Adaptive Weighted Scheduling in Cognitive Radio Networks

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

A problem in modern wireless communications is the scarcity of electromagnetic radio spectrum. The traditional fixed spectrum assignment strategy results in spectrum crowding on most frequency bands. Due to limited availability of radio spectrum and high inefficiency in its usage, cognitive radio networks have been seen as a promising solution to reducing current spectrum under-utilization while accommodating for the increasing amount of services demands and applications in wireless networks. Compared with the traditional networks, cognitive radio networks exhibit some distinct features, which result in necessity of further research in the resource allocation and scheduling that have been solved for the traditional networks.

In this thesis, we focus on the packet scheduling in a single cell cognitive radio system with a single channel. An adaptive weight factor is introduced to adjust the priority of different cognitive radio users to be selected for service. The purpose of this research is to solve the unfairness problem of the traditional proportional scheduling schemes when used directly in a cognitive radio network, which lead to a user starved for a long time if it experiences a poor channel condition when the channel is available and experiences a good channel condition when the channel is not available. An adaptive weighted scheduling scheme is proposed to improve the performance in terms of throughput and fairness by jointly considering the instantaneous propagation conditions, adaptive weighted factor and the channel availability.

The saturated traffic and non saturated traffic cases are considered. Some important performance metrics are investigated in the simulation, such as the system throughput, fairness, and service probability, and are quantified by the impact of weights and channel conditions. Extensive simulations have been conducted to demonstrate the effectiveness and efficiency of the proposed scheduling scheme.

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To my truly loved parents,

for their support, encouragement, and endless love.

Contents

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List of Abbreviations

ARQ	Automatic repeat request
AWF	Adaptive weight factor
AWSS	Adaptive weighted scheduling scheme
CRBS	Cognitive radio base station
CRN	Cognitive radio network
CRU	Cognitive radio user
FCC	Federal Communication Commission
HDR	High data rate
MAC	Media access control
PDF	Probability density function
PF	Proportional fairness
PU	Primary user
RF	Radio frequency
RWP	Random waypoint
SDR	Software defined radio
SNR	Signal to noise ratio
SU	Secondary user
TCP	Transmission control protocol
TDMA	Time-division multiple access
WiMAX	Worldwide interoperability for microwave access

List of Symbols

a	The scale factor of Weibull distribution
AT_{ij}	The packet j 's arrival timeslot of CRU i
b	The shape factor of Weibull distribution
B	Bandwidth
c	A constant in pathloss
C_{sys}	System capacity
d_i	The distance between the CRBS to CRU i
DT_{ij}	The packet j's departure timeslot of CRU i
$F(\cdot)$	Jain fairness index
h_i	Channel gain of CRU i
k	The path loss distance exponent
L	The payload size of a packet size
$Length(t_{tr})$	The length of the t_{tr}
m_i	The multipath fading
M	The number of the CRUs
n_{end}	The simulation ending timeslot
N_0	Background noise
N_G	The sample of a white Gaussian random process
N_i	The number of consecutively inactive timeslots
P_1	The probability of a channel staying in inactive state
P_2	The probability of a channel staying in active state
P_i	The received power of CRU i

P_{r1}	The transfer probability of a channel from inactive state to active state
P_{r2}	The transfer probability of a channel from active state to inactive state
P_w	The transmission power of the CRBS
PD_{sys}	The system packet delay
R	The radius of a cell
s_i	The slow fading
S	The number of the packet
t_{tr}	Transmission time
t_s	Sensing time
T	The file size of each call
T_i	The time length of consecutively inactive timeslots
Th_i	The throughput of CRU i
TT_{ij}	The packet j's transmission time of CRU i
v_i	The velocities of CRU i
$Weibull(a, b)$	Weibull Distribution with factor a and b
WT	Waiting time
X_i	The user i's relative channel condition adjusted by AWF
Y_i	The user i's relative channel condition
γ_i	the instantaneous channel gain for user i
$\bar{\gamma}_i$	The average channel gain for user i
$\Delta\xi$	The step increment of the AWF
ζ	The correlation between two points separated by one meter
$\theta(n)$	The channel availability for the CRU at the n^{th} timeslot
ϑ_i	Moving direction of CRU i
λ	Call arrival rate
$\xi_i(n)$	The AWF value for user i at the n^{th} timeslot

π_i	The service probability of CRU i
τ	The number of packets in a call
φ	The index of the selected CRU at a timeslot
χ_i	The attenuation due to shadowing in dB

Chapter 1

Introduction

A problem in modern wireless communications is the scarcity of electromagnetic radio spectrum. Wireless networks today follow a fixed spectrum assignment strategy, where spectrum resources are assigned to license holders or services by government agencies for exclusive use on a long term basis for large geographical regions. While this traditional spectrum assignment policy ensures that the licensed users cause minimal interference to each other, it has also created spectrum crowding on most frequency bands already assigned to different licensed users. Fig. 1.1 shows the frequency allocation chart of the Federal Communications Commission (FCC) [1] [2], which indicates multiple allocations over essentially all of the frequency bands.

Extensive FCC measurements indicate that temporal and geographical variations in the utilization of the licensed radio spectrum range from 15% to 85% [1]. If we were to scan portions of the radio spectrum in urban areas, we would find that [3] [4] [5]:

- Many frequency bands in the spectrum are largely unoccupied or only partially occupied for most of the time, and
- the remaining frequency bands are heavily used.

Fig. 1.2 shows the spectrum utilization in the frequency bands between 30 MHz and 3 GHz averaged over six different locations [6]. It can be observed from Fig. 1.2

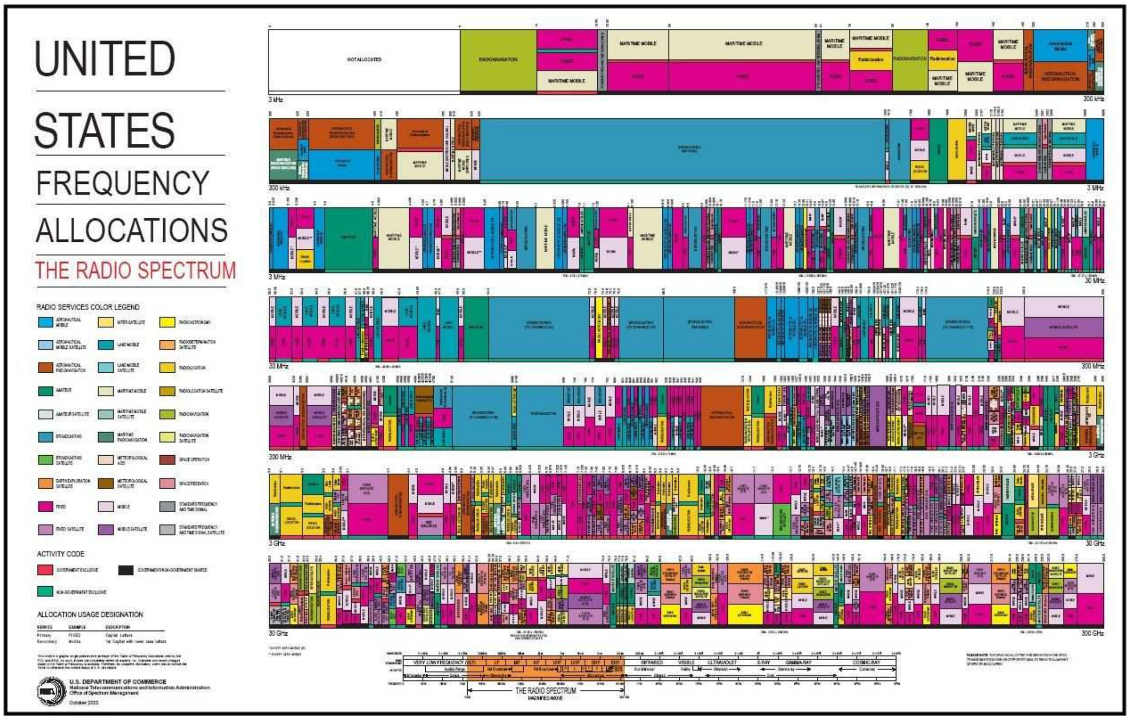

Figure 1.1: Illustration of the frequency allocation chart of FCC [2].

that a large portion of the assigned spectrum is used only intermittently or not at all due to various factors such as the amount of traffic load of licensed users or geographical variations [7]. Therefore, within the current static regulatory policy, radio spectrum appears to be a scarce resource.

