Cognitive Radio and Coexistence for Multicasting Communication Systems

PhD Thesis

Mengfei Yang

Communications Research Group

Department of Electronics

University of York

July 2010

Abstract

This thesis focuses on the performance of terrestrial communication systems that use channel assignment schemes to allocate base stations in a scenario that implements the coexistence of mixed terrestrial communication systems based on cognitive radio technology. Interaction and coexistence of different channel assignment schemes is investigated. Reinforcement learning is applied into multicast downlink transmission with power adjustment to develop the intelligence of cognitive radio.

We focus on investigating channel assignment schemes that select channels based on optimizing the coverage area supported by a terrestrial network. Four channel assignment schemes are developed and compared individually followed by an interaction of mixed schemes. It was found that for mixed schemes, different combinations will affect performance, either delivering better coexistence or more interference. It is shown in this thesis that the dynamic channel assignment used in different situations can efficiently improve the performance of spectrum management.

We investigate how channel assignment in multicast terrestrial communication systems with distributed channel occupancy detection can be improved using intelligence based on reinforcement learning and transmitter power adjustment. A weighting factor is used to determine the highest priority channels and help in controlling the performance of the system. It is shown how such schemes significantly reduce the number of reassignments and improve the dropping probability at the expense of increased blocking. It is found that using different minimum quality of service threshold percentages can partly control and improve performance in place of the more traditional SINR (Signal to Interference plus Noise Ratio) threshold levels. We also show how a power adjustment technique is developed, that significantly reduces the level of overlap between adjacent base stations and further reduces interference and transmitter power.

Contents

CONTENTS **3**

ACKNOWLEDGEMENT **7**

DECLARATION **8**

LIST OF ABBREVIATIONS AND ACRONYMS **9**

LIST OF FIGURES **12**

LIST OF TABLES **16**

1. INTRODUCTION **17**

1.1 OVERVIEW 17

1.2 PURPOSE 21

1.3 SYSTEM SCENARIO 22

1.4 THESIS STRUCTURE 25

2. GENERAL BACKGROUND AND LITERATURE REVIEW **28**

2.1 INTRODUCTION 28

2.2 COGNITIVE RADIO 30

2.2.1 Spectrum Usage 30

2.2.2 Research and Development of Cognitive Radio 34

2.2.3 Cognitive Radio Architecture 37

2.3 SPECTRUM AND CHANNEL MANAGEMENT 43

2.3.1 Spectrum Management 43

2.3.2 Channel Assignment 46

2.4 PROPAGATION AND RELATED TECHNOLOGIES 53

2.4.1 Free space Propagation Model 54

2.4.2 Okumura- Hata Model Propagation 55

2.4.3 Cost 231-Hata Propagation Model......56
2.4.4 Shadowing......57
2.4.5 Multicasting......58
2.5 REINFORCEMENT LEARNING......60
2.5.1 Introduction to Reinforcement Learning......60
2.5.2 Reinforcement Learning Model......61
2.6 CONCLUSION......65

3. SIMULATION AND PERFORMANCE EVALUATION METHODOLOGIES......66

3.1 INTRODUCTION......66
3.2 SIMULATION MODELING TECHNIQUE......67
3.3 SIMULATION TOOLS......71
3.4 PARAMETERS AND PERFORMANCE EVALUATION......75
3.4.1 Performance Parameters......76
3.4.2 Capacity Variation and Bandwidth Efficiency......80
3.4.3 Error Bars......81
3.5 CONCLUSIONS......82

4. COEXISTENCE PERFORMANCE AND CHANNEL ASSIGNMENT......84

4.1 INTRODUCTION......84
4.2 COEXISTENCE SCENARIO AND PERFORMANCE PARAMETERS......85
4.3 CHANNEL ASSIGNMENT SCHEMES AND COMPARISON......88
4.4 STATISTICAL PERFORMANCE OF THE CHANNEL ASSIGNMENT SCHEMES......100
4.5 DISCUSSION......106
4.6 SPECIFIC IMPROVEMENTS FOR CHANNEL ASSIGNMENT......107
4.7 CONCLUSIONS......110

5. INTERACTION AND COEXISTENCE OF MIXED CHANNEL ASSIGNMENT SCHEMES......112

5.1 INTRODUCTION 112

5.2 COEXISTENCE SCENARIO 113

5.3 MIXED SCHEMES 114

5.4 DISCUSSION 131

5.5 CONCLUSION 134

6 REINFORCEMENT LEARNING APPLIED TO MULTICAST DOWNLINK TRANSMISSION 135

6.1 INTRODUCTION 135

6.2 DISTRIBUTED OCCUPANCY DETECTION 136

6.3 DISTRIBUTED CHANNEL ASSIGNMENT SCHEMES WITH REINFORCEMENT 137

6.4 RESULTS AND DISCUSSIONS 145

6.4.1 Performance Analysis 145

6.4.2 Distributed Occupancy Detection Analysis 153

6.5 CONCLUSIONS 159

7 ADVANCED IMPROVEMENTS WITH REINFORCEMENT LEARNING 161

7.1 INTRODUCTION 161

7.2 SCENARIO AND DISTRIBUTED DETECTION 162

7.3 PERFORMANCE ANALYSIS AND OVERLAPPING PROBLEM 163

7.4 POWER ADJUSTMENT 168

7.4.1 System with Power Adjustment 168

7.4.2 Performance of Adjustment 171

7.5 CONCLUSIONS 175

8 FURTHER WORK 177

8.1 DESIGN AND MODIFICATION OF THE LEARNING SYSTEM 177

8.2 LEARNING EFFICIENCY 178

8.3 GAME THEORY AND PRICING WITH RADIO RESOURCE DEPLOYMENT 179

8.4 CONSIDERATION OF PRIMARY USERS 180
8.5 UPLINK CONSIDERATION AND USER PERSPECTIVE 181
8.6 COEXISTENCE WITH OTHER EXISTING COMMUNICATION SYSTEMS 181

9 SUMMARY AND CONCLUSIONS 183

9.1 SUMMARY AND CONCLUSIONS 183
9.2 SUMMARY OF ORIGINAL CONTRIBUTIONS 188

PUBLICATIONS 192

BIBLIOGRAPHY 194

Acknowledgement

I would like to express my sincere gratitude to my supervisor, Dr. David Grace, for his continued encouragement and invaluable advice as my mentor to my PhD study.

I would like to thank Dr. Paul Mitchell, who has given me very useful comments and helpful suggestions.

I would like to thank all my colleagues and friends in the Communications Research Group. They are really very friendly and helpful. The more important thing is we are always like a big family and they make my life much easier in York.

Finally, my deepest gratitude is expressed to my parents, for their selfless love and enormous support.

Declaration

Some of the research presented in this thesis has resulted in some publications, which are listed at the end of the thesis.

All contributions specified in this thesis as original are so to the best knowledge of the author. Appropriate references and acknowledgements to other researchers in the field have been given.

List of Abbreviations and Acronyms

4G	The Fourth Generation
BWRC	Berkeley Wireless Research Center
BuNGee	Beyond Next Generation Networks
CAP	Cognitive Access Point
CDF	Cumulative Distribution Function
CN	Cognitive Networks
COGCOM	Cognitive Networks and Communications
CORVUS	Cognitive Radio Approach for Usage of Virtual Unlicensed Spectrum
CR	Cognitive Radio
CRA	Cognitive Radio Architecture
CREW	Cognitive Radio Experimentation World
CRN	Cognitive Relay Node
CROWN	Cognitive Radio Oriented Wireless Networks
CS	Channel Segregation
CWT	Center for Wireless Telecommunications
DARPA	Defense Advanced Research Projects Agency
DCA	Dynamic Channel Assignment
DVB-H	Digital Video Broadband-Hand
EC	European Commission
FCA	Fixed Channel Assignment

FCC	Federal Communications Commission
FFR	Fractional Frequency Reuse
FP	Framework Programme
GMSK	Gaussian Minimum Shift Keying
HAP	High Altitude Platform
HCA	Hybrid Channel Assignment
IEEE	Institute of Electrical and Electronic Engineers
IET	Institution of Engineering Technology
LTE	Long Term Evolution
MIMO	Multi-input and Multi-output
NSF	National Science Foundation
Ofcom	Office of Communications
OFDM	Orthogonal Frequency Division Multiplexing
OODA	Observe-Orient-Decide-Act
QAM	Quadrature Amplitude Modulation
RAT	Radio Access Technology
RRM	Radio Resource Management
SACRA	Spectrum and energy efficiency through multi-band cognitive radio
SCC41	Standards Coordinating Committee 41
SDR	Software Defined Radio
SINR	Signal to Interference Plus Noise Ratio
TDMA	Time Division Multiple Access

WLAN	Wireless Local Area Networks
WiMAX	Worldwide Interoperability for Microwave Access
WMAN	Wireless Metropolitan Area Networks
WPAN	Wireless Personal Area Networks
WRAN	Wireless Regional Area Networks
WUN-COGCOM	Worldwide Universities Network Cognitive Communications Consortium
XG	NeXt Generation

List of Figures

Figure 1-1 Usage of the radio spectrum in different areas of the UK……………..18

Figure 1-2 The coexisting scenario model with 3 channels and 10 base stations....22

Figure 1-3 Heterogeneous multicast system scenario……………………………24

Figure 1-4 Distributed detection scenario……………………...………………..24

Figure 2-1 The United States frequency allocations………………………………31

Figure 2-2 Cognition cycle of Cognitive radio……………………………………39

Figure 2-3 Modified Cognition cycle……………………………………………..40

Figure 2-4 Base station and service users with interference consideration……….47

Figure 2-5 Basic transmitter and receiver of path loss…………………………….54

Figure 2-6 standard reinforcement learning model………………………………..61

Figure 3-1 User location and coverage area situation……………….…………..68

Figure 3-2 Basic scenario of terrestrial communication system………………….69

Figure 3-3 Average proportion of reassignments, probability of dropping and blocking for two distributed channel assignment schemes………………………70

Figure 3-4 Matlab simulation process……………………………………..……73

Figure 3-5 Flowchart for a single iteration of distributed channel assignment..….74

Figure 3-6 Contour plot for two base stations when subject to mutual interference ……………………………………………………………………………………78

Figure 3-7 Single and multi-channel CDF comparison……….……………........80

Figure 4-1 The coexisting scenario model with 3 channels and 10 base stations....86

Figure 4-2 Single and multi-channel CDF comparison…………………………...88

Figure 4-3 Least Interference scheme with contour, channel and base station plots ……………………………………………..………………………………90

Figure 4-4 Example of the Maximal Difference scheme………………………...97

Figure 4-5 Maximal difference scheme with contour, channel and base station plots

……………………………………………………………………..……………98
Figure 4-6 Different schemes comparison with different numbers of BSs…..…..101
Figure 4-7 Error bar of different schemes comparison with different numbers of BSs…………………………………………………………………...……..……102
Figure 4-8 Percentage of coverage area with SINR greater than 2.3dB with different numbers of BSs………………………………………………..………103
Figure 4-9 Percentage of BSs that are allocated for different schemes with different numbers of BSs……………………………………………...………………104
Figure 4-10 Capacity and coverage comparison…..…………………………...105
Figure 4-11 Different schemes for different numbers of Channel……………….106
Figure 4-12 Multicast scenario ……………………………………………….108
Figure 4-13 Base stations with different operators' situation……………………109
Figure 4-14 Different coverage area for specific groups of users………………110
Figure 5-1 Coexistence Scenario………………………………………………114
Figure 5-2 The simulation steps of schemes combination……………………….116
Figure 5-3 Median SINR value for mixed scheme………………………………119
Figure 5-4 Error bars for two schemes mixed together…………………………120
Figure 5-5 Unassigned base stations for two mixed scheme schemes…………122
Figure 5-6 Probability of Channel usage in 5:5 ratio…………………………..…123
Figure 5-7 Capacity variation of the Channel Priority and Maximal Difference schemes when operating in the same spectrum…………………………………124
Figure 5-8 Bottom 5% SINR value for mixed schemes………………………….125
Figure 5-9 Error bar for mixed scheme ………………………………………….127
Figure 5-10 Probability of channel usage in ratio 7:3 and 3:7 of two schemes….128
Figure 5-11 Percentage of BSs operating different transmission rates..…………130
Figure 5-12 Percentage of used channels with different transmission rate requirements……………………………………………………………………...131

Figure 6-1 Distributed detection scenario……………………..………………137
Figure 6-2 Flowchart for channel assignment with reinforcement learning……..139
Figure 6-3 Flowchart for reassignment, blocking and dropping situation of distributed channel assignment………………………………..……………142
Figure 6-4 Average proportion of reassignments, probability of dropping and blocking for two distributed channel assignment schemes……………………...147
Figure 6-5 Probability of reassignment, dropping, blocking after 1000 iterations with changing a New Acceptance Threshold……………………………….....151
Figure 6-6 Probability of reassignment, dropping, blocking in 1000 iterations with changing the number of channels……………………………………………...152
Figure 6-7 Reassignments, dropping and blocking in 1000 iterations…………154
Figure 6-8 Probability a user is connected to one or more base stations (20 users per BS) ……………………………………………………………………..156
Figure 6-9 Probability of reassignment, dropping and blocking with 20 users per base station…………………………………………………………………158
Figure 7-1 Probability of reassignments, probability of dropping and blocking with 15 users per base station……………………………………….……………164
Figure 7-2 Probability a user is connected to one or more base stations (15 users per BS)……………………………………………………………………..165
Figure 7-3 Probability of reassignment, dropping and blocking with 15 users per base station of modified thresholds……………………….…………………...168
Figure 7-4 Base station nominal service area with power adjustment-All base stations are in different channels………………………………………………169
Figure 7-5 Flowchart for channel selection and assignment with power adjustment in system…………………………………………………………………171
Figure 7-6 Multiple base station connection for individual users with power adjustment……………………………………………………………………..172

Figure 7-7 Power reduction (dB) of original transmit power with different SINR thresholds after 100 iterations……………………………………………………173
Figure 7-8 Performance of power adjustment for reassignments, dropping and blocking with 15 users per base station…………………………………………..175

List of Tables

Table 2-1 FCA and DCA comparison in homogeneous environment…..…………50

Table 3-1 The parameters for different modulation schemes……………………...81

Table 4-1 System parameters………..…………………………………………….87

Table 6-1 State of BS and weighting factors……………………………………..141

Table 6-2 State of BS and modified weights…………………..…………………157

Table 7-1 State of BS and modified weights……………………………………..167

1. Introduction

1.1 OVERVIEW 17

1.2 PURPOSE 21

1.3 SYSTEM SCENARIO..22

1.4 THESIS STRUCTURE..25

1.1 Overview

With the rapid development of wireless communications in the 20th century, the rate of user and service growth continues to increase at a tremendous speed. Simultaneously, most of the usage is concentrated in some crowded frequency bands [1]. This means that the spectrum is often underutilized and inefficiently used. Studies by the FCC (Federal Communications Commission) show that 70% of the allocated spectrum is not utilized. Taking the usage of radio spectrum in the UK in Figure 1-1 as an example, we can see the frequency usage situations of different places in and around London for spectrum between 50 MHz and 1 GHz. The top frequency band shows the spectrum usage in a rural area, the middle one is near Heathrow airport and the bottom one is in central London. The area in blue is the frequency that is under used; part of the spectrum is yellow, red and even dark, which represents heavily used spectrum. There are plenty of spectrum opportunities, but they are not efficiently used in both space and time simultaneously, especially in rural areas. This discrepancy between allocation and use provides the motivation for opportunistic use of the spectrum. It then becomes more and more urgent to improve the spectrum utilization efficiency to meet the large bandwidth requirements of software and multimedia applications and the significant growth in the number of wireless users. To accomplish this, some related technology of radios need to be developed immediately that can sense the existing spectrum and identify and use free frequency bands [2].

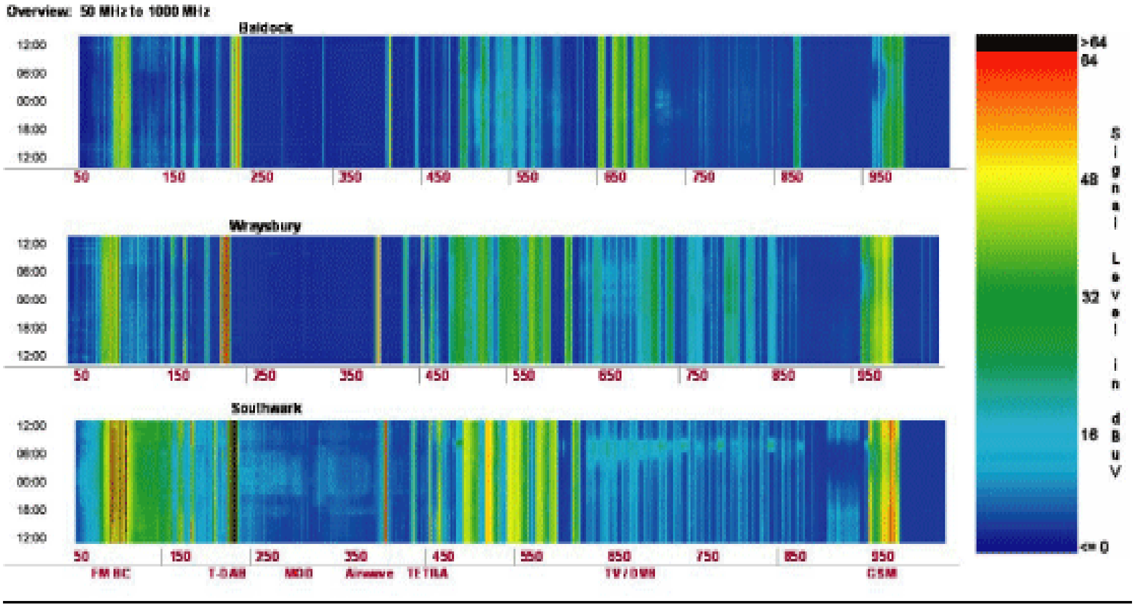

Figure 1-1 Usage of the radio spectrum in different areas of the UK (reproduced directly from [3])

In this case, the radio resource requires efficient reuse of the radio spectrum allocated to wireless communication systems in order to support the enhancement of applications within the limited radio resource [4, 5]. The reason for this inefficient usage of spectrum is that existing spectrum management techniques are not intelligent, or flexible enough to satisfy most of the requirements from users. If a radio is intelligent, it could learn about services available in locally accessible wireless networks, and could interact with those networks using their preferred signaling protocols. Additionally, it could use the frequencies and choose waveforms that minimize and avoid interference with existing radio communication systems [6]. An intelligent radio, which is called a cognitive radio, has the potential to realize the dynamic usage of frequency bands on an opportunistic basis, by identifying and using under-utilized spectrum [7], that is enabling significant spectrum reuse. Intelligent techniques will let the user find free spectrum at that moment and quickly use it. Thus, cognitive radio technology could be seemed as a very good solution for spectrum efficiency that is expected to lead to a revolution in the field of wireless communications.

It is necessary to point out that dynamic channel assignment is the significant issue when we start to investigate the cognitive radio technology. In radio systems and wireless networks, channel assignment schemes are required to assign channels to base stations and access points and to avoid co-channel interference among nearby cells. A number of approaches have been tried to assign bandwidth to users in an efficient manner while minimizing interference to other users using dynamic spectrum management. The number of research activities related to cognitive radio is steadily increasing. Most of their earlier research work of cognitive radio is from dynamic channel assignment and software-defined radio. We study the dynamic channel assignment first, and based on that, we develop our original schemes and their own characteristics to be compared and analysed. We give more detailed on the latest work carried out by others in Chapter 2 and show the connections between their work and ours. It is very novel to use mixed channel assignment schemes to allocate base stations in a more realistic scenario with different considerations. The interaction exists when the schemes are combined, causing positive and negative reactions with different combinations.

Multicasting could be used in many different areas. It is also a very important technique for cognitive radio to use. Most of its usage from the work of other researcher is concerned with the multi-hop cognitive radio networks or multicast routing, which could also enhance spectrum utilization. What is particularly interesting here for our work is the multicast communications applied to terrestrial communications directly, and the idea that multicast groups would help to minimize the energy cost and be more efficient in satisfying the requirements of cognitive users. Considering these connections, the novel idea for using dynamic channel assignment in this thesis is that we focus more on the multicasting scenario. When cognitive radio is combined with multicasting, it could determine the spectrum that satisfies a group of users, while not seriously affecting other groups of multicast users sharing the pooled spectrum.

Dynamic channel assignment cannot satisfy the intelligent perspective of cognitive radio. Based on dynamic channel assignment, we assume that the schemes can learn the information from the previous iterations and give feedback to their respective systems. Reinforcement learning is motivated as a way of potentially reducing the requirements of spectrum sensing by alternatively enabling cognitive radio users to exploit the preferred resources based on historical experience. Applying reinforcement learning into the distributed channel assignment schemes is aimed at improving the performance of more conventional schemes by using previously obtained knowledge to aid future decisions, in order to further improve the assignment stability and general performance of the cognitive radio system. By utilizing the reinforcement learning approach, users are able to discover the best available resources autonomously, which could result in significantly improved performance, while reducing the requirements for spectrum. One distinguishing feature of cognitive radio is the ability to incorporate learning [8, 9]. Based on dynamic channel assignment, we assume that the schemes can learn the information from the previous iterations and give feedback to their respective systems.

Many people have approached the learning research of the cognitive radio system with game theory or other learning schemes. We chose reinforcement learning because it has more novelty; our complex channel assignment schemes and the flexibility of the channel assignment schemes were also considered. Reinforcement learning was chosen in this thesis as a very new improvement for cognitive radio. Unlike to other learning strategies, reinforcement learning uses the weighting factor which could indicate the importance of the resources of cognitive radio users and be updated in each communication process. Its emphasis on the learning of each individual user from direct interference with the environment make it perfectly suited to our distributed occupancy scenario.

The main problem we want to solve is how to improve the spectrum utilization efficiency by using cognitive radio technology. In order to satisfy this, we will need to investigate channel assignment schemes that select channels based on optimizing the coverage area supported by a terrestrial network. We will also need to figure out how channel assignment in multicast terrestrial communication systems with distributed channel occupancy detection can be improved using intelligence based on reinforcement learning and transmitter power adjustment.

1.2 Purpose

The purpose of this investigation is to understand the implications of using cognitive radio with systems of different transmission range. We also aim to compare the performance of terrestrial communication systems that use different channel assignment schemes to allocate base stations in a scenario that implements the coexistence of mixed terrestrial communication systems based on cognitive radio technology. To demonstrate this, the interaction and coexistence of different channel assignment schemes should be analyzed. Artificial intelligence techniques like distributed reinforcement based learning should be developed to ensure that spectrum usage is maximized.

1.3 System Scenario

The coexisting scenario as shown in Figure 1-2 is initially based on three channels with 10 terrestrial base stations in random locations [10], in order to suitably model the behaviours of the channel assignment schemes in a multicast cellular system. The number of base stations and channels will be changed as required by the system and scenario later. The scenario here, unlike other familiar terrestrial downlink models that pay attention to the individual user, focuses instead on simultaneously delivering good coverage to many users in a coverage area.

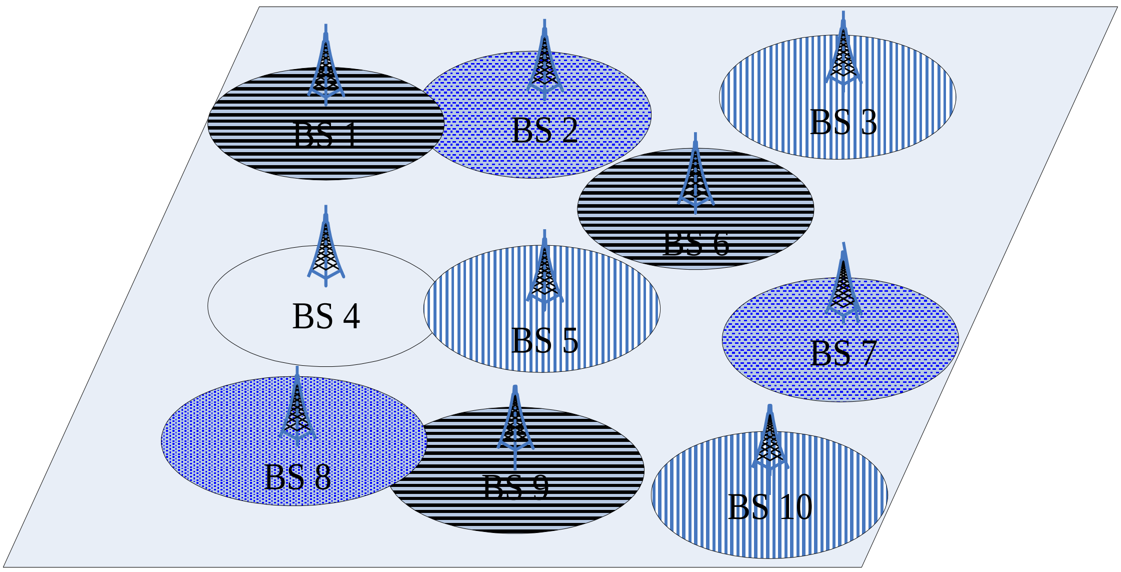

Figure 1-2 The coexisting scenario model with 3 channels and 10 base stations

Some specific groups of users and general requirements of services will also be considered later in this thesis with a multicast scenario. Multicasting technology can simultaneously transmit signals to multiple services to satisfy different requirements, which can save radio resources. Applying multicasting in cognitive radio and developing a multicast scenario with coexistence situations is a novel aspect of this thesis, and we will further investigate more applicable developments of this in spectrum usage. To do this we simulate a more realistic system which is described below. In general, customers use different mobile networks, so different base stations belong to different mobile companies and control their transmit power to best serve their own users in their coverage area.

Figure 1-3 shows the multicast scenario that is implemented by different operators. The dotted lines show the uplink. Heterogeneous multicast systems here can belong to different operators, each using CR-based channel assignment to satisfy users. The schemes select a channel based on the highest percentile of SINR across the coverage area. In this thesis, all the channel assignment schemes look at the SINR at multiple points within the coverage area, enabling multicast transmissions. These schemes are discussed throughout the thesis. There are many potential applications for our techniques; for example, our scenario is sufficiently similar to time division multiple access (TDMA). The TDMA technique allows several users to share the same frequency channel by dividing the signal into different time slots, which is a type of time-division multiplexing, where instead of having one transmitter connected to one receiver, there are multiple transmitters. In our multicast scenario, customers can use different mobile networks, so different base stations like multiple transmitters belong to different mobile companies and control their transmit power to best serve their own users in their coverage area.

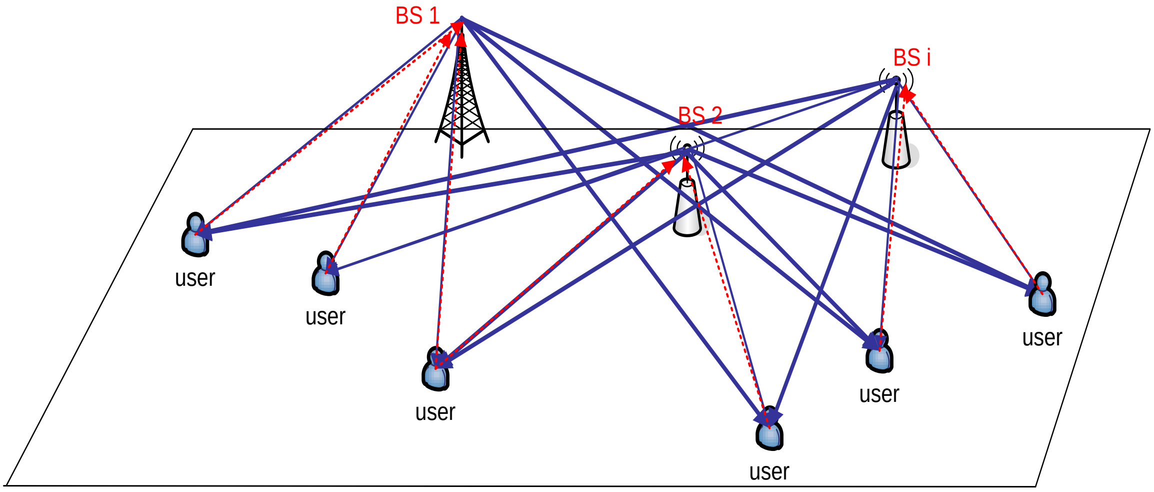

Figure 1-3 Heterogeneous multicast system scenario

Furthermore, we analyse the effect on performance of different user populations based on distributed occupancy. Figure 1-4 shows the distributed detection scenario, which including three different base stations with multiple users. The users in red, yellow and blue are the users for each individual base station. The users in black can be assigned to more than one base station. The users in white are unable to connect to any base station. Distributed detection is helpful for solving shadowing and “hidden node” problems [11]. Also, by considering the different user population, it is more scalable and provides systems with a lower complexity which is helpful in the implementation of cognitive radio.

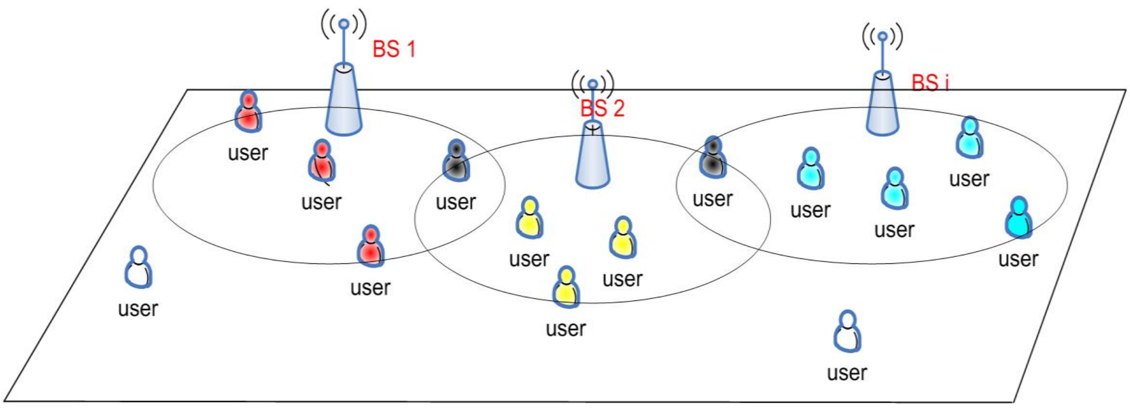

Figure 1-4 Distributed detection scenario

1.4 Thesis Structure

This thesis consists of eight further chapters, the contents of which are outlined in this section.

Chapter 2

Background knowledge relating to the research work will be given in this chapter. The history and development of Software-Defined-Radio and Cognitive Radio technology will be shown firstly. Next, spectrum management will be introduced, especially relating to spectrum etiquettes, spectrum pooling and spectrum pricing. Then different propagation and antenna information will be shown. Channel assignment for fixed, dynamic and hybrid strategies and further related research work of channel assignment are presented, followed by the introduction of multicasting then the reinforcement learning.

Chapter 3

The purpose of this chapter is to give a brief introduction to simulation techniques and performance evaluation. Firstly, a description of the system scenario model and related knowledge of modeling are shown. Then the appropriate measure and performance verification are presented, and then the simulation tools that have been used to generate the results shown in this thesis, to generate the results shown in this thesis, and then a description of the system scenario model and related knowledge of modeling are shown. Then the appropriate measures and performance verification are presented. Finally, the performance evaluation and parameters are also discussed.

Chapter 4

This chapter will describe the model of the coexisting scenario with related simulation parameters, followed by the equations for evaluating the performance of the system and the benefits of using multiple channels. 4 different channel assignments will be introduced. Then the different scheme comparisons will be discussed in the context of channels and base stations plots. After that, the scheme with best performance will be found. As an addition, the different requirements of users will be satisfied.

Chapter 5

The purpose of this chapter is to present the interaction and coexistence of mixed channel assignment schemes. The four schemes that were introduced in Chapter 4 will be combined two by two, within one scenario and the effect of scheme interaction observed. Firstly, the detailed scenario will be shown. Then the performance of different types of mixed scheme will be evaluated, followed by the same type of mixed schemes. After that, the optimal scheme for each combination will be found after considering interaction and coexistence, followed by the discussions of the results of mixed schemes.

Chapter 6

This chapter briefly overviews the model of the multicast scenario and distributed detection. This is followed by the introduction of two different distributed channel assignment schemes and their characteristics, and then the reinforcement learning rules. The performance and improvement of distributed reinforcement schemes will be then analyzed and discussed.

Chapter 7

This chapter describes the user population analysis of the distributed occupancy detection model. The results arising from different user populations influencing the distributed reinforcement learning schemes will be then analyzed and discussed, followed by the power adjustment applied in the system.

Chapter 8

This chapter provides a detailed description of potential further work, based on the work in this thesis.

Chapter 9

Summary and conclusions of this thesis and research work will be shown, followed by the highlights of novel contributions and originality of the research work.

2. General Background and Literature Review

2.1 INTRODUCTION 28

2.2 COGNITIVE RADIO 30

2.2.1 Spectrum Usage...*30*

2.2.2 Research and Development of Cognitive Radio......................................*34*

2.2.3 Cognitive Radio Architecture..*37*

2.3 SPECTRUM AND CHANNEL MANAGEMENT 43

2.3.1 Spectrum Management *43*

2.3.2 Channel Assignment *46*

2.4 PROPAGATION AND RELATED TECHNOLOGIES 53

2.4.1 Free space Propagation Model *54*

2.4.2 Okumura- Hata Model Propagation..*55*

2.4.3 Cost 231-Hata Propagation Model...*56*

2.4.4 Shadowing *57*

2.4.5 Multicasting..*58*

2.5 REINFORCEMENT LEARNING...60

2.5.1 Introduction to Reinforcement Learning..*60*

2.5.2 Reinforcement Learning Model *61*

2.6 CONCLUSION...65

2.1 Introduction

Cognitive radio has been suggested as a new way to implement efficient reuse of the pooled radio spectrum assigned to multiple wireless communication systems, by exploiting a wide variety of intelligent behaviour [12]. Cognitive radio detects the unused portion of the spectrum, and selects the unused spectrum holes by taking suitable steps to avoid interference with future licensed users [13]. Radios can monitor the spectrum and choose frequencies that minimize interference to existing communication activity in order to optimize the usage, especially the reuse of spectrum [14]. In order to satisfy multi-users' requirements for cognitive radio, multicasting will be applied to the system. Multicasting, especially on the downlink, will be an important feature of future pooled spectrum systems instead of unicasting because it is more efficient and can serve different groups of user simultaneously. As a starting point of investigating cognitive radio technology, channel assignment schemes will be studied here. Channel assignment can be divided into fixed channel assignment (FCA); dynamic channel assignment (DCA), which is often used for cognitive radio; and hybrid channel assignment (HCA) [15]. For making radio more intelligent, reinforcement learning is a method to describe the behaviour of an agent that learns through trial-and-error interactions with a dynamic environment so as to maximize some notion of long-term reward [16], which could be used for the learning part of cognitive radio. The agent receives and learns the information based on the external environment and previous states, which then influences the current activation [12].

The object of this chapter is to provide the background knowledge related to cognitive radio, channel assignment techniques and reinforcement learning. The history and development of software-defined-radio and cognitive radio technology is shown firstly. Next, spectrum management will be introduced, especially relating to spectrum etiquettes, spectrum pooling and spectrum pricing, and then, different propagation and antenna information will be shown. Channel assignment for fixed, dynamic and hybrid strategies will be introduced and further related research work of channel assignments are represented. This is followed by the introduction of multicasting and the knowledge of reinforcement learning.

2.2 Cognitive Radio

2.2.1 Spectrum Usage

The radio spectrum is an important natural resource. It is currently divided into bands that obey appropriate spectrum etiquettes by regulators and are licensed to operators, or left unlicensed for specific devices to use. This approach means that spectrum is often underutilized and inefficiently used. The figure shown below is the United States frequency allocations, which can be used to show the underutilized radio spectrum. The radio spectrum is generally considered to occupy the range from 3 kHz to 300 GHz. There are many different ways that organizations or companies can use the radio. The bands from 30 MHz to 3 GHz is where cognitive radio is likely to be applied because of its excellent propagation characteristic, but studies have shown that despite these bands still remains relatively unoccupied at less than 13% [17]. However, they may not be simultaneously used in the same geographic area or at the same time. It is worthy to note that frequency bands in general have been allocated multiple times. Obviously, the spectrum is scarce in some specific bands, but overall actual measurement shows that more than 70% of the spectrum is unused [18]. Thus, it is necessary and important to consider efficient spectrum usage.

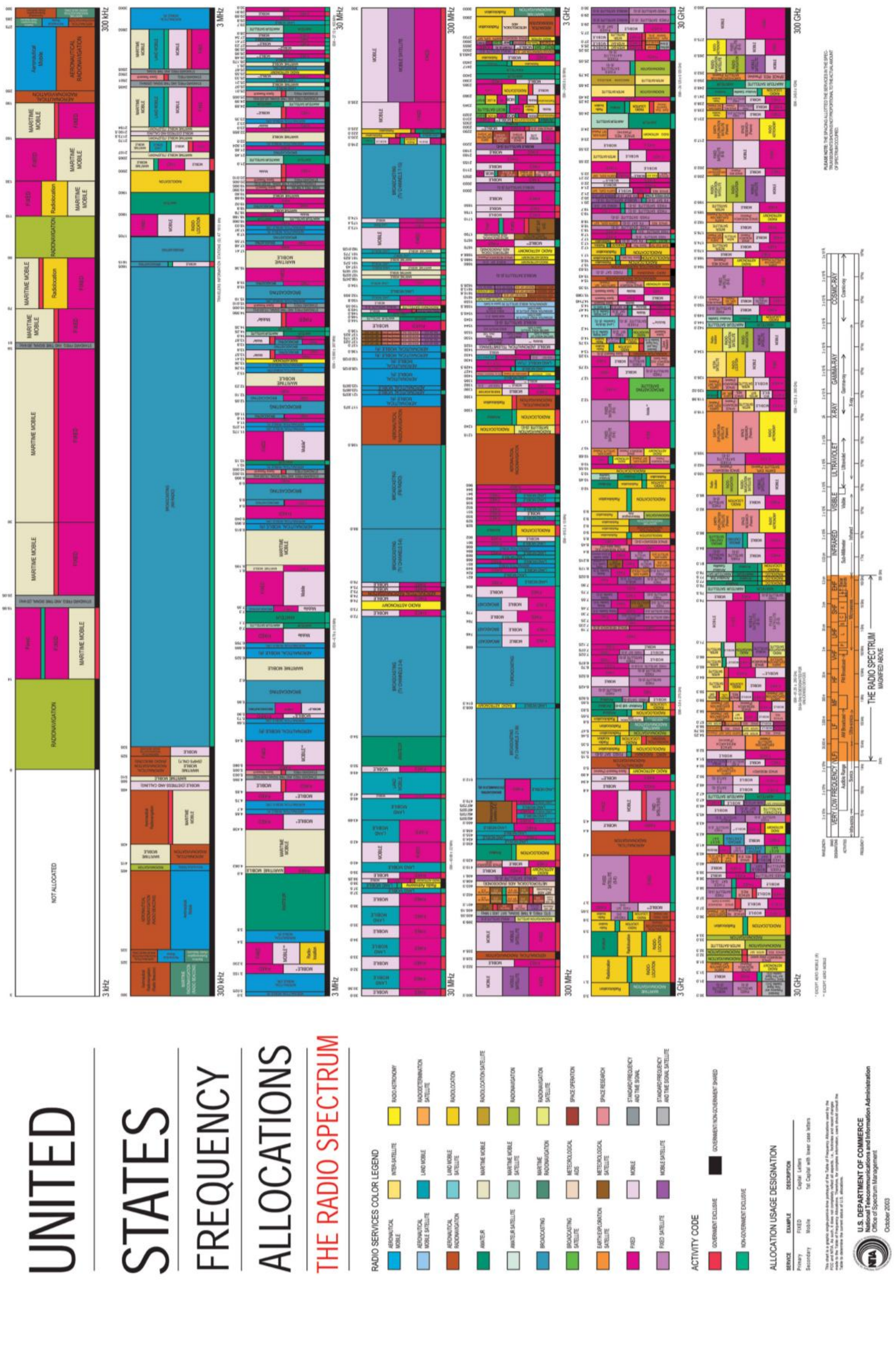

Figure 2-1 The United States frequency allocations (reproduced directly from [17])

Frequency Allocation

Frequency allocation is also known as spectrum allocation. It is defined as a discrete band of the radio spectrum that has been determined by a regulator. The frequency assignment is the frequency or frequencies on which a particular user is allowed to operate within a given frequency allocation [17]. It can represent the spectrum usage and development of radio resource management. According to the traditional spectrum sharing policy, the spectrum is licensed to the authorized users by the regulators, as shown in Figure 2-1 shown. In the UK, Ofcom also mentioned the details of frequency allocation in their report describing the usage of various frequency bands in the UK and which bodies are responsible for planning and managing them, including making frequency assignment to individual users or installation at particular locations. The entire spectrum allocation needs to be agreed on by the International Telecommunication Union [19].

Normally, the users rely on allocation of frequencies for efficient use of different objects, like cellular, broadcasting, emergency services, satellite, business radio frequency and so on, which shows the distribution of radio spectrum usage. In the communication aspects, GSM networks operate in a number of different carrier frequency ranges, which include the frequency ranges for 2G and UMTS frequency bands for 3G, with most 2G GSM networks operating in the 900MHz or 1800MHz bands. Most 3G networks in Europe operate in the 2100 MHz frequency bands. The competitor, W-CDMA transmits on a pair of 5 MHz-wide radio channels, while CDMA2000 transmits on one or several pairs of 1.25 MHz radio channels [20].

For WiMAX, the original 802.16a standard specified transmissions in the range 10 - 66 GHz, but 802.16d allowed lower frequencies in the range 2 to 11 GHz. The lower frequencies used in the later specifications means that the signals suffer less from attenuation and therefore they provide improved range and better coverage within buildings. This brings many benefits to those using these data links within buildings and means that external antennas are not required. Different bands are available for WiMAX applications in different parts of the world. The frequencies commonly used are 3.5 and 5.8 GHz for 802.16d and 2.3, 2.5 and 3.5 GHz for 802.16e but the use depends upon the countries [21, 22].

LTE devices operate in either of two modes: TDD (time domain duplex) or FDD (frequency domain duplex). In FDD transmission and reception takes place at different frequencies whereas in TDD transmission and reception takes place at the same frequency but different time slots. They are separate frequency allocations for these two modes but some bands are common between the two modes. The LTE standard can be used with many different frequency bands. In North America, 700/ 800 and 1700/ 1900 MHz are planned to be used; 800, 1800, 2600 MHz in Europe; 1800 and 2600 MHz in Asia; and 1800 MHz in Australia. As a result, phones from one country may not work in other countries. Users will need a multi-band capable phone for roaming internationally. S-E Elayoubi and B Fourestie develop an analytical model for collisions in 3G LTE OFDMA system for an arbitrary number of users in the different cells, and calculate the capacity of the system applying this Markov model to compare different frequency allocation schemes [23-25]. P Lee and T Lee propose an interference management scheme in the LTE femtocell systems using Fractional Frequency Reuse and show that proposed scheme enhances total/edge throughputs and reduces the outage probability in overall network, especially for the cell edge users [26].

Underutilised spectrum can be described as a spectrum hole in a cognitive radio system. A spectrum hole can be defined as a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user [27]. There are many spectrum holes existing in Figure 2-1. The reason for this inefficient usage of spectrum is that the existing spectrum management techniques are not flexible enough to always satisfy the primary users and secondary users simultaneously; that is, the radio is not intelligent enough to dynamically control its usage of spectrum. If a radio is intelligent, it could learn about services available in locally accessible wireless networks, and could interact with those networks using their preferred signaling protocols. Additionally, it could use the frequencies to minimize and avoid interference with existing radio communication systems [28]. At the same time, however, it must be recognized that such an intelligent radio may also have drawbacks. For example, it has the possibility of reducing the benefits of primary users, if the cognitive radio system shares the licensed bands with the wrong spectrum etiquette, or even worse if they were to break the rules of communication.

