, respectively.

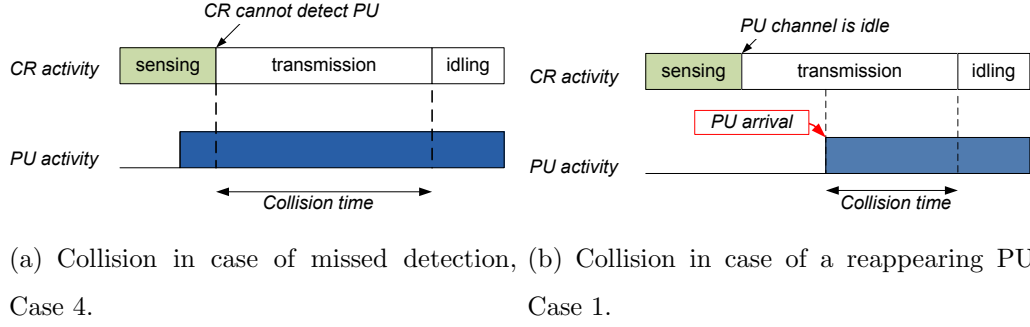


Figure 7.2. Cases resulting in PU interference.

$$U_{i,f} = \begin{cases} \frac{R_{i,f}}{E_{i,f}} & \text{for } EE_{max} \\ \frac{(1 - \omega_i)R_{i,f}}{E_{i,f}} & \text{for } EE_{max} - fair \\ R_{i,f} & \text{for } Thr_{max} \\ (1 - \omega_i)R_{i,f} & \text{for } Thr_{max} - fair \end{cases} \quad (7.27)$$

7.2.2. Calculation of Interference Ratios ($I_{i,f}$)

A PU is exposed to interference if a CR simultaneously transmits at the same channel. This simultaneous transmission may happen in two cases. First, a CR cannot detect an ongoing PU transmission, and it begins transmission. In this case, collision is not detected till the end of the transmission (Case 4). Second, a CR starts transmission at a spectrum opportunity, but after some time a PU reappears (Case 1). In this case, interference time is shorter than the first case depending on the arrival time of the PU traffic. These two cases are depicted in Figure 7.2.

For the first case, interference time (T_1^I) is t_{tx} . We assume that PU traffic lasts longer than CR traffic, hence the interfering period spans the whole CR transmission duration. Collision probability of CR_i at frequency f with a reappearing PU is given

in (7.12). Interference time T_2^I in this case is calculated as follows:

$$\begin{aligned} T_2^I &= \int_0^{t_{tx}} (t_{tx} - t) p_{off}(t) dt \\ T_2^I &= t_{tx} - \beta_f \left(1 - \exp\left(\frac{-t_{tx}}{\beta_f}\right) \right) \end{aligned} \quad (7.28)$$

Considering these two cases, expected total interference time is:

$$\begin{aligned} T^I &= P_{S_4} T_1^I + P_{S_1} T_2^I \\ &= (1 - P_{idle}^f)(1 - P_d)t_{tx} + P_{idle}^f(1 - P_{fa})q \left(t_{tx} - \beta_f(1 - \exp(\frac{-t_{tx}}{\beta_f})) \right) \end{aligned} \quad (7.29)$$

Given that mean PU activity duration is α_f , the interference ratio is:

$$I_{i,f} = \frac{T^I}{\alpha_f} \quad (7.30)$$

which must be less than Γ_{thresh}^f , the tolerable interference ratio at this frequency [32].

7.2.3. Control Messaging Overhead

Scheduling overhead in the control messaging period is calculated as in [41]. Briefly, uplink (t_{up}) and downlink overhead (t_{down}) in terms of time can be calculated as follows:

$$t_{up} = \frac{N(F(n_F + L) + n_{CR})}{R} \quad (7.31)$$

$$t_{down} = \frac{F(n_F + n_{CR})}{R} \quad (7.32)$$

where n_{CR} , n_F , and L denote the number of bits to represent CR index, frequency index, and number of packets that CR can send through that frequency channel, respectively. R is the average channel rate. Since uplink control messaging is simply

Table 7.2. System parameters.

