Machine Learning Approach for Spectrum Sharing in the Next Generation Cognitive Mesh Network

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Abstract

Machine Learning Approach for Spectrum Sharing in the Next Generation Cognitive Mesh Network

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Nowadays, there is an unexpected explosion in the demand for wireless network resources. This is due to the dramatic increase in the number of the emerging web-based services. For wireless computer network, limited bandwidth along with the transmission quality requirements for users, make quality of service (QoS) provisioning a very challenging problem. To overcome spectrum scarcity problem, Federal Communications Commission (FCC) has already started working on the concept of spectrum sharing where unlicensed users (secondary users, SUs) can share the spectrum with licensed users (primary users, PUs), provided they respect PUs rights to use spectrum exclusively. Cognitive technology presents a revolutionary wireless communication where users can exploit the spectrum dynamically. The integration of cognitive technology capability into the conventional wireless networks is perhaps the significant promising architectural upgrade in the next generation of wireless network that helps to solve spectrum scarcity problem.

In this work, we propose integrating cognitive technology with wireless mesh network to serve the maximum number of SUs by utilizing the limited bandwidth efficiently. The

architecture for this network is selected first. In particular, we introduce the cluster-based architecture, signaling protocols, spectrum management scheme and detailed algorithms for the cognitive cycle. This new architecture is shown to be promising for the cognitive network. In order to manage the transmission power for the SUs in the cognitive wireless mesh network, a dynamic power management framework is developed based on machine learning to improve spectrum utilization while satisfying users requirements. Reinforcement learning (RL) is used to extract the optimal control policy that allocates spectrum and transmission powers for the SUs dynamically. RL is used to help users to adapt their resources to the changing network conditions. RL model considers the spectrum request arrival rate of the SUs, the interference constraint for the PUs, the physical properties of the channel that is selected for the SUs, PUs activities, and the QoS for SUs.

In our work, PUs trade the unused spectrum to the SUs. For this sharing paradigm, maximizing the revenue is the key objective of the PUs, while that of the SUs is to meet their requirements and obtain service from the rented spectrum. However, PUs have to maintain their QoS when trading their spectrum. These complex conflicting objectives are embedded in our machine learning model. The objective function is defined as the net revenue gained by PUs from renting some of their spectrum. We use a machine learning to help the PUs to make a decision about the optimal size and price of the offered spectrum for trading. The trading model considers the QoS for PUs and SUs, traffic load at the PUs, the changes in the network conditions, and the revenues of the PUs. Finally, we integrate all the mechanisms described above to build a new cognitive network where users can interact intelligently with network conditions.

Acknowledgement and/or Dedication

First and foremost I would like to thank Allah for giving me the strength and patient to accomplish this work. I could never have done this without the faith I have in you, Allah.

I would like to thank my parents for constantly supporting and encouraging me. All the support they have provided me thought my life. They have given me more than I deserve.

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My special appreciation goes to my sisters and brothers for all their moral support and encouragement. Finally, I am forever indebted to my beloved wife Shorook, my little prince Hamza, and my lovely son Omar for their understanding, endless patience and encouragement when it was most required.

To them, I dedicate this thesis.

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Chapter 1: Introduction

Spectrum scarcity problem will get worse due to the unexpected explosion in the number of the emerging web-based services. Users want to access the internet anywhere-anytime. As a result, the frequency spectrum becomes congested while supporting these web-based applications. Furthermore, guaranteeing the QoS for multimedia applications requires huge bandwidth resources [1-8]. Unfortunately, dedicated bandwidth becomes increasingly scarce and expensive.

In most countries, spectrum is allocated to the licensed user exclusively. However, if the licensed users do not use this spectrum, it will be considered as used while it is actually wasted. For example, some users, such as the military radio system, require spectrum infrequently. As a result, efficient spectrum utilization is an essential requirement to support emergent services. Unfortunately, recent spectrum utilization measurements have shown that the usage of spectrum is concentrated on certain portions of the spectrum while significant amounts are severely underutilized and this can be noticed from the Federal Commission Communication (FCC) chart as shown in Fig 1.1 [9].

Inefficient spectrum usage necessitates rethinking of the new spectrum sharing paradigm that exploits the wasted spectrum. Toward efficient utilization, FCC allows unlicensed users (secondary users, SUs) to utilize the unused spectrum provided they respect PUs' rights. The unused licensed spectrum is used in this work to build a cognitive network (CN) that serve SUs.

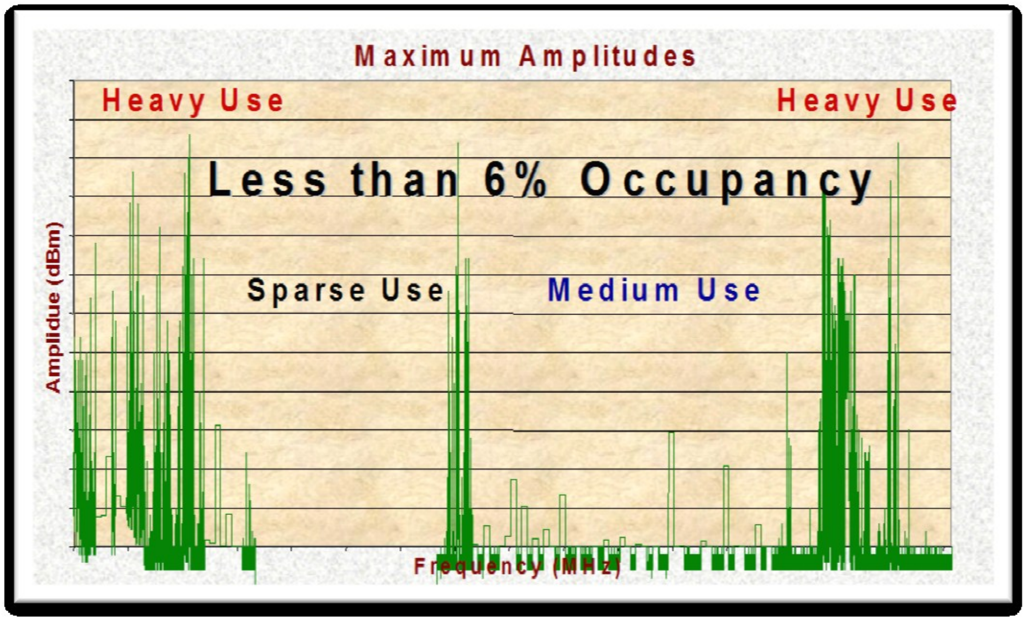

Fig 1.1: spectrum utilization

Dynamic spectrum access (DSA) is proposed to mitigate spectrum scarcity through utilizing spectrum dynamically. It enables users to adjust communication parameters (such as operating frequency, transmission power, modulation scheme) in response to the changes in the wireless environment [1-3]. DSA enables implementation of CN that brings a promise to increase spectrum at a minimum cost by using licensed spectrum whenever spectrum owners do not use it. This technology provides up to 85% of the unused spectrum [1-13]. Hence, it enhances the capability of traditional wireless networks to support broadband systems.

Cognitive technology encourages implementing new more flexible spectrum sharing paradigms. These sharing paradigms include overlay, underlay and spectrum trading approach. In cognitive network, SUs can access the unused spectrum using underlay, overlay or spectrum trading approaches [8]. In the overlay approach, users can access a portion of the spectrum that is not used by licensed users. As a result, interference to the primary system is avoided. In the underlay approach, SUs can coexist with PUs. After collecting spectrum data, a SU can transmit if its signal power does not exceed a certain threshold. This power is regarded as noise by the PU [1, 8]. In spectrum trading, SUs get permission from a PU to access spectrum for a certain period of time by paying for getting this access right [8, 17-19]. These new types of spectrum sharing paradigms impose several research challenges such as:

1- Regulating unlicensed usages to avoid causing interferences to the PUs. SUs should manage their power transmission to avoid interference with PUs.
2- Managing spectrum access among SUs
3- Managing spectrum holes. The changes in the spectrum status should be detected quickly and accurately especially when using underlay and overlay schemes. The size and the price of the offered spectrum for trading should be specified to maximize the profit of PU's and to maintain the QoS for PUs.
4- Assuring the QoS of the SUs and protecting the PUs' rights for exclusive usage of spectrum.

In this dissertation, cognitive radio is used to build a network for the SUs. Wireless mesh networks (WMNs) are posed to be the best candidate for the infrastructure of this cognitive network (CN) due to their advantages. WMNs help to solve a spectrum scarcity problem by extending Internet access and other networking services. For the users, WMNs provide higher bandwidth, low cost and low power consumption.

Machine learning is used to solve the spectrum scarcity problem in our work. Machine learning offers the promise of creating a new generation of intelligent wireless network where nodes can learn and adapt to utilize the unused licensed spectrum. We describe a machine learning model for a generic CN that is able to exploit the unused spectrum efficiently. Our focus is not to propose new machine learning algorithms, but rather to apply this methodology in wireless network to develop new generation of intelligent users that can learn and make decision in the dynamic network environment.

The main problem that we approach in our work is managing spectrum efficiently using a cognitive technology in a wireless mesh network. Specifically, we approach the following problems:

1- The architecture of the cognitive mesh network.
2- Allocating spectrum for SUs using overlay spectrum sharing technique.
3- Managing the powers of SUs in the secondary network and using the underlay scheme to serve SUs. SUs power should support the required data communication rate. The power should not be dropped indefinitely but it should be bounded to support the QoS for the SUs while protecting the PUs.
4- Spectrum sharing using spectrum trading in a multi-service cognitive network.

1.1 Motivation

Many factors motivate our research in the area of spectrum management. These factors include:

1- The limited available spectrum. Spectrum is a finite natural resource and there are no means to increase it. In order to solve the spectrum scarcity problem, new solutions for spectrum management should be presented. Unfortunately, the static nature of the previous schemes prevents them from utilizing the unused spectrum efficiently. In our work, we develop new schemes to solve spectrum scarcity problem by enabling SUs to access the unused spectrum using overlay, underlay, and trading approach.

2- A dramatic increase in the usage of the limited spectrum. Recently, there is remarkable increase in the number of electronic devices that demand spectrum access, most of the existing spectrum is claimed and often is far from being fully utilized. Previous spectrum assignment policies could not utilize the sparse spectrum to serve the extra traffic for unlicensed users. More users can access the unused spectrum using our accessing schemes. Our schemes consider the requirement of SUs.

3- The inefficiency in the spectrum usage. Previous studies have shown that more than 85% of the spectrum is not efficiently used [11-13]. As a result, reallocating this spectrum will contribute to solving today's spectrum scarcity problem. Despite the fact that fixed spectrum assignment policies generally served well in the past, they become inadequate to meet user communication requirements nowadays [1-8].

4- Cognitive technology: Emerging wireless technologies such as cognitive network (CN) make dynamic spectrum allocation a reality. CNs are able to provide greater flexibility and access to spectrum, and improve the spectrum utilization by searching and utilizing radio resources efficiently. However, there is several open research challenges that motivate our work and that are embedded in our designs. These challenges include architectural complexity, deciding the best free band for SUs, developing new spectrum sharing schemes which are able to meet the conflicting objectives of PUs and SUs [1, 8]. Next Chapter details these challenges.

5- Reinforcement learning (RL): In cognitive network, a node not only makes a mechanical adaption, but also interacts and learns from its environment and intelligently adapts itself to dynamic conditions to achieve the desired objectives under various conditions. Therefore, a machine learning layer that provides awareness, reasoning, and adaptation functions is required for the next generation of CN. RL is an effective tool to deal with rational entities that makes decisions to maximize their benefits with whatever little information they have. It provides a mathematical framework for modeling decision-making in situations where the decision maker is not sure about the outcome. In order to adapt to changing conditions in cognitive network, a learning algorithm is used to update the state of wireless environment state by selecting one of the available actions. This action is selected according to an objective function (e.g. minimize cost or maximize profit).

1.2 Objectives and Contributions of the Proposed Research

This Section includes in detail the objectives and contributions of this work. Some of research questions are presented to guide us to specify our objectives precisely.

1.2.1 Research Objectives

The principal objective of this work is to propose new schemes and protocols to utilize the unused spectrum efficiently and to serve the maximum number of the SUs. To achieve this goal we develop methodologies and mechanisms to make our system able to interact with changes in wireless environment. Efforts will be geared towards the following tasks:

1- To design a new CN architecture that achieves the following objectives:

- To enhance scalability of the proposed system by distributing the users into clusters.
- To increase throughput of CN by reducing the communication overhead in the CN.
- To decrease the delay of SUs' requests by reducing contention at the centralized server and distributing the load of the centralized server among cluster heads.
- To develop robust CN where failures of cluster heads do not cripple the network. The mobility of SUs should also be considered properly.

2- To develop the key functions of the CN. These functions include:

- Radio environment recognition, which is important for the CN to achieve the environment awareness.
- Adaptation to radio environment.
- Learning from the environment.

3- To evaluate and characterize free channels for the SUs.

4- To consider the requirements of SUs while allocating a spectrum.

5- To manage the transmission power of SUs in CN. SUs can transmit concurrently with a PU if their power is below the interference threshold of PUs.

6- To provide a spectrum sharing mechanism among PUs that guarantees a full utilization of spectrum and maximizes the total revenue of PUs.

7- To use RL to extract an optimal control policy that helps a PU to trade the unused spectrum to SUs. This policy can combine the following conflicting objectives:

   - Enabling a PU to adapt the size and price of the offered spectrumfor trading.
   - Reducing the time delay for SUs.
   - Maximizing the reward of PUs.
   - Maintaining the QoS of PUs and SUs.

8- Finally, to integrate these mechanisms in order to create an intelligent spectrum management scheme.

1.3 Key Contribution

Much research has been conducted on the CN. Most of this research focuses on individual component and we notice very few detailed research and discussion from the system point of view. Therefore our goal is to propose a complete system where SUs can adapt intelligently to the radio environment. With this goal in mind, we have planned contribution on different aspects of cognitive radio network:

1- A new architecture for CN is proposed. This architecture provides robustness against any failure in CN and minimizes the communication overhead.

2- In the second contribution, a new function is proposed to quantify the quality of the free spectrum. Different characteristics of channels are combined in this function. A new channel assignment scheme is used in CN, which ranks the channels based on their quality and assigns them based on the SUs requirements. Furthermore, a new scheme for managing transmission power of the SUs in the CN is proposed.

3- A new scheme for trading free spectrum to SUs is proposed. In spectrum trading, the objective of a PU is to maximize its revenue, while that of a SU is to get a service from this spectrum. These objectives are embedded in our RL model that is developed and implemented as shown in this thesis. Available spectrum is managed by the PU which executes the extracted control policy. RL is used as a means for extracting an optimal policy that helps a PU to adapt to the changing network conditions, so that the PU's profit is maximized continuously over time. The proposed scheme integrates different requirements such as rewards for PUs, QoS for PUs, and the radio environment conditions. The contributions of our trading scheme are:

   - A new spectrum sharing scheme among PUs is proposed.
   - How the concept of RL can be used to obtain a computationally feasible solution to the considered spectrum trading problem is described.
   - An extensive numerical evaluation, based on analysis and simulation, of the RL-based method for spectrum trading is presented.

4- Our final contribution is the proposal of a complete CN system. Previous researches had proposed some cognitive network systems. However, these systems are insufficient to provide a complete solution. Some critical functions were missing in their system such as controlling the size of the offered spectrum for trading based on PUs QoS, guaranteeing QoS of SUs, spectrum allocation in CN, and analyzing the quality of the free spectrum.

1.4 Organization of the Thesis

The rest of the thesis is organized as follows. Chapter 1 elaborates on overview of CN, our thesis motivation, our objectives and contributions. Chapter 2 discusses the challenges of CN technology and the related work to these challenges is presented. Chapter 3 comprehensively describes the proposed overlay scheme, and the architecture for the CN which enables opportunistic access and efficient sharing of spectrum holes. Chapter 3 also presents the signaling protocols among SUs. Finally, Chapter 3 demonstrates the performance of the proposed overlay management scheme through comparing its performance with other schemes using the simulation.

Chapter 4 describes a novel underlay scheme for spectrum access. A new model for evaluating the quality of channels in CN is described. We discuss the significant relevant works that deal with spectrum allocation followed by presenting a new channel assignment scheme. Some of the new heuristics are merged together in one decision function, which is presented in this Chapter for selecting the best channel that meets the QoS of the current SU.

In Chapter 5, we present our spectrum trading scheme. Firstly, our assumptions and work environment are shown. Next, we formulate the trading problem and describe our model for solving the problem using RL. Then we illustrate RL implementation and describe how to optimize the obtained revenues using RL algorithm.

In Chapter 6, we present our system for CN. The system contains all cognitive network functions. Firstly, the system requirements are presented. Then, we describe the system architecture. After that, we present the main functions in our system and then we describe a new scheme for accessing the unused spectrum where all proposed spectrum access schemes are merged into one scheme. Finally, Chapter 7 concludes the work.

1.5 Summary

In this Chapter, we highlight the contributions of our work and the objectives of the thesis. These can be summarized as follows:

- Introducing a complete system for CN.
- Introducing a new architecture for managing SUs' activities.
- Proposing a new model for characterizing free channels.
- Proposing new channel assignment scheme for SUs in the CN. The new scheme takes into account the requirements of the SUs and the constraint of using the spectrum.
- Bridging the machine learning with radio engineering and wireless communication.
- Developing an intelligent cognitive user that is able to reason, learn all gathered information, and make the right decision is one of our main objectives in this work. Therefore, a machine learning layer that supports awareness, reasoning, and adaptation is added to our system.

Chapter 2: Challenges of Spectrum Management and Related Work

Several challenges prevent developing schemes and protocols to help SUs access the licensed spectrum. In this Chapter, we describe the challenges of developing cognitive network that uses the unused licensed spectrum for serving SUs. The Chapter is organized as follows. Firstly, the challenges of building CN are presented. Next, related work to these challenges is introduced. After that, an overview of our methodology to handle the challenges of building the CN is given. We use machine learning to help SUs and PUs to adapt to the network conditions. Finally, the Chapter is concluded.

2.1 Challenges for developing CN

There are several challenges that prohibit SUs from exploiting the unused spectrum efficiently. In this Section, we identify and describe these most fundamental challenges.

2.1.1 Architectural Complexity

In order to enhance spectrum efficiency and provide flexible access to the spectrum holes, SUs should be adequately managed. Generally, there are three basic types of architecture that are used to manage the spectrum in CN: the centralized architecture, the distributed architecture and the clustering architecture.

2.1.1.1 Centralized Architecture

In the centralized approach, a single server is used to manage spectrum. SUs gather information about spectrum holes and send the results to a centralized entity where the collected results are used to build a database about spectrum [21-23]. Then, based on the complete network environment information, a decision to access the spectrum is made. The decision takes into account the desired objectives and constraints of accessing the unused spectrum. Although this architecture is simple and the optimal spectrum utilization can be achieved, the centralized approach suffers from the following drawbacks:

- Large communication overhead: the detection results of SUs are sent simultaneously to the server. However, these results contain redundant information about the new licensed users. Fig. 2.1 shows many users send the same data to the server.

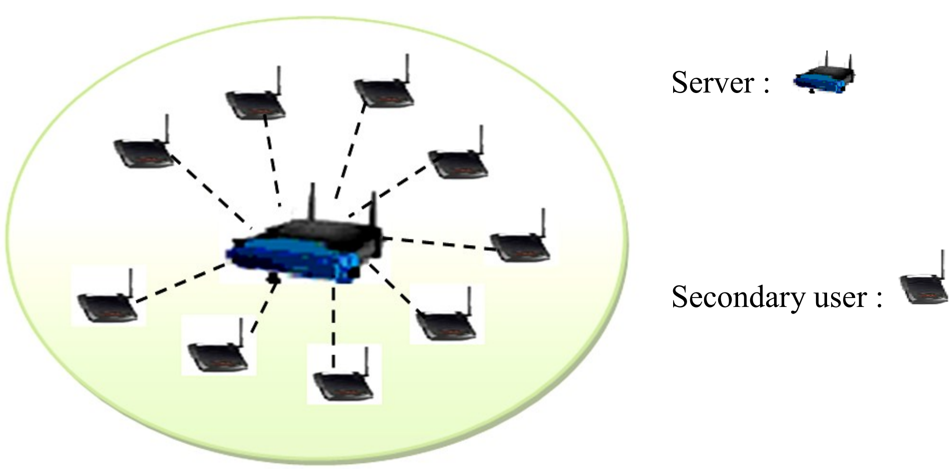

Fig 2.1: Gathering spectrum data at server

- Failure of the centralized entity: a server crash results in complete service failure. Scalability: the centralized solution has limited scalability. When the size of the network increases, the network performance is degraded significantly.
- Excessive load on a server : servers include heavy-duty network connections in order to manage the spectrum efficiently.
- Centralized approach is infeasible in some applications such as ad hoc network.

2.1.1.2 Distributed Architecture

In distributed architecture, SUs sense the spectrum and make decisions to access spectrum independently [15, 19-20]. Generally, distributed architectures can be classified into:

- Non-cooperative architecture: in a non-cooperative solution, each SU senses the spectrum and identify spectrum opportunities, and accesses the spectrum selfishly without coordinating with other users, but it should avoid interfering with PUs. No communication overhead is required for this solution. Besides there is no guarantee to full utilization of the spectrum, the accuracy of spectrum sensing is less than cooperative architecture. Furthermore, the fairness among SUs is another disadvantage of this solution.
- Cooperative architecture: in cooperative solutions, SUs cooperate with each other to manage spectrum access. Spectrum data is exchanged between SUs and there is no central entity for managing spectrum. Although they provide more accurate information about spectrum status, distributed schemes cause undesirable effects in

resource-constrained networks due to additional operations and overhead traffic. In the distributed system, the bandwidth is consumed dramatically because of the coordination between SUs. For coordination purposes, traditional distributed schemes assign common channel known to all users. However, assigning one channel for all users has drawbacks such as: scalability, common channel congestion, channel contention and existence of common channel. SUs should release the common channel and look up for a new one quickly as soon as the channel owner starts using it.

2.1.1.3 Clustering architecture

In clustering solution, SUs are divided into clusters where a cluster head manages the spectrum for its members. Unfortunately, previous clustering schemes do not consider the following [24-30]:

- The pre-defined control channel between cluster heads and the common receiver limit the available bandwidth for data communication.
- As the number of clusters, the common server processing complexity increases resulting in scalability.
- Cluster management issues such as cluster head failure and mobility of cluster members.
- Balancing the load at the cluster head. For example, if one cluster contains too many users, the time required for performing the cognitive cycle is increased significantly due to the huge number of users and the size of sensing results.

2.1.2 Spectrum detection

For overlay approach, in order to reliably protect the PUs from SUs' activities, the unused spectrum need to be accurately identified. An important requisite of overlay approach to successes is to detect the presence of PUs as quickly as possible. For this reason SUs should sense the spectrum continuously, quickly and accurately. However, identifying unused spectrum is a challenging problem due to [19-23]:

- Detection Speed: because spectrum status changes over time and space, the management scheme should keep track of wireless environmental changes. Any changes during communication should be detected quickly and proper action should be taken. Environmental changes include detecting new PUs, traffic changes, user mobility and identifying new free band.
- PU detection: in a wireless environment, SUs may interfere with PU due to incorrect detection of the PU signal. However, many factors cause SUs to have incorrect judgment of the wireless environment. These factors are multi-path fading, shadowing and building penetration. Fig.2.2 shows that some SUs cannot detect primary user signal due to obstacles.
- Spectrum data size: wide range of spectrum should be detected quickly, resulting in a huge amount of data. These data should be distributed amongst SUs as quickly as possible. However, exchanging spectrum information has several drawbacks that include:

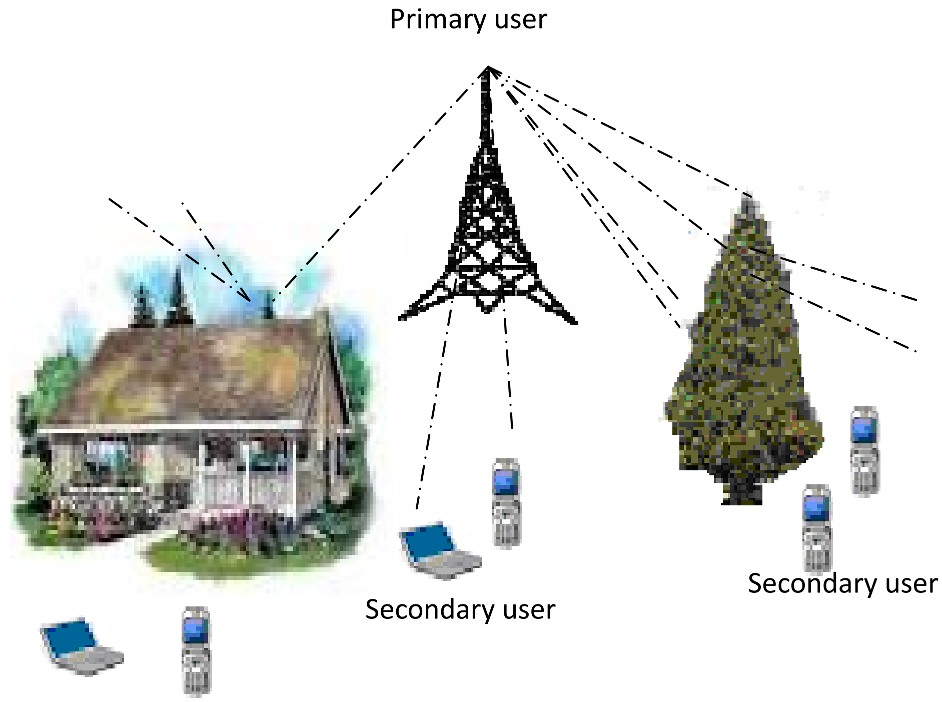

Fig 2.2: Some secondary users cannot detect primary user signal due to obstacles

- Consuming bandwidth: spectrum data will consume a bandwidth significantly due to the rapid change in spectrum status in time and space.
- Scalability: this problem appears in centralized sensing schemes where centralized entity receives results from all SUs at the same time. In these schemes, as the number of SUs increases the performance is degraded significantly.

2.1.3 Spectrum Assignment for SUs

The main function of spectrum management scheme in CN is to control access to the spectrum. Spectrum management scheme should consider the requirements of SUs when scheduling access to the spectrum. Spectrum assignment scheme consists of spectrum analysis function and spectrum decision function. In spectrum analysis function, spectrum data is analyzed to quantify the quality of the spectrum holes. Then, a decision function plans accessing the spectrum. Previous spectrum analysis functions [31-36] do not consider the following:

- PU activities: The activities of PUs affect spectrum sharing. The idle time for PUs refers to the expected time duration that a PU can hold and does not occupy the spectrum. Obviously, more idle times mean better spectrum sharing. After evaluating the spectrum, channel assignment algorithm should choose the channel that has the highest idle times to reduce the likelihood of interrupting a SU. In CR, SUs release a channel as soon as possible when a PU signal is detected.
- Channel error rates: this depends on many factors such as modulation scheme, interference level, power transmission, etc.
- SUs requirements: None of these schemes consider the QoS requirements of SUs.
- Spectrum adaptation time: SU may change their working frequency for many reasons such as improving communication performance, detection of the PU user and user mobility. Channel assignment should select the channel that has the less adaptation time. The decision function should decide which SUs use which unused channel based on the requirements of the SUs and the constraints of accessing PUs spectrum.

For the underlay access scheme, spectrum management scheme should limit the transmit power of the SU so that the interference caused to the PUs remains below the interference threshold.

2.1.4 Quality of Service Assurance

Another key challenge for a CN is to maintain the service of SUs when PUs need its spectrum. In overlay approach, the spectrum management scheme should find another channel for the SUs that release their channel for a PU. For the underlay approach, the power management scheme should monitor the wireless environment continuously and interact with changes of the PUs transmission power.

2.1.5 Challenges for using underlay scheme

For underlay spectrum sharing scheme, spectrum management scheme should protect PUs by constraining the transmission power of SUs so that their transmission power should be less than the interference threshold of PUs. Moreover, it should prevent SUs from interfering with each other. Spectrum sharing scheme should be able to identify spectrum holes, and manage spectrum access among SUs when using overlay sharing scheme. To achieve sustainable spectrum usage, SUs need to operate in compliance with a set of spectrum rules or protocols.

2.1.6 Spectrum Trading Challenges

In spectrum trading, PUs can rent idle spectrum to SUs for a certain of time to earn revenue [37-47]. PUs need an optimal policy to solve the following dilemma. When a request for spectrum arrives, the PU recognizes that it should give part of its spectrum to gain the revenue from rent. However, the QoS for PU might be degraded due to renting the spectrum. The PU might reject serving because it needs this spectrum and loses the reward. As a result, the PU waits for its demand for the spectrum to subside before renting spectrum. Consequently, the likelihood of losing a reward of serving SUs increases, which pushes the PU to become more spectrum demanded in order to reduce its loss.

Under the emerging spectrum market, when a PU rents the available spectrum to other parties (i.e. SUs), the PUs need to consider the economic factors, such as the spectrum price, the revenue obtained. In addition to economic factor, the QoS for PUs and SUs should be taken into account. Unfortunately previous studies [37-47] do not consider the following:

- Utilizing spectrum efficiently. Previous studies assume the competition among PUs for spectrum to maximize their revenues regardless of efficient spectrum utilization.
- Maximizing total revenues of PUs through utilizing the whole spectrum. The cooperation between PUs to maximize total revenues is neglected in these schemes.
- Developing a control policy that helps PUs to adapt the size and price of the offered spectrum based on the changes in the network condition such as traffic load, cost of services and spectrum price.

- The heterogeneity of SUs. All of these works concentrated on trading for a single class of user.

2.1.7 Spectrum sharing among PUs

Usually several PUs are willing to trade free spectrum for SUs to get more profits. A competition occurs when each PU wants to maximize its profit. However, this competition may not result in optimal profits for PUs and efficient spectrum utilization. Contrary to that, PUs may cooperate to maximize their profits by borrowing spectrum to accommodate a new spectrum requests. Collaboration is the capability of PUs to share the spectrum under a prearranged policy. The goal of collaboration is to achieve efficient and flexible spectrum usage. A control mechanism is needed to manage spectrum sharing among PUs.

2.2 Related Work

As mentioned in the previous Section, the main challenges that are faced integrating cognitive technology with next generation of wireless network are architectural complexity, spectrum allocation, power management and trading the free spectrum in the secondary market. Previous studies focus on an individual component. Our objective is to propose a complete cognitive network such that a node can adapt to the changes in the wireless network environment. With this goal in mind, we introduce literature review for these challenges and the most important articles related to each challenge.

2.2.1 The state of art for Cognitive Network Architecture

Spectrum management architectures in the secondary network are classified into centralized, distributed and cluster-based approaches. An overview about the state of art for each of these schemes is given in this Section.

2.2.1.1 Distributed architecture

In distributed architecture, SUs coordinate with themselves to manage accessing the unused spectrum in the secondary network. In [15], a new distributed approach for managing data spectrum is proposed. Users are divided into groups based on an existing common channel. User groups coordinate and exchange information via a common channel. Although the simulation results have shown that the scheme outperformed some of the existing schemes, the scheme suffers from several drawbacks. These drawbacks include scalability due to the use of a common channel, coordination overhead and crippling the network when the PU starts using the common channel. In [19], a new local bargaining scheme is proposed. Users negotiate spectrum assignment within local self-organized groups. The algorithm provides a fair service guarantee for each user. This collaboration-based approach requires neighbors to exchange coordination information frequently. Furthermore, it needs developing common coordination protocol and a communication path, resulting in implementation complexity and communication overhead. In order to build the cognitive network in [20], each SU specify the accessible spectrum bands and chooses one as its operating frequency.

