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Transmit-power control for cognitive radio networks: Challenges, requirements and options

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TRANSMIT-POWER CONTROL FOR COGNITIVE RADIO NETWORKS: CHALLENGES, REQUIREMENTS AND OPTIONS

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A Research Report submitted to the Faculty of Engineering and the Built Environment, University of the Witwatersrand, in part fulfilment of the requirements of the degree of Master of Science in Engineering

Johannesburg, 2012

Declaration

I declare that this research report is my own, unaided work, except where otherwise acknowledged. It is submitted for the degree of Master of Science in Engineering at the University of the Witwatersrand, Johannesburg, South Africa. It has not previously been submitted for any degree or examination at any other university.

Candidate Signature : .....

Name : .....

Date : (Day)..... (Month)..... (Year).....

Abstract

A critical design challenge for cognitive radio networks is to establish a balance between transmit power and interference. In recent years, several approaches for regulating the transmit power of secondary users in cognitive radio networks have been proposed. This report explores the challenges and requirements of power control in cognitive radio networks. The report details two algorithms that have attracted research attention, namely the iterative water-filling algorithm and the no-regret learning algorithm. The two algorithms are compared by considering their application to a simple model, given the same conditions and assumptions. Furthermore, an adaptive scheme is introduced. The scheme incorporates both algorithms into the design of the cognitive engine, which is the functional unit responsible for power control. The conceptual architecture of the cognitive engine is presented.

Simulation results for the iterative water-filling algorithm and the no-regret learning algorithm are presented. The number of iterations it takes for the algorithms to attain equilibrium are compared and used as a basis to establish the operational procedures of the hybrid-adaptive scheme. The operational procedures of the scheme are illustrated with a test application scenario. Several application scenarios are further presented to show how secondary users in cognitive radio networks can adaptively switch between the two operational strategies.

Dedication

To Veritas

Acknowledgement

Foremost, I wish to acknowledge Professor Rex Van Olst, whose support, advice and guidance made it possible for me to successfully go through my master's program. I also thank Dr. Ling Cheng for being a great teacher and friend. I feel fortunate to have benefitted from their combined academic mentoring, technical insights, practical sensibility and critical reviews.

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I thank my elder brother, Dr. Richard Ifeh, who bore the financial burdens of a period I consider the most challenging in my entire career pursuit. May the Lord richly reward him. Special thanks to Veritas and little Amber for coping with my absence all through the period. Thanks to other members of my immediate and extended family and my friends, whose prayers, faith, friendship and love saw me through.

Abbreviations

ADC	Analogue to Digital Converter
API	Application Programming Interface
CDMA	Code Division Multiple Access
CIR	Channel Impulse Response
CRA	Cognitive Radio Architecture
CRN	Cognitive Radio Network
CSI	Channel-state Information
CSMA	Carrier Sense Multiple Access
DAC	Digital Analogue Converter
DMT	Discrete Multitones
DSA	Dynamic Spectrum Access
DSL	Digital Subscriber Line
FCC	Federal Communications Communication
FDMA	Frequency Division Multiple Access
FSMC	Finite-State Markov Channel
GPS	Global Positioning Satellite
IF	Intermediate Frequency
INFO SEC	Information Security
ISI	Inter-symbol interference
ITU	International Telecommunication Union
JCPC	Joint Coordination and Power Control
LAN	Local Area Network
MAC	Media Access Control
OFDMA	Orthogonal Frequency Division Multiple Access

OOPDAL	Observe-Orient-Plan-Decide-Act-Learn
OSI	Open System Interconnection
RF	Radio Frequency
SDH	Synchronous Digital Hierarchy
SDR	Software Defined Radio
SIR	Signal-to-Interference Ratio
TDMA	Time Division Multiple Access
WWRF	Wireless World Research Forum

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Chapter 1

1 Introduction

1.1 Introduction

A fundamental trend in the world today is the convergence of telecommunication, broadcasting and information technology industries. Convergence describes the tendency of these industries to come together in various ways and seek ubiquitous access to content and services [1]. The increasing demand for access to content and services, and the exponential growth in wireless applications and technologies, results in a crowded spectrum. Although regulatory bodies exist to manage allocations and operations, spectrum is frequently inefficiently used, yet inevitably limited. Thus, the concept of Dynamic Spectrum Access (DSA) is considered a solution to the problem of inefficient use of the spectrum.

The key enabling technology of DSA is known as cognitive radio. Cognitive radio is an intelligent wireless communication system that learns from the environment and can regulate its operation parameters to suite efficient utilisation of unused radio frequencies [2] [3]. Cognitive radio users can coexist with primary spectrum users, and are able to sense and exploit unused bands or “holes” for opportunistic access. Holes in cognitive radio terms are electromagnetic spectrum sub-bands assigned to primary users, which are partially or fully underutilised at various times and locations.

J. Mitola [4] first described the logical operational functions of the cognitive radio. S. Haykin [2] modified the cognitive radio functions to emphasis its three fundamental physical layer processes, namely radio scene analysis, channel-state estimation, and predictive modelling, and transmit-power control. Our focus is on the determination of transmit power as a tool to facilitate a fair sharing of radio frequencies.

Spectrum access in cognitive networks can be categorised as either cooperative or non-cooperative schemes. Under cooperation, secondary users can negotiate with each other and agree on how to utilise and distribute the spectrum resources. Under non-cooperation, the users can selfishly aim to maximise their transmit power.

1.2 Research Problem

Transmit power of secondary users in cognitive radio networks will inevitably introduce interference to primary users. Hence, a critical design challenge for cognitive radio is to establish a balance between transmit power and interference.

At the core of the cognitive radio architecture is the cognitive engine, which is the functional unit responsible for the control of transmit power. Research concerns about the design and operations of the cognitive engine focus on two different algorithms that have foundations in game theory and information theory. These are the no-regret learning algorithm and the iterative water-filling algorithm respectively. Unfortunately, these algorithms have certain disadvantages that have to do with their convergence properties. This poses a challenge to the control of transmit power in cognitive networks. Hence, this research report is drafted to answer the following question:

"How can the transmit-power control algorithms being proposed, the no-regret learning algorithm and the iterative water-filling algorithm, be made to fulfil the requirements of power control in cognitive networks?"

1.3 Motivation

The current spectrum management policy in which spectrum bands are assigned statically, results in spectral under-utilisation. Furthermore, traditional regulatory policies of most countries like South Africa, conform to the vertical integration model of the communications industry. With convergence and the merger of telecommunication and broadcasting regulatory bodies, present regulatory policies fall short of consistency with the horizontal layered model of a converging environment [2][5].

Firstly, this work is motivated by the need to further the advancement of research in cognitive radio technology as a platform for spectrum management. Secondly, it is also motivated by the need to seek an efficient solution to the problems posed by the control of transmit power in cognitive radio networks.

1.4 Scope and Objectives

The key objective of this research is to use scientific tools to evaluate and compare the two distributed transmit-power control algorithms. In achieving this, we attempt to:

i. Carry out a literature survey on the application of no-regret and iterative water-filling algorithms for transmit-power control in cognitive radio networks;
ii. Make theoretical enquiry into the two algorithms under review and establish deductions based on computer simulations; and
iii. Lay a theoretical foundation for further research on the coexistence of no-regret learning algorithm and iterative water-filling algorithm in the same cognitive radio system.

1.5 Organisation of this Research Report

Chapter One is a brief introduction into the subject of transmit-power control in cognitive radio networks; why it should be researched, the problem statement and the objectives of this research.

Chapter Two introduces spectrum licensing, its usage and the importance of spectrum sharing, dynamic sharing and cognitive radio. This chapter briefly explains the three aspects of cognition cycle and dynamic spectrum sharing, namely spectrum sensing, spectrum analysis and spectrum decision. It presents a relationship between the problem of transmit-power control in cognitive radio networks and the algorithms being proposed to resolve this problem, namely iterative water-filling algorithm and no-regret learning algorithm.

Chapter Three extends the literature survey in Chapter Two to a review of specific application scenarios considered in some research papers. The literature review is, firstly, from the perspective of contextual assessment of the two algorithms proposed for the control of transmit power in cognitive networks. The second approach is based on key considerations for the design of transmit-power control schemes.

Chapter Four presents the two options, which are under consideration, of transmit-power control in cognitive radio networks in sufficient theoretical detail. The approach is to define a simple scenario in which to apply the two algorithms separately, given the same conditions and assumptions. The chapter also introduces the proposed hybrid-adaptive scheme, presents the

conceptual architecture of the cognitive engine and illustrates the operational procedures of the scheme given particular application scenarios.

Chapter Five presents the research methodology and simulation results.

Chapter Six presents the research findings, recommendations, future work and conclusion.

1.6 Summary

This chapter is an introduction to the subject of transmit-power control for cognitive radio networks. It introduces the research in perspective, presents the research problem, the objectives and the motivation. It also presents a summary of the organisation of the research report.

Chapter 2

2 Background Technical Details

2.1 Introduction

The exponential growth in wireless services and technologies results in a crowded spectrum. Research studies indicate that the spectrum is underutilised at various times and locations [6]. This motivates research enquiry into the concept of Dynamic Spectrum Access (DSA) as a new spectrum management paradigm. Cognitive radio, which enables secondary users to coexist with primary users and exploit unused radio frequencies, has been introduced as the key enabling technology of DSA.

The coexistence of primary users and secondary users in the same spectrum network will inevitably introduce interference. Hence, a critical design challenge for cognitive networks is to establish a balance between transmit power and interference. The scope of power control, learning and adaptation requirements for cognitive networks has been the subject of enormous research.

This chapter presents the concept of spectrum licensing, its usage and the importance of spectrum sharing. It explains the three fundamental operational processes of the cognition cycle and dynamic spectrum sharing, namely spectrum sensing, spectrum analysis and spectrum decision. The concept of spectrum decision is then linked to transmit-power control and hence, the challenges of transmit-power control in cognitive radio networks.

The concluding subsections deal with the introduction to game theory and information theory, and the two derivative algorithms, namely no-regret learning algorithm and iterative water-filling algorithm, as solutions to the challenges of power control in cognitive networks.

2.2 Spectrum Licensing, Usage and Sharing

The electromagnetic spectrum is generally considered scarce due to the limited availability of usable frequency bands. Hence, in most countries, the use of spectrum is regulated by the government for public good.

Standard bodies like the International Telecommunication Union (ITU), European Conference of Postal and Telecommunications Administration (CEPT), European Telecommunications Standard Institute (ETSI) and International Special Committee on Radio Interference (CISPR) are responsible for the standardisation of radio frequency (RF) bands. The allocation of frequencies, as specified by standards, is assigned in three ways:

- ***Restricted Frequency Bands***: These bands are restricted from use by anyone; they are exclusively reserved for radio astronomy;
- ***Open Frequency Bands***: These bands are allocated by government and are free for use by anyone as long as they operate within certain transmit power limits. Some of the commonly identified ranges of open frequencies in most countries are 2.4 GHz, 5.2/5.3/5.8 GHz and those above 60 GHz; and
- ***Licensed Frequency Bands***: These are spectrum set aside for commercial purposes and only licensed users may transmit within the range of procured frequency bands. Examples of services operated in this band of frequencies are TV channels, radio, cellular services, and so forth.

Within the range of licensed spectrum, not all users are active all the time and at all locations. In fact, a recent survey on spectrum utilisation in New York by the Federal Communication Commission (FCC) in the USA indicates that between the frequencies range of 30 MHz to 3 GHz, there is only 13.1% occupancy [6]. Hence, the concept of cognitive radio is built on the principles that spectrum has to be shared with either (i) unlicensed radio systems, or (ii) licensed radio systems that are typically designed for exclusive use of otherwise unused spectrum [7].

A secondary user can only exploit the use of idle or partially used licensed spectrum if it does not cause interference. There are two ways spectrum can be shared. These are:

- ***Horizontal Sharing***: This is a sharing scheme between radio systems with equal regulatory priority, without causing interference. The operations of such radios can either be in the licensed or unlicensed frequency bands; and
- ***Vertical Sharing***: This is a sharing scheme between primary licensed users and secondary unlicensed users. The secondary users opportunistically exploit the licensed spectrum when the primary users are not active.

The operations of cognitive radio fall within the scope of vertical spectrum sharing. However, cognitive users can also take advantage of horizontally shared spectrum.

2.3 Dynamic Spectrum Access (DSA)

Dynamic Spectrum Access (DSA) can be regarded as a decentralised spectrum allocation technique, which allows communication devices to have access to idle frequency spectrum, subject to availability with regards to time and location. It is the direct opposite of the current static spectrum management policy, which does not allow any form of sharing. DSA strategies, as stated in [8], can broadly be categorised into three models (see Figure 2.1). These are:

- ***Dynamic exclusive use model***: In this model, spectrum bands are allocated to licensees for exclusive usage. It involves two different approaches, namely spectrum property right and dynamic spectrum allocation. Under the spectrum property rights, licensees are allowed to sell shared usage. Dynamic spectrum allocation involves the reserve of spectrum bands to specific services at particular times and locations;
- ***Open sharing model***: This model allows communication equipment operating within the specified spectrum range to be able to share with peer users; and
- ***Hierarchical access model***: Under this model, secondary users, or unlicensed users, can coexist and share spectrum bands with primary users, or licensed users, within defined interference temperature limits. Interference temperature is used by regulators to set the transmit power limits within specified frequency bands, which operators must not exceed. The hierarchical access model involves three types, namely spectrum underlay, spectrum overlay and spectrum interweave approaches. Spectrum underlay restricts the transmit power of secondary users, so they operate below the noise aggregation, or noise floor, at the receiver of primary users. Spectrum overlay allows the coexistence and cooperation

of secondary users and primary users in the same frequency band in such a way that the secondary users can transmit beyond the noise floor of primary users. However, interference from the secondary users can be compensated with the gain for primary user signal quality through energy cooperation. In the underlay approach, both secondary and primary users can also simultaneously co-exist at the same frequency band. The licensed spectrum is shared between secondary and primary users using spread spectrum techniques like Code Division Multiple Access (CDMA). The secondary users operate with very low transmit power, existing below the noise floor of the primary users. In the interweave approach, the secondary users can only access licensed spectrum when they sense that the channel is idle. In this access mode, the secondary users can operate at higher transmit-power levels within defined power constraint [9].

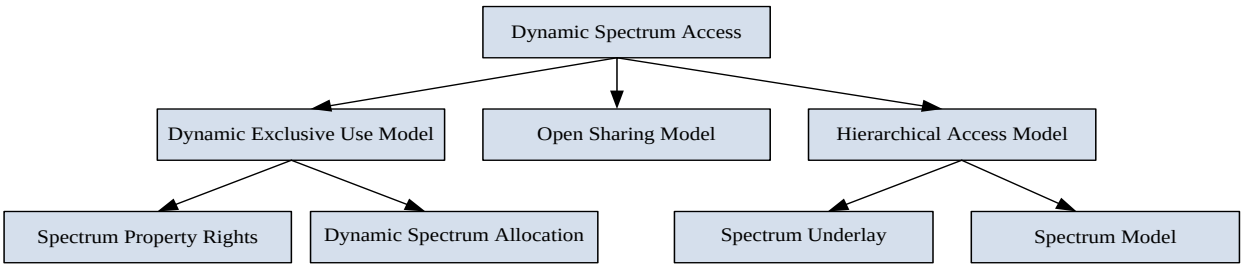


Figure 2.1: A taxonomy of dynamic spectrum access [9].

2.4 Cognitive Radio

The idea of cognitive radio was first presented by J. Mitola [10], primarily as a means of exploring effective utilisation of the radio spectrum. The term is derived from the English word, "cognition," which is defined by the ***Encarta dictionary*** as, "the mental faculty or process of acquiring knowledge by the use of reasoning, intuition, or perception."

In [2], a cognitive radio is defined as, "an intelligent wireless communication system, built on software-defined radio, that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g. transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:

- “highly reliable communications whenever and wherever needed”,
- “efficient utilization of the radio spectrum”.

The above definitions simplify our understanding of the functions of cognitive radio in a network as a transceiver that is able to determine its geographic location, identify and authorise its user, encrypt or decrypt signals, sense neighbouring wireless devices in operation and adjust its output power and modulation characteristics for efficient communication and utilisation of the spectrum. The operation of cognitive radio is assisted by its core, the Software Defined Radio (SDR).

2.5 Software Defined Radio (SDR)

Joseph Mitola, who first presented the idea of SDR, defines it as, “a radio whose channel modulation and waveforms are defined in software. That is, waveforms are generated as sampled digital signals, converted from digital to analogue via a wideband digital analogue converter (DAC) and then possibly up converted from intermediate frequency (IF) to RF. The receiver, similarly, employs a wideband analogue to digital converter (ADC) that captures all of the channels of the software radio node. It then extracts, down converts and demodulates the channel waveform using software on a general purpose processor." [11]

Software incorporated into digital radio enhances its flexibility and performance, making it possible for all physical layer functions to be defined by programs. The digital radio is equipped with re-configurability to tune to any frequency band and receive any modulation to suite its efficiency at any time and location [10]. SDR brings flexibility to the operations of cognitive radio by making it able to interoperate with different wireless protocols, incorporate new services and upgrade to new standards.

2.5.1 Software Architecture

As illustrated in Figure 2.2 below, SDR architecture is characterised by physical layer flexibility; being able to access multi-band channels at once. In [12], Mitola models the integral features of SDR architecture. Channel set depicts all forms of physical layer RF channels including, but not limited to, the electromagnetic air interface, fibre and cable. The channel coding and decoding functions performed by programmable RF channel access, IF processing and modems, span

multi-mode functionality. Information systems security (INFOSEC) provides a means of optional data encryption. The source-set spans multiple applications like video, data and voice sources connected through Synchronous Digital Hierarchy (SDH), a Local Area Network (LAN) and other networks. The features of SDR radio node have capabilities to code and decode information from varied sources.

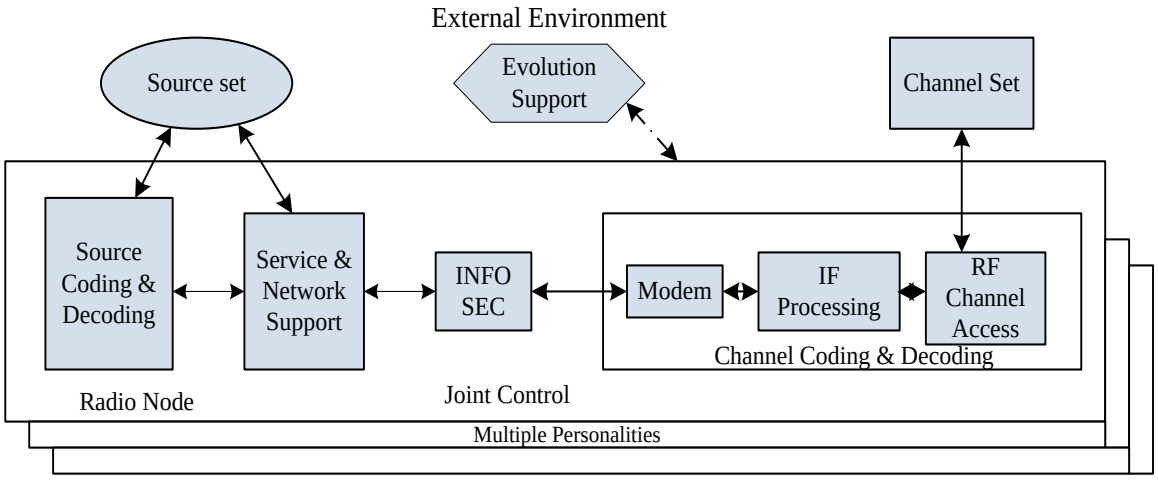


Figure 2.2: Functional model of a software radio communications system [12].

2.6 Cognition Cycle

In his theoretical model of the ideal Cognitive Radio Architecture (iCRA) [13][14], J. Mitola described the states of various mental processes of a cognitive radio as Observe-Orient-Plan-Decide-Act-Learn (OOPDAL). He contends that these include, but are not limited to, observation of user actions, RF detection, location detection, interference temperatures sensing, radio broadcast analyses, planning technologies, signal transmission, and so forth.

The Wireless World Research Forum (WWRF) developed a more concise abstraction of J. Mitola's ideal model in [15]. Figure 2.3 below illustrates the mental processes, ranging from observing the environment through decision-making based on learning and culminating with action. The processes of learning and decision-making can be regarded as reasoning.