Due to limited availability of radio spectrum and highly inefficient spectrum usage, new insights into the use of spectrum have challenged the traditional approaches to spectrum management and have motivated a reform to the traditional fixed spectrum regulation policy. Spectrum utilization can be significantly improved by giving opportunistic access to the frequency bands instead of employing static spectrum allocation. This necessitates a new approach to exploiting the available wireless spectrum in an opportunistic manner [7].

Cognitive radio is an intelligent wireless communication system that relies on opportunistic communication between unlicensed cognitive radio users (CRUs) or secondary users (SUs) over temporarily available spectrum bands that are licensed to primary users (PUs). The FCC suggests that any radio having adaptive spectrum

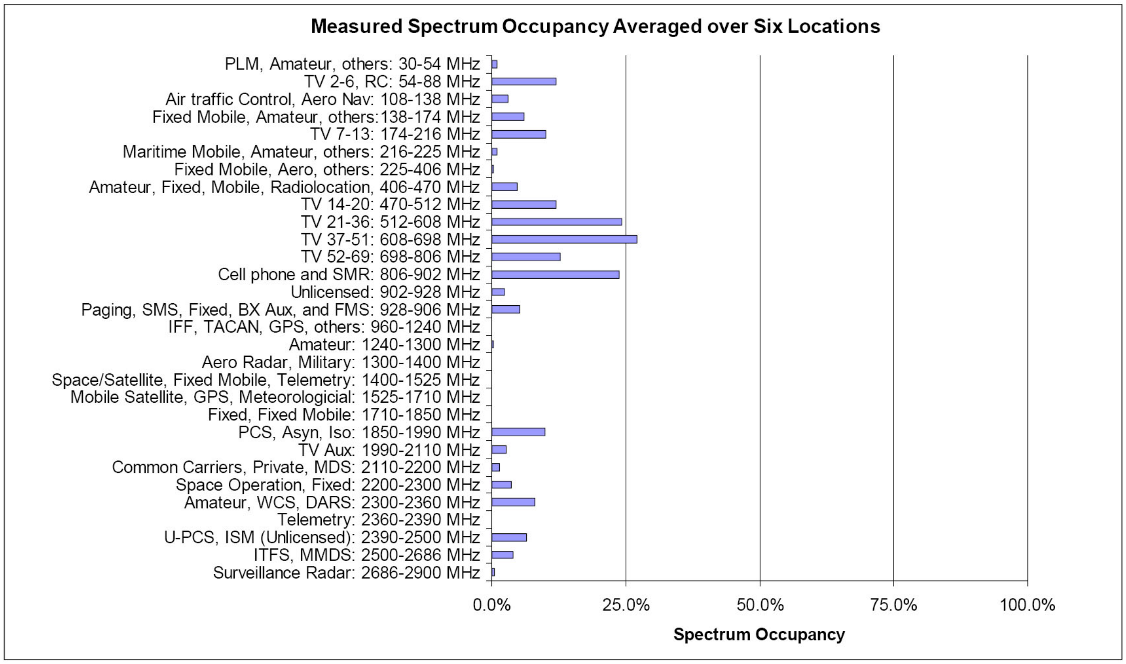

Figure 1.2: Spectrum occupancy in each band averaged over six locations [6].

awareness should be referred to as "Cognitive Radio" [8]. Cognitive radio networks (CRNs) have been seen as one of the most promising solutions to reducing spectrum under-utilization and hence better accommodating the increasing amount of service demands and applications in wireless networks. As cognitive radio systems must operate in unlicensed frequency bands, it possesses cognitive characteristics with which it can choose the transmission mode according to learnt transmission conditions. A classical cognitive radio system has a cognitive cycle proposed in [9], containing wireless environment sensing, spectrum resource estimation and resource allocation schemes.

The concept of cognitive radios has been considered the key technology behind the upcoming spectrum regulation reform and as such has garnered great attention from both academia and industry. For a CRN to be deployed for practical use, a number of new technologies and schemes need to be developed for improved efficiency and harmless access and sharing of opportunistic radio spectrum. Such technologies include network parameter measurement, reliable spectrum sensing (unused spectrum detecting), spectrum mobility (maintaining seamless transition to a new spectrum), coexistence with PUs and other CRUs, spectrum management, reliability in CRNs, and resource allocation (power allocation, scheduling, and dynamic spectrum sharing). Of these technologies, resource allocation and scheduling are amongst the most important topics that have attracted a lot of research attention.

1.1 Research Motivation and Objectives

Scheduling policy design is a part of the spectrum sharing and plays an crucial role in the network performance. A packet scheduling scheme decides the order of packet transmission from different users, which plays an important role in achieving high resource utilization and system throughput. In traditional wireless networks, the total available resources, such as the number of channels or the number of timeslots, are fixed in each media access control (MAC) frame.

Compared to traditional wireless networks, cognitive radio networks exhibit some distinctive features:

- The spectrum used by CRUs for transmission is dynamic in nature. This means that a CRU has to stop its transmission and withdraw from the wireless channel when the PUs need to utilize the spectrum, and
- the transmission time of CRUs is not fixed, but depends on the activity of the PUs.

Therefore, the CRUs can access certain spectrum resources only when they are not being used by the PUs. Due to these unique features, existing schemes designed for traditional wireless networks cannot be easily extended to a CRN. As such, the scheduling problems that have been previously solved for the traditional networks must be reassessed for the CRN. The unique characteristics of cognitive radio systems pose new challenges in terms of meeting the fairness and other system performance requirements in a CRN environment.

How to design a scheduling scheme to efficiently and fairly allocate the available spectrum(s) or channel(s) is a challenging and fundamental issue in CRNs. Users in a wireless scenario may have different channel conditions. The selection of a CRU to use an available spectrum at any time should take into consideration the balance between the current possible throughput and fairness. If a user with the highest signal to noise ratio (SNR) is chosen at each slot, then other users with low SNRs will be starved and such an allocation scheme would be considered unfair. Fair scheduling can provide better opportunity to the users with lower SNRs but will reduce the overall maximum possible throughput. Therefore, how to improve the resource utilization to get a high throughput and make a compromise between the system throughput and fairness is an important issue. Moreover, we need to carefully consider the medium access control frame structure when designing a scheduling scheme because of the unique features of the CRNs. As such, we are motivated to investigate schedule policies that address the distinct characteristics of CRN environments while finding a balance between fairness and system throughout.

The objective of this research is to design an efficient resource allocation and scheduling scheme to ensure an interference-free environment for the PUs by exploiting the MAC frame design, meanwhile, achieve a good tradeoff between system throughput and fairness by jointly considering the CRU's channel condition, the availability of the channel, and the adaptive weighted factor in a centralized cognitive radio network.

1.2 Thesis Outline

The remainder of the thesis is organized as follows. The background concepts behind CRNs as well as a literature survey of scheduling schemes are presented in Chapter 2. The system model of the CRN, including the network architecture, mobility model, traffic model and channel model, along with the MAC frame structure used by the proposed scheme, is described in Chapter 3. In Chapter 4, an adaptive weighted scheduling scheme is proposed for achieving an efficient and effective resource allocation among different CRUs considering their channel conditions. In Chapter 5, simulation results are presented to evaluate the performance of the proposed adaptive weighted scheduling scheme. Simulations in scenarios characterized by saturated traffic and non-saturated traffic are discussed separately. Finally, conclusions are drawn and future work is discussed in Chapter 6.

Chapter 2

Background

2.1 Cognitive Radio Networks

The concept of cognitive radio was first introduced by Mitola [10] and is derived from software defined radios (SDR) [11], a platform for multi-band and multi-mode personal communication systems where devices are able to operate in many different frequency bands, under multiple transmission protocols, and employ a variety of modulation and coding schemes. According to this concept, cognitive radio is a radio system that can sense its operating environment and utilize available radio resources in a dynamic manner. Cognitive radio systems is promoted by the FCC and is considered a promising solution for addressing the spectrum scarcity problem by using an opportunistic spectrum access approach [7], where frequency bands that are not used by their licensed users, such as the TV users, can be utilized by cognitive radios.