2.2.1.2 Centralized architecture

In centralized architecture, a server is used to perform the cognition cycle that includes spectrum sensing, spectrum managing and spectrum allocation. In [21], SUs collect information on their wireless environment (e.g. free spectrum, power of PUs) and report this information to a centralized instance, termed network. After gathering spectrum data, the network builds an online model of the communication space state. In order to reduce signaling overhead, a new boosting protocol is proposed in [22]. Furthermore, a robust method to broadcast information on spectral resources back to the SUs is presented. According to the boosting protocol, the bands which are occupied by the PUs are signaled to amplify user signal at first phase. The server detects the incoming signals and tries to identify the new PUs signals which are boosted by SUs. However, the proposed approach does not consider crashing of the server. Although broadcast approach is reliable [21], it contains more redundant information. A central server controls the communication in the secondary network in [23] so that SUs do not interfere with each other or PUs. To specify the status of the spectrum, SUs sense the spectrum and send the allocation vector and their locations to the server where the final database about the network is stored.

2.2.1.3 Cluster-based architecture

Several studies propose using clustering as the construction design for the secondary network architecture. Clustering architecture is used in [24] to manage communication among vehicular nodes. The authors consider the QoS for SUs in the secondary network while assigning channels for SUs. In [25], a cluster-based framework is proposed to form a secondary network in the context of open spectrum sharing. A common channel is used to construct clusters and these clusters are connected to form the network. A new mechanism is used to enable each node to efficiently exchange neighbor information over multiple channels.

Cluster-based cognitive network is established in [26] where a new algorithm for resource allocation is proposed. The results indicate that the performance depends on the number of nodes in the network, the structure of the cluster, the active traffic, the active link, and the amount of relay traffic. Cluster-based architecture is used for spectrum sensing in cognitive network [27]. All SUs sense the spectrum and report the results to their cluster head that forwards the results to a base station. The base station sends the final spectrum status to the MRs. In [28], a new approach for spectrum data management in wireless mesh network is proposed. MCs gather spectrum information and send them to mesh routers. MRs send spectrum to a gateway where all MRs can access it.

In [29], where clustering is also used to manage the spectrum, SUs send their spectrum sensing results to a cluster head; after that, the cluster head forwards the collected information into a common receiver. Conventionally, the common receiver gathers spectrum data from SUs and processes them. The secondary network is divided into clusters in [30], where each cluster head manages the spectrum for its users. Cluster heads exchange the spectrum data in order to determine the accurate status of the whole spectrum.

2.2.2 Spectrum Allocation and Power management in Cognitive Radio

Previous work related to channel allocation and power management in the secondary network is reported in [31-36]. In [31], the concept of opportunistic access is used to utilize spectrum efficiently. In opportunistic access, SUs utilize spectrum in a manner that limits the interference at PUs. In other words, the spectrum is shared with PUs on a non-interfering basis. The authors only used signal-to-noise ratio for spectrum allocation. The main idea of the proposed spectrum management scheme in [32] is to exploit the opportunities occurring during retransmissions of a PU to allow the coexistence of SUs. The requirements of SUs are neglected when exploiting the free spectrum in [32]. The power allocation problem in cognitive networks is considered in [33]. The proposed scheme takes into account reliability of available channels. However, the model does not consider the dynamic nature of wireless environment where PU's sensitivity to noise is changed over time. In [34], a new scheme for power management and spectrum utilization in WMNs is presented. The proposed scheme allows SUs to opportunistically access the licensed spectrum while not causing harmful interference for the PUs. Although the proposed scheme considers SUs requirements when allocating bandwidth, it neglects the physical properties of channel and the PUs spectrum usage manner. Moreover, the authors assume only one existing PU, which is not realistic. A new framework of joint spectrum allocation and power control to utilize unused spectrum in cognitive networks is considered in [35]. The framework takes into account both interference temperature constraints and spectrum dynamics. The authors in [36] consider spectrum sharing among SUs with a constraint on the total interference temperature at a particular measurement point and a QoS constraint for each secondary link.

2.2.3 Spectrum Trading state of the art

In a CN, PUs can rent their unused spectrum to SUs. The problem of spectrum trading is considered in [37] where each node charges other nodes for relaying its traffic. The objective function is defined as the revenue obtained from transmitting the node traffic plus other nodes charges minus the price paid for other nodes along the route to the destination. In [38], multiple PUs sell unused spectrum resources to SUs to get monetary gains while SUs try to get permissions from PUs for accessing the rented spectrum. In order to maximize the payoffs of both PUs and SUs, game theory is used to coordinate the spectrum allocation among PUs and SUs through a trading process. The payoff of a PU is defined as the difference between the price of the sold spectrum and the cost of buying spectrum. However, the model does not consider the QoS of PUs.

In the framework proposed in [39], a PU may lease the owned spectrum to SUs in exchange for cooperation in the form of distributed space-time coding. For the PU, the main concern is maximizing its quality of service in terms of either rate or probability of outage, accounting for the possible contribution from cooperation. However, SUs compete among themselves for transmission within the leased time-slot following a distributed power control mechanism. PU charges SUs for the leased spectrum in [40]. The problem is formulated as an oligopoly market competition and a non-cooperative game is used to obtain the spectrum allocation for SUs. Nash equilibrium is considered as the solution of this game. In [41], a non-cooperative game is extended to multiple PUs selling the spectrum to SUs. The model considers the behavior of other PUs to specify the price of spectrum. In [42], the advantages of employing market forces to address the issues of wireless spectrum congestion and the allocation of spectrum. It is shown that when unlicensed spectrum is assigned to all competing SUs during periods of excess demand an inefficient outcome is likely to result. PUs compete to sell a spectrum to a set of buyers in [43]. Game theoretic approach is proposed to obtain the selling quantities and bidding price.

Several studies tackle the issue of spectrum sharing among PUs. In [44], PUs compete with each other to get the spectrum. To analyze the dynamic spectrum allocation of the unused spectrum bands to PUs, an auction theory is used. The problem is formulated as a multi-unit sealed-bid sequential and concurrent auction. In [45], PUs dynamically compete for portions of available spectrum. PUs are charged by the spectrum policy for the amount of bandwidth they use in their services. The competition problem is formulated as a non-cooperative game and new iterative bidding scheme that achieves Nash equilibrium of the operator game is proposed. In the proposed system in [46], two spectrum brokers offer a spectrum for a group of PUs. The broker wants to maximize their own revenue. Brokers' revenues are modeled as the payoffs they gain from the game. On the other hand, PUs want to maximize their own QoS satisfaction at minimum expense.

Centralized regional spectrum broker distributes a spectrum among PUs in [47]. PUs do not own any spectrum; instead they obtain time bound rights from a regional spectrum broker and configure it to offer the network service. In [19], users adjust their spectrum usage based on a defined threshold called poverty-line. A PU can borrow from its neighbors if the neighbors have number of idle channels greater than a poverty-line. However, this scheme does not consider the availability of channels and the load of PU. It is possible that the neighbors have a number of idle channels less than their poverty line and these channels will be unused.

2.3 Using Reinforcement learning in Cognitive Network

In this Section we give an overview about cognitive network and machine learning, and then we explain how machine learning can be used to enable SUs to interact with the wireless network environment.

2.3.1 Overview of Cognitive Network

The term "cognitive network" has different interpretations with different emphasizes on the node behavior, operational objective, or the scope of the target problem. The following are examples of such definitions:

- According to Mitola who created the buzz word "cognitive radio", wireless terminals have a cognition level if they are sufficiently computationally intelligent about radio resources and are able to do the following: (1) detect user communication requirements, and (2) provide radio resources that can meet user needs [16].
- The FCC suggested that a node having the capability to adapt to the wireless environment is referred to as a "cognitive network" [11-13].

- Simon Haykin defines a cognitive radio as “an intelligent wireless communication system that is aware of its environment and uses the methodology of understanding by-building to learn from the environment and adapt to statistical variations in the input stimuli” [14].

Although the major motivation of CN research is to manage the spectrum efficiently, CN is expected to be more than spectrum-agile. It is expected to change the conventional wireless network into a network that consists of intelligent agents that can learn from wireless environment and adapt the transmission parameter to optimize the communication performance. Spectrum agility is one dimension of its optimization parameters. Transmission parameters that may be adjusted to improve communication quality include operating frequency, modulation scheme, transmission power and communication technology [1].

CN enables spectrum sharing. Spectrum sharing allows several secondary users to share a spectrum with PUs. To utilize the spectrum efficiently, CN needs to explore the spectrum accurately and exploit it resourcefully. The objectives of spectrum exploration are to maintain statistics about spectrum status and identify unused portions of the spectrum. After detecting the unused spectrum, the decision should be made on whether and how to exploit the free spectrum [1,8,14]. Optimization and decision theory techniques can be used to determine the optimal transmission parameters. For example, to increase data transfer rate, CR may detect and switch to a new empty spectrum hole.

2.3.2 Reinforcement learning

Reinforcement learning (RL) is a sub-area of machine learning concerned with how a system administrator takes actions in different circumstances in a work environment to minimize long-term cost [48]. Let $X = \{X_0, X_1, X_2, X_3 \dots X_t\}$ be the set of possible states an environment may be in, and $A = \{a_0, a_1, a_2 \dots a_t\}$ be a set of actions a learning agent may take. In RL, a policy is any function: $\pi: X \rightarrow A$ that maps states to actions.

Each policy gives a sequence of states when executed as follows: $X_0 \rightarrow X_1 \rightarrow X_2 \dots \rightarrow X_t$ where X_t represents the system state at time t and $\mathrm{a_t}$is the action at time *t*. Given the state X_t, the learning agent interacts with the environment by choosing an action $\mathrm{a_t}$, then the system transits to the new state X_{t+1} according to the transition probability $P_{X,X_{t+1}}$ and the process is repeated. The goal of agent is to find an optimal policy $\pi^*(X)$ which minimizes the total cost over time.

2.3.3 Using RL for Resource Adaptations in Cognitive Network

In our work, we use RL for the SU to select the available channels among the licensed channels and we use it in trading scheme to specify the optimal price and size of the offered spectrum. Our objective is to improve the secondary network throughput and serve the maximum number of SUs. For example, the learning engine is used to learn the channel conditions such as error rates and PU pattern usage of channel in order to select a channel that provides higher throughput. Wireless environment of the secondary network has very unique characteristics that make it too difficult to develop a spectrum management scheme that predicts the dynamic nature of the environment. Therefore it is important to develop new techniques that can achieve approximately optimal behaviors without requiring models of the environment.

We propose to use RL in order to develop an intelligent user that is able to deal with conflicting objectives in wireless environment. RL is an attractive solution for this problem for a number of reasons. It provides a way of finding an optimal solution purely from experience and it requires no specific model of the environment; the learning agent builds up its own environment model by interacting with environment [4].

2.4 Summary

Many factors make spectrum management in CN a challenging problem, and require extra attention during the spectrum allocation. From the architecture point of view, communication overhead degrades the performance of the distributed architecture. Moreover, the detection results of spectrum contain redundant information. Many SUs collect the same information about the spectrum and exchange it. All neighbors' nodes coordinate among themselves for managing the spectrum. Each node should have necessary functions for networking, and thus, can also work as a router. Hence, the load on end-user devices is significantly increased, which causes higher energy consumption and low-end application capabilities to possibly mobile and energy constrained end-users. Moreover, because end-user devices have extra functions, the cost of devices is higher than other networks. The centralized architecture has many drawbacks. These drawbacks include scalability, centralized entity failure, excessive load at server and feasibility. Exchanging detection result would still take a lot of time.

Channel assignment for SUs is not a trivial task in CN. Many characteristics can be used to evaluate available channels. These characteristics include noise, interference level and wireless link errors. Combining these factors in a decision function is a challenging problem.

In CN, any change in the spectrum status should be perceived and SUs should be updated in short time. Moreover, new algorithms should be developed for fair spectrum sharing between SUs and between PUs. Spectrum status should be generated accurately and interference with PUs should be prevented in overlay scheme. PUs need a control policy to choose the optimal price and size of the offered spectrum for trading. The objective is to adapt the size and price of spectrum in order to continuously maximize PUs' net revenues while maintaining PUs' QoS and QoS for SUs.

In all to all, to exploit the spectrum efficiently, novel spectrum management algorithms need to be developed such that they provide the following functions [5]:

1- Spectrum sensing: an important requirement of management scheme is to detect the unused spectrum speedily and accurately.
2- Spectrum evaluation: the free spectrum should be evaluated first. Then, according to the assessment, the appropriate channel should be selected for the current SU.
3- Awareness and adaptation: the operating parameters of SUs (such as frequency, power, modulation, etc) should be rapidly reconfigured to the changing communication requirements and spectrum conditions.

4- Learning and reasoning: the cognitive engine should be able to analyze spectrum status and to understand the wireless environment, to manage how the cognitive radio reacts to the environment changes, and to attempt to achieve various communication objectives such as interference avoidance, QoS and fair spectrum sharing, etc.
5- Considering QoS for PUs and SUs: any sharing scheme should protect the rights of PUs for accessing spectrum without any interference. The sharing policy should also support the QoS for SUs.

Chapter 3: Spectrum Management using Overlay access scheme in Cognitive Wireless Mesh Network

Although considerable research has been conducted on spectrum management, it is still considered an important open problem. In this Chapter, we propose a new spectrum management scheme that supports local and global management for a wireless network. Our scheme is based on cluster architecture which is a management model where SUs are divided into clusters and a cluster head is chosen for each cluster. The MR for each cluster manages spectrum information by keeping the required information at cluster level and for the whole network. SUs identify and determine the conditions (spectrum and location) in the radio environment through the awareness function. The radio environment data is fed into cluster head, which is the decision maker of the spectrum. Based on the database of the spectrum a cluster head analyzes the radio environment and manages how the SUs react to wireless environment. Our scheme provides robust operation against any cluster head failure, as well as client's mobility.

3.1 Cognitive cycle in the Cluster-Based Architecture

The cognitive cycle is the set of states, actions and interactions that a SU makes in order to know the outside wireless environment with the aim to adapt to the changes in the network conditions [1].

In the CN, the cognition cycle is conducted in two levels: local (cluster) and global (the whole network). In our scheme, the cognition cycle is managed as follows:

- Step 1: Every SU senses spectrum and then makes a final decision about spectrum status.
- Step 2: All SUs send their detection results to a cluster head.
- Step 3: The cluster head combines detection results from all SUs and generates a final spectrum allocation vector.
- Step 4: Cluster heads in the CN exchange allocation vectors and then a final decision is made at each cluster head using logical OR operation.
- Step 5: A new status of spectrum is broadcasted to all cluster members.

Upon receiving a new spectrum data, SUs either continue using the same communication parameters or adjust some of them such as power transmission and switching to another channel. Our aim is to minimize the delay, maximize the throughput and improve system adaptability against failures in addition to mobility support. A detailed scheme for spectrum management is introduced in this Chapter.

3.2 System Architecture

In our system model, we assume two types of users: primary and secondary users. PUs are owners of licenses to access the spectrum. They are not cognitive radio aware, i.e. they do not need to exchange information with SUs unless they want to trade part of their spectrum. PUs' spectrum is divided into non-overlapping channels which is the basic unit of allocation. SUs form a wireless mesh network which is overlaid on PUs network. CN uses PUs’ spectrum to build the secondary network for SUs. It has several mesh routers (MRs) and mesh clients (MCs). MRs and MCs are referred to as SUs in this thesis. MRs have fixed locations whereas MCs are moving and changing their places arbitrarily. We assume MCs can measure PUs’ signal powers accurately. We present the architecture of the secondary network and the signaling protocols in this Chapter.

3.2.1 Forming Clusters in the CN

SUs form clusters in the secondary network. Each cluster can be imagined as a WLAN, where MRs play the role of access point and the MCs act as nodes served by MRs. MRs use the PUs’ spectrum to serve MCs. The available spectrum for each MC depends on its location. Spectrum holes are changing as MCs are moving. MCs need information about the MRs to select their cluster head. An MC executes a distributed algorithm to join a cluster. Our algorithm is beacon-based, in which the signal strength of beacon is measured by MCs to choose its MR. At set up time, each MR broadcasts a beacon that contains its ID. Upon receiving beacons from different MRs, a MC measures the signal strength of each beacon to choose its MR. The MC stores the ID and the signal strength for each MR in a table. We assume each node has a unique ID. After a certain period of time, each MC sends an association request to the MR with the strongest signal. When an MR receives an association request, it registers the ID of MC and broadcasts the final list to all MCs in the cluster. Cluster-head (MR) manages inter-cluster communication and the available spectrum. The network architecture consists of several clusters as seen in Fig. 3.1.

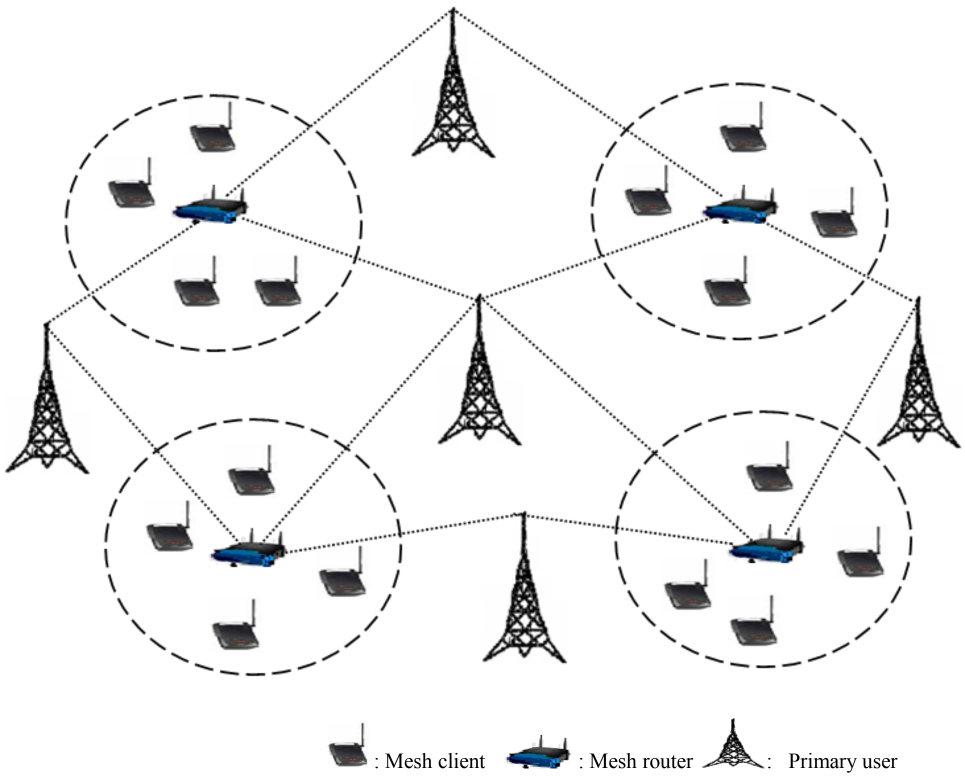

Fig 3.1.Network architecture

In our system, cluster coordinators periodically exchange spectrum data to keep themselves updated about the status of the entire spectrum. Cluster coordinator may fail for many reasons. If any user observes that its MR does not send any data during a time t, it sends a message to all cluster members about the MR failure. After receiving MR fail message, each MC looks up its table and subscribes to a cluster that has a MR with the strongest signal. In the case a cluster member does not send or receive any data during time t, a cluster head removes this user from its table and updates cluster members.

The communication quality between user and its MR may be degraded as the distance between them increases. As a result, it is better for the user to switch to another cluster if they expect getting better services. In our scheme, MCs can join another cluster dynamically based on the signal strength. While node is moving, it periodically checks the MR signal strength; if it perceives that there is another MR with signal strength higher than its MR signal strength, MC informs its MR to unsubscribe and join another cluster. Cluster head informs its clients if any node withdraws from the cluster. To join a new cluster, the MC sends a request to the MR. The MR updates users about the new user if the request is accepted.

The use of clustering enhances spectrum sensing and management. The proposed scheme has the following advantages:

- High availability: availability is defined as the capability of a system to remain working in the face of a variety of potential MRs failures. Failure of a MR will not cripple the network. If any MR fails, the effected users can subscribe to another cluster in the network.
- Scalability: by distributing the user into clusters, the communication load will be distributed onto multiple channels. Hence, better bandwidth utilization is possible.
- Reducing communication overhead: in distributed schemes each user should coordinate and exchange with all nodes in the network, while in our scheme users need to exchange information with the MR only. In centralized schemes, all nodes need to send and exchange information with the server. However, our scheme distributes the communication load between available bandwidth.

- Frequency reuse: Clustering supports bandwidth reusing, that is, the usage of the same band by multiple users separated by a distance, without interfering with each other.

In our architecture, the functionality of MRs differ according to the access technique. For each cluster in figure 3.1, MRs manage cognitive cycle which includes spectrum sensing, processing sensing results and allocating spectrum to MCs. MRs allow MCs to transmit and specify the strength of transmission in the underlay approach. Managing the power at the secondary network is the main function of MRs in this access scheme. In spectrum trading approach, MRs receive SUs requests' for spectrum and buy the spectrum to serve SUs.

3.2.2 Signaling Protocol for Exchanging Data in the CN

Signaling protocol is used in underlay and overlay approaches only. In spectrum trading, SUs do not need to sense spectrum and exchange its data but PU disseminates spectrum information and the required prices. An important requirement of the CN is to sense the spectrum holes accurately. In the secondary network, MRs need information about signal powers of the PUs at each channel. This information is necessary to specify the status of spectrum and to adapt to the changes in the radio environment. In our signaling protocol, two channels are used to exchange spectrum information between MR and MCs. The first channel is used to exchange the radio environment status between MRs and MCs, where the second one is used (emergency channel) for backup when the owner of the channel (PU) starts using it. According to our signaling protocol, a cluster

MR assigns all free channels for users to communicate except two predefined control channels. Control channels are selected by the cluster head and they are changed according to the status of spectrum. If a PU starts using any control channel then SUs switch to the emergency channel and the cluster head selects another and notifies SUs.

The frame structure in our MAC protocol consists of three periods: spectrum sensing period, collecting results period and processing results period. In sensing period, a MR requests MCs to gather spectrum data through a "sensing frame" that is broadcast to all cluster members. The sensing frame specifies the following:

- Duration of the spectrum sensing period.
- Duration of collecting sensing results.
- Control channel to send the results.

MCs send back ACK frame to the MR to confirm receiving a request packet. In collection results frame, each MC reports its results to the MR in the allocated slot. Next, the MR fuses the detection results and exchanges the results with other MRs. Finally, MR combines its results with other MR's results.

3.3 Spectrum Sensing

In underlay and overlay approaches, spectrum status should be specified accurately using spectrum sensing which is a binary decision between the following two hypotheses:

H_1: Spectrum is busy.

H_0: Spectrum is idle.

MCs measure the signal strengths at all channels. If the decision in an MC is H_0 then 1 will be stored at the allocation vector for the corresponding channel otherwise 0 will be assigned. The key metrics in spectrum management are the probability of detection $P_{\mathbb{d}}$ and the probability of miss $P_{\mathbb{m}}$ that are given by:

$$P_{\mathbb{d}} = p(H_1|H_1) \tag{3.1}$$

$$P_{\mathbb{m}} = p(H_0|H_1) \tag{3.2}$$

The user decides the presence of PU at a certain frequency if and only if the received signal strength is greater than a threshold γ. The received signal power is computed as follows:

$$S_r(d) = S_t(d) - PL(d) \tag{3.3}$$

where $S_r(d)$ is the received power at distance$d$, $S_t(d)$ is the transmitted power, $PL(d)$ is the path loss at distance d and it is computed as follows:

$$PL(d) = \overline{PL}(d_0) + 10n\log\left(\frac{d}{d_0}\right) + x_\sigma \tag{3.4}$$

where n is the path loss exponent, d_0 is the close-in reference distance, $\overline{PL}(d_0)$ is the average path loss at distance d_0, x_σ is a zero-mean Gaussian distributed random variable with standard deviation σ. Standard deviation σ describes the path loss model for an arbitrary location. Linear regression is used to estimate the value of σ. MC fails to detect a PU if the received power is less than γ. We assume the received power $S_r(d)$ has a Gaussian distribution. In our work, the probability of detecting a PU signal in equation (3.1) is computed as follows:

$$P_{d} = p(S_r(d) \geq \gamma | H_1) \tag{3.5}$$

Using Bayes theorem:

$$\begin{aligned} P_{d} &= \frac{p(S_r(d) \geq \gamma) p(H_1)}{p(H_1)} \\ &= p(S_r(d) \geq \gamma) \end{aligned} \tag{3.6}$$

$$p(S_r(d) \geq \gamma) = \int_\gamma^\infty \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(S-\mu)^2}{2\sigma^2}} dS \tag{3.7}$$

The miss probability in equation (3.2) is computed as follows:

$$\begin{aligned} P_{m} &= p(S_r(d) < \gamma | H_1) \\ &= \frac{p(S_r(d) < \gamma) p(H_1)}{p(H_1)} \\ &= p(S_r(d) < \gamma) \end{aligned} \tag{3.8}$$

$$p(S_r(d) < \gamma) = \int_{-\infty}^{\gamma} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(S-\mu)^2}{2\sigma^2}} dS \quad (3.9)$$

After sensing the spectrum, each user prepares the allocation vector that contains the new status of spectrum and sends it at its time period to a MR. When a timer reaches 0, the cluster head starts collecting spectrum data.

3.4 Spectrum Data Collection and Processing

In processing phase, MR solves spectrum data inconsistency and produces a final allocation vector that contains the current status of spectrum. MR receives allocation vectors from all users and combines them using logical OR operation. A decision function for our scheme can be described using the following two functions:

$$\Gamma_{j,m} = \begin{cases} 1, & S_{j,m} \geq \gamma \\ 0, & Otherwise \end{cases} \quad (3.10)$$

$$\varrho_m = \begin{cases} 1, & \exists S_{j,m} \geq \gamma \\ 0, & \forall S_{j,m} < \gamma \end{cases} \quad (3.11)$$

where $\Gamma_{j,m}$ is the decision that is taken by MC j for a channel m and $S_{j,m}$ is the measured signal power at channel m by user j. Each user j compares the signal strength at channel m to a pre-defined threshold γ.

At merging phase, MR executes the decision function ϱ_m to decide whether channel m is idle or not. An MR decides the presence of a PU at channel m if one MC detects the signal of a PU at this channel. Whenever at least one user decides the presence of the PU, the presence of the user is accepted by all MCs and none of the MCs will transmit its signal in that frequency band. Finally, cluster heads exchange spectrum allocation vector and each one combines its results with other cluster heads results using a decision function ϱ_m. The missing probability for cluster $\mathbb{c}$ that has $\mathbb{m}$ MCs is computed as follows:

$$P_{\mathbb{m}}^{\mathbb{c}} = 1 - \prod_{j=1}^{\mathbb{m}} (1 - p_{\mathbb{m},j}) \tag{3.12}$$

The detection probability for cluster $\mathbb{c}$ is computed as follows:

$$P_d^{\mathbb{c}} = 1 - \prod_{j=1}^{\mathbb{m}} (1 - p_{d,j}) \tag{3.13}$$

where $P_d^{\mathbb{c}}$ and $P_{\mathbb{m}}^{\mathbb{c}}$ are the j^{th} MC local probability of detection and probability of missing.

After merging phase, MR has knowledge about the actual spectrum allocation vector. The task is to distribute this information among all associated cluster members if the MR encounters any change in the spectrum status. The collected information about spectrum at MRs can be used for managing the whole network. Cluster coordinators exchange information periodically to improve the system performance. Upon receiving a new status of spectrum from the MR, MCs check if there is any change. Allocation algorithm is requested to assign a new portion of spectrum if new information is distinguished. If the user is satisfied, no action takes place. If MC wants to initiate new communication with another user, it requests an appropriate channel from its MR.

Based on the prior channel/spectrum assignments and prescribed policy, the MR responds with a message. In this message the MR indicates a channel that users can use for their communication, as well as another emergency channel. During communication, if a PU uses a channel then MCs should release the channel immediately and switch to the emergency channel.

3.5 Performance Evaluation

In this Section, we show some simulation results to demonstrate the performance of our cluster-distributed scheme in large scale networks. For comparison the conventional method is simulated where all secondary users send their sensing results to a centralized server. Moreover the cluster-centralized scheme used in [29] is also simulated. The loads at MRs are not balanced in the cluster-distributed scheme. The performance metrics considered are:

- Throughput, which is the average rate of successful message delivery over a communication channel.
- Delay, which is the time it takes for accessing the unused spectrum. It includes spectrum sensing time, transmission time, queuing time and processing time.

The network parameters chosen for evaluating the algorithm and the methodology of the simulation are shown in Table 3.1.

TABLE 3.1

SIMULATION PARAMETERS

Parameter	Value
Number of mesh routers	10
Number of clients (secondary users)	100
Number of primary users	4
Total number of channels	16
Number of messages per client	Random
Type of interface per node	802.11 b
MAC layer	IEEE 802.11 b
Path loss exponent	4
d_0	5 m
Transmission power	0.1 watt
Packet size	512
λ_1 (arrival rate of SUs class 1)	1
λ_2 (arrival rate of SUs class 2)	1
Blocking probably constraint for a PU	0.015

Note that some of these parameters are varied according to the evaluation scenarios. We run each experiment 100 times and compute the average for each result.

3.5.1 Scalability of the proposed scheme

Simulations are done to investigate the effect of the number of SUs on the probability of detecting a primary user. Fig. 3.2 shows the detection probability for different numbers of SUs in a cluster.

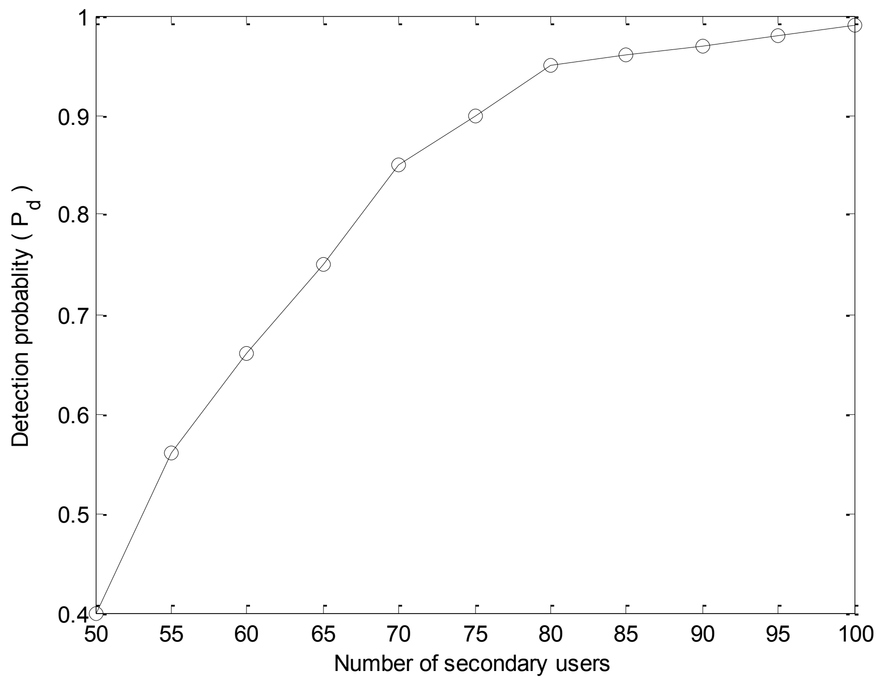

Fig 3.2 : Probability of detecting a primary user by SUs

It can be seen from Fig.3.2 that the detection probability certainly increases with the increase of the number of the SUs. Although increasing number of users improves the spectrum sensing capability, the performance of the network may be decreased. The throughput comparison of the three different schemes is shown in Fig.3.3. The overhead of using control channels is considered in the simulation. The figure shows that the throughput increases as the number of SUs increases but after certain number of users the throughput starts decreasing. By increasing the number of SUs the unused spectrum is utilized efficiently which improves the throughput. However, after a certain number of users the time overhead that is required to exchange and process data reduces the likelihood of utilizing unused spectrum.