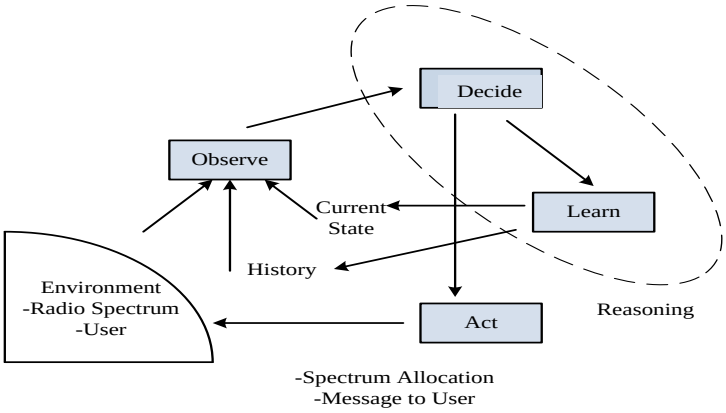


Figure 2.3: Mental processes of a cognitive radio based on the cognition cycle.

In [2] S. Haykin presented a cognitive cycle model, which depicts the cognitive radio's physical layer functions. According to him, the fundamental cognitive tasks are radio-scene analysis, channel identification, transmit-power control and dynamic spectrum management.

In [13] J. Mitola presented a model, which integrates Haykin's cognitive cycle into the physical layer of the Open System Interconnection (OSI) protocol stack. In this model, as seen in Figure 2.4, the physical layer comprises of the core function of cognitive radio, namely spectrum sensing, channel state estimation and data transmission. The link layer encompasses group management, link management and Media Access Control (MAC). The cognitive nodes are then integrated into the network by means of the universal control channel.

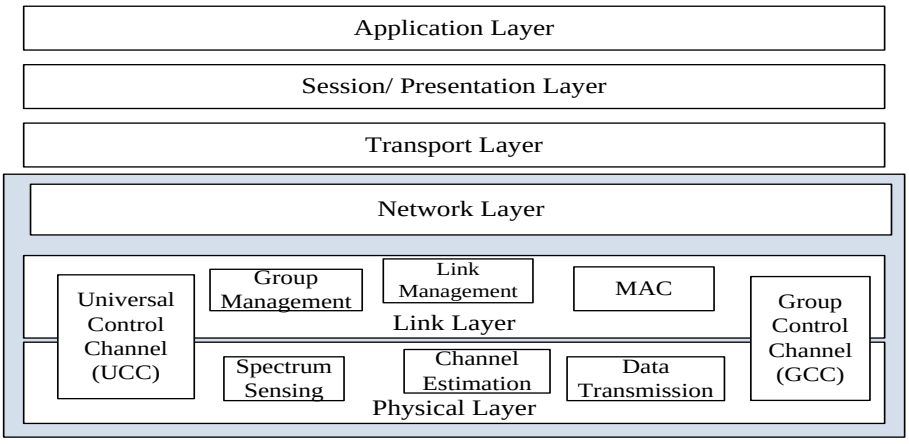


Figure 2.4: Representation of Haykin's DSA processes on the OSI [13].

Irrespective of the variations of cognitive radio functions presented by various authors, it is possible to categorise the cognitive radio physical layer functions under three broad dynamic sharing processes, namely spectrum sensing, spectrum analysis and spectrum decision [16]. Figure 2.5 below illustrates the cognitive cycle for dynamic spectrum sharing.

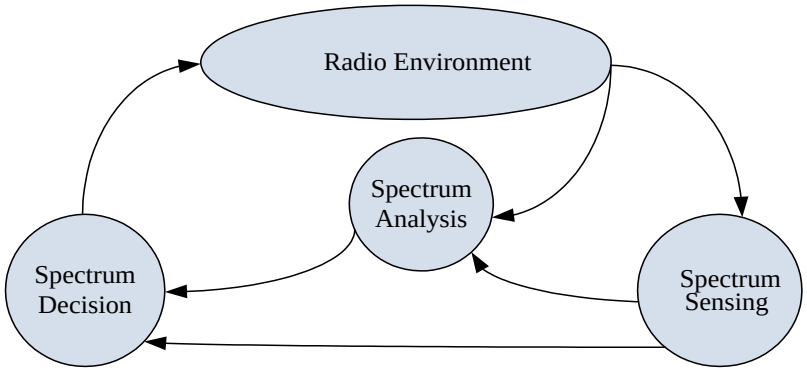


Figure 2.5: Basic cognitive cycle for dynamic sharing.

2.7 Overview of Dynamic Sharing and the Cognition Cycle

As stated in the preceding subsection, the three broad dynamic spectrum sharing processes are spectrum sensing, spectrum analysis and spectrum decision. A summary of these processes are presented below.

2.7.1 Spectrum Sensing

The first integral of cognitive radio task is spectrum sensing. The cognitive radio monitors the spectrum bands, captures information and detects spectrum holes [16]. In cognitive radio parlance, spectrum holes are sub-bands of the electromagnetic spectrum assigned to primary users, but can be exploited by secondary users when partially or fully underutilised at various times and locations.

Sensed spectra can be classified into the following [2]:

i. *Black Spectrum Holes*: These are spectra that are fully occupied and are to be avoided when their emitters are ON;
ii. *Gray Spectrum Holes*: These are spectra that are partially occupied and are candidates for use by prospective service operators; and

iii. *White Spectrum Holes*: These are spectra that are free and are also candidates for use by prospective service operators.

Spectrum sensing can broadly be categorised either based on the architecture of the sensing nodes or the kind of information to be sensed. Figure 2.6 illustrates the various sensing categorisations [17].

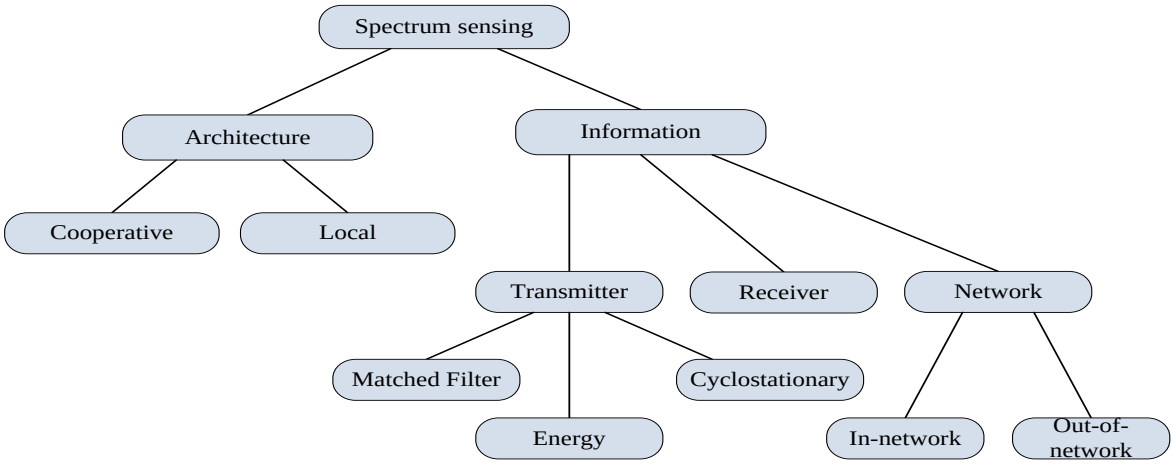


Figure 2.6: Spectrum sensing options [17].

2.7.1.1 Architecture-Based Sensing

Architecture-based sensing can either be cooperative or local based spectrum sensing. These terms are explained below:

- ***Cooperative Spectrum Sensing*:**

Cooperative spectrum sensing refers to spectrum sensing method where multiple cognitive radios cooperate towards the detection of a primary user's spectrum holes. Users within the group share their local spectrum sensing measurements.

- ***Local Spectrum Sensing*:**

In local spectrum sensing, each user makes decision on the presence of a primary user's spectrum holes based on its local sensing measurements

2.7.1.2 Information Detection

Transmitter detection, receiver detection and network-based detection are grouped under information detection.

- ***Transmitter Detection***

Transmitter detection techniques are used to determine if the signals from a primary transmitter are present in a certain spectrum. This is done by detecting the weakest transmitted signal from a primary user with the idea that the weakest signal produced by a primary transmitter would be the one furthest from the radio, but still susceptible to RF interference from the radio [17].

The approaches of transmitter detection techniques are stated below [16]:

i. *Energy Detection*: The energy detection method is a means of detecting signals overshadowed by Gaussian noise[1] and the receiver cannot get enough information about the primary user's signal. The major drawbacks of this method is that (a) the decision threshold is subject to changing Signal-to-Noise Ratios (SNR), (b) it cannot distinguish interference from the user signal, and (c) it is not effective for signals whose power has been spread over wideband;

ii. *Match-Filter Detection*: Match-filter detection is a method of signal detection done by maximising the received SNR in the presence of Gaussian noise. The matched-filter works by correlating a known signal, or template, with an unknown signal to detect the presence of the template in the unknown signal; and

iii. *Cyclostationary Detection*: The cyclostationary detection technique is a method of detecting modulated signals, characterised as being cyclic, at low SNR. This form of detection is used where energy detection is ineffective. However, it requires a long observation time and large computational capacity [16].

- ***Receiver Detection***

Secondary users in cognitive networks need to be able to detect other receivers in the network to avoid interfering with their communications. The first way to achieve this is to ensure the cooperation of the sensed receivers. The second way of achieving this is by interference-based

[1] Gaussian Noise is the noise that has probability equal to that of the normal distribution, which is also known as the Gaussian distribution.

detection technique, which derives from the measurement of the collective interference temperature from surrounding transmission in the cognitive network. Communication is allowed at the participating receiver when the summation of interference received is below a certain threshold.

- ***Network Detection***

Network detection can be regarded as the sensing of information from the network, beyond the domain of the sensing cognitive user. Network sensing can be categorised under two sub-divisions, namely in-network detection and out-network detection.

By in-network detection, a cognitive user monitors information from neighbouring nodes in the network, both from cooperative and distributed nodes. Monitoring information from other nodes in the network will assist the sensing node to find a channel that is optimal for communication. Out-network monitoring can be regarded as the gathering of information related to higher layers of the communication protocol stack. Such information includes routing protocol messages, beacons sent by the MAC protocol, applications that are currently in use, and so forth.

2.7.2 Spectrum Analysis

After the procedure of spectrum sensing, the secondary users would have obtained certain measurements with which to build a model of the wireless communication scene. This process is regarded as channel-state estimation [2]. Channel-state estimation involves analysing the behaviour of a channel to determine its impulse response characteristics and using the results to derive a model for increased efficiency. Channel identification can be viewed from two perspectives. These are:

- ***Estimation of Channel State Information (CSI)*:**

Channel State Information (CSI) refers to a Channel's Impulse Response (CIR) characteristics when a signal is propagated through the channel, from transmitter to receiver, subject to scattering, fading and distance varying power decay. With knowledge of the CSI, the receiver and transmitter can be fine-tuned to overcome negative CIR characteristics. On the receive path, Inter Symbol Interference (ISI) generated due to multipath fading is removed by equalisation.

Similarly, on the transmit path, the transmitter can transmit a signal that would absorb effects of the CIR.

- ***Predictive modelling*:**

Predictive modelling in a cognitive radio network is the process of creating a model to predict the probability of possible channel behaviour and traffic pattern.

Beyond using the knowledge gained from detection to adapt strategies for increased efficiency, predictive modelling builds on observations and statistical measures to derive a model that will suit the predictive behaviour of the channel. By making use of predictive modelling, cognitive radio can predict the availability and duration of spectrum holes and hence, is able to determine transmit power strictures.

2.7.2.1 Spectrum Analysis Classification

Spectrum analysis can be carried out either in a centralised or distributive fashion. The spectrum model built can be classified, as illustrated in Figure 2.7 below. In some models, analysis is based on instantaneous spectrum sensing results, while other models tend to keep track of the spectrum-usage history [17].

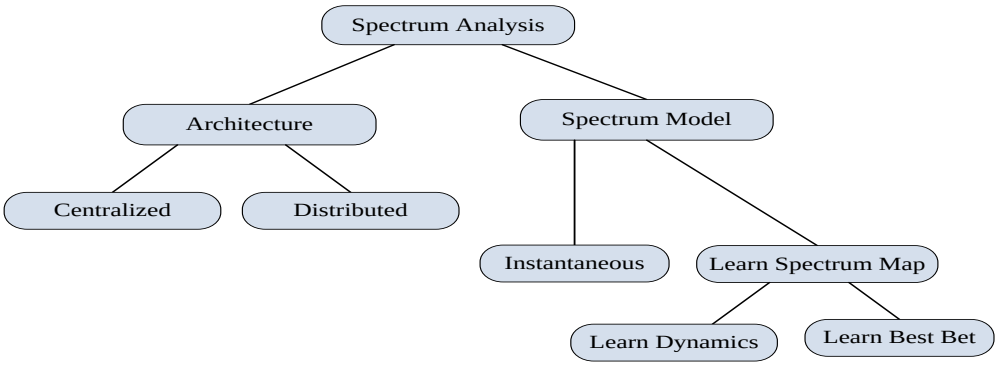


Figure 2.7: Spectrum analysis classification [17].

2.7.3 Spectrum Decision

Transmit-power control is the imperative of spectrum decision. By spectrum decision, the transmit power of a cognitive node is adapted to access the spectrum based on the model developed in the spectrum analysis stage. Generally speaking, spectrum decision addresses the feasibility and how transmit power should be adapted in the network.

2.7.3.1 Spectrum Decision Classification

Figure 2.8 illustrates the various classifications of spectrum decision.

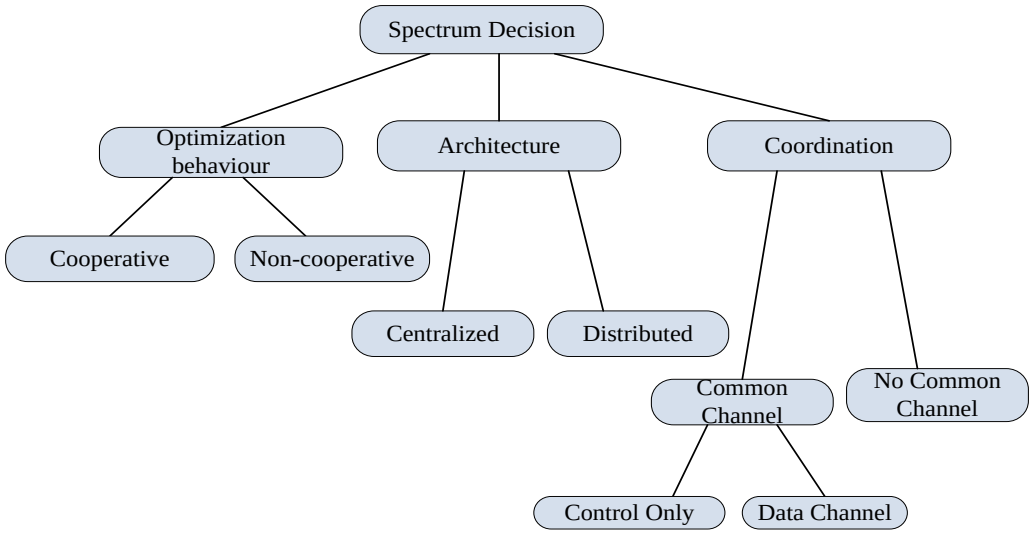


Figure 2.8: Spectrum decision classification [17].

The framework for spectrum decision can broadly be classified into three groups, namely optimisation behaviour, architecture, and coordination. Under optimisation behaviour, two types of behaviours are possible in order to decide on spectrum use and these are non-cooperative and cooperative. By non-cooperative spectrum utilisation, cognitive nodes are usually selfish and only strive for self-optimisation goals. On the other hand, cooperative decision usually considers other nodes in utilising the spectrum.

Under architecture, nodes can either have centralised operational architecture or a decentralised operational architecture.

Information can be communicated to the other nodes through the presence of a common channel. However, if a common channel of communication is not available, the system will have to rely on other communication techniques.

2.8 Transmit-Power Control in Cognitive Radio Networks

As mentioned in the preceding subsection, the essence of spectrum decision is transmit-power control. The remaining part of this report is focused on subjects that apply to the control of transmit power in cognitive radio networks.

2.8.1 Challenges of Transmit-Power Control in Cognitive Radio Networks

We proceed to group the challenges of power control in cognitive radio networks under different broad categorisations. The categorisations are listed and described below.

- ***Opportunistic access to unstable spectrum holes***:

Secondary users in cognitive radio networks compete for access to available limited resources. The fact that the availability of spectrum holes for opportunistic access by competing nodes vary with regards to time and location informs the concept of dynamic cognitive network.

Competing nodes have to exploit unstable spectrum holes, while ensuring that their individual activities do not cause unequal distribution of network resources, and hence instability of the network. Therefore, the design of suitable algorithms capable of driving the cognitive users to adopt rational behavioural tendencies, as a means of dealing with the situation, is fundamental to the cognitive network.

- ***Balance between transmit power, bandwidth and interference***:

In wireless communication systems, three fundamentally connected, but conflicting theoretical concepts are transmit power, bandwidth, and interference. It is impossible to increase any in a network without correspondingly causing conflicts in the others. Hence, a criterion for the efficient use of resources in any wireless network is to maintain a balance between them.

The cognitive network is complicated by the existence of two types of users, namely primary and secondary users. The traditional problem of interference management through power control in wireless networks is different from that obtained in a cognitive radio environment. Secondary cognitive radio users are engaged in the conflicting interest of meeting up to performance data rates requirements, while minimising interference to the active primary users and other secondary users. Hence, a critical design challenge for cognitive radio is to establish a balance between transmit power, bandwidth and interference.

- ***Autonomous Operability***:

The dynamic nature of cognitive networks demands that cognitive radios are autonomous and independent in their operational functions. Such functions include, but are not limited to, self-organisation mechanisms to perceive the radio environment, to establish links and cooperation with neighbouring peer nodes and to keep track of historical decisions on spectrum holes and interference [18]. Hence, autonomous operability is considered a fundamental design criterion of cognitive networks.

2.9 Cognitive Radio Networks, Game Theory and Information Theory

Several tools for resolving problems, such as the one posed by transmit-power control in communication systems, have been developed in recent times. This research focuses on the use of fundamental tools related to game theory and information theory for resolving problems of interactions between agents with such conflicting interests. The remaining part of this section lays the foundation for a logical link between the basic concepts of game theory and information theory, and the algorithms that will be evaluated as tools to resolve the problem of power control in cognitive radio networks.

2.9.1 Definition and History of Game Theory

Game theory is a set of mathematical tools used to model and analyse interactive, iterative and strategic decision processes among multiple decision-makers concerned about their own benefit. Each decision-maker has preferences over the set of possible outcomes of the game and each strives to obtain the outcome that is most profitable.

The foundation of game theory as a field was laid by J. von Neumann and O. Morgenstern in their publication of 1944, entitled *Theory of Games and Economic Behavior* [19]. The book provided the method for finding mutually consistent solution for two-person zero-sum games. A game is said to be zero-sum if the sum of payoffs to all decision-makers, herein after referred to as ‘players’ or ‘users,’ is zero. Hence, in a two-player zero-sum game, one player’s gain is the other player’s loss.

In 1950, John Nash developed an equilibrium concept, which today is known as Nash equilibrium. Nash equilibrium is a point at which players choose their best strategies, given the strategy choices are available to their opponents. Nash equilibrium, which can also be applied to zero-sum game, provides a general solution to mutually consistent strategies of players. This furthered the development of the concept of non-cooperative game theory.

From the 1960s, game theory was applied in war, politics, sociology, psychology, and biological evolutionary theory. In 1974, the concept of correlated equilibrium, which will be explained later in this chapter, and common knowledge was introduced by R. Aumann. The concept of mechanism design theory, which focuses on the consequences of the different types of rules of a game, was further introduced. Today, game theory is applied in many fields, such as social sciences, biology, engineering, political science, international relations, law and so forth.

2.9.2. Definition of Game

Though there are various details used to define a game, the formal description takes the following into consideration; the players, their preferences, their information, the strategic actions available to them, and how these influence the outcome. In the scope of this generalisation, there are two types of games, namely **cooperative games and non-cooperative games**.

Cooperative games define situations where a group is involved in strategic decision processes and the members are in agreement with the adopted strategy and payoff function that accrues to the group. It describes the potential strategic positioning of a coalition and how proceeds derived from successful feats are shared.

In contrast, **non-cooperative games** are concerned with the analyses of strategic interactions between selfish players competing in a game for their own interest. In certain non-cooperative games, players are sometimes faced with the option to cooperate when they find it in their own best interest.

2.9.2.1 Normal and Extensive Form Game

Non-cooperative games are usually described as either a normal or an extensive form. A normal form is a way of describing a game by listing each player's strategies and the corresponding

payoffs associated with each possible combination of choices. An extensive form describes how a game is played over time. This includes the rules of the game, the choices of strategies available to each player, the information a player has when it is his turn to move, and the payoffs each player receives at the end of the game. When all information of past strategies and corresponding payoffs are known to each player, it is called a game with perfect information, otherwise it is regarded as a game with imperfect information [3].