The following formal definition for cognitive radio was given by Haykin [9]: *Cognitive radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming radio frequency (RF) stimuli by making corresponding changes in certain operation parameters (e.g., transmit-power, carrier frequency,* *and modulation strategy) in real-time, with two primary objectives in mind:*

- *highly reliable communications whenever and wherever needed*
- *efficient utilization of the radio spectrum.*

CR technology takes an opportunistic spectrum utilization approach and aims to find available spectrum resources in a crowded spectrum. The goal of a cognitive radio is to maintain connectivity with its peers on unlicensed spectrum while avoiding interference with licensed customers as well as other CRUs. Therefore, cognitive radios should be flexible, efficient and reliable to utilize unused spectrum resources in an intelligent way while not interfering with other primary users in the frequency band.

A CRN structure is shown in Fig. 2.1. In this figure, the main spectrum is TV bands that are used by the CRNs. Cognitive node is capable of sensing its environment and making decisions instantaneously, and is capable of communicating over the most appropriate spectrum bands which may be licensed or unlicensed. The key features of CR include [12]

- awareness of the radio environment in terms of spectrum usage, RF environment, the available node in the network, and the available power [12] based on interaction with the environment,
- dynamic adaptability, such as adaptive tuning to system parameters which includes the transmit power, carrier frequency, modulation strategy, etc., and
- highly efficient cooperative or non-cooperative behavior.

The functionalities of capturing or sensing the information in a CRN include sensing spectrum used by neighboring devices, changing frequencies, altering parameters and characteristics of its transmission, and learning from the surrounding network environment. By learning from their environment, cognitive radios can dramatically improve link reliability and help networks autonomously improve coverage and capacity.

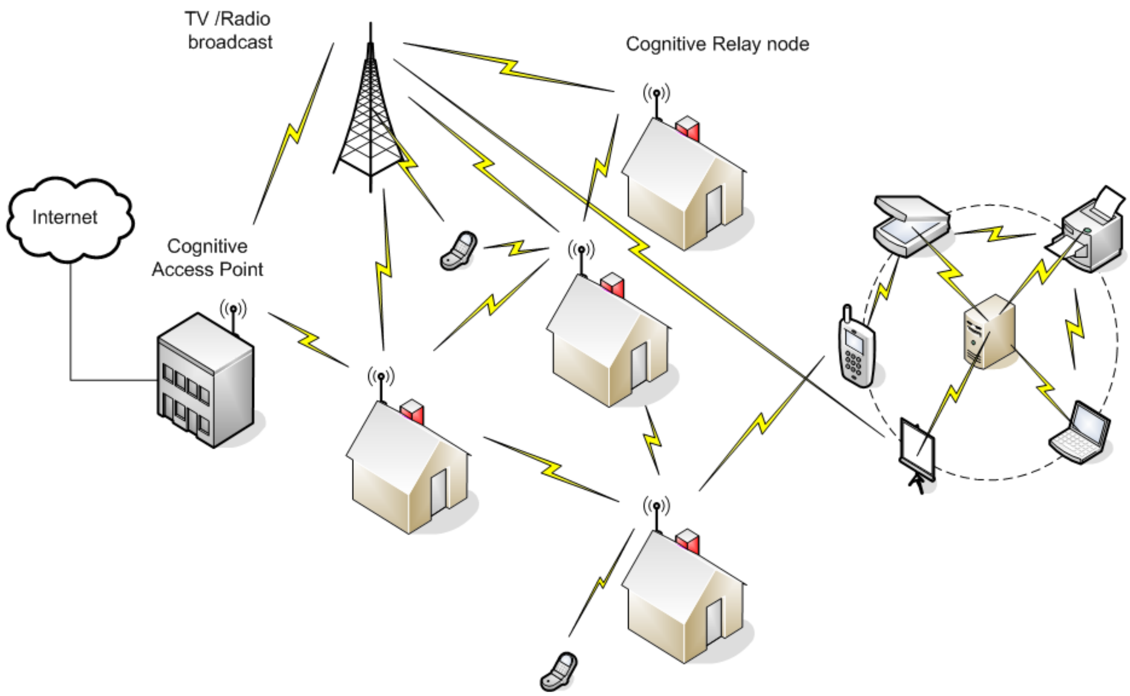

Figure 2.1: A structure of the cognitive radio network.

According to [7], cognitive radio technology enables users to opportunistically access the available licensed or unlicensed spectrum bands through four main functionalities:

- spectrum sensing - determine which parts of the spectrum is available and detect the presence of licensed users when a user operates in a licensed band;
- spectrum management - select the best available channel;
- spectrum mobility - vacate the channel when a licensed user is detected;
- spectrum sharing - coordinate access to a channel with other users.

Spectrum sharing is one of the main challenges in open spectrum usage, and is responsible for providing efficient and fair spectrum allocation or scheduling among licensed and unlicensed users in CRNs. In the current network infrastructure, the increasing demands of wireless spectrum and limited radio resources are largely imbalanced, leading to a big challenge in spectrum sharing. In order to have efficient and effective dynamic spectrum sharing, the allocation of a channel to a network node should not only be based on the spectrum availability, but also based on internal or possibly external policies. Due to the characteristics of CRNs, several difficulties must be addressed: i) various network structures, ii) the unreliability of wireless channels, iii) the mobility of subscribers, and iv) different behaviors of network users. All of these challenges must be taken into consideration when designing scheduling policies for CRNs.

2.2 Scheduling Schemes

In a time-division multiple access (TDMA) system, the wireless link scheduling problem can be viewed as one of deciding which users should transmit in each time frame. The underlying challenge is to intelligently determine which and when users can access the allocated spectrum bands or channels to transmit their packets. In data networks, the packet scheduler is important for resource management. It needs to account for unique characteristics of time-varying and location-dependent channel conditions. Some research results in the literature have shown that the overall system performance, such as the system throughput, fairness, delay, and loss rate, will be significantly affected by the scheduling policy being used [13]. Many scheduling schemes have been proposed to address the resource allocation problem for traditional wireless networks as well as cognitive radio networks.

A scheduling policy has two contradictory goals: i) to maximize the overall network throughput, and ii) to guarantee fairness amongst users. In [14], a scheduling scheme is proposed to maximize cell throughput under the constraint that all the users have equal normalized average throughput, where the normalization factor reflects the users' required quality of service. In [15], another scheduling scheme is presented to achieve the same objectives as in [14] but with a different constraint, where the allocated time fraction of each user is given. This scheduler maximizes the objective function, which depends only on the signal-to-noise ratio. Several works have dealt with scheduling policies in multichannel systems [16], where the scheduling of multiple users on multiple channels in a wireless system is considered. At the base station, a centralized scheduler controls the downlink scheduling, and a polling mechanism is used to collect transmission requests of the mobile nodes at the uplink.

Many opportunistic scheduling schemes for time varying channels in the multiple access and multiple antennas have been proposed [17, 18]. In [17], the scheduling problem is formulated such that the average system performance needs to be maximized, with the constraint that the minimum performance requirements of each user must be met. In [18], a scheme is proposed for a random fading channel where multiple antennas at the base station are used to transmit the same signal.

Indeed, if a scheduler fully exploits the time-varying channel condition, the maximum cell throughput can be obtained by serving the user with the best channel condition, which however leads to a serious fairness problem. Therefore, a packet scheduler should achieve a reasonable balance between throughput and fairness.

For cellular network scheduling, many schemes have been developed for achieving a high throughput and good fairness by considering wireless channel conditions [19]. Fair sharing lowers the total throughput from the maximum, but can provide a more acceptable service to users with poorer SNRs. An example is presented in [13], where the short-term and long-term fairness and throughput are jointly considered during the scheduling process. The scheduling scheme combines the deficit round robin scheduling and an explicit compensation counter to achieve flexible scheduling with variable-size packets. In [20], scheduling algorithms are developed that exploits multi-user diversity benefits while maintaining fairness in the downlink of high data rate (HDR) system, where the downlink SNR of each user is measured based on a common pilot and fed the information back to the base station. Channel-condition independent packet fair queuing is proposed in [21] to perform fair scheduling with guaranteed throughput.

A proportional fairness (PF) scheme is proposed to achieve a tradeoff between the throughput and fairness by transmitting data with the highest data rate relative to its present realized mean data rate. In the PF scheme, there is a tendency that short-distance sessions have priority over long distance ones when compared with other fairness mechanisms [22]. The PF scheduler has low complexity and can achieve good fairness performance due to the identical long-term resource allocation. Some PF scheduling schemes are introduced and received much attention [23] [24] [25]. The forward link data throughput performance is studied in [23] for a high data rate wireless access network. In [24], a proportional fair algorithm is given which sets the equal power and time to users who only differ in the distance from the base station. The results show that the user class with more fading variability has more throughput with a lower fraction of transmitting time. The work in [25] concerns with the allocation of the base station transmitter time in time-varying mobile communications with many simultaneous data users. In addition, PF takes advantage of multi-user channel diversity to obtain a high system throughput. However, it is generally difficult to conduct a quantitative analysis. In [26], a modified proportional fairness scheduling scheme is proposed, where the scheduler selects a user with the highest ratio of the instantaneous channel condition to its average channel condition. By replacing the achieved average throughput with the average channel condition, the scheme is more tractable than the original proportional fairness scheme.