2.2.2 Research and Development of Cognitive Radio

Cognitive radio is a very hot topic that is expected to lead to a revolution in the wireless communications. A number of research activities about related to cognitive radio are steadily increasing. A summary of related research work are shown below:

- CR came to prominence with the publication of the doctoral thesis by Joseph Mitola III in 2000. He defined the cognitive radio as a way of incorporating machine-based learning into software-defined radio [29]. He is based at Stevens Institute of Technology and his team work on topics that are expected to have a broad impact on wireless networking and spectrum policy making. Joseph Mitola III's papers now focus more on the cognitive radio architecture evolution [30].

- In 2002, the FCC showed that the unlicensed frequency devices had the ability to identify the unused frequency bands. It established a "spectrum policy task force" to investigate CR as a means of improving spectrum efficiency. In 2003, the FCC developed the workshop on cognitive radio technologies and has made several contributions to CR [31].

- In the USA, under the funding from Defense Advanced Research Projects Agency (DARPA) [32], there have been a number of research activities: The NeXt Generation (XG) group was established in 2003, which showed how XG communications could not only make a significant impact on spectrum efficiency of defence communications, but also significantly reduce the complexity of defining the spectrum allocation for each defense user [33]. CWT, the Center for Wireless Telecommunications for Virginia Tech is funded by the National Science Foundation (NSF) and has also developed cognitive radio technologies [34]. Berkeley Wireless Research Center (BWRC) built the CORVUS system, researching the unlicensed frequency system and paid most attention to physical layer, analogue and multi-user issues in cognitive radios [35].

- The Office of Communications (Ofcom) is the communication regulator for the UK. Their work includes releasing and reallocating spectrum for new uses as well as developing policies to ensure that the spectrum is used efficiently. They monitor the airways 24-hours a day to identify cases of interference and take action against illegal broadcasters and the use of unauthorized wireless devices [19]. Their research work in cognitive radio includes the CR terminology, technologies, potential development timescales, user scenario and regulators.

- In the University of York, UK, the Cognitive Radio Lab is expanding rapidly. The Communications Research Group has one of the largest academic teams in the UK dedicated to Cognitive Radio (CR) and Cognitive Networking (CN). The field requires 'cross-layer' thinking to maximize the utility of the radio spectrum and can be applied to several layers of the protocol stack. In 2008, the lab was supported by a UK Ministry of Defense Competition of Ideas Project 'Cognitive Routing for Tactical Ad Hoc Networks', which also involves members of the Intelligent Systems Research Group [36].

- Beyond Next Generation Networks (BuNGee) [37] is a 30 months research project funded by the European Union under their Framework Seven research initiative, which is active until June 2012. The BuNGee project aims to design a new architecture for next generation (beyond 4G) systems that can achieve maximum data rate densities up to 1 $Gbit/s/km^2$, and forms the basis of a fifth-generation of mobile communication networks. The University of York is contributing to MIMO techniques and interference cancellation (including contribution to channel modeling), and cognitive radio and distributed intelligent resource management.

- There are now many projects related to cognitive radio in the European Commission (EC) 7th Framework Programme (FP7) [38]. E.g. Cognitive Radio Experimentation World (CREW), Spectrum and energy efficiency through multi-band cognitive radio (SACRA) and Cognitive Radio Oriented Wireless Networks (CROWN) projects. These show an increasing number of academic and industrial organizations in EU now consider it important to investigate cognitive radio technology and solving the spectrum efficiency problems. They have been published some related papers recently [39, 40].

- The Worldwide Universities Network Cognitive Communications Consortium (WUN-COGCOM) led by the University of York was established at the end of 2008. The Consortium aims to promises to revolutionize the way wireless communication devices and networks behave through ‘intelligent’ assignment of resources and operation [41].

- The IEEE Standards Coordinating Committee 41 (SCC41) focuses on researching Dynamic Spectrum Access Networks, which include Cognitive radio. It was formerly the IEEE 1900 standards Committee, and the work of the IEEE 1900.x Working Groups continues under SCC41. SCC41 is seeking proposals for standards projects in the areas of dynamic spectrum access, cognitive radio, interference management, coordination of wireless systems, advanced spectrum management, and policy languages for next generation radio systems [42, 43].

- IEEE 802.22 represents the Wireless Regional Area Networks (WRAN). It is developing a standard for a cognitive radio-based PHY/MAC/air-interface for use by license-exempt devices on a non-interfering basis in spectrum that is allocated to the TV Broadcast service [44].

2.2.3 Cognitive Radio Architecture

Cognitive radio is a paradigm for wireless communication in which either a network or a wireless node changes its transmission or reception parameters to communicate efficiently avoiding interference with licensed or unlicensed users

[45]. This alteration of parameters is based on the active monitoring of several factors in the external and internal radio environment, such as radio frequency spectrum, user behaviour and network state. First of all, the meaning of cognition has three-point computational view as 'Haykin' wrote [6]:

1) Mental states and processes intervene between input stimuli and output responses.

2) The mental states and processes are described by algorithms.

3) The mental states and processes lend themselves to scientific investigations.

There are six key words which to describe cognitive capability: awareness, intelligence, learning, adaptively, reliability, and efficiency [46].

Mitola defined five complementary perspectives of cognitive architecture (CRA), called CRA I through CRA V, which defines the functional components, perspective, examines the flow of inference through the cognition cycle, the related levels of abstraction for aware, adaptive and cognitive radios (AACR) and the mathematical structure of this architecture. In this thesis, we pay more attention to the cognition cycle which is in CRA II. The figure below shows the cognition cycle, which can be called Observe-Orient-Decide-Act (OODA) loop. It is a complex system that at the core of it is a radio that "knows". The radio knows where to observe, how to orient, when to decide and finally act. When the conditions of the outside world change, the radio needs to do corresponding changes based on the loop [12].

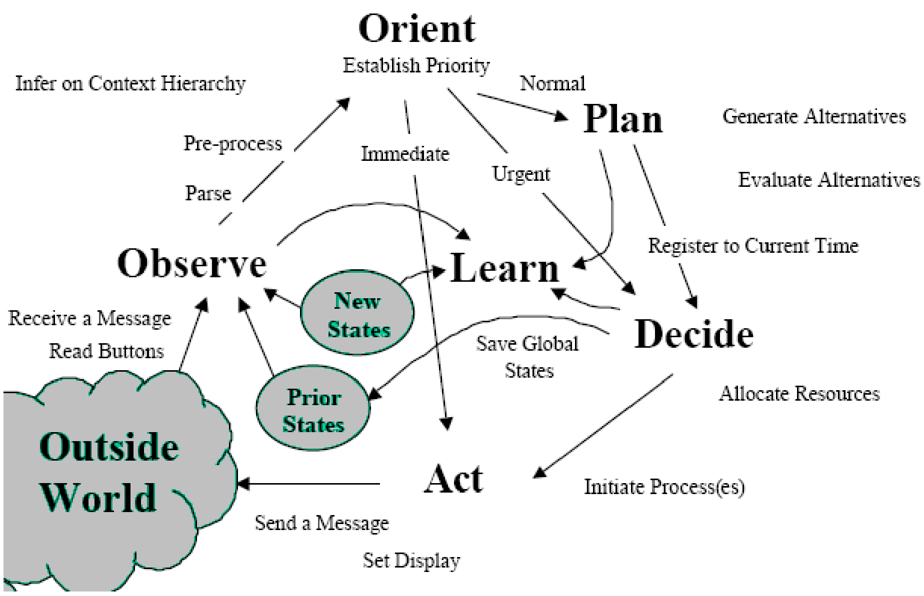

Figure 2-2 Cognition cycle of Cognitive radio (directly reproduced from [46])

From Figure 2-2, it is found that the cognitive radio is able to observe messages from outside world and taking information as an input. Through orienting and planning steps, the radio decides the further options and making the possible actions that the cognitive radio can perform. Learning is a significant middle step; it allows information exchange from different steps and enhance the whole performance of the CR system. Intelligence is one of key features of cognitive radio systems and it can be enhanced through learning [47]. The learning could come from either from the environment or from other cognitive radio systems, or the previous behaviors. The figure below is the cognition cycle directly from [48], which simplifying OODA loop.

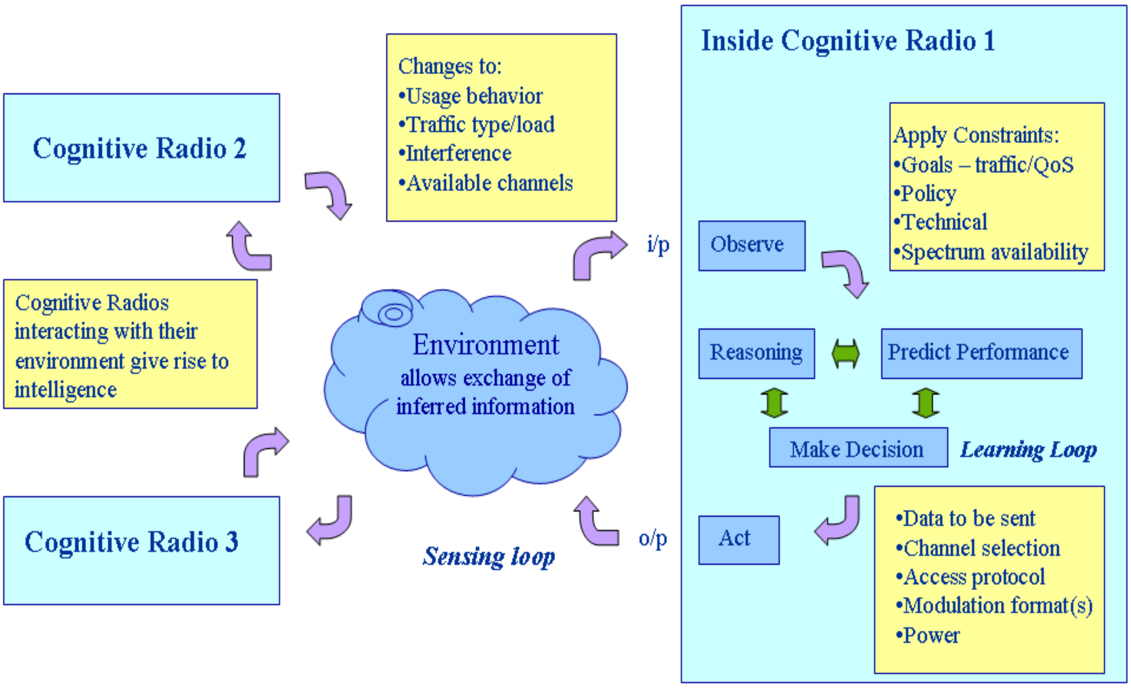

Figure 2-3 Modified Cognition cycle (reproduced directly from [48])

Between different cognitive radios, environment calls can exchange inferred information. Cognitive radios interacting with their environment give rise to intelligence. Inside the cognitive radio, objectives are set that are supported by a number of possible actions. We can see that in the learning loop, intelligence can be exploited to help the cognitive radio to adapt intelligently in response to the environment.

Cognitive radio networks are a logical generalization of cognitive radios. They are based on Cognitive Access Points (CAPs) and fixed Cognitive Relay Nodes (CRNs) in the scenario. A cognitive radio network is an intelligent multi-user wireless communication system that embodies the following list of primary tasks [49]:

- To perceive the radio environment by enhancing the receiver of each user to sense the environment on a continues time basis

- To learn from the environment and adapt the performance of each transmitter to statistical variations
- To control the communication processes among competing users through the available proper allocation
- To facilitate the communication between multi-users through cooperation in a self-organized manner
- To create intension and self-awareness process

A cognitive radio has the potential to enable significant spectrum reuse. Intelligent techniques will improve the ability of the user to find the free spectrum at that moment and quickly use it. However, there are two major challenges for Cognitive Radio research:

- Protection of the incumbents
- Coexistence (Spectrum Etiquettes)

When people consider cognitive radio technology, they often consider two kinds of users. One is primary users, which means the users or services with more important usage. They have the right to accept or reject subsequent users and their benefits need to be protected, e.g. military use or paid for bands assigned to mobile companies. The other group is secondary users, which represents the users which have the secondary right to use the spectrum. The combined interference caused by all secondary users in geographical area at specific time on existing primary users should be below a specified threshold. CR based systems aim to sense and exploit the opportunities of spectrum which are not being used by the primary users as secondary systems, which can result in a dramatic increase in spectrum utilization efficiency. How to protect the performance of primary users of the spectrum is the main problem, because socially important services may deserve priority in a band and legacy systems may not be able to change [50]. After protecting the benefits of primary users, CR should allow the secondary users to operate in otherwise unused bands. Primary users of the band usage may vary in time and the secondary users may have to coordinate with other secondary users.

Coexistence is based on the interaction at different levels (primary users and secondary users) or the same level (between different secondary users) of users. Interaction may present itself as an increase or reduction in interference in different wireless communication systems. How to avoid or reduce the interference, at the same time as increasing the usage of spectrum is the main object of coexistence for cognitive radio. Efficient and reasonable spectrum management will help to improve coexistence situations. Channel assignment is one of the specific ways to obtain the benefits of coexistence which is investigated in this thesis.

Software Defined Radio (SDR)

The forerunner of Cognitive radio (CR) is based on Software Defined Radio (SDR) [14]. SDR is a radio that can control a significant range of RF bands and air interface modes through software [51]. A SDR system is a radio communication system which can potentially tune to any frequency band and receive any modulation across a large range of the frequency spectrum by means of as little hardware as possible and processing the signals through software. SDR is a developing technology that can offer users many advantages, such as allowing them to move seamlessly between different types of network to optimize their quality of service or minimize the cost of using the service. Its current usage includes the Joint Tactical Radio System and Amateur or home use. Joint Tactical Radio System is a program of the US military to produce radios that provide flexible and interoperable communications [52, 53]. If SDR technology is properly used, it could provide a path towards the realization of concepts such as reconfigurability, run time reconfiguration, and eventually a self-governed learning radio which could be considered as a cognitive radio. These technologies could be very helpful for enabling new applications, e.g. dynamic handling of the spectrum and radio resource.

Compared with software defined radio, cognitive radio could reach the level where each radio can conceivably perform beneficial tasks that help the users, help the network, while helping to minimize the spectral congestion. Radios are already demonstrating one or more of these capabilities in limited ways [54]. Cognitive radio enhances the control process by adding some additional aspects over and above software defined radio: intelligence, autonomous control of the radio, an ability to sense the environment, the processes for learning about environmental parameters, awareness of capabilities of the radio [55].

This section described the current spectrum problem and introduced the background knowledge of cognitive radio, which will help us to understand the cognitive radio technology, especially the cognition cycle.

2.3 Spectrum and Channel Management

2.3.1 Spectrum Management

Inefficient spectrum usage is the reason why cognitive radio technology should be developed, so how to implement efficient spectrum management for existing radio resources is especially attention-grabbing. With the advent of a new generation of telecommunication technology, new techniques must be developed for the intelligent management of spectrum among the radio access technologies (RATs) forming a heterogeneous infrastructure [1]. Flexible spectrum management is needed for wireless devices that operate in either the licensed or the unlicensed bands, or both, as illustrated in Figure 2-4. Cognitive radio will provide the technical means to determine, in real time, the most suitable band to provide the services desired by the user at any time.

Spectrum etiquettes

In communication systems, the radio spectrum is divided into different frequency bands, and then the license for the usage of each of the frequency bands are provided to different operators or systems. A radio system represents a group of communication services, like the WLAN, WPAN and WMAN. A spectrum etiquette is a set of rules for radio resource management to be followed by all the radio systems that operate in the same unlicensed band [56]. Spectrum etiquettes could help the system to identify a reasonable way to allocate spectrum to the radio more efficiently in the radio resource management system. Different situations and people will have different etiquettes in communication systems. What interests us in this area is to understand and try to find an etiquette for the coexistence of networks in licensed and unlicensed frequency bands [15].

Spectrum pooling

Spectrum pooling is an innovative strategy to enhance the spectrum efficiency. It enables public access to the already licensed frequency bands [15]. The pooling can be described as the way users obtain access to spectral ranges they have not yet been allowed to use, and the actual licensed owners can tap the new sources of revenue. Orthogonal frequency division multiplexing (OFDM) modulation scheme could provide a useful modulation scheme for use with spectrum pooling. The basic idea of OFDM based spectrum pooling is to match the bandwidth available to a sub-band of the licensed system with an integer multiple of the carrier spacing frequency used in the cognitive system [57] , which aims to enable public access to these spectral ranges without sacrificing the transmission quality of the actual licensed owners. For both the economics and engineering aspects, spectrum pooling also needs to find the balance.

Spectrum pricing

The approach to spectrum management currently used in the UK and most other countries does not work well in this environment, in the sense that it is likely to result in economically and technically inefficient use of spectrum. This is not surprising given that no account is taken of the value of spectrum in different uses and users have few economic incentives to change their behavior in response to increased demand from others. When we consider the spectrum management, engineering and economics should be considered together for many realistic reasons that they are highly interconnected. For example, the tremendous growth of the wireless users, will increase the bandwidth requirements of multimedia traffic, and also require efficient reuse of the scant radio spectrum allocated to the wireless communication systems.

Efficient use of radio spectrum is also very important from a cost of service point of view, where the number of base stations required to service a given geographical area is an important factor. If there is a reduction in the number of base stations, while considering the cost of service, more efficient reuse of the radio spectrum can be achieved when other factors are the same. The costs and benefits analysis of spectrum pricing are difficult to quantify, because there is little evidence of how much efficiency could be improved by changing existing allocations and assignments of spectrum [58].

Engineering and economics need to be balanced when we consider the spectrum pricing with the development of cognitive radio. Whether incumbent wireless carriers or new entrants will get benefits of spectrum management is not decided. For new entrants and small players, many applications in small areas would be enabled. At the same time, the development of the new technology will cut costs, and then have further economic benefits. For incumbent ones, carriers are consumers of spectrum, not merely holders, so they could use cognitive radio to deploy new services on an experimental basis and using cheap devices only sublicense bands are needed [59].

2.3.2 Channel Assignment

Flexible spectrum usage is an essential aspect of the cognitive radio paradigm. It impacts regulation, especially in the context of spectrum sharing [47]. Based on the limited frequency spectrum, coupled with the inefficient use and an increasing demand for cellular communication services, the problem of channel assignment becomes increasingly serious. The objective of assigning channels is to implement and develop a spectrum-efficient and conflict-free allocation of channels among the cells in the wireless communication systems [60]. *Spectrum-efficient* here means to allocate the base stations into different channels by using the spectrum efficiently, to allocate more base stations. *Conflict-free* means that the interference between each service will be reduced or avoided. This issue is commonly referred to as frequency assignment or channel assignment. We use different channel assignment schemes to satisfy the performance of users' shares in either a single channel or different channels.

The basic prohibiting factor in radio spectrum reuse is the interference caused by the environment or other mobiles or services. There are many ways to help us reduce the interference; for example, deployment of efficient modulation schemes can be used to suppress interference with the chosen suitable code rate [61]. However, the main constraining factor that is caused by frequency reuse is the co-channel interference, and the main idea behind channel assignment algorithms is to exploit the radio propagation path loss characteristics in order to minimize interference and hence increase the radio spectrum reuse efficiency. In Figure 2-4 [62], T is the main transmitter and R is the user, and there are five other base stations in the area that can affect the performance of the users. The distances between the five different base stations are not the same, so the transmitters will give the user R different levels of interferences. Generally speaking, if the signal powers of the five base stations are the same, the shorter the distance, the more interference they will give to the requested user which is based on the calculations and analysis shown in section 2.4.

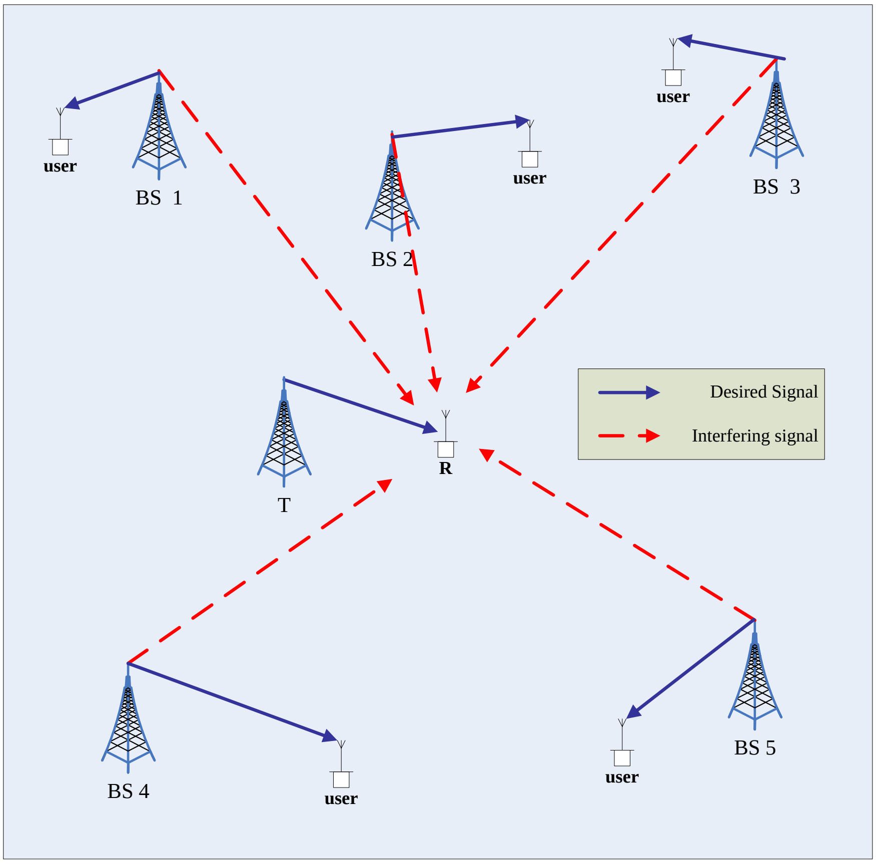

Figure 2-4 Base station and service users with interference consideration

Channel assignment schemes can be classified into: fixed channel assignment (FCA), dynamic channel assignment (DCA) and hybrid channel assignment (HCA). HCA is sometimes called flexible channel assignment. In fixed channel assignment, each cell is given a predetermined set of channels. Any user can only connect via an unused channel. If all the channels are occupied then a call is blocked in this system. With dynamic channel assignment, channels are not assigned to a cell or system permanently. The channel is assigned following an algorithm that accounts for the likelihood of future blocking within the cell. Hybrid channel assignment was designed by combining FCA and DCA [63]. The different channel assignment schemes that exist today are based on the basic meaning of the FCA, DCA and HCA. They are commonly used in wireless communication systems. The characteristics of the different channel assignment schemes will be introduced below:

- In FCA, channels are permanently allocated to each cell for exclusive use. FCA schemes are very simple; however, they cannot follow the requirements of users and the changing traffic conditions [61]. So the simple FCA strategy is not been used for main stream wireless communications since GSM because it is manually assigned by the network operator [62].

- Due to the short-term temporal and spatial variation of traffic in cellular systems, FCA schemes are not able to provide high channel efficiency. In DCA, channels are all available in every cell, and can be allocated with the requests dynamically. This means there is no fixed relationship between channels and cells in DCA. DCA schemes can be divided into centralized DCA, distributed DCA and can extend to SINR measurement based DCA schemes. Most of the time DCA has better performance than FCA except under heavy traffic load conditions [64]. CR is mostly based on DCA.

- HCA is a combination of FCA and DCA. In HCA, the total number of channels that are available for services is divided into fixed and dynamic sets. The working principle of it is: The fixed set contains a number of nominal channels that are assigned to cells as in the FCA schemes that base stations prefer to use in their respective cells in all the cases. The other set of channels is shared by all users in the systems to increase flexibility. When a call requires service from a cell and all of its nominal channels are busy, a channel from the dynamic set is assigned to the cell.

From the results of comparison in Table 2-1, in a homogeneous environment, DCA has many advantages compared to FCA in different practical transmitting situations. DCA is more complex than FCA and can be used in much wider fields. Some of the relative comparison results are shown in Table 2-1. FCA works better under heavy traffic because normally it is implemented by the controller and not flexible. In heavy traffic there is not enough time or space for other flexible channel assignments, so FCA is more suitable than DCA. Combine with the introduction of FCA and DCA and the comparisons in Table 2-1, we found that because of the different algorithms, DCA is relatively complex but more flexible, it could also be used in centralized or distributed systems, a feature we will use later. HCA combines the two together. The channel assignment schemes simulated in this thesis are based on dynamic channel assignment, which is the basis of cognitive radio technology. Dynamic spectrum management is the primary problem that needs to be solved. The details of the schemes including the channels to be allocated, the performance analysis and further discussion will be presented in Chapter 4.

FCA	DCA
Performance better under heavy traffic	Performs better under light/moderate traffic
Low flexibility in channel assignment	Flexible allocation of channels
Maximum channel reusability	Not always maximum channel reusability
Sensitive to time and spatial changes	Insensitive time and spatial changes
Low implementation complexity	Moderate to high implementation complexity
Low signaling load	Moderate to high signaling load
Centralized control	Centralized, decentralized, distributed control depending on the scheme
Suitable for large cell environment	Suitable for micro-cellular environment
Low flexibility	High flexibility

Table 2-1 FCA and DCA comparison in Homogeneous environment

The studies of DCA and related research work

There are several academic studies examining different aspects of DCA, we introduce the most important aspects of the research here:

- Based on the other researcher's previous work on channel assignment schemes, Katzela and Naghshineh presented a comprehensive survey of the detailed channel allocation schemes of wireless communication in 1996 [62]. This provides a very good guide and is significant for understanding how the different schemes work. It provides a large number of published papers in the area of FCA, DCA HCA, and also discusses them in different aspects, e.g. reuse partitioning schemes, the effect of handoffs and the prioritization schemes. In DCA, they discuss the centralized DCA, distributed DCA, CIR measurement DCA and one dimensional DCA schemes. Some of the common channel assignment schemes are reviewed here, e.g. first available, least interfered, channel reuse optimization and channel segregation schemes. Based on this paper, we studied the other related previous papers and also extend to more new papers of DCA and CR.

- Prior to Katzela and Naghshineh, there were other important papers which provide related knowledge and strategies of DCA, i.e. S. Tekinay and B. Jabbri which present the handover and channel assignment in mobile cellular networks in 1991 [64], T. Kanai discussed the DCA in cellular radio in 1992 [65], J.Chuang discusses the performance issues and algorithms for DCA in 1993 [66] and K. Ishii paper of 1994 showed the dynamic channel allocation algorithm with transmitter power control [67].

- In the last 10 years, cognitive radio technology has been developed, and more people investigated the related DCA work. i.e. O. Lazaro and D. Girma built a computational model with hopfiled neural network with DCA and obtain the performance in terms of call blocking probability in 2000 [68]. A. Lozano and D.C. Cox discuss the Distributed DCA in TDMA mobile communication systems in 2002 [69]. In 2006, K. B. Letaief and Y. J. Zhang focus on the dynamic multi-user resource allocation for MIMO and OFDM systems [70]. P. Also in 2006, K. Chowdhury and W. Ivancic discuss the channel assignment and handover schemes in satellite networks [71]. Back in 2007, H. Skalli and S. Ghosh investigated the issues and solution of channel assignment strategies of multiradio wireless mesh networks [72]. M. Y. Elnainary, D. H. Friend formulated the channel allocation and power control for dynamic spectrum cognitive networks in 2008 [73]. There are also some recent radio resource management strategies: R Skehill, M Barry and W Kend introduce the common RRM approach to admission control for converged heterogeneous wireless networks [74]. C Han and S Armour discuss the energy efficient radio resource management strategies for green radio and the scheduling algorithm is applied to an LTE downlink simulator and its performance is evaluated for various traffic load conditions [75].

Four main different channel assignments are implemented in this thesis. They are Least Interference, Channel Priority, Maximal Sum and Maximal Difference schemes, which will be described in detail in Chapter 4. Our original idea of channel assignment schemes is based on Katzela and Naghshineh's paper. In DCA, we combine the minimum interference scheme using SINR with the common 'least interfered (centralized)', and finally obtain our first scheme in the project – the Least Interference scheme. The Channel Priority scheme is based on the 'system dimensioning procedures for prioritized channel assignment' [62], which decides the minimum number of guard channels required in each cell in order to satisfy the quality of service. We apply this idea into our Channel Priority scheme and consider this as a relatively simple scheme when applying reinforcement learning into the system. The Maximal Sum and Maximal Difference schemes have been developed as part of our research and can be considered original.

There is some recent research work in Fractional frequency reuse. In WiMAX, subchannel management allows the dynamic bandwidth allocation among cells or sectors according to the interference conditions. Users at the cell or sector edge are able to exploit the fractional of the total bandwidth and have to reduce their peak rates. The global reuse factor of the system assumes a fractional value and this kind of scheme is called Fractional frequency reuse (FFR) [76]. R Giuliano and C Monti analyze the FFR scheme in the rural areas evaluating the increase of the overall system capacity and they found that this can provide extra capacity, slightly penalizing the users at the cell edge [77]. P Lee and T Lee proposed an interference management scheme in the LTE femto-cell systems using FFR and the results show that the proposed scheme enhances total throughputs and reduces the outage probability in overall network, especially for the cell edge users [26]. S.H. Ali and V.C.M. Leung propose a dynamic fractional frequency reused cell architecture and show how the dynamic frequency allocation in fractional frequency reuse improves the OFDMA networks [78].

Section 2.3 focuses on the spectrum management, especially the channel assignment, which will be the significant part of our project: every subsequent chapter will use the knowledge of this section.

2.4 Propagation and Related Technologies

In this section, suitable measures like bandwidth efficiency, SNR/SINR values for different modulations need to be obtained. Under different propagation conditions, the same cognitive radio networks may obtain extremely different results. So not only for cognitive radio networks, but also for channel assignment, all the schemes need to adapt to different situations and real communication environments. Some propagation models are discussed here for different usage situations. Three propagation models are discussed in the following section, the free space propagation model, Okumura-Hata and COST231-Hata propagation models. Shadowing and multipath are then discussed [79]. They will all be used in our simulation.

2.4.1 Free space Propagation Model

Figure 2-5 shows the path loss is the ratio of the transmitted power to the received power in detail. It includes all of the possible elements of loss associated with interactions between the propagating wave and any objects between the transmit and receive antennas.

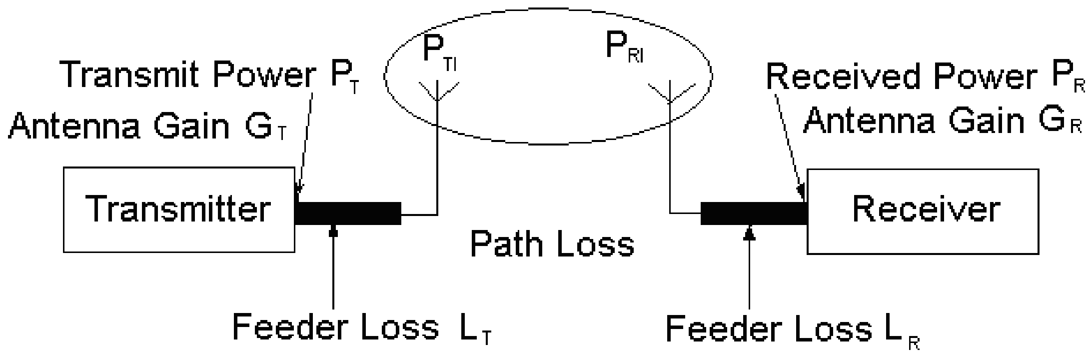

Figure 2-5 Basic transmitter and receiver of path loss

The free space model is used predict received signal strength when the transmitter and receiver have a clear, unobstructed line of sight path between them. S is the power density which could be calculated as shown below:

$$S = \frac{P_t G_t}{4\pi r^2} \qquad (2.1)$$

where G_t is the maximum gain of the transmitter's directional antenna [80]. r is the distance between transmitter and receiver, Applying equation (2.1), the received power for user, P_r, is the significant factor for obtaining SINR (in next chapter). It has the relationship with transmitted power P_t as follows:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi r} \right)^2 \qquad (2.2)$$

Where G_t and G_r are the gains of the terminal antennas, r is the distance between the antennas and λ is the wavelength. The antenna applied is isotropic, which radiates power equally in all directions that means no angle and boresight effects. This expression defines L_F, the free space loss, as P_r here. Expressing the free space loss in decibels, with frequency in megahertz and distance R in kilometers, we obtain

$$L_{F(dB)} = 32.4 + 20\log R + 20\log f_{MHz} \qquad (2.3)$$

From the equation, the free space loss increases by 20dB per decade in either frequency or distance.

Although the free space model is an idealized and simple model for system, it is chosen for the first step of the simulation model in this thesis because what we want focus is on to how to assign base stations and users in a coverage area to the most suitable channels, not the absolute performance of the system. The Okumura-Hata model is more accurate for small city and rural areas. The Cost-231-Hata model improves the accuracy of transmitter and receiver in different cities.

2.4.2 Okumura- Hata Model Propagation

This model is entirely based upon many different extensive measurements around Tokyo city between 200MHz and 2GHz. It is built by Okumura and improved by Hata [80]. This method divides the prediction area into open, suburban and urban area.

Urban areas $L_{dB} = A + B\log R - E$ (2.4)

Suburban areas $L_{dB} = A + B\log R - C$ (2.5)

Open areas $L_{dB} = A + B\log R - D$ (2.6)

Where

$$A = 69.55 + 26.16\log f_c - 13.82\log h_b$$

$$B = 44.9 - 6.55\log h_b$$

$C = 2(\log(f_c / 28))^2 + 5.4$

$D = 4.78(\log f_c)^2 + 18.33\log f_c + 40.94$

$E = 3.2(\log(11.75h_m))^2 - 4.97$ for large cities, $f_c \geq 300\,\text{MHz}$

$E = 8.29(\log(1.54h_m))^2 - 1.1$ for large cities, $f_c \leq 300\,\text{MHz}$

$E = (1.11\log f_c - 0.7)h_m - (1.56\log f_c - 0.8)$ for medium to small cities

h_b : base station antenna height above local terrain height [m]

f_c : carrier frequency [MHz]

h_m : mobile station antenna height above local terrain height [m], often take as 1.5m

The model is normally applicable for $30\text{m} \leq h_b \leq 200\text{m}$, $1\text{m} \leq h_m \leq 10\text{m}$ and R > 1km. The path loss exponent is given by B/10, which is a little smaller than 4, and decreases with increasing base station antenna height [41].

2.4.3 Cost 231-Hata Propagation Model

The Okumura-Hata model is used for small or medium cities. The frequency bands of it have been extended to cover the band $1500\,\text{MHz} \leq f_c \leq 2000\,\text{MHz}$ [80].

$$L_{dB} = F + B\log R - E + G \qquad (2.7)$$

Where

$F = 46.3 + 33.9\log f_c - 13.82\log h_b$

E is as defined for small or medium cities and then

$$G = \begin{cases} 0\text{dB} & \text{medium-sized cities and suburban} \\ 3\text{dB} & \text{metropolitan areas} \end{cases}$$

Other parameters are defined as same as Okumura-Hata model defined.

There are some other models which are not used in this project, including the Lee or Clutter Factor and other models [80], which are not described in detail. They are suitable for the usage with different frequency bands or in more complex situations. For the coexistence, which is the main point of the project, we pay more attention to the channel assignments in order to ensure more base stations can be allocated to the most suitable channels, and due to this, to find the optimal schemes for channel assignment. At the same time, many iterations of statistical simulation need to be performed, if we choose the even more accuracy and complex models, this may delay the simulation time and does not help to see the performance of DCA schemes. So normally we choose the Okumura-Hata model as the main model for cognitive radio system. The COST231-Hata model is used in some situations when we use them to determine more realistic behaviors.

2.4.4 Shadowing

There are also some other general propagation attenuation mechanisms. The total path gain can be identified by the distance, shadowing and multipath effects.

$$Total\ Gain = Gain_{Distance}\, Gain_{Shadowing}\, Gain_{Multipath} \quad (2.8)$$

$Gain_{Distance}$ is the gain related to the distance from user to the base station

$Gain_{Shadowing}$ is related to the shadowing by obstacles in the path, which is constant and is characterized by a log-normal variable:

$$Gain_{Shadowing}(dB) = \eta$$

Where η is a log normal distributed random variable with zero mean [81]. 'Log-normal' is means that the received power is expressed in logarithmic values, such as dB, has a normal (i.e., Gaussian) distribution. The amplitude change caused by shadowing is often modeled using a log-normal distribution with a standard deviation.

$Gain_{Multipath}$ is the gain related to the multipath interference, which is the variation in path loss of users within a few wavelengths. Multipath interference can often be averaged out to a large extent, since it changes so fast.

If we include a log-normal distribution to represent shadowing loss into the system scenario, the performance of the base station will be changed, improved or impaired. For example, when the log normal distribution is used with the Okumura-Hata propagation model, it will contribute a gain in some situations, i.e. the gain has the possibility to be bigger than 1, which will mean better performance could be obtained than with the Free-space propagation model in a small number of cases. Otherwise, when the gain is smaller than 1, they may obtain even worse performance will be realized than the average path loss at that point. Shadowing is the only extra factor we include in our work in addition to affect the propagation model. More factors will be considered and discussed in future work.

Antennas

The system in this project is based on terrestrial communications, and the antennas used here are not considered for special angular and altitude conditions. An isotropic antenna is chosen which means it is a hypothetical antenna radiating power equally in all directions. Other antennas may replace the basic one depending on the different situations.

2.4.5 Multicasting

Fixed spectrum usage that is applied in traditional communication systems uses the radio resource inefficiently. New ways of flexible spectrum usage have appeared in recent years, e.g. cognitive radio technology, which uses dynamic spectrum assignment to implement efficient utilization of the radio spectrum. The further step of flexible spectrum usage is its application to broadcasting, multicasting, such as DVB-H [82]. Unlike unicast, multicast is the delivery of information to a group of destinations. For a wireless communication system, multicasting is a more efficient mode to supporting different, specific groups of users when compared unicasting, as it consumes fewer radio resources. The motivation for using multicast here is because in heterogeneous terrestrial communication system, multi operators and multi users need to be connected and worked correctly and efficiently. When combining cognitive radio with multicasting it is important to determine the spectrum which satisfies a group of users, while not seriously affecting other groups of multicast users sharing the pooled spectrum. Multicast is also a very important technique for CR to use and the idea of multicast groups would help to minimize the energy cost and be more efficient to satisfy the requirements of cognitive users. TDMA uses the multicast technique. The multicast mobility (multimob) working group that provides guidance for supporting multicast in a mobile environment [83]. It could also be used for IP multicast and VideoLAN. In this thesis, all the channel assignment schemes look at the SINR at multiple points within the coverage area, enabling multicast transmissions. These schemes are used throughout the thesis.

Multicasting is not a new topic, and it has even been considered for use with dynamic channel assignment, like in [83, 84]. In this thesis combining multicasting with cognitive radio technology requires that the SINR be simultaneously satisfied for a high proportion of users within a group. In this case, users will choose the nearest transmitter as the SINR is most likely to be highest, after taking into account environmental conditions. Channels are chosen based on the overall performance at multiple points in the service area, rather than the performance at one specific location. Novel aspects in this thesis apply multicasting to a cognitive radio system with learning and also investigate the interaction between different channel assignment schemes. In this thesis, all the channel assignment schemes look at the SINR at multiple points within the coverage area, enabling multicast transmissions. These schemes are throughout the thesis. Further examples of multicasting will be shown later.

The knowledge in Section 2.4 is very important and useful. All of them will be directly used in the simulation and each result part.

2.5 Reinforcement Learning

2.5.1 Introduction to Reinforcement Learning

Reinforcement learning will be another important feature for our project, which shows the learning factor in our cognitive radio system. The history of reinforcement learning has two main threads to be considered, which were pursued separately before combining in modern reinforcement learning. Learning by trial and error was firstly implemented as one thread that was original from the psychology of animal learning. The other thread concentrates on the problem of optimal control and the solution by using value functions and dynamic programming.

Reinforcement learning is a sub-area of machine learning concerned with how an agent ought to take actions in an environment so as to maximize some notion of long-term reward [9]. In recent years, it has attracted rapidly increasing interest in the machine learning and artificial intelligence communities [85]. Reinforcement learning is learning what to do--how to map situations to actions--so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards. These two characteristics--trial-and-error search and delayed reward--are the two most important distinguishing features of reinforcement learning [86, 87].

2.5.2 Reinforcement Learning Model

In the standard reinforcement learning model, an agent is connected to its environment via perception and action, as depicted in Figure 2-6. On each step, the agent has an input i, current state s of the environment, an input function *I*, which determines how the agent views the environment state and then the agent choose an action a to have an output. The agent changes the state of the environment, and the value of this state transition is communicated to the agent through a reinforcement scalar signal r. The agent's behavior, B, should choose the actions that tend to increase the long-run sum of values of the reinforcement signal.

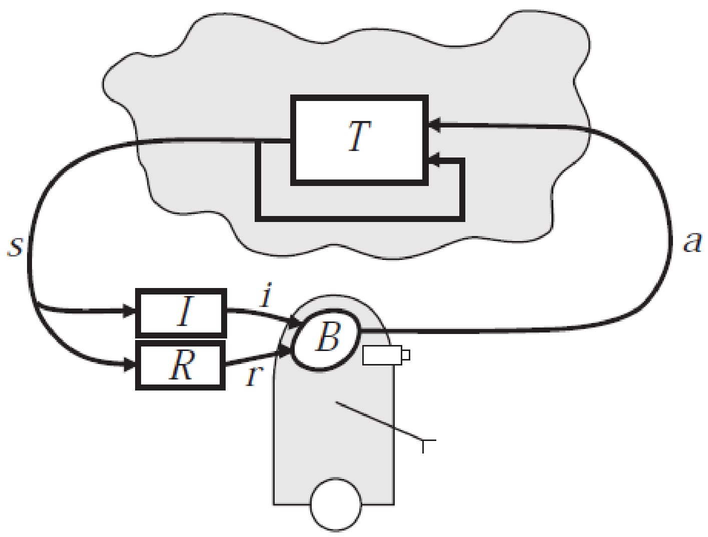

Figure 2-6 standard reinforcement learning model (directly from [8])

The model includes 3 main factors:

- A set of environment states S
- A set of actions A
- A set of scalar reinforcement signal, which is as known as numerical rewards R

The agent here is the learner, and its job is to find a policy π, mapping state to actions, and then maximize the long term measurement of the reinforcement learning. Reinforcement learning is different from supervised learning. Supervised learning is learning from examples provided by a knowledgeable external supervisor. Reinforcement learning is an important kind of learning, but alone it is not adequate for learning from interaction. In interactive problems it is often impractical to obtain examples of desired behavior that are both correct and representative of all the situations in which the agent has to act. In uncharted territory, an agent must be able to earn from its own experience where one would expect learning to be most beneficial [85].

Reinforcement learning has been applied successfully to many problems, including robot control, elevator scheduling, telecommunications, backgammon and chess. One of the challenges of reinforcement learning is the trade-off between exploration and exploitation. To obtain a reward, the agent must prefer actions that have been tried in the past and found to be effective in producing reward. However, to discover this kind of actions, it has to try actions which has not selected before. The agent has to exploit what it already knows in order to obtain reward, but it has to explore in order to make better action selections in the future. The dilemma is that neither exploration nor exploitation can be pursued exclusively without failing at the task.

The studies of RL and other artificial intelligence methods with DCA

From DCA to cognitive radio, learning is the most important factor for making radio ‘intelligence’. In our project, we choose artificial intelligence as the method to implementing learning. Artificial intelligence is commonly used in computer science, which is represented as machine learning in application, including reinforcement learning (sometimes Q-learning), game theory, and artificial neural networks. There are some academic studies examining different aspects of artificial intelligence with DCA, and we introduce the important aspects of the research here:

- Channel segregation (CS) is one important technique used in distributed channel assignment. The basic idea of CS introduces the memory of preferred channels after the training, when the interference sensing enables the base stations to determine potential interference before choosing a given channel [88, 89]. It is also known as ‘DCA with weighted orderings’, which could adapt faster than original DCA to network changes [90]. Channel segregation is the closest DCA scheme to cognitive radio. We obtained the idea from CS and apply the learning method in this work.

- S. Haykin and J. Nie discussed Q-learning based DCA for mobile communication systems and also use Q-learning in conjunction with neural network representation for DCA [91]. N. Nie used game theory as an adaptive channel allocation spectrum etiquette for cognitive radio networks. This shows how a cooperation based spectrum sharing game improves the overall network performance while satisfying an increased overhead required for information exchange [92].