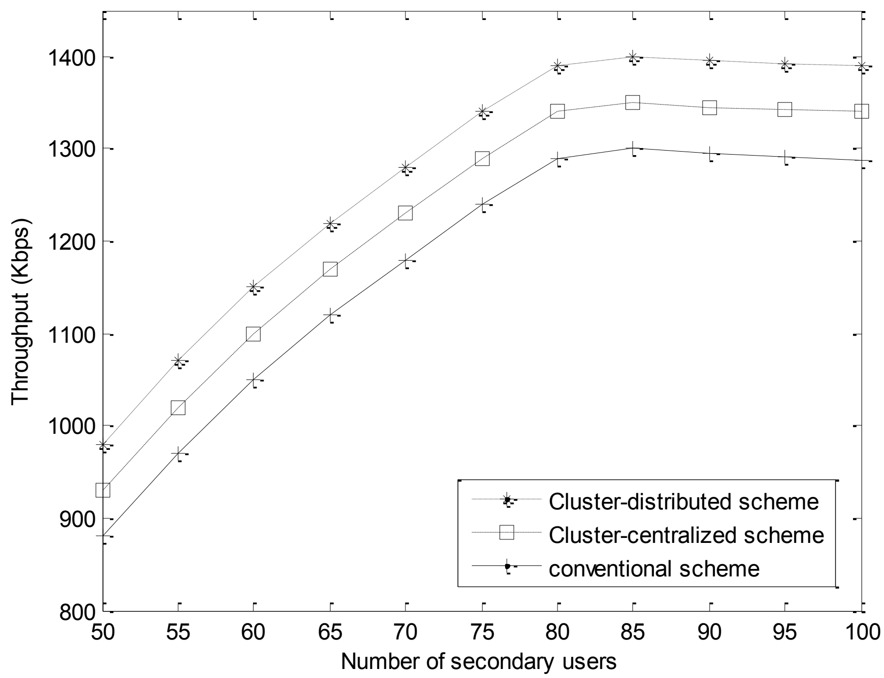

Fig 3.3 : Throughput comparison for the three schemes

The speed of spectrum sensing and processing time of spectrum detection results are the most important factors for the success of CN. The unused spectrum should be utilized as soon as possible before the PU resumes its activities. Our scheme needs less time overhead because there is no contention for the pre-defined control channel which is used for exchanging spectrum allocation vector. In the scheme used in [29] cluster heads contend for a control channel. Moreover, in the conventional method all SUs contend for a control channel to send spectrum detection results.

The comparison of the time overhead for the considered schemes is shown in Fig 3.4. In the scheme used in [29], because all detection results are merged at cluster heads, the reported delay is smaller than the conventional scheme. However, our scheme has the minimum time delay because there is no contention for a control channel between cluster heads as in scheme [29].

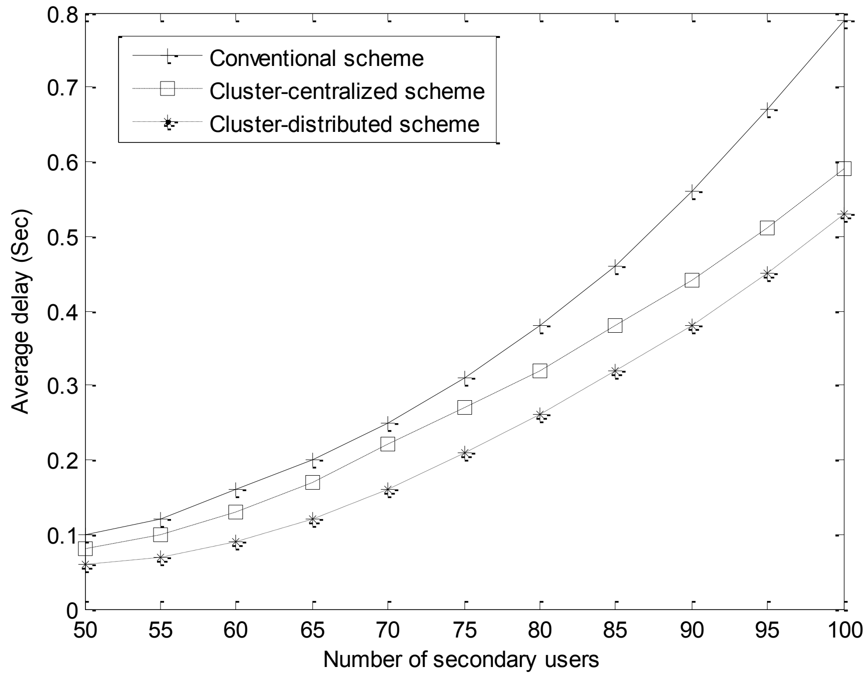

Fig 3.4 : Time delay comparison for the three schemes

3.6 Cluster Formation based on Load Balancing

In the secondary network, we cluster the MCs around a few MRs. MC selects a MR that has the strongest signal for coordination by sending an association request. Each MR collects the association requests and constructs a list of all MCs in the cluster. MRs incur cost of serving MCs. The load at each MRs is balanced based on service cost of MCs. The cost includes cost of communication with MCs and the load at the MRs. To balance the load, each MR calculates the cost of serving its MCs. After that, the cost is sent to all MRs in the network. After receiving the costs from all MRs, each MR starts accepting its MCs members based on the service cost. Finally, all MCs in a cluster are informed about the MR ID and other MCs IDs in the cluster. Each MC is associated to one MR in the secondary network. The set of MCs that can be served by a MR Y is denoted by Y_c. MC j belongs to Y_c if it satisfies the following criteria:

$$S_j^Y > \gamma \tag{3.13}$$

where S_j^Y is the power of the received signal from MR Y at MC j and γ is the detection threshold. S_j^Y is computed using equation (3.3). Each MC in the Y_c is associated with communication cost. Each MR creates a list that contains a set of MCs and the cost associated with each MC. The list is exchanged between all MRs in the system to gain information about MCs in the secondary network. Two kinds of MCs can be defined in the system:

- Unique MCs (U_Y) : the set of MCs which can be served only by a MR Y.
- Common MCs ($\check{C}$) : the set of MCs that can be served by more than one MRs.

In our model, we define the degree of MC as the number of MRs that can serve this MC. The first step toward balancing the load at the MR is to construct a list of unique MCs and the common MCs. We consider MC j belongs to the unique set of MR Y if it satisfies the following condition:

$$S_j^Y > \gamma \wedge S_j^{\acute{Y}} < \gamma\ , \quad \forall Y, \acute{Y} \in \mathbb{M}, Y \neq \acute{Y} \tag{3.14}$$

where $\mathbb{M}$ is the set of MRs in the secondary network. A unique node should join the MR that can serve it. The load on a MR Y is a function of communication load C_L^Y and processing load P_L^Y and is defined as:

$$L_Y = f(C_L^Y, P_L^Y) \tag{3.15}$$

The processing load on a MR results from processing spectrum data and managing this data. Communication cost at MR Y is computed as the summation of communication costs of all cluster members as follows:

$$C_L^Y = \sum_{\forall\, j \in Y_c} C_j^Y \tag{3.16}$$

where C_j^Y is the cost of communication among MR Y and MC j. In our model, we assume all MCs require the same data rate. Therefore, C_L^Y and P_L^Y are directly proportional to the size of the cluster (i.e. number of MCs in the cluster). Thus we have to balance the number of MCs in each cluster to assure that each cluster has the same load. Our goal is to keep the load at each MR close to the average load of all MRs. To achieve this, we choose our objective function that minimizes the variance of load of each MR in the network. The main objective of our algorithm is to balance the load as follows:

$$min_L \frac{\sum_{Y \in \mathbb{M}} (L_Y - \overline{L})}{\mathbb{M}} \tag{3.17}$$

where L is a feasible assignment of load (i.e number of MCs assigned to the MR) at each MR, $\overline{L}$ is average load of the system and $\mathbb{M}$ is the number of MRs in the system. The first step toward balancing the load is to assign MCs in the unique set to their respective MRs and compute the load. Besides considering the load as factor for balancing the load, our algorithm considers the quality of communication among MRs and MCs. Our algorithm tries to find the optimal assignment of load while maintaining the QoS for MCs by assigning each MC to the MR that has the strongest power at this MC. Our balancing algorithm works as follows:

Algorithm 3.1 Balancing load at MRs

Parameters:

Assign(j, Y), a function that maps MC j to MR Y.

Sort (Č), a function to sort a list of MCs in the common set based on the degree of MCs in increasing order.

FindHighestSignalPower(Č(1), $\mathbb{X}$) a function to return MR that has the strongest signal at MC Č(1) and does not belong to the set $\mathbb{X}$.

D_ Assign(Č(1), Y) remove MC Č(1) from MR Y cluster

τ: *is the threshold load variance.*

$\mathbb{M}$: *is the set of MRs.*

Begin
For *all* $Y \in \mathbb{M}$
    Define U_Y
End for
Define Č
For *all* MC $j \in U_Y$
    Assign(j, Y)
End for
*Sort (*Č)
While *notEmpty(*Č*)*
    $\mathbb{X} = \emptyset$
    found=false
    While *not found*
        *Y=FindHighestSignalPower(*Č(1), $\mathbb{X}$)
        Assign(Č(1), *Y)*
        Compute $\overline{L}, L_Y$
        $V = \frac{\sum_{Y=1}^{N}(L_Y - \overline{L})}{N}$
        If $V > \tau$
            $\mathbb{X} = \mathbb{X} \cup Y$
            D_ Assign(Č(1), *Y)*
        Else
            found=true
        EndIf
    End while
Č = Č − Č(1)
End while
End

It is clear that the MC joins the cluster which minimizes the load at the system. Fig 3.5 shows the flowchart for the balancing scheme.

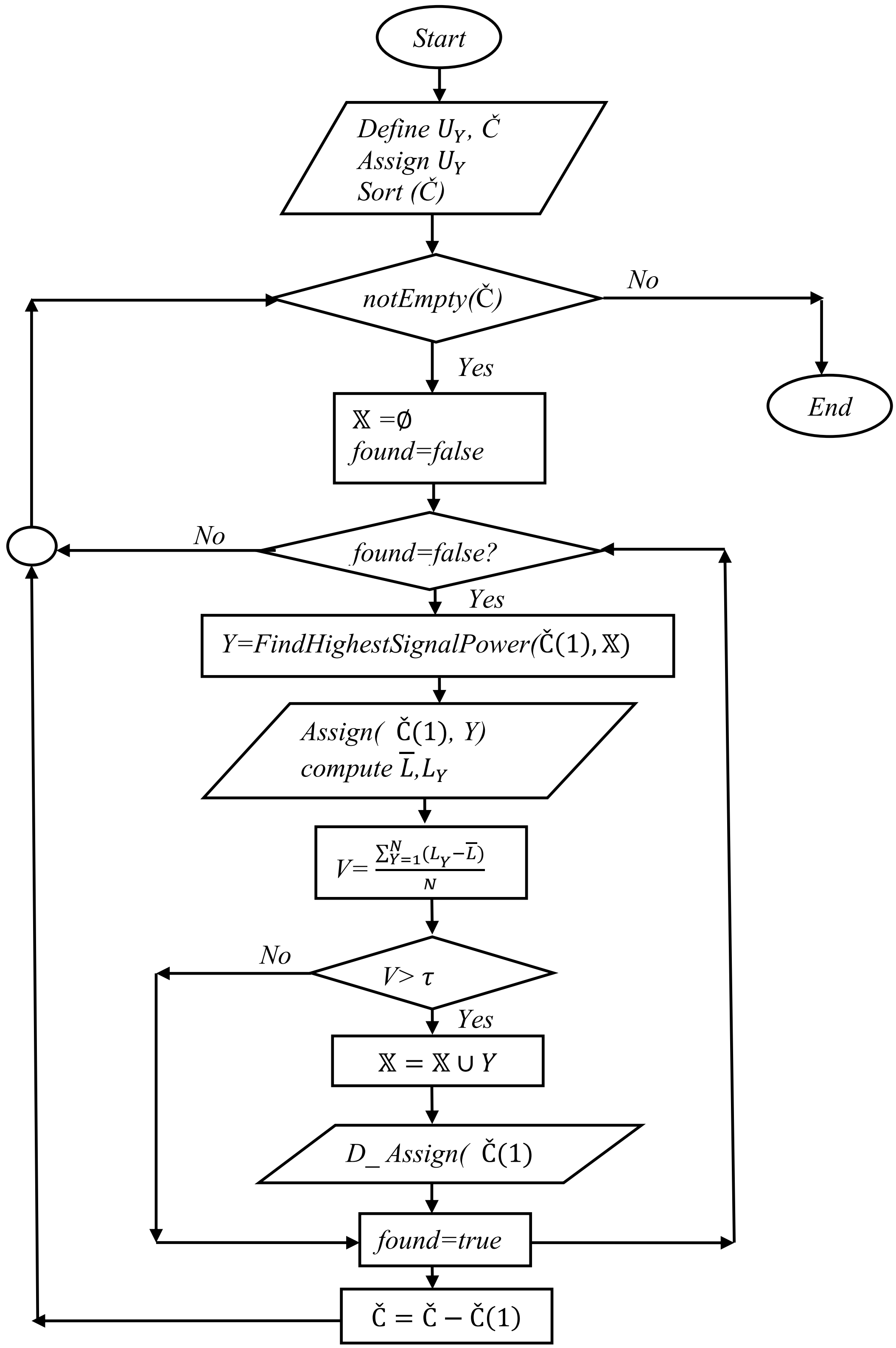

Fig 3.5: Flowchart for the load balancing scheme

3.6.1 Load-balanced Scheme Performance

In this Section we show some simulation results to demonstrate the performance of our scheme in large scale networks. For comparison the cluster-centralized scheme and our cluster-distributed scheme are simulated. Throughput comparison of the three schemes is shown in Fig 3.6. It is clear that the Load-balanced scheme outperforms other schemes because the load at the heavy-duty MR is distributed to the MRs in the network. Hence, all MRs work concurrently to serve MCs and no MR is idle. For other schemes, because the load is not distributed among MRs, some MRs serving many users while other serve less which increase the delay at heavy-duty MR.

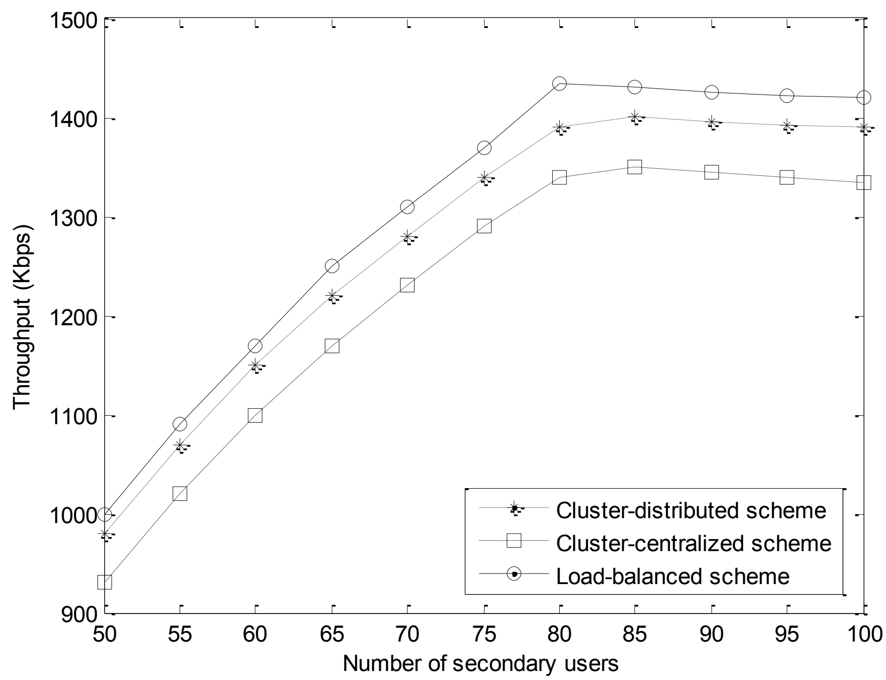

Fig 3.6: Throughput comparison for the three schemes

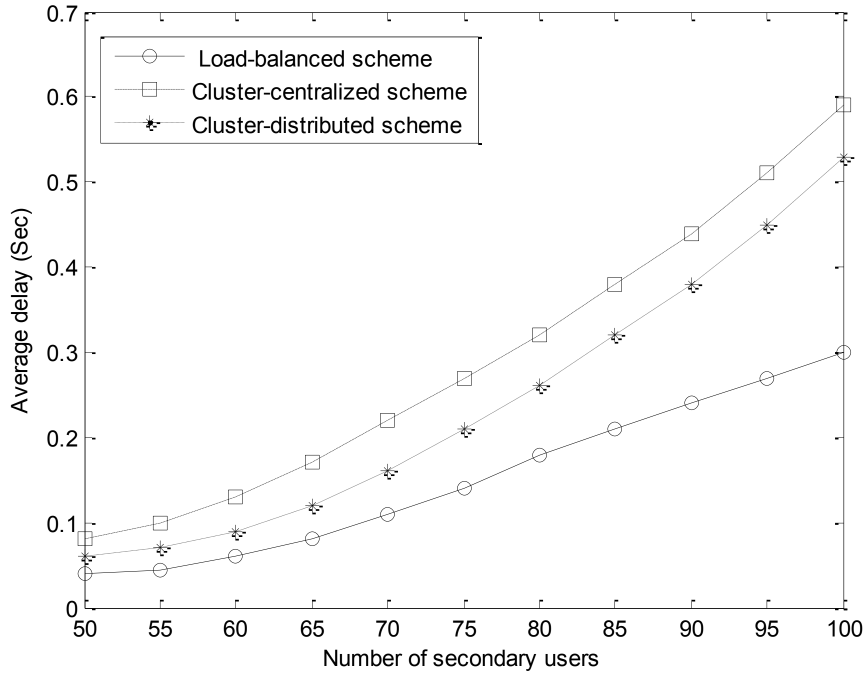

Fig 3.7: Time delay comparison for the three schemes

Our algorithm directs MCs' requests to the MRs that has the least load and therefore is capable of providing the fastest service time and achieve higher throughput. In the cluster-distributed scheme, while some MRs are busy serving MCs, other MRs has less load. Cluster-centralized scheme suffers from contention at the common channel which is used by MCs to send spectrum data to the main server. This contention increases the delay of processing spectrum and postpone allocating spectrum for MCs. The comparison of the time delay for the considered schemes is shown in Fig 3.7. It is clear, our scheme has the minimum time delay and it needs less time overhead to access the unused spectrum.

Unbalanced clusters create more contention at some of the MRs while other MRs are idle. In the cluster--centralized scheme, cluster heads contend for a control channel to send spectrum detection results. Moreover, in the cluster-distributed scheme, while some

MRs have large load and serve more users, other MRs have less load. Unfortunately, the cluster-distributed scheme ignores balancing the load at MRs. For example, all MCs may associate with a single MR due to its closeness, ignoring other MRs that are farther away but much less utilized. In other words, MCs by default associate to the MRs with the highest signal strength to get better service. Balancing the load takes full advantage of the available network resources.

To study the sensitivity of throughput to the standard deviation of load, we plot the reported throughputs for different values of standard deviation of load. It is clear from Fig. 3.8, when the system becomes more strict to the deviation of load the reported throughput is increased.

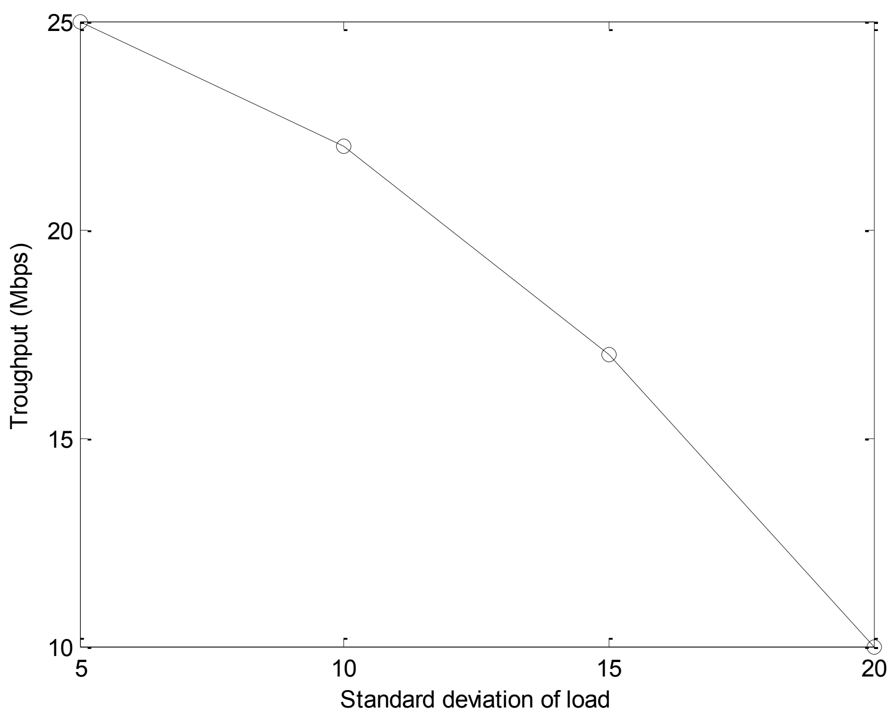

Fig .3.8: Throughput comparison for different values of load standard deviation

3.7 Summary

An efficient scheme for spectrum management is proposed. Our simulation results show a significant performance improvement with dynamic clustering scheme. Compared to the traditional schemes that do not consider accessing time to unused spectrum, our scheme has the advantages of requiring less bandwidth for managing spectrum and adapting to the radio environment. The approach presented permits all users to detect the entire spectrum and send their results to MR. Because all users sense the spectrum, the scheme allows users to detect the existence of primary user during sensing phase. The scheme is robust against any router failing. Coordination traffic congestion that resulted from coordination messages is reduced by organizing users into clusters. The scalability is also guaranteed by organizing the users into cluster. In this thesis, we also wish to consider balancing the load between cluster heads, other heuristics to choose a cluster such as cluster size. Secondary network is divided into clusters and the load at each cluster head is balanced to minimize the delay and maximize throughput. Simulation results have demonstrated the efficiency of balancing MRs load in the cognitive network. The results show a significant performance improvement with the dynamic balance that is performed based on the load traffic at MRs. Compared to the cluster-centralized scheme and our cluster-distributed that do not consider balancing the load at MRs, our load-balanced scheme has the advantages of requiring less time overhead for managing spectrum and adapting to the radio environment. The presented approach permits all users to detect the entire spectrum and send their results to MRs. Because all MRs have the same load of serving users, the network resources are fully utilized which enable the scheme to outperform other schemes in terms of throughput.

Chapter 4: Spectrum Allocation in Cognitive Wireless Mesh Networks

In this Chapter, we focus on using an underlay approach to serve SUs in the secondary network. In CN, SUs can share the spectrum with PUs on a non-interfering basis. The main challenge in CN is how to implement an efficient optimal control policy that can allocate spectrum and transmission powers for the SUs efficiently and how to adapt these resources to the changing network conditions. The power management scheme should control the SUs powers in such a way that their data communication rate is not affected. SUs power cannot be dropped indefinitely but it should be bounded such that the quality of service (QoS) for the SUs is still supported.

Our objective is to serve a maximum number of users and support their QoS while protecting the PUs' rights of using the spectrum exclusively. Due to the direct relationship between the data rate and the quality of the communication channel, we propose a new spectrum allocation scheme that exploits the physical properties of the channel to achieve better performance. In addition to consider QoS for users, our scheme uses several heuristics for selecting channels that meet users requirements. These heuristics include channel error rates, PUs activities, channel capacity and channel adaptation time. Performance evaluation of the proposed scheme shows that the scheme is able to support additional SUs traffic while still ensuring PUs QoS.

4.1 Underlay Scheme Requirements

In this approach, SUs can coexist with PUs. SUs can start transmission if they do not harm any PU. The PUs do not need to know about the presence of SUs. SUs have to periodically monitor the PUs interference threshold and vacate the spectrum as soon as their signals interfere with PU signal.

The main challenge in the underlay approach is how to design an efficient and adaptive channel access scheme that selects a suitable channel for SUs. The selected channel should be able to meet the QoS requirements for the SU applications. Another challenge is how to manage the power in the secondary network. An efficient design is one that tries to maximize the secondary network performance while avoid disturbing PUs transmissions. Another challenge is how to manage the power in the secondary network. Radio environment of the secondary network has very unique characteristics that make it too difficult to develop a power management scheme that predicts the dynamic nature of the environment. Therefore it is important to develop new techniques that can achieve approximately optimal behaviors without requiring models of the environment. We formulate the problem of power management in CN as a cost minimization problem. Such a formulation allows reinforcement learning (RL) to optimize the spectrum allocation problem.

4.2 Challenges for Channel Assignment in the CNs

CNs have some unique properties over the conventional wireless network. In this Chapter, we present the main challenges of spectrum allocation in CNs. Although there exists a significant amount of research on problems related to spectrum sensing and spectrum sharing in cognitive wireless mesh network [31-36], QoS provisioning for communication in these networks has not sufficiently been explored. Many of the existing solutions proposed for communications in wireless network are inadequate to CNs due to the following:

- Resource constraint: in CNs, the PUs have the priority to use their own channels all the time. PUs' sudden access to its channel force SUs to release the channel as soon as possible and to terminate their ongoing communication. In CNs, SUs should adapt to their communication parameters based on the available spectrum. Since the available spectrum changes over time, guaranteeing QoS in this environment is a challenging problem.
- In the CN, sometimes SUs avoid accessing channels during good channel conditions due to the priority of PUs flows.
- Spectrum mobility: SUs change their channels for many reasons such as avoiding interfering with PUs, and due to PUs activities. Channel assignment should select a new channel that has the shortest adaptation time and able to fulfill user requirements.
- Variability in channel quality: the quality of the channels is subject to temporal changes due to the dynamic radio environment. Spectrum analysis enables the characterization of different free channels, which can be exploited to choose the appropriate channel to the user requirements.
- Spectrum availability: in CN, SUs have to specify the unused channels and monitor the PU while they are accessing the PU channel.

- Optimum channel: selection of the optimum channels to use based on the radio environment information provided by SUs.

4.3 Network Overview

In this Section, we present our assumptions. SUs form a CN which is overlaid on a PU's network. The network is assumed to consist of W PUs and each PU has a set of K channels that are assigned to it in advance. The secondary network has $\mathbb{B}$ MCs and$\mathbb{M}$ MRs. MRs manage accessing to the free spectrum by accepting or rejecting MCs requests. MR specifies the transmission power of each MC in the CN. MR dynamically assigns spectrum to the SUs and all of them have the maximum and minimum required power for transmission.

We assume that the PU and the SU arrival processes follow Poisson process. The data rate (D_i) for MC i request at time t is characterized by:

- The required bandwidth,
- Poisson request arrival process with rate λ.

4.4 Spectrum Sharing Using Underlay Appraoch

In our model, we define the following components for MR y:

- Spectrum allocation vector SP_y:

  $SP_y = \left\{SP_y(m) \,\middle|\, SP_y(m) \in \{0,1\}\right\}$ is a vector of spectrum status. If $SP_y(m) = 1$ then channel m is not available currently.

- Interference vector I_y:

  $I_y = \left\{ I_y(\hat{y}) \,\middle|\, I_y(\hat{y}) \in \{0,1\}\right\}$is a vector that represents the interference among MR y and other MRs; if $I_y\,(\hat{y}) = 1$ then MR y and MR $\hat{y}$ cannot assign the same channel for their clients simultaneously.

- Channel throughput T_y:

  $T_y = \left\{T_y(m) \,\middle|\, T_y(m) \in \{0,\infty\}\right\}$ describes the throughput of MR y channels; $T_y(m)$ is the throughput that a MRgets when it assigns channel m to one of its clients. We call SP a feasible assignment if the assignment meets the interference constraint. The objective of our channel assignment is to maximize throughput of CN and to protect PUs against MCs activities. This problem can be formulated as a non-linear integer problem as follows:

$$max_{SP} \sum_{y=1}^{\mathbb{M}} T_y^t\, SP_y \tag{4.1}$$

subject to $\sum_{y=1}^{\mathbb{M}} SP_y \leq WK,$

$$SP_y(m) SP_{\hat{y}}(m) I_y\,(\hat{y}) = 0$$

where T_y^t is the transpose of T_y. The first constraint states that the capacity of the secondary network (size of spectrum) should be less than or equal the capacity of the primary network (PUs' network). The second constraint reveals that MR y and MR $\hat{y}$ cannot assign the same channel (m) for their clients simultaneously because they will interfere with each other. Any SP that includes assigning channels to interfering MCs is excluded from the search space of the optimal SP. Another objective of our algorithm is to maximize spectrum utilization as follows:

$$max_{SP} \sum_{y=1}^{\mathbb{M}} SP_{y}. \tag{4.2}$$

In this objective, we try to serve the maximum number of MCs.

- Interference threshold vector F:

  $F = \left\{ f_i \,\middle|\, f_i \in \{0, \infty\} \right\}$ describes the interference threshold of PUs; f_i is the interference that i^{th} PU can tolerate. The aggregate interference level at the PU i should not exceed a predefined f_i as follows:

$$\sum_{j=1}^{\mathbb{B}} S_r^{(j,i)} \leq f_i, \forall i \epsilon \{1,2,3 \dots W\} \tag{4.3}$$

where $S_r^{(j,i)}$ is the j^{th} MC signal power received at i^{th} PU and it is computed using equation (3.3). The probability (p_j^i) of interfering with PU i when j^{th} MC transmits is computed as follows:

$$p_j^i = p(S_r^{(j,i)}(d) \geq f_i), \tag{4.4}$$

$$p(S_r^{(j,i)}(d) \geq f_i) = \int_{f_i}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(S-\mu)^2}{2\sigma^2}} ds. \tag{4.5}$$

The probability of avoiding interfering with PU i is computed as follows:

$$p(S_r^{(j,i)}(d) < f_i) = \int_{-\infty}^{f_i} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{(S-\mu)^2}{2\sigma^2}} ds. \tag{4.6}$$

4.5 RL based Model for Power Management in CN

We present our formulation of the spectrum sharing problem in this Section. MRs are equipped with FIFO queues of size QS. MRs assign channels to MCs based on their requirements, the received power at receiver, and the PUs rights of not experiencing any interference. An MR uses a control policy to decide which channel assigns to which MC. The request is added to the queue if the required power will interfere with any PUs. The request is served if its power does not exceed any interference threshold, and if the received power at receiver (MC) is sufficient for communication. However, the request is rejected if the queue is full.

4.5.1 Problem Statement

In this work we use RL to extract the optimal control policy which helps MRs to manage MCs power in the CN so that the long-term measure of the secondary network throughput is maximized and at the same time the PUs are protected against interference. The main challenge facing a MR is to satisfy the following conflicting objectives: satisfying MCs while avoiding interfering with PUs. When the MC request is accepted it can receive and transmit and these actions satisfy the MCs requirements. However, when the request is queued, MC cannot transmit or receive traffic. As a result the QoS of the MC is degraded and other MCs in the queue will experience latency. Nevertheless, this action protects the right of the PUs to use the spectrum exclusively. If the MC request is admitted then MR has to select a suitable channel that meets the MC QoS.