Cognitive radio networks have become a very hot area of research in wireless communications. Due to the unique characteristics of CRNs, how to efficiently and fairly allocate the available spectrums or channels is a challenging and fundamental problem. Given its importance, the aforementioned scheduling schemes cannot be directly used in CRNs since they do not account for the uncertainty of the available resources. In CRNs, it is possible that the resources (i.e., spectrum) are not available when a node has a very good channel condition, and when the resources are available, the node may be experiencing deep channel fading. If a scheduling scheme designed for a traditional network is directly applied in CRNs, it may lead to unfair resource allocation and cannot achieve a high throughput. Therefore, new algorithms are needed to deal with these challenges and to achieve efficient and fair resource allocation. In [27], a two-phase resource allocation scheme is proposed to improve the system throughput. In the first phase, channels and power are allocated to base stations with the aim of maximizing their total coverage while keeping the total interference caused to each CRU below a predefined threshold. In the second phase, each base station allocates channels within its cell so that the number of active CRUs being served is maximized. In [28], a resource allocation algorithm is proposed to maximize CRN spectrum utilization based on a dynamic interference graph, and a realistic control framework is formulated to guarantee protection to primary users and reliable communications for cognitive nodes. In [29], an adaptive packet scheduling algorithm for real-time and non-real-time multi-service applications is presented, which makes the resource allocation adapt to the varying available spectrum in a CRN. A combined channel and power allocation strategy is proposed in [30]. This scheme guarantees a certain transmission data rate to each user in a CRN. Scheduling the secondary users under partial channel state information is considered in [31], which uses a probabilistic maximum collision constraint with the primary users. In [32], opportunistic scheduling policies for CRNs are developed, which maximize the throughput utility of the CRUs subject to maximum collision constraints with the PUs is developed. It uses the technique of Lyapunov optimization to design an online flow control, scheduling and resource allocation algorithm that provides explicit performance guarantees. Unfortunately, this algorithm has relatively high complexity. Furthermore, existing works do not jointly consider resource availability and the channel condition.

Due to the uncertainty of the available resources in CRNs, an efficient scheduling scheme should take into account both the channel diversity and the dynamics of available resources. To address these issues, an adaptive weighted scheduling scheme is proposed in this work to achieve a high system throughput as well as good fairness performance in a CRN by jointly considering the variable channel availability and channel condition and taking advantage of the channel diversity among multiple users.

Chapter 3

System Model

In this research, we consider an infrastructure-based CRN providing communication services to CRUs, making use of the leftover radio resources from licensed networks for PUs. The CRUs can sense the usage of the channels (i.e, frequency band) licensed to PUs. If a frequency band is used by a PU, it is called an active band. Otherwise, it is called an inactive band. The inactive bands are also referred to as spectrum holes or white space. Spectrum can be classified into three types depending on the amount of interference in a specific band:

- black spaces - These spaces are highly occupied by local interferers some of the time;
- grey spaces - These spaces are partially occupied by low-power interferers;
- white spaces (spectrum holes) - These spaces are free of local interferers.

The only additional interference is due to ambient noise such as thermal or impulsive noise [8] [9]. This classification shows that black spaces are not proper candidates for dynamic spectrum allocation. However, grey spaces (to a certain degree) and white spaces can support dynamic spectrum allocation and can be occupied by CRUs.

By effectively detecting the existence of inactive channels and efficiently allocating these available resources, a CRN is able to provide different types of services (e.g., data service, multimedia service) for CRUs. Meanwhile, it must guarantee low interference to maintain the performance of coexistent PUs.

3.1 Network Architecture

A multi-cell CRN is illustrated in Fig. 3.1 for a cellular system. Since this infrastructure-based network consists of multiple cells, we need to consider not only the spectrum sharing among users in each cell but also the spectrum sharing among multiple cells. In the multi-cell framework, at different time and/or location, each cell experiences different PUs' activities, leading to the heterogeneous resource availability [33]. Further, the number of neighbor cells influences the performance of spectrum sharing because of the inter-cell interference. Since the interference range is generally larger than the cell cover range, the current transmission in a cell will influence its neighbor cells.

For simplicity, we consider the resource allocation only in a single-cell system with one channel as shown in Fig. 3.2. The cognitive radio network consists of a cognitive radio base station (CRBS) and M CRUs.

The CRBS detects the transmission of primary networks, determines the channel availability, and allocates the channel to CRUs based on these local measurements when the channel is inactive. At a specific timeslot, we assume that only one user transmits data on this inactive channel and the CRU does not share this inactive channel with the other CRUs. We focus on the downlink scheduling for transmission from the CRBS to CRUs.

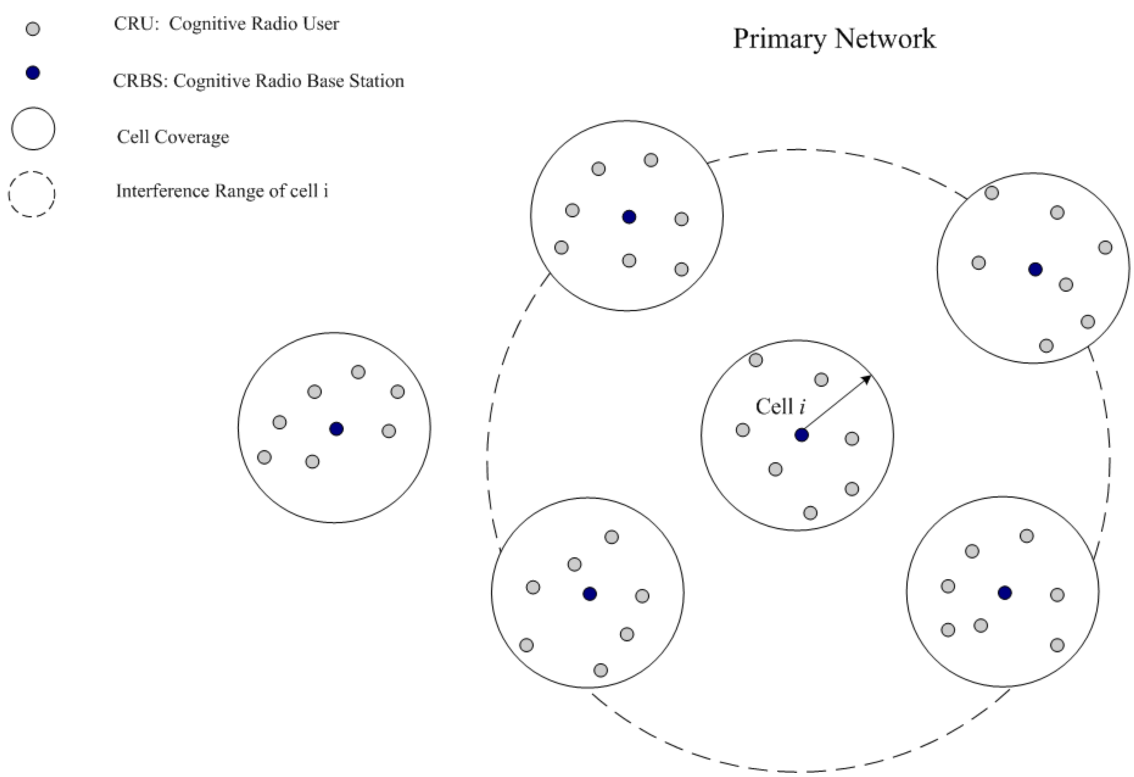

Figure 3.1: Illustration of a multi-cell cognitive radio network with centralized control.