2.9.3. Non-Cooperative Cognitive Radio Networks Viewed as a Game Theoretic Problem

Cognitive networks can exist as either a cooperative or a non-cooperative scheme. Cooperation among cognitive users requires that all participants agree on the best strategies for coalition. The disadvantage of this approach is that cooperation comes with a great amount of signalling, information overhead and co-channel interference caused by communication between users. In a non-cooperative scheme, the users access the network by distributive means and there is no need for overbearing signalling and information overhead. However, the price users have to pay for non-cooperation is poor utilisation efficiency because individual users selfishly aim at maximising their revenues. Hence, this is the motivation for adopting game theory as a solution.

The formulation of a framework for the non-cooperative game of secondary users in cognitive radio networks are based on stochastic games concepts. A stochastic game is a game that is played in a sequence of stages by players for the purpose of benefits, known as payoffs, based on the state of the system and players' chosen actions or strategies. The strategy of a player concerned in the game that takes it from one state to the other is known as **pure strategy**. With the game occurring in repeated sequences and the task of each player is to choose the best responses based on information of repeated strategies of the opponents, the continuous randomisation of a player's actions is termed **mixed strategy**.

The definition above identifies three basic concepts that are integral to the formulation of stochastic games [2][20]. These are:

- *State space* - Defines the product of the individual players' states;
- *State transitions* - Defines the joint actions taken by the players in a game; and
- *Payoffs* - Accrues as a result of the actions of the players.

Stochastic games are described by the following ingredients $\{n, S, \vec{A}, P, \vec{R}\}$, where:

- n is a finite number of players, $\{1,2,\ldots,n\}$;
- S is a set of states, $\{s_1, s_2,\ldots,s_n\}$;
- $\vec{A}$ is a collection of action sets, $\{A_1, A_2,\ldots,A_n\}$
- P is the transition probability of the system in moving from one state to the other caused by the actions of the players.
- $\vec{R}$ is the players' payoff function, given as $\{r_1 \times r_2 \ldots \times r_n\}$, and determined by the current system state and the actions chosen by the players,

Two decision processes worth noting under stochastic games are Markov decision process and matrix games. A Markov decision process is a special case of a stochastic game with a single player, that is $n = 1$. A matrix game, on the other hand, is a special case of a stochastic game with a single state, $|S| = 1$. Figure 2.9 depicts these definitions.

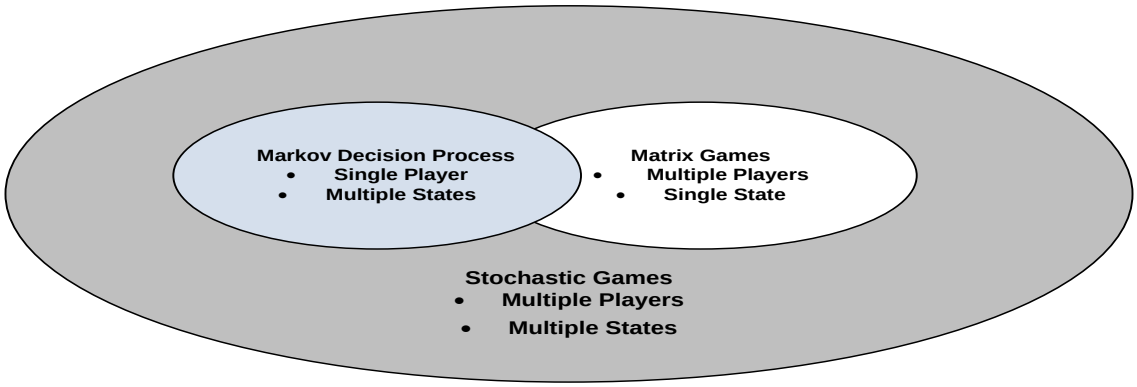


Figure 2.9: Highlighting the differences between Markov Decision Process, Matrix Games, and Stochastic Games [2].

2.9.4 The Concept of Iterated Dominance

Using stochastic game concept to model the interactions between secondary users in cognitive radio networks is a means to an end. After the formulation of the game, the next thing to do is to solve it. The way to solve a game is to predict the strategy of each player, given all the ingredients of the game and considering that the players are rational. There are several methods that are suggestive of ways to solve a game. Here, we focus on two simple methods, namely

iterated dominance and the Nash concept. While the iterated dominance is explained below, the succeeding subsection explains the Nash equilibrium in details.

The concept of dominance in game theory is used to measure the best options out of strategic choices in a game. For example, if a player is faced with two strategies, α and β, his strategy α strictly dominates the other strategy β if his payoff from α is greater than that from β, regardless of what others do. If players in a game are rational, the choices they make are determined by the strategies that will give them the best benefits, hence they will never choose to play a dominated strategy.

The Forwarder's Dilemma [21], which is regarded as the Prisoners' Dilemma in classical literatures, is represented by Table 2.1. It gives insight into the idea of iterated dominance as a solution concept. The game is represented by the following attributes:

- Two players, p_1 and p_2, are involved in the game and each of them wants to send a packet to his destination, d_1 and d_2 respectively, using the other player as a forwarder. Hence, a player can only communicate with his pair receiver if the other player, the opponent, forwards his packet;
- The two players have two strategy options; either to forward (*F*) packet of the other player or to drop it (*D*). The payoffs of their actions are defined in the corresponding columns and rows; and
- Let c represent the cost earned by forwarding a packet. When a player forwards a packet and his opponent drops, he is charged a fixed packet-forwarding energy cost, 1-*c*, where $0 < c < 1$, and the opponent's benefit is 1. However, if both forward a packet, they are individually charged the fixed cost 1-*c*. If they both drop, they get no benefit and no cost charge, which represents 0.

p_1/p_2	*F*	*D*
F	(1-*c*,1-*c*)	(-*c*,1)
D	(1,-*c*)	(0,0)

Table 2.1: Tabular representation of the Forwarder's Dilemma game.

- ***Iterated Dominance Solution***:

The above game can be solved by the concept of iterated dominance, following the principles of iteratively eliminating strictly dominated strategies. Considering the situation from the viewpoint of player p_1, the *F* strategy is strictly dominated by the *D* strategy, because the *D* strategy always gives a better benefit. Hence, we start by eliminating the first row of the matrix, since rational player p_1 will never choose a strategy from the cells in the first row. Similarly, following the same procedure, rational player p_2 will never choose from the first column of the matrix. Hence, the solution of the game is (*D*, *D*), where the payoffs are unfortunately (0, 0). The decision of the players can be regarded as suboptimal, as (*F*, *F*) would have guaranteed a combined higher payoff for each player. It is the lack of trust on their part that leads to such a decision. Hence, the situation poses a dilemma to the players.

The logical significances of the Forwarders' dilemma are:

- Best response strategy can, in some instances, lead to bad outcomes; and
- Each player can get incentive, can do better, by choosing to "free ride"- by choosing either strategies that dominates or dominated strategies.

2.9.5 Nash Equilibrium

John Nash's work on the concept of equilibrium for non-cooperative games [22] [23], introduced the concept of an equilibrium of a game, which later became known as the Nash equilibrium. The Nash equilibrium defines fair-sharing approaches and outcomes of selfish interactions in a game, and is regarded as the most important solution concept in game theory. The Nash equilibrium of a strategic-form game is a mixed strategy profile wherein every player is playing a best response to the strategy choices of his opponents. A player's best action depends on the opponents' chosen actions. When players in a game apply their best strategies, the game ultimately reaches the Nash equilibrium point.

The above premise is anchored on two assumptions:

1. *The choice of strategy adopted by each player is a rational* ***best response strategy*** *based on impressions or beliefs formed about the actions of his opponents; and*

2. *Every player's belief about the other players' actions is correct*.

From these underlining assumptions, it is important to note the philosophical motivations for adopting the Nash equilibrium as a solution concept. These are:

- ***No-regret***: The concept of no-regret is based on the notion that no player can do strictly better by deviating from the best response strategy, given that the other players also follow the equilibrium policy; and
- ***Self-fulfilling beliefs***: Players in a game of Nash equilibrium form self-fulfilling beliefs about their adopted strategy, because it is the best response to the other opponents' strategies.

The relevance of the Nash equilibrium to cognitive radio networks is best understood when we consider the following example [17] [21]:

Consider a multiple-access game, as illustrated by Table 2.1, involving two transmitters, which we denote as p_1 and p_2, who want to send data packets over a shared channel to their receivers, r_1 and r_2 respectively. The game shows two strategies that the players can use. Each can decide to transmit a packet or remain quiet (not transmit), denoted by *T* and *Q* respectively. The payoffs of their actions are defined in the corresponding columns and rows. The cost earned by transmitting a packet is denoted by *c*, where $0 < c < 1$. Since the channel is shared, the transmission by both players results in a collision, which results in the loss of packets.

From this table, it is apparent that the optimal solution to the multiple-access game is as follows:

p_1/p_2	*Q*	*T*
Q	(0,0)	(0,1-*c*)
T	(1-*c*,0)	(0,0)

Table 2.2: Tabular representation of the multiple-access game.

- If player p_1 chooses to transmit, then the best response for player p_2 will be to remain quiet.

- Also, if player p_2 chooses to transmit, the best response for player p_1 will be to remain quiet.

From the above game, we can reach a fundamental conclusion that in the Nash equilibrium points, there is no incentive for any player involved in the game to deviate from the best response strategies.

2.9.6 Inefficiency of the Nash Concept and Equilibrium Selection

The game represented by Table 2.2 is one of many examples of illustrating the Nash concept. There are exceptional cases where the Nash equilibrium leads to unstable outcomes. Since the Nash equilibrium is the most widely used solution concept in game theory, it is important to review some of such instances:

- **A Nash equilibrium may involve a weakly dominated strategy by some players**: The Nash equilibrium is engendered by the use of best response strategies against an opponent with a similar goal. However, rational decisions are not always suitable in a game. For example, in the two-player game represented by Table 2.2, when a player changes strategy and adopts a non-equilibrium strategy, the optimal response of his opponent would be a relative non-equilibrium strategy too. Hence, in such circumstance, the Nash equilibrium does not apply.
- **Nash equilibrium need not exist in a game**: The Nash equilibrium only gives us the equilibrium value, which tells how the outcome of a game will be, but it does not give information of how to attain the equilibrium state.
- **Existence of many Nash equilibria in a game**: In some circumstances, multiple Nash equilibria could exist in a game and so, there is the challenge of choosing the appropriate solution.
- **Inadequate deductive intelligence**: The Nash equilibrium assumes that players have unlimited computing capabilities and hence, can resolve infinite loops from logical reasoning. In practice, players do not have such ability.

2.9.7 The Concept of Pareto-Optimality

The concept of Pareto Optimality, named after Vilfredo Pareto, can be described as a measure of efficiency. An outcome of a game is termed Pareto optimal if no player in the game could be better off without another becoming worse off.

A set of Pareto optimal strategy profiles in a game is termed *Pareto-frontier*. If a game has more than one Nash equilibrium candidate, the ones on the Pareto-frontier are generally regarded to be superior. Hence, Pareto optimality can be used to eliminate weaker Nash equilibia.

2.9.8 Correlated Equilibrium

The Nash equilibrium could appear unstable, given its limitations. This informs our enquiry into another equilibrium concept relevant to this research theme, namely correlated equilibrium.

The idea of correlated equilibrium was introduced by Aumann in 1974. The following describes the concept of correlated equilibrium. Assume that before the start of the game, each player receives a signal or information from a private source; the joint distribution is however, known to all the players in the game. With the start and progression of the game, each player in the game then chooses his strategies based on the value of the signal, realising that the instruction received provides a best response to the random estimated play of all players. In the event that no player deviates from the recommended strategy, the distribution of the players' actions converges to what is regarded as a correlated equilibrium [24]-[26].

Correlated equilibrium applies to cooperative games, but its significance to non-cooperative games lies in the fact that the discretion lies with the players of the game to enforce the recommendations of the received signals.

In terms of application to cognitive radio networks and spectrum utilisation efficiency and fairness, correlated equilibrium is considered better as compared to non-cooperative Nash equilibrium, because it tends to offers fairer payoffs in a game. Chapter Four of this report details how correlated equilibrium can be used by distributive secondary cognitive radio users to adjust their transmission probabilities over available channels, so that payoffs are optimised.

2.9.9 The No-Regret Learning Algorithm

Statistical learning theory is used as a framework to develop algorithms with rational behavioural tendencies for solving game theoretic problems. In this context, the no-regret learning algorithm, which is attracting attention in the machine learning literatures [2], is being proposed as an antidote to the problem of power control in cognitive radio networks.

The following illustration describes the nature of the no-regret learning algorithm in sufficient details [27]. Consider an infinitely repeated game where an agent is faced with the challenge of making a decision. Assume the agent has a choice of actions from which to choose and any choice he makes has a corresponding reward. If the action set is finite and the reward associated with each action is stable, all the agent needs in order to maximise his reward forever is to do a linear search for an action that derives the best benefits. However, if the rewards associated with each action vary across iterations of the decision game, a more complex strategy, or rather, a learning algorithm is required to assist the decision of the agent. The no-regret learning algorithms are geared towards maximising average reward in such decision processes. The no-regret learning algorithm is composed of a mapping of history of no-regret past actions, outcomes, and rewards to current choice of actions. Its composition is in such a way that the reward derived from using the algorithm is always greater than the reward that can be derived from using any set of alternative strategies.

There are two types of no-regret learning algorithm, namely *no-external regret* and *no-internal regret*. An algorithm is said to exhibit no-external regret if the difference between its payoffs as compared with that of a fixed or the same sequence of strategies is negligible. Similarly, an algorithm is said to exhibit no-internal regret if the difference between its payoffs as compared with that of a remapped sequence of strategies is negligible. The theoretical details of the no-regret learning algorithm are presented in Chapter Four.

2.9.10 Information Theory

Information theory was founded in 1948 with Claude Shannon's seminar work, "*A Mathematical Theory of Communication.*" The most fundamental results are two theoretical derivatives, namely *Shannon's Source Coding Theorem* and *Shannon's Noisy-Channel Coding Theorem*.

Shannon's Source Coding Theorem provides the mathematical tool for assessing data compaction, that is, lossless data compression, generated by a discrete memory-less source. *Shannon's Noisy-Channel Coding Theorem* characterises the limits of reliable communication and establishes how channel capacity can be computed from the statistical properties of the communication environment. Shannon showed that reliable communication between a transmitter and receiver is possible, if and only if, the rate of communication is below a certain quantity called channel capacity. The channel capacity, also known as the Shannon limit, is the maximum rate at which data can be sent over a channel with zero error.

In the context of Shannon's specifications, researchers have in recent years focused on the use of information theory to study the fundamental limits of communication possible over a network when using cognitive devices. In order to study this problem, researchers have used information theoretic models to simplify the essence of communication characteristics particular to cognitive devices. These models can be grouped under three categorisations [21], as follows:

- ***Interference mitigating cognitive behaviour***: Under this model, secondary users wait for a channel to be idle before communicating in order to mitigate interference caused to the primary users;
- ***Interference controlled cognitive behaviour***: Under this scheme, when secondary users exist in a network and have no information to transmit, they serve as relay and collaborate with primary users to assist the primary link; and
- ***Interference avoiding cognitive behaviour***: This behaviour allows secondary users to communicate so as to completely avoid interfering with primary users. This is done by first sensing the channel to determine the part of the spectrum that they can use for communication.

Each of the models above can be applied to both techniques of sensing and transmit-power control.

2.9.11 Iterative Water-Filling Algorithm

Iterative water-filling provides an algorithm for computing optimal transmit covariance matrices for users in a multiuser system. The algorithm was originally applied, in the context of Discrete Multitones (DMT) to the problem of multiuser distributed power control in Digital Subscriber

Line (DSL). The name "water-filling" derives from its classical description, which assumes water is poured over the inverse of noise variance at each subcarrier frequency. For instance, if we have a given channel SNR information in a frequency domain, SNR (*f*) with a given Power Spectral Density (PSD), the maximum data rate can be obtained by allocating more power to the frequency bands with higher channel SNR. This strategy, which is the same as pouring the total power into the bowl of the inverse SNR (*f*) curve, defines the name water-filling [29]-[31]. Figure 2.8 (a) and (b) illustrate the water-filling for single user and two users respectively.

Recently however, the algorithm finds relevance in its application to the problem of transmit-power control in non-cooperative multiuser cognitive radio networks. In information-theoretic terms, the algorithm makes it possible for each user to water-fill by updating their transmit power vectors, like water is poured over the inverse of the combined interference and noise. In the end, the PSD of the users tend to converge to the game-theoretic solution concept of the Nash equilibrium. Hence, in this context, we can say that information theory provides the means to a game theoretic end [17].

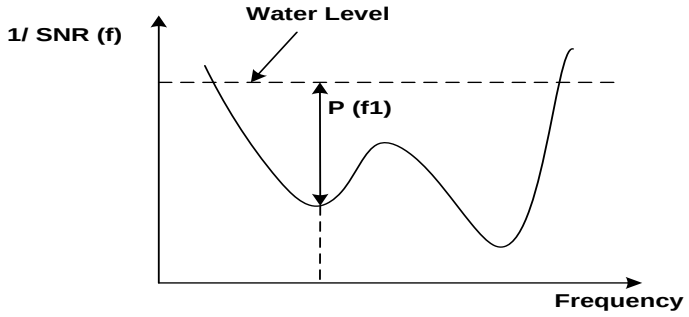


Figure 2.8 (a): Water-filling for a single user [30].

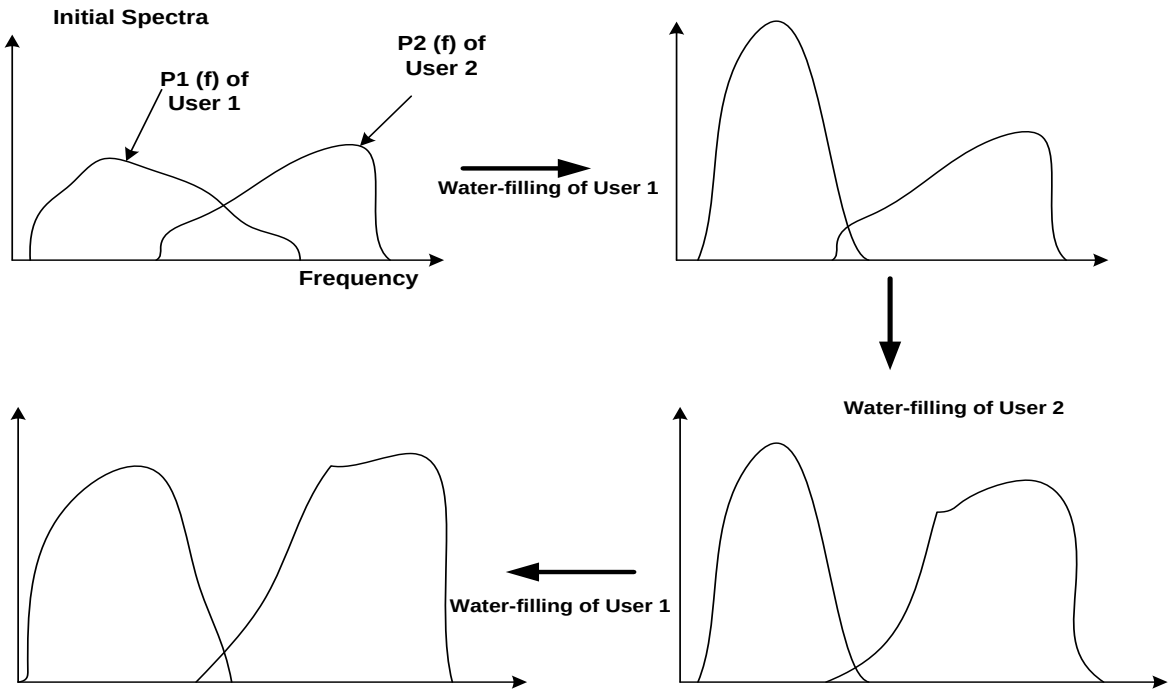


Figure 2.8 (b): Water-filling for two users [30].

2.10 Summary

This chapter builds on the concept of transmit-power control introduced in Chapter One. It presents a summary of various subjects that relate to the theme. The introductory subsections present a review of the concept of spectrum licensing, its usage, the importance of spectrum sharing, and the concept of dynamic spectrum access. Following this, background technical details of cognitive radio, software defined radio and cognitive radio architecture are presented. The chapter then analyses the challenges of power control in cognitive networks. Conclusively, the chapter gives background insight into how game theory and information theory relates to algorithms, which can be used to provide solutions to the problems of power control in cognitive radio networks.