Selecting a channel for an MC is not a trivial task. Assume we have K free channels and V requests; we attempt to develop an intelligent channel assignment scheme that maps the available channels to the SUs with the goal of avoiding using the busy channels and minimize the interference at the CN for maximizing the secondary network throughput. There are H possible ways to assign the K channels:

$$H = \frac{K!}{V!(K-V)!} \tag{4.7}$$

4.5.2 Reinforcment Learning model

In this Section, we define RL model applicable to control the power of MCs in the CN. For the basic formulation, we describe the elements that facilitate the definition of the RL model. These elements are states, actions, transition probability and cost function.

4.5.2.1 State Space

For power management, MR adopts a policy that is state-dependent rather than static, which means that the decision to admit or reject MC request to transmit depends on the current state. In our work, the state of the system X_t represents the number of accepted MCs requests in the queue at time t. Let $\{X_t, t \geq 0\}$ denote a random variable which represents system states; X is the state space. All possible states are limited by the following constraints:

- $\sum_{j=1}^{\mathbb{B}} S_r^{(j,i)} \leq f_i$, $\forall i \epsilon \{1,2,3 \ldots W\}$
- $X_t \leq QS$

where QS is the queue size. The first constraint specifies that the sum of interference at the i^{th} PU should not exceed f_i. The second constraint reveals that the number of accepted MCs requests should not exceed the queue size. From a state, the system cannot make a transition if the constraints conditions are not met.

4.5.2.2 Cost Function

In this Section, we define objective function for RL. To maximize throughput of the secondary network and serve the maximum number of MCs, each MR manages MCs' power so that the total path loss at time t is minimized as much as possible. The cost function for RL is computed as follows:

$$min_{SP_y} \sum_{t=1}^{G} PL\, , \ \forall y \epsilon \{1,2,3 \ldots \mathbb{M}\} \tag{4.8}$$

where G is the time horizon. Each MR determines the transmitted power based on the interference thresholds of PUs and the requested data rate D_j. MR should check the transmitted power constraint before permitting a MC j to transmit. This constraint can be expressed as follows:

$$S_L^{(j)} \leq S_t^{(j)} \leq \min_{\forall f_i \epsilon F} f_i \tag{4.9}$$

where $S_L^{(j)}$ is the minimum acceptable signal power that can support D_j. The power transmitted by MC j is directly proportional to the received signal power at the receiver. At each state X_t, MR calculates the interference threshold at each PU as follows:

$$f_i = f_i - S_r^{(j,i)}(d), \ \forall i \epsilon \{1,2,3 \dots W\}, \forall j \epsilon \{1,2,3 \dots \mathbb{B}\}. \tag{4.10}$$

The path loss is a control parameter that a system administrator can use to achieve different objectives. Because our work concerns with QoS provisioning in CN, MR tries to find the optimal power that minimizes the path loss under QoS constraints.

4.5.2.3 State and Action Space

At each decision epoch, MR has to decide among all possible actions. In our work, when any change in the radio environment is perceived, MR has to decide whether it is possible for the MC at the head of queue to start transmission or it should wait in the queue. The action space is given by:

$$A = \{a: a \in \{0,1\}\} \tag{4.11}$$

where a =0 denotes a MC has to wait in the queue, a =1 indicates that the MR permits a MC to start transmission. The state transition probability is given by:

$$P_{X_t,X_{t+1}}(a) = \begin{Bmatrix} P(S_r^{(j,i)}(d) < \min_{\forall f_i \epsilon F} f_i) & , X_t = X_t - 1 \\ P(S_r^{(j,i)}(d) \geq \min_{\forall f_i \epsilon F} f_i) & , \; otherwise \end{Bmatrix} \tag{4.12}$$

For each policy π, the average path loss for a policy π is calculated as follows:

$$\overline{PL}(\pi) = \frac{\lim_{G\to\infty} \sum_{t=1}^{G} PL}{G}. \tag{4.13}$$

An optimal policy is a policy that achieves the minimum cost over the long run. MR adopts the optimal policy to manage MCs power. A policy π outperforms $\overline{\pi}$ if its cost is less than $\overline{\pi}$. We apply a value iteration algorithm to find an optimal policy. The optimal value function is given [48] as:

$$V^*(X_t) = \; PL + \min_{a \in A} \acute{\gamma} \sum_{X_{t+1} \in X} P_{X_t,X_{t+1}}(a) V^*(X_{t+1}) \tag{4.14}$$

The optimal policy is given as follows [48]:

$$\pi^*(X_t) = \arg\min_{a \in A} \sum_{X_{t+1} \in X} P_{X_t,X_{t+1}}(a) V^*(X_{t+1}) \tag{4.15}$$

We define an optimal policy π^* as follows:

$$\overline{PL}(\pi^*) \leq \overline{PL}(\pi) \tag{4.16}$$

4.6 Spectrum Allocation in CN

The objective of the problem described in this Section involves assigning channels from a set of free channels to a set of MCs so that the interference at PUs is minimized and MCs requirements are met.

4.6.1 Channel Quality Analysis

Recent work on channel assignment in wireless network uses capacity and interference as heuristics for allocating channels. However, other factors should be taken into account to improve the performance of the network. These factors include PU activities, channels error bit rates, and delay due to mobility. In our model, we define the following components:

- B_m^i is the probability of channel $m$that belongs to i^{th} PU to be idle. This probability can be estimated from a database that contains the idle times of the i^{th} PU. SUs monitor the PUs signals and store the busy and idle times of channels. The observed traffic information of PUs is reported to the MR. MR computes the probability for a channel m of i^{th} PU to be available for a given period of time $\mathbb{E}$ is calculated as:

$$B_m^i(t = \mathbb{E}) = \frac{\mathbb{Y}.\mathbb{E}}{\mathbb{T}} \tag{4.17}$$

where $\mathbb{Y}$ represents the number of idle times which equals $\mathbb{E}$, $\mathbb{T}$ is the length of the measurement period (history). $\mathbb{E}$ is chosen so that its value is greater than packet transmission time plus cognition cycle time (i.e. spectrum sensing time + spectrum data processing time + channels allocation time). PUs' traffic database can be used to extract some patterns and facts such as forecasting future traffic, distribution of idle and busy times, and utilization percentage of a channel.

- $\mathbb{L}(m, \grave{m})$ is the time MC needs to start using channel m when it releases channel $\grave{m}$. As pointed out previously, often SU changes its channel of operation frequently. It is essential for a channel assignment algorithm to consider the adaptation time that SU needs to start using the new channel. This time is normalized as follows:

$$\acute{\mathbb{L}}(m, \grave{m}) = \frac{\mathbb{L}(m,\grave{m})}{\max_{\mathbb{L}(x,y)\in ST}\{\mathbb{L}(x,y)\}} \tag{4.18}$$

where ST is the list of switching times between channels in the network. $\acute{\mathbb{L}}(m, \grave{m})$ and its weight are set to 1 if the MC does not change its channel.

- C_m is the capacity of channel (m) and it is computed using Shanon's formula. The normalized capacity of channel m is computed as follows:

$$\acute{C}_m = \frac{C_m}{\max_{C_i \in CH}\{C_i\}} \tag{4.19}$$

where CH is the list of channels in the PUs network.

- E_m is the error rate of channel m. Error rates for a channel changes and it depends on the modulation scheme and the interference level in the radio environment.

- $\acute{R}_m$ is the rank of channel m and it is computed as follows:

$$\acute{R}_m = \frac{\Omega P_m^n \Psi \acute{C}_m}{\acute{\alpha} E_m \theta \acute{\mathbb{L}}(m,\grave{m})} \tag{4.20}$$

where Ω is the weight of the idle time probability, Ψ is the weight of the channel capacity, $\acute{\alpha}$ is the weight of the channel error rate, and θ is the weight of the switching time. Our channel assignment algorithm sorts the free channels in decreasing order according to their rank and assigns them for the MCs. MCs are sorted according to their data rates in decreasing order. Each MC is assigned a channel if it does not interfere with PUs. Once the power received from a MC at any PU exceeds the interference sensitivity value, that user becomes a candidate for returning back to queue. Each MR collects a measurement from a radio environment and allocates free channels to its MCs using the following algorithm:

- *Step 1*: Sort the queue list *Q* which contains MCs requests in descending order according to their average data rate.
- *Step 2*: Compute the rank of channels at the list *CH* which contains channels IDs using equation (4.20).
- *Step 3:* Sort *CH* in descending order according to channel ranks.
- *Step 4:* If *CH* is not empty then assign the first channel at CH to the user at the head of *Q*. It is clear we give the priority for users who need higher QoS in terms of bandwidth.

- *Step 5:* Remove the assigned channel from *CH* and the served user from the queue list.
- *Step 6:* If *Q* is not empty go to step 4. Fig 4.1 shows the flowchart for the assignment scheme.

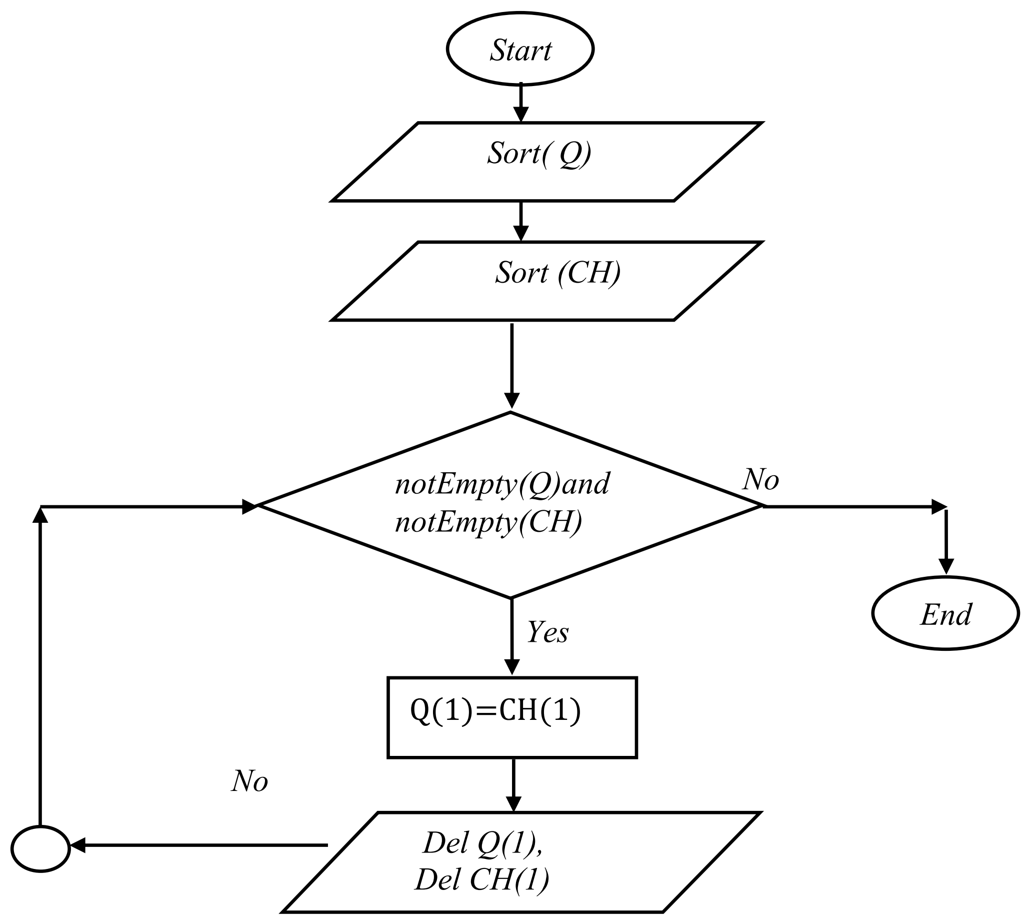

Fig 4.1: Flowchart for channel assignment scheme

where *Del* is a function to delete the first element from the target list.

4.7 Performance Evaluation

In this Section, we show simulation results to demonstrate the performance of our spectrum scheme. The key performance measures of interest in the simulations are: average cost, throughput and delay. Average cost, which represents the average of path loss per unit time and is calculated using equation (4.13).For comparison, the scheme used in [34] is simulated.

In the first experiment, we compare the performance of policy obtained through RL with the algorithm used in [34] (power management scheme). We apply the algorithm in [34] on multiple PUs and SUs.

We compute the average cost at 1×10^7 steps for different numbers of PUs and take the average cost. From Fig.4.2, we notice that the average cost increases as the number of PUs increases. By increasing the number of PUs the likelihood of interfering with PUs increases, resulting in more path loss. To protect PUs, the power management scheme should reduce the signal power when MCs transmission harms PUs. Because our scheme considers a path loss when assigning channel, it achieves the lowest cost. The scheme in [34] does not attempt to minimize the path loss when allocating spectrum.

We compare the secondary network throughput when applying the two schemes. The comparison is shown in Fig 4.3. The figure shows that the throughput decreases as the number of PUs increases. The likelihood of accessing the spectrum is decreased when increasing the number of PUs since more PUs occupy the same spectrum and PUs always have the priority to access the spectrum. It is clear from the figure that our scheme outperforms the scheme used in [34].

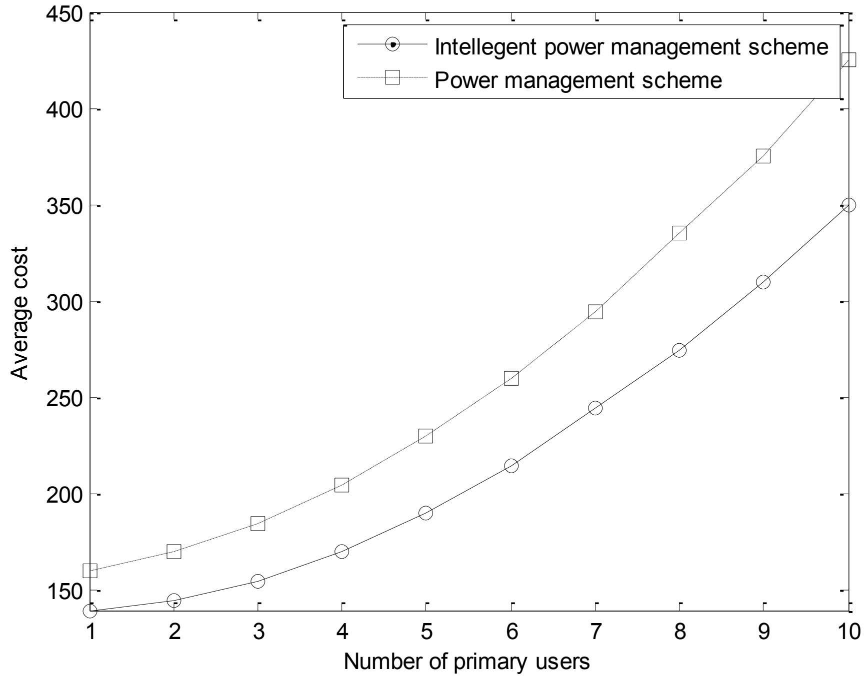

Fig 4.2. Average cost comparison for the two schemes

Our scheme considers MCs data rates and it assigns the channel that has the highest quality to a MC that needs the highest data rate. The likelihood to release a channel in our scheme is less than the scheme used in [34] because our scheme considers the activities of PUs. Our algorithm reduces the interruption of MCs significantly because it adapts to PUs' way of using a spectrum. However, the algorithm used in [34] achieves a good performance since it maintains the QoS of SUs and assigns channel based on the requirement of SUs. Fig.4.4 displays time delay comparison for the two schemes. It can be seen that when the number of PUs increases, the reported time delay of MCs increases due to the reduced available channel resources and the likelihood of releasing channels will be increased. Our scheme can access the free spectrum for longer periods of time than the other scheme because it tries to access PUs whose channels are idle more than the other PUs' channels. Although the algorithm used in [34] considers MCs' requirements when assigning channels, it neglects the PUs' spectrum usage manner. Moreover, channel switching times and channel error rates are not considered. As a result, the likelihood of releasing PU channel is higher than our scheme.

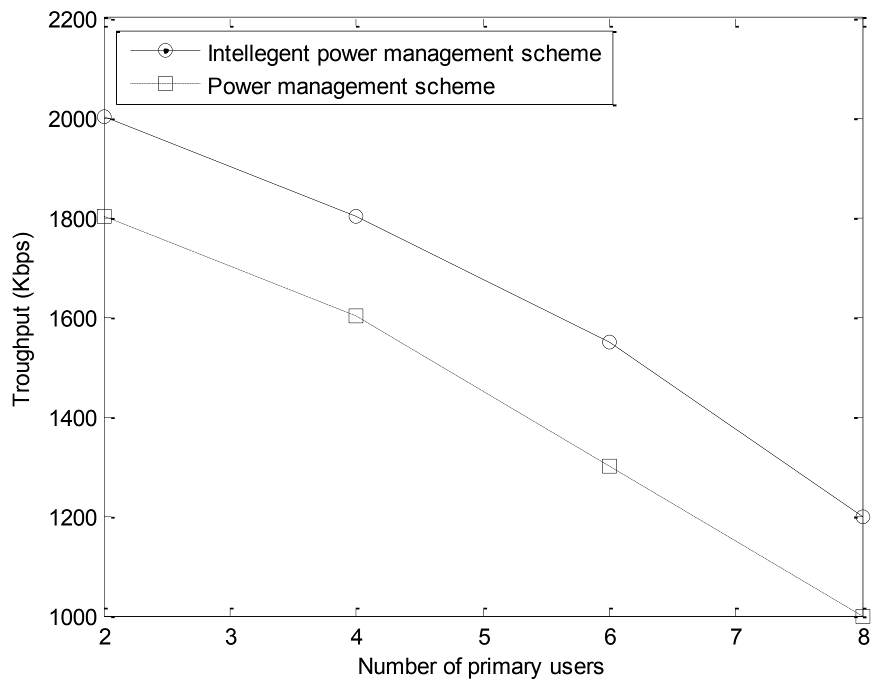

Fig 4.3. Throughput comparison for the two schemes

Fig.4.5 depicts the number of MCs that are served versus different numbers of PUs. It is clear that our scheme outperforms the other scheme. Our scheme assigns channels that have less path loss and it adapts to the pattern usage of PUs which enables it to serve more users and gives a better performance.

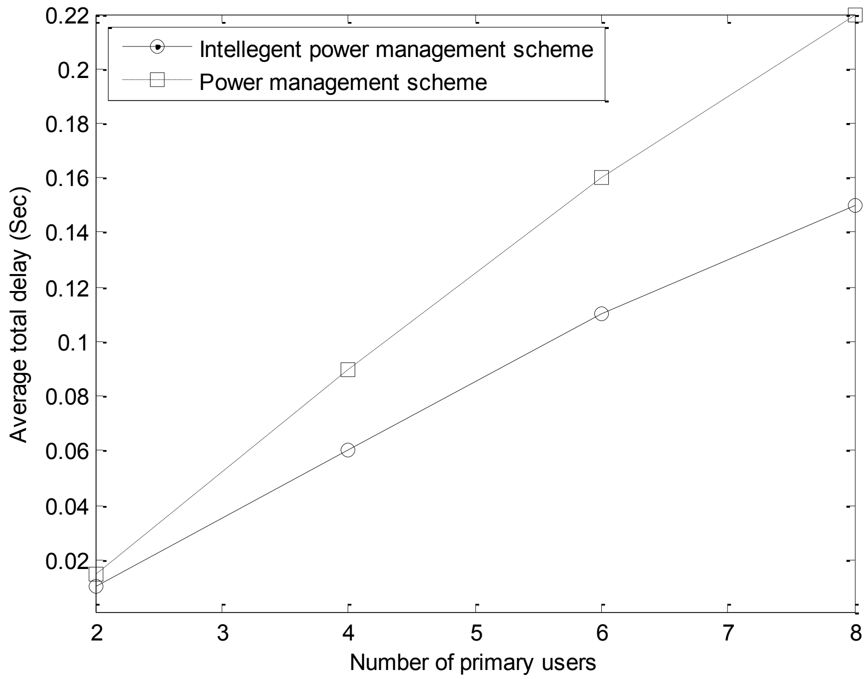

Fig 4.4. Time delay comparison for the two schemes

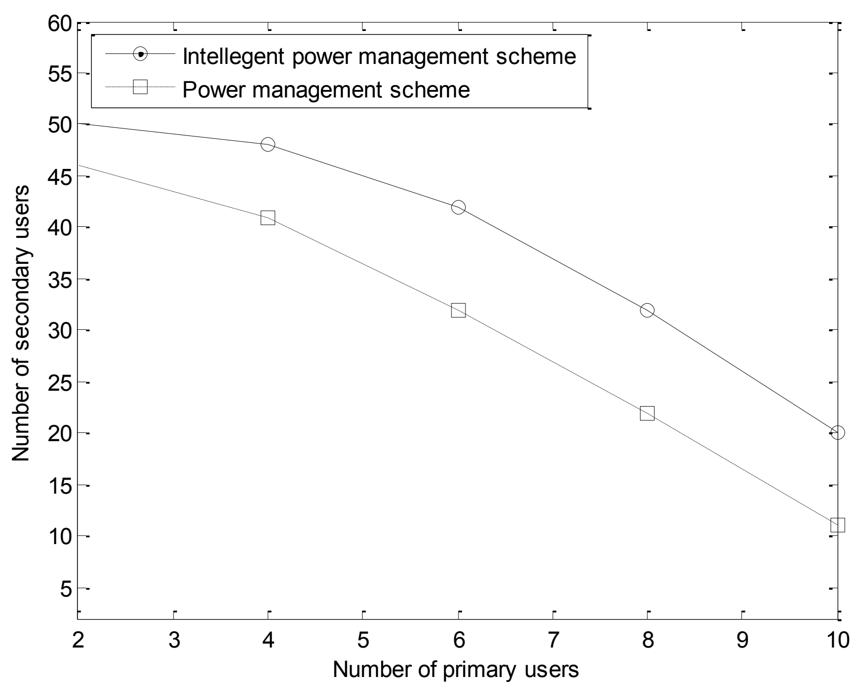

Fig 4.5. Spectrum utlization for the two schemes

4.8 Summary

In this Chapter, an efficient scheme for spectrum allocation is proposed. SUs monitor the wireless environment and report their information to MR. These information includes channel usage in a given area, PUs signal power, and interference level for PUs. Then, based on the channel information obtained from SUs, MR selects the optimal channels to use for each MC that needs to access the spectrum.

We present complete analysis and modeling of spectrum in a cognitive wireless network. We combined different characteristics of channels to decide the ranks of channels. We have shown by simulation that considering more heuristics in decision assignment function improves the throughput and spectrum utilization significantly.

RL is the model presented to obtain an optimal policy for controlling power in CN. The model will guide the MRs to adaptively serve MCs. MR tries to allow MC to transmit with the maximum signal strength but at the same time it should not interfere with PUs. This complex contradicting requirement is embedded in our RL model that is developed and implemented as shown in this Chapter.

Compared to the scheme used in [34], our scheme has the advantages of adapting to the work environment. It considers PUs manner of work and the MCs requirements. The proposed scheme has the advantages of adapting to the work environment. It considers PUs manner of work and SUs requirements.

The proposed allocation scheme also improves fairness among SUs since it balances spectrum assignments by allocating a spectrum of higher quality to heavily loaded SUs. Through building wireless systems based upon this concept, we demonstrate significant improvements in spectrum utilization and the efficiency achieved by these systems, and thus confirms the effectiveness of the proposed concept of our scheme.

Chapter 5: Profit Optimization in Multi-Service Cognitive Network Using Machine Learning

Cognitive technology enables PUs to trade the surplus spectrum and to transfer temporarily spectrum usage right to SUs to get some reward. The rented spectrum is used to establish a secondary network. However, the rented spectrum size influences the quality of service (QoS) for the PU and the gained rewards. Therefore, the PU needs a resource management scheme that helps it to allocate optimally a given amount of the offered spectrum among multiple service classes and to adapt to changes in the network conditions. The PU should support different classes of SUs that pay different prices for their usage of spectrum.

We propose a novel approach to maximize a PU reward and to maintain QoS for the PUs and for the different classes of SUs. These complex contradicting objectives are embedded in our reinforcement learning (RL) model that is developed to derive resource adaptations to changing network conditions, so that PUs' profits can continuously be maximized. Available spectrum is managed by the PU that executes the optimal control policy, which is extracted using RL. Performance evaluation of the proposed RL solution shows that the scheme is able to adapt to different conditions and to guarantee the required QoS for PUs and to maintain the QoS for multiple classes of SUs, while maximizing PUs profits. The results have shown that cognitive mesh network can support additional SUs traffic while still ensuring PUs QoS. In our model, PUs exchange channels based on the spectrum demand and traffic load. The solution is extended to the case in which there are multiple PUs in the network where a new distributed algorithm is proposed to dynamically manage spectrum allocation among PUs.

CN enables SUs to access the unused licensed spectrum using underlay, overlay or spectrum trading approaches [1-3]. In overlay and underlay approaches as described in Chapters 3 and 4 respectively, SUs access the licensed spectrum without paying any usage charge to PUs. Their access is allowed as long as their usages do not harm the PUs. For example, in IEEE 802.22, SUs can access to TV bands. Although these approaches help in solving a spectrum scarcity problem, it is not likely to be accepted in the current market since the PUs do not have any financial incentive from SUs usage of spectrum.

CN applications range from public to commercial network. In this Chapter, we focus on commercial applications of CN. Spectrum Broker (e.g., FCC in USA) sells radio spectrum through an auction process to the PUs. The PUs transfer their spectrum rights temporarily to SUs for some revenue [3]. Hence, CN presents tremendous opportunities for widely spread wireless commercial to generate more revenues through renting the unused spectrum.

Despite of obvious advantages of using CN in WMNs, there are still several issues that require more investigation such as economic factors that include PUs revenues, maintaining QoS for the PUs and SUs satisfaction. Moreover, spectrum trading presents the challenge of sharing spectrum among PUs.

In this work, we consider a CN environment where PUs can temporarily rent their spectrum to SUs to get some reward by charging for spectrum usage. For example, we can imagine a HotSpot located at popular public sites (e.g. coffee shops, airports, hotels) as a PU that owns the spectrum and provides users Internet access over a wireless local area network. The PU offers its prices for accessing unused spectrum and customers set up a short term contract with the PU. In the primary network, PUs may borrow channels from other PUs based on spectrum demand. Our design objective is to improve spectrum utilization (among PUs) and maximize revenue for spectrum owners (spectrum trading), while meeting some defined constraints.

PUs are expected to support various kinds of applications defined by their different QoS requirements. This need for the next generation of networks complicate designing their architecture and protocols. Even in the case of wired networks, no agreement has emerged and the proposed solutions are constantly challenged by the emerging services.
In this Chapter, we propose to use adaptive, machine-learning based approach to develop an intelligent radio that is able to deal with conflicting objectives in radio environment. We formulate the spectrum trading problem as a revenue maximization problem. RL is an attractive solution for spectrum trading problem in WMNs. It can provide real time control while it is in the process of learning without any supervision. The agent adapts to the environment through ongoing learning [48].

5.1 Expected Contributions of Proposed Trading Scheme

We address the problem of maximizing the PUs revenues in a commercial network by controlling the price and the size of the offered spectrum using RL. To the best of our knowledge, this is the first attempt to jointly optimize the PUs revenues and maintain QoS for PUs and SUs. In the game-theory based approach [49-53], users make decisions based on other user's strategies and do not interact with the changes in the network conditions. Moreover, none of these schemes consider the following:

- Utilizing the entire spectrum efficiently. Most of previous work assumes competition among PUs to maximize their revenues. However, cooperation among PUs to utilize the whole spectrum efficiently is neglected.
- Maximizing total revenues of PUs through exchanging spectrum among PUs.
- Using a machine learning method to extract the optimal control policy for managing PUs resources.
- Heterogeneity of the SUs. All of the above studies consider one class of the SUs while maximizing the PUs revenue. Multiple class of services for SUs are not considered. Previous studies do not attempt to find a trade-off between PUs revenue and QoS for the PUs and SUs.

The contributions of trading scheme are as follows:

- A new distributed spectrum management scheme is proposed that manages spectrum sharing among PUs.
- We analyze the behavior of PUs in a secondary market, as they make sequential decisions on what price and size of spectrum to trade, according to dynamic traffic demands and QoS for PUs and SUs.
- A computationally feasible solution to the spectrum trading problem is obtained using RL.

We show using simulations our scheme's ability to utilize spectrum efficiently. We compare its performance with the poverty-line scheme [19]. Moreover, we conduct experiments to show how our scheme can adapt to different network conditions such as traffic load.

5.2 System Overview

In this Section, we present our assumptions. We define a PU as a spectrum owner that may rent a spectrum to SUs. Each PU has K channels assigned to it in advance and it offers an adaptable number of these channels to MRs (SUs). PUs actions affect the profits of other PUs. A competition among PUs to maximize their own profits decreases the total reward of PUs and reduces spectrum utilization significantly. Moreover, this competition limits the ability of the system to serve SUs. In our system, instead of competing we assume PUs cooperate by borrowing from each other for trading the unused spectrum to the SUs. The collaborative behavior among PUs is defined and is studied to show its effect on the gained revenues. Therefore our system consists of borrowing among PUs and trading (or renting) among PUs and SUs.

MRs use the rented channels to serve different classes of MCs. Each PU_i, i=1, 2,….,W, specifies $\mathbb{S}_i$ the spectrum size for renting, its QoS requirements (blocking probability), and the price of spectrum. We assume that these parameters are changed over time corresponding to the network conditions, such as traffic load, spectrum demand, and spectrum cost. A PU therefore needs to change the price and the size of the offered spectrum when needed. SUs can access a licensed spectrum if they rent a spectrum from a PU. We assume that spectrum request arrival follow Poisson distribution and each MC class j has arrival rate λ_j. The service time μ_j for each request of j^{th} class is assumed to be exponentially distributed. These assumptions capture some reality of wireless applications such as phone call traffic. Each SU of j^{th} class pay a price p_j for a spectrum unit.The total capacity of the network is given as:

$$H = KW. \tag{5.1}$$

5.3 Spectrum Sharing Between PUs (On-demand-based spectrum sharing scheme)

In our scheme, PUs can exchange channels if the borrowed channels do not interfere with the channels of its neighbors. In our model, we define the following components for primary user i (PU_i):

- Spectrum allocation vector $\boldsymbol{\mathcal{A}_i}$:

  We model a channel as an ON/OFF where the ON period indicates the duration of PUs' activities. $\mathcal{A}_i = \left\{\mathcal{A}_i(m) \,\middle|\, \mathcal{A}_i(m) \in \{0,1\}\right\}$ is a vector of spectrum status. If $\mathcal{A}_i(m) = 1$, channel m is not available currently.

- Interference vector $\boldsymbol{\mathcal{I}_i}$:

  $\mathcal{I}_i = \left\{\mathcal{I}_i(\hat{\imath}) \,\middle|\, \mathcal{I}_i(\hat{\imath}) \in \{0,1\}\right\}$ is a vector that represents the interference among PU_i and other PUs; if $\mathcal{I}_i(\hat{\imath}) = 1$ then PU_i and $PU_{\hat{\imath}}$ can not use the same channel at the same time because they would interfere with each other.