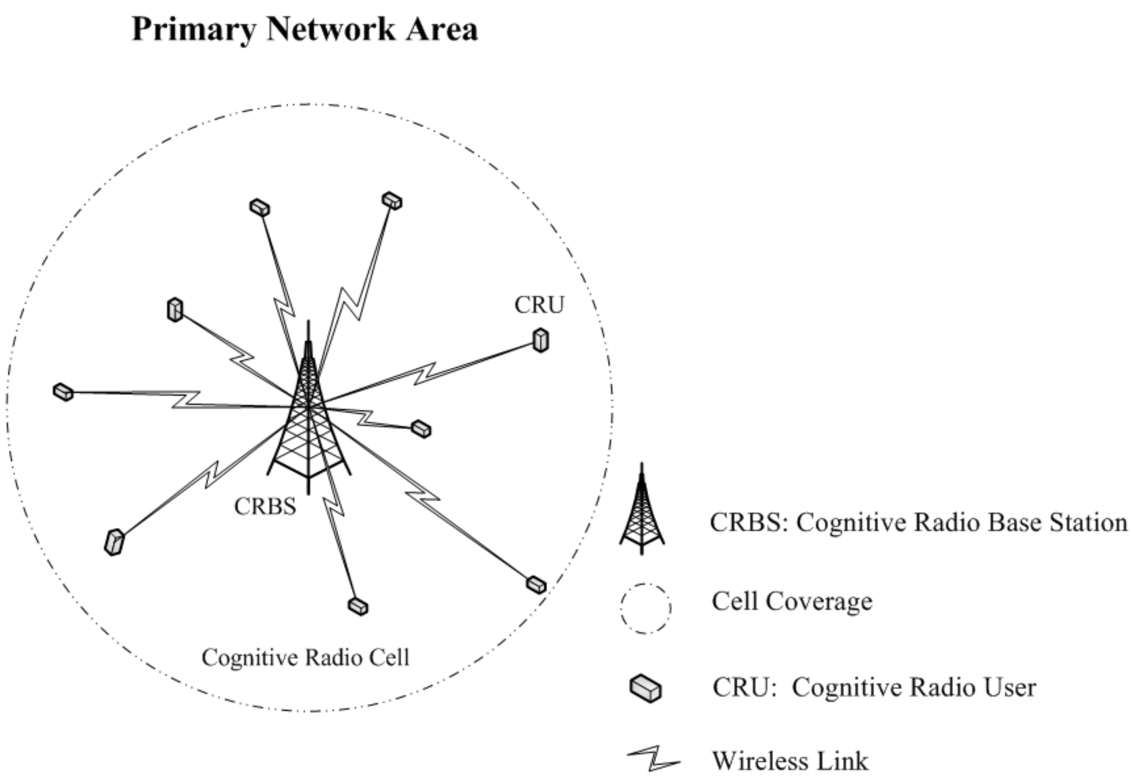

Figure 3.2: Illustration of a single cell cognitive radio network with centralized control.

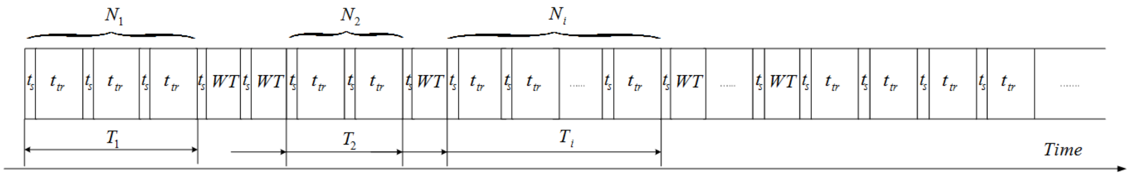

Figure 3.3: Link-layer frame structure.

3.2 Link-Layer Frame Structure

At the link layer, time is partitioned into three parts: i) sensing time (denoted by t_s), ii) waiting time (denoted by WT), and iii) transmission time (denoted by t_{tr}), as shown in Fig. 3.3. During a sensing time t_s, the CRBS senses the channel to determine whether the channel can be used by CRUs. If the channel is busy (used by PUs), the CRBS waits for WT before sensing the channel again. Whenever the channel is available for a CRU, it can use the channel for t_{tr} and then the CRBS needs to sense the channel again. In Fig. 3.3, N_i is the number of consecutive timeslots that the channel is inactive, and T_i denotes the time length that the channel is inactive.

When PUs have synchronized transmission with an equal transmission unit of duration $t_s + t_{tr}$, the CRBS needs to sense the channel once every unit and we can choose $WT = t_{tr}$. As the sensing time t_s is generally a short period, it can be assumed to be negligible, i.e., $t_s << t_{tr}$.

The channel that the CRN can access is assumed to be licensed to primary networks. The channel in the active state represents PUs are currently using the channel, and the channel in the inactive state represents the unused period by PUs. Here, we use an ON-OFF model [34] to characterize the activity of the channel, where the duration of the two states ON and OFF are independent and exponentially distribution [35] [36] [37] [38]. The ON and OFF state transitions are characterized by probability P_1 and P_2 [39], as shown in Fig. 3.4.

There are two cases that can occur after a sensing process:

Case 1: Given that the channel is inactive, it will remain inactive with proba-

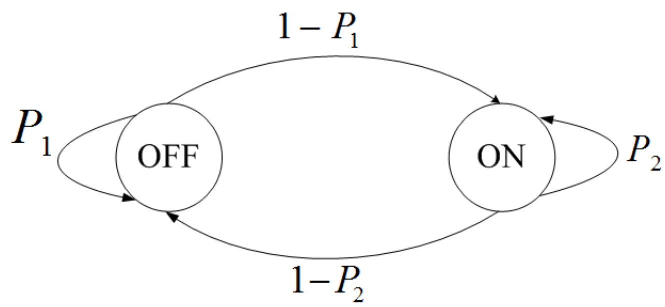

Figure 3.4: ON-OFF model.

bility P_1. Let ζ_1 denote the number of the units that the channel remains inactive before changing to active, which follows a geometric distribution with parameter P_1,

$$P(\zeta_1 = i) = P_1^{i-1}(1 - P_1). \tag{3.1}$$

Case 2: Given that the channel is active, it will remain active with probability P_2. Let ζ_2 denote the number of the units that the channel remains active before changing to inactive, which follows a geometric distribution with parameter P_2,

$$P(\zeta_2 = i) = P_2^{i-1}(1 - P_2). \tag{3.2}$$

On the other hand, the exponential distribution may be viewed as a continuous counterpart of the geometric distribution. If a random variable with an exponential distribution is rounded up to the nearest integer, then the result is a discrete random variable with a geometric distribution. That is:

$$N_i = Integer[\frac{T_i}{Length(t_{tr})}] \tag{3.3}$$

where $Length(t_{tr})$ is the length of the t_{tr}, T_i is an exponential random variable, and N_i is a geometric random variable.

3.3 Traffic Model

Generally, traffic in wireless communications can be classified into one of two categories: i) real time, and ii) non-real time. Examples of real time traffic include voice and video.

In this research, we will mainly focus on the non-real time traffic for data applications

Data traffic is usually viewed as non-real time traffic, and the number of data packets generated at a time can fluctuate greatly depending on applications, such as just a single packet in an interactive command or a mass of packets transferring in a large file. However data traffic is usually error sensitive, meaning that it can tolerate little transmission errors. Hence, error control mechanisms, such as the automatic repeat request(ARQ) in the link layer and transmission control protocol (TCP) or other reliable transport protocols used in transport layer, should be deployed to satisfy the transmission error requirement. For traffic modeling, the data packet arrivals from a single source can be depicted by a Poisson process.

For data traffic, we consider that the call arrival is a Poisson process for each user with rate λ, and each call has a file size T following the Weibull distribution, i.e. $T \backsim Weibull(a, b)$. The probability density function (pdf) of the Weibull distribution is given by [40] [41]

$$f(x; a, b) = \begin{cases} \frac{b}{a}\left(\frac{x}{a}\right)^{b-1} e^{-\left(\frac{x}{a}\right)^{b}} & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{3.4}$$

where b is the shape factor and a is the scale factor.

Meanwhile, let L denote the payload size of a packet size, which is treated as constant. Therefore, from the file size and the packet payload, the number of packets in a call can be determined by

$$\tau = \left\lceil \frac{T}{L} \right\rceil. \tag{3.5}$$

3.4 Mobility Model

In this work, we consider the two-dimensional random waypoint (RWP) mobility model to describe the movement pattern of CRUs and how their speeds and directions vary over time. Each CRU moves towards a randomly chosen destination in a given area at a constant speed, which is uniformly distributed in $[v_{min}, v_{max}]$ and independent of the CRU's initial and destination locations. After reaching the destination, the CRU may pause for a random amount of time. A new destination and speed is then selected, independent of all previous values. To simplify the problem, we assume that the velocities of all CRUs are the same as with $v_{min} = v_{max} = v_i$.