Chapter 3

3 Related Work

3.1 Introduction

Existing research studies propose different variants of the iterative water-filling algorithm and the no-regret learning algorithm. In the second section, the chapter presents a contextual literature review of the different approaches and identifies the one, in either case, that best suits the cognitive radio environment.

In the third section, we review key considerations for the design and implementation of spectrum access games. In recent years, a variety of control algorithms have been proposed for organising cognitive radio networks. Two different management paradigms have been proposed for these control algorithms. These are coordination through a central spectrum server and coordination through distributed negotiation. Firstly, we review the two transmit-power control schemes, which are specified in existing research papers, namely centralised and distributed transmit-power control schemes. Secondly, we review some research papers that deal with equilibrium solutions in the implementation of the transmit-power control schemes.

3.2 The Variants of Transmit-Power Control Algorithms

The succeeding subsections, namely subsection 3.2.1 and subsection 3.2.2, present a contextual review of research papers, and compare the different approaches of the iterative water-filling algorithms and the no-regret learning algorithm respectively.

3.2.1 Competitive Optimality Water-Filling Algorithm versus Distributed Power Control Water-Filling Algorithm

In [28], Yu specified two information theoretic procedures for transmit-power control in a two-user DSL environment, competitive optimality power control water-filling, or rate-adaptive water-filling and distributed power control water-filling, or power-adaptive water-filling.

In competitive optimality water-filling algorithm, users compete to maximise achievable data rates by adjusting their power allocation subject to fixed power constraints. All users competitively adjust their transmit power over available frequency bands, or spectrum holes, until they reach equilibrium, regarded as the Nash equilibrium. At Nash equilibrium, each player's strategy is the best response to the other players' strategies. Conversely, distributed power control water-filling aims at minimising transmission power subject to the constraint imposed by fixed target rates. The system ultimately converges to equilibrium when the set of target data rates are achieved. Although some research papers on iterative water-filling algorithm favour the competitive optimality procedure, our focus here is distributed power control because, as will be explained in the next section, multiuser cognitive radio networks perform optimally when the network structure is distributed.

Yu's work on distributed power control water-filling algorithm [28] has inspired the application of the iterative water-filling algorithm to the problem of cognitive radio transmit-power control in some research papers. We identify four of such, namely [2] [32]-[34].

In [2] and [32], Haykin proposed distributed water-filling algorithm for multiuser cognitive radio environment and developed useful mathematical notations to characterise the cognitive radio channel properties. Liao et al. [33] showed the characteristics of power control game for two users sharing two channels by water-filling strategy, first, as a cooperative and then, as a non-cooperative game. The results indicated that if the players are irrational, they will both choose to cooperate, and a channel each will be allocated until the end of the finite stage. Otherwise, if the players are rational they will adopt competition and allocate power on both channels and thus obtain maximum payoffs.

In [34], Laufer and Amir showed certain condition when the iterative water-filling procedure was suboptimal due to the occurrence of what is known as the Prisoners' Dilemma in game theoretic papers. They proposed a modified version of the algorithm, which was shown to perform optimally.

3.2.2 No-External Regret versus No-Internal Regret Learning Algorithm

In [27], Greenwald et al. defined two important regret variations, namely external regret and internal regret. An example of external regret is the concept of "boosting," as espoused by

Freund and Schapire in [35], which refers to the process of training a machine to accurately make predictions by a combination of logical deductions from history. An example of internal regret, on the other hand, is the concept of "regret-matching," as espoused by Gordon in [31]. Regret-matching is the probability distribution over the actions of a player, proportional to the regrets for having not played the other possible action sets. While the concept of boosting is limited because the predictions are inaccurate because they are chosen from a small discrete set of hypothesis, the advantage of regret-matching is based on the fact that the algorithm derives from procedures that adaptively adjust to accuracy over time.

Hart and Mas-Colell showed in [26] that correlated equilibrium can be attained by a procedure of play called "regret-matching." This work has inspired the application of no-regret to the problem of cognitive radio power control in some research papers, for example papers [36]-[38]. The procedure of regret-matching leading to correlated equilibrium was applied for distributed access point selection in a wireless network [36] and distributed opportunistic spectrum access for cognitive radio networks [37]. However, in [38] a modified version of the regret-matching learning algorithm was considered, where each player only needs to know his own realised payoffs and actions.

3.3 Considerations for the Implementation of Transmit-Power Control Techniques

In this section, we concentrate on the key design considerations required to achieve the control of transmit power at the transmitter. The objective is to have insights into various approaches, appreciate the performance issues associated with them and identify the most suitable for implementation in cognitive networks.

3.3.1 Transmit-Power Control Techniques

There are two ways of implementing power control in cognitive radio networks, namely centralised and distributed power control schemes. These are explained further below.

- ***Centralised Power-Control Scheme***:

In centralised cognitive radio networks, a central manager exists in the network to exchange information and control the transmission power of all secondary users within its coverage area.

The users cooperate fully and follow the instructions of the central controller. Figure 3.1 illustrates the centralised power-control scheme.

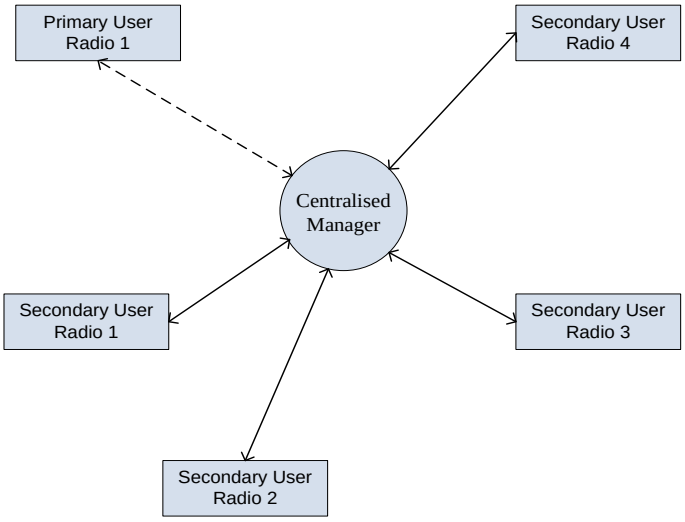


Figure 3.1: Centralised spectrum sharing scheme.

In the scenario specified in [39] and [40], transmission by secondary users in the network can only take place when secondary users are authorised by the central manager through information exchange. In [39], Le and Liang proposed that a Fuzzy Logic System (FLS) be integrated into cognitive networks. The FSL acts like an in-built fuzzy power controller to aid the secondary users to dynamically adjust their transmission power in response to the changes of the interference caused at the primary user. In [40], the optimal power control is modelled as a concave minimisation problem, considering the channel interference temperature constraints. Certain properties of the power control problem are then exploited to efficiently improve the power control of the system. Although [39] and [40] offer innovative ways of improving the interference in cognitive networks, there is the major problem of excessive signalling and information overhead caused by the distribution of global information about all links from the central controller to the users in the network.

A means of improving the efficiency of centralised power control are proposed in [41] and [42]. In [41] Raman and Mandayam investigated the efficiency of a centralised spectrum server that coordinates a group of links sharing a common spectrum, using a linear programming approach. In the procedure proposed by the paper, the server calculates link schedules to maximise the total throughput in the network. Ileri, Samardzija and Mandayam [42] developed a framework, which

can be used as a model for operators to broker spectrum resources to competing customers. In the model, the system collects spectrum requests, matches them to available spectrum, and makes use of demand responsive pricing to ensure fairness in frequency distribution. The improvements of centralised power control, as proposed by [41] and [42], does not however, address the problem of overhead generated when users communicate with the central manager.

- ***Distributed Power-Control Scheme***:

In the distributed settings, there is no centralised server or moderator and each user controls its transmit power by itself using only local information. Figure 3.2 illustrates the distributed power control scheme.

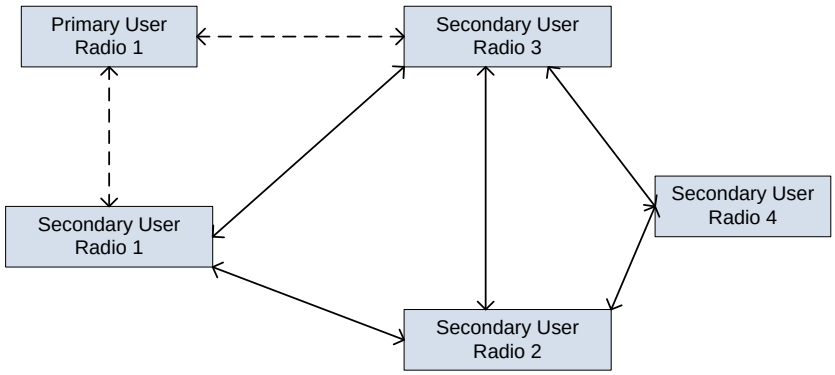


Figure 3.2 Distributed spectrum sharing scheme.

Distributed power control avoids the signalling bottlenecks and information overhead associated with having users communicate with a centralised manager. However, the problems with the distributed power-control scheme are due to, (i) the severe non-cooperation of the secondary users and, (ii) the interference from the transmit power of the all distributed secondary users being above the interference temperature threshold. The problem of non-cooperation can be solved by the use of game theoretic concepts, as applied in [43], while the problem of interference can be solved by the use of distributed algorithms, as defined in [44] and [45].

In [43], Neel and Reed modelled a low-complex autonomous distributed channel assignment algorithm based on game theory. They showed by simulations that if the algorithm is applied to

cognitive radio networks, each node derives the same utility from the available spectrum. The nodes then decide on the maximisation of their utility, subject to the actions of their neighbours.

In [44], a distributed joint coordination and power control algorithm, regarded as Joint Coordination and Power Control (JCPC) algorithm, is proposed to maximise the system capacity of secondary users in a cognitive radio network. The JCPC algorithm works by allocating transmission power to all secondary users in the network.

In [45], Qian et al. proposed a distributed cognitive radio network aided by a "genie" placed near the primary receiver to monitor the interference level and inform the secondary users when the interference level caused by their opportunistic activities becomes too high, or above the interference temperature limit.

3.3.2 Learning for Better Equilibrium

Chapter Two clearly establishes the fact that game theory provides us with defined equilibrium solution concepts with which to measure the optimality of any game under various conditions. Most research papers that focus on the use of the algorithms to correct the problem of transmit-power control in cognitive radio networks are based on the Nash equilibrium [46] and correlated equilibrium [37] [46]-[48], as necessary solution concepts. Other equilibrium concepts that are also defined for the same purpose are dominant equilibrium, Stackelberg equilibrium [49], conjectural equilibrium, and so forth.

In [46], the authors propose a non-cooperative power control game via linear pricing. The outcome of the game results in a Nash equilibrium that is efficient, but unfair to the cognitive radio users. In [47], the authors defined a power control algorithm and a new pricing function with interference temperature constrains to control the network's power consumption in a distributed cognitive radio network game model. The Nash equilibrium is identified as the outcome of the game with optimal power allocation policy. Though the game was measured to guarantee some extent of fairness for the users, the Nash equilibrium is not considered as an efficient solution concept for stochastic games, due to the fact that it is based on only local information available to users. The efficiency of the system can significantly be improved when users are made to have information about the environment and other users.

In [48], Maskery et al. proposed a game theoretic approach to opportunistic spectrum access. In the model, Carrier Sense Multiple Access (CSMA) is used with an adaptive concept known as "regret-tracking," to capture the activities of every user in the network. The game converges to correlated equilibrium and each radio learns to respond optimally to its environment.

Han [37] proposed a distributed protocol based on an adaptive learning algorithm for multiple secondary users using only local information. The distributive users adjust their transmit power probabilities over the available channel and their actions converge towards correlated equilibrium.

3.4 Summary

This chapter reviewed existing research work related to cognitive radio transmit-power control. The second section presented literature review on the different variants of the no-regret learning algorithm and the iterative water-filling algorithm. Based on the analysis of these variants, the no-internal regret learning algorithms and the distributed iterative water-filling algorithms are preferred.

The third section dealt with literature review on the key considerations for the design and implementation of spectrum access games. Based on the analysis, the distributed transmit-power control scheme is more advantageous than the centralised transmit-power control scheme, because it avoids signalling and information overhead generated when secondary users communicate with a centralised manager.

Literature review of various equilibrium concepts suggests that better equilibrium solutions exist than the Nash Equilibrium when game theory is applied to transmit-power control problem in a cognitive radio.

Chapter 4

4 Theoretical Framework of Transmit-Power Control Techniques

4.1 Introduction

This chapter presents in-depth theoretical survey of the two options of transmit-power control under review, namely the iterative water-filling algorithm and the no-regret learning algorithm. A simple scenario is defined in which the algorithms can be separately applied, given the same conditions and assumptions. Furthermore, the chapter introduces a hybrid-adaptive scheme which combines the two algorithms into its operational functions.

We consider a system in which secondary users opportunistically exploit the wireless spectrum licensed to primary users. We assume that secondary users can intelligently make decisions on the approach to adopt in accessing the licensed spectrum, depending on the wireless access protocol, which is obtained at the primary user network. Figure 4.1 below demonstrates the basic system design of cognitive radio networks sharing the unused licensed spectrum with primary users.

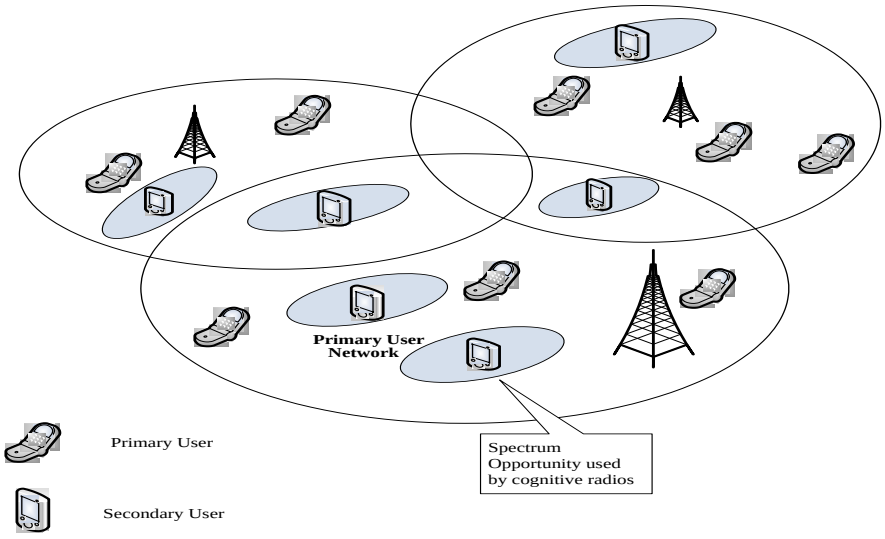


Figure 4.1: Illustration of channel availability for secondary users.

In this thesis, a two-user cognitive network is considered for analysis. We appreciate that the application of both the iterative water-filling algorithm and the no-regret learning algorithm to cognitive network extends far beyond two-user games. Indeed, in most research studies, there are several participants. However, the assumptions, derivations and submissions made here can be generalised to multi-user scenarios.

Section 4.2 and 4.3 presents theoretical details on the iterative water-filling algorithm and the no-regret learning algorithm respectively.

4.2 Iterative water-filling algorithm

Section 3.2.1 describes two procedures for transmit-power control in DSL multiuser environment; these are competitive optimality power control, or rate-adaptive water-filling, and distributed power control, or power-adaptive water-filling. We focus on the application of distributed power control strategy to cognitive radio.

Consider that in Figure 4.1, two secondary users communicate across a flat-fading Frequency Division Multiple Access (FDMA)-based RF channel in a non-cooperative manner. Assume that the first transmitter, transmitter 1, transmits the signal x_1 with power $\mathbf{P}_1$, and the second transmitter, transmitter 2, also transmits x_2 with power $\mathbf{P}_2$. Assume also $ij \, \epsilon \, \{1, 2\}$ defines the communication link between the transmitters and receivers, as shown in Figure 4.2.

We thus model the signals at the two receivers as:

$$y_1 = h_{11}x_1 + h_{21}x_2 + n_1$$
$$y_2 = h_{22}x_2 + h_{12}x_1 + n_2 \quad (1)$$

Where n_1 and n_2 are additive noise. The transmit and receive signals are vector-valued and hence, communication links can be represented by the complex-valued baseband channel matrix.

$$\mathrm{H} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}. \quad (2)$$

The channel matrix represented by (2), is a function of the geographical positioning between transmitters and receivers. Assume that the secondary users are equipped with Global

Positioning Satellite (GPS) receivers to enable them to be aware of the geographical differences between transmitters and receivers. This difference is a factor in calculating the path loss incurred in the course of electromagnetic propagation of the transmitted signal to each receiver in the transmitter's operating range [2]. From [50], we get an idea to calculate for the complex-valued channel coefficient from transmitter *i* to receiver *j*, which is denoted as h_{ij}

$$|h_{ij}|^2 = \frac{P_{R,j}}{P_{T,i}} = \frac{\beta}{d_{ij}^m}, i = 1,2, \dots n; j = 1,2, \dots n \quad (3)$$

Where P_R denotes the received signal power, P_T is the transmitted signal power, m denotes the path-loss exponent, which varies from 2 to 5 depending on the environment, β is the attenuation parameter, which is dependent on frequency, and d denotes the distance from transmitter to receiver.

We may express the received signal power P_R in terms of the transmitted signal power P_T as follows:

$$P_R = \left(\frac{\beta}{d^m}\right) P_T \quad (4)$$

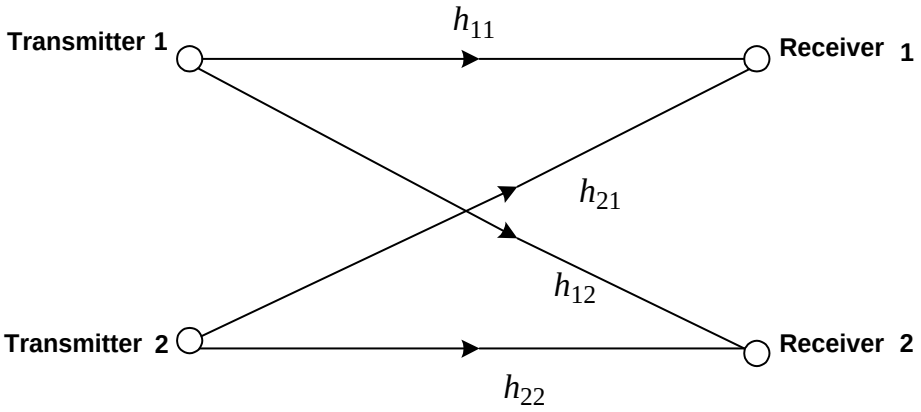


Figure 4.2: Signal flow graph of two-user communication scenario.

Figure 4.3 [28] illustrates the operations of a distributed power control algorithm. It involves a two-loop process; inner loop and outer loop.

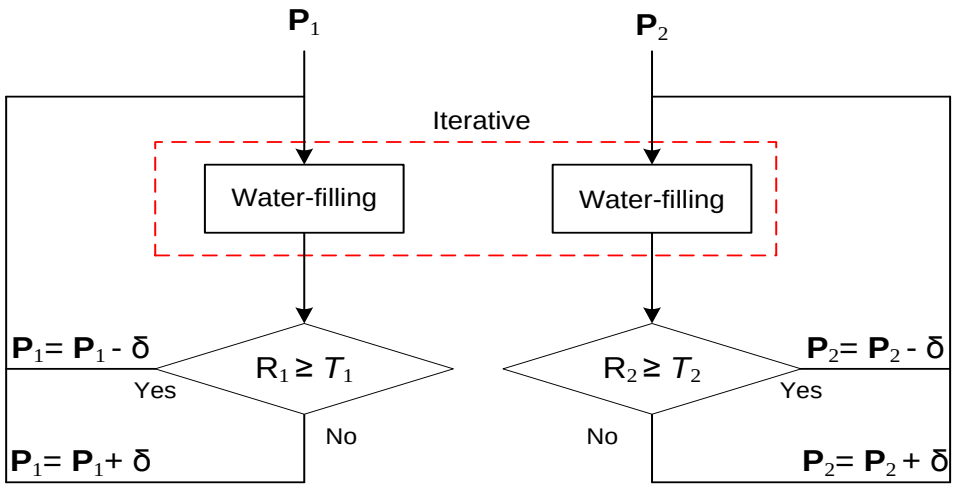


Figure 4.3: Distributed power control by iterative water-filling.

- ***Inner Loop***

At the initial stage of the inner loop, Power Spectral Densities (PSD) or pure strategies for transmitter i, are set to zero, $P_i(f) = 0$. Target data rates, T_i, and maximum transmission power, $\mathbf{P}_i$, are identified for users $i \in \{1,2\}$, within permissible interference temperatures limits, so that:

$$\int_0^{F_s} P_i(f)df \leq \boldsymbol{P}_i \tag{6}$$

The PSD, $P_i(f)$, as represented by (6), is intended for continuous spectra. The integration of the PSD over a given frequency band gives the average power in the signal over that frequency band [28].