- Borrowable channel set BC_i:

  Our scheme allows two neighbors to exchange channels to maximize their reward while complying with conflict constraint from set of the neighbors. We define that two PUs are neighbors if their transmission coverage area is overlapped with each other. The set of channels that PU_i can borrow from $PU_{\hat{\imath}}$ should not interfere with PU_i neighbors. We refer to these channels as $BC_i(PU_i, PU_{\hat{\imath}})$:

$$BC_i(PU_i, PU_{\hat{\imath}}) = \mathcal{L}(PU_{\hat{\imath}}) \setminus \mathcal{L}(\mathcal{G}(PU_i) \setminus PU_{\hat{\imath}}) \tag{5.2}$$

  where $\mathcal{L}$ gives the set of channels assigned to the given user(s) (e.g. $\mathcal{L}(PU_{\hat{\imath}})$ represents the list of $PU_{\hat{\imath}}$ channels), $\mathcal{G}$ *(*PU_i*)* is a list of neighbors of a primary user PU_i.

After serving a request, the PU returns back borrowed channels to the owner users. PUs adjust their spectrum usage based on demand. As a result, the PU decides to borrow channels if the spectrum is not available to accommodate SUs requests and it is profitable to serve new SUs in terms of revenue. In our scheme, spectrum is shared among PUs as follows:

- *Step 1*: PU computes the revenue of serving new SUs based on the reward function as described in Section 5.5.3.
- *Step 2*: If the revenue is positive and worthy, a PU requests neighboring PUs for a spectrum through a “borrowing frame” that is broadcast to all neighbors. The request frame specifies the size of required spectrum.

- *Step 3:* Each neighboring PU receives a "borrowing frame", checks its idle channel list and if there are idle channels, the PU temporarily gives up a certain amount of idle spectrum for a specific period of time, and sends an "accept frame" that includes channel IDs. If all channels are busy then the request is ignored.
- *Step 4:* After receiving "accept frame(s)", the PU specifies a borrowable channel set BC and ranks its elements based on their capacity. If the PU does not receive any "accept frame", it queues the requests.
- *Step 5:* After selecting channels, the PU informs the owners of the selected channels.
- *Step 6:* After the PU finish serving SUs, it returns the borrowed channels.

Our scheme guarantees high utilization by using all system channels provided that the interference constraint is met. Fig 5.1 shows the flowchart for the On-demand-based spectrum sharing scheme.

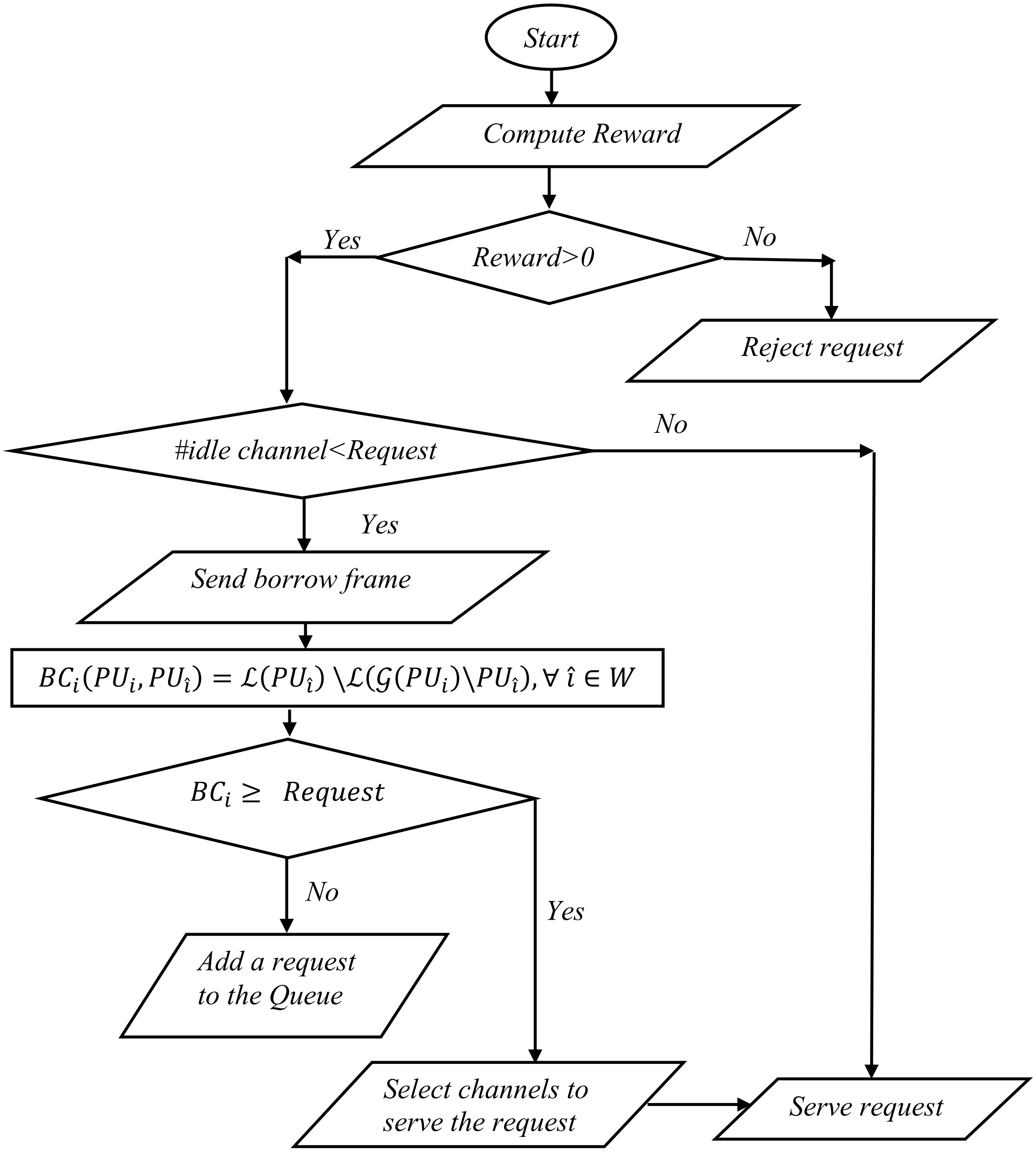

Fig 5.1: Flowchart for On-demand-based spectrum sharing

5.4 Spectrum Trading between PUs and SUs

In spectrum trading, the main concern of PUs is to maximize their own revenue while supporting the QoS for SUs. PUs trade the surplus spectrum to the SUs to generate revenue. This Section details the algorithms to manage the spectrum trading process.

5.4.1 Spectrum Management in a Multi-Service Network

The problem of optimal resource allocation for satisfying QoS for multiple classes of SUs is a challenging problem in the design of the future multi-service cognitive network. The main motivation for the research in this problem is to adapt the services to the changes in the structure of the spectrum secondary market. Most of the research that has been conducted in this field assumes one class of SUs and one type of service. Nowadays, with an explosion in the diversity of real-time services a better and more reliable communication is required. Moreover, some of these applications require firm performance guarantees from the PUs.

In the future, multiple classes of SUs will pay the PUs for their spectrum usage based on short term contract. From PUs point of view, the optimal resource management scheme is the one which maximizes their revenue. However, some constraints prevent PUs from maximizing such as resource optimization and QoS for PUs. In this Chapter, we address the problem of optimizing spectrum trading in the secondary spectrum market for satisfying both QoS for multiple class of services for SUs and for PUs and maximizing the revenue of PUs.

In this work, the main concern is how the PUs can maximize their revenue by controlling the offered spectrum size and price while maintaining the QoS for PUs when the spectrum demand varies at PUs. This particular scheme for controlling radio resources can be generalized to other management problems and applications such as a sensor network, or a military network. Since spectrum access charges differ between user classes, serving new SUs whenever there is available spectrum may not maximize the PU's revenue. The PU has to compute the gained reward and decide whether to serve the request or reject it and wait till a user with worthy reward arrives. Therefore, the optimal resource management scheme is mandatory to the reward maximization. A policy for maintaining the QoS for the PUs plays an important role in protecting the right of the PUs to access the spectrum exclusively. Since PUs are given priority over SUs, PUs protection is achieved by a properly organized price and the size of the offered spectrum.

5.4.2 Reinforcement Learning Model

The revenue maximization at each PU faces a unique challenge due to time-varying spectrum availability. Therefore, a PU should jointly consider serving SUs requests and maintain QoS for itself to maximize its profit. We formulate RL by accounting for time-varying spectrum demand and spectrum availability. The basic and essential components of the RL are derived by considering system states and the possible actions to be taken for revenue optimization at each state. We use Q-learning to extract the optimal policy for controlling the trading process. Q-learning is a reinforcement learning technique that works by learning an action-value function that gives the expected reward of taking a given action in a given state and following a certain policy.

5.4.2.1 Reinforcment Learning Formulation

The agent developed provides the trading functionality at the PU level of CN in a distributed manner. Each agent uses its local information and makes a decision for the events occurring in the PU in which it is located. In our system, an event can occur in a PU (agent) when a new request for spectrum arrives or a SU releases its assigned spectrum. These events are modeled as stochastic variables with appropriate probability distribution.

5.4.2.1.1 State and Action Space

At any time the PU is in a particular configuration defined by the size, the price of the offered spectrum and the number of admitted SUs of each class. In our work, the state is indicated by the set $Z_t = \{z_j\}$ where z_j is the number of accepted requests for j^{th} class. All possible states are limited by the following constraints:

- $\sum_{j \epsilon \mathbb{F}} z_j \leq \mathbb{B}$,
- $\sum_{i=1}^{W} \mathbb{S}_i \leq H$,

where $\mathbb{S}_i$ is the size of PU_i rented spectrum for SUs and $\mathbb{F}$ is a set of SUs classes. From a state, the system can not make a transition if the constraints conditions are not met. When an event occurs, a PU has to decide among all possible actions. In our work, when a request from SU arrives, a PU either serves the request or rejects it. The action space is given by:

$$A = \{a_t : a_t \in \{0,1\}\} \tag{5.3}$$

where a_t=0 denotes request rejection, a_t=1 indicates that the PU accepts serving new SU.

5.4.2.1.2 Reward Function

Spectrum demand is changing over time. Since the size and the price of the rented spectrum should be adapted from time to time; PUs need a mechanism that can indicate when and how to adapt the spectrum size to maximize its revenues while guaranteeing QoS for a PU. A PU i (PU_i) incurs cost C_i of obtaining its spectrum from the spectrum broker, which is computed as follows:

$$C_i = \mathbb{S}_i * \delta \tag{5.4}$$

where δ is the cost of one spectrum unitand $\mathbb{S}_i$ is the size of spectrum that PU_i would rent to the SUs at a price p_j for each class j. The average reward for PU_i is given by:

$$\bar{R}_i = \sum_{j \epsilon \mathbb{F}} p_j \bar{\lambda}_j \tag{5.5}$$

where $\bar{\lambda}_j$ is the average rate of accepting SUs request of class j. The PU_i average net revenue is computed as follows:

$$\bar{V}_i = \bar{R}_i - \mathcal{C}_i = \sum_{j \epsilon \mathbb{F}} p_j \bar{\lambda}_j - \mathcal{C}_i. \tag{5.6}$$

At state Z_t, the received revenue is computed as follows:

$$R_i(Z_t, a_t) = a_t(\sum_{j \epsilon \mathbb{F}} p_j z_j \mu_j - \mathcal{C}_i) \tag{5.7}$$

where μ_j is the service rate of j^{th} class. We assume the key objective for the PU is the maximization of revenue $R_i(Z_t, a_t)$ with respect to S_t, under the condition that the blocking probabilities for a PU_i (B_i) does not exceed B_i^C. Then, revenue maximization problem can be formulated as follows:

$$max_{\mathbb{S}_i} \sum_{t=1}^{G} R(Z_t, a_t) \tag{5.8}$$

subject to $\sum_{i=1}^{W} \mathcal{A}_i \leq KW,$

$$\mathcal{A}_i(m)\mathcal{A}_{\hat{\imath}}(m)\mathcal{I}_i(\hat{\imath}) = 0,$$

$$B_i \leq B_i^C.$$

The first constraint states that the capacity of the secondary network (size of spectrum) should be less than or equal the capacity of the primary network (PUs' network). The second constraint reveals that PU_y and PU_j cannot assign the same channel (m) for their clients simultaneously because they will interfere with each other. Finally, third constraint defines that blocking probability for a PU_y should not exceed the blocking constraint for a PU_y applications.In this formulation, the maximization of revenue can be achieved by adapting the size and the price of the spectrum periodically based on (5.7) and the blocking probability of PUs. Our goal of RL is to choose a sequence of actions that maximize the total value of the received revenue for a PU_i:

$$\mathcal{T}_i(\pi) = \lim_{G\to\infty} \sum_{t=1}^{G} R_i(Z_t, a_t) \tag{5.9}$$

where $\mathcal{T}_i$ indicates the total net revenue of PU_i when policy π is executed and G represents the time horizon. At each state Z_t, $e_j(Z_t)$ is the dynamic cost of serving new requests of class j. It is used to decide the new admitted requests. A PU chooses the requests with maximum positive gain as follows:

$$g(Z_t) = \max_{j=1,\ldots,\mathbb{F}}(p_j - e_j(Z_t)) \tag{5.10}$$

If there is no request with positive gain, all requests are neglected. The average net gain for class j requests under policy π can be defined as follows:

$$\overline{g_j}(Z) = E_Z[g_i(Z_t)] = lim_{G\to\infty} \sum_{t=1}^{G} \mathcal{P}(Z_t)\, g_j(Z_t) \tag{5.11}$$

where $\mathcal{P}(\mathrm{Z_t})$ denotes the states probability, and $g_i(Z_t)$ is the gain of accepting class j requests.

Theorem 1: Average reward for a PU_i is sensitive to the arrival rate of class j and thissensitivity can be calculated as follows:

$$\frac{\partial \bar{R}_i}{\partial \lambda_j} = E_Z\left[g_j(Z_t)\right] \tag{5.12}$$

Proof: the net gain for class j at state Z_t under policy π can be expressed as follows:

$$g_j(Z_t) = (Z_t + \Delta_j) - (Z_t) \tag{5.13}$$

where $(Z_t + \Delta_j)$ denotes the new state of the system after accepting the j^{th} class requests. The right-hand side of equation (5.12) can be written as [57]:

$$\frac{\partial^+ \bar{R}_i}{\partial \lambda_j} = \lim_{D \to \infty} E[\int_{t_0 - G}^{t_0 + G} \left(R_i(Z_{t+1}, a_t) - R_i(Z_t, a_t)\right) dt] \tag{5.14}$$

where $R_i(Z_{t+1}, a_t)$ denotes the reward rate after taking the action a_t of accepting new request of j^{th} class at time t. By using equation (5.13) it can be shown that (5.14) is equivalent to:

$$\frac{\partial^+ \bar{R}_i}{\partial \lambda_j} = E_Z\left[g_j(Z_t)\right] \tag{5.15}$$

Analogous proof holds if one request is served. This analysis is helpful for a PU to decide if a request is to be admitted or rejected based on the sensitivity of reward to arrival rates of different classes.

Lemma 1. The average reward for PU_i, $\bar{R}_i$, increases by offering more spectrum for trading.

Proof. LetPU_i use the optimal policy for specifying the optimal price and size of the offered spectrumsize for trading and let $PU_{\hat{\imath}}$ operates under policy and selects price p_j for j^{th} class. Assume PU_i offers $\mathbb{S}_i$and $PU_{\bar{\imath}}$ offers $\mathbb{S}_{\hat{\imath}}$. Assume $\mathbb{S}_i$is greater than $\mathbb{S}_{\hat{\imath}}$.

Now assume that both PUs have identical spectrum requests stream. We say two PUs have identical stream requests if the they have the same arrival and service rates of all MCs classes. Let the initial number of requests that arrive to both PUs be 0. Then, the two PUs will behave identically until the first $\mathbb{S}_{\hat{\imath}}$ is allocated to MCs. The next requests will be served by PU_i but will not be served by $PU_{\hat{\imath}}$, making the average reward of PU_i more than the total reward of $PU_{\bar{\imath}}$ by Δ_R which is computed as follows :

$$\Delta_R = \sum_{j \epsilon \mathbb{F}} p_j (\mathbb{S}_i - \mathbb{S}_{\hat{\imath}}) \tag{5.16}$$

5.4.2.1.3 Using RL to find an Optimal Policy

In a trading process, when an event occurs at time *t*, a PU senses the environment (such as spectrum price, available spectrum size, and SU class). Then, the state of the system Z_t is specified. After that, the PU can find the possible actions at this state. Next, the PU finds a set of possible action in state Z_t. Then, the action a_t with the maximum reward is selected. According to the selected action the environment will transit to the next state Z_{t+1} and the PU adapts its resources in the new state (such as spectrum price, and size of the offered spectrum). In the next Section we show how the PU adjusts its resources to meet the network blocking probability constraint and maximizes its revenue.

5.5 Resource adaptation using cognitive network

One of the important capabilities of CN is to adapt to the changing environment conditions and user requirements. In this Section, we propose a new adaptation method which is used by PUs to optimize their revenues.

5.5.1 Spectrum Size Adaptation in Radio Environment

The conditions of the system are changing randomly. These conditions include traffic level, spectrum demand from SUs and the size of available spectrum. Therefore PUs should adapt its resources to achieve its objectives. Several parameters can be tuned by PU to adapt to the new conditions. These parameters include price and the size of the offered spectrum. Revenue maximization can be achieved by spectrum size adaptation. In this case, the necessary condition for optimal solution can be formulated as a requirement of having the network revenue gradient with respect to PUs offered spectrum equal to zero vector:

$$\nabla\bar{V}(O) = \left(\frac{\nabla\bar{V}_1}{\nabla\mathbb{S}_1}, \frac{\nabla\bar{V}_2}{\nabla\mathbb{S}_2}, \frac{\nabla\bar{V}_3}{\nabla\mathbb{S}_3}, \dots\dots, \frac{\nabla\bar{V}_{\mathrm{W}}}{\nabla\mathbb{S}_{\mathrm{W}}}\right) = 0. \tag{5.16}$$

In our model, the PU_i revenues sensitivity to the number of the offered spectrum size can be derived from (5.6):

$$\frac{\partial\bar{V}_i}{\partial\mathbb{S}_i} = \left(\frac{\partial\bar{R}_i}{\partial\mathbb{S}_i}\right) - \left(\frac{\partial\mathcal{C}_i}{\partial\mathbb{S}_i}\right) = \left(\frac{\partial\bar{R}_i}{\partial\mathbb{S}_i}\right) - \delta. \tag{5.17}$$

We assume the average reward sensitivity to the offered spectrum size can approximated by the average spectrum price of the SUs class with unit spectrum requirement, $\frac{\partial\bar{R}_i}{\partial\mathbb{S}_i} = \bar{p}(\mathbb{S}_i)$. As a result, equation (5.17) can be written as:

$$\frac{\partial\bar{V}_i}{\partial\mathbb{S}_i} = \bar{p}(\mathbb{S}_i) - \delta \tag{5.18}$$

Where $\bar{p}$ is the average spectrum price and it is computed as follows :

$$\bar{p} = \frac{\sum_{j\epsilon\mathbb{F}}\bar{\lambda}_j p_j}{\sum_{j\epsilon\mathbb{F}}\bar{\lambda}_j}. \tag{5.19}$$

The PU’s revenue is maximized when spectrum size equals the root of:

$$\frac{\partial\bar{V}_i}{\partial\mathbb{S}_i} = \bar{p}(\mathbb{S}_i) - \left(\frac{\partial\mathcal{C}_i}{\partial\mathbb{S}_i}\right) = 0. \tag{5.20}$$

We used Newton's method of successive linear approximations to find the root of equation (5.20). The new spectrum size $\mathbb{S}_{n+1}$ (PU index is omitted in the notation) at each iteration step *n* is computed as follows:

$$\mathbb{S}_{n+1} = \mathbb{S}_n - \frac{\bar{p}_n - \delta}{\frac{\partial(\bar{p}(\mathbb{S}) - \delta)}{\partial \mathbb{S}}}. \tag{5.21}$$

Approximating the derivative in equation (5.21) at step *n*:

$$\frac{\partial(\bar{p}(\mathbb{S}) - \delta)}{\partial \mathbb{S}} = \frac{\partial \bar{p}(\mathbb{S})}{\partial \mathbb{S}} = \frac{\bar{p}_n - \bar{p}_{n-1}}{\mathbb{S}_n - \mathbb{S}_{n-1}} \tag{5.22}$$

and substituting (5.22) in (5.21), the new spectrum size will be :

$$\mathbb{S}_{n+1} = \mathbb{S}_n - (\mathbb{S}_n - \mathbb{S}_{n-1}) \frac{\bar{p}_n - \delta}{\bar{p}_n - \bar{p}_{n-1}}. \tag{5.23}$$

Spectrum size adaptation is then realized using the following algorithm:

Algorithm 5.1 Spectrum size adaptation

Parameters:

$\mathbb{S}_{n+1}$:*spectrum size at step n+1.*

$\bar{p}_n$ *: spectrum size at step n.*

δ: *is the cost of one spectrum unit.*

ε: *is the tolerable error.*

AdaptSpectrumSize ($\bar{p}_n$,$\mathbb{S}_{n+1}$,$\mathbb{S}_n$, ε)

Begin

if ((*Abs(*$\bar{p}_n$ - δ*) <ε*))
return $\mathbb{S}_{n+1}, \bar{p}_n$;
else
{
$\mathbb{S}_n = \mathbb{S}_{n+1}$;
compute $\bar{p}_n, \mathbb{S}_{n+1}$;
AdaptSpectrumSize ($\bar{p}_n$,$\mathbb{S}_{n+1}$, $\mathbb{S}_n$, ε);
}

End

Fig 5.2 displays the flowchart for the spectrum size adaptation scheme.

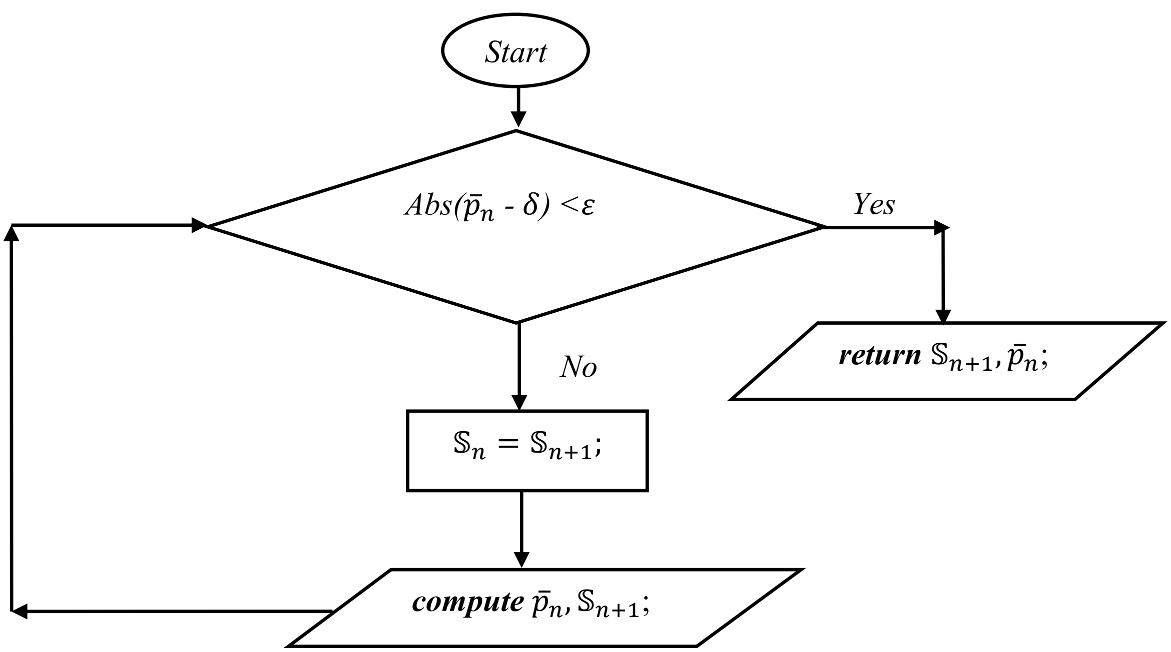

Fig 5.2: Flowchart for spectrum size adaptation scheme

5.5.2 QoS Support for PUs and SUs in CNs

The presented solution for revenue maximization does not take into account the QoS for PUs. The request of spectrum from the PU is blocked if it arrives while a PU is already using its entire spectrum. Therefore, the probability of blocking for PU_i is computed as follows [54]:

$$B_i = \frac{\rho^K}{K!} (\sum_{k=0}^{K} (\frac{\rho^k}{k!})^{-1}) \tag{5.24}$$

where ρ is computed as follows:

$$\rho = \frac{\lambda}{\mu}. \tag{5.25}$$

The blocking probabilities of PUs may exceed their constraints in some scenarios. The offered price in the secondary network is adapted to meet the blocking constraints for the PUs. It is clear when a PU increase the prices the arrival rates of SUs classes will be decreased. Hence, the spectrum demand at the secondary network will be decreased. The surplus spectrum can be used to serve the PUs applications. The arrival rate of SUs classes depends on the offered price. The new arrival rate of j^{th} class is calculated as follows [55]:

$$\lambda_j = \tau e^{-\omega_j \acute{p}_j} \tag{5.26}$$

where τ is the maximum number of users arriving at a PU, ω_j represents the rate of decrease of the arrival rate as spectrum price increases and it is related to the degree of competition between the PUs and $\acute{p}_j$ is the new price for the j^{th} class. Here we assume ω_j is given a prior. There is an inverse relationship between the price and the demand of the spectrum. A PU has to meet its blocking probability constraint B_i^C, which is a function of the number of available channels and the traffic load. PU continues increasing the prices in the secondary market till its blocking probability is satisfied. PUs tries to minimize the price increment as much as possible to keep the PUs revenues positive. A PU calculates the new revenue as follows:

$$\Delta V_i' = \sum_{j \in \mathbb{F}} \lambda_j (\acute{p}_j - p_j) \geq 0. \tag{5.27}$$

This leads to the following problem formulation:

$$max_{\mathbb{S}_i} \bar{V}_i = \sum_{j \in \mathbb{F}} \acute{p}_j \bar{\lambda}_j - \mathcal{C}_i - \min_{\acute{p}_j} \sum_{i \in F} \lambda_j (\acute{p}_j - p_j) \tag{5.28}$$

subject to: $\quad \sum_{i=1}^{W} \mathcal{A}_i \leq KW,$

$$\mathcal{A}_i(m) \mathcal{A}_{\hat{\imath}}(m) \mathcal{I}_i(\hat{\imath}) = 0,$$

$$B_i \leq B_i^C,$$

$$\Delta V_i' = \sum_{j \in \mathbb{F}} \lambda_j (\acute{p}_j - p_j) \geq 0.$$

Theorem 2. The increment in the arrival rate for spectrum request of j^{th} classwill not increase the average reward of the PU without allocating more spectrum for trading**.**

Proof. Assume the new arrival rate for j^{th} classis $\acute{\lambda}_j = \Delta_{\lambda_j}\lambda_j$, and $\Delta_{\lambda_j} > 1$. If a PU increases the price to get more reward, the arrival rate will be decreased according to equation (5.28) and the average reward will be affected negatively. Hence, the PU has to increase the service rate μ_j to serve the increment in the number of the users. In order to get the reward of the new user, PU has to increase the service rate by Δ_{λ_j}. Then, the new average reward is Δ_{λ_j}times the old average reward. Therefore, the optimal average reward is $\Delta_{\lambda_j}\bar{R}_i$. This implies the optimal price for spectrum remains unaffected if the increment in the arrival rate equals the increment in the service rate. The service rate is increased by offering more spectrum for MCs. In our work, spectrum price is used to support the QoS for SUs and PUs.

In our proposed adaptation scheme the new values of spectrum prices reflect the amount of spectrum required by a PU. Because of competition in the market, a price increment is limited due to the possibility of losing customers. If the blocking constraint of a PU is not met, a PU increases the values of all service prices by applying a common multiplier γ to all spectrum prices. After each increment, a PU computes its blocking probability and if it is not met it continues to increase the prices till a blocking constraint is met. If a blocking constraint for a PU is met then it tries to meet the blocking constraint for SUs. If some of the SUs blocking constraints are not met, it decreases the service prices while increasing those of SUs classes for which blocking probability are smaller than their constraints, in such a way that total offered spectrum price is maintained.

Lemma 2. Average reward of PU can be increased if the price of spectrum is increased and the new increment does not affect the arrival rate of spectrum request.

Proof. Assume the arrival rate for the system for j^{th} class is λ_j and the offered price is p_j and the PU admits all the newcomers to the system. The reward of class j^{th} is computed as follows:

$$R_j = \lambda_j p_j \tag{5.29}$$

Assume PU changes its policy and selects price $\acute{p}_j$, $\acute{p}_j > p_j$ in state Z_t and assumes the SUs do not response to this change and the spectrum demand of the SUs does not change. Clearly, the new system reacts in the same manner even if the PU charges different price for spectrum. Therefore, PU achieves more reward under the new policy since the spectrum demand does not change for the increased price. This analysis reflects the importance of selecting the spectrum prices.

5.5.3 Revenue Optimization for multiple PUs

In our work, an iterative gradient approach is used for revenue maximization in equation (5.16), where a successive projection of the revenue gradient is performed to converge $\nabla\bar{V}$ to 0. We use a step-size factor φ to scale the projected spectrum size changes $\Delta O = (\Delta\mathbb{S}_1, \Delta\mathbb{S}_2, \dots, \Delta\mathbb{S}_W)$ at each iteration step to improve the convergence.

We use Newton successive projection to find $\Delta\mathbb{S}_W$ approximating the solution to

$\frac{\partial\bar{V}}{\partial\mathbb{S}_W} = 0;\ \Delta\mathbb{S}_W = -\frac{\frac{\partial\bar{V}}{\partial\mathbb{S}_W}}{\frac{\partial^2\bar{V}}{\partial^2\mathbb{S}_W}}.$

Assume O_n and $\bar{V}(O_n)$ denote the vector of offered spectrum sizes and the average revenue at iteration n, respectively, and let ψ_i be the vector of size W with 1 in the i position and 0 in all other positions. The first and second derivative with respect to the PU_i offered spectrum, $\frac{\partial \bar{V}}{\partial \mathbb{S}_i}$ and $\frac{\partial^2 \bar{V}}{\partial^2 \mathbb{S}_i}$ can be approximated by the following differentials:

$$\frac{\partial \bar{V}}{\partial \mathbb{S}_i} \cong \bar{V}(O_n + \psi_i) - \bar{V}(O_n)$$

$$\frac{\partial^2 \bar{V}}{\partial^2 \mathbb{S}_i} \cong \bar{V}(O_n + 2\psi_i) - \bar{V}(O_n + \psi_i) - [\bar{V}(O_n + \psi_i) - \bar{V}(O_n)]$$

$$=\bar{V}(O_n + 2\psi_i) - 2\bar{V}(O_n + \psi_i) + \bar{V}(O_n) \tag{5.30}$$

Using these approximations we compute $\Delta\mathbb{S}_i$ as follows:

$$\Delta\mathbb{S}_i = -\frac{\bar{V}(O_n+\psi_i)-\bar{V}(O_n)}{\bar{V}(O_n+2\psi_i)-2\bar{V}(O_n+\psi_y)+\bar{V}(O_n)} \qquad (5.\ 31)$$

We apply the following adaptation algorithm to find the optimal offered spectrum size at each PU within a specified relative accuracy ε:

Algorithm 5.2 Spectrum size adaptation

Parameters:

O_n: *the vector of offered spectrum sizes.*

$\bar{V}(O_n)$:*the average revenue at iteration step* n.