$X_{i,f}$	Decision variable for CR_i to sense channel f .
$t_{i,f}$	Minimum sensing duration of CR_i at f given the target (P_d, P_{fa}) pair.
t_s	Duration of the sensing period
P_{idle}^f	Probability that channel f is idle
$I_{i,f}$	Interference ratio of frequency f if CR_i transmits at this band.
Γ_{thresh}^f	Maximum tolerable interference ratio at frequency f .
(P_d, P_{fa})	Target probability of detection, target probability of false alarm.
q	Probability of collision of a CR with a reappearing PU
α_f, β_f	Mean busy duration and mean idle duration of channel f
S	State of CR $\in \{\text{transmission (tx), receive (rx), switching (sw), sensing (s), idling (id), control messaging (ctrl)}\}$
P_S	Power consumption in state S
E_S	Energy consumption in the state S
t_S	Time spent in the state S

transmission of some bits while downlink control messaging is the reception of a broadcast message, energy consumption in this period (E_{ctrl}) is:

$$E_{ctrl} = P_{tx}t_{up} + P_{rx}t_{down} \quad (7.33)$$

7.3. Simulation Results

In this section, we first analyze the effect of frame length on throughput efficiency. After tuning the frame length, we analyze the energy efficiency under various parameters and conditions. Energy efficiency, throughput and PU collision ratio are the performance metrics. We derive results using our discrete event simulator developed in Java. We assume the following relationship holds among the power consumption values:

$$P_{tx} = 5P_{id} = 4P_{sw} = 2P_s = 2P_{rx} = 100P_c \quad (7.34)$$

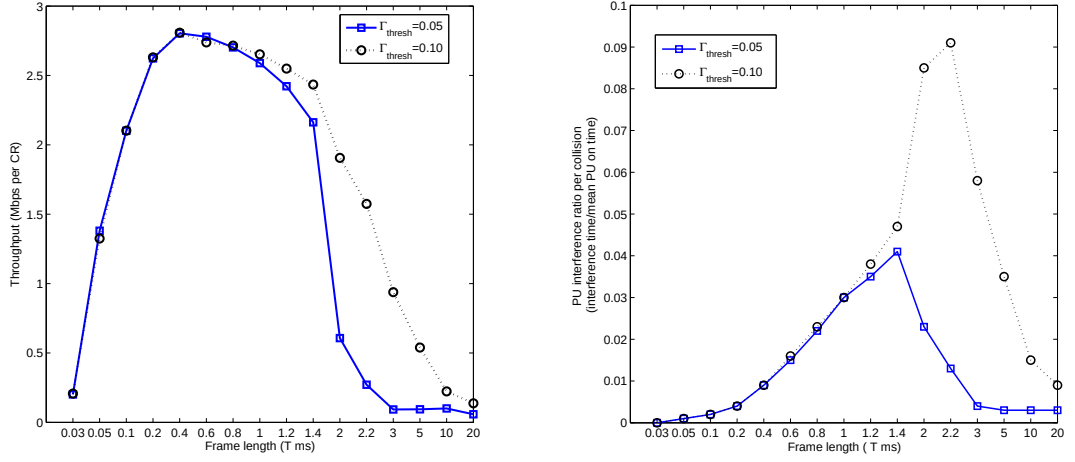
where P_c is the circuit power. Since we focus on a cellular network, the transmission power is much higher compared to the circuit power as opposed to short-distance communications. We assume all channels have the same maximum tolerable interference ratio, hence we drop the frequency index and refer to it as Γ_{thresh} in the following sections.

7.3.1. Analysis of Frame Length

In our system under consideration, spectrum sensing is performed only before transmission in a frame. Hence, the period of sensing depends on the frame length. As the sensing period determines the maximum time during which the CR will be unaware of a reappearing or missed PU in the same band, frame length is paramount to tune for non-harmful operation. On the other hand, each frame incurs an overhead of control messaging, sensing and channel switching. Therefore, longer frames are more favorable at first sight. However, the longer is the frame, the higher is the probability that a PU reappears in the band. This in turn increases the probability of collision and interference ratios which will result in CBS to avoid resource allocation in these bands. Hence, this trade-off must be considered in setting an appropriate frame length.

In this set of runs, we examine the performance of EE_{max} with increasing frame duration (T_{frame}). Sensing and channel switching overhead as well as interference with PUs are analyzed. We set $t_{sw} = 0.5ms/1MHz$, $N = 50$, $F = 50$, $\Gamma_{thresh} = \{0.05, 0.10\}$, $P_d = 0.9$, and $P_{fa} = 0.1$. All channels are identical, and we set $\alpha = 2T$ and $\beta = 2T$ for these channels.