Receiver 1 and 2 will first evaluate the channel capacity. The transmitters are equipped with centralised agents, which gain knowledge of the environment through feedback channel from the receivers. The transmitters will then attempt to adjust their transmit power processes up to a given "water-filling level." The water-filling level is a function of channel capacity and a derivative of PSD, cross-coupling effect and noise.

User 1 and 2 will sequentially perform water-filling procedures to increase the PSD by a factor (δ) to occupy the channel capacity. We represent cross coupling between user 1 and user 2 as $\propto_1$and $\propto_2$:

$$\propto_1 = \frac{\Gamma|h_{12}|^2}{|h_{22}|^2} \tag{7}$$

$$\propto_2 = \frac{\Gamma|h_{21}|^2}{|h_{11}|^2} \tag{8}$$

The term Γ is "SNR gap," which measures the proximity of data rates to a highest theoretically achievable data rate known as the channel capacity.

SNR gap, Γ, is defined by:

$$\Gamma = \frac{1}{3} . \left[Q^{-1}\left(\frac{P_S}{4}\right)\right]^2, \Gamma \geq 1 \tag{9}$$

Where $Q^{-1}(\cdot)$ is the inverse Q –function, and P_S defines symbol error probability.

We represent noise terms $N_1(f)$ and $N_2(f)$ as:

$$N_1(f) = \frac{\Gamma\, \sigma_1(f)}{|h_{11}|^2} \tag{10}$$

$$N_2(f) = \frac{\Gamma\, \sigma_2(f)}{|h_{22}|^2} \tag{11}$$

Where $\sigma_1(f)$ and $\sigma_2(f)$ defines the noise power of the channel, and h_{11} and h_{22} denotes the direct channel between the transmitter and receiver.

Hence, we represent the water level, L_1 and L_2 as:

$$L_1 = P_i(f) + \alpha_2(f)P_2(f) + N_1(f) \tag{12}$$

$$L_2 = P_i(f) + \alpha_2(f)P_2(f) + N_1(f) \tag{13}$$

At the first iteration, transmitter 1 first attempts to occupy the channel. This procedure by user 1 is done taking maximum permissible transmit power and noise into consideration. In the next sequence, transmitter 2 follows the same procedure subject to its own maximum permissible transmit power, taking interference by user 1 and noise into account.

The results of the iterative water-filling procedure at the inner loop stage are values of competitive optimal power allocation for user 1 and user 2 with the associated data rates. We formulate the achievable data transmission rates R_1 and R_2 using Shannon's equation:

$$R_1 = \int_{hole\ 1} \log_2 \left(1 + \frac{p_1(f)}{N_1(f)+\propto_2 p_2(f)}\right) df \quad (14)$$

$$R_2 = \int_{hole\ 2} \log_2 \left(1 + \frac{p_2(f)}{N_2(f)+\propto_1 p_1(f)}\right) df \quad (15)$$

- ***Outer Loop***

At the outer loop stage, the two receivers compare and evaluate the resulting data rates from the inner loop iteration against the target data rates. If the data rate of any user is found to be less than its target data rate, the transmit power of the user is increased. If however, the data rate is found to be greater than its target data rate, the transmit power of the user is reduced. This process goes on iteratively and convergence to equilibrium is reached when the target data rates of the two users are attained.

Algorithm 1 presents the sequence of the iterative water-filling algorithm:

Algorithm 1: Iterative Water-Filling Algorithm

---

1. *Initialisation*: Set the transmit power for the two users to zero. Identify the target data rates and power constraints: $T_i = T$; $\mathbf{P}_i = \mathbf{P}$; $P_i(f) = 0$ for $i = 1,2, \dots, K$.
2. *Inner loop (iteration)*: For $i = 1$ to K users **do**

   Set $P_i(f)$ to be water-filling spectrum with noise $N(f)$, cross coupling effect ($\propto_i$) and total power $\mathbf{P}_i$

   Where,

   $N(f) = \frac{\Gamma\, \sigma_i(f)}{|h_{ii}|^2}$

   $\propto_i = \frac{\Gamma |h_{ii}|^2}{|h_{ii}|^2}$

   Where $\sigma_i(f)$ defines the noise power of the channel, and h_{ii} denotes the direct channel between transmitter and receiver.

   Calculate R achieved with current power
3. *Outer loop*: If $R_i > T_i$, set $\mathbf{P}_i = \mathbf{P}_i - \delta$
4. If $R_i < T_i$, set $\mathbf{P}_i = \mathbf{P}_i + \delta$
5. If $\mathbf{P}_i > \mathbf{P}$, set $\mathbf{P}_i = \mathbf{P}$

4.3 No-Regret Learning Algorithm

As explained in Chapter 2, the no-regret learning algorithm has its root in game theory and it serves as an alternative to the iterative water-filling algorithm for dealing with the problem of transmit-power control in cognitive radio networks. This section details with the theoretical representation of the various game theoretic ingredients necessary for the formulation of the no-regret learning algorithm. These ingredients are equilibrium, strategy, utility function and the no-regret function, based on [17], [21], [26] and [37].

- ***Equilibrium***

The essence of applying game theory to the problem of power control in cognitive radio is to develop strategies that can lead to optimum utilisation of radio frequencies. The concept of equilibrium in game theory has been extensively reviewed in Chapter 2. The Nash equilibrium is a widely known solution concept for analysing the outcome of a game. At Nash Equilibrium point, each player's strategy is optimal, given the strategies of all other players. A game can have either a pure-strategy or mixed-strategy Nash equilibrium.

Definition 4.1: *The pure strategy profile, s*, of a game is a Nash equilibrium if, for each player i:*

$$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*), \forall\, s_i \,\epsilon\, S_i \tag{16}$$

where S_i represents the pure strategy space of player i, u_i defines the payoffs or utility that quantifies the outcome of the game of player i, s_i and s_{-i} represents the strategy of player i and that of player i's opponents respectively.

A pure strategy Nash equilibrium is one in which a player chooses any action with a probability of either 0 or 1.

Definition 4.2: *The mixed strategy Nash equilibrium, $\sigma_i(s_i)$, of a player i is one in which the player plays his available pure strategies, $s_i \epsilon\, S_i$, with certain probabilities. Player i's payoff to profile σ is thus given as:*

$$u_i(\sigma) = \sum_{s_i \epsilon S_i} \sigma_i\,(s_i) u_i(s_i, \sigma_{-i}) \tag{17}$$

Where σ defines the mixed strategy of player i and $\sigma_i \epsilon\ \Sigma_i$ defines his mixed strategy space.

Next, we show how to derive pure strategy Nash equilibrium and mixed strategy Nash equilibrium of a game using a reward table.

Consider the two-secondary user game, as shown in Table 4.1:

$\boldsymbol{p_1 \backslash p_2}$	**0.5**	**1**
0.5	4,4	2,5
1	5,2	0,0

Table 4.1: Reward table.

The table illustrates two secondary users, $\boldsymbol{p_1}$ and $\boldsymbol{p_2}$, with different possible actions, 0.5 and 1, representing the transmit power of the users respectively. The utility function is listed in corresponding rows and columns. As indicated, when the two users transmit at high power, for instance 1, they have no corresponding payoffs, but if any user transmits more aggressively, for example 1, than the other, for example 0.5, the aggressive user has a better utility, while the other has a lower utility and the overall benefit is not optimal, for instances a utility of 7. If, however, they both transmit with moderate transmit power, they have higher utilities and the best overall benefit, an 8 for instance.

Table 4.2 below illustrates the pure-strategy Nash equilibrium of the game represented in Table 4.1. Two Nash equilibria is shown, where one user dominates the other. As stated in Definition 4.1, it is shown that the probability of any player to choose an equilibrium strategy is 1, while the probability of not choosing equilibrium strategy is 0. At the pure strategy Nash equilibrium positions, which is also the best response strategy of the players from individual perspectives, the dominating user has a utility of, 5 while the dominated user has a utility of 2, which is unfair.

$p_1 \backslash p_2$	**0.5**	**1**
0.5	0,0	0,1
1	1,0	0,0

Table 4.2: Nash equilibrium.

To solve for mixed Nash equilibrium using Table 4.1, we make reference to Definition 4.2, which indicates that a player's strategy of play follows a probability distribution. Calculus is used to calculate the optimal mixed strategy of $\boldsymbol{p_1}$ and $\boldsymbol{p_2}$.

Let *a* be the probability that player $\boldsymbol{p_1}$ chooses to transmit at a high power, 1 in this case, and 1- *a* is the probability that he chooses to transmit at a lower power, 0.5. Similarly, let *b* be the probability that player $\boldsymbol{p_2}$ chooses to transmit at a high power and 1- *b* is the probability that it chooses to transmit at a low power.

Solving the mixed strategy using (16), we get:

$$E(\Pi_2) = (1-a)*(1-b)*4 + a*(1-b)*5 + (1-a)*b*2 + a*b*0$$
$$= (1-a-b+ab)*4 + (a-ab)*5 + (b-ab)*2$$
$$= 4 - 4a - 4b + 4ab + 5a - 5ab + 2b - 2ab$$
$$= 4 - a - 2b - 3ab$$

Differentiating with respect to *a*, we get:

$$\frac{dE(\Pi_2)}{da} = 0 + 1 + 0 - 3b = 0$$

Therefore, $1 - 3b = 0$

$b = \frac{1}{3}$, which is the probability of a high power transmission for player $\boldsymbol{p_2}$

Hence, the probability of a low power transmission for player $\boldsymbol{p_2}$ is given as:

$$1 - b = 1 - \frac{1}{3} = \frac{2}{3}$$

$1 - b = \frac{2}{3}$

$$E(\Pi_1) = (1-a)*(1-b)*4 + a*(1-b)*2 + (1-a)*b*5 + a*b*0$$
$$= (1-a-b+ab)*4 + (a-ab)*2 + (b-ab)*5$$

$$= 4 - 4a - 4b + 4ab + 2a - 2ab + 5b - 5ab$$
$$= 4 - 2a - b - 3ab$$

Differentiating with respect to *b* we get:

$$\frac{dE(\Pi_1)}{da} = 0 + 0 + 1 - 3a = 0$$

Therefore, $1 - 3a = 0$

$a = \frac{1}{3}$, which is the probability of a high power transmission for player $\boldsymbol{p_1}$

Hence, the probability of a low power transmission for player $\boldsymbol{p_2}$ is given as:

$$1 - a = 1 - \frac{1}{3} = \frac{2}{3}$$

		2/3	1/3
	$\boldsymbol{p_1 \backslash p_2}$	**0.5**	**1**
2/3	**0.5**	4/9	2/9
1/3	**1**	2/9	1/9

Table 4.3: Mixed Nash equilibrium.

Table 4.3 shows the mixed Nash equilibrium where both users have 1/3 for action 0.5 and 2/3 for action 1 respectively. Further, it is essential to calculate the utility for each player.

If $\boldsymbol{p_1}$ transmits at a high power with probability of 2/3 and transmits at a low power with probability of 1/3, then his expected utility is valued at:

$$U_{p_1} = \left(\frac{2}{3} * \frac{2}{3} * 4\right) + \left(\frac{2}{3} * \frac{1}{3} * 2\right) + \left(\frac{1}{3} * \frac{2}{3} * 5\right)$$
$$= \left(\frac{16}{9}\right) + \left(\frac{4}{9}\right) + \left(\frac{10}{9}\right) = \frac{30}{9}$$
$$= 3.33$$

Since the game is a zero-sum game, the same value of utility also applies to $\boldsymbol{p_2}$. Hence, with mixed strategy Nash equilibrium, both $\boldsymbol{p_1}$and $\boldsymbol{p_2}$ have utility of 3.33.

Next, we compare the utility of both users using the mixed strategy with the utility they will have with correlated equilibrium, which is considered to be a better solution concept than the Nash equilibrium.

Definition 4.3: *A correlated equilibrium is a probability distribution p on* $S_1 \times S_2 \times ... \times S_N$ *strategy set for every player i, and for any* s_i', $s_i \in S_i$, *it holds that:*

$$\sum_{s_{-i} \epsilon S_{-i}} p(s_i, s_{-i})\, u_i(s_i, s_{-i}) \geq \sum_{s_{-i} \epsilon S_{-i}} p(s_i, s_{-i})\, u_i(s_i', s_{-i}) \qquad (18)$$

Again, with reference to the game illustrated in Table 4.1, assume that the users have an idea of the past outcomes of such games. Assume also that the users can make trusted decisions based on lessons of the past. These lessons only apply to individual users' decisions, and do not influence the thinking of each user on the decisions the other user will make. The probability distribution of play converges to correlated equilibrium if no player deviates from the trusted history lessons.

Judging from history, the users are individually equipped with the knowledge of probabilities of the possible outcomes of any strategy they choose. The strategies where both users transmit aggressively are situations, they will both want to avoid, hence such a combination has a probability of 0. The probabilities that each user will choose any combination of action 0.5 and 1 are defined in percentages and distributed accordingly to all possible combinations of the game. Table 4.4 shows correlated equilibrium as probability distribution of play in terms of percentages.

p($p_1 = 0.5 | \, p_2 = 0.5$) = 0.50

p($p_2 = 0.5 | \, p_1 = 0.5$) = 0.50

p($p_1 = 0.5 | \, p_2 = 1$) = 0.25

p($p_2 = 1 | \, p_2 = 0.5$) = 0.25

p($p_1 = 1 | \, p_2 = 1$) = 0.00

p($p_2 = 1 | \, p_1 = 1$) = 0.00

$p_1 \backslash p_2$	**0.5**	**1**
0.5	0.5 |50%|	0.25 |25%|
1	0.25 |25%|	0 |0%|

Table 4.4: Correlated equilibrium.

Following the recommendations of history, the utility $\boldsymbol{p_1}$ is expected to derive is given as:

$$U_{p_1} = (4 * 0.5) + (2 * 0.25) + (5 * 0.25)$$
$$U_{p_1} = 3.75$$

This value is 11.2% more than their expected utility using mixed strategy Nash equilibrium.

- ***Strategy***

Consider the model represented in Figure 4.1. Assume that secondary cognitive users exist to opportunistically access primary users' licensed spectrum using the various ingredients of stochastic games listed in Section 2.9.3. Assume that the network has *M* primary users located in a network of *N* licensed frequency bands. When the primary users are idle and depending on their activities, there will be *n* channels available for secondary users to access. Assume that there are *K* secondary users waiting to compete for the available channels. Let each channel represent a unit bandwidth and a set of user *i* is represented by the finite set *I*, where $i = 1, 2, 3 \ldots K$. Competition for available channels are in terms of packet transmission. If collision occurs as a result of competition, it will result in packet wastes or losses.

We define the channel availability, *A*, at time, *t*, as a function of secondary users $i = 1, 2, 3 \ldots K$, and available channel, *N*. This we represent by a *K* by *N* matrix function with elements, defined as:

$$\boldsymbol{A}_{in}(t) = \begin{cases} 1, \text{if channel } n \text{ is available for secondary,} \\ \quad \text{user } i \text{ at time } t, \\ 0, \text{otherwise.} \end{cases} \tag{19}$$

When the secondary users have access to the channel, the interference between adjacent secondary users, dependent on their geo-location, is defined as a *K* by *K* matrix with elements:

$$\mathbf{L}_{ij} = \begin{cases} 1, \text{if } i \text{ and } j \text{ interfere with each other,} \\ 0, \text{otherwise.} \end{cases} \quad (20)$$

Let r_i^n represent the actions of user *i* over channel *n*, while r_{-i}^n denotes the actions of user *i*'s opponent over the same channel.

Assume that a secondary user can select $L + 1$ discrete rates over every available channel. User *i's* actions causes corresponding rates of $v_0, v_1, \ldots v_L$. Hence, we can express the rates over available channels as:

$$\boldsymbol{\gamma} = \{v_0, v_1, \ldots, v_L\} \quad (21)$$

Where $v_0 = 0$.

Thus, strategy space of user *i* on the available channel can be represented as:

$$\Omega_i = \prod_{n=1}^{N} \boldsymbol{\gamma}^{\mathrm{A}_{in}} \quad (22)$$

The strategy space of user *i*'s opponents can also be given as:

$$\Omega_{-i} = \prod_{n=1}^{N} \boldsymbol{\gamma}_{-i}{}^{\mathrm{A}_{in}} \quad (23)$$

The strategy profile of all secondary users over channel *n* is given as:

$$\mathbf{r}^n = (r_1^n, r_2^n, \ldots, r_K^n)' \quad (24)$$

From (24), we can define the strategies of all user *i*'s opponents over channel *n* as r_{-i}^n.

The strategy profile for all secondary users over all channels is thus given as:

$$\mathbf{r}_i = (r_i^1, \ldots, r_i^N)' \quad (25)$$

From (24), we can define the strategies of all user *i*'s opponents' action as $\mathbf{r}_{-i}$.

- ***Utility function***

The result of resource competition between user *i* and his opponents for channel *n* can be expressed as:

$$R_i\,(r_i^n, \mathbf{r}_{-i}^n) \quad (26)$$

When user *i* has packets to send, it first senses the channel. If it finds the channel busy, it persists to wait and transmits as soon as the channel becomes idle. Hence, the channel is always used if there is a user with a packet.

In order to proceed further, it is essential to make some assumptions and specifically define the term utility function as it applies to our model. The assumptions are based on the specifics of un-slotted 1-persistent CSMA as the random multiple access protocol for the secondary users [51] [52].

Assumptions:

i. Assume that τ is the propagation delay over packet transmission time between every pair of secondary users;
ii. Assume that packet payload in the network is defined by the function, *G*, and the summation of user *i*'s action, $\sum_i r_i^n$, results in average packet payload for channel *n*, given as G^n. Hence, $\sum_i r_i^n = G^n$;
iii. Secondary users can increase in the network to compete for the unused channel. If multiple secondary users transmit their data at the same time, collision will occur and there will be an increase in the average payload in the network. We define the maximum attainable network payload or channel bandwidth as G_0;
iv. The increase in network payload causes an increase in average delay. Penalties due to network collision are in the form of packet losses and packet wastes. We define a function to characterise average network losses and denote this by the function, *S*.

The throughput for channel *n* is thus given as:

$$S^n = \frac{G^n[1+G^n+\tau G^n(1+G^n+\tau G^n/2)]e^{-G^n(1+2\tau)}}{G^n(1+2\tau)-\left(1-e^{-\tau G^n}\right)+(1+\tau G^n)e^{G^n(1+\tau)}}, \quad (27)$$

Hence, following the above assumption, we can define the result of resource competition in the network, $R_i(r_i^n, \mathbf{r}_{-i}^n)$, by:

$$R_i(r_i^n, \mathbf{r}_{-i}^n) = \begin{cases} \frac{r_i^n S^n}{\sum_i r_i^n}, \text{if G} \leq \text{G}_0 \\ 0, \text{ otherwise} \end{cases} \quad (28)$$

The utility function can be regarded as a measure of benefits derived when certain actions are applied in a game. In the model, utility is a function of the achievable data rates of the secondary users. Hence, putting (19) and (28) together, utility function for user *i* over all available channels can be denoted as:

$$U_i = \sum_{n=1}^{N} \boldsymbol{A}_{in} R_i(r_i^n, \mathbf{r}_{-i}^n) \tag{29}$$

- ***The no-regret function***

Next, we undertake to apply the utility function previously derived to a class of game theoretic algorithm called regret-matching algorithm [31]. Here, the algorithm is revealed in sufficient theoretical details.

Assume user *i* has two actions to choose from, $\mathbf{r}_i \neq \mathbf{r}'_i$ in Ω_i. His average regrets at period *t* for not having played, every time that $\mathbf{r}_i$ was played in the past, the different strategy $\mathbf{r}'_i$ is given as:

$$R_t^T(\mathbf{r}_i, \mathbf{r}'_i) := \max\{D_t^T(\mathbf{r}_i, \mathbf{r}'_i, 0\} \tag{30}$$

Where:

$$D_i^T(\mathbf{r}_i, \mathbf{r}'_i) = \frac{1}{T} \sum_{t \leq T} \Big(U_i^t(\mathbf{r}'_i, \mathbf{r}_{-i}) - U_i^t(\mathbf{r}_i, \mathbf{r}'_i) \Big). \tag{31}$$

$D_i^T(\mathbf{r}_i, \mathbf{r}'_i)$ can be defined as the average payoff that user *i* would have obtained, had it played action $\mathbf{r}'_i$ every time in the past instead of $\mathbf{r}_i$. The probability for user *i* to take action $\mathbf{r}_i$ is a linear function of regret and $R_t^T(\mathbf{r}_i, \mathbf{r}'_i)$ is a measure of average regret.