ψ_i: *the vector of size* W *with 1 in the* i *position and 0 in all other positions.*

φ:*step-size factor to scale the projected spectrum size.*

Begin

n=0;

initialize O_n *to any arbitrary spectrum size vector*

compute $\bar{V}(O_0)$

do

    for *each* PU_i

        compute $\bar{V}(O_n + 2\psi_i)$, $\bar{V}(O_n + \psi_i)$, $\Delta\mathbb{S}_i$

    end for

    search *for the scalar size* $\bar{\varphi}$ *such that:*

        $\bar{V}(O_n + \bar{\varphi}\Delta\mathbb{S}) = max_{\varphi}\bar{V}(O_n + \varphi\Delta O)$

        If $|\bar{V}(O_{n+1}) - \bar{V}(O_n)| \leq \varepsilon\bar{V}(O_n)$

          $O_{n+1} = O_n + \varphi\Delta O$;

          return O_{n+1};

        end if

        else

          n=n+1;

while $|\bar{V}(O_{n+1}) - \bar{V}(O_n)| > \varepsilon\bar{V}(O_n)$

End

Fig 5.3 displays the flowchart for the spectrum size adaptation.

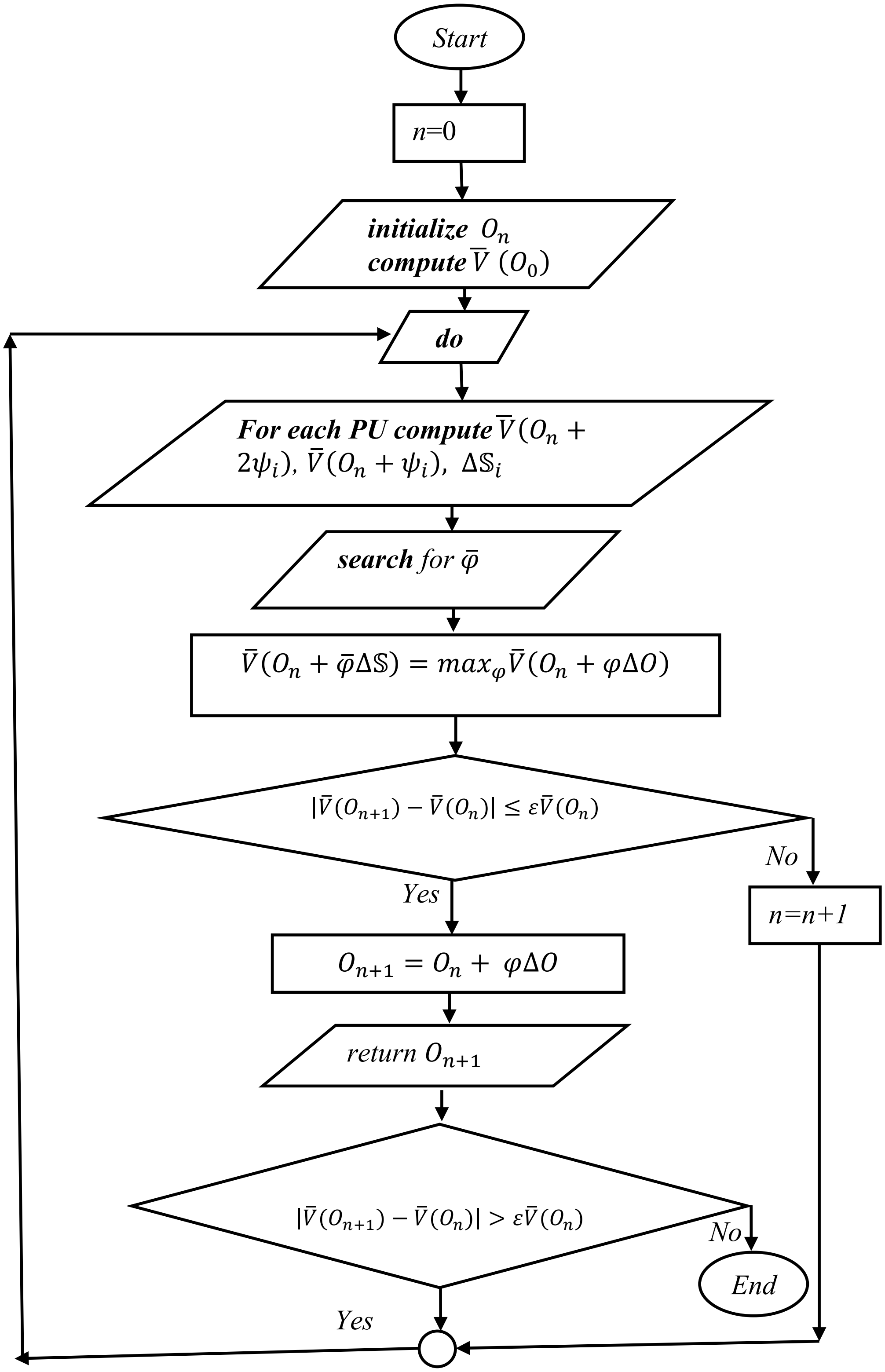

Fig 5.3: Flowchart for spectrum size adaptation for multiple PUs

5.6 Performance Evaluation

In this Section, we show simulation results to demonstrate the ability of our spectrum scheme to adapt to different network conditions. The system of PUs and SUs is implemented as a discrete event simulation. Simulation results are found to closely match the analytical results. The results presented are for several system settings scenarios in order to show the effect of changing some of the control parameters.

5.6.1 Performance of On-demand sharing scheme

The PUs behaviors impact the performance of the secondary network significantly. PUs' strategies for spectrum sharing with other PUs specify the total revenues, spectrum utilization and the size of the spectrum that might be allocated for the secondary network. In our work, PUs are modeled as being cooperative for spectrum sharing. We adopt the collaboration mechanism among PUs based on our on-demand based spectrum sharing scheme. In this Section, we analyze the performance of this behavior. We compare the performance of our on-demand based spectrum sharing scheme with the poverty-line heuristic [19] through simulations. For PU_i, the poverty-line is computed as follows:

$$PL(y) = \frac{L(PU_i)}{NG(PU_i)}. \tag{5.32}$$

The performance metrics considered are: throughput, and spectrum utilization which is the percentage of busy spectrum at time *t* and is computed as follows:

$$u = \frac{\sum_{w=1}^{W} SP_w}{KW}. \tag{5.33}$$

We examine the performance under different parameter settings. Throughput comparison of the two schemes is shown in Fig.5.4. The figure shows that the throughput increases as the number of total channels increases. This is due to more spectrum that can be employed. Our scheme utilizes the unused spectrum resourcefully because there is no limit to channels borrowing among PUs. For poverty-line heuristic [19], a PU cannot exceed a certain number of channels that can be borrowed from its neighbors even if the neighbors have idle channels.

We further present the results of spectrum utilization with different spectrum sizes in Fig.5.4. Our scheme performs better than the poverty-line heuristic. Our scheme utilizes the whole spectrum because PUs can have access to neighbor's channels based on availability of channels and on-demand. This improves the cognitive network throughput and overall spectrum utilization. However, some unused spectrum is not utilized under poverty-line heuristic because of the threshold constraint. It is clear from Fig.5.4 that our scheme is not sensitive to the number of channels in the network. However, the only constraint that prevents our scheme from full utilization of spectrum is the interference factor. In the poverty-line based scheme, spectrum sharing is limited by the poverty-line that depends on the number of idle channels. From the figure, we can see that as the number of channels increases the utilization of channels decreases because of an increment in idle channels.

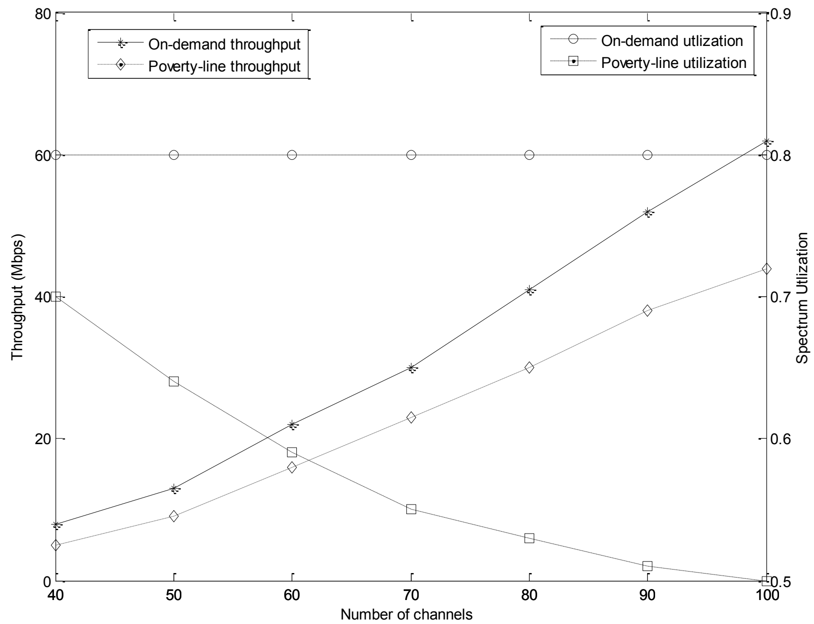

Fig 5.4. Throughput and spectrum utilization comparison

for the two schemes

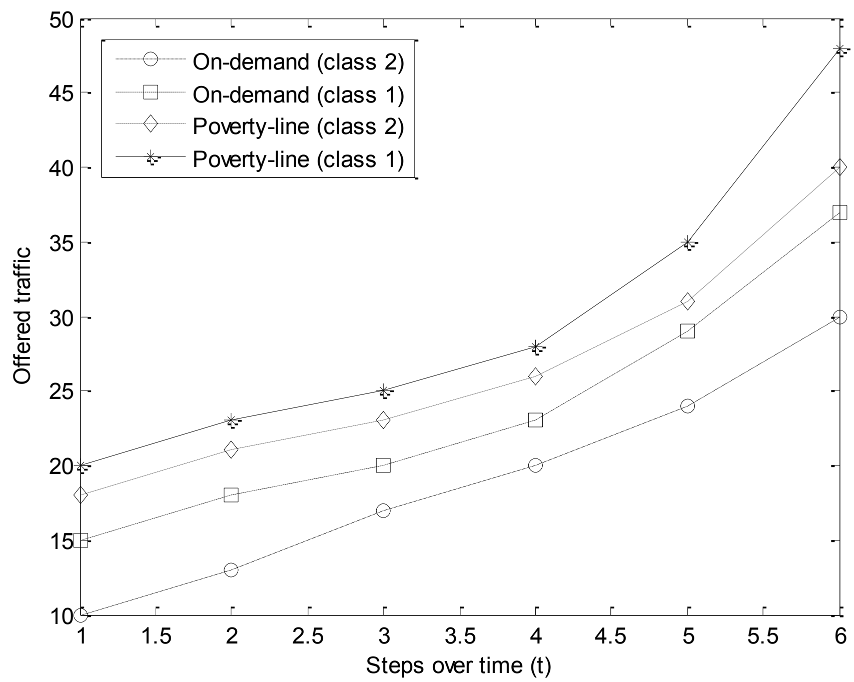

Fig 5.5. Offered traffic for different classes of SUs

5.6.2 Effect of On-demand scheme to Support QoS for SUs

In this Section, we analyze the impact of our on-demand scheme on the performance of the secondary network. Fig. 5.5 presents the offered traffic using on-demand and poverty-line scheme for all SUs classes in the secondary network. In this experiment the arrival rate for all classes are equal (λ_i =1). It is clear from the figure that the on-demand scheme supports much higher traffic than poverty-line. The main reason is utilization of the entire spectrum in the on-demand scheme. Moreover, we can see the offered traffic for class 1 is higher than other classes flow. Because class 1 pays more than other classes, the PUs assign more spectrum for this class. The results stress our scheme ability to support QoS for SUs classes.

Fig. 5.6 measures the average delay for the two schemes (e.g. the delay of a network specifies how long it takes for a packet to travel from one sender to the receiver). For the poverty-line scheme, because it does not utilize the entire free spectrum, the reported delay is higher than our scheme. Class 1 has the minimum time delay in our scheme because it gets more spectrum than other classes. The figure shows that the resulting performance of all schemes depends on both the spectrum demand at the PUs. The result emphasis that as the demand of spectrum increases at PUs the performance at the secondary network is degraded. Each PU needs a spectrum for its usage and to support the QoS for classic traffic. If an additional network overlaid its traffic over the unused spectrum it should not affect the B_y^C of the PU_y .

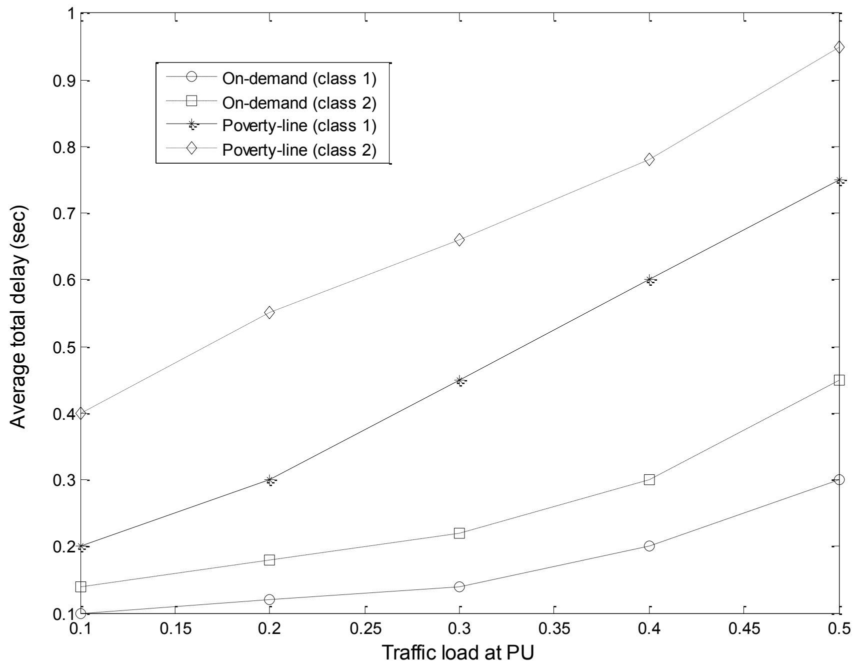

Fig 5.6.Time delay comparison for different classes of SUs

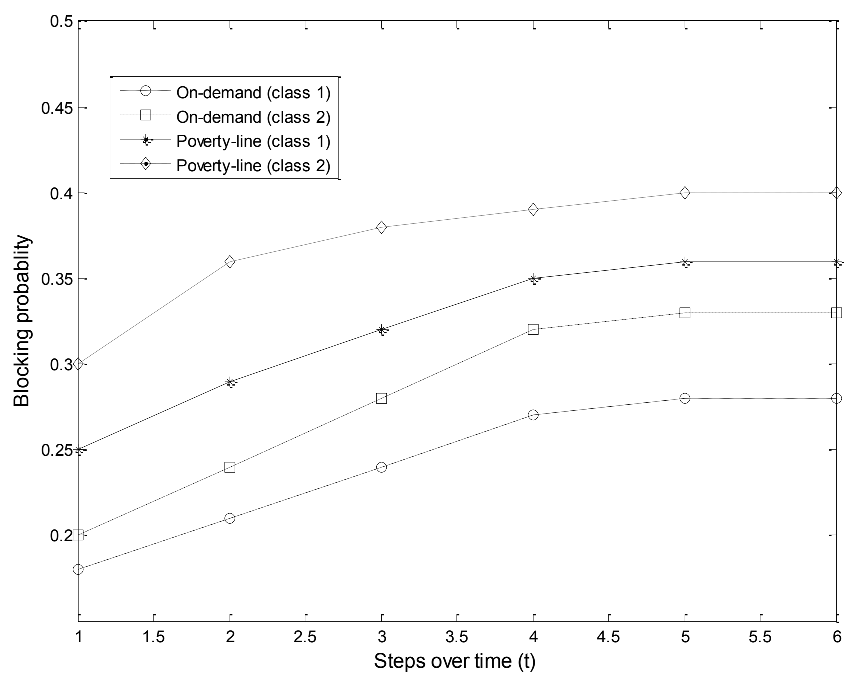

Fig 5.7. Offered traffic comparison for different spectrum

size and number of PUs

Fig. 5.7 displays the blocking probability for the two classes under the two schemes. The reported blocking probability for the on-demand scheme is less than the poverty-line. Because it gives the higher reward, the PU assigns the largest amount of spectrum to the class 1. As a result, the proportion of rejecting class 1 requests is less than other classes. Fig. 5.8 displays the spectrum size for each class of SUs. The on-demand scheme allocates more spectrum for trading in the secondary network. The entire free spectrum is offered for trading if it is worthy to trade the spectrum. For commercial reasons, PU allocates more spectrum for class 1. Fig. 5.9 shows how the PU satisfies the QoS for SUs classes. Fig 5.9 (a) shows that PU increases the spectrum price for class 1 to assign more spectrum for class 2. Increasing a spectrum price will reduce the demand for a spectrum and it gives the PU advantage of taking the surplus spectrum and assign it to other classes whose blocking probability are not met. In Fig.5.9 (a), the PU continues increasing the price for class 1 while its blocking probability is met. For class 2, we notice from Fig.5.9 (b) how a PU meets the blocking probability by allocating the extra spectrum that is resulted from increasing the price for class 1.

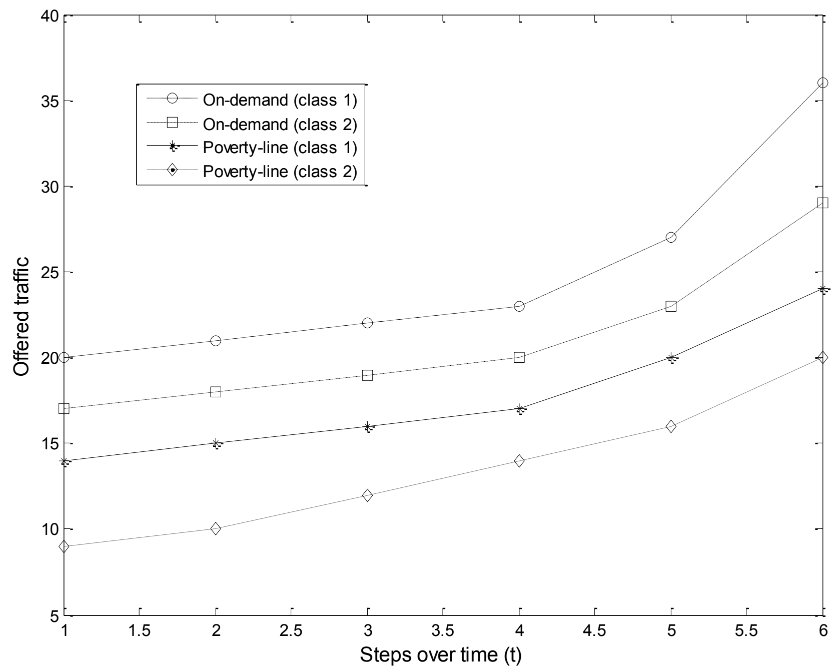

Fig 5.8. Offered spectrum size for different classes of SUs

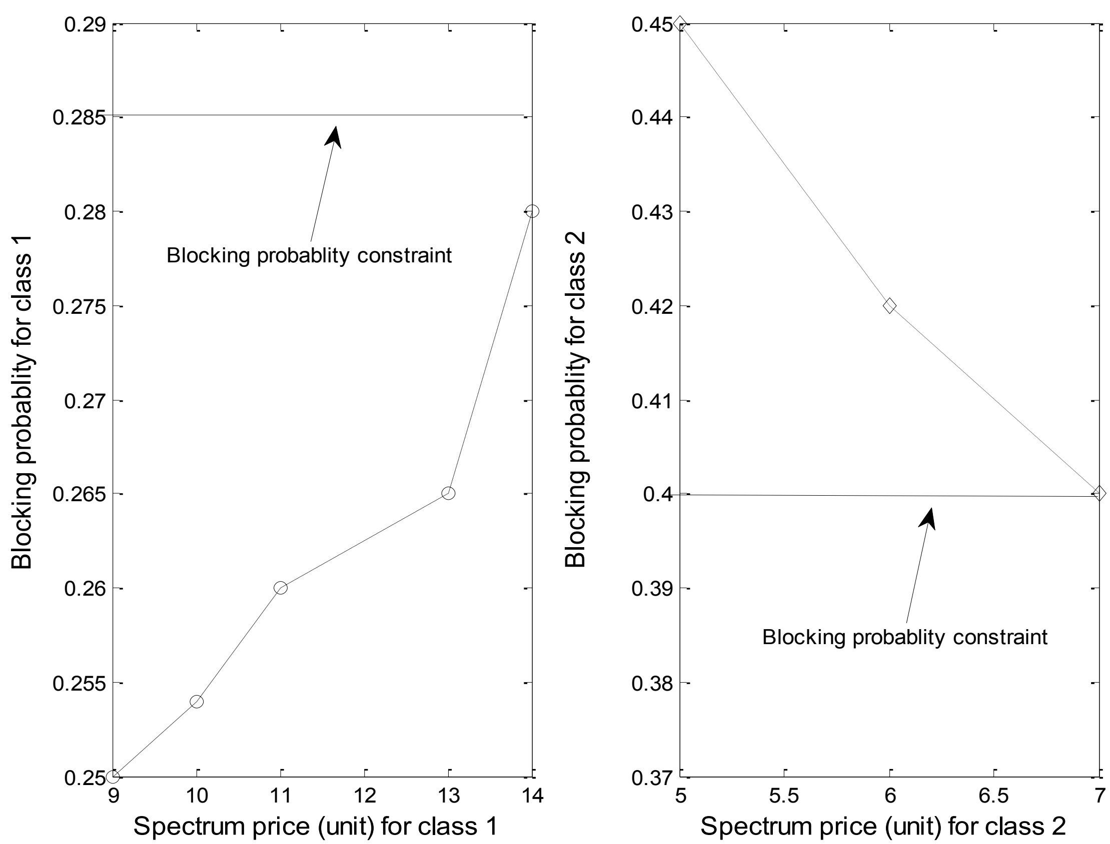

Fig 5.9 Adjusting Spectrum Prices to Support QoS for SUs classes

5.6.3 Tradeoffs Between a PU Revenue and its QoS Constraints

Fig. 5.10 plots the tradeoff between a PU revenue and its QoS. To show the relationship between the two, we vary the blocking probability constraint for a PU (the QoS requirement for a PU). From the figure we notice when the blocking constraint becomes stricter, PUs offer less spectrum for all SUs classes to maintain its QoS. As a result, the rejection ratio for SUs requests is increased especially for class 2. However, as this constraint is relaxed, a PU offers more spectrum for all classes of SUs. For large values of blocking probability, a PU can easily maintain a QoS for its applications and therefore it increases the spectrum for all classes but class 1 get the largest part of the offered spectrum. The gained revenue for PU is increased when it becomes less strict.

Fig. 5.11 plots the reported average revenue for PUs under different blocking probability constraints and spectrum demand. The results show that the revenue is increased under large value of blocking probability constraints and spectrum demand. Because our scheme adapt to these changes by computing the revenue at each state, it allocates more spectrum to trade for large values of arrival rates of SUs and PUs blocking probability constraints. The figure stresses the adaptability of our scheme to the changes in the spectrum demand. We notice from the figure when spectrum demand is increased and blocking probability does not surpass B_y^C, PU_y increases the size of the offered spectrum to generate more revenue. However, when the demand decreases, PU reduces the size of the offered spectrum to avoid a waste of spectrum. When the spectrum demand for SUs classes increases, blocking probabilities at PUs normally increase beyond their constraints because of willing of PU to generate more revenue from trading.

It is clear as the spectrum demand increases (arrival rate), PUs increases the size of offered spectrum especially for class 1.

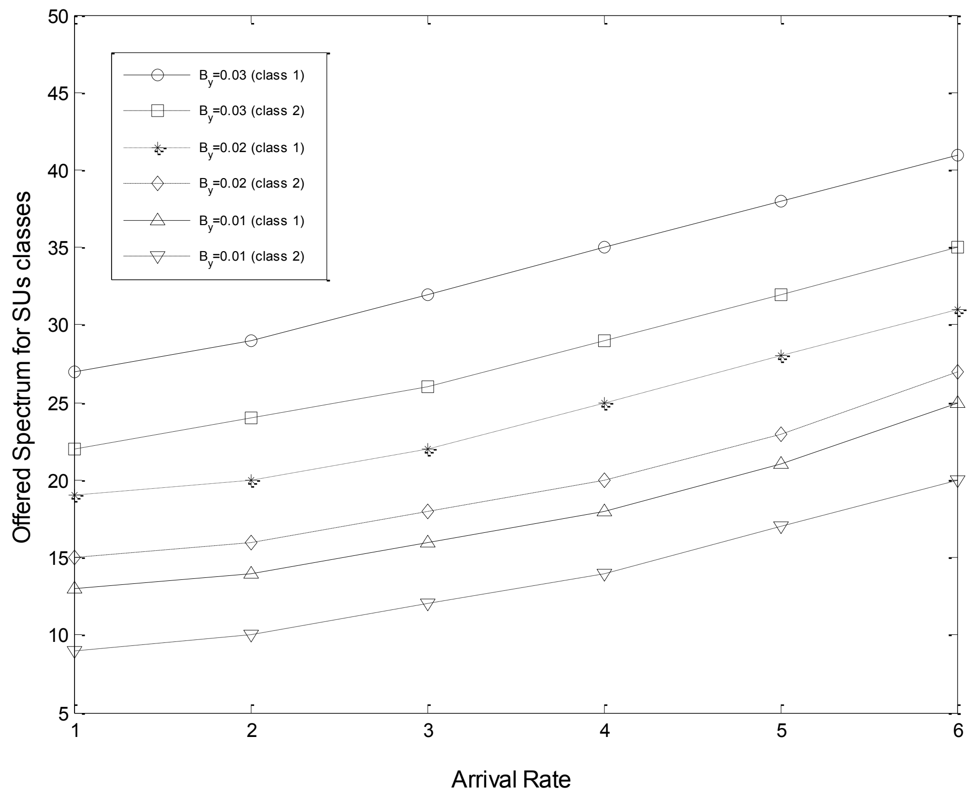

Fig 5.10. Adapting the offered spectrum size to the spectrum demand

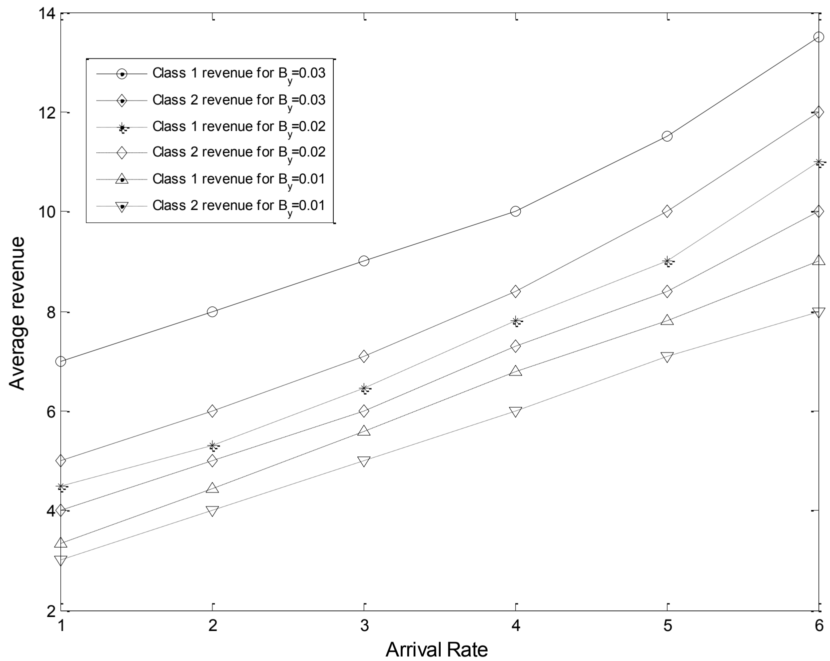

Fig 5.11. Average revenue under different traffic load

5.6.4 Spectrum Size Adaptation for PUs for Profit Maximization

If the blocking probability for a PU is met then it tries to increase the size of the offered spectrum for SUs to generate more revenue and vice versa. Fig 5.12 displays the offered spectrum sizes for trading in a network which consists of 4 PUs. From the figure, we can see that PUs continue to increase the offered size as there is a chance to maximize the revenues and its QoS is maintained. Offering more spectrum induces more revenue and less reimbursement cost due to more room available to accommodate user arrivals, however the profit will eventually be saturated due to the bounded SUs customers. Moreover, the blocking probability constraint of a PU prevents it from continuing to increase the size of offered spectrum. Hence, leasing more channels than necessary becomes unproductive in term of revenue and QoS for PUs.

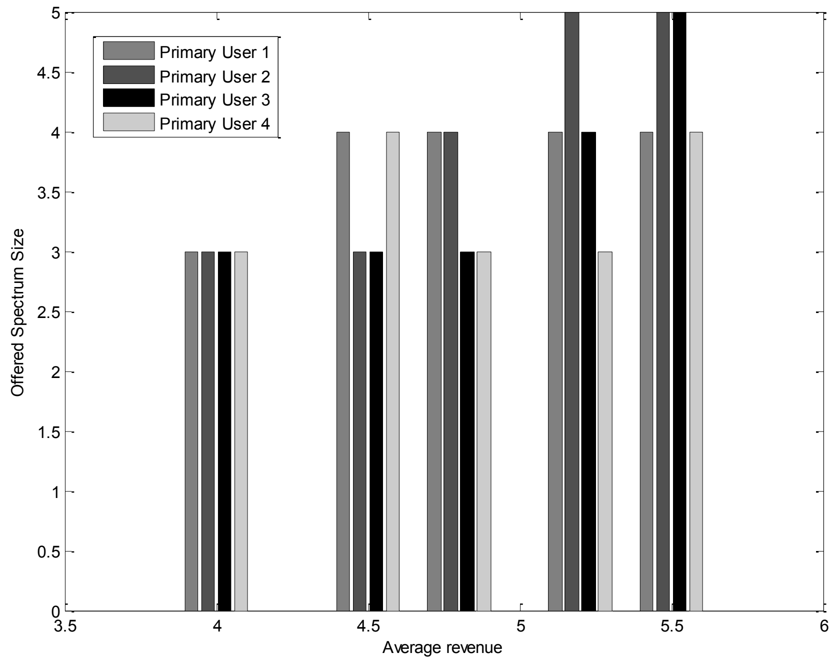

Fig 5.12. Optimal spectrum vector sizes and the average revenue

5.6.5 Maintaining QoS for PUs

A PU with well dimensioned spectrum size and correctly chosen spectrum price provides the desired QoS and maintains blocking probabilities in acceptable range. While our adaptation scheme try to maximize PUs' revenues by increasing spectrum size when the spectrum demand increase, it maintains QoS by bringing blocking probabilities back to its constrained range by increasing the spectrum price. Fig 5.13 shows the spectrum prices adaptation for all classes when the blocking probability surpasses blocking constraint. PU increases the price of spectrum to decrease spectrum demand for each SUs class and maintain QoS for PUs. The results show our scheme's ability to bring blocking probabilities back to their constrained range by adapting spectrum price.