3.5 Channel Model

Radio transmission over an open environment is characterized by reflection, diffraction, and scattering. We consider both short-term fading and long-term fading which includes path-loss attenuation and shadowing. With the transmission power P_w from the CRBS, the received power of CRU i is given by $P_i = |h_i|^2 \cdot P_w$, where h_i is the channel gain which reflects the effects of various physical phenomena such as scattering and absorption of radio waves, shadowing by terrestrial obstacles, and multipath propagation.

According to [26], the channel gain from the CRBS to CRU i can be expressed as

$$h_i = \sqrt{s_i} m_i. \tag{3.6}$$

where s_i is the slow fading, including the path-loss component and the shadow-fading effect, and m_i represents the multipath component.

The slow fading is mainly determined by the geographical environment and distance between the CRBS and the CRU. It includes shadowing effect which is generally modeled by a lognormal distribution. Therefore, the slow (long term) fading s_i is given by [42]

$$s_i = c \cdot d_i^{-k} \cdot 10^{\chi_i/10} \tag{3.7}$$

where c is a constant, d_i is the distance between the CRBS to CRU i, which varies with the CRUs' movement, k is the path loss distance exponent, and χ_i (the attenuation due to shadowing in dB) is a zero mean Gaussian random variable with variance $\sigma_{\chi_i}^2$.

The distance d_i changes as CRU i moves. Let (x_0, y_0) denote the position of the CRBS, (x_i, y_i) is the current position of user i, v_i is the velocity of user i, and ϑ_i is the movement direction. After time Δt, user i moves to a new location $(\mathrm{x}_\mathrm{i}^{'}, \mathrm{y}_\mathrm{i}^{'})$ that can be calculated by

$$\begin{cases} x_i^{'} = v_i \cdot \Delta t \cdot \cos\vartheta_i + x_i \\ y_i^{'} = v_i \cdot \Delta t \cdot \sin\vartheta_i + y_i \end{cases} \tag{3.8}$$

The distance d_i is a function of the position of user i, $(\mathrm{x}_\mathrm{i}^{'}, \mathrm{y}_\mathrm{i}^{'})$, given by

$$d_i = \sqrt{(x_i^{'} - x_0)^2 + (y_i^{'} - y_0)^2} \tag{3.9}$$

Since both slow fading and fast fading have time correlation, the fading (either fast or slow) at two time instances may be correlated to each other. Thereby, the shadowing random process $\chi_i(n+1)$ at time $t + \Delta t$ is modeled by [43]

$$\chi_i(n+1) = \zeta^{v_i \cdot \Delta t} \ \cdot \ \chi_i(n) + (1 - \zeta^{v_i \ \cdot \Delta t}) \ \cdot N_G(n+1) \tag{3.10}$$

where ζ is the correlation between two points separated by one meter, $\chi_i(n)$ is the shadowing process at time t, and $N_G(n+1)$is the sample of a white Gaussian random process at time $t + \Delta t$, which is a Gaussian random variable with zero mean and standard deviation $\sigma_{\chi_i}\sqrt{\frac{1+\zeta^{v_i \cdot \Delta t}}{1-\zeta^{v_i \cdot \Delta t}}}$.

For the multi-path fading, the Jakes fading model [44] can be used, which is a deterministic method for simulating time-correlated Rayleigh fading waveforms and is good for time-varying fast fading.

Chapter 4

Adaptive Weighted Scheduling Scheme

4.1 Traditional Proportional Fairness Allocation

Packet scheduling in wireless networks have been extensively studied in previous work. There are many scheduling schemes that have been proposed to deal with different service types based on their intrinsic characteristics in the different wireless networks. For a conventional network, the allocated radio frequency channels are always available to the network, based on which traditional scheduling schemes are proposed to achieve resource allocation fairness. For non-real time traffic, such as the data traffic, the main purpose of an efficient scheduling scheme is to achieve good throughput performance as well as fairness. However, efforts on improving system throughput and reducing experienced delay are in general contradictory since high system throughput can be achieved by assigning resources to end users with the best channel conditions, while leaving the users with poor channel conditions starved and experienced a long delay.

Proportional fairness scheduling is an effective approach to providing a good balance between the system throughput and fairness. Generally speaking, PF scheduling schemes aim at equivalently allocating the available resources among all the users. It selects a user for service according to the ratio of the instantaneous SNR and average SNR of users at a certain frame or timeslot. The user who has the maximum ratio will be assigned the channel to transmit its data traffic. It is rather efficient when the resources can always be used by the users.

However, the traditional PF scheduling strategy can cause unfairness when used in a CRN. If the transmissions are scheduled based on the channel condition, it can lead to some users deprived of spectrum resources for a long time if it experiences a poor channel condition when the channel is available and experiences a good channel condition when the channel is not available. As such, we aim to address this issue with an adaptive weighted scheduling scheme.

4.2 Adaptive Weighted Scheduling Scheme

Compared with the conventional wireless communication systems, such as the cellular systems or WiMAX, etc., the uncertain availability of the channel is a unique feature of CRNs. A channel that can be used by CRUs is variable and not always inactive (i.e. not occupied by PUs). As such, the design requirements of the traditional PF scheduling strategy mentioned in the previous section is not suitable for use in CRNs. If the PF scheme is adopted in a CRN directly, the following spectrum resource deprivation scenario can occur. When user i has the maximum ratio of instantaneous SNR and average SNR, this indicates that user i has the best channel condition at this timeslot. But if the channel is busy, the user i cannot use the channel. Next, in the succeeding sensing cycles, user i also has the best channel condition while this channel is still being used by PUs. On the other hand, when the channel becomes idle, the channel condition of user i is not the best, and user i cannot be assigned the channel. That is the user i is continuously deprived of spectrum resources and as such experiences a long delay. This results in an unfairness scenario for user i and indicates that traditional PF based scheduling schemes are not suitable for CRNs.

The uncertainty associated with channel availability has posed new challenges on the design of an efficient scheduling scheme for CRNs. Such a scheme should be able to allocate the available resources among different CRUs in an adaptive and flexible way according to the availability of the resources, so that network resources can be used effectively and efficiently based on some historical and current channel conditions of different CRUs.

In order to solve the unfairness problem when using the traditional PF scheduling schemes in the spectrum resource deprivation scenario described earlier, and taking into account the characteristics of the CRN, we propose an adaptive weighted scheduling scheme (AWSS) for data services in the CRN for achieving flexible resource allocation according to resource availability and channel conditions. An adaptive weight factor (AWF) is introduced to the proportional fairness scheduling strategy to adjust the priority of different CRUs to be selected for service. At a certain timeslot, the selection probability of a CRU changes with the adjustment of the AWF. If the AWF has an appropriate value, even the CRU with a bad channel condition has the reasonable chance to be selected for transmission.

In a proposed adaptive weighted scheduling scheme, the adaptive weighted factor, the ratio of instantaneous SNR and average SNR, and the channel availability are jointly taken into consideration when selecting a CRU to assign spectrum resources to. The criterion by which the adaptive weighted scheduling scheme selects a CRU and provides the available resources for data service to this user is formulated as

$$j^*(n) = arg \max_j X_j(n) \quad j \in S_{ne}(n), \quad S_{ne}(n) \subseteq \{1, 2, \cdots M\} \tag{4.1}$$

$$X_j(n) = \xi_j(n) \frac{\gamma_j(n)}{\bar{\gamma}_j(n)} \quad j \in S_{ne}(n) \tag{4.2}$$

$$Y_i(n) = \frac{\gamma_i(n)}{\bar{\gamma}_i(n)} \quad i = 1, 2, \cdots M \tag{4.3}$$

$$\xi_i(n+1) = \begin{cases} \xi_i(n) + \Delta\xi, & if \quad \theta(n+1) = 1 \\ 1, & if \quad \theta(n+1) = 0 \end{cases} \tag{4.4}$$

where $\gamma_i(n)$ and $\bar{\gamma}_i(n) = \frac{\sum\limits_{n=n-n_t}^{n} \gamma_i(n)}{n_t}$ are the average and instantaneous channel gain for user i at the n^{th} timeslot, respectively, n_t is the time period used to calculate the average SNR, $S_{ne}(n)$ is defined as the set of CRUs whose traffic queues are not empty with the packet to transmit at the time slot n, $X_i(n)$ represents the user i's weighted relative channel condition, $Y_i(n)$ represents the user i's relative channel condition, $\xi_i(n)$ expresses the value of adaptive weight factor (AWF) for CRU i at the n^{th} timeslot, and $\Delta\xi$ denotes the step increment of the weight. Furthermore, $\theta(n)$ indicates channel availability for the CRU at the n^{th} timeslot: if the channel is idle, $\theta(n) = 0$; otherwise, $\theta(n) = 1$.