- S.M. Senouci and G. Pajolle solve the Semi-Markov decision process problem by using an approach based on reinforcement learning applied in DCA at 2003

[93]. N. Lilith and K. Dogancay investigated the dynamic channel allocation for mobile cellular traffic using reduced-state reinforcement learning in 2004 [94]. Recently, M. Bublin discussed the distributed spectrum sharing by reinforcement and game theory [95]. T. Jiang et al discussed reinforcement learning based cognitive radio with exploitation and exploration control [8]. P Zhou, Y Chang and J.A. Copeland discuss the reinforcement learning for repeated power control game in cognitive radio networks. The performance of the learning based power control algorithm they developed is thoroughly investigated with simulation results, which demonstrate the effectiveness of the proposed algorithm in solving variety of practical CR network problems for real world applications [96].

Compared to the dynamic channel assignment schemes we introduced before, reinforcement learning based schemes will also detect the unoccupied frequency first, and then consider the historical information of successful or unsuccessful channel usage with the current interference level. Furthermore, the information obtained from the previous step will help the service make a current or future decision on which resource to use in order to maximize the probability of success.

In our work, reinforcement learning is used as a way to implement the learning engine for a cognitive radio and channel assignment. Applying intelligence into cognitive radio systems is a very new topic, and this thesis investigates how to apply different learning techniques to cognitive radio [97, 98]. We start from a simplified distributed reinforcement learning algorithm to see how it works in a multicasting cognitive radio system, focus on the reward and punishment parts of reinforcement learning, and will use the weighting factor to define and record these aspects. Finally, we will make the decision of preferred channel set to help us figure out the optimal option of channel assignment, especially for distributed schemes. Compared to others' work, we aim to further improve the performance of DCA schemes in the aspect of intelligent, reducing the probability of reassignment, blocking and dropping by considering different user population. The knowledge of reinforcement learning will be used in Chapter 6 and 7.

2.6 Conclusion

This chapter has introduced the background knowledge relating to this research work. From the background reviews, we understand the principle of cognitive radio and how it works, and the research work and development of cognitive radio around the world. We use dynamic channel assignment to implementing the flexible spectrum assignment that cognitive radio requires. Propagation models with the required parameters will depend on the communication environments they will operate in. Multicasting is potentially very useful for delivering point-to-multipoint traffic in cognitive networks. Reinforcement learning models are introduced as a very useful way to implement the learning and cognition part of a cognitive radio system.

3. Simulation and Performance Evaluation Methodologies

3.1 INTRODUCTION 66
3.2 SIMULATION MODELING TECHNIQUE 67
3.3 SIMULATION TOOLS 71
3.4 PARAMETERS AND PERFORMANCE EVALUATION 75
3.4.1 Performance Parameters 76
3.4.2 Capacity Variation and Bandwidth Efficiency 80
3.4.3 Error Bars 81
3.5 CONCLUSIONS 82

3.1 Introduction

In engineering research, it is necessary to develop quick and cost efficient approaches to characterize systems. The development of simulation-based models is an approach that is widely used in modern engineering activities [99]. Simulation can be used to show the eventual real effects of alternative conditions and courses of action [81]. Simulation can also be used to build complex models and to show the results obtained quickly, allowing for flexible situation changes.

The purpose of this chapter is to briefly introduce simulation techniques and to conduct a performance evaluation of modeling. Firstly, we provide a description of the system scenario model and related information on modeling. Then, the appropriate measures and performance verification are presented, and the simulation tools are used to generate the results shown in this thesis. Finally, the performance evaluation, and parameters are discussed.

3.2 Simulation Modeling Technique

The simulation method used for channel assignment, which will be introduced in Chapters 4 and 5, is based on a widely used statistical simulation technology —the Monte Carlo simulation. The Monte Carlo simulation method is suited to calculation using a computer, and is used with computer modeling techniques because of its repetitive nature and the large number of calculations involved. It is nondeterministic and use random numbers (in practice, pseudo-random numbers) to vary one or more parameters to explore system behaviour, as opposed to deterministic algorithms [100-102].

Typically, in this work, 1000 sets (random locations with random activation orders) of users' location are considered as an adequate number of trials for obtaining statistically accurate results. The simulation is based on a coexistence scenario that is applied in a terrestrial communication system. Unlike other familiar terrestrial downlink models that pay attention to the individual user, this method focuses on many users in a coverage area. In this case, the area as a whole will be considered.

Figure 3-1 shows the area of interest, which is a square coverage with sides of 8 km. In this square area, all of the user locations are located on a 100m grid, so in this simulation process, there are 81×81 different potential user positions. A selection of these will be used at random and the resulting system performance evaluated. The transmitters (i.e. the base stations) are represented as a circle and a point in Figure 3-1.

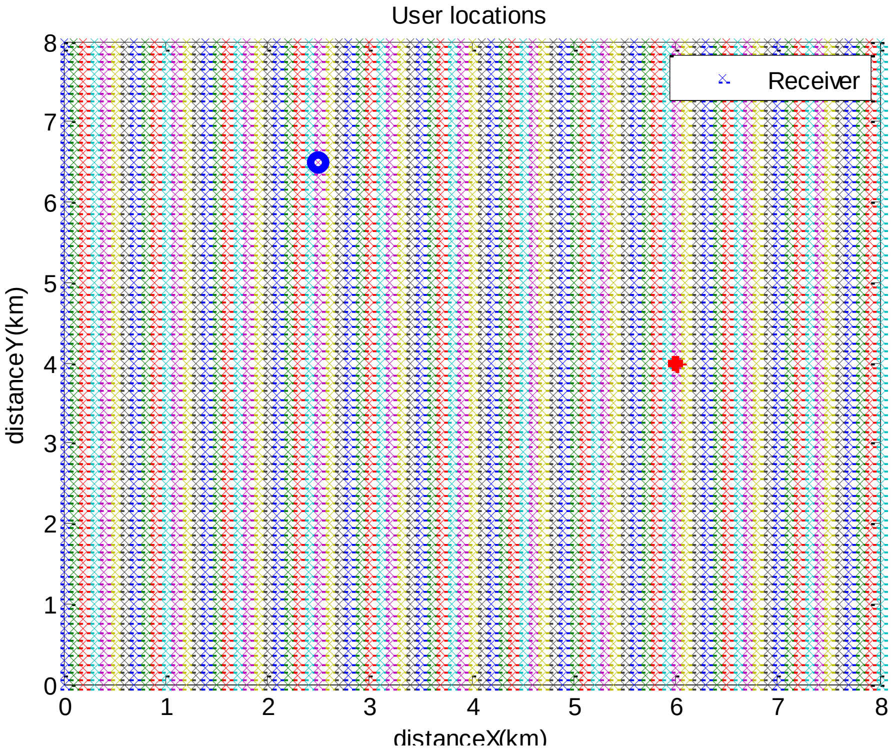

Figure 3-1 User location and coverage area situation

In Figure 3-2, the system originally used here models a coexistence scenario with 10 different base stations. In this scenario, the locations of base stations are always randomly located in the coverage area, in order to get statistical representation of behavior. Due to the random base station locations, the area of influence of each base station is not fixed. All the evaluation of performance will be done for all the base stations.

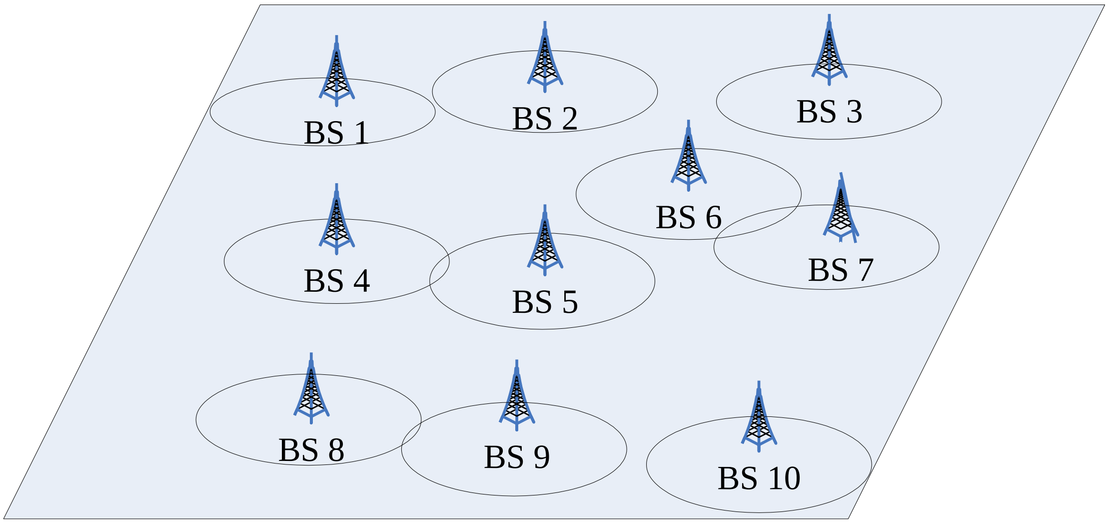

Figure 3-2 Basic Scenario of terrestrial communication system

We consider two ways of grouping users in this thesis. The first method is into a single user group with the same operator. The other is into more than one group of users each associated with a different operator. We measure performance in the multicasting scenarios based on the performance of these groups.

In Chapters 4 and 5, we focus on the characteristics of four channel assignment schemes and combined schemes based on the average reward. A large number of simulation events are required to identify the performance of various channel assignment schemes. Normally, the more simulation runs, the more accurate the result obtained. However, due to the complexity of the schemes, we used 1000 iterations to provide an adequate number of trials for obtaining statistically accurate results. In order to make the radio more ‘cognitive’, a second set of simulations was used in this thesis based on reinforcement learning. Previously we stated that reinforcement learning is concerned with how an agent ought to take actions in an environment so as in order to maximize some notion of long-term reward [98]. The learning based simulation is similar to Monte Carlo, but is not a true Monte Carlo simulation as the learning takes the place of only the repeated calculation. Using the weighting factor, reward and punishment function instead of the no learning system, we will obtain the reinforcement results. Figure 3-3 shows the performance applying reinforcement learning to the system; this will be explained more fully in Chapter 6. Here, the performance of schemes is based on a cumulative process as the current weight value used is based on the previous value, and increases or decreases after each activation. Reinforcement learning has memory, as the learning process never stops. In these circumstances most of the results are shown from zero to 1000 iterations. This is considered sufficient to illustrate the learning behaviour.

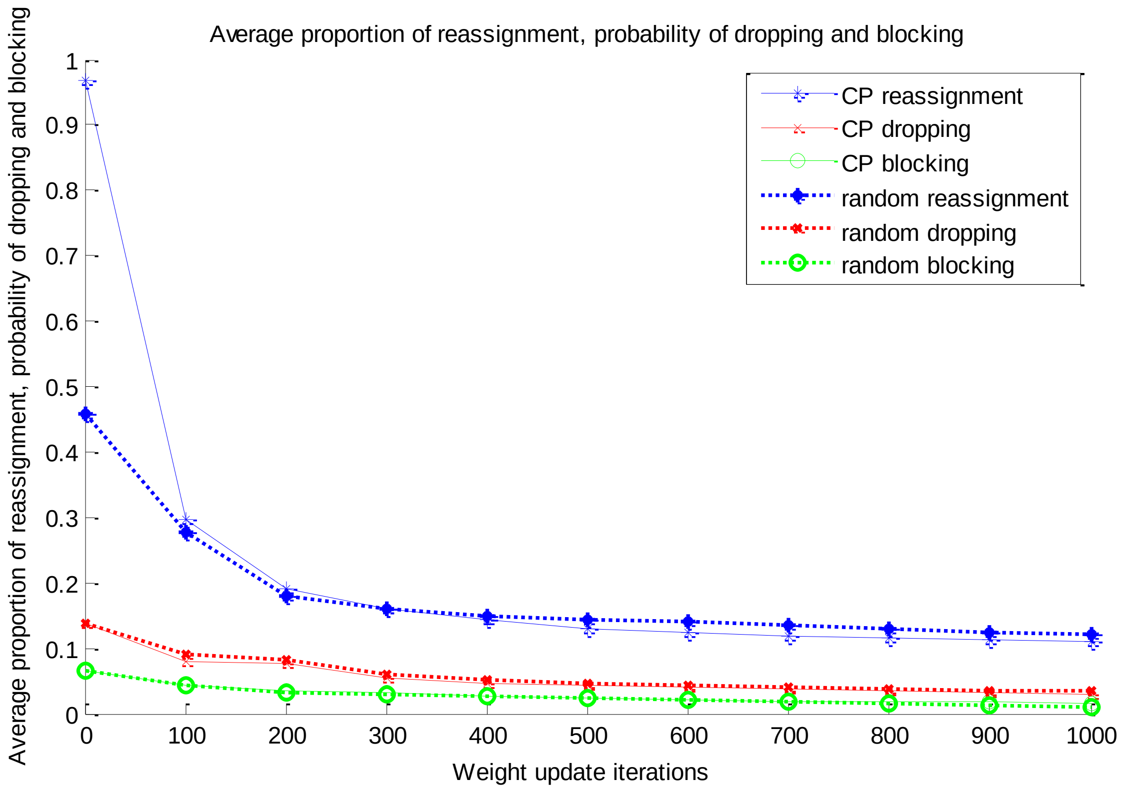

Figure 3-3 Average proportion of reassignments, probability of dropping and blocking for Channel Priority and Random Picking schemes

All the experiments have been conducted for the same load. In order to make sure that the simulation results are correct, we undertook to verify and validate the simulation process: Firstly, after obtaining the system performance, the related variable equations can be used to verify the simulation results, taking into account different related variables. Different representations of the results figures are also helpful. Secondly, simulating an adequate number of trials is important to ensure statistically accurate results. They are used when we analyze the performance of different schemes with or without of reinforcement learning. Error bars are used to indicate the degree of confidence one can achieve from a particular number of simulation trials. Finally independent verification and validation have been performed. Theory and reference from other independent works have been used for comparison.

3.3 Simulation Tools

There are many programming tools for developing simulations in engineering research activities. The MATLAB and C languages are widely used in this kind of simulation work. The main drawback of MATLAB is that it has a slower execution speed than that of the C language. C is compiled into the assembly language (machine language), which operates faster than interpreted MATLAB code. However compared to C, MATLAB is more suitable for our research work for the following reasons:

1. MATLAB is based on dealing with matrices and arithmetic; it offers matrix based computation that allows users to perform numerical computation more easily than does C [103].

2. It has many different kinds of graphical display capabilities to satisfy the different requirements of development and modeling algorithmic behaviours.

3. MATLAB has many professional toolboxes and predefined functions, which are very helpful in reducing programming time and in performing simulations, for example, the communication tool box is used.

Due to the reasons above, MATLAB can fulfill the system level oriented simulation tasks required for our work. The figure below shows the steps of the MATLAB simulation work. Figure 3-4 shows the basic process of channel assignment when using MATLAB. After using the reinforcement learning methods in the system to improve the performance, this iterative loop will be modified in the real simulation process. The iteration number is also initialized and a variable is used to record its process.

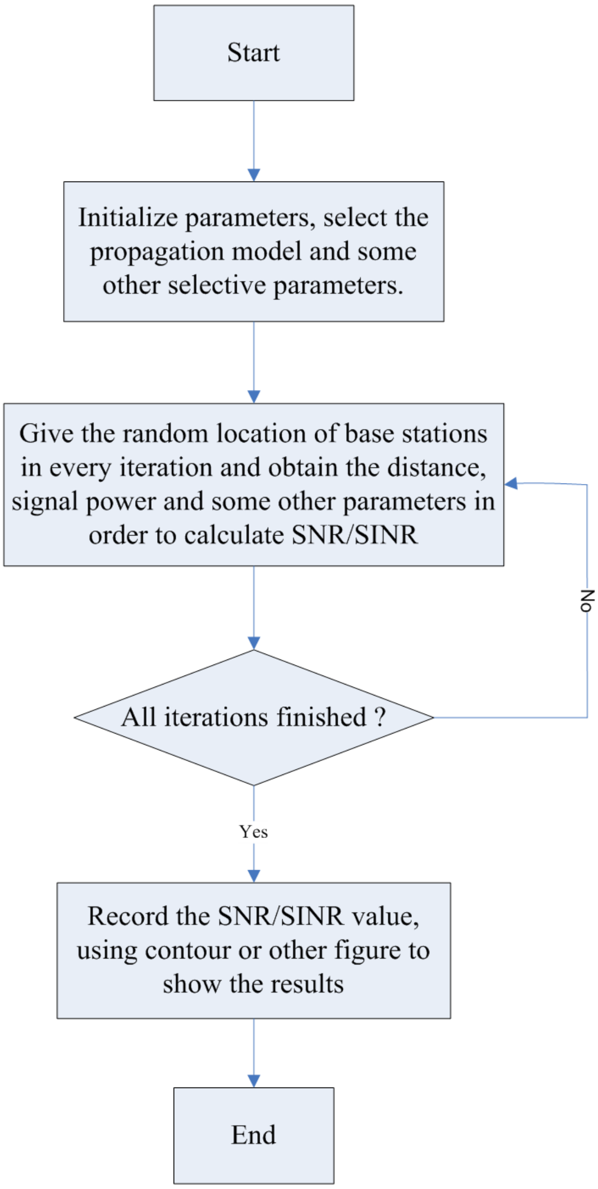

Figure 3-4 Matlab simulation process of base channel assignment scheme

Blocking probability and dropping probability are two main factors that will be used in the simulation of our DCA schemes, especially with reinforcement learning in Chapter 6 and 7. Normally, blocking probability is used to measure the probability that a call will fail during the set up phase. In this thesis, when an arrival cannot be assigned to a channel, the request will be blocked. The blocking probability represents the ratio of the number of blocked connection requests to the total numbers of connections. Dropping probability can be used to provide the measure for a call that fails when it is in progress. The dropping probability here provides a measure for the number of calls interrupted by new activations. Compared to blocking, dropped calls are significantly worse in terms of customer perception [99].

Figure 3-5 shows a more detailed flowchart illustrating the different situations of reassignment, blocking and dropping when reinforcement learning applied, to show how the simulation is executed to obtain the desired results in Chapter 6. In this flowchart, *i* and *j* are current base station and current channel.

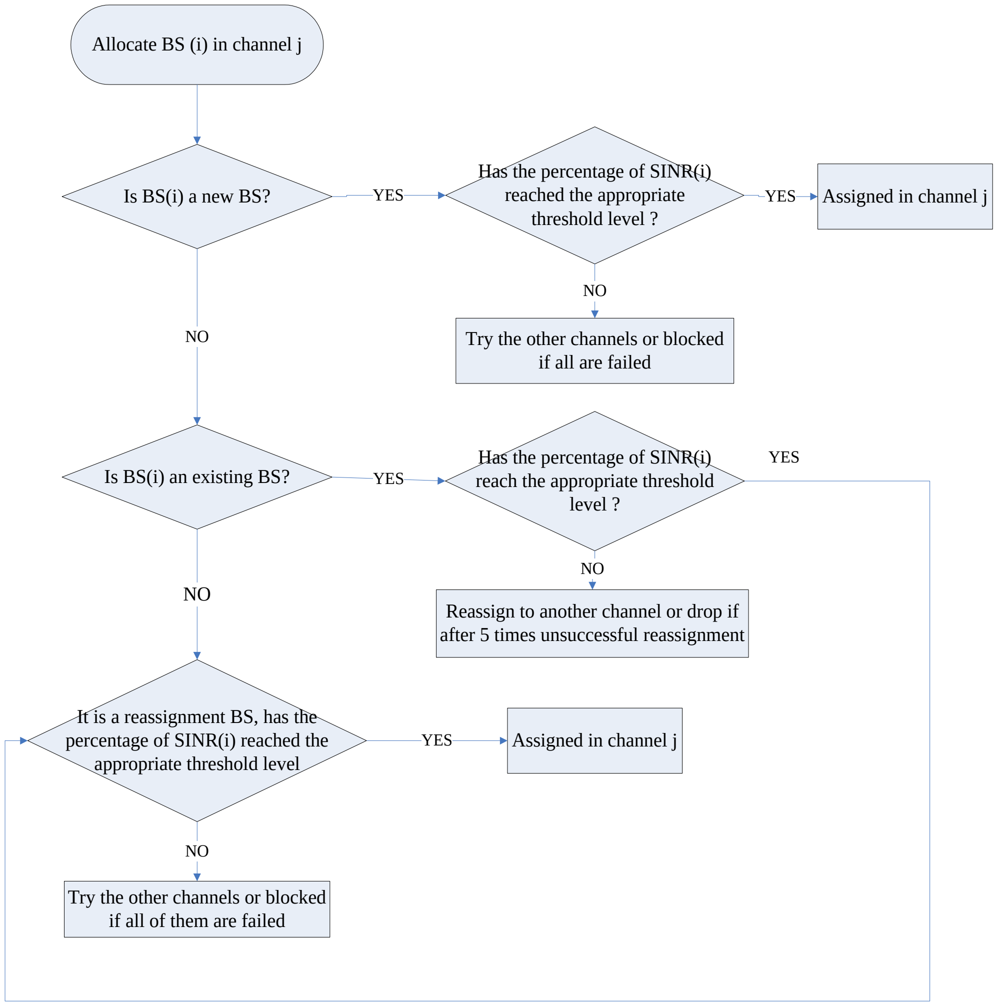

Figure 3-5 Flowchart for a single iteration of distributed channel assignment

3.4 Parameters and Performance Evaluation

There are interactions that always exist in a terrestrial communication system. For channel assignment, the positive or negative interactions are an important issue. Interaction will just affect interference and correspondingly the SINR. So when we perform a simulation resulting performance will appear included in the results. In this chapter, the interaction will be considered from two aspects: when the users are on the same channel or on the different channels.

Same channel

Basically, the performance of an individual user can be calculated by using Signal-to-Noise ratio (SNR). However, if we assume that more than one user is on the same channel, the evidence of interaction here is the interference, which exists between users. To determine the performance of the system, it is necessary to determine the Signal-to-Interference-plus-Noise Ratio (SINR). SNR and SINR will be shown in more detail in the Performance parameter section.

Different channels

Normally, the base stations, which are assigned on to different channels, will not influence the SINR value at the other base stations, i.e. we assume that the adjacent channel interference is negligible. In a coverage area, the coexistence of radio systems within multiple frequency bands can result in a more efficient reuse of the radio spectrum. In this case, multiple channels can give additional benefits to users by giving them greater choice, hence improving the SINR and providing higher user capacity. For example, if 3 channels are available in the coverage area, the 10 base stations can distribute in these 3 channels, will allow us to select three different SINR values for each user providing an indication of the best channel available to each user from the maximum of these three values.

SNR and SINR are the main measures we used to evaluate the performance of the system. The parameters to calculate SNR and SINR will be shown in this section. Due to the overall performance in the coverage area, at the same time we need to obtain the value of the statistics of SINR, so the Cumulative Distribution Function (CDF) is used here. The statistical performance of SINR will be applied in the channel assignment schemes to select the most appropriate channels. A CDF is used to derive their collective behaviors. In this section we will discuss Capacity variation and Bandwidth Efficiency. Finally, the use of Error bars will be presented in the last part of this section, which can be used to determine how statistically meaningful the simulation results are. Appropriate performance measures are required to verify these dynamic channel assignment schemes employed by our cognitive radio systems.

3.4.1 Performance Parameters

Signal-to-Noise Ratio (SNR) and Signal-to-Interference-plus-Noise Ratio (SINR)

Signal-to-noise ratio (often abbreviated SNR or S/N) is an electronic engineering concept defined as the ratio of a signal power to the noise power corrupting the signal [61]. It is always used to identify the performance of the users when ignoring the interference from other users. According to the signal power equation we introduced in Chapter 2, the equation can also be calculated as below:

$$SNR = \frac{P_s}{P_n} = \left(\frac{\lambda}{4\pi r}\right)^2 \frac{G_t G_r}{P_n} \qquad (3.1)$$

Where P_s is the base station transmitted power. It is calculated as P_r in equation 2.2. P_n is the noise power which will be shown later.

Noise power

Normally, the major noise that contributes to a communication system will usually come from the receiver itself, although external noise contributions may also be significant in systems. The total noise associated with the communication system can be calculated by assuming that the system consists of a single input and a single output. The network is characterized by a gain G_n, being the ratio of the signal power at the output to the signal power at the input, and by a noise factor F. The noise factor is the ratio between the output noise power of the element, divided by G_n and the input noise [80].

The noise power is available at the input of the network from a resistor with an absolute temperature of T kelvin is $P_n = kTB$. The noise power is another important factor in the determination of SINR, at the same time adding the noise factor F which depends on the design of device. T his can be expressed by:

$$P_n = 10\log(FkTB) \tag{3.2}$$

where k is the Boltzmann's constant $=1.379\times10^{-23}$ [$WHz^{-1}K^{-1}$], and B is the effective noise bandwidth of the system.

In our work, these parameters for calculating noise power are all constant, so the noise power is a constant [105]. After calculation, the noise power is equal to -102.7dBm in this simulation.

If we consider the interference between base stations, the Signal-to-Interference-plus-Noise Ratio (SINR) will be used here for the simulation in most of the time.

$$SINR = \frac{P_s}{P_n + \sum P_i} \tag{3.3}$$

The interference is caused by the base stations in the same frequency band, i.e. the same channel. The shorter the distance between two base stations, the more interference they will receive. P_i is the interference between the base stations. If we assume P_s here is the signal power of the first base station, P_i can be calculated by:

$$\sum P_i = P_{s2} + P_{s3} + \ldots + P_{sj} = \sum_{j=1}^{N} P_{sj} - P_{s1} \qquad (3.4)$$

Where j is the total number of interfering base stations, N is the total number of base stations. The power that the current user receives from other base station will be the interference power.

Figure 3-6 is an example to show the interference between two base stations using the same channel by using a contour plot [106].

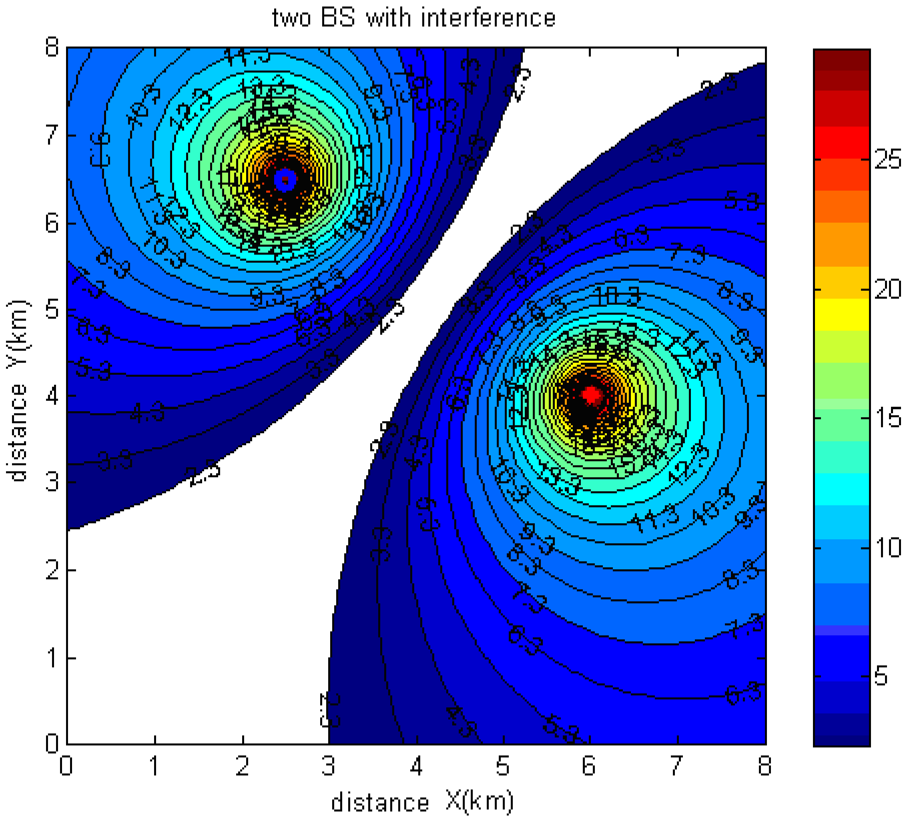

Figure 3-6 Contour plot for two base stations when subject to mutual interference

Each contour line represents a 1dB reduction from the highest contour value. If we assume that the SINR values of the users that are below 2.3dB (from Table 3-1) are not shown in the contour plot, then the white space between the two base stations illustrates the existence of harmful interference. With the relative length of the signal and interference paths, the shorter the distance between the two base stations, the more interference they receive. Contour plots that are more complex will be shown in later chapters to represent the interaction between base stations when different schemes are used.

Cumulative distribution function (CDF)

In probability theory, the cumulative distribution function (CDF) is the integral of the probability distribution function [107]. The Cumulative Distribution Function (CDF) of SINR (presented as SINR cdf later) across the coverage area on each channel is calculated and a certain percentile is used in order to obtain a measure of SINR on the channel. The percentile threshold is used to take into account the different number of base stations in the system because this number will affect the coverage area of each base station.

Figure 3-7 shows a comparison between single and multi-channel Cumulative Distribution Function (CDF) and the benefits of multiple channels. In a coverage area, the coexistence of radio systems within multiple frequency bands can result in a more efficient reuse of the radio spectrum. In this case, multiple channels can give additional benefits to users by giving them greater choice, hence improving the SINR. In Figure 4-2, a CDF of three single channels is shown based on all the users over the entire service area when the threshold value is 2.3dB. X is the SINR value. For example we see from the ‘channel together’ curve, which is derived from the highest SINR on all of the 3 channels when 10 base stations are assigned in the system, that 90% of the coverage area has a SINR below 15.2dB compared with 7.6dB, 12.1dB and 13.4dB in the single channel cases. Chapter 4 will explain in detail how to use this in the real system with SINR.

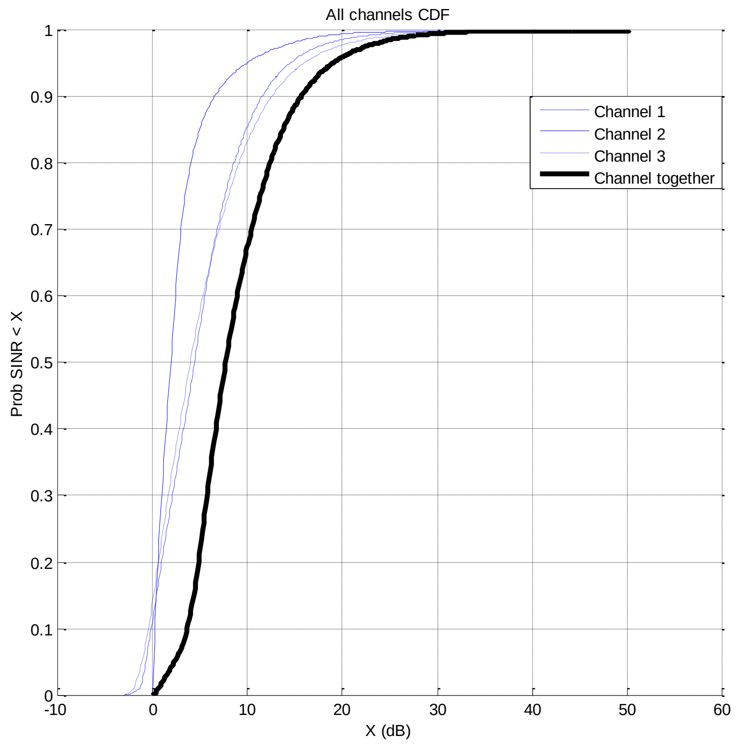

Figure 3-7 Single and multi-channel CDF comparison

3.4.2 Capacity Variation and Bandwidth Efficiency

Capacity variation and bandwidth efficiency are other two important elements that will be considered for evaluating the system performance. These are based on the SNR and SINR explained previously. The Shannon equation [108] is the equation that combines these two elements to characterize the performance:

$$C = BLog_2\{(1+SNR)\} \qquad (3.5)$$

$$BW_{ef} = \frac{C}{B} = Log_2\{(1+SNR)\} \qquad (3.6)$$

The SINR can be used instead of SNR assuming interference is Gaussian. Where C is the capacity of the channel, B is the bandwidth, BW_{ef} is the bandwidth efficiency. The Shannon equation is theoretical and is used to obtain the ideal channel capacity for a particular level SINR and channel bandwidth. In practice, the bandwidth efficiency is affected by the modulation and coding schemes used.

The table below shows the code rate, bandwidth efficiency, example bit rate, Eb/No and SNR values for different modulations for different modulation schemes that we will use quantify the performance later. We assume the GMSK modulation scheme is used which has a minimum threshold of 2.3dB for a 10^{-3} bit error rate.

	64-QAM	64-QAM	16-QAM	GMSK
Code rate	1.0	0.69	0.69	0.69
BW efficiency (bits/s/Hz)	4.8	3.3	2.2	0.9
Example bit rate (Mbit/s)	36	25	17	7
Eb/No (dB)	18.7	10.4	6.7	2.7
SNR (dB)[2]	25.5	15.6	10.1	2.3

[2]RF bandwidth = 3MHz (we use roll-off factor = 0.25, therefore max symbol rate = 2.4Msymbol/sec)

Table 3-1 The parameters for different modulation schemes [109]

3.4.3 Error Bars

Error bars are used on graphs in the experimental sciences, to indicate the range of deviation in experimental measurement. Error bars can be used to visually compare two quantities, to determine whether differences are statistically significant. They can also show how good a statistical fit the data has to a given function [104].

There are two common ways we can statistically describe uncertainty in the measurements. One is with the standard deviation with respect to single measurement (often just called the standard deviation) and the other is with the standard deviation with respect to the mean, often called the standard error. The standard error is the appropriate measurement to use to calculate the error bars when use the mean [110].

In this thesis, error bars are used to indicate the degree of data fluctuation that is caused through randomness in parameter values used in Monte Carlo simulation iterations. The error bars we used here is an error in the sampled mean. The size of error bar is used as [104], the upper error and lower error bar are defined as:

$$e = \mu \pm z_c \cdot \frac{\sigma}{\sqrt{N}} \tag{3.7}$$

where μ is the sample mean, σ is the standard deviation, N is the number of trials, and z_c is related to the confidence interval as explained below. The confidence interval (size of error bar) is affected by the number of trials (or iterations of the simulation). In this thesis, the number of trials, N, is normally set to 1000, and the confidence interval is taken from the normal distribution. For a 99% confidence interval, z_c corresponds to 2.56, i.e. the area is assumed to be within 2.56 standard derivations of the mean. So here error bars will be used to show how the SINR varies around the sample mean value. Error bars are important for result measures and performance evaluation because they help to show how accurate a measurement is, or how far from the reported value its true value might be [109]. Further example applications of using error bars will be shown in Chapter 4 and 5, Figure 4-7, Figure 5-4 and Figure 5-9. In this thesis, symmetrical error bar are used.

3.5 Conclusions

In this chapter, the simulation techniques that are used in this thesis are described. Using the MATLAB tool, we have explained how a system can be modeled using a Monte-Carlo simulation and reinforcement learning. The base stations in the same or different channels are used to evaluate the simulation result. SNR and SINR statistics and the associated CDFs are used to determine performance, e.g. noise power has already been included. Error bars have been briefly introduced. Some simple examples are given here for better understanding. All of the simulation elements will be used in later chapters.

4. Coexistence Performance and Channel Assignment

4.1 INTRODUCTION 84
4.2 COEXISTENCE SCENARIO AND PERFORMANCE PARAMETERS 85
4.3 CHANNEL ASSIGNMENT SCHEMES AND COMPARISON 88
4.4 STATISTICAL PERFORMANCE OF THE CHANNEL ASSIGNMENT SCHEMES 100
4.5 DISCUSSION 106
4.6 SPECIFIC IMPROVEMENTS FOR CHANNEL ASSIGNMENT 107
4.7 CONCLUSIONS..110

4.1 Introduction

Channel assignment schemes can be divided into fixed channel assignment (FCA), dynamic channel assignment (DCA), and hybrid channel assignment (HCA) as mentioned in Chapter 2. Here we use an area based optimization method to determine the most suitable channels to use. This method uses the statistics of the SINR obtained from users in the coverage area to select the most suitable channel base station combinations. The schemes that are implemented in this chapter select a channel based on a specific percentile of SINR across the coverage area. The performance of each scheme is affected by the number of base stations and channels in the system.

This chapter describes the coexistence scenario with related simulation parameters, followed by the equations for evaluating the performance of the system and the benefits of using multiple channels. Then, the scheme comparisons are discussed in the context of channels and base station plots. After this, the scheme with the best performance is determined. Additionally, the different requirements of users are considered satisfied. Finally, conclusions are presented.

4.2 Coexistence Scenario and Performance Parameters

Unlike other familiar terrestrial downlink models that pay attention to the individual user, the schemes developed in this thesis focus on simultaneous delivery to many users in a coverage area [112, 113]. In our scenario, the area as a whole is considered. To simplify the multicast scenario, the coexistence scenario in this chapter is based on three channels with 10 terrestrial base stations situated in random locations. Due to the random base station locations, the coverage area of each base station is variable. These three channels simulate a multi-channel terrestrial communication system, with the findings generally applicable to a number of frequency bands below 6 GHz which is based on the current communication system.

In later chapters, the number of base stations and channels is changed to 30 channels and 100 base stations as required by the system and scenario. Figure 4-1 shows an example of the coexistence scenario model. After using the channel assignment scheme, we assume that BS1, BS6 and BS9 are assigned to channel 1, BS2, BS7 and BS8 are assigned to channel 2 and BS3, BS5 and BS 10 are assigned to channel 3. BS 4 is not assigned to any channels because it causes a lot of interference to the other base stations.

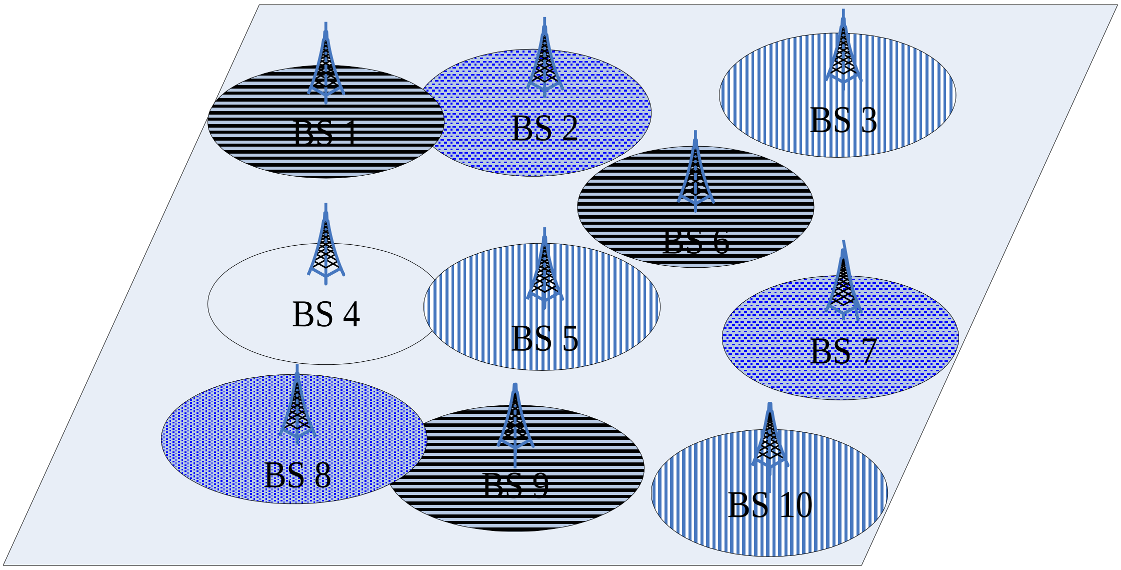

Figure 4-1 The coexistence scenario model with 3 channels and 10 base stations

The parameters of the terrestrial system are shown in Table 4-1. The transmitted power is 21dBm, which is a typical transmitter power for mobile stations [114]. In order to ensure a sufficiently high SINR value, a threshold is used as a way of controlling the appropriate interference between each user and to determine the performance. Here 2.3 dB will be used, which corresponds to the use of GMSK modulation [109]. Coexistence means the multiple users in the same system can be served in the same coverage area together and could be worked well with less interference. We focus on simultaneously delivering good coverage to many users in a coverage area.

Parameter	Value
Service Area	8 km x 8km
Transmitter Height	100 m
Transmit Power	21 dBm
BS Antenna gain	10 dB
User Antenna Height	1.5 m
User Antenna Gain	1 dB
Antenna Efficiency	100%
Bandwidth	3MHz
Frequency	900 MHz
Noise Power	-102.7dBm

Table 4-1 System parameters

The benefits of multiple channels

In a coverage area, the coexistence of radio systems within multiple frequency bands can result in a more efficient reuse of the radio spectrum. In this case, multiple channels can give additional benefits to users by giving them greater choice, hence improving the SINR. In Figure 4-2, a Cumulative Distribution Function (CDF) of three single channels is shown based on all the users over the entire service area.

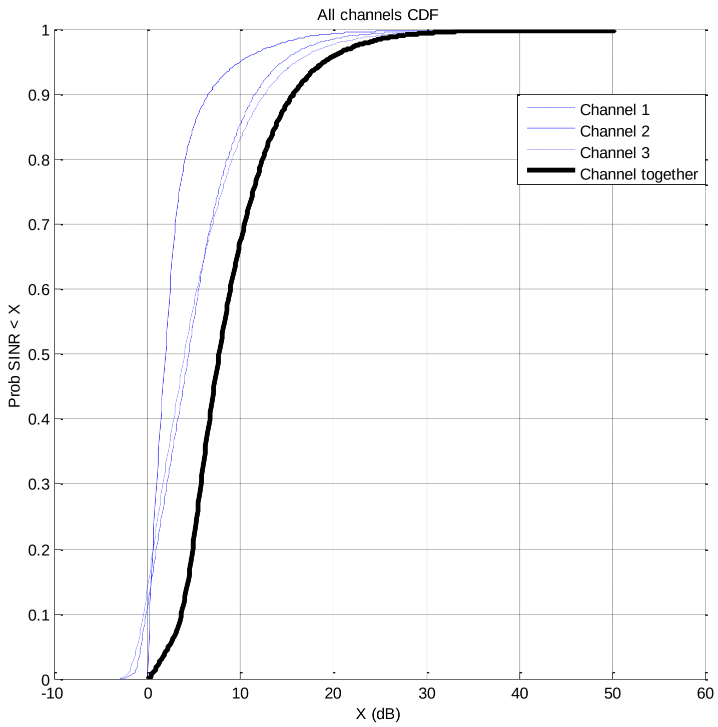

Figure 4-2 Single and multi-channel CDF comparison

4.3 Channel Assignment Schemes and Comparison

According to the basic channel assignment schemes presented before (FCA, DCA and HCA) and all the parameters introduced, four different channel assignment schemes that determine the system performance are analyzed in this part. They are the Least Interference, Channel Priority, Maximal Sum and Maximal Difference schemes. As we mentioned in Chapter 2, the Least Interference and Channel Priority schemes are reproduced from the previous DCA schemes, also with our own consideration of characteristics. The main different point between the previous DCA schemes and ours are the results of CDF and the service area. The Maximal Sum and Maximal Difference schemes are all new schemes.

Least Interference

The Least Interference scheme is a relatively simple model used by existing channel assignment schemes [15]. This scheme aims to find the least interference channel for users quickly. The allocation process with the model is as follows:

1. Number BS (base stations) from 1 to 10
2. For BS(i), check the SINR of all the users in the coverage area on channel 1, channel 2 and channel 3
3. Determine the mean SINR over user locations for each channel
4. Select the channel with the highest SINR and allocate it to BS(i)
5. Repeat for the next BS in the list, BS(i+1)
6. Finish the process after BS10 is allocated

$$\max(\mathit{mean}(\mathit{SINR}_{BS(i)1}), \mathit{mean}(\mathit{SINR}_{BS(i)2}), \mathit{mean}(\mathit{SINR}_{BS(i)3}))\mathit{channel} \Rightarrow \mathrm{BS(i)}$$

The pseudo code of the Least Interference scheme are shown below:

```
Set max-BS, max-channel
for (BS(i)=1:max-BS)
    for (channel(j)=1:max-channel)
        Obtain the mean SINR value
    end
    choose the channel with the highest SINR
    allocate current BS into this channel
end

end
```

Scheme advantages: All base stations are allocated channels. It is a simple algorithm that can assign the channels to the base stations directly and quickly, e.g. in wireless mesh networks

Scheme disadvantages: Coverage is relatively poor and a CDF is not applied with SINR value

The first graph in Figure 4-3 uses a contour plot to show the gradual changes of the SINR of users from the corresponding base stations. The white space is used to highlight the area of users whose SINR value is below the 2.3dB threshold and so cannot be covered by any base station. Different colors in the channel plot (the left-hand plot in Figure 4-3) and the BS plot (the right-hand plot) show the area that is controlled by each base station and the channel in use respectively. For example, the area with dark red in the channel plots represents the coverage area that uses channel 1. The area with the yellow colour, which is the largest area of colour in the BS plot represents the area that is covered by BS 6. The stars indicate the base station locations.