As an illustration, if $\mathbf{r}_i \in \Omega_i$ is a strategy last chosen by user *i* at time *t*, the probability distribution action for next period, p_i^{t+1}, is defined as:

$$\begin{cases} p_i^{t+1}(\mathbf{r}'_i) := \frac{1}{\mu} R_i^T\ (\mathbf{r}_i, \mathbf{r}'_i), \text{ for all } \mathbf{r}'_i \neq \mathbf{r}_i \\ p_i^{t+1}(\mathbf{r}_i) := 1 - \sum_{\mathbf{r}'_i \neq \mathbf{r}_i} p_i^{t+1}(\mathbf{r}'_i), \end{cases} \tag{32}$$

Where μ is a constant that is sufficiently large.

For every time, *T*, let $z_T \in \Delta(\Omega)$ be the distribution of strategies played until time, T:

$$z_T(\mathbf{r}) := \frac{1}{T} |\{t \leq T : \mathbf{r}_t = \mathbf{r}\}|, \tag{33}$$

Where $\mathbf{r}_t$ defines all users' action at time t.

Algorithm 2 presents the no-regret learning algorithm in sequential details.

Algorithm 2: No-regret learning Algorithm

---

1. *Initialisation*: User i, where $i = 1, 2, 3 \ldots K$, starts from a reference point and selects an action with arbitrary probability from a strategy, $\mathbf{r}_i \neq \mathbf{r}'_i$ in Ω_i.
2. *Find average payoff*: Using the utility function (29), find the average payoff user *i* would have obtained if it had chosen the alternative strategy through a period of time *t* = 1,2,3,…,*T*. The numerical value of the term "regret" is the difference in payoff between the chosen strategy and alternative strategy.
3. *Derive average regret*: The average regret is proportional to the average payoff that would have been derived over time *t* = 1,2,3,…,*T*, if the alternative strategy had been chosen every time.
4. *Derive iterative probability distributions from equilibrium theory*: Using the same strategy that was used to compute average regret, $\mathbf{r}_i$ or $\mathbf{r}'_i$ in Ω_i, calculate the joint probability distribution of the users' equalising strategy for the four possible combinations (p_{11}, p_{12}, p_{21} and p_{22}), using any notion of equilibrium and based on the requirement define below:

$$\begin{cases} p_i^{t+1}(\mathbf{r}'_i) := \dfrac{1}{\mu} R_i^T\ (\mathbf{r}_i, \mathbf{r}'_i), & \text{for all } \mathbf{r}'_i \neq \mathbf{r}_i \\ p_i^{t+1}(\mathbf{r}_i) := 1 - \displaystyle\sum_{\mathbf{r}'_i \neq \mathbf{r}_i} p_i^{t+1}(\mathbf{r}'_i), \end{cases}$$

Where μ is a constant that is sufficiently large.

5. *Confirmation step*: Confirm that the decision converges to equilibrium with each iterative procedure. If not, go back to stage 1, otherwise declare the number of iterations.

4.4 Hybrid No-Regret and Iterative Water-Filling Adaptive Scheme

The cognitive engine of the envisioned hybrid no-regret and iterative water-filling adaptive scheme is shown in Figure 4.4. In the architecture, the cognitive engine combines the iterative water-filling algorithm and the no-regret learning algorithm into its operational functions, to perform modelling, learning and optimization processes.

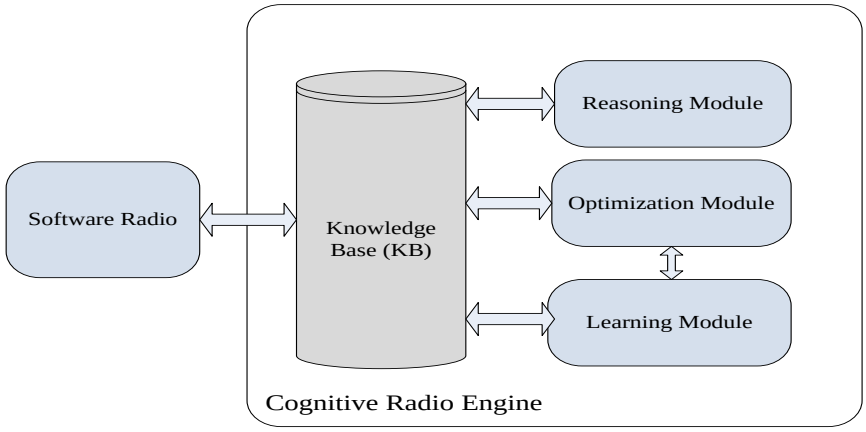


Figure 4.4: The cognitive engine.

The diagram shows the interaction between the core components of the cognitive engine and the SDR. It is consistent with a similar model presented in [53], but it however differs with the introduction of an optimization module into the operations of the cognitive engine. In the model, the cognitive engine interfaces with software radio through application programming interface (API). The cognitive engine controls software modification of external signal processes and comprise of knowledge base, reasoning module, optimization module and learning module.

The knowledge base is a repository of information connecting different external states to series of actions. At every given time, the reasoning module searches and evaluates all possible actions in the knowledge base to determine the most suitable executable action. The optimization and learning module are responsible for populating and updating the list of actions in the knowledge base. The optimization module creates power optimizing actions based on the scarcity of resources and limitations caused by interference. The learning module generates actions based on game theoretic learning processes.

The optimization module and the learning module are equipped with algorithms like the iterative water-filling algorithm and the no-regret learning algorithm respectively. In Figure 4.4, the two modules are interfaced to provide a means of synchronizing their functions. When a wireless device is powered-up for the first time, the learning module and the optimization module auto-generates actions with the aid of these algorithms. When the software radio exports information about the system to the knowledge base at any given time, the information is mapped to the generated actions. The reasoning engine then looks at the current state and evaluates the entire possible actions executable in that state to guarantee optimality.

Under the operations of the proposed hybrid no-regret and iterative water-filling adaptive scheme, the cognitive radio can at all times be able to favourably adapt its transmission strategies to mitigate the effects of environmental changes, which can be due to network resources, application data and user behaviours. The cognitive engine is built with some forms of intelligence to enable it to analyse various environmental scenarios and then make judgments on switching between the operational functions of the two algorithms.

4.4.1 Operational Procedures of the Hybrid-Adaptive Scheme

The aim is to combine the functionalities of the two algorithms so that the new hybrid algorithm conducts both global and local evaluations, and hence, the probability of finding the optimal transmission strategies is increased significantly. The following illustrates the operational procedures of the hybrid-adaptive scheme:

1. *Initialisation*: After the initial set-up procedure, the cognitive users will attempt to establish communication in the cognitive radio network.
2. *Spectrum sensing and evaluation*: The cognitive radio devices will sense the available spectrum holes and perform general assessment of the air interface, to determine how to adapt their operations for effectively communication to be established.
3. *Procedure 1*: Based on results obtained from the sensing and evaluation stage, the devices will commence the first procedure towards gaining opportunistic assess of the wireless medium. In this stage, the users will choose to adopt either the functionalities of the optimisation module, i.e. the iterative water-filling algorithm, or the learning module,

i.e. the no-regret learning algorithm. After procedure 1, the transmit power processes of the users are adjusted to required values.

4. *Evaluation using threshold*: Thresholds are defined and associated with certain performance metrics to guide against any form of unevenness in spectrum distribution among the users.

   A kind of centralize agent will exist in the network to track generated alert and check the performances of the cognitive users against the defined threshold. If the differences in the performance metrics of the users exceed the defined threshold an alert is generated. The devices are then induced to switch functions to the second procedure, otherwise stability is reached and the process is stopped and restarted after certain time duration. The essence of looping the first procedure based on a time duration is to ensure that the transmit power of users are checked all through the time that they make use of the available spectrum holes.

5. *Procedure 2*: The system reaches the second procedure if the performance metrics of the users in the first procedure exceed the defined threshold. However in the second procedure, the other of the two algorithms used in the first procedure is employed by the cognitive users to find the optimal utilization of the radio spectrum.

6. *Convergence evaluation*: After the second procedure, the central agent evaluates the transmit power of the users to determine if convergence is reached and there is a fair distribution of the available spectrum. If convergence is reached, the procedure is looped after a fixed time duration, otherwise Procedure 2 is restarted.

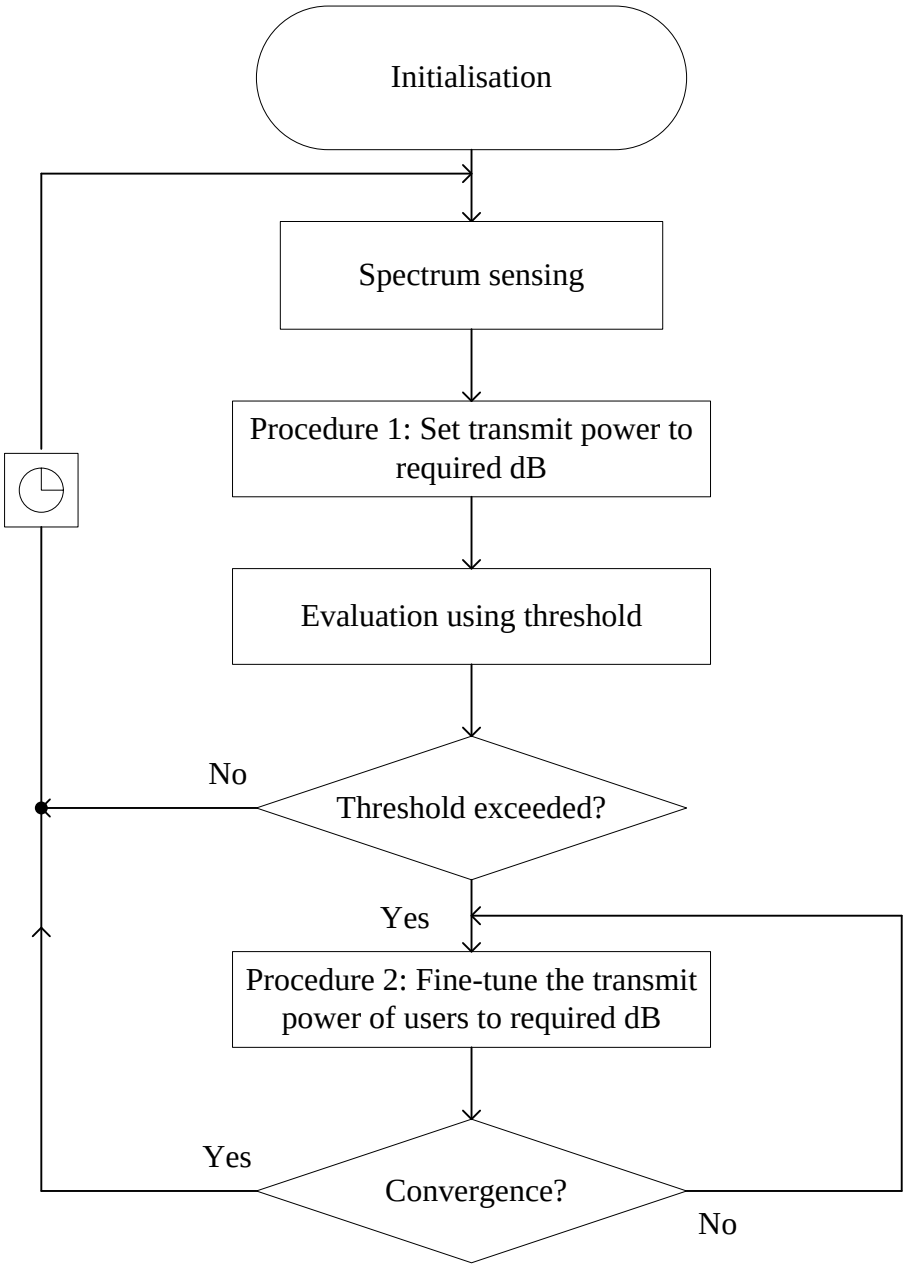


Figure 4.5: Flow chart of the operational procedure of the hybrid-adaptive scheme.

4.4.2 Test-Case Analyses of the Hybrid-Adaptive Scheme

This section presents a model of the operations of the hybrid-adaptive scheme based on a specific test-case problem.

- ***Punishment for an errant user***

  In modern day, communication systems and access devices are designed based on standards. When the cognitive radio technology becomes fully operational, standards will be created to define its functionalities. In some instances however, manufacturers may develop more efficient products that selfishly seek performance advantages over other network equipment at the expense of the entire network. In other instances, devices may have certain intelligent features that can be invoked by end users to make them behave selfishly. Such informs the necessity to design systems that can cope with selfish users, and if possible, make such behaviours unprofitable [55].

  The following describes the operations of the proposed hybrid-adaptive scheme based on the test-case of an errant user in the network:

1. *Initialisation*: Consider that two secondary cognitive users existing within the range of a cognitive radio network attempt to establish communication after completing the set-up procedures. Also consider that the cognitive engines of the two users are designed based on the architecture of hybrid-adaptive scheme shown in Figure 4.4.
2. *Spectrum Sensing*: The devices will first sense the channel to have an idea of the available spectrum holes and determine the first strategy of opportunistic access.
3. *Procedure 1 - Water-filling Convergence*: Assume the users invoke the optimization functionalities of the cognitive engine, because of the water-filling algorithm's fast convergence properties. They then attempt to adjust their transmit power processes up to the channel's water-filling level. We assume that a centralised agent exists in the network to aid the convergence of the secondary users.
4. *Evaluation using threshold*: Assume that a defined threshold, representing the difference in the values of the transmit power between the users that must not be exceeded, is pre-set to regulate the activities of the users. Consider that the schedule of transmit-power increment for one of the users, hereafter regarded as the greedy user, is slightly above that of the other

user. At the point where the difference in the transmit power of the users is above the defined threshold, the centralised agent automatically detects the imbalance and induces the two users to stops the water-filling process.

5. *Switch functionality to Procedure 2*: By intuition and self-evaluation, the users will switch functionality to the learning engine. The users pre-programs conditional probabilities for their actions and continues to adjust their transmit power processes towards convergence.
6. *Punishment for the errant User*: Ultimately, the transmit power schedules of the two users converges to equilibrium and the errant user is penalised and forced to behave in a manner that is optimal for the system as a whole.

4.5.2 Other Test Scenarios in Perspective

- ***Learning in a unified wireless access technology***

The exponential growth in the demand for wireless data services and application has created the imperative for migration to 4G wireless technologies, as shown in Figure 4.6 below.

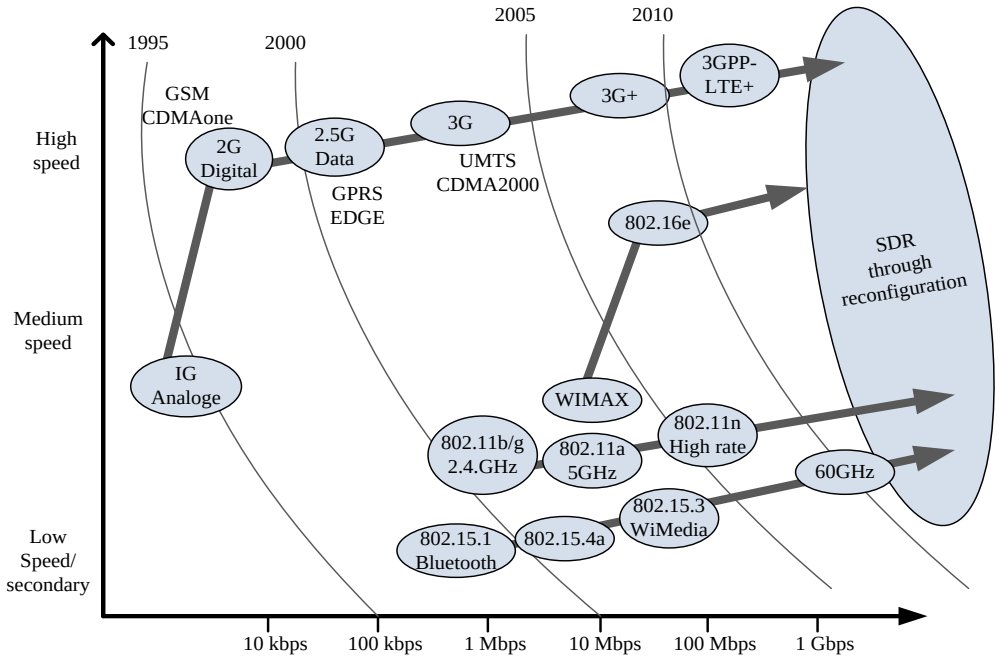


Figure 4.6: The evolution of wireless communication scene [17].

Some scientific papers like [56] [57], have suggested future evolution to what is being described as 5G. Under 5G, it is expected that different systems, i.e. systems with different transmission characteristics and different network architectures, will be able to coexist and cooperate, and user-terminals will simultaneously access different wireless technologies and be able to choose the most suitable one for optimal performance [57]. Cognitive radio is being proposed as the key enabling technology of 5G.

In a unified wireless access protocol environment, where terminals can simultaneously connect to several wireless access platforms and seamlessly roam between them, it is required that the terminals are equipped with flexible radios.

The extensive research studies on transmit-power control algorithms for the cognitive radio are based on applications to specific air interface communication protocols and multiple access systems. For instance, the iterative water-filling algorithm is specified for use in Orthogonal Frequency Division Multiple Access (OFDM) systems. However, in its operational definition, a cognitive radio should be able to adapt to any multiple access technique. The hybrid-adaptive scheme proposed in this work has provision for sensing and evaluation of the environment, to be able to determine the adaptation strategies to adopt at any given time.

- ***Flexibility in the midst of high spectrum handover probability***

Spectrum handover occurs when a secondary user changes frequency due to either the appearance of a primary user or channel degradation. Such dynamic change in frequency by a secondary user could result in severe service disruption. Hence, the design of a seamless handover scheme is integral to the efficiency of the cognitive radio network.

The adaptive scheme proposed in the work is capable of ensuring efficient seamless handover and enhanced spectrum utilisation in situations where the probability of spectrum handover is very high due to the activities of primary users' spectrum usage. The scheme will operate in favour of the iterative water-filling algorithm, which can guarantee fast convergence and speedy utilisation of spectrum holes. The timer function can be used to check the activities of errant users and enable switching to the no-regret learning algorithm when necessary.

4.5 Summary

This chapter presents the iterative water-filling algorithm and the no-regret learning algorithm in theoretical details. Both algorithms are applied to a simple scenario, given the same conditions and assumptions. The chapter also introduces the concept of a hybrid-adaptive scheme, which combines the functionalities of the two algorithms together, to find the optimal spectrum utilisation for cognitive radio networks.

The iterative water-filling algorithm has been explained in the context of two operational procedures, namely an inner loop and an outer loop. The mathematical notations of the channel properties have also been presented. The no-regret learning algorithm has been defined in the context of four ingredients that are integral to its formulation. These are equilibrium, strategy, utility function and the no-regret function.

The chapter presents the conceptual architecture of the hybrid-adaptive scheme showing the interaction between the internal components. A step by step description of a generalised operational procedure for the scheme is presented. The concluding subsections illustrate some specific application scenarios where the operations of the hybrid-adaptive scheme may find relevance.

Chapter 5

5 Methodology and Simulation Results

5.1 Introduction

This chapter deals with the methodology and simulation results for the two algorithms, namely the iterative water-filling algorithm and the no-regret learning algorithm. The second section defines the approaches adopted, the scenarios set-up, the assumptions made and the methods used. The third section presents comprehensive simulation results derived from using MATLAB to simulate the two algorithms. The convergence properties of the two algorithms, based on the two different simulation results, are then compared and analysed in the concluding section.

5.2 Methodology

The formulation of the iterative water-filling algorithm and the no-regret-learning algorithm was performed using the step-by-step approach, as outlined in Chapter 4. The simulations were conducted in two phases using MATLAB software, which is readily available in the laboratory. In the first phase, the iterative water-filling algorithm was simulated and results were derived. In the second phase, the no-regret learning algorithm was also simulated. The two phases of the simulations are explained in sequential details below.

- ***The Iterative Water-Filling Algorithm***

The simulation for the iterative water-filling algorithm is set up using MATLAB and according to the procedure described in the flow chart of Figure 5.1. The set-up represents two users communicating across a flat-fading RF channel. The following outlines all parameters and assumptions used for the simulation.