Figure 7.3 illustrates the change in throughput and PU interference ratio with increasing frame length. Values in the x-axis are represented as multiples of T , e.g., 0.1 stands for $T_{frame} = 0.1T$. For short frames, a significant portion of the frame (50%-90%) is consumed for control messaging and 5%-6% for spectrum sensing. Thus, short frame length results in low throughput. As maximum transmission duration for a frame (i.e. $T_{frame} - t_{ctrl} - t_{sw} - t_s$) is very short compared to the PU mean busy duration α , PU interference ratio is almost zero in this case. With the increase in



(a) Throughput.

(b) PU interference ratio.

Figure 7.3. Throughput and PU interference ratio with increasing frame length,

$$N = 50, F = 50, \lambda_{CR} = 3Mbps \text{ for } \Gamma_{thresh} = \{0.05, 0.10\}.$$

frame length, control messaging overhead decreases to 2%-3%. Therefore, more time is left for transmission. However, throughput only increases until a certain frame length, e.g. $T_{frame} = 1.4T$ for $\Gamma_{thresh} = 0.05$ and $T_{frame} = 2.8T$ for $\Gamma_{thresh} = 0.10$ in the considered scenario. When frame length is greater than these values, scheduler cannot assign most of the channels since collision with a PU is quite probable and interference ratio may exceed Γ_{thresh} . With regard to energy consumption, energy consumption due to sensing and control messaging decreases while transmission and idling energy consumption increases.

As Figure 7.3b shows, average interference time increases with increasing frame length. Because scheduler performs conservatively in order to keep the expected interference ratio below the limit, for $T_{frame} > 1.4T$ and $T_{frame} > 2.8T$, PU interference begins to decrease. Since larger Γ_{thresh} means that PU can tolerate collisions for longer durations, increase in Γ_{thresh} is expected to enhance throughput in general. However, from Figure 7.3a, such an increase is only noticeable for long frame lengths. The rationale behind this is that, for short frame lengths, control overhead is the determining factor rather than Γ_{thresh} parameter. In short frames, operation under harmful interference is almost guaranteed since maximum transmission time of a CR is bounded by the frame length which is far from creating harmful interference to the PUs. However,

for longer frames, effect of Γ_{thresh} becomes dominant. Therefore, throughput is higher for $\Gamma_{thresh} = 0.10$ compared to $\Gamma_{thresh} = 0.05$.

Simulation results agree with our analytical analysis. The CRN can ensure that a CR transmission never results in exceeding the interference threshold ratio by appropriately tuning the frame duration according to the interference threshold ratios of the primary channels. Let η be the portion of a frame spent for total overhead, i.e. control messaging, channel switching and spectrum sensing. The maximum time a CR can transmit in this frame then reduces to $(1 - \eta)T_{frame}$. Even in the worst case, i.e., the CR transmits during the whole frame time, interference time with the PU must be smaller than what is allowed. We can formulate it as follows:

$$(1 - \eta)T_{frame} \leq \frac{\alpha_f \Gamma_{thresh}^f}{1 - P_d} \quad (7.35)$$

However, for a multi-channel system, since each channel should be protected, we reorganize the above equality as follows:

$$(1 - \eta)T_{frame} \leq \min_{\forall f} \left(\frac{\alpha_f \Gamma_{thresh}^f}{1 - P_d} \right) \quad (7.36)$$