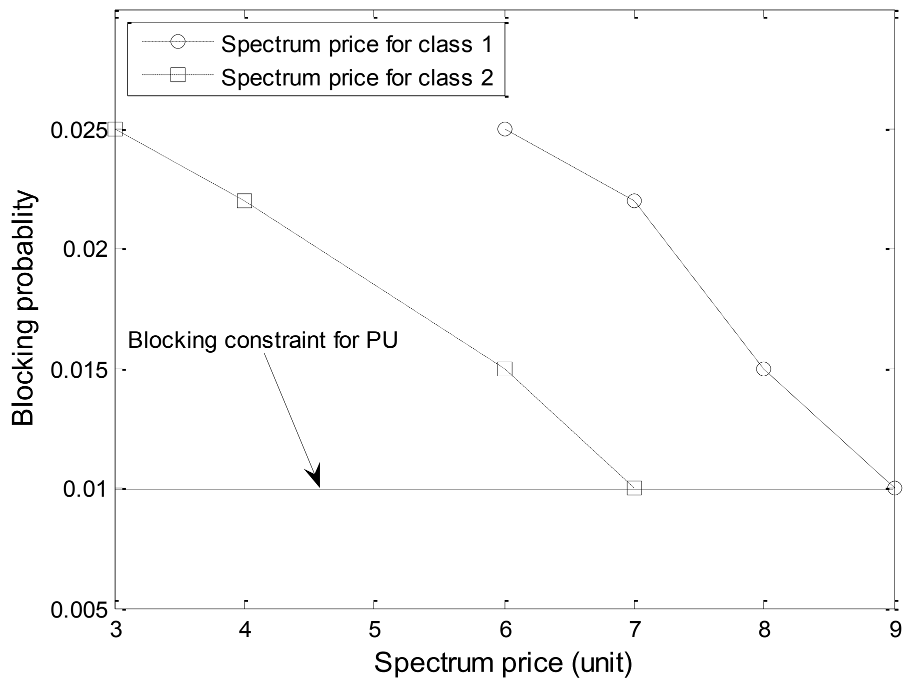

Fig 5.13. Adapting spectrum price to meet spectrum demand and maintain QoS for PU

5.7 Summary

The main objective in this Chapter is to analyze the ability of CN to maximize PUs revenues, maintain QoS for PUs and serve the maximum number of SUs. CN uses the rented spectrum from PUs to overlay SUs traffic. The resulting CN has been modeled, analyzed and simulated.

Machine learning model is presented to obtain an optimal policy for controlling spectrum trading in cognitive wireless multi-service networks. The proposed model has two contributions to cognitive networks. From the application side, the main contribution is developing a control policy that considers different requirements such as rewards for

PUs, wireless requirement (channel interference), QoS for PUs and SUs. All basic functions are integrated and optimized into one homogenous, theoretically based model.

From the modeling side, we formulate a spectrum trading problem as a reward maximization problem. Such a formulation allows reinforcement learning to optimize the spectrum trading problem. In this formulation, each SU is classified by its revenue. We define a reward function and cost functions for the RL model. The approach presents a general framework for studying, analyzing, and optimizing other resource management in cognitive mesh networks.

To make the solution feasible, we model a queuing system of spectrum requests. The request is served by a PU which has an adaptable spectrum size, limited by some conditions and constraints. Our scheme can be used to manage resources in any system where the administrator is looking to obtain an optimal policy in order to maximize outcome rewards.

We propose a new scheme for the PUs to control spectrum trading for the emerging spectrum secondary market. PUs can employ the proposed scheme to choose the optimal price and size of the offered spectrum. The objective is to adapt the size and price of spectrum in order to continuously maximize PUs' net revenues while maintaining PUs' QoS.

Simulations were also conducted and demonstrated the ability of our algorithm to support SUs requirements and obtain the potential performance gains by applying cognitive radio. It has been verified that cognitive technology can support additional users without deteriorating the QoS for the PUs. Moreover, the results demonstrated our scheme's ability to maintain QoS for users by adapting the size and price of the offered spectrum under different conditions.

We also propose a new distributed spectrum sharing scheme among primary users. PUs share spectrum based on demand whereby they can borrow spectrum from their neighbors while complying with interference rules. The benchmark in our experiments is the poverty-line heuristic which was proposed in [19]. Because it utilizes the unused spectrum efficiently for trading to the poverty-line heuristic, our scheme achieves higher net revenues. The poverty-line heuristic restricts borrowing by a threshold called poverty line which los the chance of using this spectrum for trading.

Chapter 6: Optimal Spectrum Utilization in Cognitive Network Using Combined Spectrum Sharing Paradigms: Overlay, Underlay and Trading

In previous Chapters we considered different spectrum sharing approaches, namely overlay, underlay, and trading, to improve spectrum utilization. However, these approaches when considered individually do not maximize spectrum utilization. To improve further spectrum utilization, we propose a new approach to merge them into one combined complete distributed system for cognitive network that contains all cognitive network functions. The new combined scheme increases the size of spectrum in the cognitive network because of using different access techniques based on their availabilities and requirements. Integrating spectrum sharing techniques in one system enables the cognitive network to exploit spectrum efficiently and to serve the maximum number of the SUs. Simulation results show the ability of the combined scheme to serve extra traffic in the cognitive network.

In the overlay approach, SUs detect the existence of PUs and specify the unused spectrum accurately. Developing an efficient scheme for utilizing spectrum using overlay approach faces its own many challenges. These challenges include: detecting PUs signals, exchanging spectrum data, coordinating among SUs, accessing unused spectrum, assigning the unused spectrum to the SUs, and evaluating the available spectrum. Using underlay approach, SUs are constrained to operate below the noise threshold of PUs if they access spectrum. Protecting the PUs against interference and supporting QoS for SUs are the main challenges for this approach. In this approach, there is no need to detect

PUs signals or to specify the unused spectrum. SUs may buy the right to access free spectrum temporarily from PUs. Specifying the size and the price of the offered spectrum for renting is the main challenge for PUs in the trading approach. PUs are required to maintain their QoS while simultaneously satisfying SUs.

In addition to the challenges of developing spectrum access techniques in CR, there are other difficulties that face developing the secondary network such as the deployment of new infrastructure for the secondary network, managing the network and hardware support.

6.1 Contribution

The novelty of our work is presenting a new architecture for cognitive mesh network. The architecture combines all spectrum sharing techniques. Our architecture is flexible to use any spectrum sharing technique. One advantage of this architecture is that it allows SUs to access unused spectrum for free if there is a chance. However, in the case when there is no opportunity for free usage, SUs purchase the spectrum. For hard QoS applications SUs may buy the rights to access the spectrum from PUs. We propose a new spectrum access for CN where all our access scheme is combined. We call the new scheme a combined scheme.

The combined scheme solves all the drawbacks of all access schemes. Combined scheme uses underlay scheme to serve SUs when the overlay access scheme is degraded significantly due to the activities of PUs. Overlay scheme performance is very sensitive to the PUs pattern usage for the spectrum. The likelihood of service interruption is increased significantly if the load at PUs is increased. To handle this situation the combined scheme uses underlay to guarantee the continuity for SUs. The new scheme tries to maximize the revenue in spectrum trading by preempting the free charge usage requests and serve the requests which pay more.

6.2 System Requirements

The basic requirements of our system are as follows:

1) Protecting PUs: spectrum is a valuable resource and PUs have invested a lot to acquire the exclusive right of the spectrum. Therefore, PUs will not allow sharing of their spectrum without getting some financial benefit. The charge free usage of the PUs' spectrum is allowed as long as SUs do not interfere with PUs.
2) Spectrum availability: SUs use PU's spectrum to communicate.
3) PU's rights and responsibilities: we define a PU as a spectrum owner that has the right to access given frequency band at any time exclusively. PUs do not need to communicate with SUs except if they decide to rent part of their spectrum. PUs are responsible for maintaining their QoS. They have to guarantee the QoS for SUs if they trade the unused spectrum.
4) SU's responsibilities and rights: the rights and the responsibilities of SUs differ with respect to the access techniques they use to access the spectrum as follows:
    - Overlay approach: in this approach, it is possible to have SUs concurrently transmit with PUs in a given interference region, but only one

communication takes place at a given time. SUs are responsible for detecting the unused portion of spectrum and they should vacate the spectrum as soon as the PU resumes its activities. Managing access to the free spectrum is the responsibility of the SUs. After specifying spectrum holes, SUs should follow a certain allocation scheme for utilizing the unused spectrum. In this approach, it is clear that the essential requirement for the SUs is monitoring the PUs' signals and specifying the spectrum status.

- Underlay approach: SUs can coexist with PUs in this approach. SUs can start transmission if they do not harm any PU. SUs should periodically check the PUs interference threshold and vacate the spectrum as soon as their signals interfere with PU signal. SUs are responsible for managing their power in the secondary network. They should monitor radio environment and adapt their transmission according to the changes in the wireless environment.
- Spectrum trading: SUs should inform the spectrum owner about the spectrum size and the duration of spectrum usage and the required QoS. After paying the PUs, SUs have the right to access the spectrum exclusively. SUs require information about their rights, the size and the price of the offered spectrum.

6.3 System Architecture

In this Section, we introduce our architecture. The architecture consists of all cognition cycle functions. These functions include: spectrum sensing, spectrum data gathering, processing spectrum, spectrum allocation.

6.3.1 Secondary Network Architecture and assumptions

SUs form clusters in the secondary network. Each cluster can be imagined as a WLAN, where MRs play the role of access point and the MCs act as nodes served by MRs. MRs use the PUs' spectrum to serve MCs.

6.3.1.1 Managing Clusters in the Secondary Network

The algorithm proposed in Section 3.2 is used to form the clusters. MRs manage the spectrum at each cluster. The functionality of MRs differ according to the access technique. In overlay approach, MRs manage cognitive cycle which includes spectrum sensing, processing sensing results and allocating spectrum to MCs. MRs allow MCs to transmit and specify the strength of transmission in the underlay approach. Managing the power at the secondary network is the main function of MRs in this access scheme. In spectrum trading approach, MRs receive SUs requests' for spectrum and buy the spectrum to serve SUs.

6.3.1.2 Signaling Protocol

Signaling protocol is used in underlay and overlay approaches only. In spectrum trading, SUs do not need to sense spectrum and exchange its data but PU disseminates spectrum information and the required prices. In the secondary network, MRs need information about signal powers of the PUs at each channel. This information is necessary to specify the status of radio environment and to adapt to the changes in the radio environment. The signaling protocol that is proposed in Section (4.2.1.2) is used to manage spectrum data in the CN.

6.4 Cognitive Mesh Network Design

Our system design only includes two OSI layers: the physical and the link layer. Other layers can use standard protocols.

6.4.1 Physical Layer Functions

Physical layer functions include the following:

1) Spectrum Sensing

In CN, the success of overlay and underlay access scheme is strictly conditional on the reliable detection of PUs signals. This requirement creates a new type of functionality on the physical layer for CN which is spectrum sensing. The spectrum status should be specified accurately using spectrum sensing. Spectrum sensing is not required for the trading scheme. The proposed scheme in Section 4.3 is used to sense the spectrum.

2) Spectrum Evaluation

In order to meet SUs requirements, the quality of the unused spectrum should be quantified. However, in wireless environment, the quality of the available spectrum holes fluctuates over time. Equation (5.20) is used to quantify the quality of the free spectrum in our system.

3) Power Management

For underlay approach, the main function is to manage the power of SUs. Transmission power determines the QoS for SUs, namely the data rate (i.e., more transmission power means higher data rate). However, increasing the transmission power of SUs will cause more interference for PUs and other SUs. Our algorithm that is proposed in Section 4.4 is used to manage the power of SUs.

6.4.2 Link Layer Functions

Link layer functions include the following:

1) Spectrum Data Management

Spectrum data should be processed and organized as needed. After receiving sensing results, MR combines the results using the decision function in equation (4.20) to generate the final status of spectrum. For overlay and underlay schemes, the MR uses a channel assignment scheme to serve SUs request after managing spectrum data. In spectrum trading approach, MR serves free charge requests of SUs using underlay and overlay scheme. If the rented spectrum is not sufficient to serve the requests which are not free, MR preempts spectrum allocated for free requests and serves the requests that have paid for accessing the spectrum.

2) Spectrum Allocation

In the overlay and the underlay approaches, MRs sort the free channels in decreasing order, according to their rank R_m in equation (5.20), and assign them for the MCs. At the same time, MCs are sorted according to their data rates in decreasing order by MRs. In the underlay approach, each MC is assigned a channel and the transmission power if it does not interfere with PUs. The overlay scheme assigns the unused spectrum to the SUs. In spectrum trading, MRs accept requests from different classes of MCs and buy channels to serve these requests.

3) Managing Power using underlay approach

In the secondary network, MCs generate different requests for data rates that require different transmission power. If a MR cannot serve the request, it places it in a FIFO queue. MR monitors the transmission power of all MCs and if any MC interferes with PU it stops it and returns this MC to the queue. The extracted policy using RL is used to assign channel for MC.

4) Spectrum Trading

In our spectrum trading framework, a spectrum adaptation algorithm is required in conjunction with the admission control algorithm. When the demand for the spectrum at the PU is less, the admission control algorithm can admit more MRs' requests and offer more spectrum for trading to increase the profit as much as possible. However, the demand for spectrum at PU may increase significantly and the QoS for PU is degraded. In this case, MRs requests should be rejected and the size of the offered spectrum should be reduced to maintain the QoS for PUs. If some channels are released, the PUs should decide which requests should be accepted and which should be rejected. We use RL as described in Chapter 6 to extract trading policy that helps the PUs to adapt to different situations.

6.5 Spectrum Allocation using Combined Scheme

In the combined scheme, the main objective is to maximize the availability of channels for users while they are communicating in the secondary network. Combined scheme merges the three spectrum access techniques in to one spectrum access scheme. After receiving the requests for spectrum, MR places the free-charge requests which are not charged for spectrum usage in a low-priority queue and other requests which are charged for spectrum in a high-priority queue.

First, MR uses the trading scheme to serve the requests in the high-priority queue. It uses the spectrum rented from PUs to serve the high-priority requests. If this spectrum is not sufficient to serve high-priority requests, the combined scheme uses underlay and overlay schemes to serve the remaining high-priority requests while continuing to serve the low priority-requests which are already in service. If the overlay and underlay schemes cannot serve the high-priority requests, it preempts some of the lower-priority requests and uses their spectrum to serve the high-priority requests. The combined scheme works as follows:

Algorithm 6.1 Combined Scheme

Parameters:

$\mathbb{L}_{\mathbb{q}}$*: low-priority queue*; $\mathbb{Y}_{\mathbb{q}}$*: high-priority queue.*

$\mathbb{S}_{\mathbb{t}}$*: The available spectrum for trading scheme;* $\mathbb{S}_{\mathbb{o}}$*: overlay spectrum;* $\mathbb{S}_{\mathbb{u}}$*: underlay spectrum.*

Trade($\mathbb{G}$*,* $\mathbb{B}$*): a trading scheme that uses the spectrum* $\mathbb{B}$ *to serve the requests in queue* $\mathbb{G}$*.*

Overlay_Underlay($\mathbb{G}$*,* $\boldsymbol{\mathcal{B}}$*): a scheme that uses the overlay and underlay schemes to serve the requests in queue* $\mathbb{G}$ *using spectrum* $\boldsymbol{\mathcal{B}}$*.*

size_req($\mathbb{G}$*): a function that gives the size of spectrum required to serve all requests in queue* $\mathbb{G}$*.*

preempt($\mathbb{V}$ *): a function to preempt the low-priority requests of size* $\mathbb{V}$.

Begin
while *(size_req(*$\mathbb{Y}_{\mathbb{q}}$*)* $\neq 0$ *)*
if*(* $\mathbb{S}_{\mathbb{t}} \geq$ *size_req(* $\mathbb{Y}_{\mathbb{q}}$*))*
{
Trade*(*$\mathbb{Y}_{\mathbb{q}}$, $\mathbb{S}_{\mathbb{t}}$)
Overlay_Underlay*(*$\mathbb{L}_{\mathbb{q}}$*,* $\mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$*)*
}
else
if*(size_req(*$\mathbb{Y}_{\mathbb{q}}$*)*$- \mathbb{S}_{\mathbb{t}} \leq \mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$ *)*
{
Trade*(*$\mathbb{Y}_{\mathbb{q}}$, $\mathbb{S}_{\mathbb{t}}$)
Trade*(*$\mathbb{Y}_{\mathbb{q}}$, $\mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$*)*
Overlay_Underlay*(*$\mathbb{L}_{\mathbb{q}}$*,*$\mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$*)*
}
else
{
Trade*(*$\mathbb{Y}_{\mathbb{q}}$, $\mathbb{S}_{\mathbb{t}}$)
Pre-empt *(size_req(* $\mathbb{Y}_{\mathbb{q}}$*))*
Trade*(*$\mathbb{Y}_{\mathbb{q}}$, *size_req(* $\mathbb{Y}_{\mathbb{q}}$*))*
}
EndWhile
Overlay_Underlay*(*$\mathbb{L}_{\mathbb{q}}$*,* $\mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$*)*

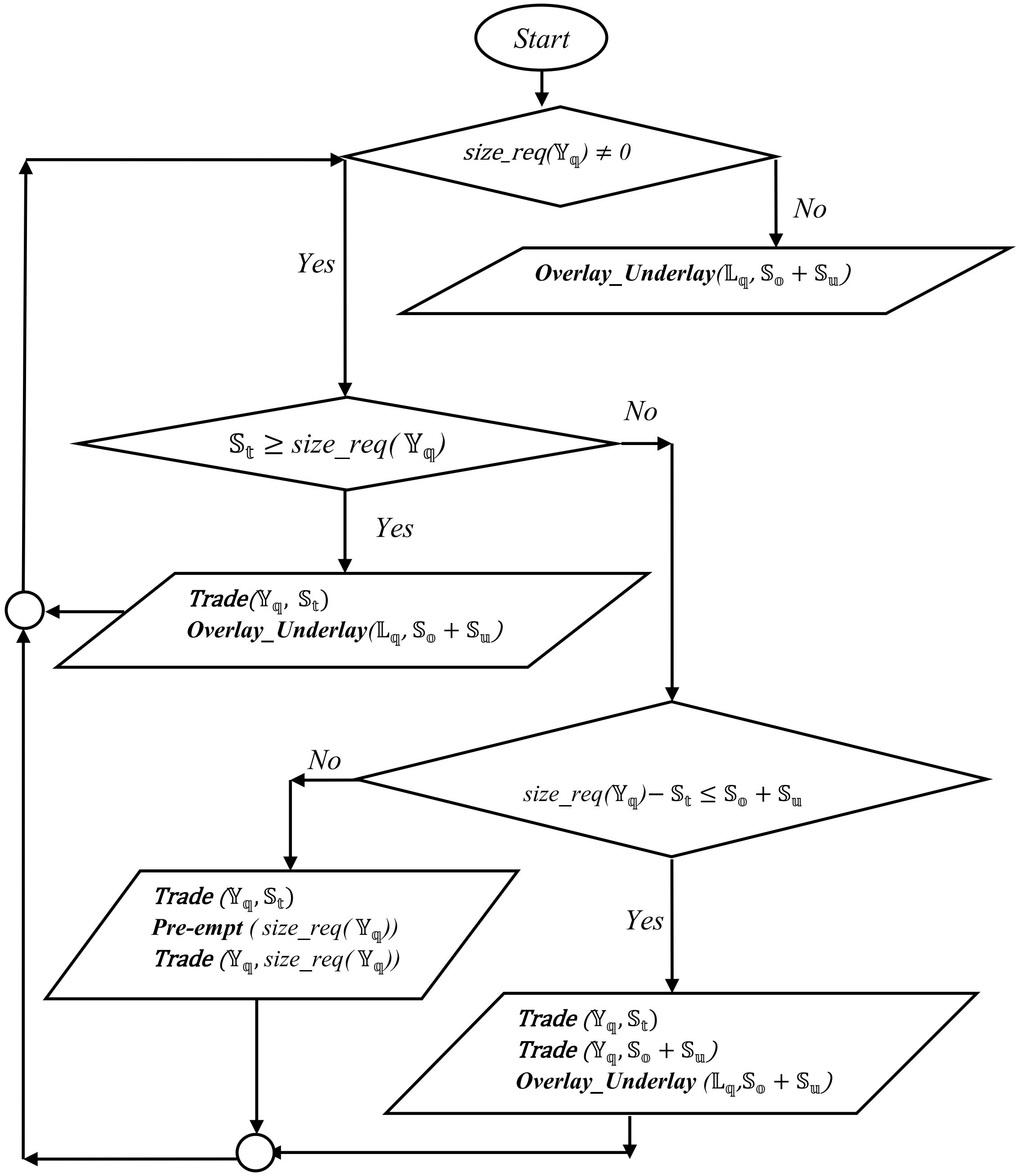

Fig 6.1: Flowchart for the combined scheme

Fig 6.1 shows the flowchart for combinedspectrum sharing scheme. The performance of the overlay scheme is highly dependent on the PUs pattern usage. Hence, guaranteeing spectrum using overlay scheme is impossible. For each overlay channel $\mathbb{s}_{\mathbb{o}}$, there exists an underlay channel $\mathbb{s}_{\mathbb{u}}$ that can be used to replace $\mathbb{s}_{\mathbb{o}}$ if the PU starts using the $\mathbb{s}_{\mathbb{o}}$. This can be expressed as follows:

$$\mathbb{s}_{\mathbb{o}} \in \mathbb{S}_{\mathbb{o}} \rightarrow \exists \mathbb{s}_{\mathbb{u}} \in \mathbb{S}_{\mathbb{u}} \qquad (6.1)$$

where $\mathbb{S}_{\mathbb{o}}$ is the overlay spectrum, and $\mathbb{S}_{\mathbb{u}}$ is the underlay spectrum. Each spectrum request consists of more than one link in a path. Overlay_Underlay scheme consists of two phases: allocation phase, and maintenance phase. In the spectrum allocation phase, the scheme uses the overlay channels first to serve a request. If the overlay channels are not sufficient to serve all links, Overlay_Underlay scheme uses the underlay spectrum to serve the links that are not served. In the maintenance phase, MR monitors all communication in the network and if any failure occurs because of PU activity, Overlay_Underlay scheme replaces the overlay channel by its corresponding underlay channel. Overlay_Underlay scheme is presented as follows:

Algorithm 6.2 Overlay_Underlay scheme

Parameters:

$\mathbb{L}_{\mathbb{q}}$: *low-priority queue*; $\mathbb{Y}_{\mathbb{q}}$: *high-priority queue.*

$\mathbb{S}_{\mathbb{t}}$: *The available spectrum for trading scheme;* $\mathbb{S}_{\mathbb{o}}$: *overlay spectrum;* $\mathbb{S}_{\mathbb{u}}$: *underlay spectrum.*

Overlay($\mathbb{r}$, $\mathbb{B}$) : *an overlay scheme to serve the request* $\mathbb{r}$ *using spectrum* $\mathbb{B}$

Underlay($\mathbb{r}$, $\mathbb{B}$) : *an underlay scheme to serve the request* $\mathbb{r}$ *using spectrum* $\mathbb{B}$

NotComplete($\mathbb{r}$*)* : *a function to check if all the links of the request* $\mathbb{r}$ *are served by overlay scheme*

Begin

while *((* $\mathbb{S}_{\mathbb{o}} + \mathbb{S}_{\mathbb{u}}$ *) > 0 and size_req(*$\mathbb{L}_{\mathbb{q}}$*) ≠ 0)*

    Overlay*(*$\mathbb{r}$,$\mathbb{S}_{\mathbb{o}}$*)*

    if *NotComplete(*$\mathbb{r}$*) then*

        Underlay*(*$\mathbb{r}$,$\mathbb{S}_{\mathbb{u}}$*)*

    endif

EndWhile

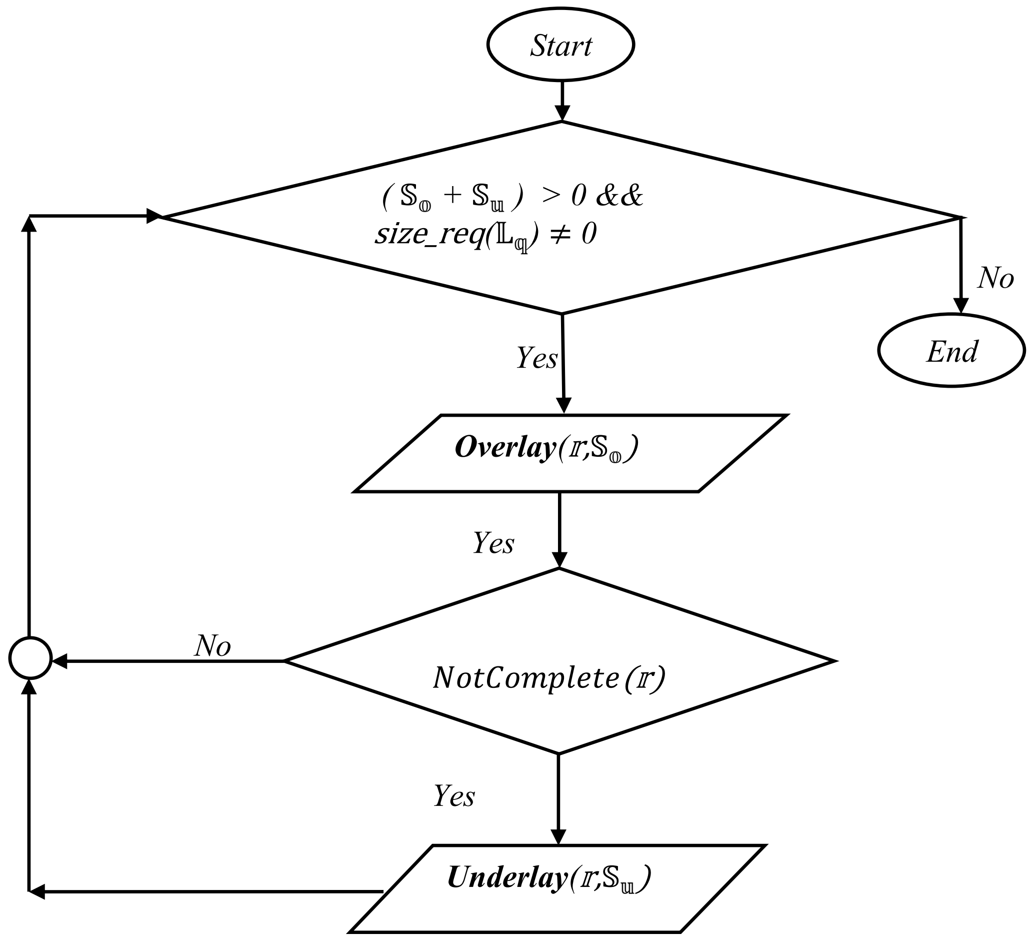

Fig 6.2: Flowchart for Overlay_Underlay scheme

Fig 6.2 shows a flowchart for Overlay_Underlay scheme.

6.6 Performance Evaluation

In this Section, we show the simulation results to demonstrate the performance of our proposed system. We study the behavior of our system under different parameter settings.

6.6.1 Overlay scheme performance

In this Section we extend our experiments in Section 3.5 to demonstrate the performance of our overlay scheme (cluster-distributed scheme) in the new system. We compare the performance of our overlay scheme (with the conventional method where all secondary users send their sensing results to a centralized server and the cluster-centralized scheme used in [29].

The speed of spectrum sensing and the processing time of spectrum detection results are the most important factors for the success of the overlay approach. The unused spectrum should be utilized as soon as possible before the PU resumes its activities. The results about the speed of the clustered-distributed sensing scheme are reported in Section3.5. Our scheme needs less time to access the unused spectrum because there is no contention for the pre-defined control channel which is used for exchanging spectrum data in the other methods. In the scheme used in [29] cluster heads contend for a control channel. Moreover, in the conventional method all SUs contend for a control channel to send spectrum detection results.

The key success factor for the overlay scheme is the speed of utilizing the unused spectrum and reducing the chance of service interruption in the secondary network. The available spectrum in the secondary network under different values of load traffic at PUs for the three overlay schemes is shown in Fig. 6.3. The figure shows that the available spectrum decreases as the traffic load increases at the PUs. A higher traffic at the PUs increases the likelihood of service interruption in the secondary network. Because our scheme needs less time to access the unused spectrum, its spectrum size is more than that of the other schemes.

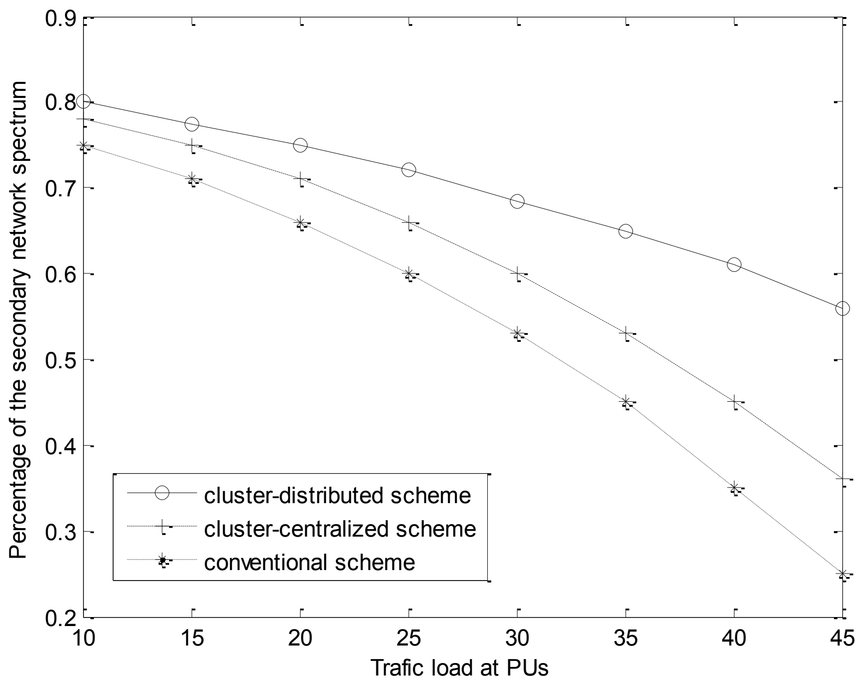

Fig 6.3. Overlay Scheme: Spectrum used for different values of traffic load at PUs

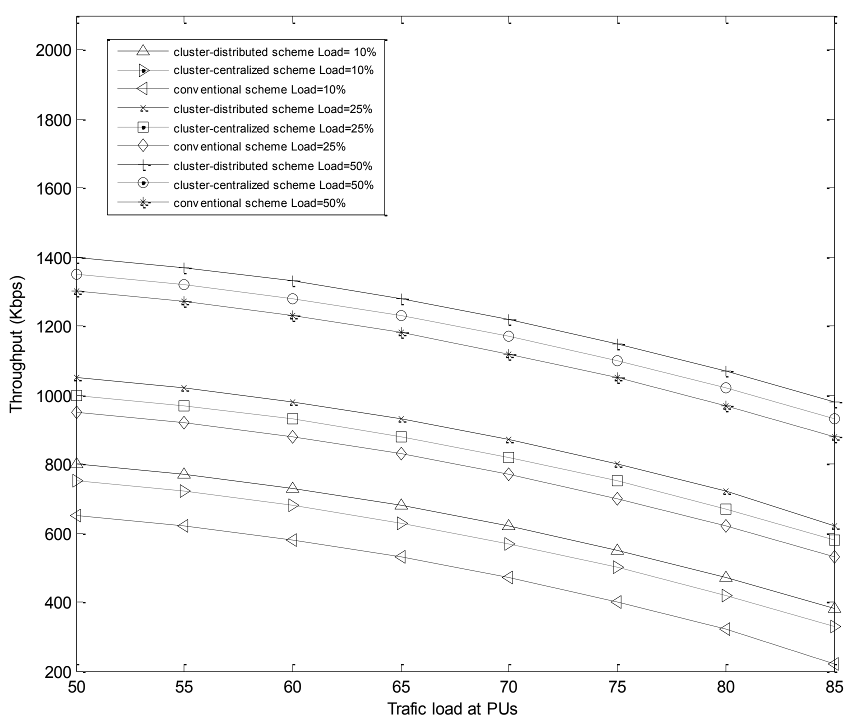

Fig 6.4. Overlay Scheme: Throughput comparison for different values of traffic loads at PUs

The throughput comparison of the three different overlay schemes is shown in Fig. 6.4. The figure shows that the throughput decreases as the traffic loads at the PUs increase. Small values of work load at PUs means that the PUs rarely need the spectrum. Therefore, interruption of the SUs is rare in this scenario. The results show that our scheme outperforms other schemes when the number of SUs is increased and also for different traffic loads. By increasing the traffic load at PUs the available spectrum in the secondary network is decreased significantly. Hence, the requirements of the PUs prevent overlay scheme to keep increasing the throughput. These results stress the need for other spectrum sharing techniques that can guarantee QoS in the secondary network.