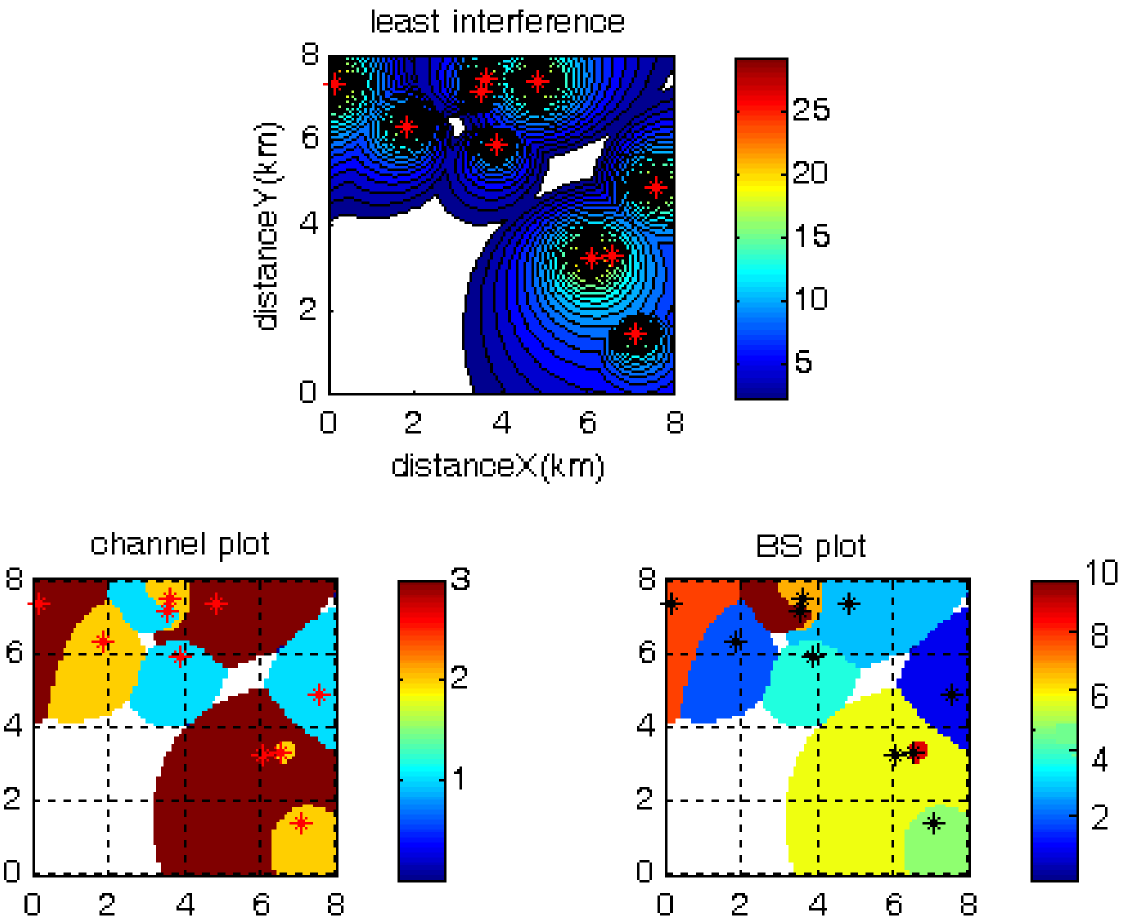

Figure 4-3 Least Interference scheme with contour, channel and base station plots

Like the scheme shown above, existing distributed channel assignment schemes have some common drawbacks:

- They often pay more attention to the performance of the individual user; rarely do they consider the area as a whole with multiple channels. One reason for this is that it is difficult to obtain spatial information directly.
- Frequency bands are often used inefficiently. There can be unequal numbers of base stations assigned in each channel.

Due to the drawbacks of existing channel assignment schemes, several new channel assignment schemes are introduced in this chapter. The purpose of the new channel assignment schemes is to try and use a base station to cover as much of the coverage area as possible with the highest SINR. We calculate the Cumulative Distribution Function (CDF) of SINR (presented as SINR cdf later) across the coverage area on each channel and then select a certain percentile threshold in order to obtain a measure of SINR on the channel. The percentile threshold is used to take into account the different number of base stations in the system. If we have ten BSs, we would like each to cover on average 10% of the coverage area.

Hence we define the Percentile Threshold as $(1-1/N)\times 100\%$, where N is the number of BSs. The CDF of SINR across the coverage area at a particular percentile threshold is very helpful for measuring the performance and identifying the service level when serving a different group of users. For example, in Figure 4-2, by using the percentile threshold with 10 base stations, we set the Percentile Threshold as 90%, so we can see that the SINR value of the curve for channel 2 is about 7dB, which means 10% of the coverage area gets at least 7dB, with 90% below this value. It is hoped that the other BSs are suitably located to cover area below 7dB. The schemes using this CDF Performance Threshold are presented next. They are Channel Priority, Maximal Sum and Maximal Difference schemes.

Channel Priority

The Channel Priority scheme compares the Percentile Threshold SINR value with the 2.3dB threshold, selecting the channels in a specific priority order as required (in this chapter, increasing order, that is, 1, 2, 3…). In this case, base stations remain unassigned if they do not reach this threshold after testing on all the channels. The model works as follows:

1. Number BS from 1 to 10
2. Allocate BS(i) in channel 1, calculate its SINR cdf
3. Compare the SINR cdf value from step 2 with the 2.3dB threshold
4. If the SINR cdf value determined at the Percentile Threshold is bigger than 2.3dB, allocate BS(i) in channel 1. Then repeat for the next BS, until the value from step 2 is smaller than the 2.3dB threshold
5. Allocate BS(i) in channel 2. Then BS(i) is also tested and be compared with 2.3dB in channel 2
6. Repeat step 2 to 5 using channel 2, until channel 2 cannot accommodate any more BSs, then allocate the remaining BS to channel 3
7. Finish when channel 3 cannot allocate any more of the remaining BSs

The pseudo code of the Channel Priority scheme are shown below:

```
Set current-channel to 1
Set max-BS, max-channel
Set SINR-thres
for (BS(i)=1:max-BS)
    record SINR cdf value of BS(i) in current-channel
    if SINR cdf of BS(i) > SINR-thres
        allocate BS(i) into current-channel
    else
        current-channel++
        if (current-channel > max-channel)
            return
        else
            continue the operation on BS(i)
        end
    end
end
```

Scheme advantages: The SINR cdf replaces the SINR mean values

Scheme disadvantages: Selecting channels in order priority as required sometimes means that base stations are not allocated on the optimal channel

Maximal Sum

The Maximal Sum scheme aims to allocate base stations on the optimal channel by comparing the linear sum. The linear sum of a statistical SINR value is calculated from the users served by each base station allocated on each channel. This sum tends to increase initially as the number of base stations on a channel is low, but then it stabilizes as the number of bases stations increases within the service area. Channels do not have any priority in this scheme. The model of the scheme works as follows:

1. Number BS from 1 to 10
2. Allocate BS(i) in channel 1, record every SINR cdf of all the BSs (including BS(i)) that are allocated in channel 1 respectively and add together the SINR cdf values collected at each base station. This sum is recorded as $sum_i(1)$
3. Repeat step 2 for channel 2 and 3, recorded as $sum_i(2)$ and $sum_i(3)$
4. Choose channel with the maximum SINR sum from $sum_i(1)$, $sum_i(2)$ and $sum_i(3)$, then calculate SINR cdf of BS(i) in this channel, if it exceeds the 2.3dB threshold then allocate BS(i) to this channel, otherwise do not assign.
5. Repeat for BS(i+1)
6. Finish when all the channels cannot accommodate any more remaining BSs

This scheme has very good performance, but the problem is that it in order to gain the maximal sum, the scheme focuses less on the efficiency of each base station. The pseudo code of the Maximal Sum is shown below:

```
Set max-BS, max-channel
Set SINR-thres
for (BS(i)=1:max-BS)
    for (channel(j)=1:max-channel)
        sum(j) = 0
        foreach BS(k) in channel(j)
            sum(j) += SINR cdf of BS(k)
        end
    end
    choose channel(j) with the maximum sum(j)
    if SINR cdf of BS(i) in channel(j) > SINR-thres
        allocate BS(i) into channel(j)
    else
        do not assign
    end
end
```

Scheme advantages: More flexible than the previous schemes in choosing appropriate channels because it focuses on all served users, and users receive better performance.

Scheme disadvantages: Relatively complex and computationally intensive

Maximal Difference

This scheme aims to further reduce the influence of base stations on the same channel by obtaining the adjacent tested sum values first, then calculating the difference between the sum values that are compared and selecting the one that performs best. It obtains better performance and increases system stability. In this scheme, a new BS is tested on each channel. The SINR cdf values of all BSs on a channel are added together, before and after the new BS is tested on the channel. The channel delivering the maximum before-and-after difference is used to assign the new BS. The model of the scheme as follows:

1. Number BS from 1 to 10

2. Record the SINR cdfs of all the existing BSs that have already been allocated to channel 1 respectively and add the SINR cdf Percentile Threshold values together, recorded as $sum_{i-1}(1)$. Repeat for channel 2 and channel 3, obtain $sum_{i-1}(2)$ and $sum_{i-1}(3)$
3. Try to allocate a new BS(i) on channel 1. Record every SINR value of all the BSs (including BS(i)) on channel 1 respectively and add once again the SINR Percentile Threshold values together. The sum is recorded as $sum_i(1)$. Repeat the work process for channel 2 and 3, recorded as $sum_i(2)$, $sum_i(3)$
4. Obtain the difference between $sum_i(1)$ and $sum_{i-1}(1)$, and repeat the process for channel 2 and channel 3
5. Compare the differences from step 4 and choose the channel with maximum difference in the SINR values and then allocate it to BS(i), providing the Percentile Threshold exceeds 2.3dB (as described previously)
6. Repeat for BS(i+1)
7. Finish when all the channels cannot accommodate any further BSs

The pseudo code of the Maximal Difference is shown below:

```
Set max-BS, max-channel
Set SINR-thres
for (BS(i)=1:max-BS)
    for (channel(j)=1:max-channel)
        sum(j) = 0
        foreach BS(k) in channel(j)
            sum(j) += SINR cdf of BS(k)
        end
    end

    for (channel(j)=1:max-channel)
        assume allocate BS(i) into channel(j)
        sum'(j) = 0
        foreach BS(k) in channel(j)
            sum'(j) += SINR cdf of BS(k)
        end
        diff(j)=sum(j)-sum'(j)
    end

    choose channel(j) with the maximum diff(j)
```

```
    if SINR cdf of BS(i) in channel(j) > SINR-thres
        allocate BS(i) into channel(j)
    else
        do not assign
    end
end
```

Figure 4-4 shows how the Maximal Difference scheme works. The current base station which needs to be assigned is BS 7. It is assumed that BS1, BS2, BS3, BS4, BS5 and BS6 have already been assigned to Channel 1, Channel 2 or Channel 3 as shown. The sum values are calculated as described, before and after BS7 is assigned to each channel. The differences between the sum values are obtained, in order to determine the channel that should be chosen. Finally Channel 1 is assigned to BS7. We use 6 and 7, not *i*-1 and *i* because it is a clear direct example. Now, *i* is equal to 7.

	Channel 1	Channel 2	Channel 3
Existing	BS1, BS5	BS2, BS4	BS3, BS6
Current	$sum6(1) = SINRcdf_{BS(1)1} + SINRcdf_{BS(5)1}$	$sum6(2) = SINRcdf_{BS(2)2} + SINRcdf_{BS(4)2}$	$sum6(3) = SINRcdf_{BS(3)3} + SINRcdf_{BS(6)3}$
	$sum7(1) = SINRcdf_{BS(1)1} + SINRcdf_{BS(5)1} + SINRcdf_{BS(7)1}$	$sum7(2) = SINRcdf_{BS(2)2} + SINRcdf_{BS(4)2} + SINRcdf_{BS(7)2}$	$sum7(3) = SINRcdf_{BS(3)3} + SINRcdf_{BS(6)3} + SINRcdf_{BS(7)3}$
	$sum7(1) - sum6(1)$	$sum7(2) - sum6(2)$	$sum7(3) - sum6(3)$

$$\max(sum7(1) - sum6(1), sum7(2) - sum6(2), sum7(3) - sum6(3))$$

If the difference of sum in channel 1 is the biggest

$$sum7(1) - sum6(1) = \max(sum7(1) - sum6(1), sum7(2) - sum6(2), sum7(3) - sum6(3))$$

(Percentile threshold > 2.3dB)

BS7 is allocated to channel 1

Figure 4-4 Example of the Maximal Difference scheme

Scheme advantages: Better channel performance with better coverage. The number of BSs on each channel is better balanced

Scheme disadvantages: Complex and computationally intensive

In order to best compare the schemes the base stations are kept at the same random locations within the service area for each scheme. The points with a dot (not a star) showed in Figure 4-5 represent the unallocated BSs. By comparing Figure 4-3 and

Figure 4-5, obviously, the Least Interference scheme assigns all base stations, while the Maximal Difference scheme assigns only seven base stations, in this example. The base stations which are assigned by the Maximal Difference scheme are used more efficiently. The two contour plots for the Least Interference and Maximal Difference schemes illustrate the main features of behavior. The other two schemes are similar.

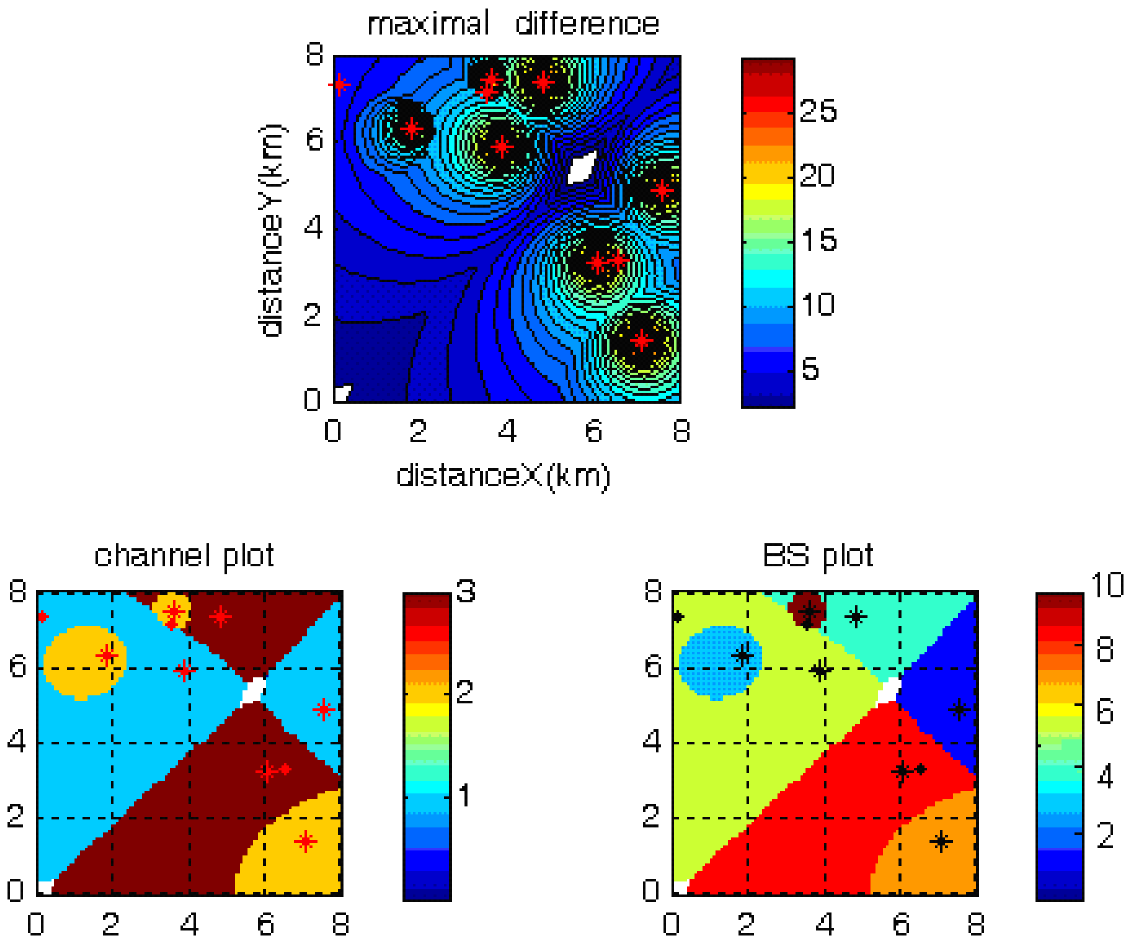

Figure 4-5 Maximal difference scheme with contour, channel and base station plots

Some empty spaces exist in the contour plot, for the same reason as given earlier. For the same geographical and frequency situation, Least Interference has a larger area that is not covered. In the Maximal Difference scheme, nearly all the area is covered despite having base stations in exactly the same locations. Using only the specific layout of base stations given above, the number of base stations assigned in this example cannot be used to describe the performance of the schemes in general. There is only one aspect of comparison. The service area covered and the SINR value of users are the two crucial factors used to determine the performance of channel assignment. From this perspective, the Maximal Difference scheme is much better than the Least Interference scheme. In the comparison between different schemes here, the Maximal Difference scheme always delivers better performance than do the other schemes because it has a bigger coverage area and a higher SINR value, but it does not mean that this scheme should be used in all circumstances. For practical implementations, different channel assignment schemes could prove to be better depending on the requirements of users. For example, the Least Interference scheme can be applied when we want to use all the base stations, if the coverage area is more important in this simple scheme. The Channel Priority scheme can be used if it is important to give some channels greater preference, because some of the channels sometimes need to be kept relatively free for high data rates. For example, changing to a higher data rate or a different transmission range will help to improve the Maximal Difference scheme given all base stations. In this situation, the Maximal Difference will improve the performance of users and will use more base stations than will other schemes.

Useful comparative results are shown in this section. However, due to the random locations of the base stations, it is likely that the results may differ for a different set of base station locations. That is the reason for measuring performance in many sets of randomly located base stations in the next section.

4.4 Statistical Performance of the Channel Assignment Schemes

Large numbers of simulation events are required to identify the performance of channel assignment. The more events in the simulation, the more accurate the resulting SINR performance that is obtained. Due to the complexity of each channel assignment scheme, one thousand sets of base locations are considered as an adequate number of trials for obtaining correspondingly statistically accurate results. Now we choose to vary the number of base stations between 6 and 15 and then to see how the SINR changes.

Before comparing different schemes, the crucial factors should first be explained. SINR and area of coverage are two significant factors that jointly decide the performance of a system. Their relative importance depends on whether the requirement of the system is for high data rates, meaning that this normally requires a higher SINR for the same bandwidth. If the requirement is to ensure that as many users as possible are covered, but without much emphasis on received quality, maximizing the coverage area is preferred. There are no specific requirements here, so a balance between these two factors will be found. Different comparisons will be shown in the following sections.

SINR (performance) comparison for different numbers of BSs

Figure 4-6 shows a situation in which the number of base stations changes from 6 to 15 (6, 8, 10, 12 and 15). There are two main factors affecting the Y axis. One is the number of base stations — more base stations may need more channels in order to be allocated. The other is the change in the SINR Percentile Threshold value. When the number of base stations increases, the percentile threshold value will be affected, i.e. each base station is required to cover proportionally less of the service area.

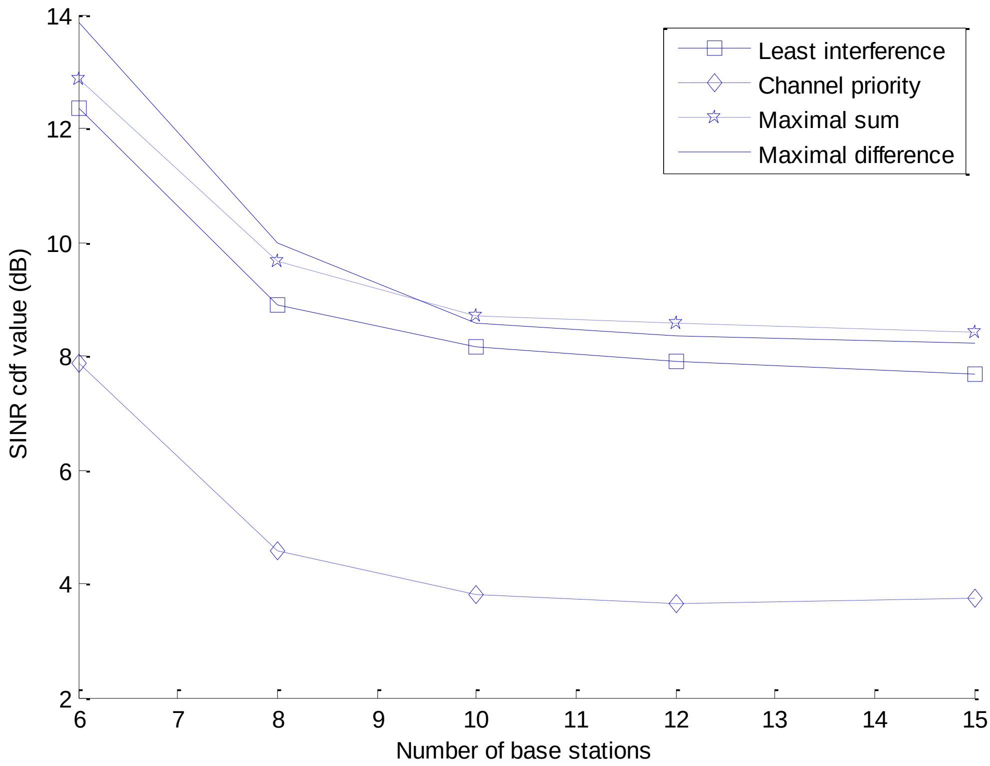

Figure 4-6 Different schemes comparison with different numbers of BSs

In the figure, all the curves decreases from 6 to 12 base stations, and then they tend to be stable beyond the 12 base stations situation. For example, when the number of base stations is six, the interference between them is correspondingly small, so the SINR value is larger. However, when there are 15 base stations, the Percentile Threshold is about 0.933, which is higher than the 0.833 for 6 base stations. In this case, each base station needs to serve a lower percentage of the service area, so the SINR cdf value stops decreasing. For the Maximal Sum and Maximal Difference schemes, the curves tend towards 9dB and the Channel priority tends towards 4dB.

Different modulation schemes have different thresholds. A higher or lower threshold will directly affect the performance of each scheme. We will analyze the results with other modulation schemes instead of with GMSK (2.3dB SINR threshold) in later chapters. Figure 4-7 shows the error bar on each of the four curves with 1000 trials. It is found that the error is relatively small. Therefore, we only show one error bar for these results.

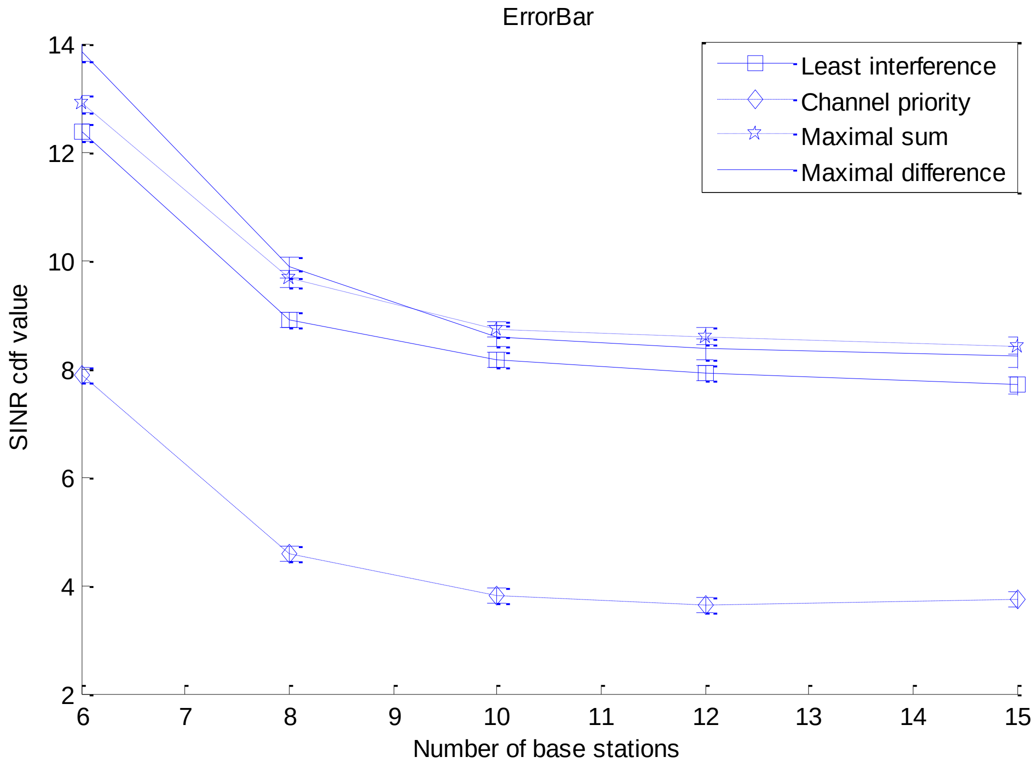

Figure 4-7 Error bar of different schemes comparison with different numbers of BSs

Coverage area and capacity for different numbers of BS

Two factors determine the degree of coverage situation for the different schemes. The first is coverage area and the other is the percentage of BSs that are allocated to each channels. These two composite parameters are the measure of capacity of the service area, as each base station can serve a given number of users. We first present results that show these two factors separately and then use them to obtain the final coverage results in the service area.

Figure 4-8 shows the percentage of the coverage area, which has a SINR level higher than 2.3dB for different numbers of base stations changes. Again, as the number of base stations deployed increases, the SINR decreases. More BSs produce more interference so they cover a smaller area than before. The maximal sum and Maximal Difference schemes obtain better results by comparison.

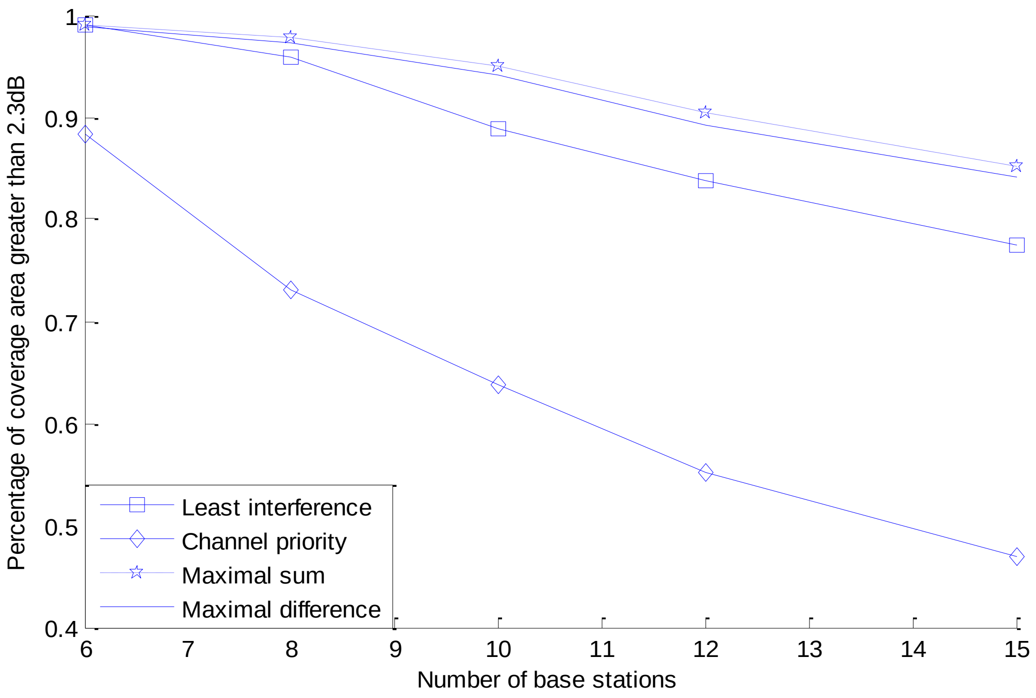

Figure 4-8 Percentage of coverage area with SINR greater than 2.3dB with different numbers of BSs

In Figure 4-9, the Least Interference scheme stays at 1 because it does not consider the acceptance threshold, so the base stations are all allocated, irrespective of the resulting SINR level. The other three schemes obtain similar results.

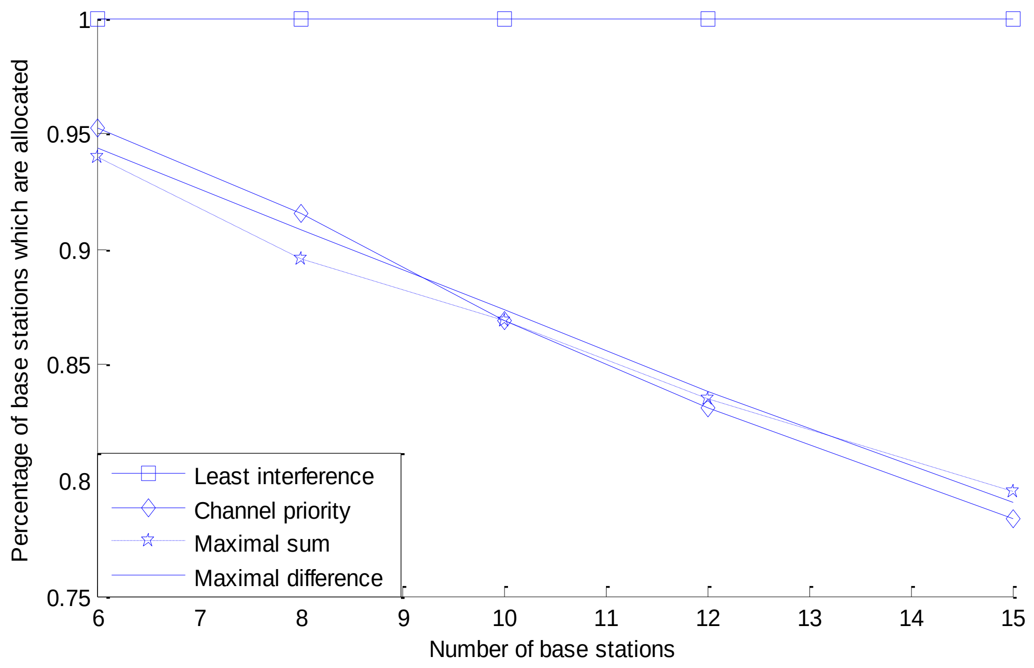

Figure 4-9 Percentage of BSs that are allocated for different schemes with different numbers of BSs

The result of combining these two figures above is presented in Figure 4-10. The coverage and capacity are represented by a combined parameter which is equal to the product of the Percentage of coverage area with an SINR greater than 2.3dB and Percentage of BSs that are allocated, i.e.:

$$C_{caco} = K_{CO} P_{CO} K_{BS} P_{BS} \qquad (4.1)$$

If we assume the capacity factor is K_{CO} and the coverage area factor is K_{BS}, these two factors both affect the product of capacity coverage parameter. P_{CO} and P_{BS} are obtained by the results which have been shown in Figure 4-8 and Figure 4-9. The Least Interference scheme has the best result in this case. However, it is not an effective channel assignment method because it obtains a poor SINR value. For other schemes, Channel Priority has the worst composite performance with Maximal Sum and Maximal Difference again having similar results.

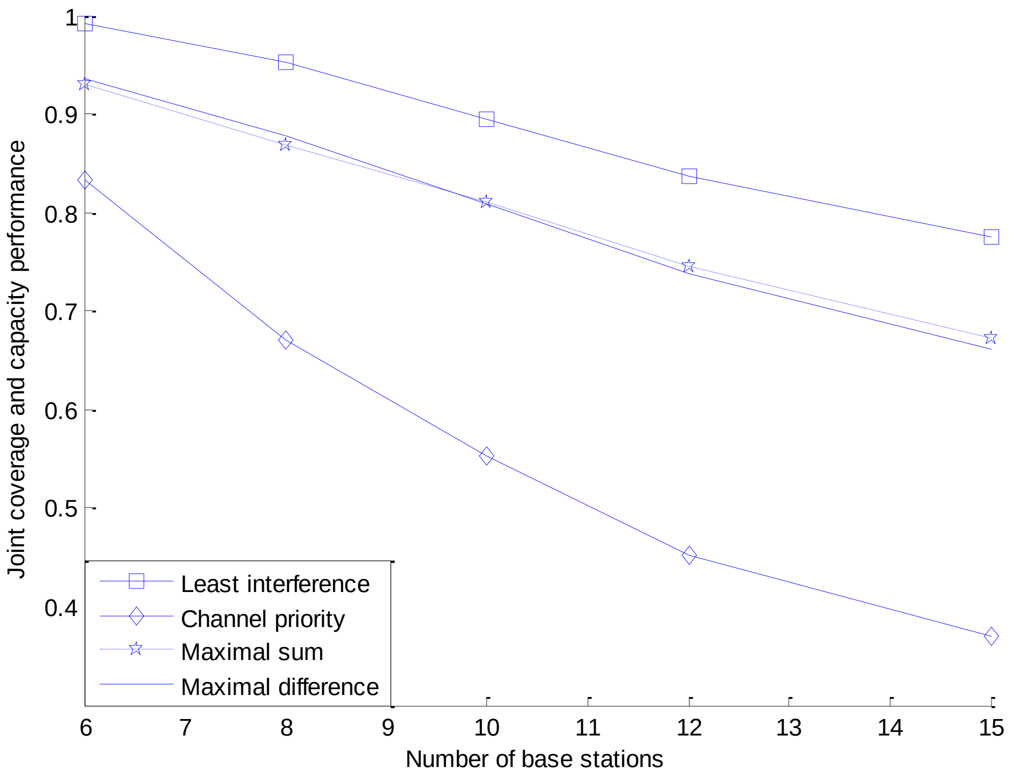

Figure 4-10 Capacity and coverage comparison

For the further work, different weights of these two factors could be combined. For example, if combined 75% K_{CO} and 25% K_{BS} are combined together, then this gives capacity more attention in cognitive networks. Further capacity variations will be discussed in Chapter 5.

Different schemes for different numbers of Channels

In Figure 4-11, the number of channels is changed from 2 to 5 with a fixed number (10) of base stations. There are two affected factors which will affect the results. One is the increasing number of channels. Apparently, more channels, will allow base stations to be assigned more flexibly since they will receive less interference. The other factor is the percentile threshold calculation, which has the same meaning to that discussed before. In this statistically based threshold, all the SINR values are considered acceptable which exceed a 2.3dB threshold.

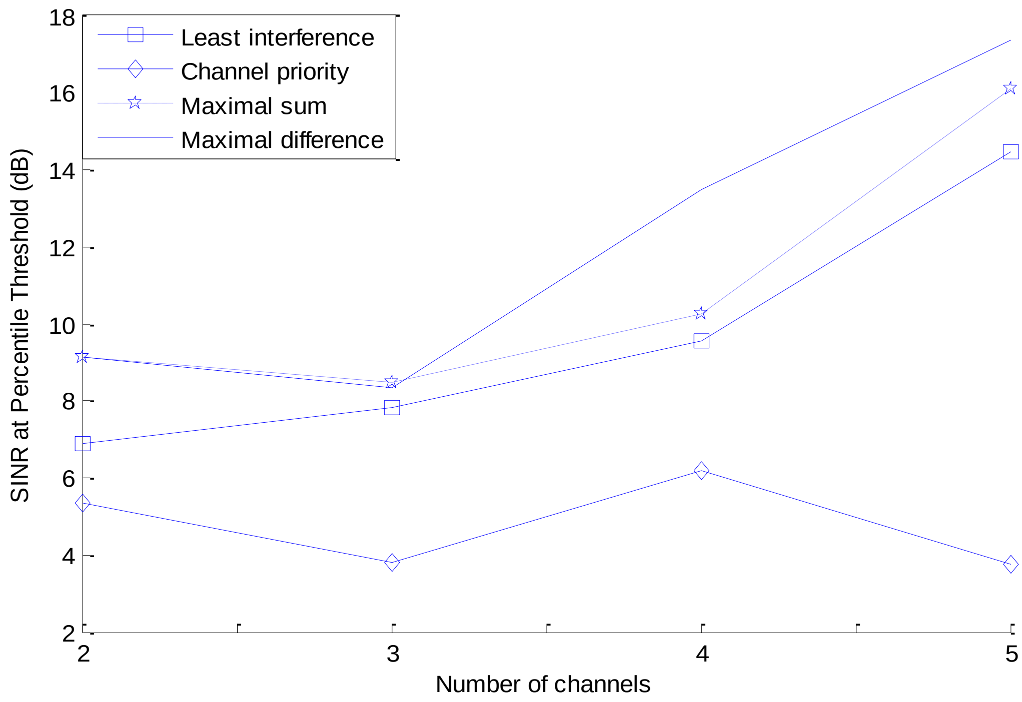

Figure 4-11 Different schemes for different numbers of Channel

The comparisons of SINR performance and coverage situations for different schemes are presented above. Good channel assignment schemes should satisfy both these factors. From the statistics, the Maximal Difference scheme has the best performance and the Channel Priority scheme has the worst. The last two schemes have similar results in most the aspects, since they only have very few analyzed differences; however, the Maximal Difference scheme is more flexible.

4.5 Discussion

After considering the SINR performance and total area covered the Maximal Difference scheme obtains better performance results. This scheme has an SINR value of 9dB (when measured at the Percentile Threshold), and at the same time, a larger coverage area to support users. The Channel Priority scheme has the worst performance, with only 4dB SINR at the chosen percentile of performance; it also covers less area. The Maximal Sum has similar results to the Maximal Difference scheme. The Least Interference scheme has the benefit of assigning all the base stations, but the area covered tends to be much lower; however, it is a simple scheme to implement.

Each scheme has its advantages and disadvantages. Using them depends on the specific circumstances and system requirements. For example, if there is one licensed band and one unlicensed band in the system to serve the users, it is better to allocate base stations in the unlicensed bands in order to protect the benefits of primary users. The Channel Priority scheme could be chosen in this situation, since the unlicensed band could be given a higher assignment priority than is the licensed band. The Maximal Difference scheme could be implemented in circumstances where best performance is needed and the device could satisfy its relatively complex process. The Least Interference will work in situations where it is necessary to assign all the base stations no matter what SINR values are obtained at the percentile threshold.

4.6 Specific Improvements for Channel Assignment

After considering the performance of different channel assignment schemes to assign the base stations in a more realistic scenario, we focus on the situation in which channels are chosen based on the overall performance at multiple points in the service area, not for one specific location or one group of users. In this case, based on multicasting technology, we can develop a simulation that focuses more on satisfying the different requirements of users or on changing specific features of the transmitter, as in a real communication system.

Multiple operator systems

To do this we simulate a more realistic system which is described as below. In general, customers use different mobile networks, so different base stations belong to different mobile companies and control their transmit power to best serve their own users in their coverage area. Figure 4-12 shows the multicast scenario which is implemented by different operators.

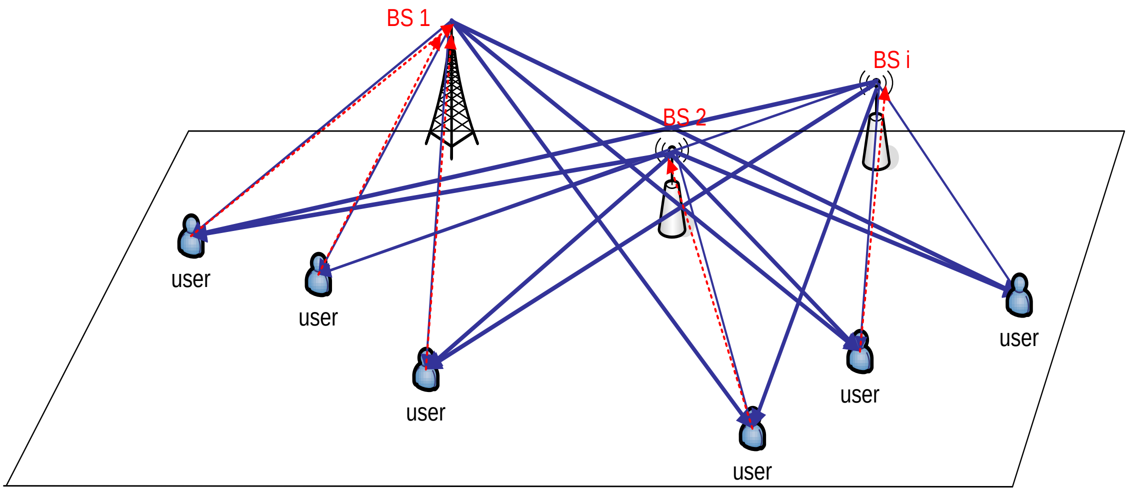

Figure 4-12 Multicast scenario

Heterogeneous multicast systems here can belong to different operators, each using CR based channel assignment to satisfy users. The schemes select a channel based on the highest percentile of SINR across the coverage area. There is one user and 10 base stations controlled by two different operators in Figure 4-13. The blue circles represent base stations controlled by one operator and the red points represent the base stations controlled by another operator, in an 8×8 km coverage area. The black point is the user that has its requirements, and we set the rule that this user must be controlled by the blue base station. The location of base stations with different operators is shown below. Although the nearest base station for the user is a red point base station, BS7, the user chooses the blue circle base station, BS8. Obviously, in this case, this user does not obtain the best performance because the nearest base station is controlled by the red point company. Figure 4-13 shows random numbers of different operators for the terrestrial coexistence systems, 2, 5, 6, 7, 9 are the base stations belonging to the red point service and 1, 3, 4, 8, 10 are the base stations belonging to the blue circle service.

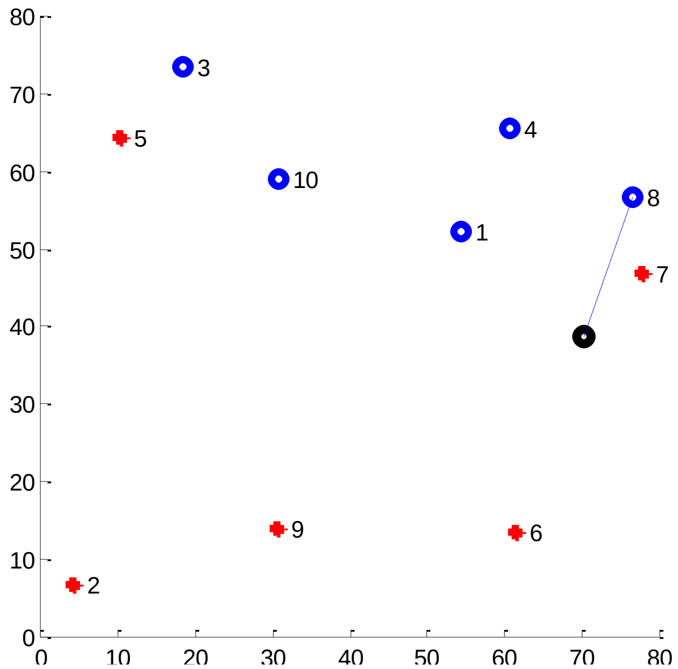

Figure 4-13 Base stations with different operators

Figure 4-14 shows that the area is divided into 10 parts, which refer to the area covered by 10 base stations based on the base stations locations shown in Figure 4-13. There are at least two base stations in each part to transmit power to the users in their coverage area. The different colors show the coexistence of different base stations controlled by different operators. It is found that the SINR in this figure is all above the threshold and all the 8×8 km area is completely covered. Compared to the schemes we introduced in this chapter and the contour plots, base stations with different operators could serve the entire area, which means that the delivery in Figure 4-14 has a better area of coverage, which means in this simple example, therefore, multicasting improves the performance from the user's perspective. At the same time, the other parameters can be changed in the future for multicasting usage that is more complex.