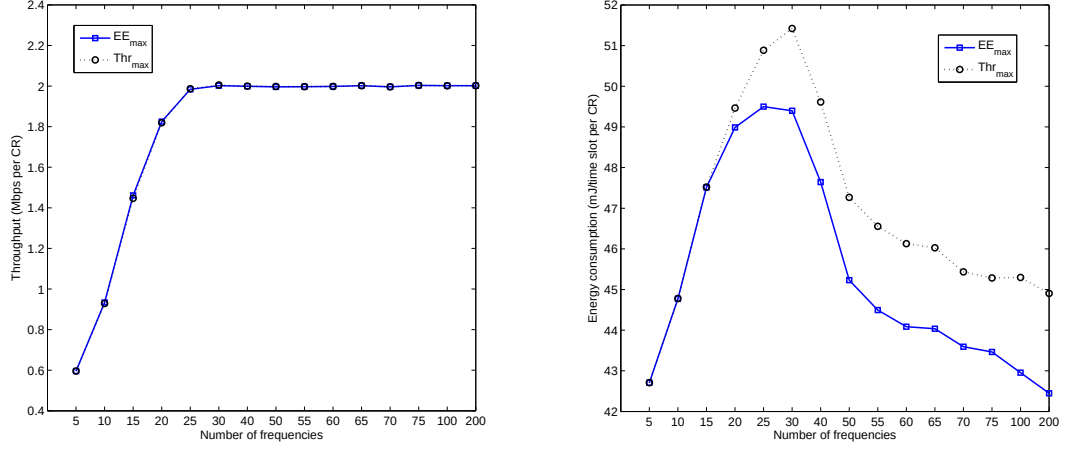
As an example, for a single channel with $\alpha = 2T$, $\Gamma_{thresh}^f = \{0.05, 0.10\}$, $\eta = 0.3$, and $P_d = 0.9$, T_{frame} is $1.42T$ for $\Gamma_{thresh}^f = 0.05$ whereas it is $2.84T$ for $\Gamma_{thresh}^f = 0.10$. These values agree with sharp break points presented in Figure 7.3b. However, tuning the frame length as in Equation 7.36 in case of heterogenous channels with shorter busy durations may lead to very short frame length which is not desirable in general due to the sensing and scheduling overheads per frame. Instead, we set T_{frame} shorter than expected mean PU busy time and enforce the scheduler guarantee the interference restrictions are complied with via Equation 7.5.

7.3.2. Comparison of EE_{max} with Thr_{max}

Figure 7.4 illustrates the throughput and energy consumption for EE_{max} and Thr_{max} with increasing F . As the figure shows, EE_{max} has almost the same throughput as Thr_{max} . For $F = 5$, both have low probability of success as expected due to the scarcity of resources. However, for higher F , both schedulers can achieve high throughput performance.

Considering energy consumption, it can be seen from Figure 7.4b that Thr_{max} consumes higher energy compared to EE_{max} resulting in lower energy efficiency. Increase in F leads to an increase in throughput, however total throughput is limited by the generated CR traffic. Therefore, throughput is stable after $F \geq 25$, and almost all traffic generated by the CRN is transmitted with success. Given this fact, we can conclude that increase in energy consumption for $F < 25$ with increasing F is due to transmission. Energy consumption reaches to its maximum at $F = 30$ under this specific setting, and it decreases with increasing F . If we consider the CR and frequency pairs as the entities in the state space, state space size increases with increasing F . From this state space, a better solution can be selected due to the increased diversity in frequency resources. Related to this, energy efficiency increases. On the other hand, control messaging increases with F . For very large F , number of bits to represent each frequency becomes larger. This increases the control messaging overhead. Although this cost does not dominate the total energy consumption for realistic operation parameters, the CBS can decide to operate on a specific portion of the spectrum and can leave the other portions to other operators in the same region.

From an operator's perspective, number of frequencies for operation can be selected in high throughput region, i.e., $F \geq 25$. On the other hand, from energy efficiency viewpoint, frequency count should be larger than 30. As multiple operators may coexist in an area, spectrum can be shared among these operators. Therefore, an operator can select the possible minimum number of frequencies that simultaneously provide high throughput and energy efficiency performance. It should operate over 40 or similar number of frequencies for the considered system with $N = 50$, $\lambda_{CR} = 2Mbps$



(a) Throughput.

(b) Energy consumption.

Figure 7.4. Comparison of EE_{max} and Thr_{max} under increasing F , $N = 50$, $\lambda_{CR} = 2Mbps$ and $\Gamma_{thresh} = 0.05$.

and $\Gamma_{thresh} = 0.05$.

7.3.3. Heterogeneity of CRs

Consider a network in which half of the CRs have favorable channel conditions with average SNR = 6 dB, while the second group of CRs have inferior channel conditions with average SNR = -2 dB. Users in the first group generate traffic with $\lambda_{CR} = 4Mbps$ while those in the second group generate traffic with $\lambda_{CR} = 1Mbps$.