We define Eq. (4.2) as the preference metric of AWSS. By averaging out the long-term channel condition in the preference metric, AWSS improves the short-term fairness. To implement the AWSS scheduling scheme, we assume the base station has knowledge of the channel information of each CRU.

The proposed scheduling algorithm is described as follows:

Step 1. Initialize parameters. Assume $\xi_i(n) = 1$ at the timeslot $n = 1$ and set the ending timeslot n_{end}.

Step 2. Check the availability of the channel

Step 2a. If the channel is active, go to Step 3

Step 2b. If the channel is inactive, go to Step 5

Step 3. According to Eq. (4.3), a CRU i^* which has the largest Y_i is chosen, and the AWF of the CRU i^* is updated to $\xi_i(n+1)$ in the next timeslot $n+1$ according to Eq. (4.4), $i = 1, 2, \cdots M$.

Step 4. Update $n = n + 1$; check whether the timeslot $n = n_{end}$ or not

Step 4a. If Yes, go to Step 9

Step 4b. If No, go to Step 2

Step 5. Check all users' traffic queues and get a set $S_{ne}(n)$ in which the user's traffic queue is not empty at the timeslot n.

Step 6. If $S_{ne}(n) = \phi$, go to step 8; otherwise, according to Eq. (4.2), a CRU j^* which has the largest X_j is selected, $j \in S_{ne}(n)$ and $S_{ne}(n) \subseteq \{1, 2, \cdots M\}$.

Step 7. Allocate the channel to user j^* for data transmission. The user j^*'s AWF in the next timeslot $n+1$, $\xi_{j^*}(n+1)$, is reset back to 1.

Step 8. Update $n = n + 1$; check whether the timeslot $n = n_{end}$ or not

Step 8a. If Yes, go to Step 9

Step 8b. If No, go to Step 2

Step 9. End

Based on the channel availability and the parameters AWF, the BS selects a CRU with the largest value of weighted preference metric (X_i) and allocates the channel timeslot for data service to it. On the other hand, when the channel is not available, the weight of the user which has the largest preference metric (Y_i) is increased. Then, in the next channel available timeslot, if the ξ_i is large enough, the user will be selected as a result of the weight ξ_i even if it has a lower channel condition. The scheme flowchart is shown in Fig. 4.1.

By manipulating the AWF in the preference metric Y_i, the proposed scheme is expected not only to provide flexible resource allocation among all CRUs, but also to achieve a satisfying fairness performance due to the consideration of the channel availability after each sensing circle.

In the next chapter, we study some important performance metrics, such as the throughput, fairness, and service probability, and evaluated the impacts of the adaptive weighted factor and channel conditions on these performance metrics to evaluate the performance of the proposed AWSS scheme.

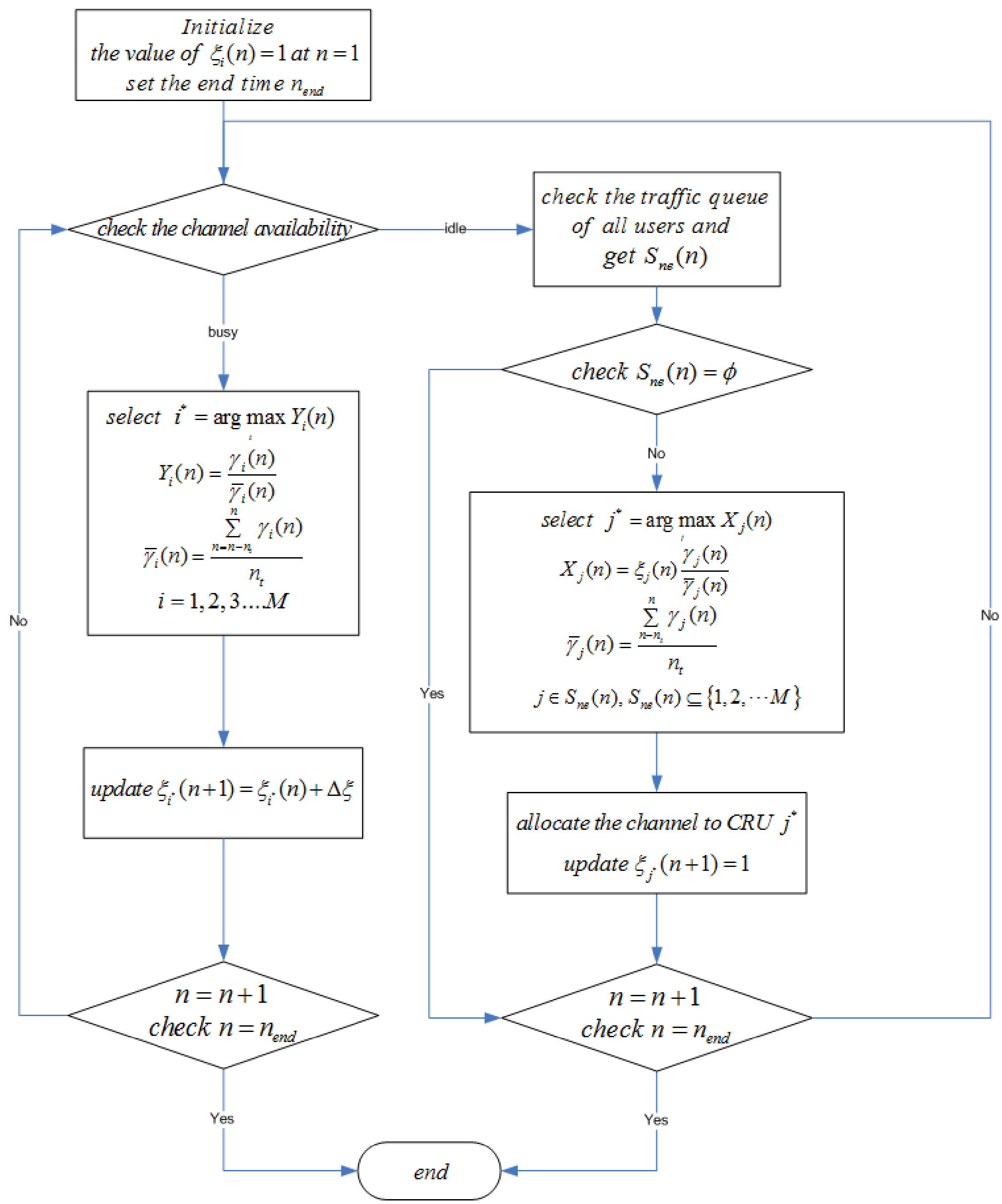

Figure 4.1: The scheduling procedure of AWSS scheme.

Chapter 5

Performance Evaluation

In this chapter, the proposed adaptive weighted scheduling scheme is evaluated through simulation. The performance of the proposed scheduling scheme under saturated traffic and non-saturated traffic is discussed. Extensive simulations have been conducted to demonstrate the effectiveness of the proposed scheme in terms of system throughput and fairness, as well as to investigate the impact of the weight factor on these performance metrics.

5.1 Simulation Setup

Extensive simulations have been conducted using MATLAB. To demonstrate the performance of the proposed adaptive weight scheduling scheme in terms of balancing the throughput and fairness, we compare the proposed scheme with the random scheduling scheme (denoted as RAN) [45] and opportunistic scheduling scheme (denoted as OPT) [15]. The RAN scheme can achieve a good fairness performance by allocating resources to different users with equal probability while the OPT scheme can achieve maximum system throughput by allocating resources to the user with the best channel quality.

According to the discussion of the traffic model in Section 3.3, there are two traffic cases that needs to be studied in simulation:

Table 5.1: THE SIMULATION PARAMETERS

Symbol	**Value**	**Symbol**	**Value**
R	$200m$	Δt	20ms
P_w	$10w$	t_{tr}	20ms
M	40	WT	20ms
N_0	$10^{-9}w$	P_{r1}	0.2
k	4	P_{r2}	0.2
c	$1/1259$	$\Delta\xi$	10
v_i	$0.2m/s$	λ	10 call/s
ϑ_i	$[0, 2\pi)$	T	$T \sim Weibull(2, 2)$
ζ	0.9	L	1536bits
σ_χ	4dB	B	5MHz

1) Each node has saturated traffic (buffer is never empty). In this case, we do not need to consider the traffic model.