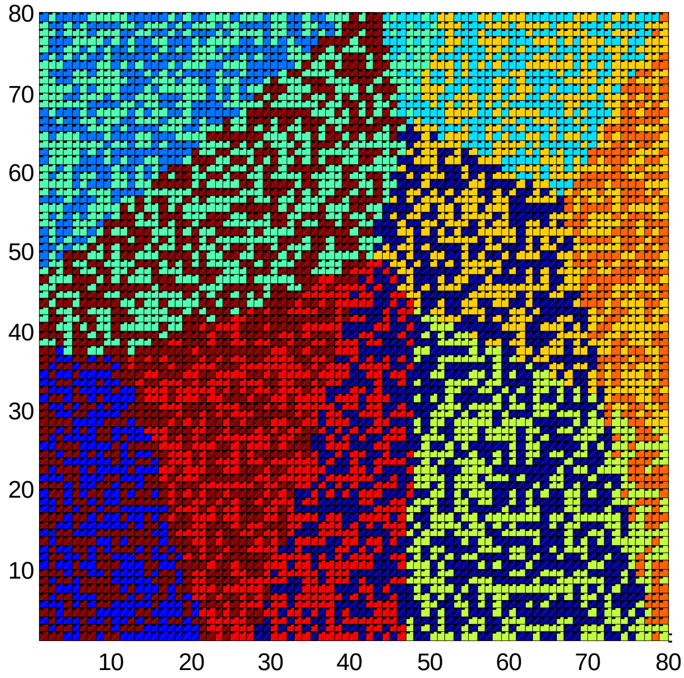

Figure 4-14 Different coverage area for specific groups of users

4.7 Conclusions

This chapter has focused on investigating channel assignment schemes that select channels based on optimizing the coverage area supported by a terrestrial network. The coexistence scenario here is based on different base stations in the same service area, with performance assessed in terms of the area of coverage and available link SINR. Channels are chosen based on the overall performance at multiple points in the service area, rather than the performance at one specific location. It is found that best overall performance is achieved by choosing schemes that aim to maximize the number of base stations on a channel while still meeting a required minimum SINR threshold value.

To conclude, the Least Interference scheme maximizes the number of base stations on a channel but not all base station locations will be able to necessarily satisfy the SINR threshold value well. The Channel Priority scheme cannot maximize the number of base stations on every channel but only the high priority channel(s). It is found that best overall performance is achieved by choosing schemes that aim to maximize the number of base stations on a channel while still meeting a required minimum SINR threshold value, The Maximal Sum and Maximal Difference schemes can deliver the best overall performance level. The channel assignment schemes discussed in this chapter are all centralized schemes. The distributed occupancy detection will be extended and will be considered with further user perspectives in Chapter 6.

5. Interaction and Coexistence of Mixed Channel Assignment Schemes

5.1 INTRODUCTION 112
5.2 COEXISTENCE SCENARIO 113
5.3 MIXED SCHEMES...114
5.4 DISCUSSION 131
5.5 CONCLUSION...134

5.1 Introduction

The coexistence discussed in Chapter 4 showed how different channel assignment schemes selected channels to optimize the coverage area supported by a terrestrial network. The performance of each individual scheme was presented and compared from different aspects. Instead of using or developing more complex channel assignment schemes, it is more helpful to find the connection between the schemes and figure out their interaction when investigating cognitive radio systems. Coexistence and interaction between schemes are interesting and novel ideas. This chapter will extend these ideas by using mixed channel assignment schemes to allocate base stations in a more realistic scenario with different considerations. Interaction exists when the different schemes are combined and such interaction includes the positive and negative interactions with different combinations. In future cognitive radio scenarios it is highly likely that different user groups in each geographical area will operate different channel assignment schemes, as white space spectrum can be used by any user, in principle (subject to regulatory constraints). The purpose of this work is to show how such groups interact. Using mixed assignment schemes could potentially improve the performance (SINR, blocking and dropping) of individual users and reduce spectrum underutilization.

The four schemes that were introduced in Chapter 4 will be combined two-by-two, in one scenario, and the effect of scheme interaction will be observed. Firstly, the detailed scenario will be shown with similar system parameters. Then the performance of different types of mixed scheme will be evaluated. After this, the optimal scheme for each combination will be found after considering interaction and coexistence, followed by a discussion of the results of mixed schemes. Finally, conclusions will be provided.

5.2 Coexistence Scenario

The scenario here shows that the channel assignment scheme in a cognitive radio system requires that the SINR be simultaneously satisfied for a high proportion of users. Unlike the coexistence scenario introduced in Chapter 4, which was based on three channels with 10 terrestrial base stations in random locations, larger numbers of base stations and channels are used here to represent a more realistic terrestrial environment. The main model assumes 30 channels with 100 terrestrial base stations. This more complex scenario will help us to understand how the schemes react with each other and why the interaction appears more frequently. More details will be shown in the results section of this chapter.

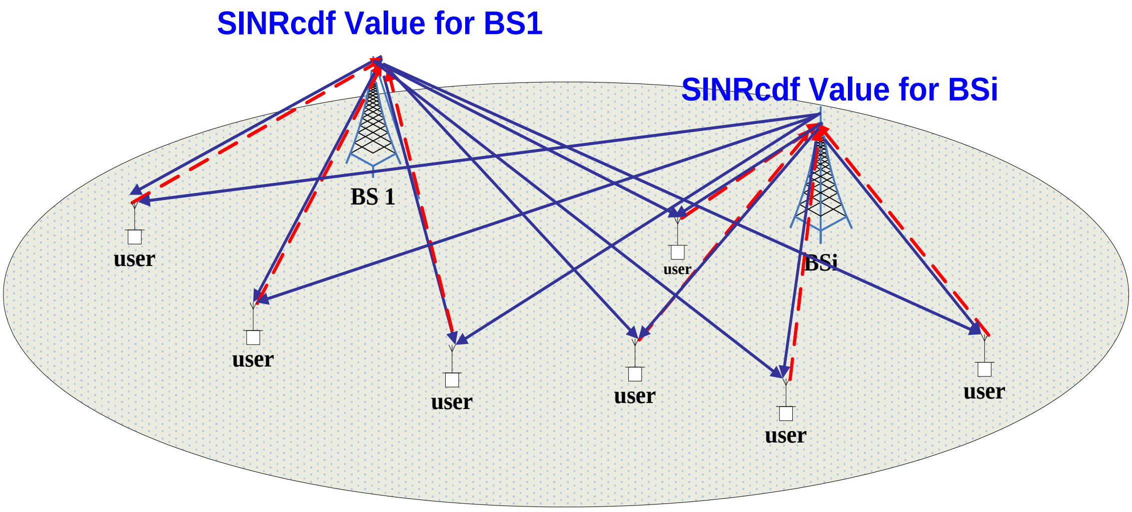

Figure 5-1 Coexistence Scenario

The signal power, noise power, propagation models and other system parameters are all the same as in section 3.4 and Table 4-1.

5.3 Mixed Schemes

Meaning of mix

In this stage, **mix** refers to mixing two schemes selected from among four different schemes mentioned in Chapter 4. This means that part of the base stations will use one scheme for assignment while the others will use a second scheme. In this chapter, the locations of base stations are still random, and at the same time, the assignment order of base stations and choice of scheme to be assigned are also random in order to obtain more realistic statistical data. In this chapter, the simulation implemented is still Monte- Carlo.

Different Ratio

We use the term ‘ratio’ to represent the proportion of base stations using each scheme. Ten different ratios for regulating the component elements of the mixed schemes are selected:

10:0, 9:1, 8:2, 7:3, 6:4, 5:5, 4:6, 3:7, 2:8, 1:9, 0:10

The number before the colon represents the proportion of base stations using the first scheme in the mixed scheme, and the number after the colon in each ratio represents the proportion of base stations using the second scheme. The 10:0 and 0:1 ratio results are the same as those shown in Chapter 4 when using individual channel assignment schemes.

The following flowchart describes how the mixed scheme is simulated. Firstly, the two channel assignment schemes are defined: either the Least Interference and Channel Priority schemes, or the Channel Priority and Maximal Difference schemes. Secondly, the ratio for the mixed scheme is defined and a random order of base stations is given for each individual scheme. Following the order of base stations, according to the channel assignment schemes, the corresponding base stations are allocated to the channels and the results of the SINR cdf are recorded from the users served by each base station. At this stage, the simulation process is completed for one ratio. The same process is repeated for the next ratio. After all the different ratios of mixed schemes are completed, the results are recorded. The result for each individual scheme and the mixed scheme are recorded separately.

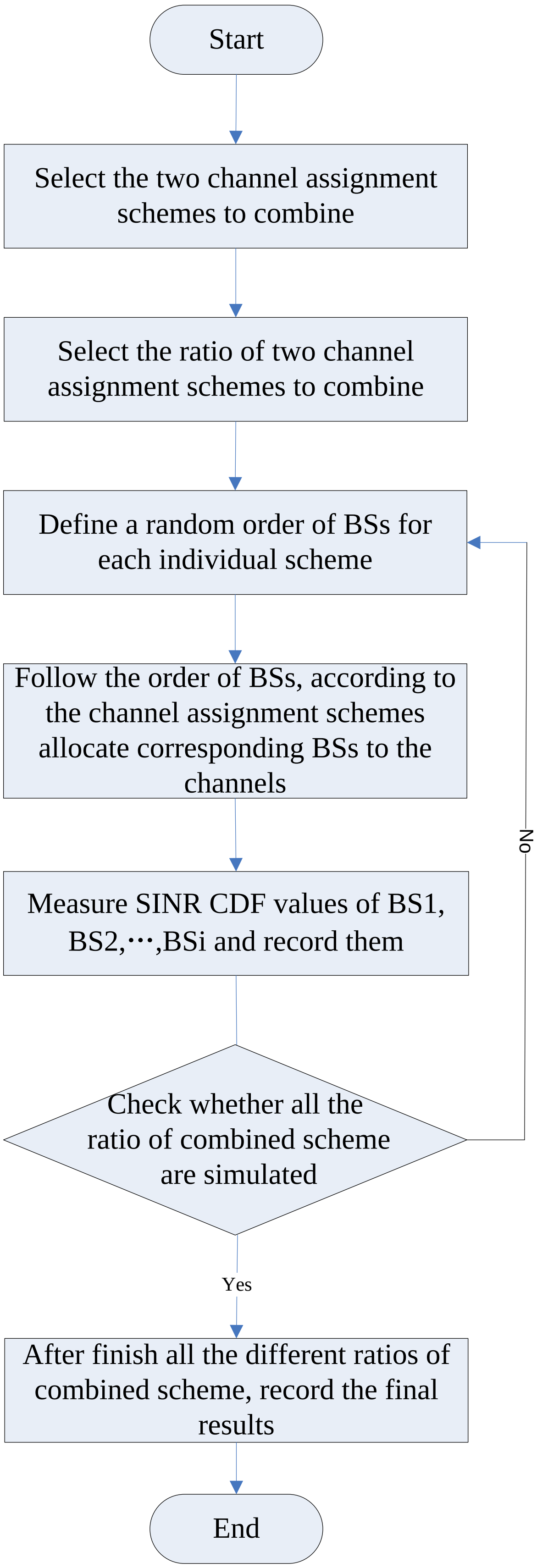

Figure 5-2 The simulation steps for the schemes in combination

Random order of base stations

In each iteration, we set the base stations using each scheme randomly to obtain the statistical results evaluating the performance. The order of activation of the base stations is chosen randomly.

How two schemes are combined

One scheme assigns the current base station to the channel using its own algorithm, after that, the other scheme recalculates the SINR cdf values of the existing base stations on each channel, and then uses its algorithm to allocate the next base station. Since each scheme has its own advantages and disadvantages, when combined together, the scheme which has the higher SINR value may be adversely affected by a scheme that has a worse SINR value, so the overall result may worse than with a single scheme. However the other scheme may cover more area or assign more base stations.

The reason for choosing these two combinations of mixed schemes

The four different schemes that have been shown in Chapter 4 include two different types of channel assignment schemes. In this chapter, for comparison, we choose two typical examples of mixed scheme combinations, rather than all combinations of the schemes, in order to supply enough information to investigate overall performance. One of the combinations used is Least Interference and Channel Priority, while the other is Channel Priority and Maximal Difference. The Least Interference scheme is different from the three other schemes. Therefore, it needs to be chosen with another CDF scheme to figure out the connections. The reason for not choosing the Maximal Sum scheme is because it is similar to the Maximal Difference scheme. From these two mixed schemes, interaction and coexistence will be obtained for the different proportions of base station of each scheme. When we perform the comparison between the different mixed schemes, all the results are obtained using the same overall traffic load with the locations of base stations remaining unchanged to allow a more accurate direct comparison.

Least Interference and Channel Priority combined

We combine the Least Interference and Channel Priority schemes because they do not use the same method to obtain performance: one uses SINR directly while the other uses SINR cdf. We want to see how different types of schemes can be combined. As shown in Chapter 4, the Least Interference scheme has the characteristics of maximizing coverage area (without consideration of the SINR), with all the base stations assigned. The Channel Priority scheme forces the base stations into the earlier ranked channels. When these two schemes are combined, the assigned situation should be changed and more results should be found. We analyze and compare the performance of the combined schemes and compare them with each individual scheme’s performance. The SINR cdf value is a crucial factor in this thesis, and the percentile threshold median value of SINR is used to compare performance. Another two factors that will be considered are the probability of channel usage and the capacity variation of two schemes when they are mixed.

Figure 5-3 shows the median SINR value for the mixed schemes for different ratios. The x axis shows the ratio between two schemes, from 10:0 to 0:10. The Y axis shows the median SINR value of the different schemes. The result of the mixed schemes is a relatively smooth curve with a stable trend that decreases slowly from about 18dB to 7dB. The combined schemes obtain worse performance when the proportion of the Channel Priority scheme decreases. As discussed in the last section, the Least Interference scheme does not use a SINR threshold value, and the Channel Priority scheme uses a 2.3dB SINR minimum at the Percentile Threshold. Due to the relatively large number of channels used here, the SINR cdf values are much higher than 2.3dB. In the case of the Channel Priority scheme, more base stations are assigned to the channels earlier in the sequence, resulting in tighter packing.

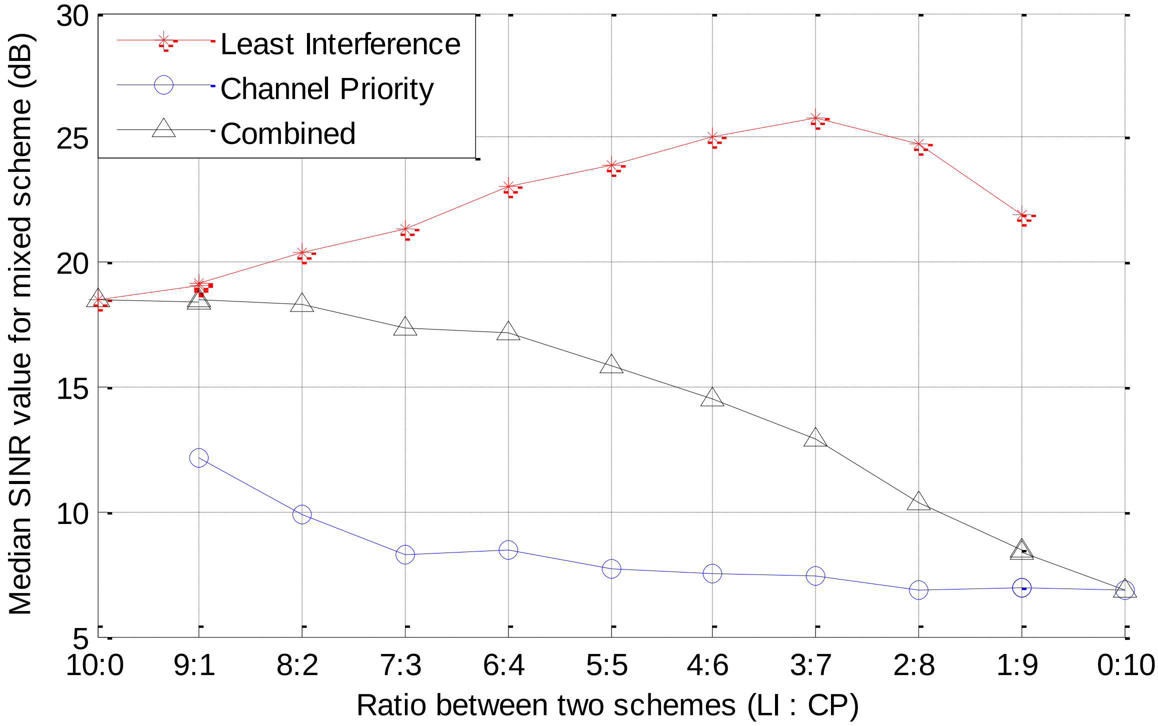

Figure 5-3 Median SINR value for mixed scheme

From Figure 5-3, it can be seen that when the proportion of the Channel Priority scheme is small, the Least Interference scheme will avoid assigning channels earlier in the sequence helping the Channel Priority scheme, which is forced to assign channels in sequence order. This also benefits the Least Interfered scheme as there is a lower probability that some of the channels will be occupied. However, when the proportion of base stations using the Channel Priority scheme is high, meaning that relatively few base stations will use the Least Interference scheme for channel assignment, base stations will be concentrated in the channels earlier in the sequence, causing the combined line to decrease. From the simulation results, when the ratio of Least Interference and Channel Priority schemes is higher than 3:7, all 30 channels are used. When the ratio is lower than 3:7, fewer base stations are assigned by the Least Interference scheme. Since when more channels are used, less interference is obtained, capacity peaks at 3:7. In other words, these results are of the largest overall capacity. Since the SINR values of mixed schemes are the main determinants of performance, from Figure 5-4 to 5-7, we analyze the error bars. Unassigned base stations and probability of channel usage are shown as the complementary explanation and justification of the performance shown in Figure 5-3. Figure 5-4 shows the error bars on each of these three curves from ratio 9:1 to 1:9 of the 1000 trials.

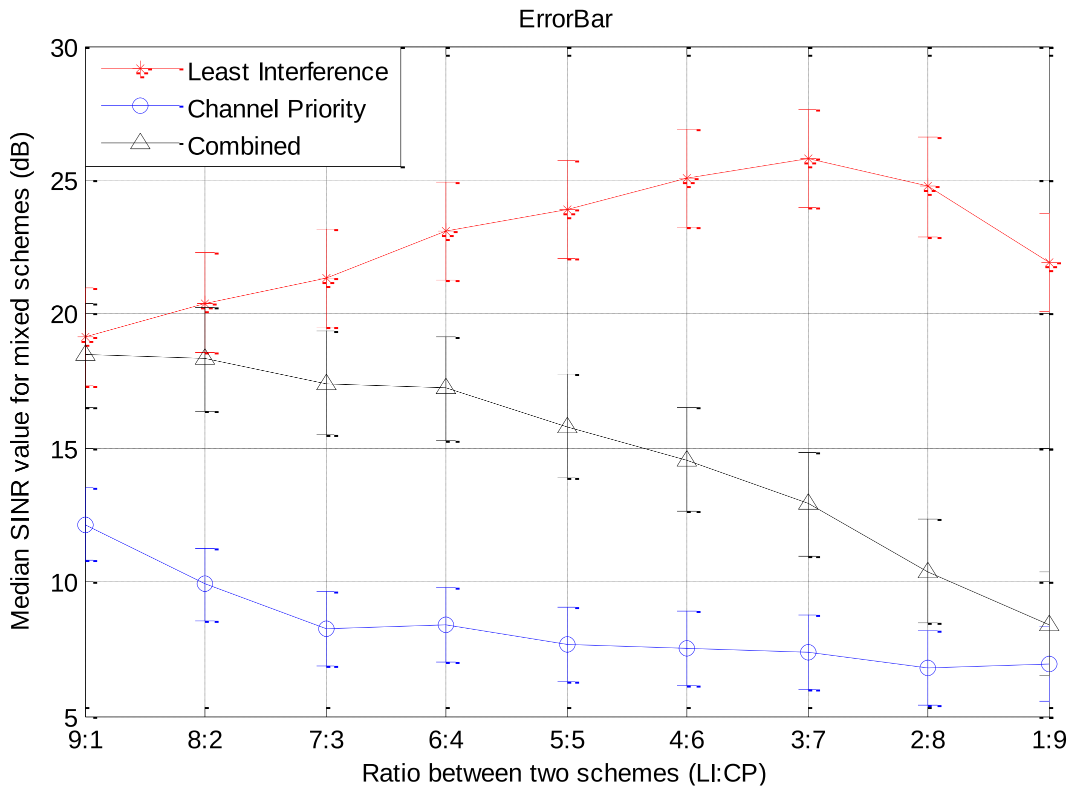

Figure 5-4 Error bars for two schemes mixed together

Figure 5-5 shows the percentage of unassigned base stations with each scheme and the two schemes combined. The result of the Least Interference scheme always remains zero because the Least Interference scheme does not have a threshold, which means all the base stations using this scheme must be assigned to the channels. For the Channel Priority scheme, as the ratio of the base stations increases, the two schemes assign more base stations. The reason for this is when the ratio of base stations using Least Interference decreases, it cannot help Channel Priority to assign more base stations into any channels without a threshold, so it causes the unassigned proportion to increase. However, we cannot say that Channel Priority is a bad scheme for a high ratio of base stations, because if we consider the SINR figure and unassigned figure together, we find that even if the curve of the unassigned proportion decreases when the ratio of Channel Priority increases, the SINR value of it is increasing. This means that when the Channel Priority scheme is used in a combined way, although it assigns fewer base stations, it obtains better performance. The result of the mixed schemes lies somewhere between the two individual schemes. It also has an increasing trend.

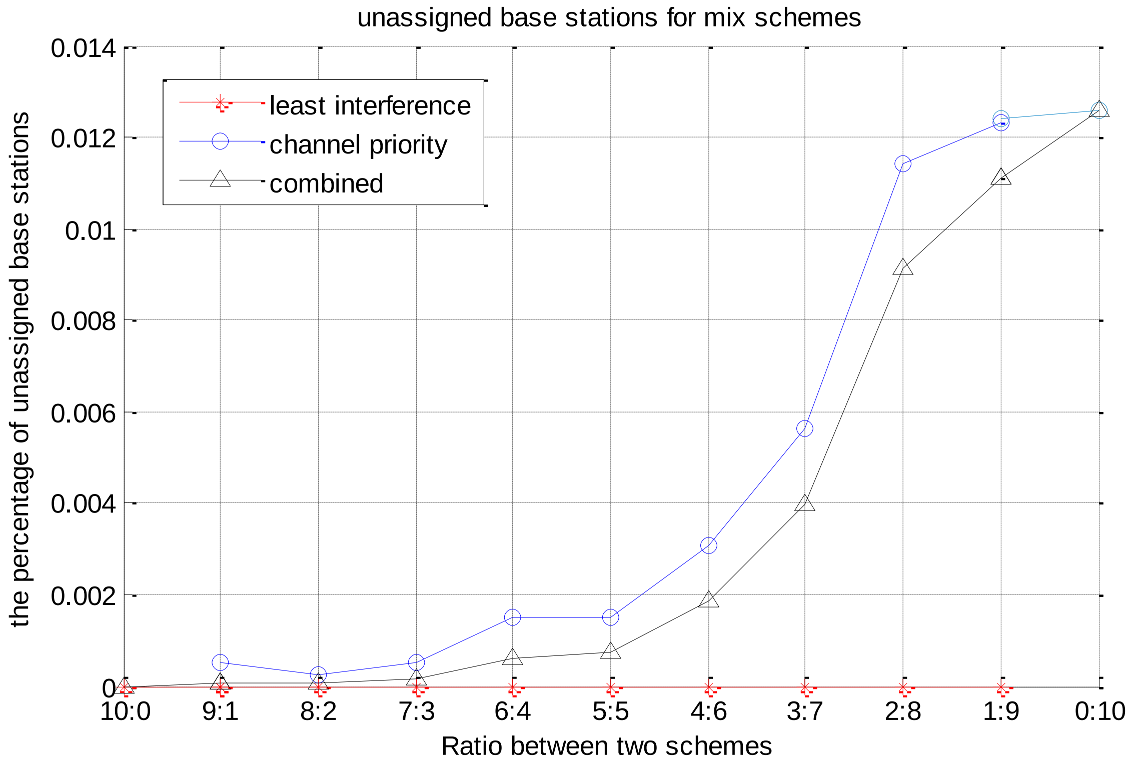

Figure 5-5 Unassigned base stations for two mixed schemes

Figure 5-6 below shows the Probability of Channel Usage for the mixed schemes when the ratio is 5:5. As discussed earlier, the characteristic of the Least Interference scheme is to assign the current base station in the channel that has least interference. Generally, the current base station will be assigned to the channels that have the smallest number of base stations because they cause less interference. This will mean that channels earlier in the sequence are avoided as they tend to be used by the Channel Priority scheme. So the Least Interference scheme in the Figure 5-6 tends to 1 after channel 11. When more than 25 channels are used, the line will decrease, because the system is not fully loaded. Conversely, the channels in the Channel Priority scheme are concentrated on 1, 2 and 3, since they are able to accommodate the base stations, while still maintaining the minimum SINR threshold.

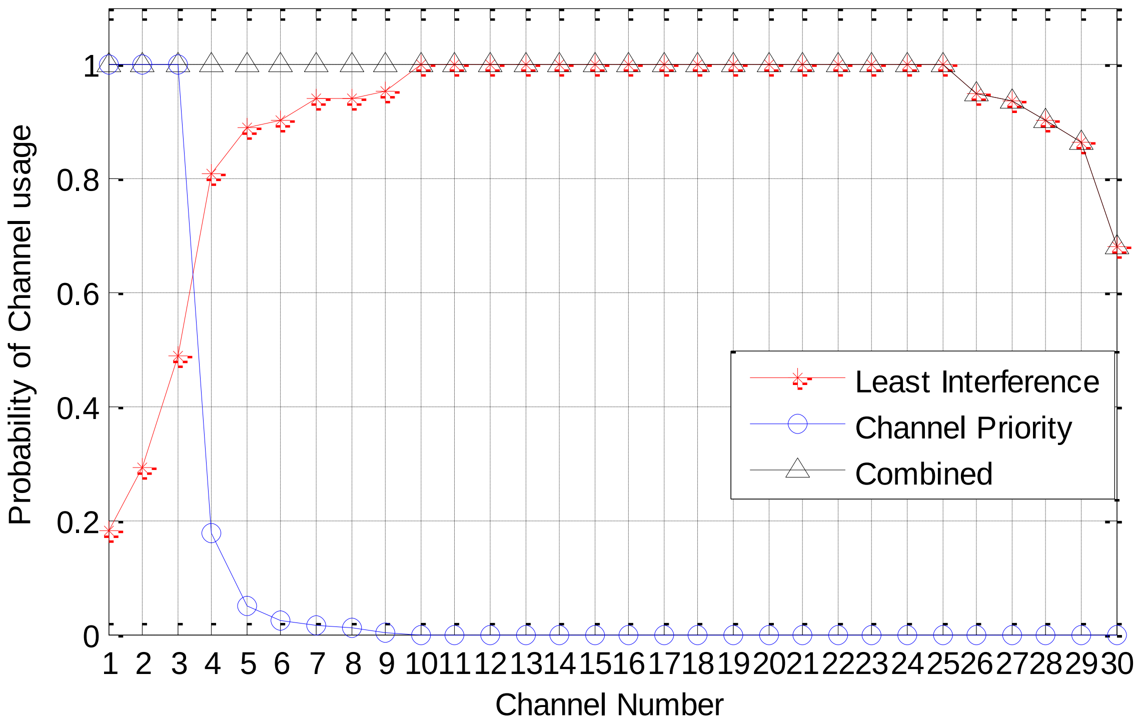

Figure 5-6 Probability of Channel usage in 5:5 ratio

These results show that it is beneficial to combine the two schemes together, since they obtain more benefits in total. From a complementary perspective, if we put the channel usage efficiency as the primary consideration, then the Channel Priority scheme obtains better performance than the Least Interference scheme for this proportion.

All the base stations are assigned with both schemes at this traffic level, but if we increase the number of base stations, or change the minimum modulation scheme threshold for a higher one, there are likely to be some unassigned base stations that cannot be assigned by the Channel Priority scheme. It is because the channels earlier in the sequence have more chance to be overloaded and affected by more interference.

Figure 5-7 shows the capacity variation of two individual schemes mixed in different ratios. This is calculated by translating the SINR into an upper bound of capacity using the Shannon equation (shown in Chapter 3). The equation to define the capacity variation can be shown as:

$$C_a(i)_{percentage} = (C(i) - \frac{i}{\ell}C(\ell)) / \frac{i}{\ell}C(\ell), \ \ell > 0 \qquad (5.1)$$

Where C_a is the final capacity variation, *C(i)* is the current capacity supplied, ℓ is the maximum number of base stations operating in the scheme of interest which is equal to 10 here. i/ℓ is the current ratio. Schemes operating individually are assumed by definition to have no capacity variation. When combining the two schemes together, with the increasing ratio of each scheme, in both cases it is seen that mixing the schemes delivers the higher capacity compared with the schemes operating individually. That shows the capacity is increased for each individual scheme when they are operated together.

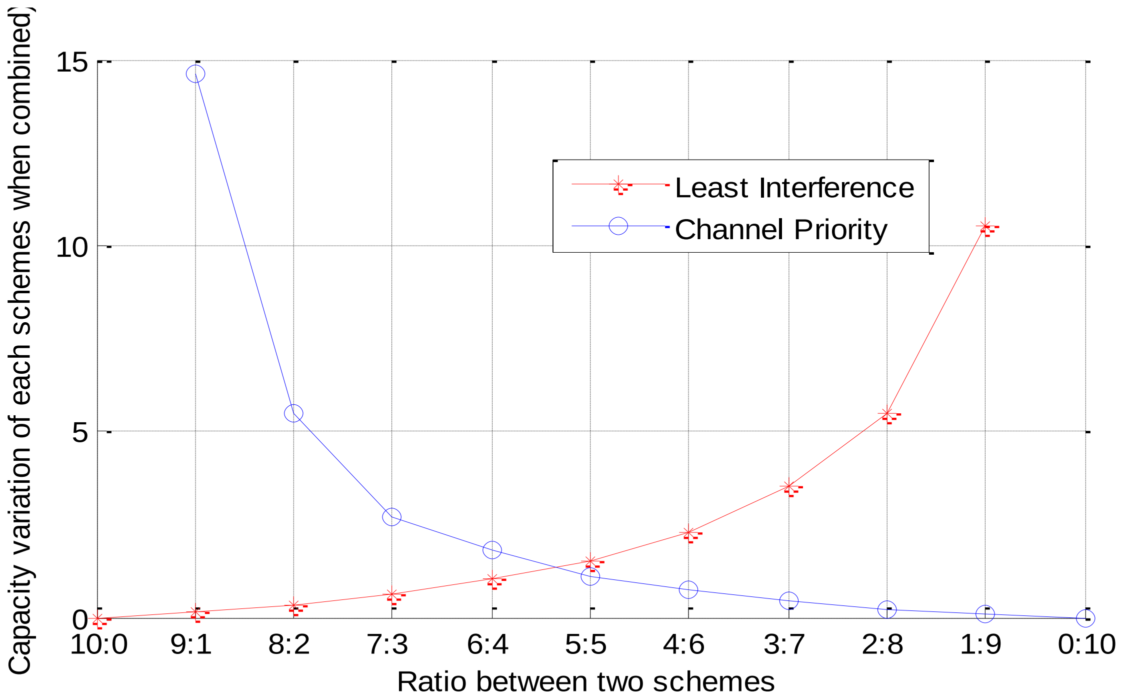

Figure 5-7 Capacity variation of the Channel Priority and Maximal Difference schemes when operating in the same spectrum

Channel Priority & Maximal Difference

The Channel Priority and Maximal Difference schemes are mixed. The Maximal Sum is not used here because it is similar to the Maximal Difference behavior as shown in Chapter 4. In Figure 5-8， the ratio between Channel Priority and Maximal Difference schemes ranges from 10:0 to 0:10 on the *x* axis. The bottom 5% of the SINR value is shown on the *y* axis for the two schemes and the combined performance. The combined curve is relatively smooth and has a stable trend that increases from about 8dB to 24dB. The schemes here still use a 2.3dB SINR minimum value at the Percentile Threshold. Every base station should cover on average 1% of the service area. Since the system has 100 base stations allocated in 30 channels, so the SINR cdf value is much larger than the 2.3dB threshold, as channel occupancy can be quite low. The reason that the bottom 5% value is chosen here instead of median value is because it is often sufficient to provide adequate maximum performance to all but the bottom 5% of users, which is a usual quality of service threshold.

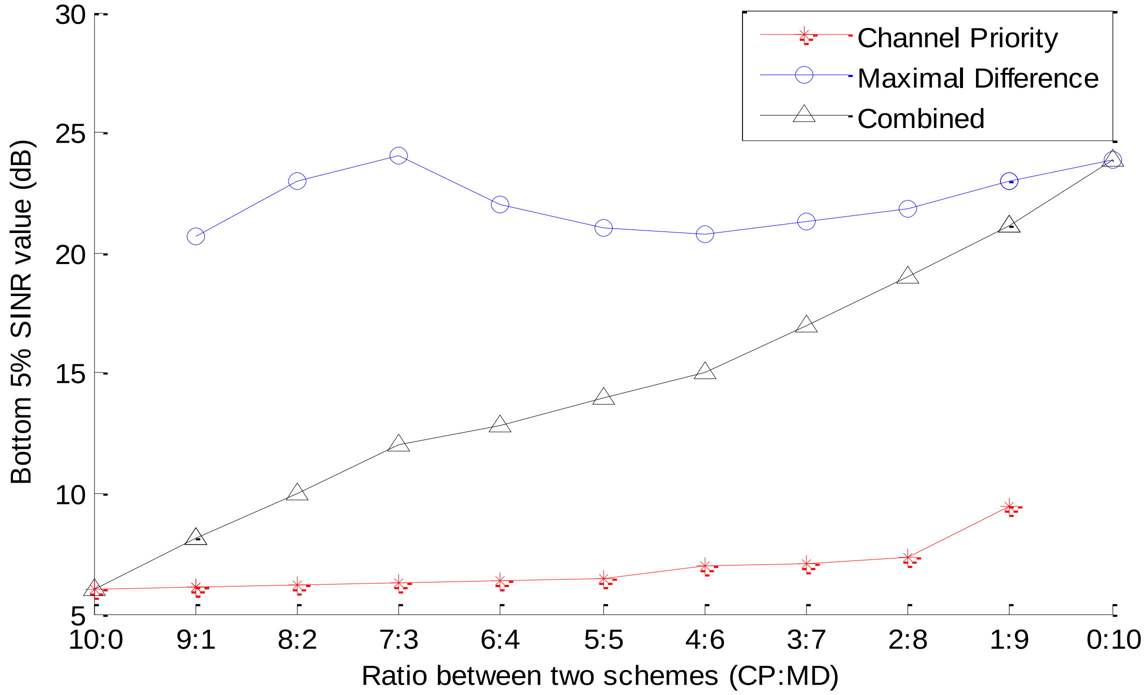

Figure 5-8 Bottom 5% SINR value for mixed schemes

From the introduction and the features in Chapter 4, the Maximal Difference scheme has better performance, because it can further reduce the influence between the BSs on the same channel, while also being able to choose ‘the best channel’ for assignment. When the proportion of the Channel Priority scheme is small, the Maximal Difference scheme can avoid allocating channels earlier in the sequence to help the Channel Priority scheme which is forced to assign channels in sequence order. However, when the proportion of the Channel Priority scheme is large, the Maximal Difference scheme will be used for relatively fewer base stations, so more BSs will concentrate in the channels earlier in the sequence, causing the combined performance to be worse.

From the simulation results, when the ratio of the Channel Priority and Maximal Difference is 7:3, there is a peak point in the Maximal Difference curve. The reason for this is as the proportion of Maximal Difference base stations increase, all channels will become used, and since the more channels that are used, the less interference that is obtained. In other words, this ratio results in the largest overall capacity. The error bars on each of these three curves from ratio 9:1 to 1:9 are all shown in Figure 5-9, based on 1000 trials and a confidential interval of 99%.

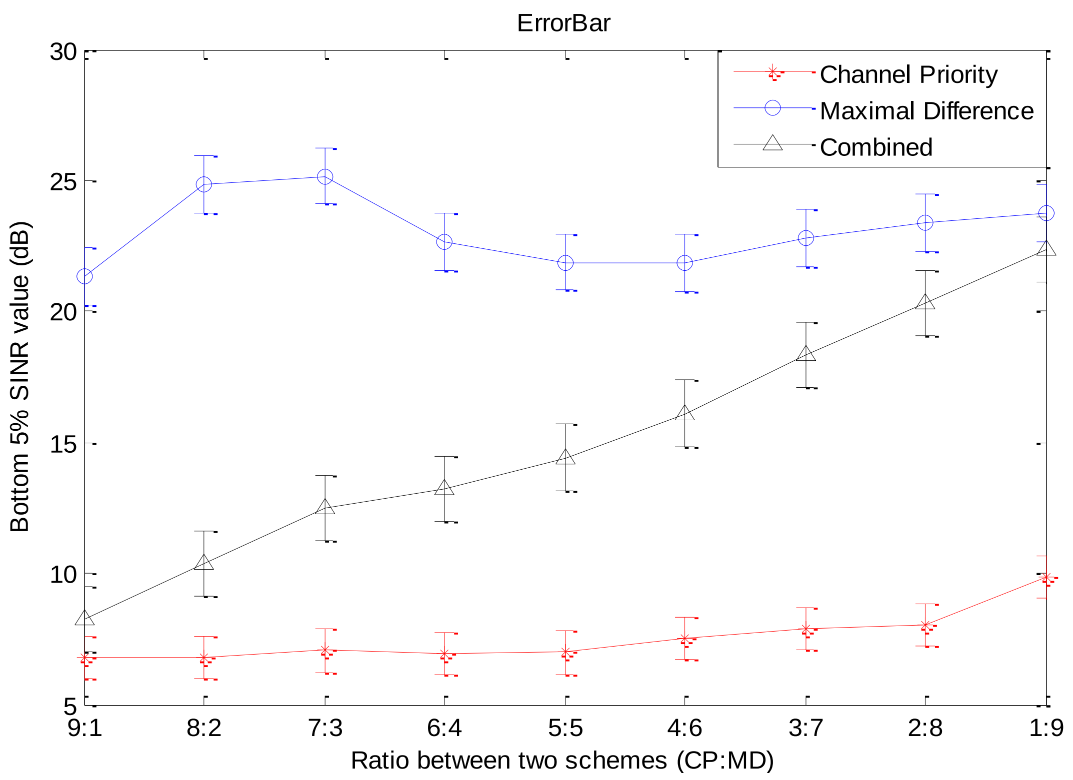

Figure 5-9 Error bar for mixed scheme

In Figure 5-10, the probability of channel usage for each of the two individual and mixed schemes is shown when the ratio is 7:3, which is the peak point we obtained from Figure 5-8. One of the advantages of the Maximal Difference scheme is the balance between the number of base stations on each channel. So in the simulation, the current base station will generally be assigned in the channels that have the smallest number of base stations, regarding in the maximum change in SINR caused by a new user activation on the channel, i.e. where occupancy is low because in this situation they will cause less interference. This feature of the Maximal Difference scheme will cause the channels earlier in the sequence to be avoided as they tend to be used by the Channel Priority scheme. So that explains why the Maximal Difference curve increases from channel 1 to channel 10, and then when the channel number is after 25, the curve decreases, because the capacity is not fully used. From the simulation, when the ratio of Maximal Difference is lower than 7:3, the channels later in the sequence have a lower probability of use. So the curve in Figure 5-8 is increases from ratios 10:0 to 7:3. In the case of the Channel Priority scheme, it will assign the channels that are concentrated on 1, 2, 3 in the earlier part of the sequence, because with the 2.3dB threshold here, they are able to maintain the performance for the base stations.

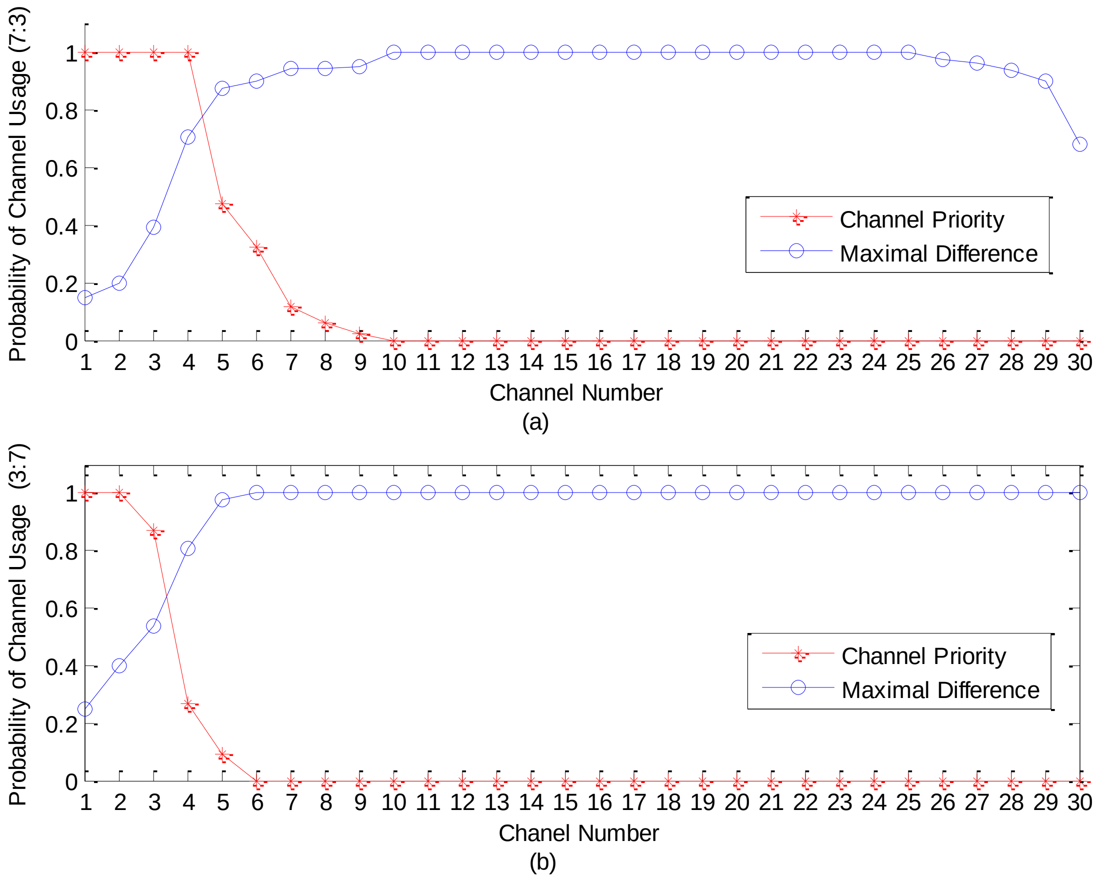

Figure 5-10 Probability of channel usage in ratio 7:3 and 3:7 of two schemes

As we mentioned in relation to Figure 5-8, the Maximal Difference scheme can avoid allocating channels earlier in the sequence to help the Channel Priority scheme. Comparing results with the ratio 7:3 with the channel usage ratio 3:7, the system is more fully loaded and fewer earlier sequence channels are allocated by the Channel Priority scheme. It is for this reason that the combined performance keeps increasing in Figure 5-8, since Maximal Difference is the better assignment scheme. So these results above show that it could be beneficial to combine the individual schemes together, since they obtain more benefits in total. By way of complementarily, if we put the channel usage efficiency as the primary consideration, the Channel Priority scheme obtains better performance.

Figure 5-11 shows when we keep using the GMSK threshold 2.3dB, the BSs in each scheme are able to use different transmission rates (here in this example for ratio 7:3), as the SINR values obtained are significantly higher than the threshold. In Figure 5-11, 100% of the BSs assigned by both schemes have SINR above 2.3dB. About 95% of the BS assigned by Maximal Difference and 10% of the BSs assigned by Channel Priority scheme, can reach 16-QAM. For the 64-QAM transmission rate, the percentages are even lower, only 35% and 4% respectively. So when different transmission rates are applied in each scheme, the overall interaction still remains positive.