Figure 7.5 depicts the performance of each CR in terms of satisfaction rate and energy efficiency under $EE_{max} - fair$. As CRs in the second group has lower traffic rate and low link SNR (-2 dB) compared to the first group of CRs, they are challenging for the operator to satisfy. However, owing to ω_i terms in our utilities, each scheme can provide a certain level of satisfaction in each group. An opportunistic scheduler with no fairness concern, e.g. EE_{max} and Thr_{max} , does not allocate resource to these disadvantaged users. In regard to energy efficiency, the CRs in the second group has significantly lower energy efficiency as expected. This is not surprising as channel capacity is a function of link quality, and it takes longer to transmit the same amount of information under low channel capacity. Thus, CRs stay in transmitting state longer

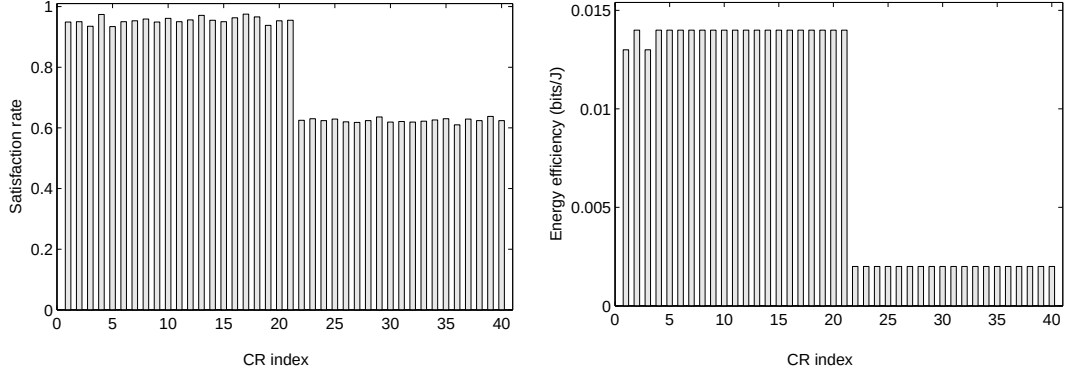


Figure 7.5. Performance of each CR.

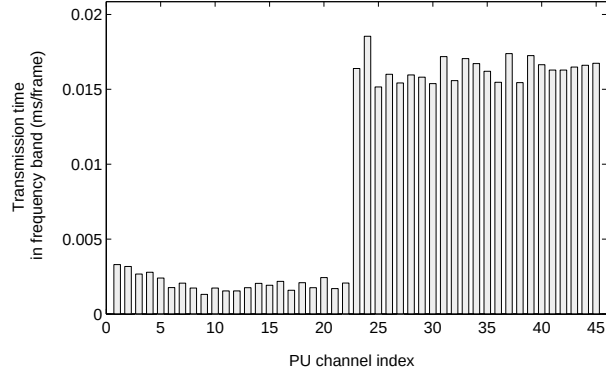


Figure 7.6. Channel usage statistics for heterogenous channels under EE_{max} . For the first channel group we set $\alpha = 2.5T$, $\beta = 2T$, and $P_{idle} = 0.56$, and for the second group we set $\alpha = 6T$, $\beta = 3T$, and $P_{idle} = 0.66$.

which leads to higher energy consumption and thereby lower energy efficiency.

7.3.4. Heterogeneity of PU channels

We consider a CRN which has $F = 45$ channels, and the first half of these PU channels have shorter on and off durations with $\alpha = 2T$ and $\beta = 2.5T$ compared to the second group of channels which have $\alpha = 3T$ and $\beta = 6T$. For the first group, $P_{idle} = 0.56$ and for the second group $P_{idle} = 0.66$. Assume that there are $N = 30$ CRs in the network. Note that this scenario represents a scenario where there are plenty of frequencies for the use of CRs.

Considering the channel utilization statistics presented in Figure 7.6, we can

conclude that our scheduler avoids transmission in the first group of channels since they have lower P_{idle} . As the scheduling overhead grows with the number of channels, under sufficient resources, we can limit our scheduler to consider the channels with high P_{idle} in frequency assignment. Therefore, control messaging overhead both in downlink (Equation 7.32) and uplink (Equation 7.31) can be decreased. Moreover, channels with lower P_{idle} can be eliminated in channel assignment. Such a scheme can both decrease control overhead as well as the cost of spectrum sensing since PU channels with less probability of being idle are avoided.