1. *Initialisation*: The power spectral densities of the two users are set to zero and target data rates, T_i. We assumed 0.512 Mbps as the target data rates of the two users. This value is only a conservative estimate chosen for the purpose of the experiment.
2. *Inner loop (iteration)*: At the inner loop, user 1 performs water-filling to derive the competitive power allocation, while undermining the noise floor of the channel and

subject to its power constraint. Noise power spectral densities per channel were assumed to be -80dBm, 2 was the assumed value of SNR gap and (10) and (11) defines the corresponding noise terms used. Following the same procedure, user 2 performs the water-filling to also derive its competitive power allocation, subject to its defined power constraint. The actions of the users are meant to account for the cross-coupling effect they both introduce against each other; the cross coupling effect is defined by (7) and (8). The transmit power of the two users is then adjusted by an incremental factor based on the results of the iterative water-filling procedures. The incremental factor used was 0.5 dBm. Using (14) and (15), associated data rates for the first procedure were obtained. The process proceeds iteratively until the target data rates for the two users are achieved.

3. *Outer loop (iteration)*: At the outer loop, the corresponding data rates of the users' transmit power, from the inner loop procedure, are compared with the target data rates. A tolerance limit of 0.003 was defined. If the difference between the data rates of the users and the target data rates are found to be greater than the tolerance value, the transmit power is reduced by the factor of increase, otherwise the transmit power is increased by the same factor. The outer loop procedure proceeds iteratively for every inner loop power spectra density increase until the target data rates are achieved.
4. *Confirmation*: The above process will enable the data rates of the two users to converge. The number of iterations with which the system attains equilibrium is declared at the end of the iterative process. The amount of time is regarded as the delay or latency experienced by the system.

The flow chart of Figure 5.1 is a pictorial representation of the procedures explained above.

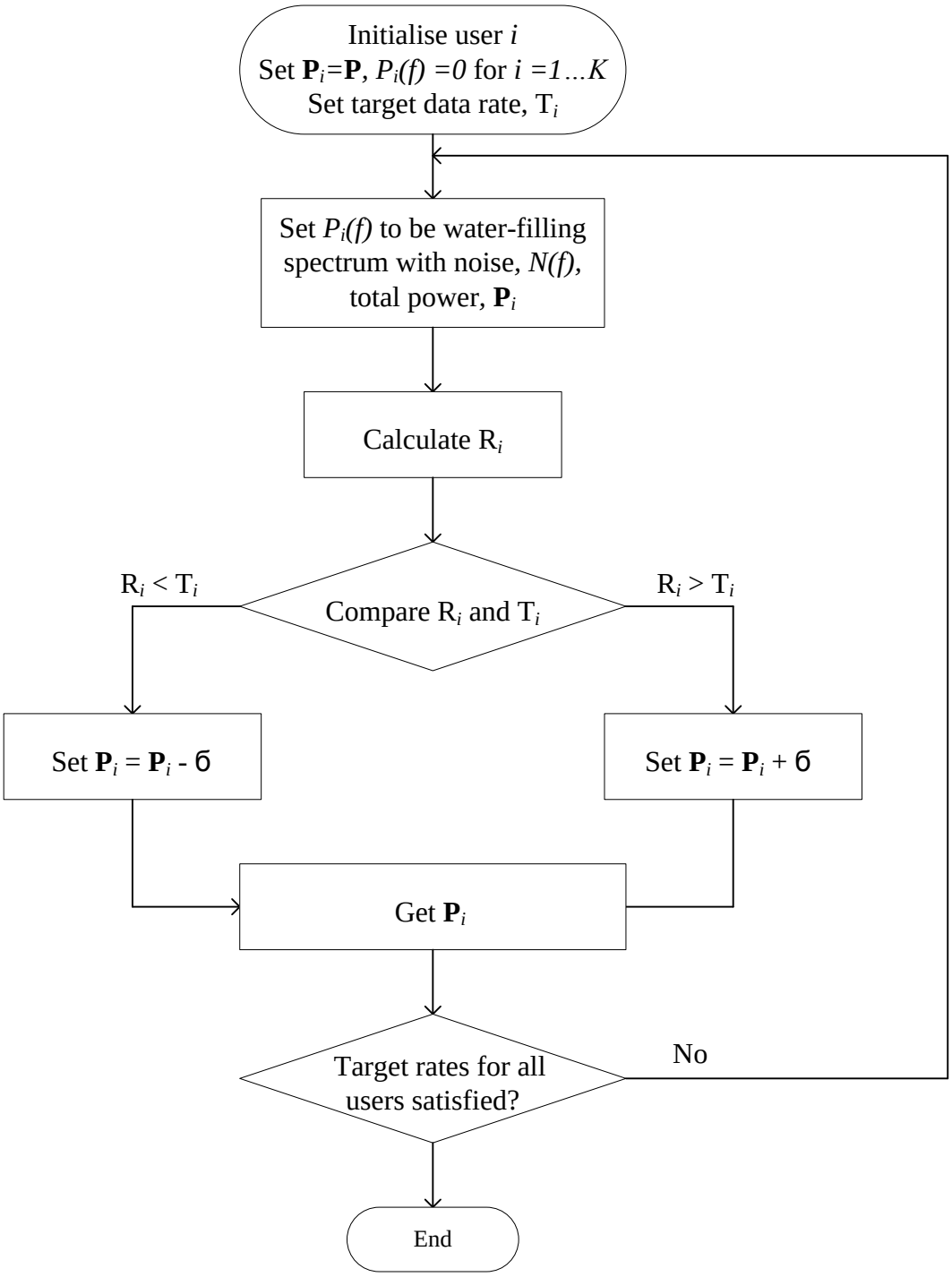


Figure 5.1: Flow chart of the iterative water-filling algorithm.

- ***The No-Regret Learning Algorithm***

The simulation for the no-regret learning algorithm is set up using MATLAB and also according to the procedure described in the flow chart of Figure 5.2. The set-up involves two cognitive

users' access on one primary user channel. The following outlines all parameters and assumptions used for the simulation.

1. *Initialization*: Two actions, 0.5 and 1, which correspond to the transmit power of the two users were assigned at initialisation. User *i* then randomly selects an action from the strategy set with arbitrary probability.
2. *Find average payoff*: The value of maximum utility achievable with user *i*'s strategy is then calculated using (27), (28) and (29). The numerical value of the term "regret" is the difference in payoff between the chosen strategy and alternative strategy. The following values were used: channel bandwidth, G_0 given as 2.8; delay parameter, τ given as 0.1; and the number of iteration given as 1000.
3. *Derive average regret*: The average regret is equated to the average payoff calculated in stage 2.
4. *Utility function*: The utility function is derived by applying (27) to the referenced secondary user game. Hence, the utility graph shown in Table 4.1 is modified to reflect channel throughput as can be obtained in the real network scenario. The utility graph used for simulation is thus presented in Table 5.1. The pure strategy Nash equilibrium of the game is also presented in Table 5.2.

$p_1 \backslash p_2$	**0.5**	**1**
0.5	0,0	0,0.9
1	0.9,0	-0.1,-0.1

Table 5.1: Utility function.

$p_1 \backslash p_2$	**0.5**	**1**
0.5	0,0	0,1
1	1,0	0,0

Table 5.2: Pure strategy Nash equilibrium.

In the pure strategy Nash equilibrium, only one of the players can transmit at a time. The player that transmits gets a utility of 0.9 while the other player gets a utility of 0.

However, in mixed strategy Nash equilibrium, both players can transmit with some probabilities to obtain the appropriate utility. Since the zero-sum game of Table 5.1 is of the same nature as the game illustrated in Table 4.1, the users' actions of Table 5.1 are replaced with the conditional probabilities of the users' actions shown in Table 4.3. Table 5.3 shows the mixed strategy Nash equilibrium of the game illustrated in Table 5.1.

		2/3	1/3
	$p_1 \backslash p_2$	**0.5**	**1**
2/3	**0.5**	0,0	0,0.9
1/3	**1**	0.9,0	-0.1,-0.1

Table 5.3: Mixed Nash equilibrium.

The same procedure adopted to derive the mixed strategy Nash equilibrium of the game is also used to obtain the correlated equilibrium. Table 5.4 shows the correlated equilibrium of the game.

$p_1 \backslash p_2$	**0.5**	**1**
0.5	0.5 |50%|	0.25 |25%|
1	0.25 |25%|	0 |0%|

Table 5.4: Correlated equilibrium.

5. *Derive iterative probability distributions from equilibrium theory*: The joint probability distribution of the users' action for four possible combinations are calculated based on (33).
6. *Confirmation step*: The above process ensured convergence to pure strategy Nash equilibrium after a number of iterations. The number of iterations with which the system attains equilibrium is declared at the end of the process.

The flow chart of Figure 5.2 represents the procedures outlined above.

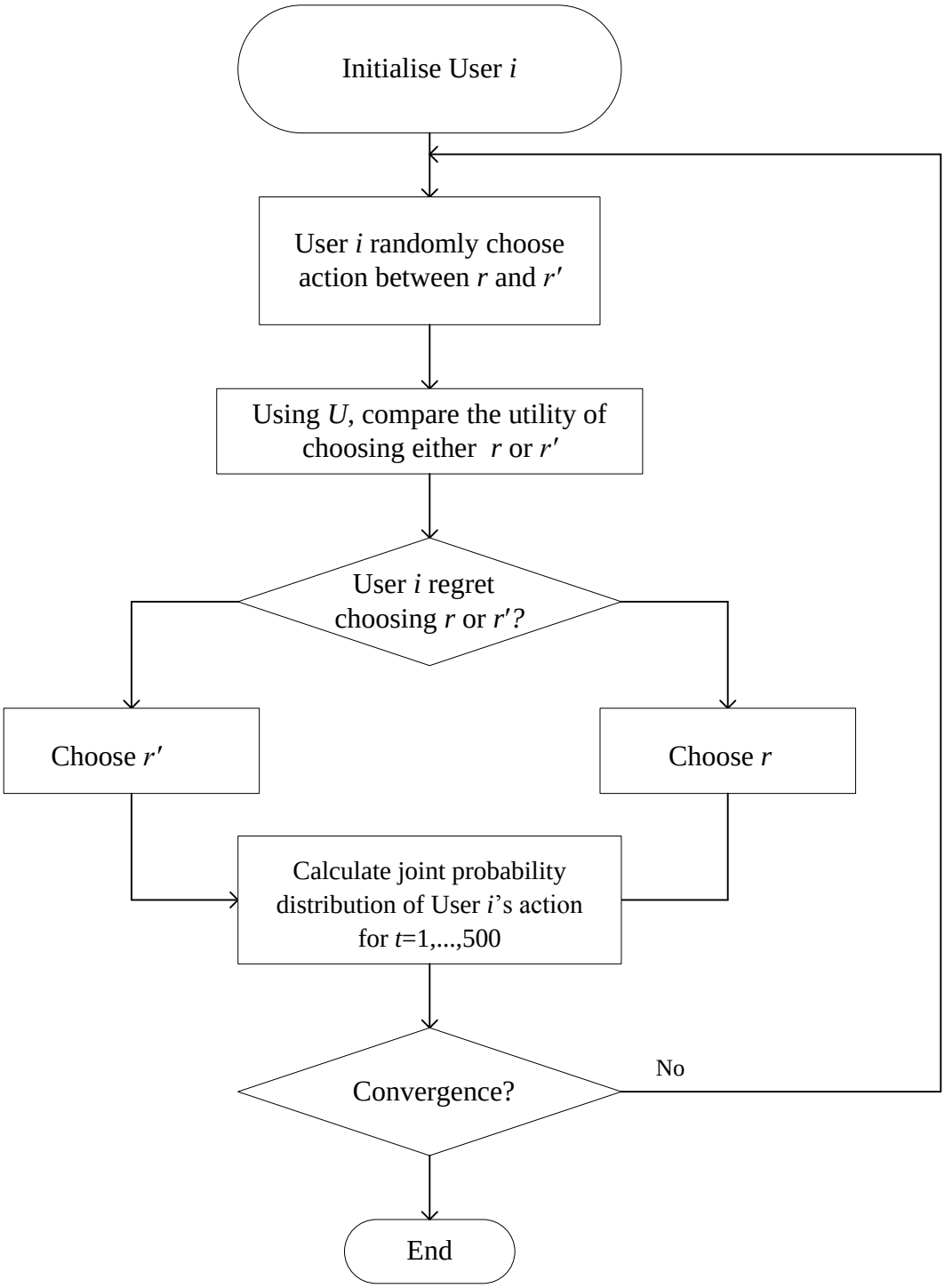


Figure 5.2: Flow chart of the no-regret learning algorithm.

- ***The Hybrid-Adaptive Scheme***

  The hybrid-adaptive scheme can be implemented using the two algorithms and according to the procedure described in the flow chart of Figure 4.5. In the following example, we illustrate how the scheme can handle the scenario with existence of greedy users.

  The iterative water-filling algorithm is first used to find the optimal transmit power of the users. However, user 1, which is the greedy user, increases its transmit power by 62.5% above that of user 2. Table 5.5 (a) and (b) shows the different values of transmit power and data rates for user 1 and user 2 respectively.

Index	$\mathbf{P}_1$	$\mathbf{P}_2$
1	3	2
2	6	4
3	9	6
4	12	8
5	15	10
6	18	12
7	16	14
8	19	14.5
9	18.5	15

Index	R_1	R_2
1	0.1752	0.1686
2	0.2946	0.258
3	0.3816	0.3135
4	0.4479	0.3513
5	0.5002	0.3787
6	0.5424	0.3995
7	0.4593	0.4884
8	0.5229	0.4556
9	0.5035	0.4765

Table 5.5 (a) and (b): Transmit power and data rates values of user 1 and 2.

At the end of the first procedure, the data rate and transmit power of $\boldsymbol{p_1}$ are 0.5035 and 18.5 respectively. The corresponding data rate and transmit power of $\boldsymbol{p_2}$ are 0.4765 and 15 respectively. The data rates of the two users is a difference of 0.027 Mbps, this is an unfair distribution. Assume that the threshold value was set at 0.005. Since the difference in the data rates of the users is above the threshold value, the users are induced to switch functions to the second procedure. In the second procedure, game theory is used to fine-tune the strategies of the users.

Table 5.6 is an example of a game theoretic matrix table based on the values of the transmit power and corresponding data rates of the users. Note that, in this example, the scheme switches to the second procedure in the step 7, when the transmit power of user 1 and user 2 are respectively 16 and 14 as shown in Table 5.6.

$p_1 \backslash p_2$	**14**	**16**
14	0.4093, 0.5252	0.3839, 0.5867
16	0.4593, 0.4884	0.4313, 0.5465

Table 5.6: Reward table based on values of transmit power and data rates.

The reward table shown in Table 5.6 is limited to a representation of two values of transmit power and corresponding data rates of the users. In fact, a very large matrix, indicative of all possible transmit power values and corresponding data rates of the users is generated in the second procedure. Mixed strategy Nash equilibrium and correlated equilibrium can then be used to derive the equalising strategies that will ensure favourable data rates for the users.

5.3 Simulation Results

In this section, we present the computer simulation results.

- ***Simulation result of the iterative water-filling algorithm***:

Figure 5.3 shows the convergence of iterative water-filling algorithm. The scenario shows the rate-adaptive water-filling of two secondary cognitive users. It is shown that the data rates of the two users converged to almost the target data rate in approximately 17 iterations.

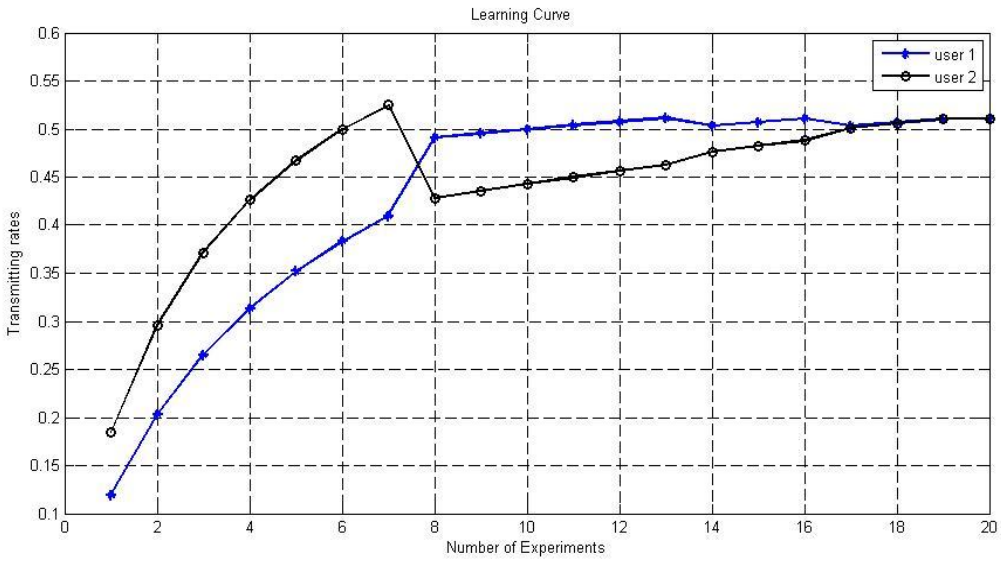


Figure 5.3: Convergence of iterative water-filling algorithm.

Figure 5.4 shows the sequential increase in the transmit PSD of the secondary users. It can be seen that their transmit power values start diverging at the point where convergence begins in Figure 5.3.

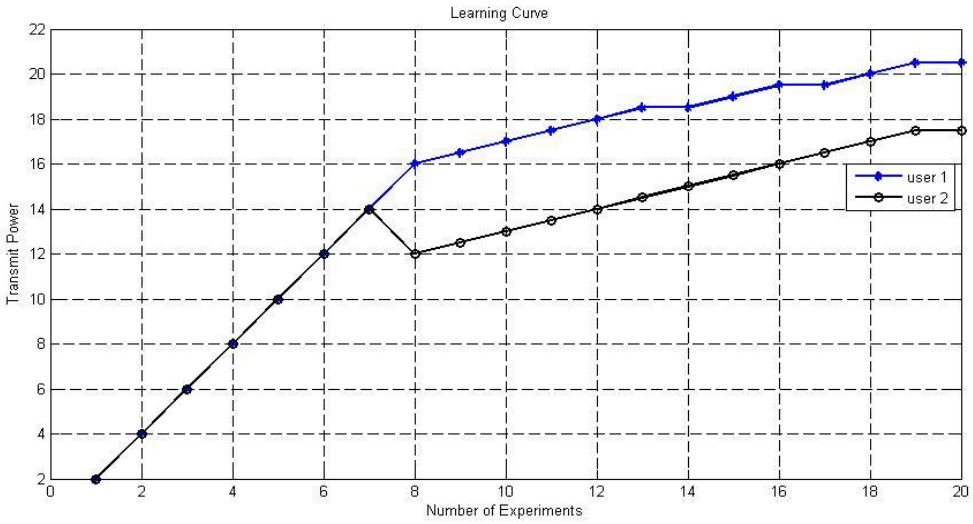


Figure 5.4: Transmit power of secondary users based on power-adaptive water-filling.

- ***Simulation results of the no-regret learning algorithm***:

Figure 5.5 and 5.6 show the convergence of no-regret learning algorithm through 500 iterations. The scenario illustrates the convergence of the probability distributions of two secondary users' actions to pure strategy Nash equilibrium, wherein the probabilities of the users' actions can be either 0 or 1. It can be seen that the probability distributions p(1,2) and p(2,1) tend to converge to 1.

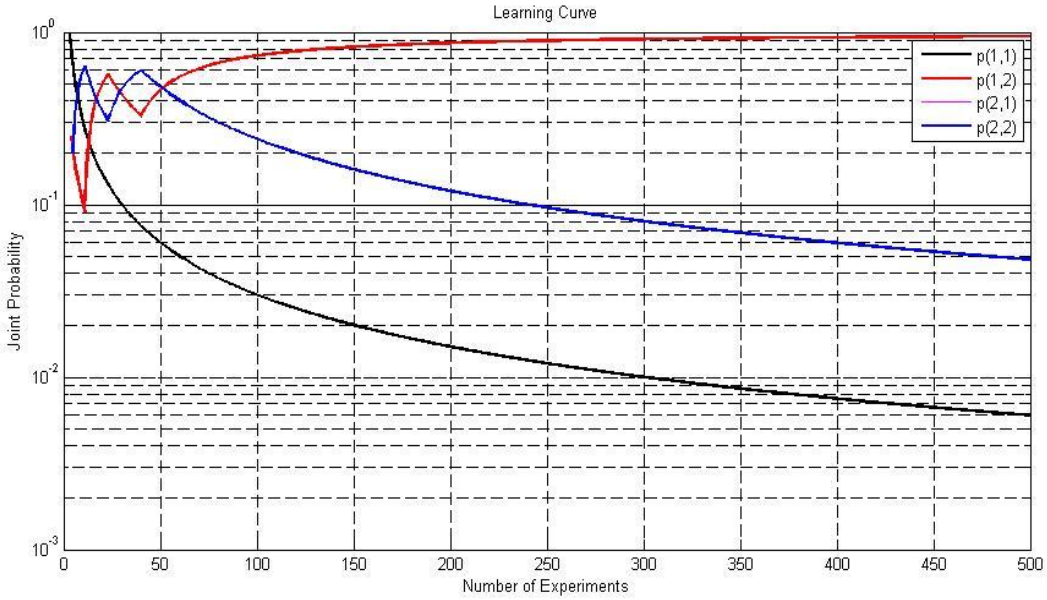


Figure 5.5: No-regret algorithm convergence towards pure strategy Nash equilibrium.