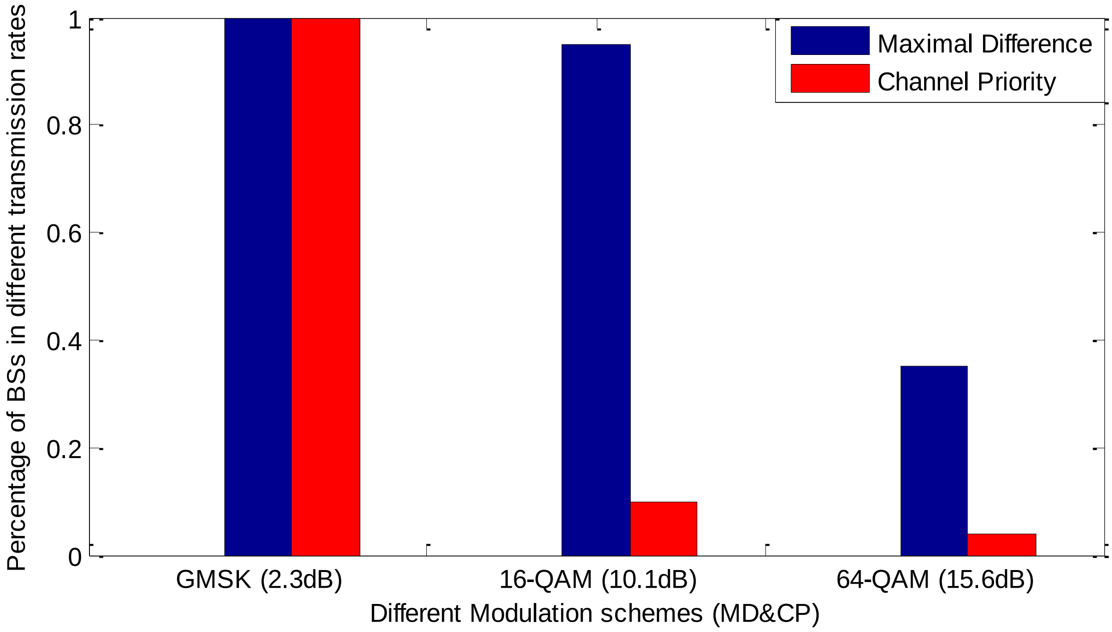

Figure 5-11 Percentage of BSs operating at different transmission rates

We set the SINR threshold higher to 15.6dB corresponding to the high performance required by a high transmission rate modulation scheme, i.e. a minimum of 64-QAM modulation is required for Channel Priority scheme. It is found that, in Figure 5-12, the SINR values of Channel Priority can be forced to be much higher than that in Figure 5-8 which used 2.3dB SINR threshold. Channel Priority now uses additional channels, instead of just using the channel set from before. In other words, the Channel Priority scheme sets the level of congestion on each channel according to the SINR threshold required. The combined performance also is enhanced. The only negative aspect here is that compared to the results shown in Figure 5-8 the schemes are not actually increasing, because the Channel Priority component when the schemes are mixed does not have a positive trend.

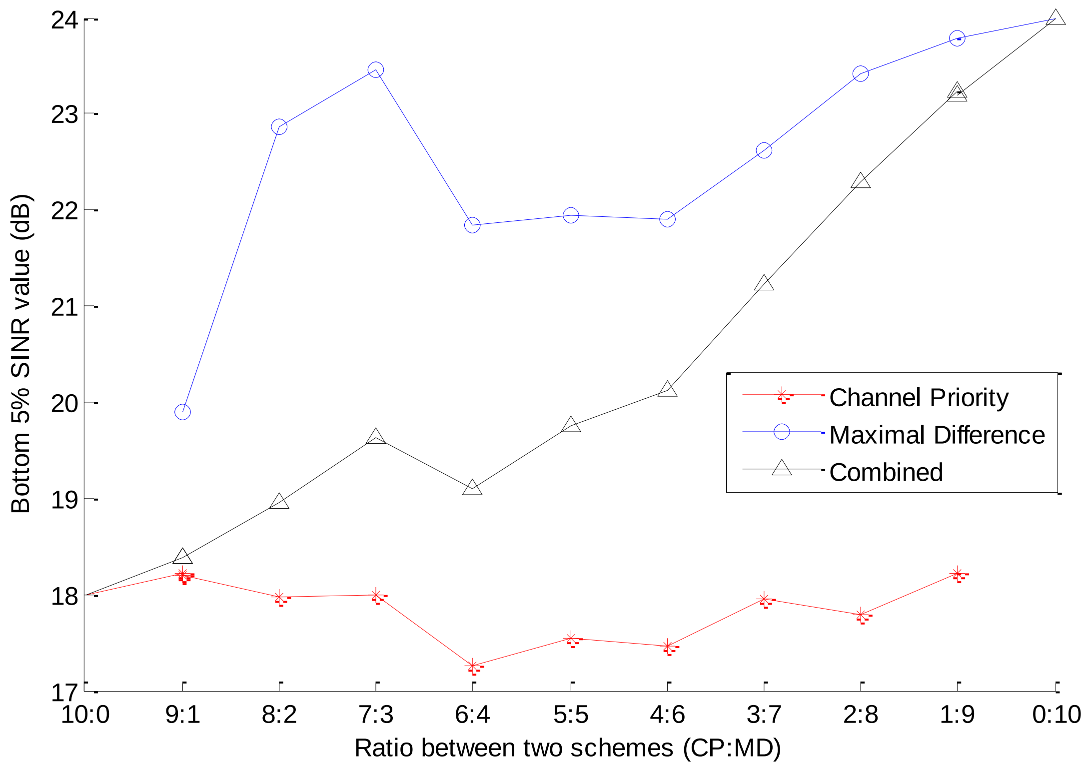

Figure 5-12 Percentage of used channels with different transmission rate requirements

5.4 Discussion

Comparing Figure 5-3 with Figure 5-8 shows the relative performance of the Least Interference and Channel Priority schemes, although one uses the median SINR value, while the other operates in the bottom 5%. The combination of the Channel Priority and Maximal Difference schemes is much better and more stable than that of the Least Interference and Channel Priority schemes. The reasons for this are:

- The Maximal Difference scheme and Channel Priority use a similar assignment principle and threshold, whereas the Least Interference uses a difference principle. For this reason, the Maximal Difference and Channel Priority schemes can combine better than the Least Interference and Channel

Priority schemes can.

- The Maximal Difference scheme could be considered as the best scheme after we compared the four schemes in Chapter 4. Therefore, the scheme that is combined with the Maximal Difference scheme delivers better performance than that scheme without the Maximal Difference scheme because the combination with the Maximal Difference scheme exploits the advantages of the Maximal Difference scheme to help other schemes and provide better performance.

- Regarding the coexistence, the Maximal Difference curve in Figure 5-8 has an increasing-decreasing-increasing trend. In this situation, the Maximal Difference part is more able to fill the empty space that is left by the Channel Priority scheme when these schemes assign channels.

The rules below provide some explanation of behaviour when we mix the different schemes:

- The discussions in Chapter 4 show that every scheme has its own advantages and disadvantages; which scheme is the best depends on the specific circumstances and system requirements. In this chapter, the advantages and disadvantages of the combined schemes are also shown.

- Different transmission rates will be important for future cognitive radio systems. In a cognitive radio system, different operators have different roles based on differing requirements, and are likely to operate in the same spectral bands and at the same time. For example, the result shown in Figure 5-3 is suitable for a situation in which secondary users work with relatively low power. This is because by using the Least Interference scheme, the base stations are maximally assigned. The result in Figure 5-12 shows how differential modulation levels will help cognitive radio operators to work with high or differential SINR conditions. Operators can obtain good combined performance over the full range of ratios of the mixed schemes and are able to satisfy the expected transmission rate requirements.

- Schemes should be combined taking into account the different circumstances of the operator. Channel Priority and Maximal Difference, when mixed, have better performance, but are more complex and needs more steps for assignment. The mixed schemes have the characteristics of both individual schemes, but because of the negative interaction, they sometimes give rise to unpredictable situations. We have tried to determine when these situations are likely to occur, and have established some rules, e.g. the analysis of the peak point of operation. The aim is for the combined schemes to exploit the best features of each individual scheme.

We use 1000 iterations for the simulations in Chapters 4 and 5. When combining the schemes, the rules are fixed so that the results of the schemes do not include any learning process but are statistically significant when we increase the number of iterations of the simulation. In this process, the advantages and disadvantages of each individual scheme and combined scheme are obtained. This enables the features of combined schemes to be observed, but it is more focused on the dynamic channel assignment aspect than on the more cognitive perspective. The results of each of the 1000 iterations separated. There is no learning applied or any memory or enhancement between different iterations. Therefore, in the next step, we assume that the schemes can learn from previous iterations and provide feedback to their respective systems. In this case, it is likely that when increased awareness and intelligence is added into the system, the performance of channel assignment will be greatly improved. The application of learning to channel assignment will be the subject of later chapters.

5.5 Conclusion

In this chapter, the combinations of different channel assignment schemes are considered and discussed. For the Least Interference and Channel Priority mixed schemes, the results show that it is good to combine them together because they can exploit the benefits from each individual scheme, particularly relating to the way the individual channels are allocated. The Least Interference scheme avoids channels used by the Channel Priority scheme, improving its performance. The performance of the Least Interference scheme is improved because the base stations assigned using the Channel Priority scheme are packed together, making the density of channel usage more suitable in those channels used by the Least Interference scheme. For the Channel Priority and Maximal Difference mixed schemes, the results show how it is also good to combine them together. It is found that the schemes interact favorably even when each scheme operates with different modulation rates, thereby allowing differential transmission rates. It is shown that the Channel Priority scheme in such circumstances can be forced to use extra channels to cope with the increased SINR threshold required for a high rate modulation scheme.

6 Reinforcement Learning Applied to Multicast Downlink Transmission

6.1 INTRODUCTION 135
6.2 DISTRIBUTED OCCUPANCY DETECTION...136
6.3 DISTRIBUTED CHANNEL ASSIGNMENT SCHEMES WITH REINFORCEMENT 137
6.4 RESULTS AND DISCUSSIONS 145
6.4.1 Performance Analysis 145
6.4.2 Distributed Occupancy Detection Analysis 153
6.5 CONCLUSIONS...159

6.1 Introduction

In Chapters 4 and 5, we introduced four different centralized channel assignment schemes and discussed their individual and combined performance. We started this project from the channel assignment perspective, but will now develop the system from a more cognitive perspective. There is a learning state in the cognition cycle shown in Chapter 2. In order to make cognitive radio more intelligent, we apply artificial intelligence to the system. There are many different types of artificial intelligence, e.g. game theory, reinforcement learning and neural networks. Our project uses the idea of reinforcement learning to improve the performance of reassignment, blocking and dropping. We focus less on environmental factors or on optimizing the convergence rate than on the original reinforcement learning model, so we implement a simplified reinforcement learning scheme in our system.

This chapter will show how channel assignment in heterogeneous multicast terrestrial communication systems can be improved using intelligence based on reinforcement learning. The purpose is to determine the possible benefits of applying reinforcement learning to the channel assignment process of multicast terrestrial communication systems that implement distributed spectrum sensing. This is achieved by adjusting the weighting factors based on the success and/or failure of each activation. Two novel distributed channel assignment schemes with reinforcement learning applied are shown. These are designed to efficiently improve the speed and quality of channel assignment by limiting the reassignments, blocking and dropping rates. A weighting factor is used in this chapter to determine the highest priority channels and to help control the performance of the system.

This chapter is organized as follows: Firstly, the model of the multicast scenario and distributed detection are briefly overviewed. This is followed by the introduction of two different distributed channel assignment schemes, their characteristics and the reinforcement learning rules. The performance and improvement of distributed reinforcement schemes are then analyzed and discussed. Finally, conclusions are presented.

6.2 Distributed Occupancy Detection

In this chapter, we analyze the effect on performance of different user populations. In Figure 6-1, there are 3 different base stations with multiple users. The users in red, yellow and blue are the users for each individual base station. The users in black are can be assigned to more than one base station. The users in white are unable to connect to any base station. If the density of the users is increased, some users can connect to more than one base station and be assigned, but sometimes also the increased density will cause more interference.

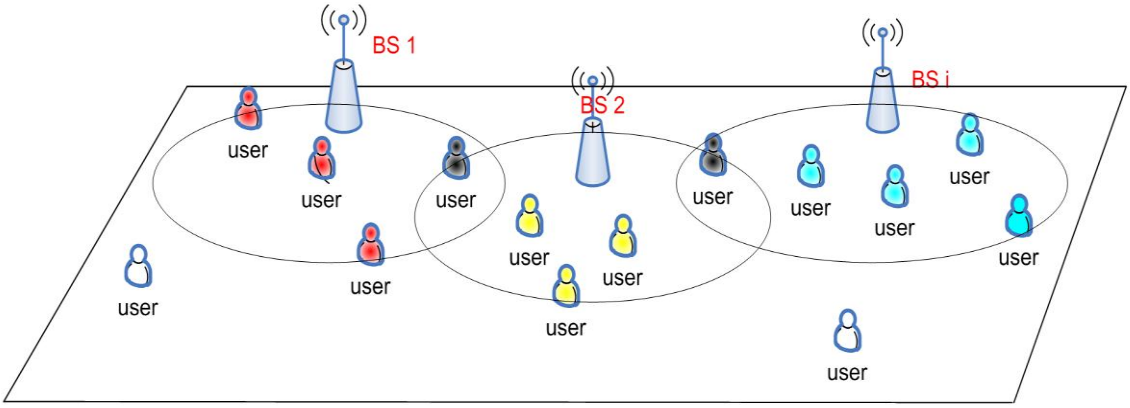

Figure 6-1 Distributed detection scenario

There are five channels with 30 base stations used for the channel assignment in this chapter, which is based on considering the complexity of schemes and the weights update iteration.

6.3 Distributed Channel Assignment Schemes with Reinforcement

Compared to the centralized schemes developed in the previous chapters, distributed schemes do not need a central controller. They infer information from the environment or users instead of exchanging information between BSs. Although the distributed schemes that infer information from power, SINR levels and channel occupancy may be more vulnerable to shadowing and hidden node problems [115]. They are more scaleable and they provide systems with lower complexity which is helpful in the implementation of cognitive radio. There are two distributed schemes presented here: the channel priority distributed scheme and the random picking distributed scheme. They both apply reinforcement learning to the scheme, which will be explained in detail later.

Reinforcement learning is the problem faced by an agent that learns behavior through trial-and-error interactions with a dynamic environment so as to maximize some notion of long-term reward [98]. It is a mathematical method used here for the learning state in the cognition cycle, which will learn the information based on the external environment and previous states, and then is used to influence the current activation [116]. The weight is used to show the influences from the previous users or the factors based on circumstance, which will be updated on each activation. In this chapter, we implement this computational method by using weights associated with each channel at each base station to provide positive or negative feedback about the suitability on each channel.

Incorporating reinforcement learning into the distributed channel assignment schemes is aimed at improving the performance of more conventional schemes by using previously obtained knowledge to aid future decisions, in order to further improve the assignment stability and general performance of the cognitive radio system.

The following briefly describes the basic rules of reinforcement learning used here and shown in Figure 6-2: Initially, the values of all the weights associated with each channel of each base station are the same, but after each activation (iteration), the weights are updated for a channel according to the conditions shown in Table 6-1. Assigning channels successfully or unsuccessfully will result in different positive or negative changes of the weights respectively. That means that the weights are increased or reduced at each activation. On the next activation, the BSs will choose the channel from a preferred channel set (which will be explained when we describe the two different channel assignment schemes) for a channel assignment attempt. The weights are changed here using weighting factors that depend on the different state of the base stations based on Table 6-1. We initialize a variable for the iterations. When all the iterations are finished, the learning process ends. Then, reinforcement learning will help the base stations to assign channels that maximally reduce interference and significantly avoid collisions.

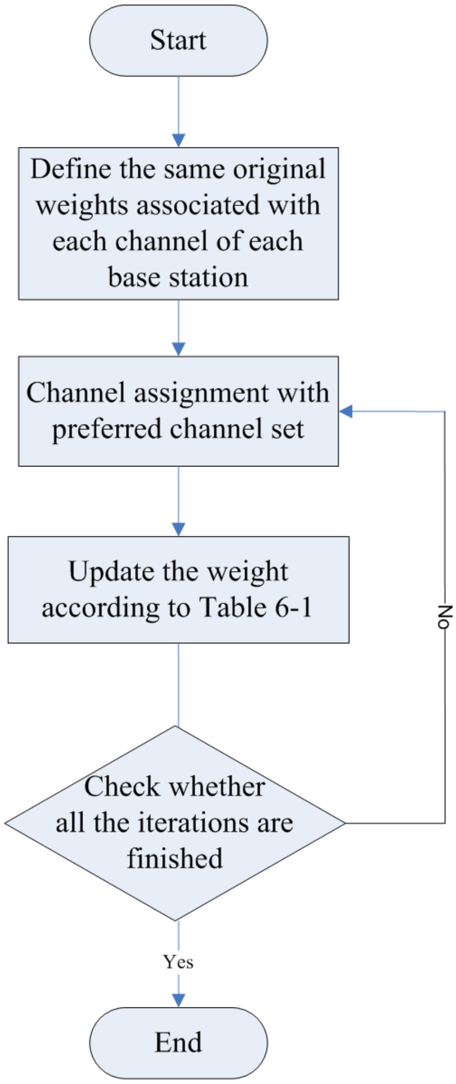

Figure 6-2 Flowchart for channel assignment with reinforcement learning

The update of the weighting factor can be represented by Equation 6.1, based on [115, 117].

$$W_i = F_1 W_{i-1} + W_f \qquad (6.1)$$

where W_i is the weight of the current iteration after the updating of the information from the previous weight W_{i-1}. W_f is the weighting factor that estimates the weight values from the operation of current system and channel assignments, as shown in Table 6-1, and can be considered a reward factor for the reinforcement learning model shown in Chapter 2. F_1 is set to 1 and the parameters that are used to adjust the proportion of the weights, which will be considered later, are set as 1 here. Here, environment states are not investigated. Therefore, Equation 6.1 can be simplified as:

$$W_i = W_{i-1} + W_f \qquad (6.2)$$

In Table 6-1, based on different base station conditions, we define the weighting factors for different thresholds. If we apply five channels in a 30 BSs system using a centralized channel priority scheme, the typical SINR acceptance threshold to deliver good performance is about 4.3dB [13]. This value is used in the table as a reasonable acceptance threshold level for all new entrants. A 2.3 dB threshold is required for GMSK modulation for it to be demodulated with an adequate bit error rate. There are three different types of assignment conditions. If a base station is newly accepted on a channel the weight associated with that channel is increased by 2 (a reward), or 0 if it fails (no punishment) as shown in Table 6-1. If an existing base station is forced off its existing assignment, we use -1 as a punishment for requiring reassignment, and -2 if reassignment fails five times and dropping occurs. For a successful reassignment, we increase the weight by +1, because although it is not as important as a new base station's initial assignment, it still needs to be rewarded for successful assignment.

These values have been chosen arbitrarily, based on the threshold levels. We start with the simplest values: 0, +1 and -1 for the basic successful or unsuccessful assignment, and a bonus +2 or punishment -2 for extra reward or strict punishment. Further work is needed to choose optimal values.

State of BS		**Threshold Levels**	**Weights (w_f)**
New (newly accepted on a channel)	Acceptance	SINR > 4.3dB	+2
	No acceptance	SINR <= 4.3dB	0
Existing	Reassignment	2.3dB=< SINR <= 3dB	-1
	Dropping	SINR < 2.3dB	-2
Reassignment	New acceptance	SINR > 4.3dB	+1

Table 6-1 State of BS and weighting factors

The flowchart below shows how base stations work in distributed channel assignment schemes with the reassignment, blocking and dropping phases. As a start, the channel assignment schemes used here are either the Channel Priority or the Random Picking schemes. When applying reinforcement learning into the system, these simple schemes will help us to see how learning factor works and how it affects the performance.

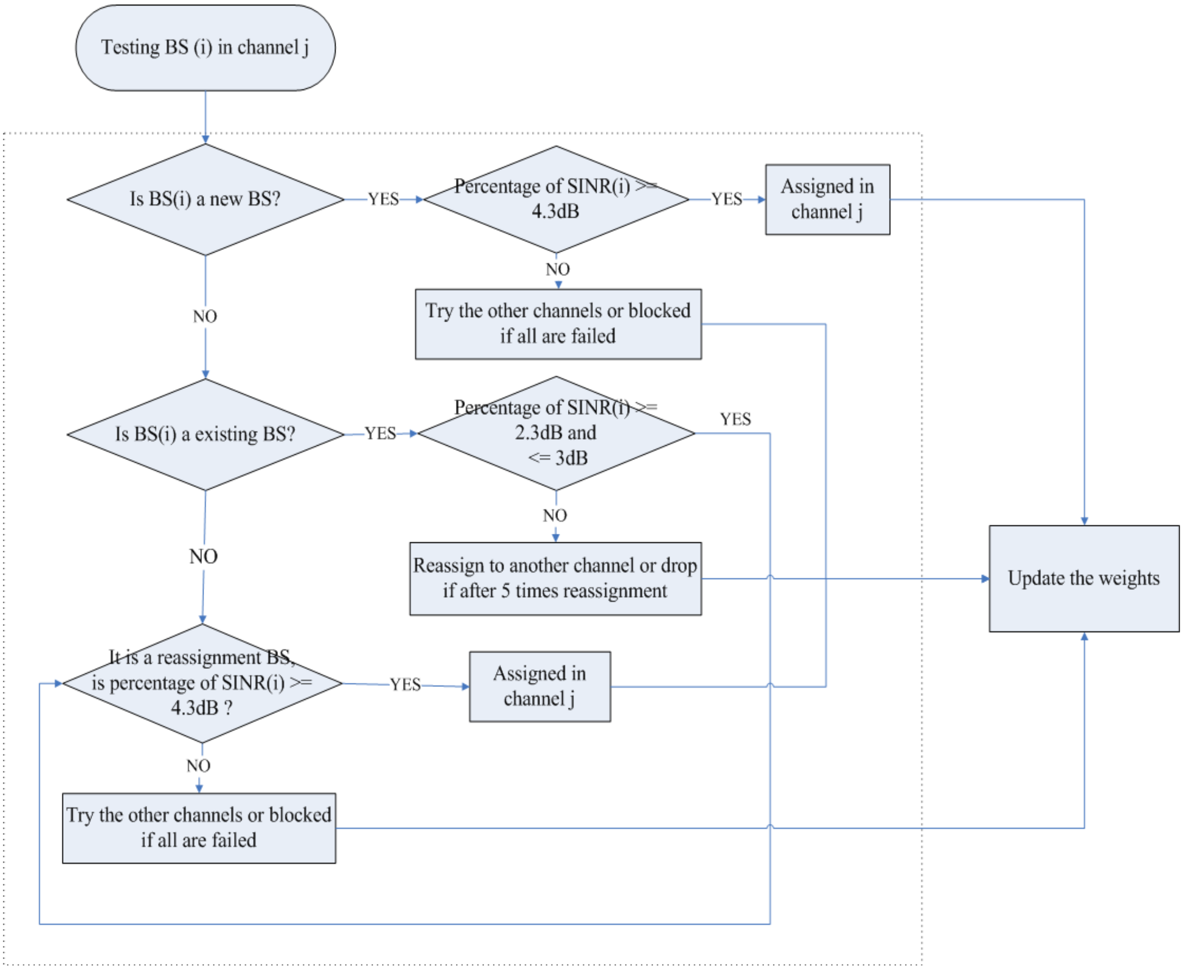

Figure 6-3 Flowchart for reassignment, blocking and dropping situation of distributed channel assignment

The simulation steps of each scheme with reinforcement learning are briefly described below:

- *Step 1: Initial step*

Number all the base stations and channels from 1 onwards. Retain the best 3 channels for each BS (the best three channel set is obtained by selecting the three highest weights for each testing BS, corresponding to each channel; the initial best three channel is chosen randomly from all the base stations).

- *Step 2: Channel assignment*

Use the Channel Priority (CP) or Random Picking (RP) schemes to assign the BSs to suitable channels by each algorithm. In this step, we will explain the differences between the two schemes:

Channel priority distributed scheme:

- Initial activation: All the weights are the same. This scheme will assume that channels 1, 2 and 3 make up the best three channel set for every BS. Three channels are chosen for the preferred channel set because this should greatly reduce the time spent on finding a suitable channel for each base station.
- Subsequent activation: The best three channel set is used at each BS. If these channels fail, the remaining channels are tested in numerical order, starting with the next highest channel on the list after the third best channel.

Random picking scheme:

- Initial activation: All the weights are the same. This scheme selects three random channels for each base station as the best three channels to start with.
- Subsequent activation: The best three channel set is used for each BS. A random channel from the best channel set is chosen, with the remaining channels from the best channel set chosen randomly if the channel(s) fail. Once the best channel set has been exhausted, the remaining channels from the pool are selected randomly.

With both schemes, the SINR cdf levels used to assign, reassign, block or drop for the channels are the same, as shown in the flowchart. For each scheme, the initial assignment and reassignment will stop after five channels have been tried.

- *Step 3: Weight setting*

The weights are changed and recorded after each activation using the values in Table 1, which means the best three channel sets may also change after each activation. From step 1 to step 3, there is a full activation.

Compared to the Random Picking scheme, the channel set selection of the Channel Priority scheme is better because it is strictly ordered by the weighting values from highest to lowest. The channel set of the Random Picking scheme, however, can still be used to analyze the totally random situation.

The pseudo code of the Channel Priority scheme are shown as below:

```
Best k channel set exist
initial: channel 1-k are best k channels
Set current-channel to 1
Set max-BS, max-channel

for (BS(i)=1:max-BS)
    record SINR cdf value of BS(i) in current-channel
    if SINR cdf of BS(i) > 2.3dB
        allocate BS(i) into current-channel
    else
        current-channel++
        if (current-channel > max-channel)
            return
        else
            continue the operation on BS(i)
        end
    end
end

update weight for every channel

for (j=1:k)
    max-weight-channel = channel(j)
    for(m=j:max-channel)
        if(weight of channel(m) > max-weight-channel)
            max-weight-channel = channel(m)
        end
    swap channel(j) and max-weight-channel
end
```

The pseudo code of the Random Picking scheme are shown as below:

```
Best k channel set are existed
initial: randomly select k channels as best k channels,
put them in channel(1) to channel(k)
Set max-BS, max-channel

for (BS(i)=1:max-BS)
    for (j=1:max-channel)
        if(j <= k)
            current-channel = randomly select one from
channel(1) to channel(k) (not selected before)
        else
            current-channel = randomly select one from
channel(k+1) to channel(max-channel) (not selected
before)
        end

        record SINR cdf value of BS(i) in current-
channel
        if SINR cdf of BS(i) > 2.3dB
            allocate BS(i) into current-channel
        else
            continue the operation on BS(i)
        end
    end
end

update weight for every channel

for (j=1:k)
    max-weight-channel = channel(j)
    for(m=j:max-channel)
        if(weight of channel(m) > max-weight-channel)
            max-weight-channel = channel(m)
        end
    swap channel(j) and max-weight-channel
end
```

6.4 Results and Discussions

6.4.1 Performance Analysis

In this section, we compare the two new distributed channel assignment schemes with the previous centralized schemes, from no weights to using weights after different numbers of weight update iterations. In this way the performance of the reinforcement learning can be quantified when applied to distributed channel assignment schemes in CR systems. Base stations are assigned in random order, and many sets of base station locations are used in order to provide an adequate number of trials for obtaining statistically accurate results.

Balancing the tradeoff between exploration and exploitation is a particular challenge existing in reinforcement learning [118, 119]. They may have a great bias on learning time and the quality of learned policies. Here exploration could be reduced because we use the preferred channel set.

The comparison between the centralized scheme without reinforcement learning and the distributed schemes with reinforcement learning is shown in every figure with weight update iterations. On the X axis, the starting value of each curve at the 0 weight update iteration are the results we simulated for the centralized schemes, allowing the distributed schemes to be compared with the centralized schemes.

In Figure 6-4, the performance with respect to the number of weight update iterations at each base station is shown. It means that the system is tested from no reinforcement learning applied in the distributed schemes (iteration 0), to weights obtained after 1000 iterations. We include the average proportion of reassignments, the probability of dropping and blocking in one figure in order to see the proportion they contribute and also for obtaining the whole trend.

The weight derivation is a cumulative process that is increased or reduced after each activation, with the results affected by the previous results. The learning process never stops. So as shown in the figure, all the curves have an improving trend. It shows the reassignment, dropping and blocking for two different channel assignment schemes respectively.

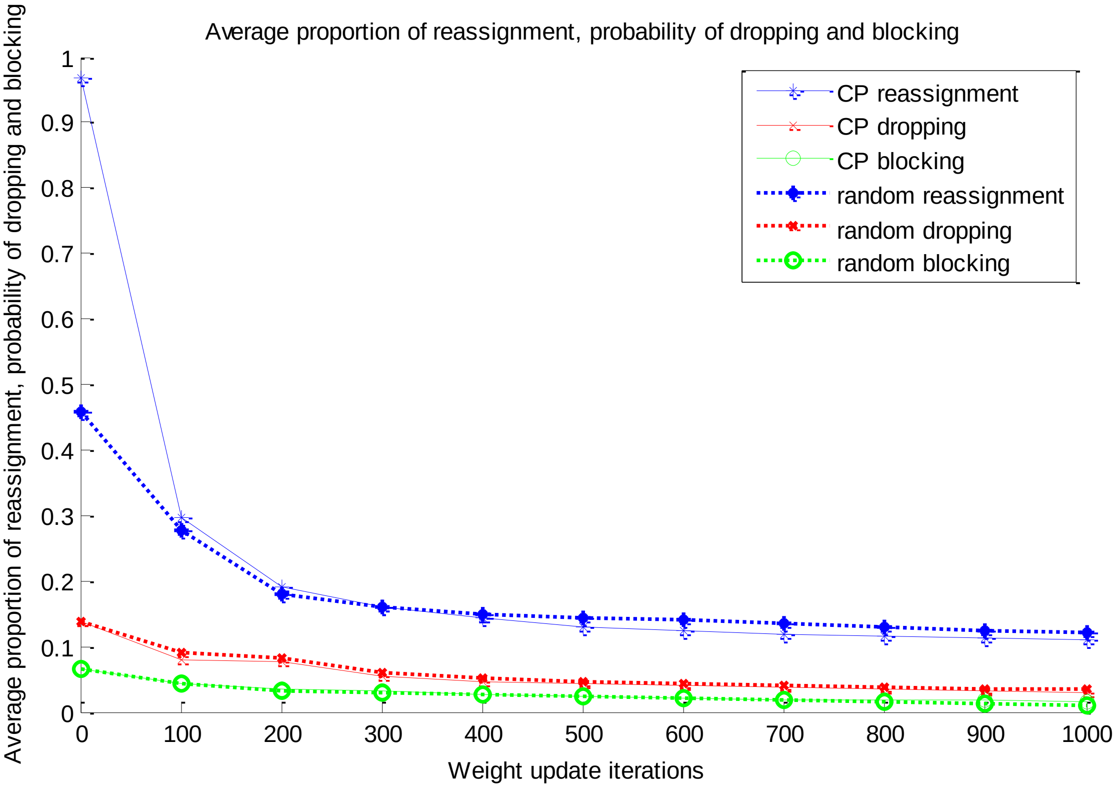

Figure 6-4 Average proportion of reassignments, probability of dropping and blocking for two distributed channel assignment schemes

From the figure, comparing dropping and blocking, it is shown how the reinforcement learning plays an important role in improving the performance, particularly in reducing the need for reassignment. The proportion of reassignments of both schemes is significantly reduced after a large number of iterations have been used to set the channel weights. The reassignment probability reduces from a value close to 1, without the weights, to about 0.14 after 1000 iterations with the CP scheme, and from about 0.46 without weights to 0.15 for 1000 iterations for the RP scheme. The average proportion of reassignments for CP is twice that of the RP one, and this is mostly due to the characteristics of CP scheme since it concentrates base station assignments into relatively concentrated channels. In other words, it is not good to use it for a decentralized channel assignment unless reinforcement learning is applied. For the random picking scheme, the loading of base stations on each channel is lower. However, the scheme even with reinforcement learning still tends to overload the channels (resulting in slightly higher dropping than is normally desirable). For example in a 5 channel system, there are only two channels left outside of the best channel set, and this causes the BSs to have insufficient assignment options. So we may need to improve the system by increasing the number of channels in order to change the channel loading.

The behavior of reassignments for the two distributed channel assignment schemes can be divided into three periods as shown in Figure 6-4:

- The first period is from 0 iterations to 100 iterations, where the rate of reassignment decreases by more than 40%. This is an *investigation* period, exploration mostly takes place. It just starts to learn but does not have many previous states to imitate and these results in reinforcement learning having a relatively small influence at this stage.

- The second period, from iteration 100 to 300, the rate of reassignment decreases by 10-40%. It is an *accumulation* period with coexistence and interaction. In this period, the reinforcement learning has some kind of basis to be used; it is really in a learning situation. The main work for the system is to store enough experience, at the same time, while further reducing the negative interaction for the system, in order to support better learning for the later period. So the needs of reassignment are continuously reduced in a relatively obvious trend.

- The third period, from iteration 300 to unlimited, the level of reassignment decreases by less than 10%, and is a *mature* period, when a stable equilibrium of coexistence has been obtained. In this period, base stations all have relatively stable best channel sets, which in general change very little, and sudden interference is unlikely. It does not have a static value, as the learning experience still improves performance in this fixed random scenario.

The result in Figure 6-4 also represents the convergence behavior of the schemes with reinforcement learning. From the 300 weight update iteration point, the users tend to find their preferred channel set, with reinforcement learning scheme converging to its relatively stable performance. This channel assignment scheme will reach equilibrium of assignment after all the base stations obtain their stable preferred channel set because the base stations are able to avoid the unsuitable channels by using their previous experience.

Reinforcement learning significantly reduces the interference, and at the same time, avoids unnecessary retrying in order to improve performance. Blocking and dropping both have a relatively gentle decreasing trends when the number of weight update iterations is increased. By choosing a suitable access threshold, the blocking curve is a little lower than dropping. This is mainly due to the overloading of the channels as we discussed before. Normally, 5% blocking probability and 0.5% dropping probability are typical ones used by operators**.** Here dropping is a little higher because the threshold for dropping is more restricted. In the case of blocking, the SINR cdf value is always bigger than 4.3dB, so this threshold does not implement the blocking function properly. So the new acceptance threshold will be changed to see the performance next. The blocking cannot be reduced to zero because reassignment will still take place and the base stations have the chance to be assigned on relatively busy channels.

Figure 6-5 shows the average proportion of reassignments, dropping and blocking probability results after 1000 iterations when the new acceptance level changes. Compared to Figure 6-4, reassignment happens initially much more frequently than blocking, but in Figure 6-5 the blocking is increased and reassignment is decreased as a higher threshold is used, crossing at 7dB. The bottom two curves with circles show the dropping results, decreasing slightly for each scheme. They still illustrate the same problem as we discussed in Figure 6-4 about the channel loading. For the RP scheme, the decrease is more obvious, because compared to the CP scheme, the higher threshold will cause more channels to be tested and used, in order to reduce the loading of channels.

When we increase the new acceptance threshold, it causes the loading of the channels to become less crowded as seen by the blocking curve. At the same time, the reassignments are reduced, but the dropping is only slightly reduced, as the reassignment is a very good alternative to blocking as way of controlling dropping. Changing the new acceptance threshold is good for improving and controlling the reassignment and blocking by reducing the channel loading, because it limits the probability of new base stations acquiring a channel in the system, in order to protect some benefits of existing users. However it is still insufficient to control dropping adequately at this stage. We need to increase the channel numbers in order to radically solve the loading problems.

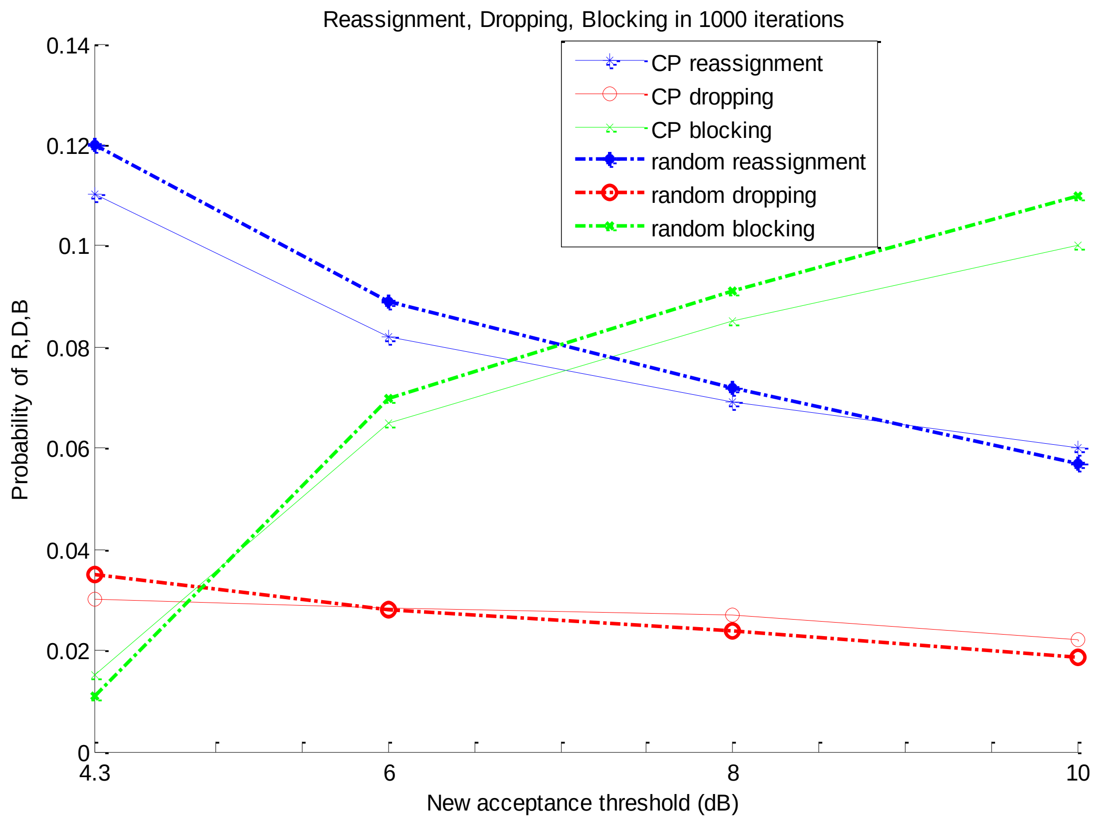

Figure 6-5 Probability of reassignment, dropping, blocking after 1000 iterations with a changing New Acceptance Threshold

In Figure 6-6, the effect of changing the number of channels is shown. As a whole, reassignment, blocking and dropping for both schemes are all improved by reducing channel loading. Compared to changing the new acceptance threshold, increasing the number of channels influences the probability of reassignment for the CP scheme, but has much more influence on the RP scheme for some random layouts. This show the limitations of the CP scheme, and the problems of channel loading still exists. This time, with the increase in number of channels, the blocking for both schemes is improved a little. Increasing the number of channels will provide the biggest improvement to the level of dropping, especially for the RP scheme. When the number of channels is above 8 for the 30 base stations used here, all the curves deliver a more suitable channel loading, meaning that the blocking and dropping are at acceptable levels. Also we can see that a reduced channel loading results in the RP scheme having a higher performance than the CP scheme.

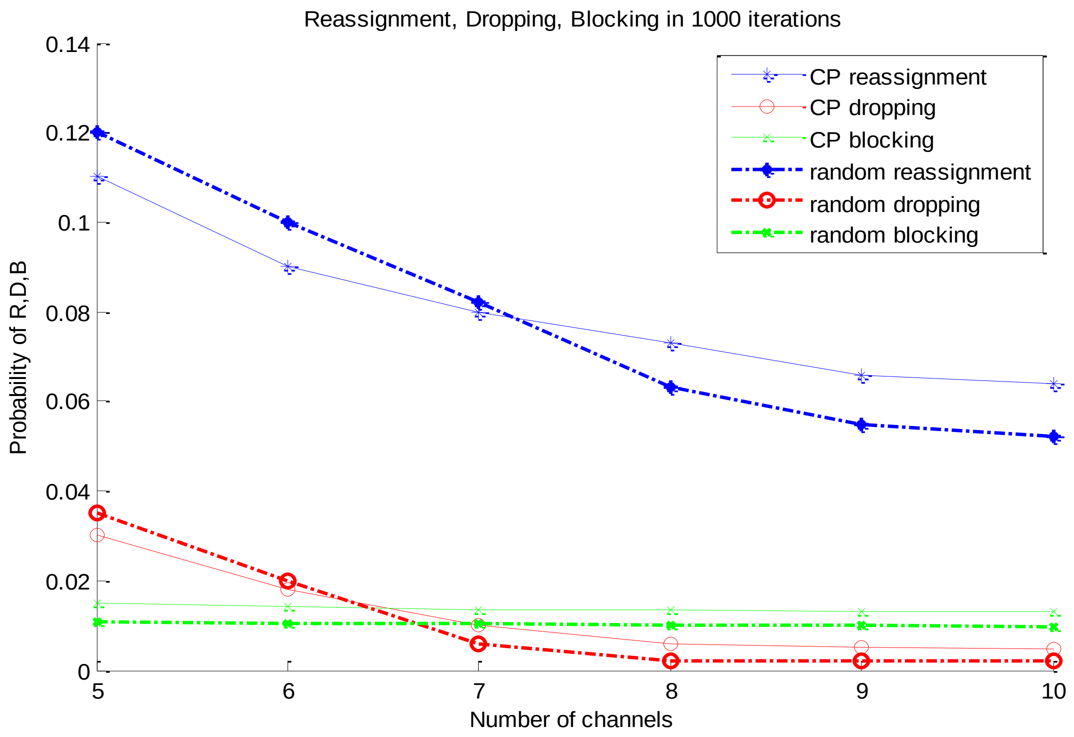

Figure 6-6 Probability of reassignment, dropping, blocking in 1000 iterations with changing the number of channels

Figure 6-5 and Figure 6-6 implement two ways of changing the channel loading for both schemes. Compared to the result after 1000 iterations in Figure 6-4, a higher number of channels along with a higher acceptance threshold could greatly reduce the influence of channel loading. All the results show that operating distributed channel assignment schemes with reinforcement learning is a possible way of achieving implementing increased intelligence in channel assignment for a CR system and has better performance.

From the results shown in this section, reinforcement learning can reduce the probability of reassignment, blocking and dropping by considering different user populations. By utilizing the reinforcement learning approach, users are able to discover the best available resources autonomously, which could result in significantly improved performance, while reducing the requirements for spectrum.

6.4.2 Distributed Occupancy Detection Analysis

In this section, we examine the effect on performance of different user populations, using the random picking distributed channel assignment scheme, after a different number of weight update iterations. Base stations are assigned in random order, and many sets of base station locations are used in order to provide an adequate number of trials to obtain statistically accurate results. A model with 10 channels and 30 base stations is used at this stage.

Figure 6-7 shows the probability of reassignment, dropping and blocking after 1000 iterations when the number of users per base station changes. Two percentages of users are compared here, serving 90% or 95% user population above the thresholds respectively. The 90% and 95% values represent two reasonable proportions that indicate the performance of users for each base station, which is good enough for the usual quality of service threshold. We focus more on the entire coverage area. If there is a 100% need access, for each individual user, the threshold may be higher. Our work deals with users being unable to get service due to coverage and capacity limits. Of mobile phone users in a cell, 100% cannot typically be served because of lack of adequate coverage due to shadowing and other fading. The X axis shows the numbers of users as 1, 10, 20, 30 and 50 per base station, i.e. from a single user to multiple users.