7.3.5. Implementation Issues

We derive our model based on the information collected from the CRs at the CBS at the beginning of each frame. Otherwise, the scheduler being unaware of the CR properties and environment dynamics cannot make resource allocation efficiently. On the other hand, such an information flow creates an overhead on the CRs and the system. Some portion of the CR energy resources and frame is spent for control messaging. If the system dynamics (e.g. link qualities) are not changing fast, period of control messaging can be made longer. Likewise, CBS can predict the CR states and link states if they follow a specific pattern. Such a prediction-based resource allocation can be efficient in terms of energy efficiency.

7.4. Chapter Summary

In this chapter, we devised a scheduling algorithm which basically aims to attain high energy efficiency for a CRN while ensuring protection of PUs at each band. Principal properties of our scheduler can be summarized as follows: (i) it makes use of channel conditions to determine the minimum sensing time of each channel as well as the data transmission capacity of that channel, (ii) it incorporates the control messaging overhead that is necessary for providing CR-state and environment awareness, (iii) channel switching cost in terms of energy consumption and time overhead are considered in channel assignment, and (iv) it ensures each CR senses the channel and even if a missed detection or PU reappearance occurs, the resulting interference is below the

harmful interference.

First, we showed that longer frame length leads to improvement in throughput as total overhead becomes a smaller portion of the frame and more time is left for data transmission. However, since CRs may fail to detect an ongoing PU communications and CRs do not constantly sense for any reappearing PUs, frame length determines the maximum transmission duration a CR may interfere with an active PU. Therefore, longer frames are more susceptible to collision with a PU which is neither desirable from PU's perspective nor efficient in terms of throughput efficiency from CR's perspective. Simulation results and our analytical derivation showed the existence of a frame length after which throughput begins to decrease drastically.

After discovering the effect of frame length, we showed that our proposal, energy efficiency maximizing scheduler EE_{max} , consumes less energy compared to a throughput maximizing scheduler Thr_{max} . Next, we analyzed performance of EE_{max} with enabling fairness in the objective function and showed that it maintains a degree of fairness among the CRs even some CRs have very unfavorable channel and traffic conditions for the efficiency of the whole CRN.

EE_{max} in general favors PU channels with higher probability of being idle (P_{idle}). Our results showed that under sufficient capacity, PU channels with lower P_{idle} are rarely assigned to CRs for communications. In order to decrease control messaging overhead, and waste of time and energy for sensing of a channel which is expected to be occupied, a selective channel allocation scheme can be developed. In this scheme, the scheduler takes a subset of frequencies in the CRN for allocation. This subset consists of frequencies that have higher P_{idle} value than the average of all channels.

8. Conclusions and Future Directions

This chapter summarizes the contribution of this thesis and presents several promising research directions that can utilize our findings and proposed solutions.

8.1. Summary of Contributions

Main contributions of this thesis can be summarized as follows:

- (i) *A distributed channel selection scheme:* This thesis proposes a general channel selection scheme independent of the sensing or channel idle time estimation algorithm. Our algorithm can be applied to any channel access scheme that has the capability of PU opportunity estimation (i.e. channel idle duration). Most of the works in the literature agree that a CR should not access a channel blindly without any auxiliary information on that channel, but should better estimate the channel availability duration. In contrast to the literature, our algorithm argues that a CR should select the channel with sufficiently long opportunity, not the one with the longest opportunity. Our analytical model and experimental results derived from simulations corroborate our claim that CRs should be non-selfish in channel selection for improving efficiency of spectrum sharing. On the other hand, our algorithm heavily relies on the accuracy of the estimation algorithm. In case of inaccurate estimation, CR transmission may result in harmful interference to the ongoing PU traffic. Hence, the best access scheme should be selected depending on the accuracy of estimations.
- (ii) *Spectrum fragmentation:* To the best of our knowledge, there is a limited number of works on spectrum fragmentation in the literature. However, using the analogy to memory allocation, fragmentation is a serious problem that may hinder the efficient use of the spectrum opportunities if not tackled. Our work highlights this phenomenon and its effect on spectrum utilization. Moreover, diverging from the solutions in the literature which are mostly at the physical layer (e.g. noncontiguous OFDMA), our solution mitigates the fragmentation at the medium

access control layer by enabling efficient spectrum sharing.