6.6.2 Underlay scheme performance

In this Section we show the performance of our power management scheme in the proposed system. In Fig. 6.5, we compare the performance of the policy obtained through RL in Section 4.4 (intelligent power management scheme) with the algorithm used in [34] (power management scheme). We compute the average cost as a function of time. Fig. 6.5 shows that the average cost increases because of serving more requests. By serving more requests, the likelihood of interfering with the PUs increases, which results in more path loss because of decreasing the signal powers of the MCs. To protect the PUs, the power management scheme should reduce the signal power when MCs transmission harms PUs. Because our scheme considers a path loss when assigning channels, it has the lowest cost. The scheme in [34] does not attempt to minimize the path loss when allocating the spectrum.

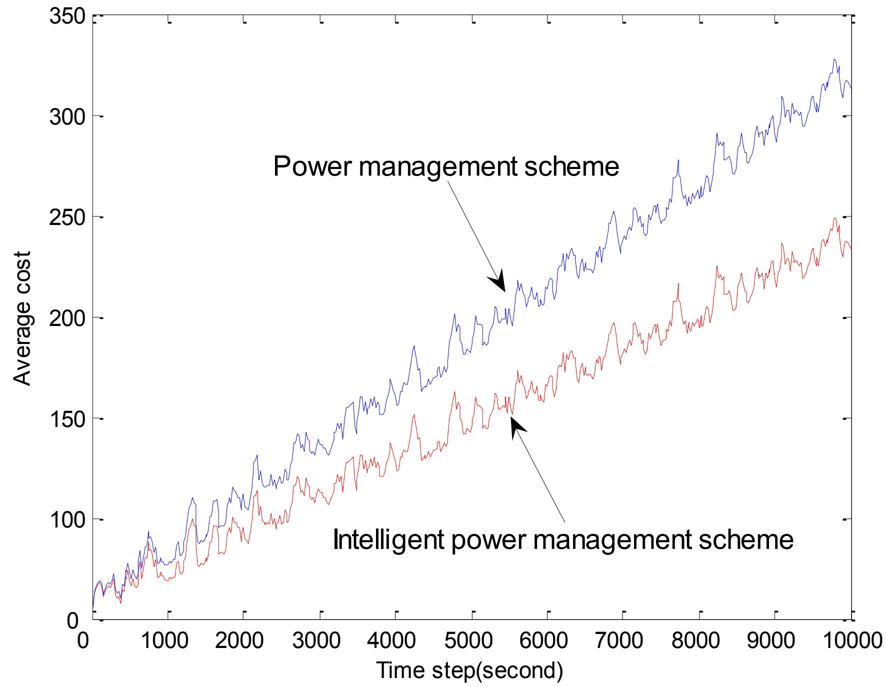

Fig 6.5. Underlay Scheme: Average cost comparison as a function of time

Fig. 6.6 shows a comparison of the reported throughput of our proposed power management scheme with the power management scheme proposed in [34] and our overlay scheme as a function of time. At the beginning, and for about 2000 seconds, the total reported throughput for all schemes is similar. The throughput is increased as the traffic load increases in the secondary network. As time elapses however, our intelligent power management scheme outperforms other schemes. The justification is that our scheme always allocates the spectrum for the SUs if they do not interfere with the PUs. Hence, more requests are allowed in the network, and therefore the total throughput increases for this scheme.

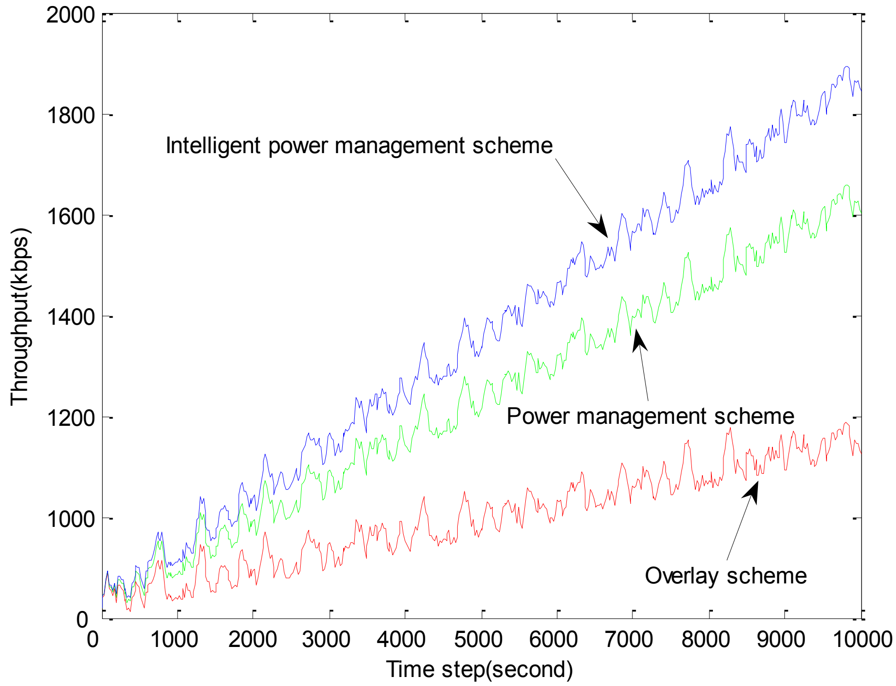

Fig 6.6. Throughput comparison for the Overlay and Underlay schemes as a function of time

The power management scheme achieves good throughput, but it does not consider the usage pattern for the PUs or the quality of channels when allocating them for the SUs and, therefore, the likelihood of channel releasing is larger than ours. Our overlay approach focuses only on identifying and avoiding PUs' signals. On the other hand, the underlay approach seeks to share the same frequency band, at the same time, between SUs and PUs. As a result, it provides a robust and scalable communication, which enables it to outperform other schemes, as can be seen in Fig. 6.6.

Fig. 6.7 shows the acceptance rate of the accepted number of SUs' requests versus the number of requests (spectrum demand). The acceptance rate $ARATE$ is computed as follows:

$$ARATE = \frac{ACPT}{ACPT+REJCT} \tag{6.2}$$

where $ACPT$ is the number of the requests accepted, and $REJCT$ the number of requests rejected. The figure shows that the intelligent scheme outperforms other schemes. The acceptance rate in all schemes is decreased as the spectrum demand increases because of the constraints of using the spectrum. Unfortunately, the performance of the underlay scheme depends on the interference threshold for the PUs. In the above figures, we assume the interference threshold I that can be tolerated at the PU to be $I = 5I_0$, where $I_0 = 10^{-15}$ W.

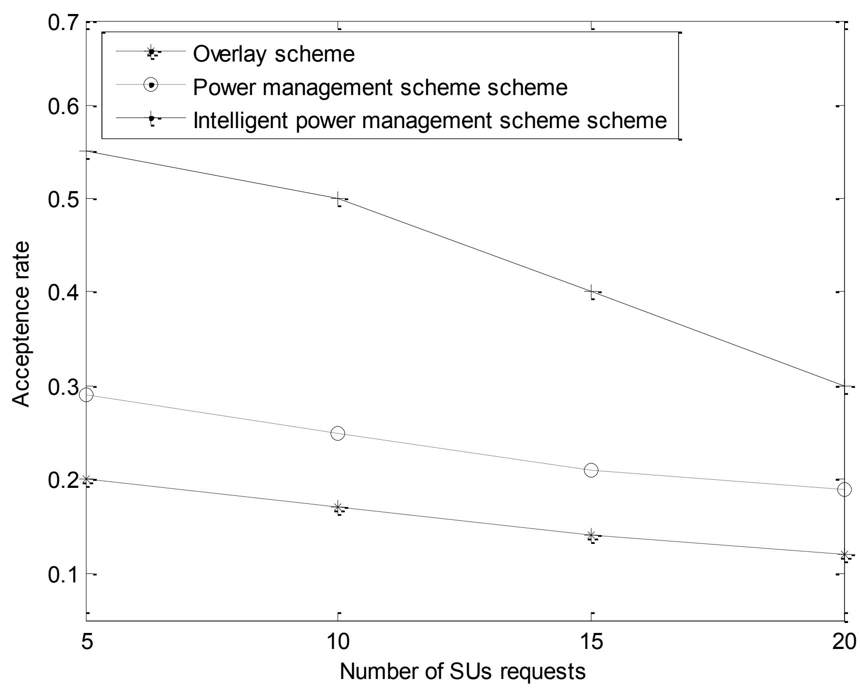

Fig 6.7. Acceptance rate of the SUs requests for the Overlay and Underlay schemes

In Fig. 6.8 we plot the network throughput under different interference thresholds settings. As expected, the throughput is degraded significantly when the interference constraint is made more stringent. The results stress that the performance of the underlay approach depends mainly on the interference constraint. Another factor that degrades the performance of the secondary network is the interference from the PUs. The SUs suffer from the PUs' interference and their QoS is degraded significantly. This spectrum sharing paradigm does not require the PUs to cooperate with the SUs. The key result when looking at Fig. 6.8 is that the performance of the underlay approach is very sensitive to the interference threshold of the PUs. We can however improve the results by finding a strategy that allows the PUs to cooperate with the SUs, as will be shown using our trading scheme.

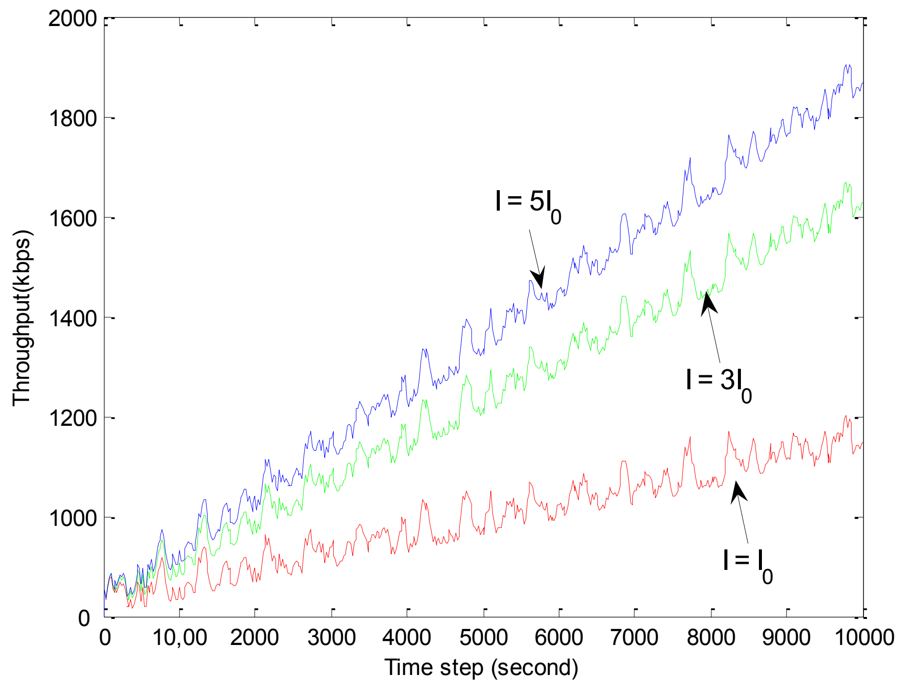

Fig 6.8. Underlay scheme: Throughput comparison for different interference constraints

6.6.3 Trading scheme performance

We conduct experiments to demonstrate the ability of PUs to adapt to different conditions in our system. Due to the dependency of the spectrum price on the traffic load at the PUs, the reported revenue will vary based on the new prices. Fig. 6.9 shows how a PU varies the prices of spectrum to reduce the amount of the offered spectrum in the secondary network and uses the new available spectrum to serve the applications of the PUs. Because it gets more revenue from class 1, the PU tries to increase the price for class 2 more than class 1. However, to maintain the QoS of class 2, the PU sometimes also increases the price of class 1. Fig. 6.10 shows the acceptance rate of both SUs classes under different traffic loads at the PU. It can be observed the admission scheme rejects more requests under large traffic loads. Furthermore, the likelihood of rejecting class 2 requests is higher than class 1 because of the higher revenue.

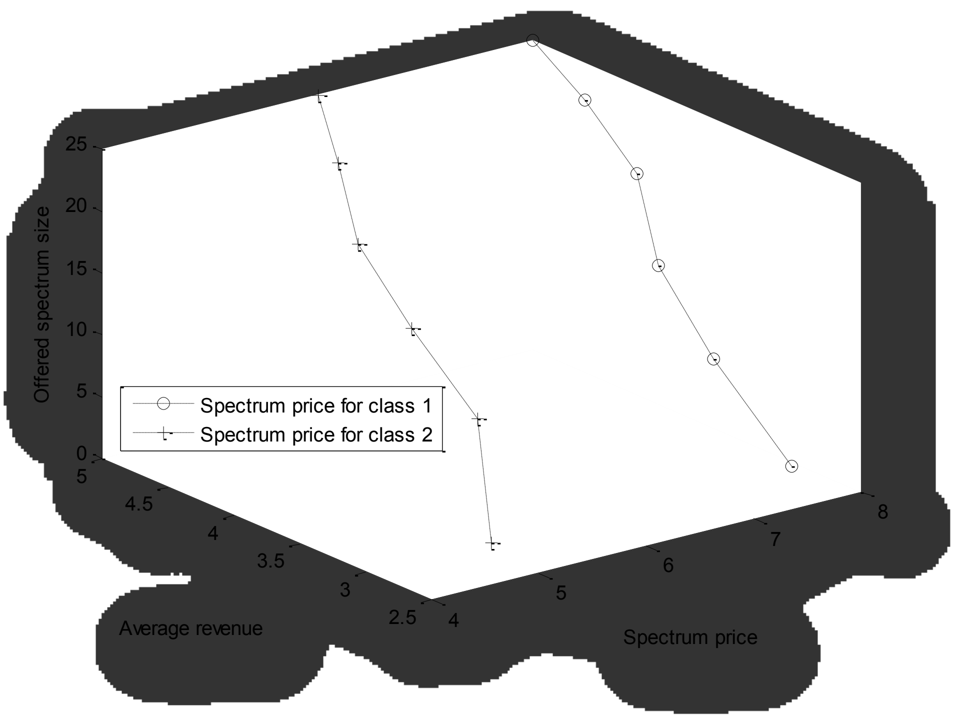

Fig 6.9. Trading scheme: Adapting spectrum price for different offered spectrum size to optimize revenue

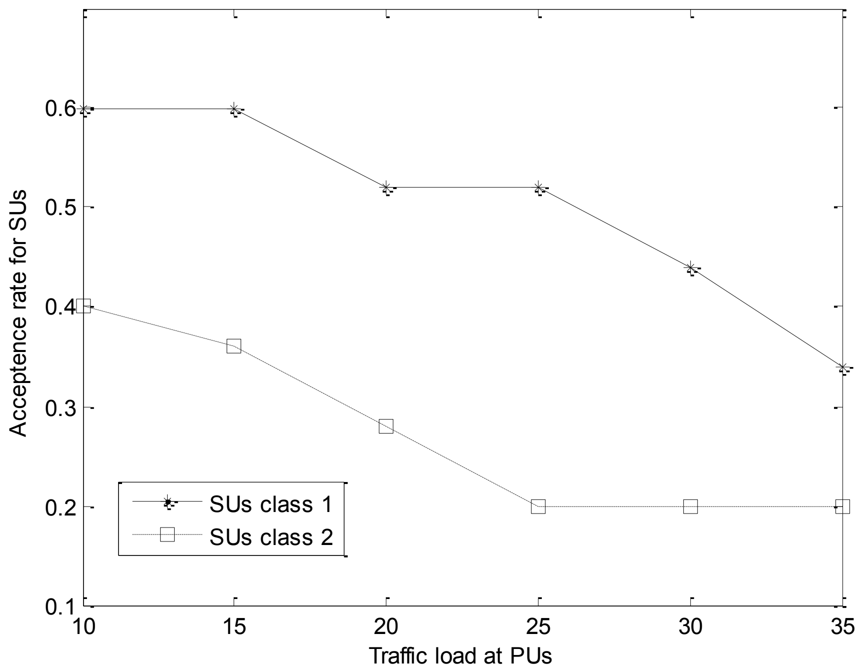

Fig 6.10. Trading scheme: Acceptance rate for SUs classes for different traffic loads

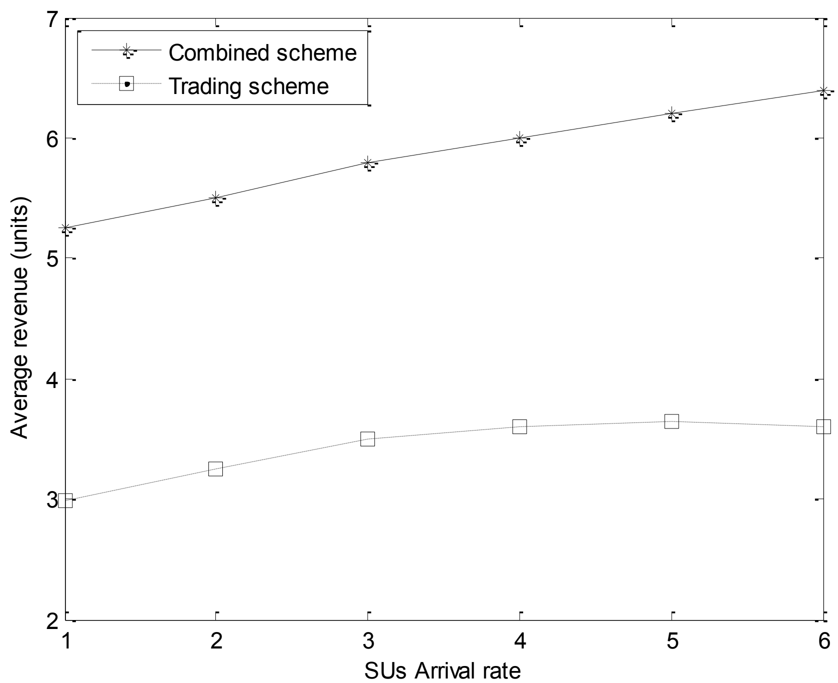

Fig. 6.11. Average revenue for the combined scheme and trading scheme for different arrival rates of SUs

6.6.4 Combined scheme performance

We compare the performance of the combined scheme with performance of trading scheme. Fig. 6.11 shows the reported revenues for the combined scheme and the trading scheme for different values of spectrum demand of SUs. It can be observed that the combined scheme outperforms the trading scheme, since it uses the rented spectrum as well as the free spectrum available using the overlay and underlay approaches more efficiently. Because it accesses more spectrum, the combined scheme generates more revenues than the trading scheme. Furthermore, the combined scheme utilizes the unused spectrum if the usage does not harm the PUs. However, for the trading scheme, the requests are rejected if there is no spectrum. From the throughput point of view, we measure the throughput for the two schemes under different values of traffic loads at PUs in Fig. 6.12. From the figure, we notice that the combined scheme achieves more throughput than the trading scheme. Combined scheme uses more access techniques which enable it to utilize more spectrum. Using more access schemes enable combined scheme to serve more users in the secondary network. Fig. 6.13 shows the acceptance rate of SUs of both queues when using the combined scheme. As expected, the acceptance rate of the SUs' requests in the high-priority queue is more than the acceptance rate of the requests in the lower-priority queue because of revenues. The acceptance rate of the lower-priority requests decreases as the spectrum demand increases because of revenue. The combined scheme tries to maximize the revenue as much as it can. Hence, it gives the priority for the requests which are charged for the spectrum as can be seen from Fig. 6.13.

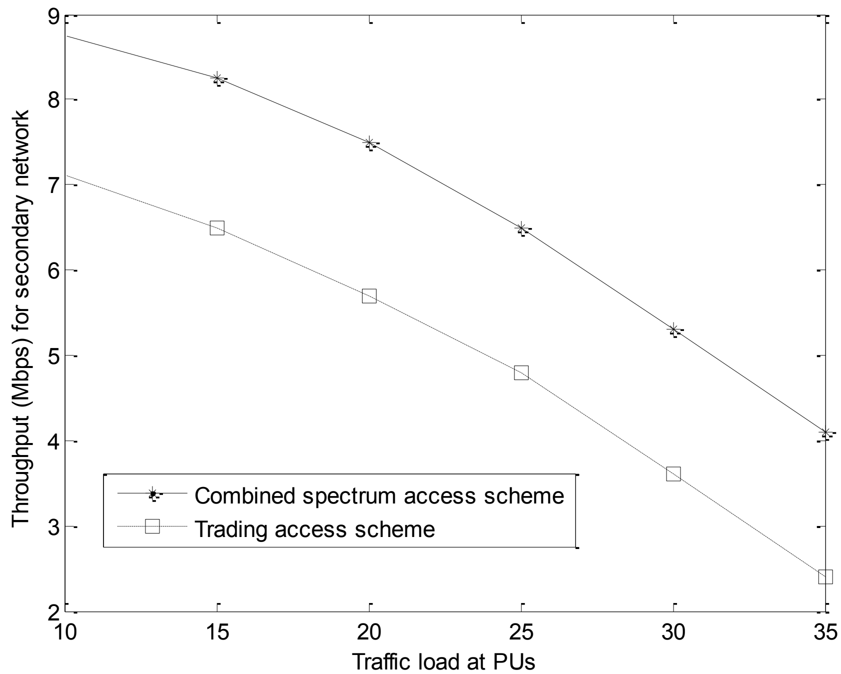

Fig 6.12. Throughput comparison for the combined spectrum access and trading technique under different traffic loads.

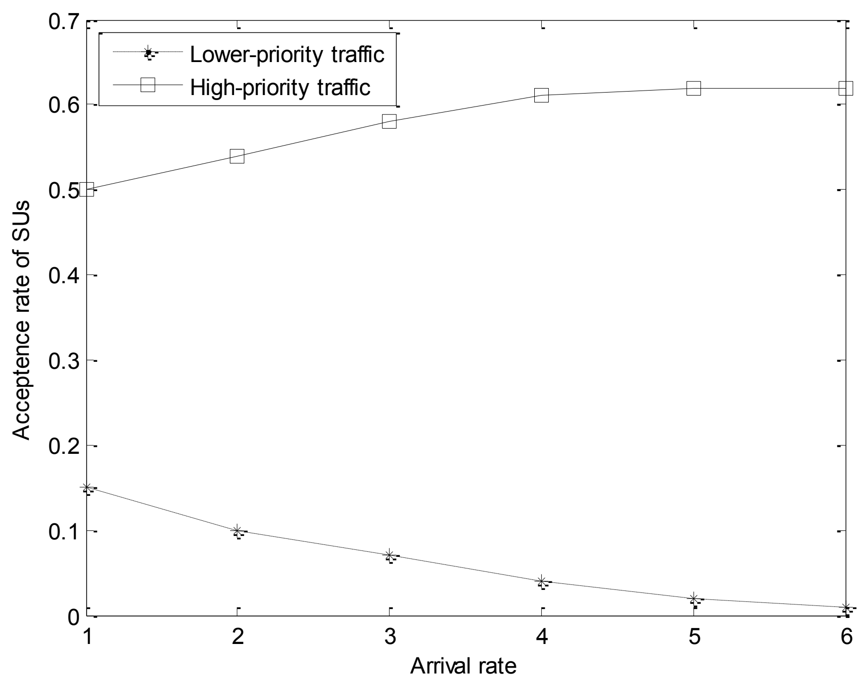

Fig. 6.13. Acceptance rate for different requests priorities

6.7 Summary

The main objective of this Chapter is to propose a complete system for cognitive network. The system contains all of cognitive cycle functions such as spectrum sensing, collecting sensing results, processing the results and managing the spectrum. Our new system combines the three known spectrum access techniques in one access scheme. For the architecture of the cognitive network, we use a clustered mesh network as proposed in Chapter 3, which is based on a novel sensing method. The sensing method is collaborative and it enables the system to specify the unused spectrum accurately and use it resourcefully. Our overlay scheme is employed to access the unused spectrum. The results show the scalability of the new scheme and its ability to utilize the spectrum more efficiently than other schemes. Although the proposed scheme outperforms other schemes in terms of throughput and spectrum utilization, its performance depends on the PUs' activities.

For higher load traffic at the PUs, the performance of the overlay scheme is degraded significantly. To solve this problem, we use the underlay access scheme to enable SUs to transmit concurrently with PUs. For the underlay scheme, RL based self-optimization algorithm is used to enable users to adapt to the changes in the network conditions. The RL algorithm enables the integration of the admission control algorithm in our scheme. The admission algorithm is used to exclude SUs' requests that may harm PUs so that the QoS for the SUs and the interference constraint for the PUs are met. Simulation results show the feasibility of the underlay solution. However, some results stress the sensitivity of the underlay performance to QoS and interference constraints. For some settings, the performance degrades significantly.

To provide better service to SUs, we propose a spectrum trading where PUs cooperate with SUs. In this scheme, PUs rent adaptable sizes of the spectrum to the SUs based on their requirements. The key objective of this scheme is to adapt the size and the price of the spectrum to maximize the PUs revenues while providing the required QoS for the PUs and SUs. The trading model is based on the RL algorithm that allows the integration of the adaptation of the spectrum size, price and admission algorithm. Simulation results show the ability of the proposed scheme to adapt to different network conditions and to achieve the required objectives. The results also confirmed the QoS requirements for the PUs can be met by the proposed price adaptation algorithm.

To take advantages of all previous schemes, we propose a combined scheme. The combined scheme integrates all spectrum sharing paradigms. Integrating all schemes enables accessing to more spectrum and serving more SUs. The numerical results reveal the usefulness of considering more than one spectrum sharing scheme on the performance of the secondary network.

Chapter 7: Conclusion and Future work

This dissertation consists of several of our contributions and publications on the performance analysis and applications of cognitive radios. In Chapter 1, we gave an introduction to the spectrum scarcity problem, and spectrum sharing techniques. We discussed the main challenges and specified our objectives and the key contributions of our research. In Chapter 2, we analyzed the difficulties of spectrum sharing and building a secondary network for unlicensed users. Related works to these difficulties were reviewed. In particular, we reviewed the state of art for CN architecture, overlay spectrum access technique, underlay sharing approach and spectrum trading. The drawbacks for pervious solutions were highlighted. An overview about our solution was given in this Chapter. Our solution includes using CN to solve spectrum scarcity problem and machine learning to help users to adapt to the radio environment.

In Chapter 3, we used a clustering approach to manage the secondary network where the network is divided into clusters. The architecture provides scalability and guarantees the availability against any failure of MR. Each cluster is managed by a MR. We balance the load at each MR to guarantee the QoS for MCs. We developed the required signaling protocols for this network. The architecture considers the activities of PUs and it guarantees their rights of exclusive access for the spectrum.

The underlay scheme was introduced in Chapter 4. RL is used to manage the power of MCs and it helps a MR to adapt to the changes in the radio environment. A path loss was defined as a measure of the cost function for RL model. The RL scheme tries to minimize the path loss as much as possible. A new decision function was defined to quantify the quality of the free spectrum. Several heuristics were used in this function. The proposed spectrum allocation scheme in Chapter 4 uses the decision function and the QoS for MCs and it also protects the PUs.

A new spectrum trading scheme was proposed in Chapter 5. PUs can use the trading scheme to trade the unused spectrum to multiple classes of MCs. RL was used to help MCs to optimize the gained revenue. It specifies the optimal price and size for the offered spectrum under different conditions. PUs change the prices to control the spectrum demand. Furthermore, it uses the price to support the QoS for all the classes of MCs and PUs. The performance of the proposed trading scheme is analyzed and demonstrated by simulations.

All the proposed spectrum sharing techniques in this thesis are merged into one scheme in Chapter 6. Combining all spectrum access techniques provides more spectrum and enhances the scalability of the system. Hence, more SUs can gain a significant capacity when allowed to use more spectrum sharing techniques share the spectrum at the same time and this is verified by simulating our system. We presented the requirements of a complete cognitive system in this Chapter. All the functions of CN are implemented in the cognitive system.

In this dissertation, we give a comprehensive overview of cognitive network. In particular, we provide the following contributions addressing the technical challenges in the design of the cognitive network:

- Proposing a complete architecture for cognitive network. CN were divided into clusters. We considered the size of clusters and we balanced the load at cluster head. Our architecture combines all the known spectrum sharing techniques and all the functions of cognitive cycle. This combination provides the flexibility for SUs to access the unused spectrum using different techniques.

- Supporting the QoS for PUs and SUs in the secondary network. We use RL to assure the QoS for PUs when renting the unused spectrum for SUs. Moreover, the trading policy supports the requirements of SUs in the secondary network. A new cooperative sensing scheme is proposed to protect PUs from harmful interference with PUs when adopting overlay approach. In underlay scheme, MRs manage the power of the MCs to prevent them from interfering with PUs.
- We propose a new distributed scheme to manage spectrum sharing among the PUs to maximize the total profit of the PUs.
- New heuristics for spectrum analyses were proposed and they were used for spectrum assignment. These heuristics include PU activities, channels error bit rates, and delay due to channel switching.

7.1 Future Work

The performance of our overlay scheme can be improved by reducing sensing errors. For example the sensing errors due to fading channel can be reduced by selecting control channels with less noise. In our work we assume the PUs have fixed locations. In the future we can extend the model to incorporate the mobility of PUs. New sensing schemes can be developed to sense the spectrum based on PUs mobility and to consider the quality of the control channels.

For underlay scheme, we wish to consider the economic factors where MR assigns the channel, signal power for the SUs and the price of service. The pricing scheme should consider the assigned power level and the state of wireless network. We will study the revenue of PUs and propose the methodology that can help MR to maximize the revenue.

For the channel assignment problem in cognitive network, we wish to consider the fairness among SUs to access the free spectrum. In our work we serve based on their requirements. Our aim is to maximize CN throughput and to serve the maximum number of SUs. However, it is important to maintain throughput fairness among SUs to avoid severe QoS degradation for users with unfavorable channel conditions.

Future work related to the spectrum trading research can be branched into several categories. One possible extension to the current work includes studying spectrum prices under different behavior of PUs. In competitive pricing model, each PU tries to maximize the individual profit, and there is a competition among PUs to sell the spectrum for SUs. This will give an opportunity to investigate how PU can adapt their spectrum prices to other PUs prices. In the presence of multiple PUs, the spectrum price setting depends on the PUs strategies. Another extension could involve quantifying the spectrum demand based on the utility. If the free spectrum provides high utility for SUs, the demand for spectrum will be high and this gives the PUs the chance to increase their profits through setting higher prices for the spectrum. For example, the utility function in [56] can be used to quantify the spectrum demand of SUs.

The algorithms developed in this dissertation are not only limited to wireless mesh network technology but also can be applied to new wireless technologies. For example, our solutions can be applied to other general purpose ad-hoc networks. The implementation of the developed algorithms in new technology will definitely lead to a better QoS performance for SUs. Furthermore, the proposed resources management scheme can be used to manage other wireless resources. Our system can be extended with design routing protocol to provide a complete cross layer design.

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