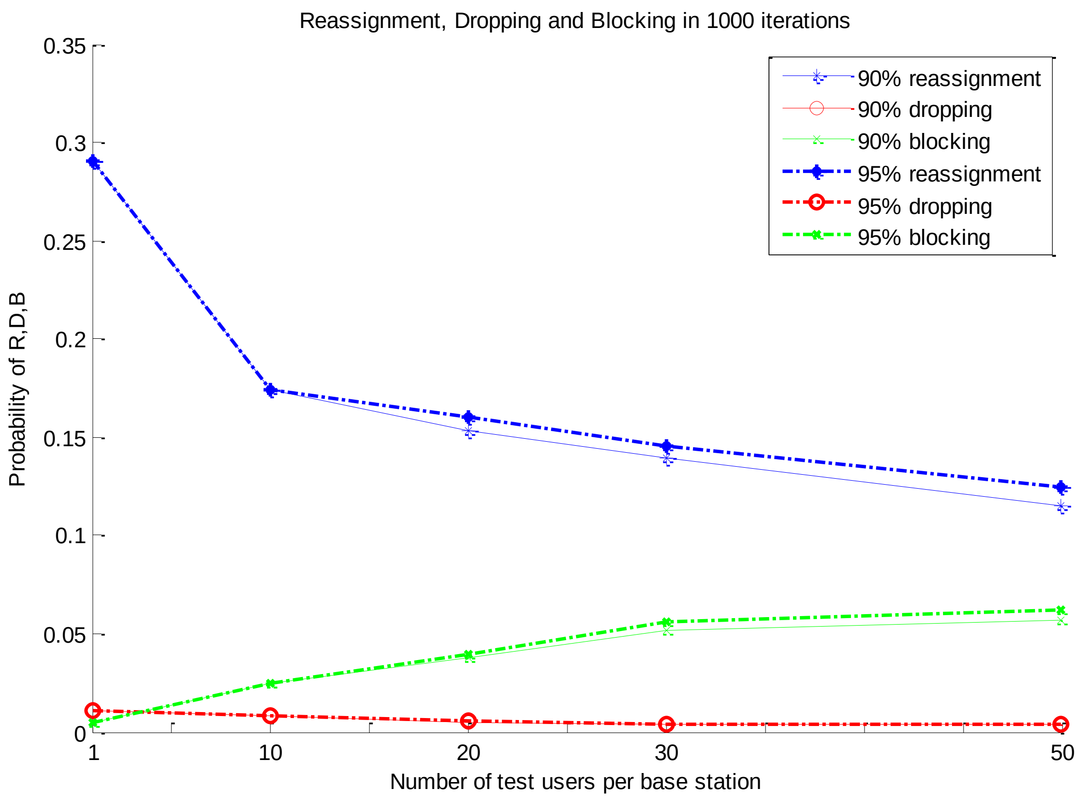

Figure 6-7 Reassignments, dropping and blocking in 1000 iterations

Figure 6-7 shows that the increasing number of users plays an important role for improving the performance, particularly in reducing the need for reassignment, but also dropping. They are at the expense of increased levels of blocking. The probability of reassignment reduces from a value about 0.29 with single user, to about 0.13 for 50 users for both of 90% and 95% threshold. A single user per base station is more vulnerable to the 'hidden node' problem in the system, so it means that the probability of reassignment is still relatively high even after 1000 iterations. When the number of users per base station increases, the benefits of distributed detection are enhanced [11], at the same time with the benefits from reinforcement learning, the probability of reassignment for user populations are improved for both 90% and 95%. Due to the density of user locations in the same coverage area, more and more users will be commonly used for detection by the base stations. This means for a fixed density of users the nominal coverage of each base station increases as more users connect to a base station. It also increases the likelihood that a user can be connected to more than one base station, i.e. there is the potential for overlapping coverage.

Dropping performance here improves as the size of multicast population increases. When the base station has only a single user, it more likely that this user will be hidden from others because it can only detect the information from one direction, which will cause more interference for itself and other base stations. With an increased number of users, the amount of dropping is greatly reduced because more hidden node situations can be prevented. In contrast for blocking, a single node per base station results in nearly zero blocking probability, because the low density user group can greatly reduce the interference and then avoid the blocking. However, reassignment is used more often to mitigate the negative effects, since ‘hidden nodes’ are more likely to occur.

From the Figure 6-7, there is no difference when the number of users varies between 1 to 10 per base station, as it has little impact on the user population requiring service. We do not examine performance when the number of users per base station increases above 50, since with coverage model used and the user density level means that the coverage per base station would be too great, with the user density selected. The result is that from 20 users the reassignment, blocking and dropping curve are relatively stable. We will use 20 users per base station to obtain better performance in later results.

Figure 6-8 shows the probability of users with the ability to connect to a different number of base stations. The total number of users here is 20 per base station. More than 90% of the users are shared by 2 base stations in different channels which show a high probability of overlap. Also, the users in the central area are more frequently used to test, which will cause the weights of them be influenced faster than others. The level of overlap is affected partly because of the random location of base stations and the density of users.

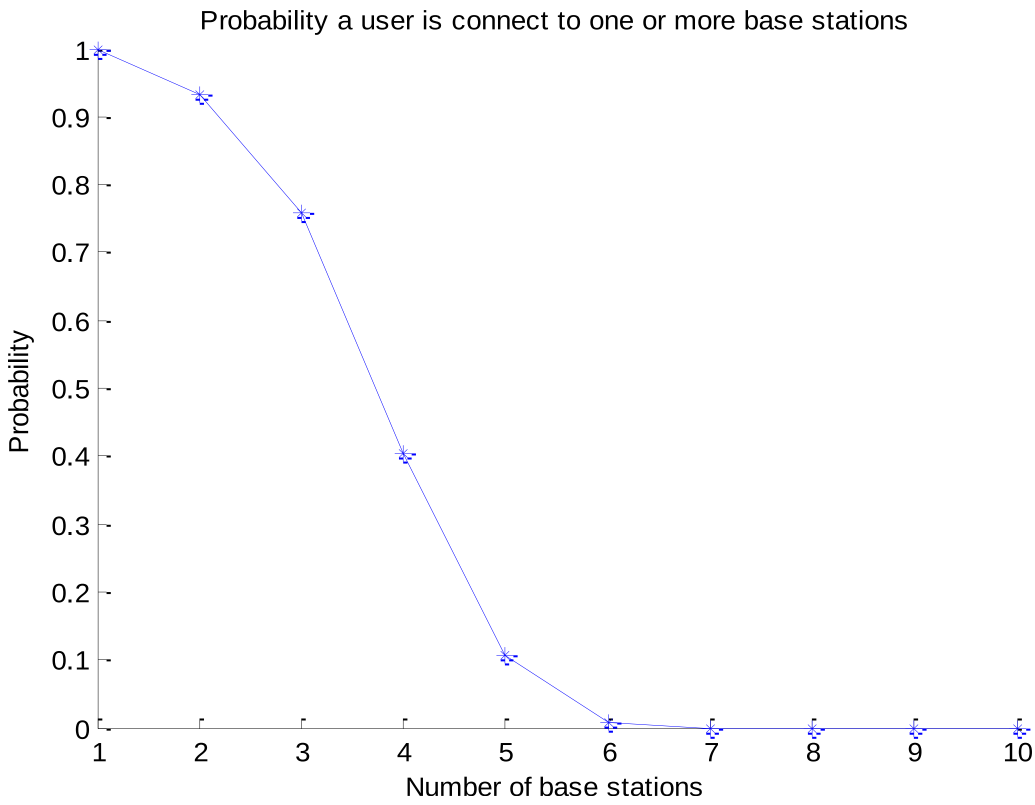

Figure 6-8 Probability a user is connected to one or more base stations

(20 users per BS)

We update the original thresholds of Table 6-1 according to Table 6-2, which is a new attempt to better assign the user population, taking into account the reinforcement learning. Here we focus more of percentages of the user population served in each category rather than SINR thresholds adjustment. For most cases we select a common 4.3dB threshold based on the acceptance threshold [11]. Although a 2.3dB threshold is the fundamental threshold of GMSK, the probability of dropping with 95% SINR coverage is still slightly higher than we expect. Instead, for dropping we set an 85% threshold at 2.3dB instead of 95%. This slightly relaxed condition provides a better balance between reassignment, dropping and at least keeping the vast majority of users active in the systems.

State of BS		**Thresholds Levels**	**Weights (w_f)**
New	Acceptance	95%SINR > 4.3dB	+2
	No acceptance	95% SINR <= 4.3dB	0
Existing	Reassignment	95% SINR <=4.3dB	-1
	Dropping	85% SINR < 2.3dB	-2
Reassignment	New acceptance	95% SINR > 4.3dB	+1

Table 6-2 State of BS and modified weights

In Figure 6-9, the performance with respect to the number of weight update iterations at each base station is shown. It means that the system is tested from distributed assignment with no reinforcement learning (iteration 0), to weights obtained by reinforcement learning after 1000 iterations with 20 users per base station. The weight derivation here is a cumulative process that is increased or reduced after each activation, with all the results obtained from the previous results. The learning process never stops. So as shown in the figure, the result of reassignment, blocking and dropping all have an improving trend.

Comparing Figure 6-9 and the 1000 iterations result in Figure 6-7, we find that using the modified percentage threshold yields better performance and is a more flexible way of controlling behavior. We use two ways to identify the thresholds, one is based on a fixed percentage of the user group and the other is the changeable percentage which is changed depending on the requirements.

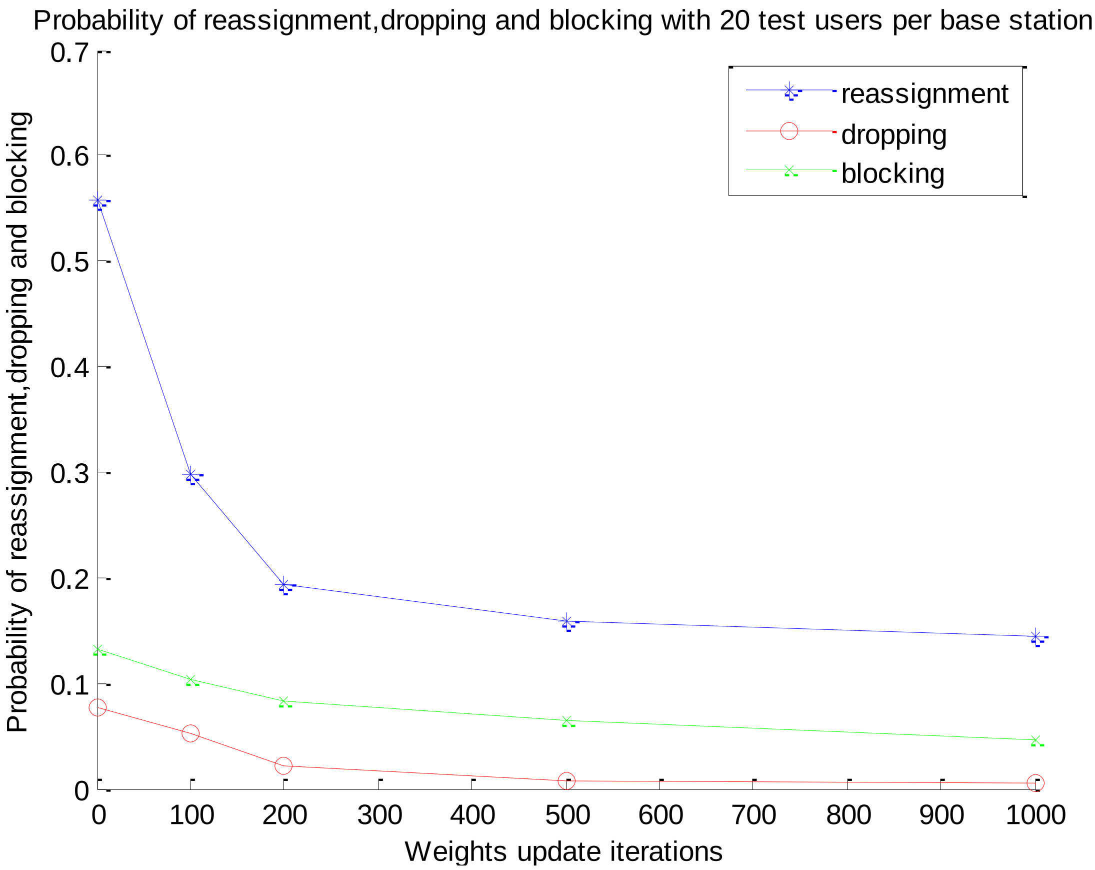

Figure 6-9 Probability of reassignment, dropping and blocking with 20 users per base station

In Figure 6-9, it is also worth considering the early performance of the system before the 1000 weight update iterations. When the weight update iterations increase, not only is the reassignment probability greatly reduced, but it also improves the rate at which base stations find suitable channels for assignment. This means that the base stations are much more likely to find a suitable channel, because the high weighted channels will help the users avoid the interference. Blocking and dropping performance are also improved after 1000 iterations; the probability of dropping decreases to a very small value, which shows that reinforcement learning when used with a multicast user population helps the system avoid dropping.

6.5 Conclusions

This chapter has presented two distributed channel assignment schemes applied in a CR system using reinforcement learning and a weighting factor. The Channel Priority and Random Picking schemes are shown, and compared for different numbers of iterations used to derive the channel weighting factors. It is found that compared to the previous schemes without reinforcement learning, distributed channel assignment schemes with reinforcement learning can efficiently improve the reliability of channel assignment by limiting the reassignment, blocking and dropping. Moreover, determining the highest priority channels helps base stations to improve the performance of the system. The results show that the proportion of reassignments of both schemes is significantly reduced after a large number of weight update iterations are used, from a value close to 1 in with no learning to 0.14 after 1000 learning iterations with the CP scheme, and from about 0.46 without learning to 0.15 for 1000 iterations for the RP scheme.

We have shown how it is possible to divide the learning process into three phases depending on the degree of accumulated knowledge. Performance improvements are achieved by learning about past successful/unsuccessful assignments, and also by increasing the new acceptance threshold or the number of channels, as the channels become less crowded. Dropping control using channel reassignment is a very good alternative to blocking of new activations. We have shown how the random picking distributed channel assignment scheme with a user population was capable of receiving multicast downlink transmissions. It is found that compared to single user channel occupancy detection, multiple user detection helps solve the hidden node problem by greatly reducing the proportion of reassignments and improving the dropping probability. However this is at the expense of higher blocking because it is more difficult to find suitable free channels that can serve an increased coverage area per base station, occupied by the multiple users. The level of overlap is affected partly because of the random location of base stations and the density of users. More details of overlapping problem will be discussed in Chapter 7.

7 Advanced Improvements with Reinforcement Learning

7.1 INTRODUCTION 161
7.2 SCENARIO AND DISTRIBUTED DETECTION 162
7.3 PERFORMANCE ANALYSIS AND OVERLAPPING PROBLEM 163
7.4 POWER ADJUSTMENT 168
7.4.1 System with Power Adjustment 168
7.4.2 Performance of Adjustment...171
7.5 CONCLUSIONS...175

7.1 Introduction

Cognitive radios have the capability to adjust their transmission parameters to achieve better performance [120]. The transmission parameters that may be adjusted to improve communication quality include: operating frequency, modulation scheme and transmit power [121]. To further improve the performance of a system with reinforcement learning applied, in this chapter, the transmit power will be adjusted to reduce overlap between neighboring base stations (which operate on different channels) thereby saving power and further reducing the interference.

The main aim for this chapter is to apply reinforcement learning to the channel assignment process of multicast communication systems, which operate with downlink transmitter power adjustment at the base station. This will exploit information from randomly distributed users, providing distributed detection. The assignment will use a threshold based on a quality of service guarantee across differing percentages of this user population. Work shown in previous chapters has adopted a SINR cdf to control the performance of a distributed channel assignment scheme with reinforcement learning.

This chapter is organized as follows: Firstly, the user population analysis of the distributed occupancy detection model is shown, the results arising from different user populations influencing the distributed reinforcement learning schemes are then analyzed and discussed, followed by the power adjustment applied in the system. Finally conclusions are presented.

7.2 Scenario and Distributed Detection

We will discuss the effect on performance of different user populations applied in the random picking distributed channel assignment scheme, after a different number of weight update iterations. Base stations are assigned in random order, and 1000 sets of user locations are used in order to provide an adequate number of trials for obtaining correspondingly statistically significant results. In the past, we used to select the model with 5 to 10 channels and 30 base stations, but due to loading quality of service dropped below that which is considered acceptable, so here a model with 10 channels and 50 base stations is used in this chapter to better illustrate the channel assignment as we mentioned before.

From the results in Chapter 6, we know that the number of users per base station plays an important role in improving the performance, particularly in reducing the need for reassignment, but also in terms of dropping. In this situation, more hidden node situations can be prevented if the number of users per base station is large enough. The suitable number of users is approximately 15 in this scenario here instead of 20 users which are used in Chapter 6, because it is corresponding to a

95% level of coverage area when we use 15 users per base station to obtain the channel assignment results. It is important that there are sufficient users to help alleviate the 'hidden node problem'. Unsuitable densities of users will result in the channel assignment performance being degraded. This number of users per base station is also linked to the power adjustment which will be discussed later.

7.3 Performance Analysis and Overlapping Problem

In Figure 7-1, the performance with respect to the number of weight update iterations at each base station is shown. It is found that with dropping and blocking, the reinforcement learning plays an important role for improving the performance, particularly in reducing the need for reassignment. The proportion of reassignments is significantly reduced after a large number of iterations have been used to set the channel weights. When the weight update iterations increase, not only is the reassignment probability greatly reduced, but it also improves the rate at which base stations find suitable channels for assignment. This means that the base stations are much more likely to find a suitable channel, because the high weighted channels will help the users avoid the interference. Blocking and dropping performance are also improved after 1000 iterations; the probability of dropping decreases to a residual value, which shows that reinforcement learning when used with a multicast user population helps the system avoid dropping.

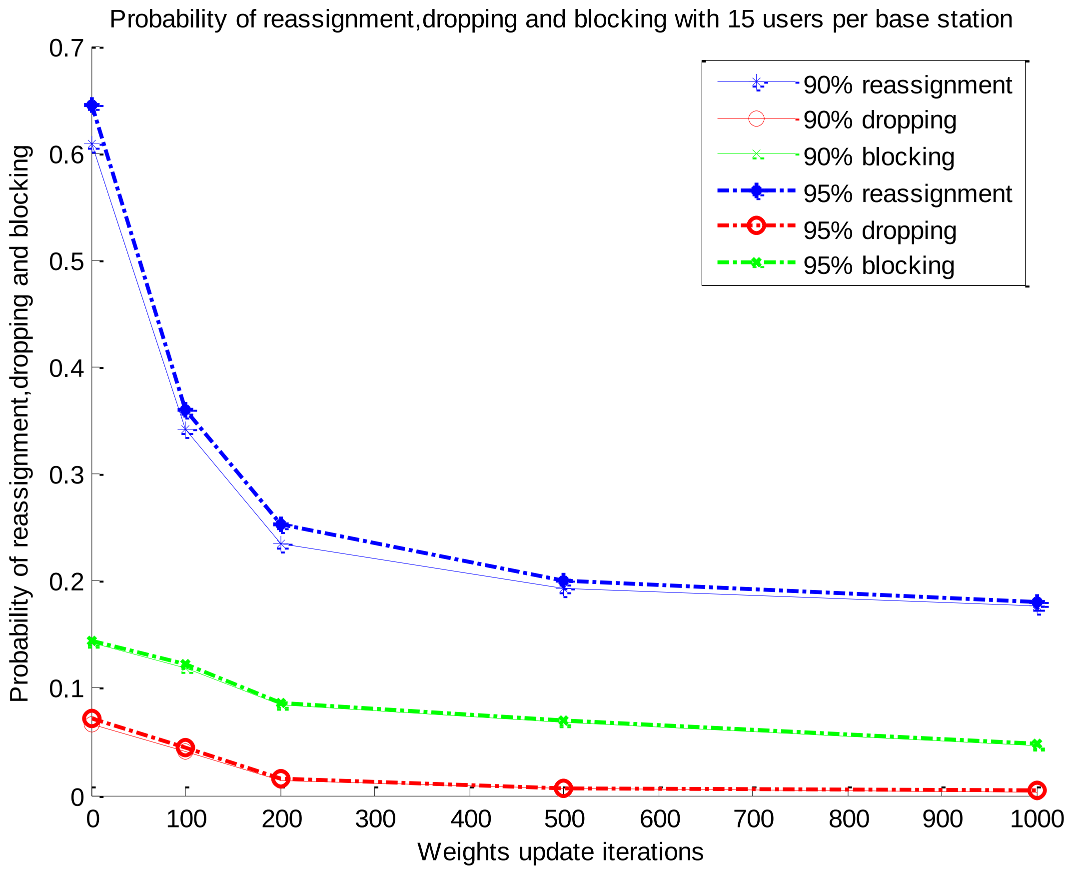

Figure 7-1 Probability of reassignments, dropping and blocking with 15 users per base station

The behavior of the assignment process in distributed channel assignment schemes can be divided into three periods (investigation period, accumulation period and mature period) based on a selection of a percentage of users across the entire coverage area. The difference between Figure 6-9 and Figure 7-1 here is the decreasing rate of reassignment here is slightly lower, which is a result of using a limited user population, rather than obtaining performance from users regularly spaced over the coverage area. These groups of users are not able to cover all the area, which may result in less information exchange in the system than before. When the density of users increases, there are more changes of detection at each base station. The number per base station can be limited by defining a nominal service area, which is less than the actual coverage area (due to minimum SINR), but coverage area overlap will still exist.

Figure 7-2 shows the probability of users with the ability to connect to a different number of base stations, which is the overlapping problem we try to solve. The total number of users here is 15 per base station. In the scenario tested here, nearly 90% of the users can potentially connect to 2 base stations on different channels, indicating that there is a high level of overlap. Also, the users in the central area are more frequently selected, which may cause the weights of the base stations to be influenced faster than others. The level of overlap is affected partly because of the random location of base stations and the density of users. This kind of situation needs to be avoided in the real communications system. Power adjustment will help to reduce the overlap and will be explained in the next section.

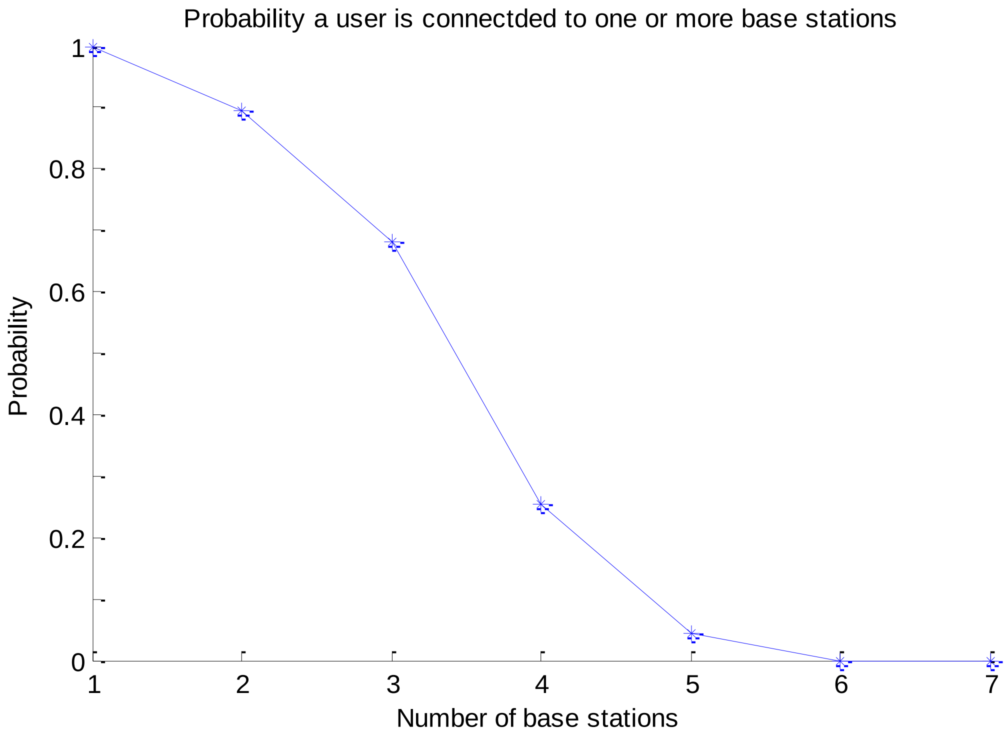

Figure 7-2 Probability a user is connected to one or more base stations (15 users per BS)

Overlapping cannot be avoided but only be reduced. At this stage, if we keep all the parameters and scenarios same, the only way for reduce overlapping is to decrease the chance of detection for each base station, which means reduce the number of users. However, it may cause the hidden node problem which we explained before. Non-overlapping case cannot be modeled here because with distributed detection, the overlapping always exist, but the power adjustment will greatly reduce the overlapping situation which we will explained in section 7.4.

Now we investigate the effects of adjusting the channel assignment thresholds. We update the original thresholds in Chapter 6 as shown in Table 6-2 (7-1), previously the same percentage of minimum user population served was adopted for blocking, dropping and reassignment, so here we focus more maintaining specific percentage of the user population served in each category and less on the SINR thresholds. The 4.3dB threshold is still based on the original acceptance threshold plus a 2dB margin, but now this is coupled with a minimum population percentage threshold. This margin is included to cope with small fluctuations in interference, e.g. as a result of new arrivals on the same channel in locations far from the coverage area, which would result in connections being reassigned or dropped. In practice, interference will also fluctuate due to other effects, such as multipath, change in transmission parameters etc. However, if the margin is too large then connections are blocked unnecessarily, hence the margin of 2dB is a compromise figure. For dropping we set an 85% threshold at 2.3dB instead of 95%, as a minimum level. This slightly relaxed condition still keeps the vast majority of users active in the systems, and seems a better option rather than forcibly dropping otherwise active users in the system. An alternative strategy that is beyond the scope of this chapter is to keep all systems active providing some users are benefiting from service, and instead recording the connection as being disturbed (for a period).

State of BS		**Threshold Levels**	**Weights (w_f)**
New	Acceptance	95%SINR > 4.3dB	+2
	No acceptance	95% SINR <= 4.3dB	0
Existing	Reassignment	95% SINR <=4.3dB	-1
	Dropping	85% SINR < 2.3dB	-2
Reassignment	New acceptance	95% SINR > 4.3dB	+1

Table 7-1 State of BS and modified weights

Comparing Figure 7-3 and Figure 7-1, we find that using the modified percentage threshold yields better performance and is a more flexible way of controlling behavior. There are two ways to identify the thresholds, one is based on a fixed percentage of the user group and another is changing performance by selecting an appropriate percentage of the user population rather than adjust the SINR threshold value. The reassignment threshold in Table 6-2 is stricter than the range of SINR values in Table 6-1, so the base station will be reallocated more frequently and this helps dropping and blocking rate decrease. Dropping is also reduced due to the more relaxed threshold.

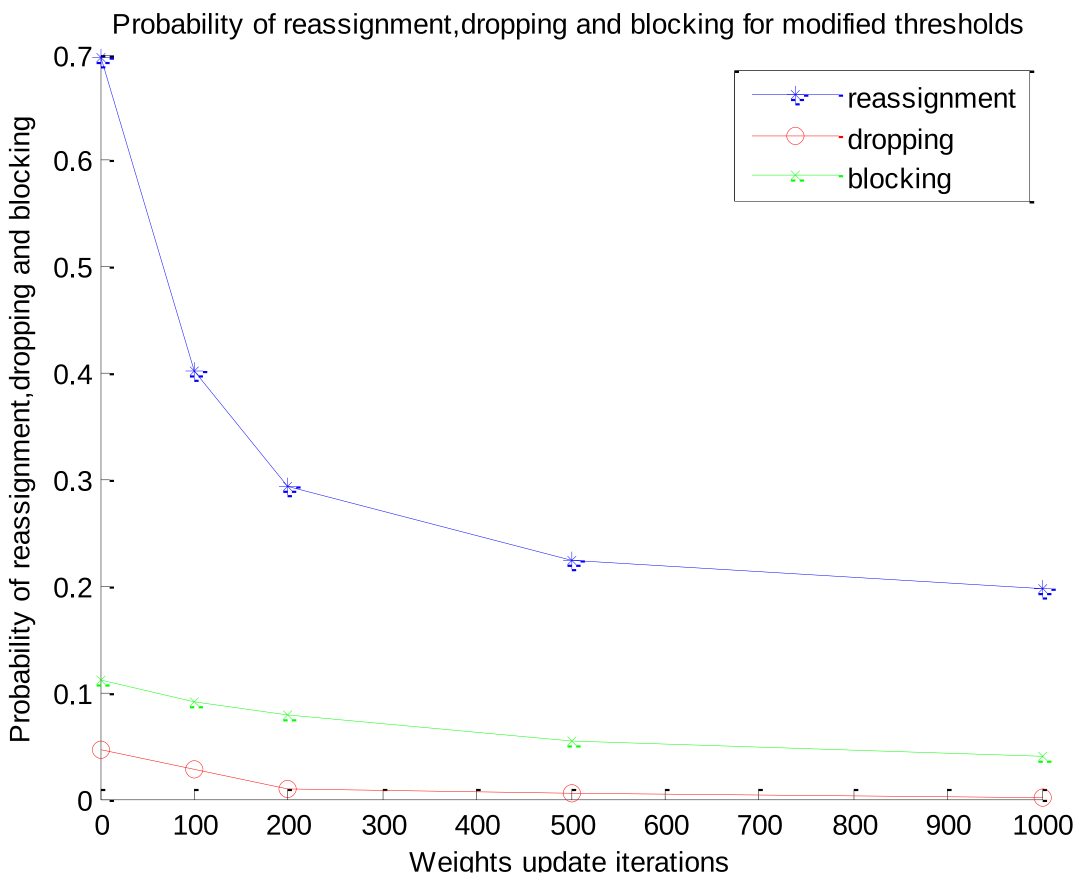

Figure 7-3 Probability of reassignment, dropping and blocking with 15 users per base station of modified thresholds

7.4 Power Adjustment

7.4.1 System with Power Adjustment

Reducing overlap is an important issue to consider further because it can result in high unwanted levels of interference. The following figure shows the spatial layout of adjacent base stations on different non-interfering channels. In order to solve the overlap problem in Figure 7-2, we will adjust the power over the coverage area, there are a number of users are connected to each BS, in order to minimize the overlap and further reduce the interference.

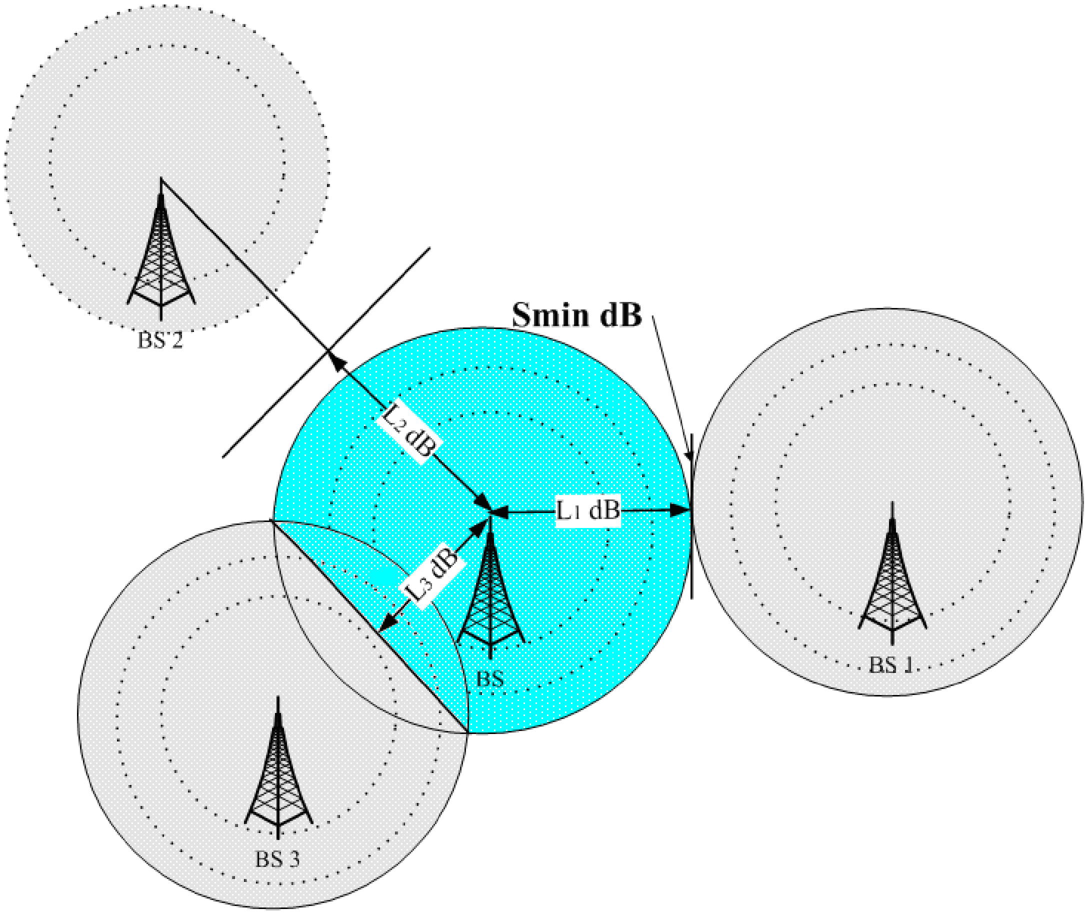

Figure 7-4 Base station nominal service area with power adjustment-All base stations are in different channels

In the base station service area with power adjustment, as an example, we assume the 'BS' is the base station whose transmit power will be adjusted, BS1, BS2 and BS3 are three adjacent BSs. The dashed circles for each base station represent different service areas, which show that they could work for different modulation schemes as required. In the fixed transmitter power situation, the higher the SINR threshold required, the smaller service area that will be covered. Initially, the minimum percentile threshold is 2.3dB, but this will be varied later. Due to the different locations of users for each iteration, the service area for each BS changes, meaning that the transmit power also needs to be changed for each iteration. To find a suitable transmit power for each BS, we need to define a minimum receive power for the users at the boundary between different BSs, which means inside this boundary, the users will belong to this specific BS, meaning that the overlap can be reduced. The position of BS, BS1, BS2 and BS3 are shown in Figure 7-4. If the service area of two base stations overlap, the users connected to each BS will decrease. Therefore, the equations for calculating the transmit power are:

$$P_{TXL'} = \max(S_{\min dB} + L_1, S_{\min dB} + L_2, ...) \quad (7.1)$$

$$P_{TXL} = \min(P_{TXL'}, P_{\max}) \quad (7.2)$$

$S_{\min}$ can be calculated from the equation below:

$$S_T = 10\log_{10}\frac{S_{\min}}{I+N} \quad (7.3)$$

$$S_{\min} = 10^{\frac{S_T}{10}}(I+N) \quad (7.4)$$

Where $S_{\min}$ is the minimum received power at the edge of coverage area. L_i is the path loss to the ideal edge of cell boundary to prevent no overlap, which is the same as the path loss in the Okumura-Hata model we used in previous chapters. S_T is the SINR threshold for different modulation schemes. We assume the INR is 10dB as a typical value to estimate the interference level, the minimum SINR threshold is used 2.3dB. After this process, the transmit power for ‘BS’ is reset, and this is repeated at each BS, in order to obtain new transmit powers; all are limited by the $P_{\max}$ constraint.

Compared to the previous flowchart, we add one more step for power adjustment between the channel selection and assignment parts. The improvement here does not directly contribute to the weight itself, but greatly improves the user distributed occupancy detection and also is independent of the channel assignment scheme. The new flowchart is shown below.

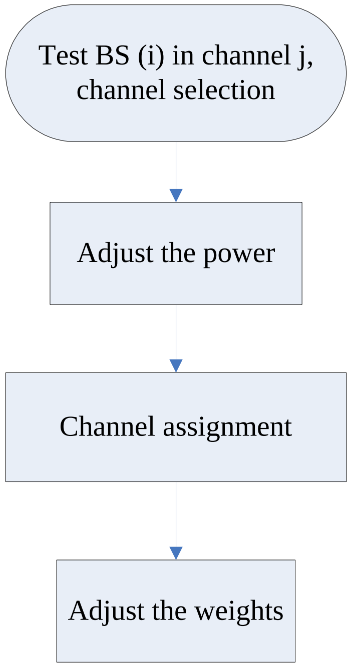

Figure 7-5 Flowchart for channel selection and assignment with power adjustment in system

7.4.2 Performance of Adjustment

Figure 7-6 shows the cumulative probability of users with the ability to connect to a different number of base stations. The total number of users here again is 15 per base station and the minimum percentage threshold is 2.3dB. Compared with the no power adjustment case, about 30% for 100 iterations and 20% for 1000 iterations of the users are shared by 2 base stations in different channels, i.e. the power adjustment reduces the level of overlap, and the overlap is further reduced by the reinforcement learning. Due to the random location of users it is only possible to reduce the overlap, not completely eliminate it. As is shown with BS and BS3 in Figure 7-4, if the service area boundaries intersect, there is still a small area of overlap, and users in this area can connect to two BSs. This is especially true for the users in the central area.

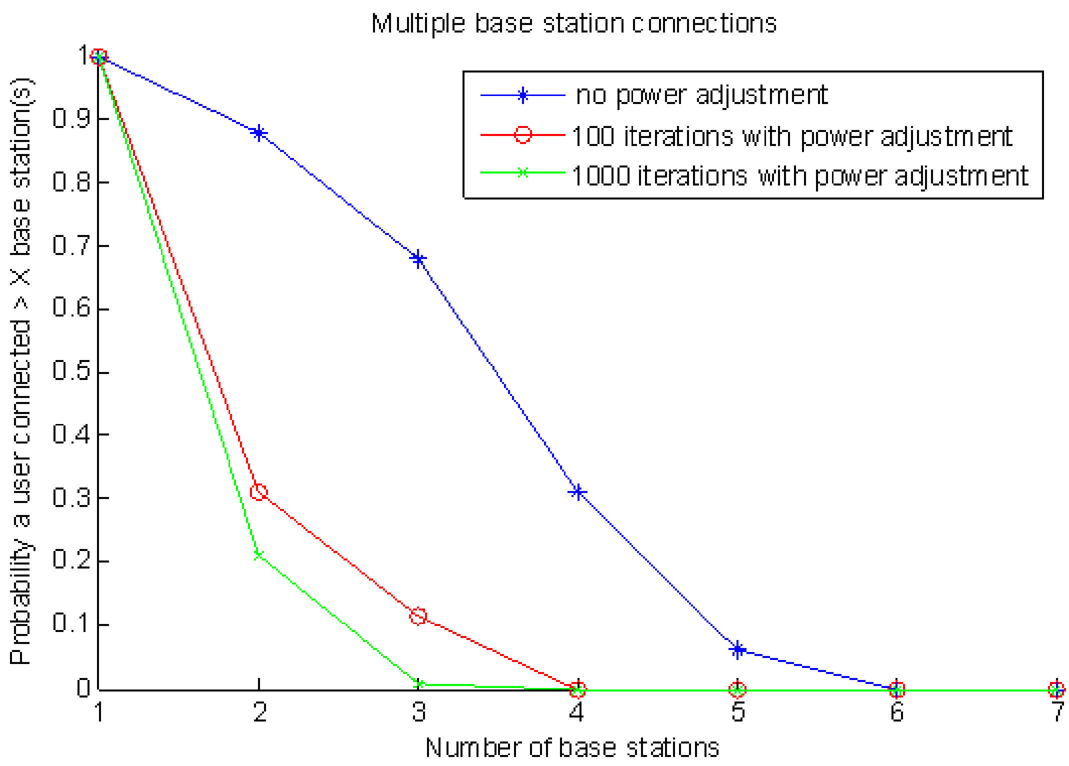

Figure 7-6 Multiple base station connection for individual users with power adjustment

Figure 7-7 shows the percentage power reduction in transmit power for different reassignment thresholds. 2.3dB is used for GMSK as a minimum threshold for reassignment, other thresholds are increased by each 2dB margin as we explained earlier in weights part. When the threshold is 2.3dB, the new transmit power is lower on average by -10.8dB for 100 iterations, and -11dB for 1000 iterations compared with the original level. For both 100 and 1000 iterations, it is found that after power adjustment, the transmit power level has been reduced significantly but the users still satisfy the acceptance threshold. This significantly reduces the overall energy required in the communications system. Learning activation here is not that obvious for power adjustment from 100 to 1000 iterations, especially when the number of iterations is close to 1000. Compared to the no power adjustment case, the learning process with power adjustment obtains enough information earlier, which means learning is more mature for this number of iterations, as service areas change little after this time.

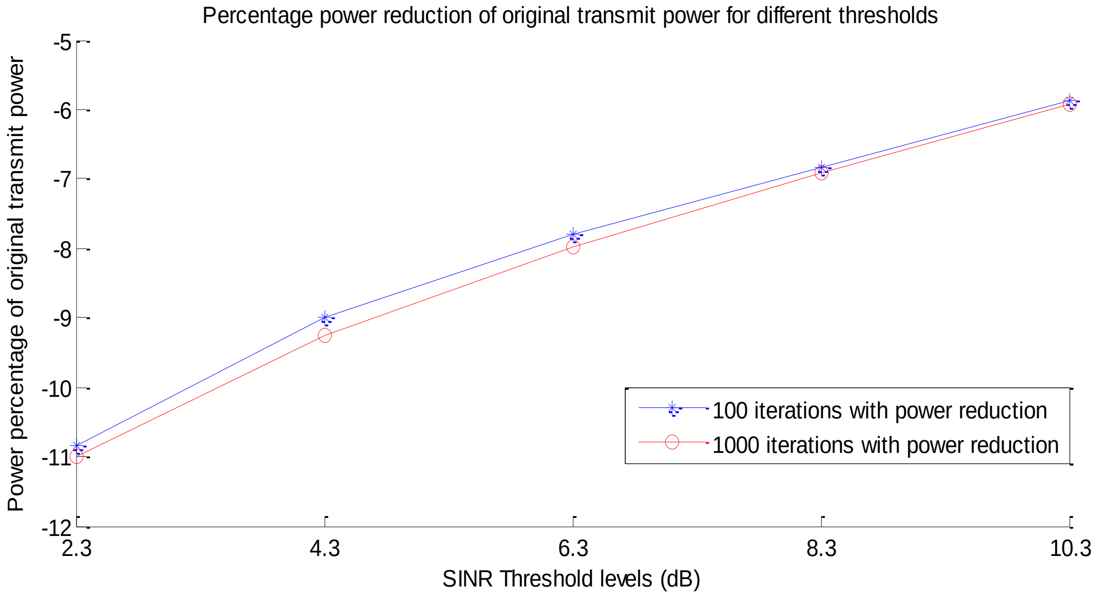

Figure 7-7 Power reduction (dB) of original transmit power with different SINR thresholds after 100 iterations

The power adjustment does not affect the weight in the reinforcement learning, but it reduces the level of overlap in the system we used. The overlap is further reduced by reinforcement learning. So the results obtained from Figure 7-8, it is found that compared to the no power adjustment scheme, the scheme with power adjustment starts with less reassignment. After a large number of iterations, the decreasing rate of reassignment is still higher than the scheme without power adjustment. When the power adjustment is based on the SINR boundary threshold of 2.3dB, the transmit power level is much lower than the original transmit power level. It shows that the reinforcement learning also works well for this scheme, as the performance is greatly improved. Due to the new transmit power being much lower than the original case, base stations can be located in relatively random positions without explicitly considering the channel assignment. In the same random location situation, the scheme with power adjustment causes a lower level of interference than the scheme without power adjustment. This also explains why reassignment using a 10.3dB threshold is worse than a 2.3dB threshold. The three periods defined before for reinforcement learning process are still seen, only that the decreasing rate of reassignment here is smaller, because the initial channel assignment for the scheme with power adjustment is much better than the scheme without power adjustment. The improvement space is not as great as for the scheme without power adjustment.

The blocking performance with power adjustment is worse than with the no adjustment cases. In the case of reduced power level situations, more base stations are being packed onto the same channel for the initial assignment, which will cause the blocking to increase. The decrease in dropping will also cause a further increase in the blocking as space is not freed up on the assigned channels. Dropping improves significantly because the reduced power means that overall there is less interference from other base stations on the same channel.