- (iii) *Energy efficiency in spectrum sensing and access:* This thesis presents an elaborate survey of the works in the literature on energy efficiency in CRNs, mainly on spectrum sensing and channel access. Although energy efficiency is a well-investigated topic in the wider domain of wireless networks, e.g., wireless sensor networks, existing approaches cannot be directly applied to the CRNs due to their inherent peculiarities of CRNs. Therefore, analysis of the current literature provides a solid background for devising new solutions tailored to the CRNs.
- (iv) *Scheduling considering the energy efficiency of a CRN:* This thesis contains a number of scheduling schemes that consider the energy efficiency of a CRN as well as throughput efficiency. First, we have concentrated on a CRN that has access to a white space database (WSDB) and therefore does not employ spectrum sensing. We formulate energy-efficient scheduling scheme as a non-linear integer programming problem that may be hard to solve. Hence, we devise a sub-optimal scheduling algorithm with polynomial time complexity. Moreover, we formulate two schedulers as linear programming problems that can be modeled as a variant of maximal bipartite matching. We show that although various scheduling schemes have almost the same throughput performance, they may differ in energy efficiency. Hence, a scheduling scheme with energy efficiency perspective should be the choice for greener CRNs rather than a pure throughput maximizing scheduler. Our proposed schedulers also have a fairness notion such that they can provide more fair resource allocation compared to the pure opportunistic schedulers. In the second part of our research on energy-efficient scheduling, we removed our assumption on access through WSDB and incorporated PU interference restrictions into our problem formulations. Experimental results and theoretical analysis show that frame length should be selected appropriately for throughput efficiency. Short frames ensure non-harmful operation to PUs at the expense of excessive control overhead. On the other hand, since our scheduler ensures that transmission of a CR does not create harmful interference to the PUs, long frame duration leads to very low throughput.
- (v) *Effect of spectrum fragmentation in frequency domain:* In this research, we also

analyze the effect of spectrum fragmentation in frequency domain on scheduling. CRs are supposed to operate in a wide range of spectrum, but the available spectrum may not be a contiguous block of bands but rather be collection of bands separated from each other. As channel switching cannot be performed instantaneously, this overhead must also be considered in frequency assignment especially under fragmented spectral resources. Since we consider this cost factor in the design of our schedulers, fragmentation is handled efficiently by our schedulers via resource allocation to closer frequencies. We show that spectrum fragmentation on the average does not affect the CRN performance as it is tackled in resource allocation.

8.2. Future Directions

In Chapter 3, we showed that the best access strategy for distributed channel access in CRNs strongly depends on the accuracy of estimations. Hence, an adaptive access scheme can be applied depending on the CRs' estimation capability. For instance, if the CRs have not acquired sufficient information on the system yet, then a selfish strategy is more appropriate. However, as the CRs learn the system and thereby estimations become more precise, they can apply non-selfish (BFC) or *p-selfish* approach with smaller p values. Additionally, as an extension to the channel selection algorithm proposed in Chapter 3 and Chapter 4, a channel opportunity estimation algorithm can be incorporated into our system and our approach can be evaluated under the applied estimation scheme.

In Chapter 6, we focused on a single CRN cell and proposed various schemes for *intra-cell spectrum sharing*. However, frequency assignment problem can be broadened to a problem that also involves multiple CRN cells and coordination among the cells for throughput and energy efficiency as well as seamless handover. Such a more complete approach, also known as *inter-cell spectrum sharing*, is more practical since a practical CRN has to manage all these tasks simultaneously. Cognitive BSs can operate in a self-organizing manner and can acquire spectrum bands based on their traffic load. Models for mobility and handover between cells can also be incorporated in this inter-

cell spectrum sharing problem.

In Chapter 6 and Chapter 7, we considered energy efficiency as a network-wide performance metric without imposing individual performance guarantees for each CR in the system. This scheduling approach may lead to some CRs deplete their batteries quickly due to inefficient resource allocation while some CRs have good battery consumption profiles. Hence, a more holistic scheme should also ensure that each CR has a satisfactory energy efficiency performance. As an extension to the proposed scheduling framework, energy efficiency performance can be taken from a CR-centric perspective and applied in a wider context.

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