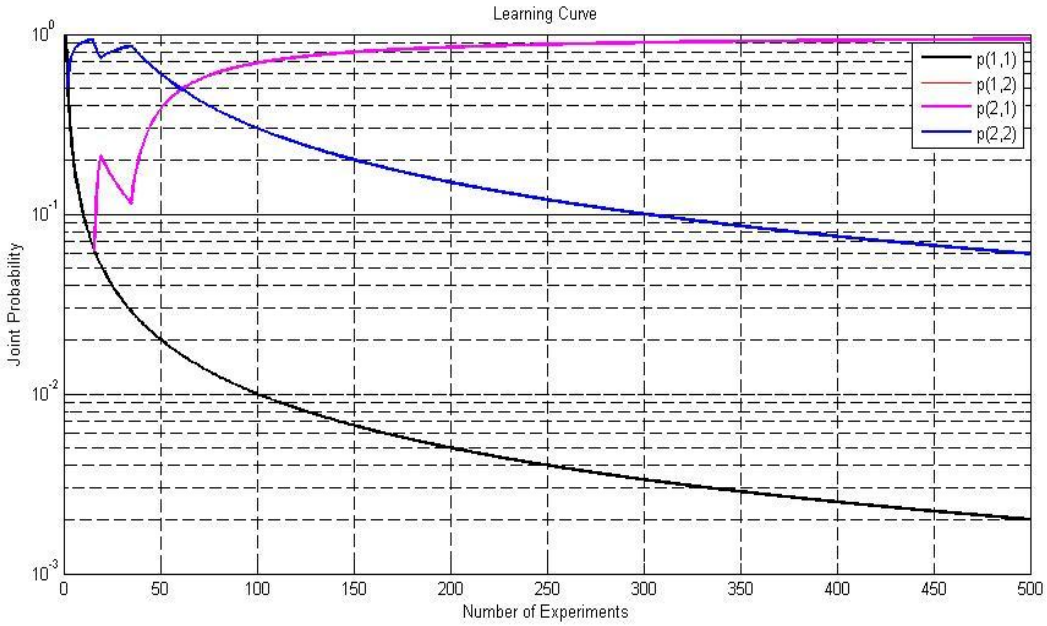


Figure 5.6: No-regret algorithm convergence towards pure strategy Nash equilibrium.

It is shown that the probabilities of p(1,2) and p(2,1), where one user transmits at high power (i.e. 1) and the other transmits at low power (i.e. 0), converges to 1 while other distributions converge towards 0. It is seen that convergence towards a probability of 1 for both cases starts at above 100 iterations.

Figure 5.7 shows the convergence of the users' actions to mixed strategy Nash equilibrium. The adopted conditional probabilities to all possible actions are 0.45, 0.225, 0.225 and 0.1 for p(1,1), p(1,2), p(2,1) and p(2,2) respectively. Under mixed strategy Nash equilibrium, the probability distribution of the players' actions will be such that can guarantee fair outcome for the players. It is shown that the mixed Nash equilibrium avoids the pure Nash equilibrium solution of the game which leads to unfair outcome, i.e. one player receiving far more payoffs that the other. The strategies that would lead to unfair outcomes for both players are also chosen with less probability.

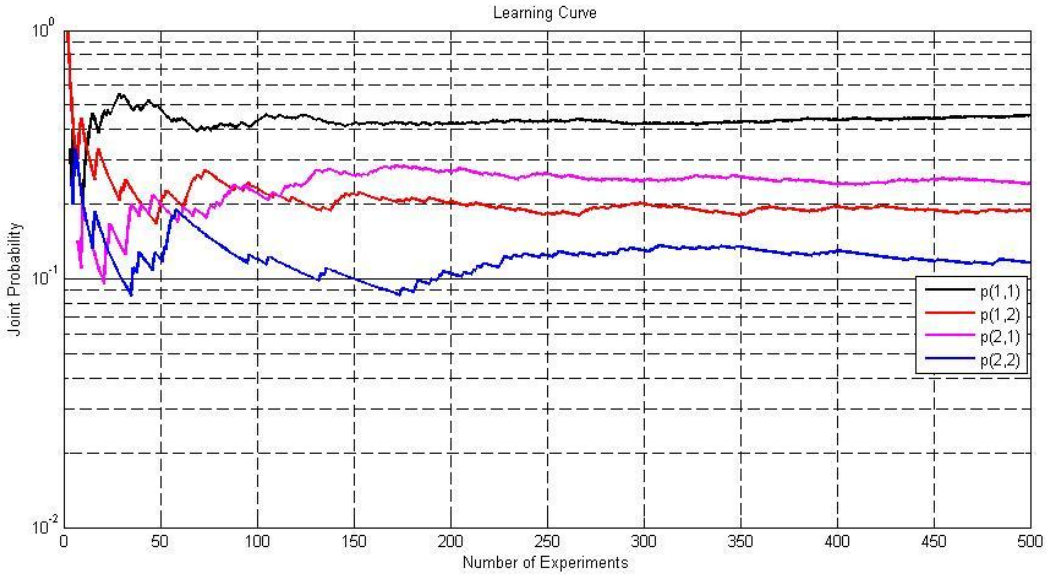


Figure 5.7: No-regret algorithm convergence towards mixed Nash equilibrium.

Similarly, Figure 5.8 shows the convergence of the users' actions to correlated equilibrium. The adopted conditional probabilities to all possible actions are 0.5, 0.25, 0.25 and 0.00 for p(1,1), p(1,2), p(2,1) and p(2,2) respectively.

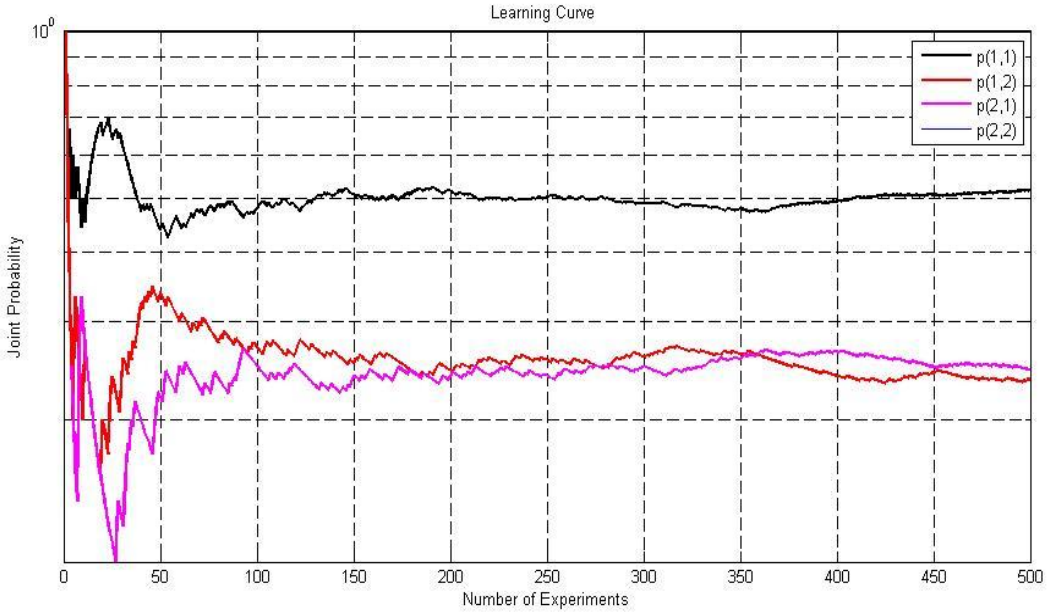


Figure 5.8: No-regret algorithm convergence towards correlated equilibrium.

Section 4.3 shows that correlated equilibrium guarantees a higher utility than the mixed Nash equilibrium. The main reason, as shown in Figure 5.8, being that the conditional probability of the users' choosing the least favourable actions is 0.

Figure 5.9 illustrates the data rates of the two users as due to the greedy behaviour of a user.

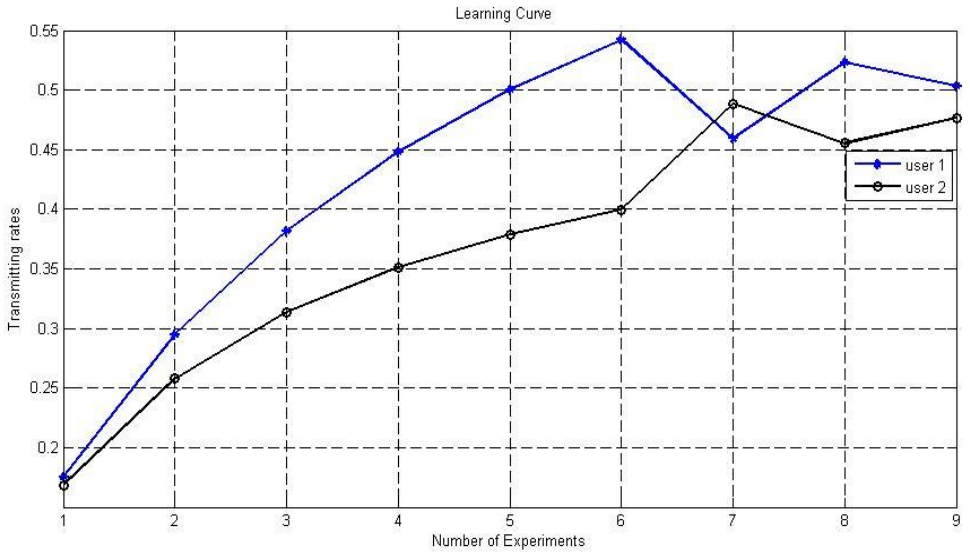


Figure 5.9: Data rates for iterative water-filling algorithm with greedy user.

It can be seen from Figure 5.9 that user 1 selfishly increases its data rates above that of user 2. At the 6^{th} iteration, when the data rates of user 1 cannot exceed the capacity of the system, it is decreased. The capacity of the system is filled at the 9^{th} iteration without the convergence of the two users' data rates.

Figure 5.10 illustrates the transmit power increment of the two users, as a result of the greedy behaviour of one of the users.

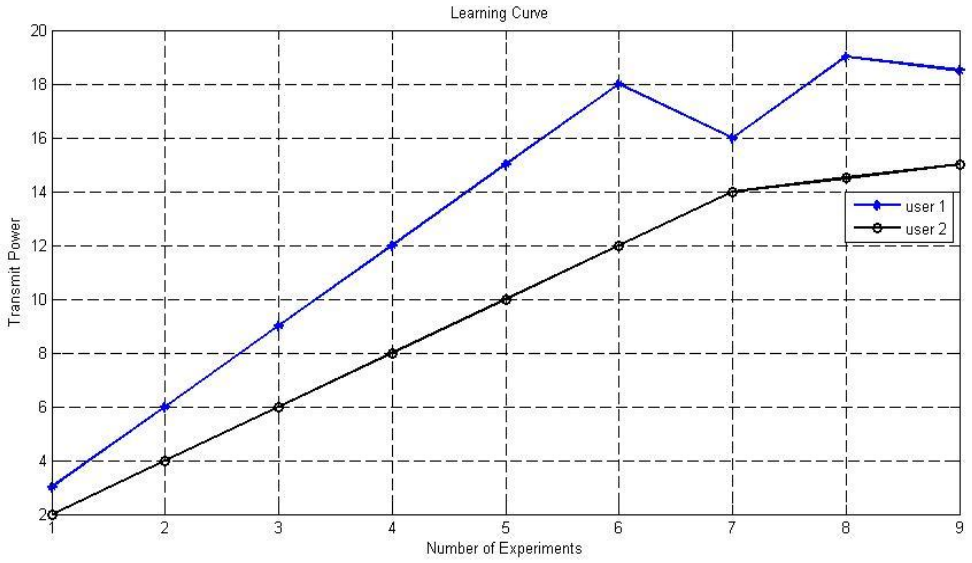


Figure 5.10: Transmit power for iterative water-filling algorithm with greedy user.

Figure 5.10 shows the sequential increase in the transmit power of the secondary users. It can be seen that user 1 selfishly increases its transmit power to 62.5% above that of user 2, and at the 6th iteration, when the PSD of user 1 cannot exceed the interference temperature limit at the primary user, it is decreased by a factor which corresponds to the defined threshold value.

Worthy of note however, is that the systems cannot converge due to the activities of the greedy user, and hence, this will bring about unfair utility in terms of data rates distribution among the users in the network. While it is acknowledged that this experiment only applies to a two-user game, the instability of the iterative water-filling algorithm will be even more in a multiuser scenario, given the activities of greedy users.

5.6 Summary

This chapter presents the methodology used in this work and the simulation results obtained.

A two-user power control game is presented showing convergence of the iterative water-filling algorithm. Simulation results show the convergence of the algorithm towards Nash equilibrium.

A two-user power control game is also presented showing convergence of the no-regret learning algorithm. The simulation results show the convergence based on three equilibria, pure strategy Nash equilibrium, mixed strategy Nash equilibrium and correlated equilibrium.

It is noted that the convergence time for the no-regret learning algorithm is more than that of the iterative water-filling algorithm.

Chapter 6

6 Key Research Findings, Recommendations, Future Work and Conclusion

6.1 Introduction

The concept of cognitive radio has emerged as an enabling technology of DSA to promote efficient utilisation of radio frequencies, while accommodating the exponential growth in wireless services and applications. However, enormous research challenges stand in the way of the implementation of cognitive networks. This research report provides theoretical and experimental solutions to one of such challenges, which is cognitive radio transmit-power control.

Chapter One of this research report introduced the topic in context and defined the research problem, aims and objectives.

Chapter Two introduced the subject of power control in context, including the concept of spectrum sharing, dynamic spectrum access and cognition cycle. A critical design challenge for cognitive radio networks is to establish a balance between transmit power and interference. This chapter also presented a technical background report on the foundation of using information and game theoretic procedures to correct the problems posed by power control in cognitive networks.

Chapter Three extended the literature survey of Chapter Two into an in-depth review of existing literatures. The review focused on research papers that deal with variants of power control algorithms and the key considerations in the design and implementation of spectrum access games.

Chapter Four put forward two state-of-the-art transmit-power control techniques in cognitive radio networks, namely the no-regret learning algorithm and the iterative water-filling algorithm. This chapter presented the algorithms in sufficient theoretical details in a two-user scenario and introduced the concept of a hybrid-adaptive scheme.

Chapter Five presented the method used and the simulation results obtained. This chapter also proposed a hybrid-adaptive scheme, which incorporates both algorithms into its design to meet transmit-power control requirements. Application scenarios where the adaptive scheme can be applied in cognitive radio networks are further analysed.

6.2 Research findings

The analysis and simulation results presented in this research report give insights into the strengths and weaknesses of the iterative water-filling algorithm and the no-regret learning algorithm. The succeeding subsection outlines these in perspective.

6.2.1 Strengths and Weaknesses of Water-Filling Algorithms and No-Regret Learning Algorithm

- ***Strengths of Iterative Water-filling Algorithm***

1. Rapid Convergence - From the simulation results presented in Chapter Five, we find that the iterative water-filling algorithm, as described in this report, converged rapidly at the 17th iteration. Rapid convergence implies that the transmission power level of the participating secondary users quickly stabilises at the optimum transmit power, which is known as the Nash equilibrium. However, once equilibrium is reached, no user can change its transmit power unilaterally.

2. Low Computational Complexity – The number of iterative computational procedures of the algorithm, involving the inner loop and outer loop, is a function of the number of secondary users in the network. Hence, the algorithm has a low computational complexity.

3. Well suited to distributed implementation – The algorithm makes it possible for the secondary users to function in a fully distributed and autonomous manner, despite the need for some small amount of coordination through a centralised agent.

4. Avoids communication links between users – Based on the fact that the algorithm makes it possible for secondary users to function by distributive means, there is no need for established communication among the users, thereby significantly simplifying the network, and hence reducing overheads.

- ***Weaknesses of the Iterative Water-filling Algorithm***

1. Cannot overcome the behaviour of greedy users – As shown in Section 5.3.1, the iterative water filling algorithm cannot overcome the behaviour of greedy users. When a selfish user is brought into the network, it causes instability, which might lead to a network breakdown.

2. Sub-optimality – The iterative water-filling algorithm is generally considered sub-optimal because the strategies of the users do not guarantee optimal performance. For instance, based on the iterative water-filling procedure of user 1 and 2 in Figure 5.3, the equilibrium strategies are 20.5 and 17.5 respectively, and the corresponding data rates are 0.5099 Mbps and 0.5108 respectively. The utility distribution is unfair, and hence the algorithm can be considered sub-optimal.

- **Strengths of the No-*Regret Learning Algorithm***

1. Guarantees learners cannot be exploited – The no-regret learning algorithm is structured in such a way that learners dynamically change their strategy selection over time, according to a probability distribution. This makes it difficult for a deceptive strategy to lure the learners from best-response strategy. Hence, the no-regret learning algorithm has a tendency to overcome exploitative actions of greedy users.

- ***Weaknesses of the No-Regret Learning Algorithm***

1. Slow Convergence - The simulation results show that the no-regret learning algorithm has slow convergence. Figure 5.5 and Figure 5.6 show that the convergence time for the algorithm is above 100 iterations, which is far more than the convergence time for the iterative water-filling algorithm.

2. High computational Complexity – The no-regret learning algorithm is a computationally efficient learning algorithm. The algorithm involves each player learning a preferred course of action by simultaneously choosing an action from a strategy set and observing only its own payoff structure.

Table 6.1 summarises the key characteristics of no-regret learning algorithm and iterative water-filling algorithm, as stated above.

	Iterative Water-filling	**No regret learning**
Strengths	-Converges rapidly -Low computational complexity -Well suited to distributed implementation -Avoid communication links between users	-Guarantees learners cannot be exploited
Weaknesses	- Its sub-optimal - Cannot overcome the behaviour of greedy users	- Slow convergence -High computational complexity

Table 6.1: Advantages and disadvantages of the iterative water-filling algorithm and the no-regret learning algorithms.

6.3 Recommendations

In wireless communication, cognitive radio technology is generally perceived as the next disruptive technology, because of its ability to autonomously adapt to changing network conditions in order to ensure a more flexible and spectrally efficient wireless network. The flexibility of cognitive radio comes with the price of dynamic control of transmit power.

In recent years, enormous research studies have been made to different algorithms for the control of transmit power in cognitive radio networks. However, some of the transmit-power control algorithms, which have been proposed, fall short of adaptive capabilities, which is a fundamental requirement for radios anticipated to operate in the evolving next generation wireless networks.

Based on the background analyses presented in this research report, the following recommendations can be made:

- In the design of the cognitive engine, which is the core of the cognitive radio, it is recommended that the iterative water-filling algorithm is interfaced with the no-regret learning algorithm. The design should be in such a way that the operations of the iterative water-filling algorithm is prioritised and the operations of the no-regret learning algorithm is turned on in scenarios where the distribution of utility is considered unfavorable to the users in the network; and

- Furthermore, the cognitive radio's sensing procedure should be enhanced with a high level of intelligence to enable it to effectively decipher the wireless environment so as to make decisions on the behaviours to adopt that would promote the maximisation of utility and efficient spectral utilisation.

6.4 Future work

The idea of a hybrid-adaptive transmit-power control scheme for cognitive radio networks is new and innovative. There is the need for further research into the operational significance of the adaptive scheme wherein the engine model should be implemented and tested via simulation, using both techniques together and showing levels of operational convergence of the two algorithms and a measure of combined learning strategies.

6.5 Conclusion

In this research report, solutions to the problem of transmit-power control in cognitive radio networks have been approached from the perspective of game and information theory.

In terms of information theory, an attempt has been made to study the fundamental limits possible over cognitive channels by the representation of communication characteristics particular to cognitive devices. In terms of game theory, an attempt has been made to characterise the resolution of conflict among multiple cognitive radio users involved in selfish interaction.

Two algorithms, the iterative water-filling algorithm and the no-regret learning algorithm, which have derived from information theory and game theory respectively, and that also serve as

options for the control of cognitive radio transmit power, have been introduced and represented in sufficient theoretical details.

A survey of background technical details, a review of existing research work and comprehensive simulation results have been presented. The simulation results presented indicate the convergence properties of the algorithms.

The strengths and the weaknesses of the algorithms have been analysed based on the simulation results. A hybrid-adaptive scheme, which combines both algorithms in operation, has been proposed.

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