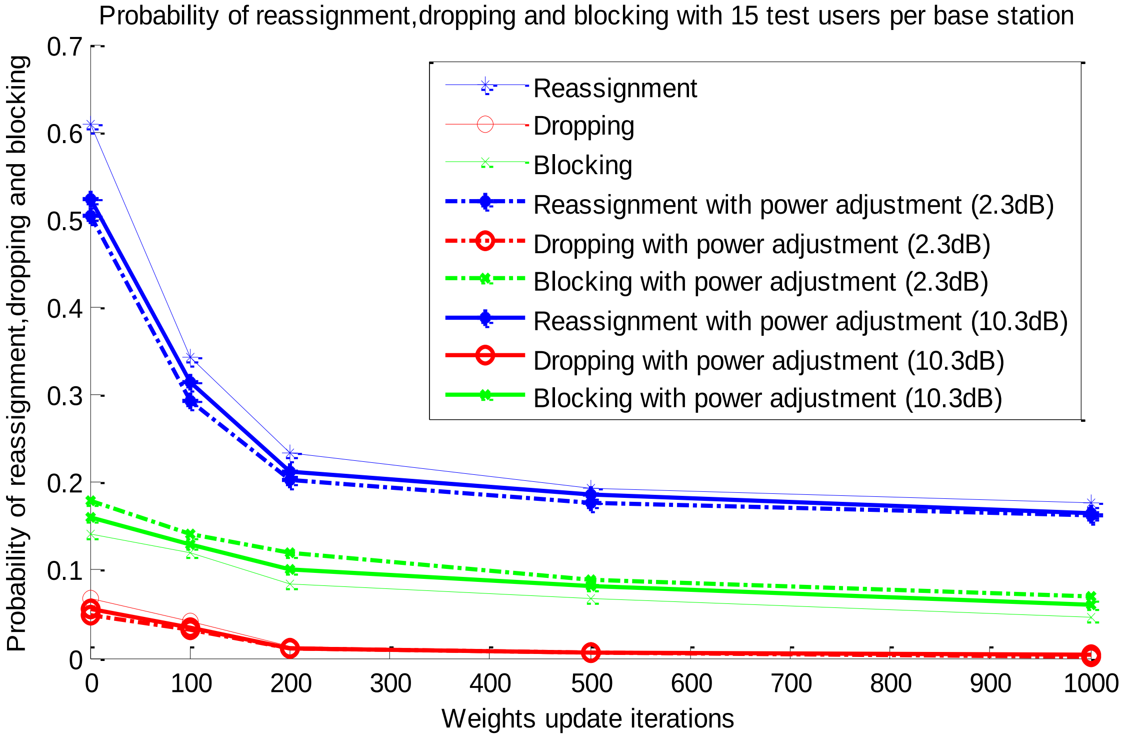

Figure 7-8 Performance of power adjustment for reassignments, dropping and blocking with 15 users per base station

7.5 Conclusions

This chapter has presented a random picking distributed channel assignment scheme applied to a cognitive radio system exploiting reinforcement learning with a user population receiving multicast downlink transmissions, with performance improved by power adjustment. It is found that distributed channel assignment schemes with reinforcement learning can efficiently improve the performance of channel assignment by limiting the reassignment, blocking and dropping rates. Moreover, adding power adjustment into the system helps base stations reduce their overlapping coverage areas and further reduces the interference from other BSs. The results show how the proportion of reassignments in the various schemes is greatly reduced after the weight update iterations are used. By using the multicast architecture it is possible to exploit channels that utilize occupancy detection from multiple users, which helps solve the hidden node problem, resulting in a reduced proportion of reassignments and improving the dropping probability. However, this is at the expense of higher blocking because it is more difficult to find suitable free channels because they are more likely to be occupied by the multiple users. Different minimum quality of service threshold percentages can be used to control and improve performance, in place of the more traditional SINR threshold levels. It is found that significantly reducing the levels of overlap between adjacent base stations improves the performance of reassignment, dropping and blocking, while also reducing interference and saving transmitter power.

8 Further Work

8.1 DESIGN AND MODIFICATION OF THE LEARNING SYSTEM 177

8.2 LEARNING EFFICIENCY 178

8.3 GAME THEORY AND PRICING WITH RADIO RESOURCE DEPLOYMENT 179

8.4 CONSIDERATION OF PRIMARY USERS 180

8.5 UPLINK CONSIDERATION AND USER PERSPECTIVE 181

8.6 COEXISTENCE WITH OTHER EXISTING COMMUNICATION SYSTEMS 181

In this thesis, the performance of channel assignment schemes using reinforcement learning has been analyzed in a coexistence scenario. Potential further areas of research work are to implement them in different situations with coexistence, and adjust the learning process. These adjustments to the learning process could include design and modification of the learning function, learning efficiency, consideration of the uplink and a more detailed user perspective, game theory and pricing with radio resource deployment, coexistence with other existing communication systems, etc. A number of suggestions for future work are given in this chapter.

8.1 Design and Modification of the Learning System

As we discussed in Chapter 6 and 7, applying reinforcement learning to cognitive radio systems can greatly improve the performance. The simplified algorithm was analyzed in Equation 6.1, which used the basic weight function [115, 117]:

$$W_i = F_1 W_{i-1} + F_2 W_e + W_f \qquad (8.1)$$

W_i, W_{i-1}, F_1 and W_f are explained in Chapter 6. W_e is the environment states which will affect the input of the current weight. F_2 is the environment parameter. In this thesis, we only consider learning from previous states and weighting factors.

In the future, the information exchanging from other cognitive radios and environment states will be investigated.

The weight selection values for W_f in Table 6-1 have been chosen arbitrarily. The arbitrary values can only satisfy the primary estimation for the improvement of learning, but cannot be the optimal values for building a modified learning system. In order to obtain relatively reasonable weighting factor, we plan to use the values of weights as linear or exponential. Compared to linear values, exponential increase or decrease of weights may help the system reduce the time of first learning period (investigation period as shown in Chapter 4). For example, if the weights are continually rewarded for more than 3 iterations, we could change W_f into an exponential factor to reward it. On the contrary, if the weights continually decrease for more than 3 iterations, which happens rarely based on the results from before, W_f could be set as the exponential damp as a strict punishment. Until now, we performed limited simulations but have not obtained the optimal ones for the weight values. Linear value, exponential value, or other kinds of values of weighting factors will greatly change the results of learning process. Nie [92] and Bublin [95] present the centralized Q-learning, game theory and reinforcement learning algorithm. Our algorithm is relatively simple since we pay more attention to dealing with multicasting and dynamic channel assignment. A whole weights system to define a more realistic and more stable system needs to be developed in the future.

8.2 Learning Efficiency

When we analyze the learning process, we focus on the overall performance of the system by using reinforcement learning. From the results we obtained so far, the learning process takes long time to obtain a relatively settled performance. The convergence is quite slow; the reason for this problem may be the unnecessary attempts of learning events which means this part of learning is wasted, so we solve this by considering the learning efficiency. In the learning process, there is successful and unsuccessful learning. Learning efficiency means how much the role successful learning plays on the whole learning process. If we do not want so many iterations before obtaining a relatively stable, we need to learn why some learning events are unsuccessful and how to improve them. Most of the unsuccessful learning may be a result of unsuitable weight selection, or for some other reasons, i.e. the overlapping location of users of base stations, or the unbalanced density of group users. The convergence rate is another way to consider this kind of problem. It could be used as the potential way is to control the ratio of unsuccessful learning and successful learning, combined with changing the weight function and weight factors.

8.3 Game Theory and Pricing with Radio Resource Deployment

There are many intelligence methods that could be used for the intelligence aspect of cognitive radio. Reinforcement learning is a quick and relatively easy way to model for many users with single or a small quantity of operators. For the channel assignment aspect, especially coexistence and interaction, game theory is a good way to deal with interaction from different operators because game theory is a methodology of studying situations of interdependence, and can be used to analyze the best strategy between cooperation and conflict [122]. This point will significantly improve our interaction investigation between different channel assignment schemes.

Compared with the modeling approach used in this thesis, game theory may open a new methodology for spectrum management and be more flexible to deal with the interaction, compared with the current coexistence system [123]. Another interesting possible way to extend game theory is by using a Neural Network analysis method. For example, neural networks could undertake training for different positions, i.e. distance and combinations of base stations, so that they will find a ‘critical’ point (as the maximum performance point) for cognitive multicasting communication systems [124, 125].

Pricing is another factor for dynamic allocation, and in the future pricing could be combined to consider together with the development of game theory. Markov decision processes, matrix games and stochastic games could be used with the mixed strategies to be considered in further work.

8.4 Consideration of Primary Users

There are two kinds of users in the cognitive radio system: primary users and cognitive users. All users considered in this thesis are cognitive users. If we incorporate primary users into the system, then they have highest priority to choose the channel to be assigned and this may cause loss of service to the existing cognitive users. We may need to add more flexible judgments to help secondary users which are below the thresholds to vacate the existing channel and find a new one, which means the channel assignment schemes need to be modified. For example, a kind of “window”, which can be closed when the primary users are assigned at a channel. During this time the existing cognitive users will be unable to be active on this channel by the closed state of “window”, in order to protect the performance of primary user. When the primary users stop using the channel, the “window” for secondary users will open again.

8.5 Uplink Consideration and User Perspective

Most of the time, the downlink is considered in this thesis. Combining the study of the downlink and uplink together will help us to build and model a more integrated system and complement the necessary factors to support our future work. Power control is a significant issue for uplinks. One problem that needs to be mentioned is that increasing the power may cause extra adverse interference. The balance between high data rate and interference needs to be considered more when modeling the coexistence scenario.

Due to the different conditions of users (investigated in Chapter 4 for a group of users and satisfying the basic requirements), there are more situations that need to be considered: different powers, different operator control, the characteristics of sets of users, and so on. To satisfy these requirements, and provide different quality of service levels for users, needs to be investigated in the future.

8.6 Coexistence with Other Existing Communication Systems

This thesis is focused on channel assignment for mixed terrestrial communication systems but pays less attention to the interaction between terrestrial and other systems when they use the same or adjacent frequency bands, e.g. satellites and high altitude platform [126]. Even for terrestrial systems, we performed a number of simulations with two operators which could be modeled as different communication systems in Chapter 4, but in other parts of the thesis, single operators were simulated. At the same time, in the same terrestrial communication system, there are also more factors that need to be considered and may also cause more coexistence problems, e.g. using variable transmitting power. For different systems the interaction will be a big problem, as it may include sharing the resource, or even producing more interference, and will need to be modeled in the future.

9 Summary and Conclusions

9.1 SUMMARY AND CONCLUSIONS 183
9.2 SUMMARY OF ORIGINAL CONTRIBUTIONS 188

9.1 Summary and Conclusions

This thesis presents the research work that was compiled during the period 2006 to 2011 at the University of York. The early parts of the thesis present the related background knowledge, the simulation techniques and evaluation that include system parameter analysis. The main part is focused on the research work, which has investigated spectrum management, and the channel assignment schemes to assign base stations in a coexistence scenario in order to implement the coexistence of mixed terrestrial communication systems based on cognitive radio technology, where the base stations communicate to users in a multicast fashion. This is followed by two distributed channel assignment schemes applied in a CR system using reinforcement learning and a weighting factor.

The summary and conclusions of the major chapters are listed as follows:

After the general introduction of Chapter 1, Chapter 2 has introduced the background knowledge relating to this research work. Some of the knowledge here may not be used directly in the following work, but to know and understand the concept is very necessary and it may be used in future work. From the background reviews, we understand the principle of cognitive radio and how it works, and the research work and development of cognitive radio around the world. We use dynamic channel assignment to implement the flexible spectrum assignment that cognitive radio requires. Propagation models with the required parameters will depend on the communication environments they will operate in. Multicasting is potentially very useful for delivering point-to-multipoint traffic in cognitive networks. Reinforcement learning models are introduced as a very useful way to implement the learning and cognition part of a cognitive radio system. Related research work applying intelligence to cognitive radio systems is also introduced.

Chapter 3 gives an overview of the simulation techniques and evaluation that is the crucial for our research work. Using the MATLAB tool, we have explained how a system can be modeled using a Monte-Carlo simulation and reinforcement learning. Base stations operating in the same or different channels are used to evaluate the simulation result. SNR and SINR statistics and the associated CDFs are used to determine performance, e.g. noise power has already been included. Error bars have been briefly introduced. Some simple examples are given here for better understanding. All of the simulation elements will be used in later chapters.

Chapter 4 describes the detail of the coexistence scenario with mixed terrestrial systems. It focuses on investigating channel assignment schemes that select channels based on optimizing the coverage area supported by a terrestrial network. The coexisting scenario here is based on different base stations in the same service area, with performance assessed in terms of the area of coverage and available link SINR. Channels are chosen based on the overall performance at multiple points in the service area, rather than the performance at one specific location. It is found that best overall performance is achieved by choosing schemes that aim to maximize the number of base stations on a channel while still meeting a required minimum SINR threshold value.

To conclude, the Least Interference scheme maximizes the number of base stations on a channel but not all base station locations will be able to necessarily satisfy the SINR threshold value well. The Channel Priority scheme cannot maximize the number of base stations on every channel but only the high priority channel(s). It is found that best overall performance is achieved by choosing schemes that aim to maximize the number of base stations on a channel while still meeting a required minimum SINR threshold value, The Maximal Sum and Maximal Difference schemes can deliver the best overall performance level. The channel assignment schemes discussed in this chapter are all centralized schemes. The distributed occupancy detection will be extended and will be considered with further user perspectives in Chapter 6.

Chapter 5 provides a deeper analysis of the combinations of different channel assignment schemes. For the Least Interference and Channel Priority mixed scheme, the results show that it is good to combine them together because they can exploit the benefits from each individual scheme, particularly relating to the way the individual channels are allocated. The Least Interference scheme avoids channels used by the Channel Priority scheme, improving its performance. The performance of the Least Interference scheme is improved because the base stations assigned using the Channel Priority scheme are packed together, making the density of channel usage more suitable in those channels used by the Least Interference scheme. For the Channel Priority and Maximal Difference mixed scheme, the results show how it is also good to combine them together. It is found that the schemes interact favorably even when each scheme operates with different modulation rates, thereby allowing differential transmission rates. It is shown that the Channel Priority scheme in such circumstances can be forced to use extra channels to cope with the increased SINR threshold required for a high rate modulation scheme.

Chapter 6 has presented two distributed channel assignment schemes applied in a CR system using reinforcement learning and a weighting factor. The Channel Priority and Random Picking schemes are shown, and compared for different numbers of iterations used to derive the channel weighting factors. It is found that compared to the previous schemes without reinforcement learning, distributed channel assignment schemes with reinforcement learning can efficiently improve the reliability of channel assignment by limiting the reassignment, blocking and dropping. Moreover, determining the highest priority channels helps base stations to improve the performance of the system. The results show that the proportion of reassignments of both schemes is significantly reduced after a large number of weight update iterations are used, from a value close to 1 in with no learning to 0.14 after 1000 learning iterations with the CP scheme, and from about 0.46 without weights to 0.15 for 1000 iterations for the RP scheme.

We have shown how it is possible to divide the learning process into three phases depending on the degree of accumulated knowledge. Performance improvements are achieved by learning about past successful/unsuccessful assignments, and also by increasing the new acceptance threshold or the number of channels, as the channels become less crowded. Dropping control using channel reassignment is a very good alternative to blocking of new activations. We have shown how the random picking distributed channel assignment scheme with a user population was capable of receiving multicast downlink transmissions. It is found that compared to single user channel occupancy detection, multiple user detection helps solve the hidden node problem by greatly reducing the proportion of reassignments and also in terms of dropping probability. However this is at the expense of higher blocking because it is more difficult to find suitable free channels that can serve an increased coverage area per base station, occupied by the multiple users. Different minimum quality of service threshold percentages can be used to control and improve performance, in place of the more traditional SINR threshold levels.

Chapter 7 has presented a random picking distributed channel assignment scheme applied to a cognitive radio system exploiting reinforcement learning with a user population receiving multicast downlink transmissions, with performance improved by power adjustment. It is found that distributed channel assignment schemes with reinforcement learning can efficiently improve the performance of channel assignment by limiting the reassignment, blocking and dropping rates. Moreover, adding power adjustment to the system helps base stations reduce their overlapping coverage areas and further reduces the interference from other BSs. The results show how the proportion of reassignments in the various schemes is greatly reduced after the weight update iterations are used. By using the multicast architecture it is possible to exploit channels that utilize occupancy detection from multiple users, which helps solve the hidden node problem, resulting in a reduced proportion of reassignments and improving the dropping probability. However, this is at the expense of higher blocking because it is more difficult to find suitable free channels because they are more likely to be occupied by the multiple users. Different minimum quality of service threshold percentages can be used to control and improve performance, in place of the more traditional SINR threshold levels. It is found that significantly reducing the levels of overlap between adjacent base stations improves the performance of reassignment, dropping and blocking, while also reducing interference and saving transmitter power.

9.2 Summary of Original Contributions

This thesis has provided a better understanding way of channel assignment applied to heterogeneous multicasting communication systems, by considering the interaction of channels and using reinforcement learning. This section highlights the original contributions and originality of the research work in this thesis. Some of them have already been published.

Dynamic channel assignment with cognition using a Cumulative Distributed Function of SINR applied to multicasting communication systems

Dynamic channel assignment is not a very new topic, either for channel assignment or cognitive radio. It has been discussed in other literature such as [93, 94]. In this thesis we focus on the novel idea of applying the multicasting scenario to cognitive radio, in that we determine the spectrum which satisfies a group of users to allow simultaneous transmission, while not seriously affecting other groups of multicast users sharing the pooled spectrum.

Moreover, this thesis focuses on investigating channel assignment schemes that select channels based on optimizing the coverage area supported by terrestrial network. The coexisting scenario here is based on different base stations in the same service area, with performance assessed in terms of the area of coverage and available link SINR. Channels are chosen based on the overall performance at multiple points in the service area, rather than the performance at one specific location. SINR CDF value to be used here is easier and quicker to obtain the overall performance over the coverage area. These contributions have been presented in the **PGNET 2007, Liverpool, UK, June 2007**.

Interaction and coexistence of schemes

Interaction is one of the important aspects of cognitive radio concept, and many people have undertaken research work on channel assignment schemes to try to modify the schemes to improve the performance. However, no one has attempted to think about the relationship between different schemes. In this thesis we extend these ideas by using mixed channel assignment schemes to allocate base stations in a more realistic scenario with different considerations. The interaction exists when the schemes are combined and this causes positive and negative reactions with different combinations.

We found that it is good to combine two systems together because a mixed set of schemes can exploit the benefits from each individual scheme, particularly relating to the way the individual channels are allocated and the schemes interact favorably even when each scheme operates with different modulation rates, thereby allowing differential transmission rates. These contributions have been presented in the **2008 IET Seminar on, 18th, Sep, 2008** and **COGCOM 2008, Hangzhou, China, Aug, 2008**

Reinforcement Learning applied into system

Reinforcement learning is one of the machine learning methods which has been applied successfully to many problems. Cognitive radio is a new technology, and very few people consider applying intelligence to the cognition cycle, especially reinforcement learning. Applying reinforcement learning in cognitive radio is a very new improvement for cognitive radio. By using this method, we modified the schemes, which efficiently improve the speed and quality of channel assignment by limiting the reassignments, blocking and dropping rates. A weighting factor is used in this thesis to reinforce the performance by identify the weights of reassignment, blocking and dropping. This kind of weighting factor has not been investigated before, and implemented them in order to help to control the performance of the system.

We found that distributed channel assignment schemes with reinforcement learning can efficiently improve the speed of channel assignment by limiting the reassignment, blocking and dropping rates. Moreover, determining the highest priority channels helps base stations to improve the performance of system. We have shown how it is possible to divide the learning process into three phases depending on the degree of accumulated knowledge. Performance improvements are achieved by learning about past successful/unsuccessful assignments, and also by increasing the new acceptance threshold or the number of channels, as the channels become less crowded. Dropping control using channel reassignment is a very good alternative to blocking of new activations. Compared to detection by single users, detection by multiple users reduces the ‘hidden node’ problem. Using different minimum quality of service threshold percentages can partly control and improve the performance, in place of the more traditional SINR threshold levels. At the same time, with reinforcement leaning, the ability to find an optimal channel for users is significantly improved, because the channel weighting can help the users avoid interference. These contributions have been presented in the **CROWNCOM 2009, Hannover, German, Jun, 2009** and **COGCOM 2009, San Francisco, USA, Aug, 2009**

Cognitive Radio with reinforcement learning applied to multicast downlink transmission with power adjustment

Another novel contribution as a result of this research work is to develop overlapping treatment and power adjustment for channel assignment in multicast terrestrial communication systems with distributed channel occupancy detection based on reinforcement learning. Overlapping treatment and analysis is from the results which are obtained from distributed channel assignment with reinforcement learning as shown in Chapter 6, and it shows that the overlapping happens frequently. We presented a random picking distributed channel assignment scheme applied to a cognitive radio system exploiting reinforcement learning with a user population receiving multicast downlink transmissions, with performance improved by power adjustment. Power adjustment is not novel, but adding it into a multicasting cognitive radio system and combining it with reinforcement learning is very novel. It will help us to further control the reassignment, blocking and dropping of the system. Moreover, adding power adjustment into the multicasting cognitive system helps base stations reduce their overlapping coverage areas and further reduces the interference from other BSs.

By using the multicast architecture it is possible to exploit channels that utilize occupancy detection from multiple users, which helps solve the hidden node problem, resulting in a reduced number of reassignments and improving the dropping probability. However, this is at the expense of higher blocking because it is more difficult to find suitable free channels because they are more likely to be occupied by the multiple users. Different minimum quality of service threshold percentages can be used to control and improve performance, in place of the more traditional SINR threshold levels. It is found that significantly reducing the levels of overlap between adjacent base stations improves the performance of reassignment, dropping and blocking, while also reducing interference and saving transmitter power. These contributions have been published by **Wireless Personal Communications -Special Issue on Cognitive Networks and Communications, Jan, 2011**

Publications

Journal

- M. Yang and D. Grace, "Cognitive Radio with Reinforcement Learning Applied to Multicast Downlink Transmission with Power Adjustment", **Wireless Personal Communications-Special Issue on Cognitive Networks and Communications,** Jan, 2011

Conference

- M. Yang and D. Grace, "Cognitive Radio with Reinforcement Learning Applied to Multicast Downlink Transmission and Distributed Occupancy Detection", **COGCOM 2009**, San Francisco, USA, Aug, 2009

- M. Yang and D. Grace, "Cognitive Radio with Reinforcement Learning Applied to Multicast Terrestrial Communication Systems", **CROWNCOM 2009**, Hannover, German, Jun, 2009

- M. Yang and D. Grace, "Cognitive radio based spectrum assignment for heterogeneous multicast terrestrial communication systems with different transmission rate requirements", **Cognitive Radio and Software Defined Radios: Technologies and Techniques, 2008 IET Seminar on,** 18th, Sep, 2008

- M. Yang and D. Grace, "Interaction and Coexistence of Multicast Terrestrial Communication Systems with Area Optimized Channel Assignments", **COGCOM 2008**, Hangzhou, China, Aug, 2008

- M. Yang and D. Grace, “Coexistence Performance of Terrestrial Communication Systems with Area Optimized Channel Assignments”, **PGNET 2007**, Liverpool, UK, June 2007.

Bibliography

[1] “Cognitive radio and management of spectrum and radio resources”, *working group 6 white paper, Wireless World Research Forum, 2005*

[2] “Cognitive radio Project”, Communications Research Group, University of York. http://www.elec.york.ac.uk/research/comms/wireless/cognitive.html

[3] The radio spectrum usages of UK area, Ofcom "http://www.ofcom.org.uk/research/technology/research/emer_tech/cograd/."

[4] “Spectrum Efficiency”, Wikipedia. http://en.wikipedia.org/wiki/Spectral_efficiency

[5] KK Leung, A Srivastava, “Dynamic allocation of downlink and uplink resource for broadband services in fixed wireless networks”, *IEEE Journal on Selected Areas in Communications, 1999*

[6] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol.23, no.2, pp. 201-220, Feb. 2005

[7] L. Berlemann, S. Mangold, G. Hiertz, B. Walke, “Policy Defined Spectrum Sharing and Medium Access for Cognitive Radios”, *Journal of communications. VOL 1, NO.1 April 2006*

[8] T. Jiang, D. Grace, and Y. Liu, ‘Two Stage Reinforcement Learning Based Cognitive Radio with Exploration Control’, provisionally accepted by *IET Communications, June 2010*

[9] R. S. Sutton and A. G. Barto, Reinforcement learning: an introduction: The MIT Press, 1998.

[10] M. Yang and D. Grace, “Coexistence Performance of Terrestrial Communication Systems with Area Optimized Channel Assignments”, *PGNET 2007, Liverpool, UK, June 2007.*

[11] M. Yang and D. Grace, “Cognitive Radio with Reinforcement Learning Applied to Multicast Downlink Transmission with Power Adjustment”, *Wireless Personal Communications-Special Issue on Cognitive Networks and Communications, April, 2010*

[12] J. Mitola III; Maguire, G.Q., Jr., "Cognitive radio: making software radios

more personal," *Personal Communications, IEEE [see also IEEE Wireless Communications]*, vol.6, no.4, pp.13-18, Aug 1999

[13] M. Yang and D. Grace, "Interaction and Coexistence of Multicast Terrestrial Communication Systems with Area Optimized Channel Assignments", *COGCOM 2008, Hangzhou, China, Aug, 2008*

[14] B.A. Fette, Cognitive radio Technology, Communications Networks Division, General Dynamic C4 System, Scottsdale, AZ, USA, printed in 2006

[15] T.A. Weiss, F.K. Jondral, "Spectrum pooling: an innovative strategy for the enhancement of spectrum efficiency," *Communications Magazine, IEEE*, vol.42, no.3, pp. S8-14, Mar 2004

[16] M. Yang and D. Grace, "Cognitive Radio with Reinforcement Learning Applied to Multicast Terrestrial Communication Systems", *CROWNCOM 2009, Hannover, German, Jun, 2009*

[17] Frequency allocation, Wikipedia.
http://en.wikipedia.org/wiki/Frequency_allocation

[18] Berkeley Wireless Research Centre
http://bwrc.eecs.berkeley.edu/Research/Cognitive/home.htm

[19] Ofcom, http://www.ofcom.org.uk/

[20]ftp://lenst.det.unifi.it/pub/LenLar/proceedings/2006/PIMRC2006/PIMRC06/pdfs/TB3_1.pdf

[21] http://en.wikipedia.org/wiki/WiMAX

[22]http://www.radio-electronics.com/info/wireless/wimax/frequencies-spectrum.php

[23] http://en.wikipedia.org/wiki/LTE_Advanced

[24]http://www.radio-electronics.com/info/cellulartelecomms/lte-long-term-evolution/lte-frequency-spectrum.php

[25] http://www.raymaps.com/index.php/lte-spectrum-allocation/band1/

[26] Poongup Lee; Taeyoung Lee; Jangkeun Jeong; Jitae Shin; , "Interference management in LTE femtocell systems using Fractional Frequency Reuse," *Advanced Communication Technology (ICACT), 2010 The 12th International Conference on* , vol.2, no., pp.1047-1051, 7-10 Feb. 2010

[27] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol.23, no.2, pp. 201-220, Feb. 2005

[28] Alsarhan and A .Agarwal, “Cluster based Spectrum Management using Cognitive Radios in Wireless Mesh Network”, *COGCOM 2009, San Francisco, USA, Aug, 2009*

[29] J. Mitola III, Cognitive radio for flexible mobile multimedia communications, *IEEE 1999 Mobile Multimedia Conference (MoMuC), November, 1999, pp. 3-10*

[30] Joseph Mitola III, Provost directory,
http://www.stevens.edu/provost/directory/faculty_profile.php?faculty_id=1328

[31] Federal Communications Commission, http://www.fcc.gov/

[32] Defense Advanced Research Projects Agency, http://www.darpa.mil/

[33] http://www.csl.sri.com/projects/xg/

[34] CWT, the Center for Wireless Telecommunications for Virginia Tech http://www.cwt.vt.edu/

[35] “CORVUS: Cognitive Radio Approach for Usage of Virtual Unlicensed Spectrum
Cognitive Radio”, *CR_White_paper_final1,July,2004,* Berkeley Wireless Research Center (BWRC)

[36] Communication Research Group, University of York
http://www.elec.york.ac.uk/research/comms/wireless/cognitive.html.

[37] BunGee project, http://www.ict-bungee.eu/

[38] FP7, http://ec.europa.eu/research/fp7/index_en.cfm

[39] A. Kortun, T. Ratnarajah, M. Sellathurai, Caijun Zhong, C. Papadias, “On the Performance of Eigenvalue-based Cooperative Spectrum Sensing for Cognitive Radio,” *IEEE Journal of Selected Topics in Signal Processing*, Vol 5, No. 1, pp. 49-55, Feb. 2011

[40] Van Wesemael, P., S. Pollin, E. Lopez, and A. Dejonghe, "Performance Evaluation of Sensing Solutions For LTE and DVB-T", *DySPAN*, Aachen, Germany, 05/2011.

[41] The Worldwide universities network Cognitive Communications Consortium (WUN-COGCOM), http://www.wun-cogcom.org/index.html.

[42] IEEE standards association http://grouper.ieee.org/groups/
[43] IEEE SCC41 Cognitive Radio Centre
http://grouper.ieee.org/groups/emc/emc/1900/crinfo/index.htm
[44] C. Cordeiro, K. Challapali, D. Birru, N. S. Shankar, "IEEE 802.22: the first worldwide wireless standard based on cognitive radios," *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on* , vol., no., pp.328-337, 8-11 Nov. 2005
[45] Cognitive radio, Wikipedia. http://en.wikipedia.org/wiki/Cognitive_radio, original reference is from Joseph Mitola III, Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio
[46] J. Mitola III, "Cognitive Radio: An Integrated Agent Architecture for Software Defined Radio", PhD Thesis, Royal Institute of Technology (KTH), *Teleinformatics, Electrum 204, Sweden, May 2000*
[47] P. Likittihanasate, Coexistence of Heterogeneous Cognitive Radio Systems, PhD Thesis, University of York, Sep, 2008
[48] D. Grace, "Cognitive radio research work in York", *Research seminar in the University of York, 2009*
[49] L. Berlemann, and S. Mangold, and B. Walke, , Policy-based Reasoning for Spectrum Sharing in Cognitive Radio Networks, *1st IEEE Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Nov 2005
[50] S. Mangold, K. Challapali, "coexistence of wireless networks in unlicensed frequency bands," *Wireless World Research Forum*, 2003
[51] J. Mitola III, Cognitive Radio Architecture: The Engineering Foundations of Radio XML, printed 2006
[52] E. Buracchini, "The software radio concept," *Communications Magazine, IEEE* , vol.38, no.9, pp.138-143, Sep 2000
[53] W.H.W. Tuttlebee , "Software-defined radio: facets of a developing technology," *Personal Communications, IEEE [see also IEEE Wireless Communications]* , vol.6, no.2, pp.38-44, Apr 1999
[54] S. Albayrak, "Introduction to Agent Oriented Technology for Telecommunications", *Intelligent Agents for Telecommunications Applications*, Edited by S. Albayrak (Amsterdam IOS Press) 98
[55] J. Neel, "*Game Theory in the Analysis and Design of Cognitive Radio Networks*", DySPAN 2007

[56] K. Feeney, D. Lewis, Argyroudis, Patroklos; Nolan, Keith; O'Sullivan, Declan, "Grouping Abstraction and Authority Control in Policy-Based Spectrum Management," *New Frontiers in Dynamic Spectrum Access Networks, 2007. DySPAN 2007. 2nd IEEE International Symposium on* , pp.363-371, 17-20 April 2007

[57] T. A. Weiss, F. K. Jondral, "Spectrum Pooling: An Innovative Strategy for the Enhancement of Spectrum Efficiency", *IEEE Radio Communications*, March 2004

[58] Ofcom, "Spectrum Pricing: a consultation or proposal for setting wireless telegraphy act license fees,"December, 2004

[59] I.F. Akyildiz, W.Y. Lee, M.C. Vuran, S. Mohanty - "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey", *Computer Networks*, 2006

[60] C.Y. Ngo, V.O.K. Li, "Fixed channel assignment in cellular radio networks using a modified genetic algorithm," *Vehicular Technology, IEEE Transactions on* , vol.47, no.1, pp.163-172, Feb 1998

[61] T. Kahwa, N. Georganas, "A Hybrid Channel Assignment Scheme in Large-Scale, Cellular-Structured Mobile Communication Systems," *Communications, IEEE Transactions on [legacy, pre - 1988]*, vol.26, no.4, pp. 432-438, Apr 1978

[62] I. Katzela, M. Naghshineh, "Channel assignment schemes for cellular mobile telecommunication systems: a comprehensive survey," *Personal Communications, IEEE [see also IEEE Wireless Communications]* , vol.3, no.3, pp.10-31, Jun 1996

[63] Channel Allocation Schemes, Wikipedia, http://en.wikipedia.org/wiki/Channel_allocation_schemes

[64] S. Tekinay, B. Jabbari, "Handover and channel assignment in mobile cellular networks," *Communications Magazine, IEEE*, vol.29, no.11, pp.42-46, Nov 1991

[65] T. Kanai, NEC Corp., Kawasaki, "Autonomous reuse partitioning in cellular systems", *IEEE 42nd Vehicular Technology Conference*, 10-12 May 1992

[66] J. CHUANG, "Performance Issues and Algorithms for Dynamic Channel Assignment", *IEEE Journal on Selected Areas in Communications*, vol. 11, no. 6, pp. 955–63, August 1993.

[67] K. Ishii, S. Yoshida, "Dynamic channel allocation algorithm with transmitter power control", *IEEE 44th Vehicular Technology Conference*, 8-10 Jun 1994

[68] O. Lázaro, D. Girma,, "A Hopfield Neural-Network-Based Dynamic Channel Allocation with Handoff Channel Reservation Control", *IEEE transaction on*

vehicular technology, vol. 49, No. 5,Sep 2000

[69] A. Lozano and D.C. Cox, “Distributed dynamic channel assignment in TDMA mobile communication systems”, *IEEE Transactions on Vehicular Technology,* Nov 2002

[70] K. B. Letaief and Y. J. Zhang, “Dynamic multiuser resource allocation and adaptation for wireless systems”, *IEEE Wireless Communications,* pp38-47, Vol.11, Aug. 2006

[71] K. Chowdhury and W. Ivancic, “Handover schemes in satellite networks: state-of-the-art and future research directions”, *IEEE Communications Surveys & Tutorials,* pp2-14, vol.8, Fourth Quarter 2006

[72] H. Skalli and S. Ghosh, “Channel Assignment Strategies for Multiradio Wireless Mesh Networks: Issues and Solutions”, *IEEE Communications Magazine*, pp86-95, vol. 45, November 2007

[73] M. Y. Elnainary, D. H. Friend, “Channel Allocation & Power Control for Dynamic Spectrum Cognitive Networks using a Localized Island Genetic Algorithm”, *New Frontiers in Dynamic Spectrum Access Networks, DySPAN 2008*. 14-17 Oct. 2008

[74] Skehill, R.; Barry, M.; Kent, W.; OÂ¿callaghan, M.; Gawley, N.; Mcgrath, S.; , "The common RRM approach to admission control for converged heterogeneous wireless networks," *Wireless Communications, IEEE* , vol.14, no.2, pp.48-56, April 2007

[75] Han, C.; Armour, S.; , "Energy efficient radio resource management strategies for green radio," *Communications, IET* , vol.5, no.18, pp.2629-2639, Dec. 16 2011

[76]“Mobile WiMAX Part I: A Technical Overview and Performance Evaluation,” WiMAX Forum, Feb, 2006

[77]Giuliano, R.; Monti, C.; Loreti, P.; , "WiMAX fractional frequency reuse for rural environments," *Wireless Communications, IEEE* , vol.15, no.3, pp.60-65, June 2008

[78] Ali, S.H.; Leung, V.C.M.; , "Dynamic frequency allocation in fractional frequency reused OFDMA networks," *Wireless Communications, IEEE Transactions on* , vol.8, no.8, pp.4286-4295, August 2009

[79] Z. Yang, A. Mohammed, T. Hult,; D. Grace, "Optimizing downlink coexistence performance of WiMAX services in HAP and terrestrial deployments in shared frequency bands," *Waveform Diversity and Design Conference, 2007. International* , vol., no., pp.79-82, 4-8 June 2007

[80] S. R. Saunders, Antennas and Propagation for wireless communication systems, University of Surry, Guilford, UK, John Wiley& Son Ltd, reprinted in August, 2004

[81] D. Pearce, "Personal and Mobile Communications", *viewfoils and notes*. September 2006

[82] DVB-H www.wikipedia.org

[83] Sirbu, G. Bogdan, I. "Dynamic channel allocation scheme simulation using agents technology", *International Symposium on Signals, Circuits and Systems, 2009. ISSCS 2009, July, 2009.*

[84] HAN I(Korea Advanced Inst. Sci. And Technol. (kaist), Taejon, Kor) CHO D-H (Korea Advanced Inst. Sci. And Technol. (kaist), Taejon, Kor) "An Efficient Channel Allocation Scheme for Multicast Traffic in Multitier Cellular Systems", *IEICE transactions on communications E84-B(4), 1087-1093, 2001-04-01*

[85] L. P. Kaelbling, M. L. Littman, and A. W. Moore, "Reinforcement Learning: A Survey," *Journal of artificial intelligence Research*, vol. 4, pp. 237-285, May. 1996.

[86] T. Jiang, D. Grace, and P. D. Mitchell, 'Efficient Exploration in Reinforcement Learning Based Cognitive Radio Spectrum Sharing', accepted by *IET Communications*, June 2010

[87] T. M. Mitchell, *Machine Learning*: McGraw-Hill, 1997.

[88] J. C. Chuang,N. R. Sollenberger, "Spectrum resource allocation for wireless packet access with application to advanced cellular Internet service", *IEEE Journal on Selected Areas in Communications*, pp 820-829, vol. 16, Aug 1998

[89] P. J. Smith, M. Shafi, A. Tokeley, "On the effectiveness of channel segregation as a channel allocation method in a variety of cellular structure", *IEEE Transactions on Vehicular Technology*, pp 2234-2243, vol.49, Nov 2000

[90] G. L. Stuber, Ming-Ju Ho, "Distributed dynamic channel assignment for in-building Microsystems", *IEEE Transactions on Vehicular Technology,* pp1292-1301, vol. 47, Nov 1998

[91] J. Nie; S. Haykin, "A Q-learning-based dynamic channel assignment technique for mobile communication systems", *IEEE Transactions on Vehicular Technology*,

pp 1676-1687, vol. 48, Sep 1999
[92] N. Nie and C. Comaniciu, "Adaptive channel allocation spectrum etiquette for cognitive radio networks," *Mobile Networks and Applications*, vol. 11, pp. 779-797, December, 2006.
[93] S. M. Senouci, G. Pujoile, “Dynamic channel assignment in cellular networks: a reinforcement learning solution”, *ICT 2003*, 23 Feb-1 Mar, 2003
[94] N. Lilith, K. Dogancay, “Dynamic channel allocation for mobile cellular traffic using reduced-state reinforcement learning”, *IEEE Wireless Communications and Networking Conference*, 21-25 Mar, 2004
[95] M. Bublin, J. Pan, I. Kambourov, and P. Slanina, "Distributed spectrum sharing by reinforcement and game theory," presented at 5th Karlsruhe workshop on software radio, Karlsruhe, Germany, March. 2008.
[96] Pan Zhou; Yusun Chang; Copeland, J.A.; , "Reinforcement Learning for Repeated Power Control Game in Cognitive Radio Networks," *Selected Areas in Communications, IEEE Journal on* , vol.30, no.1, pp.54-69, January 2012
[97] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*: Pearson Education, 2003.
[98] Reinforcement Learning, Wikipedia,
http://en.wikipedia.org/wiki/Reinforcement_learning
[99] Y. Liu, “Radio Resource Management for a Multiple High Altitude Platform System”, PhD thesis, University of York, Jan, 2007
[100] Simulation www.wikipedia.org
[101] J. Chen, “Improving Spectrum Utilization in Heterogamous Wireless System Through Cognitive Radio”, PhD thesis, University of York, Sep, 2009
[102] P. Likitthanasate, “Dynamic Spectrum Sharing for Terrestrial and High Altitude Platform Systems using WiMAX”, February, 2006
[103] Z. Yang, “Effective Coexistence of WiMAX Terrestrial and High Altitude Platform Systems”, December 2005
[104] D. Grace, “Distributed Dynamic Channel Assignment for Wireless Environment”, PhD thesis, 1999
[105] S.N. Fabri, A.M. Kondoz,., Provision of streaming media services over mobile network, *3G Mobile Communication Technologies*, No.477, pp.104 – 108, 2001
[106] MATLAB Help for color bar, contour plot. Version: MATLAB 7.3.0 (R2006b)

[107] CDF function of distribution function
http://www.ipp.mpg.de/de/for/bereiche/stellarator/Comp_sci/CompScience/csep/csep1.phy.ornl.gov/mc/node14.html
[108] Shannon equation and Channel capacity
http://www.st-andrews.ac.uk/~www_pa/Scots_Guide/iandm/part8/page1.html
[109] D. Grace, J. Thornton, G. Chen, G.P. White, T.C. Tozer, "Improving the system capacity of broadband services using multiple high-altitude platforms," *Wireless Communications, IEEE Transactions on* , vol.4, no.2, pp. 700-709, March 2005
[110] Error Bar, Wikipedia,
http://en.wikipedia.org/wiki/Error_bar
[111] S. Cho, S. Choi, P.M. Wong, "Data selection based on Bayesian error bar," *Neural Information Processing, 1999. Proceedings. ICONIP '99. 6th International Conference on* , vol.1, no., pp.418-422 vol.1, 1999
[112] A. Silvennoinen "Unlicensed reuse of licensed spectrum: case UWB", - netlab.tkk.fi
[113] M. Yang and D. Grace, "Cognitive radio based spectrum assignment for heterogeneous multicast terrestrial communication systems with different transmission rate requirements", Cognitive Radio and Software Defined Radios: Technologies and Techniques, 2008 IET Seminar on, 18th, Sep, 2008
[114] M. Yang and D. Grace, "Cognitive Radio with Reinforcement Learning Applied to Multicast Downlink Transmission and Distributed Occupancy Detection", COGCOM 2009, San Francisco, USA, Aug, 2009
[115] T.J. Harrold, P.C. Faris and M.A. Beach, "Distributed Spectrum Detection Algorithms for Cognitive", Cognitive Radio and Software Defined Radios: Technologies and Techniques, 2008 IET Seminar on, 18th, Sep, 2008
[116] T. Jiang, D. Grace, and Y. Liu, "Performance of Cognitive Radio Reinforcement Spectrum Sharing Using Different Weighting Factors," presented at International Workshop on Cognitive Networks and Communications (COGCOM2008) in conjunction with CHINACOM'08, Hangzhou, China, August, 2008.
[117] T. Jiang, D. Grace, and Y. Liu, "Cognitive Radio Spectrum Sharing Schemes with Reduced Spectrum Sensing Requirements," in *The IET Seminar on Cognitive Radio and Software Defined Radios: Technologies and Techniques*. London,

September, 2008.

[118] J. G. Maech, “Exploration and exploitation in organizational learning”, *Organization Science”,* 1991

[119] L. Lai, H. E. Gamel, “Cognitive Medium Access: Exploration, Exploitation, and Competition”, *IEEE transactions on mobile computing*, Feb 2011

[120] J. Zhao., H. Zheng, G.H. Yang, “Distributed coordination in dynamic spectrum allocation networks,” IEEE DySPAN 2005, 2005, pp. 259-268.

[121] T. A. Weiss, J. Hillenbrand, A.Krohn, F.K. Jondral, “Efficient signaling of spectral resources in spectrum pooling systems,” *10th Symposium on Communications Vehicular Technology (SCVT),* 2003

[122] R. Jin, D. Grace, P.D. Mitchell, Cognitive Radio for UWB Spectrum Sharing and Power Allocation, *WUN COGCOM 2010 Workshop part of IEEE International Symposium on Wireless Communication Systems (ISWCS) 2010,* York, UK, September 2010

[123] P. Likitthanasate, D. Grace, P.D. Mitchell, Spectrum Etiquettes for Terrestrial and High Altitude Platform based Cognitive Radio Systems with Directional User Antennas, *IET Communications Special Issue on Cognitive Spectrum Access*, Vol. 2, No. 6, pp. 846-55, July 2008

[124] Raúl Rojas, Neural networks: a systematic introduction, Springer, 1996

[125] C Clancy, J Hecker, E Stuntebeck, T O'Shea, “Applications of machine learning to cognitive radio networks”,- *IEEE Wireless Communications*, 2007

[126] P. Likitthanasate, D. Grace, P.D. Mitchell, “Multivariable Payoff Function Design for Game Theoretic Treatment of Combined Terrestrial and HAP Broadband Networks” *COST 297- HAPCOS- Wroclaw,* Poland, October, *2007*