2) Non-saturated traffic at each node using Poisson call arrivals and a Weibull file size. The buffer will become empty and non-empty from time to time.

The CRN is composed of one CRBS and M CRUs which are uniformly distributed in the circle with a radius of R. A 5MHz licensed spectrum band is taken into account. The transmission power at the CRBS is P_w [33], and the channel model described in Section 3.5 is adopted. In addition, we define $P_{r2} = 1 - P_2$, which is the transfer probability of channel from active state to inactive state. Here, P_2 is the probability of a channel staying in active state. Meanwhile, $P_{r1} = 1 - P_1$ is the transfer probability of a channel moving from inactive state to active state. Here, P_1 is the probability of a channel staying in inactive state. Note that P_1 and P_2 have the same definition as in section 3.2. The main simulation parameters are listed in Table 5.1.

5.2 Simulation Results

5.2.1 Saturated Traffic Simulation Results

In this section, we describe the simulation results for saturated traffic. We assume each node has saturated traffic, i.e. the buffer is never empty. The simulation time is 120000 timeslots (2400 seconds). Each of the simulation results represents an average of 10 random runs.

The channel capacity provided by the physical layer is defined as the amount of information that can be reliably transmitted over a communications channel, which is given by

$$C_{sys} = \sum_{i=1}^{M} B \cdot \log_2(1 + \gamma_i) \tag{5.1}$$

where C_{sys} is the system capacity, γ_i is the instantaneous SNR of CRU i, B is the bandwidth and M is the number of CRUs.

Assuming the overhead of the MAC layer is negligible, we can count the system throughput by the channel capacity, which is the average number of information bits transmitted over the bandwidth over a period of one second.

Fig. 5.1 demonstrates the system throughput versus the number of CRUs. It is observed that the system throughput increases with the increase number of CRUs. With a larger number of CRUs, a larger channel-diversity gain can be exploited, which leads to a higher system throughput.

Fig. 5.2 shows the throughput achieved by each CRU for each of the three scheduling schemes where $M = 40$. It can be seen that different users achieve different throughput due to user mobility and different locations. As such, the CRUs have different channel conditions. Furthermore, it is observed that the proposed scheme achieves a higher system throughput than the RAN scheme, while the OPT scheme achieves the highest system throughput.

Jain's fairness index, a commonly adopted fairness index, is used to evaluate

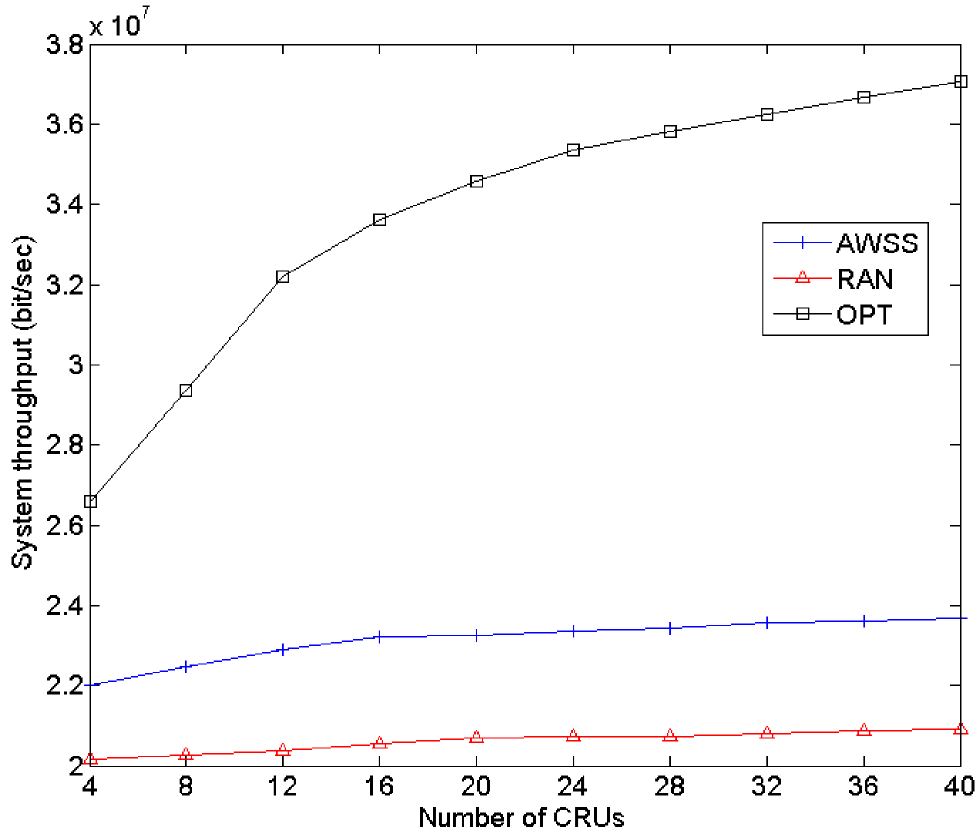

Figure 5.1: System throughput versus the number of CRUs ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

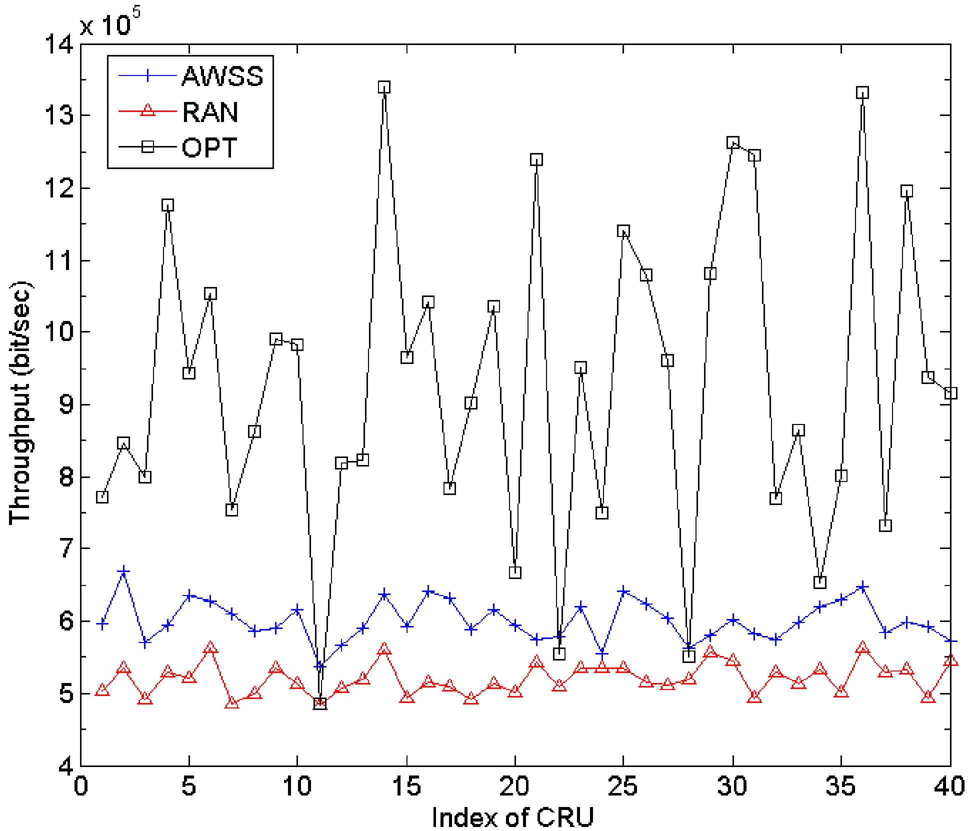

Figure 5.2: Throughput for each CRU ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

the fairness performance of the proposed scheme, which is defined as:

$$F(Th_1, Th_2, ..., Th_M) = \frac{\left(\sum_{i=1}^{M} Th_i\right)^2}{M \cdot \sum_{i=1}^{M} Th_i^2} \tag{5.2}$$

where $F(\cdot)$ is Jain fairness index and Th_i is the throughput of the CRU i.

Fig. 5.3 shows the fairness of the proposed scheme with comparison of the other two schemes. It is observed that the fairness indices of the proposed AWSS scheme are very close to one, which represents the ideal fairness performance. By adaptively adjusting the weight of the users, the proposed scheme can fairly allocate the available resource among different users. However, the fairness performance of the OPT scheme is noticeably worse than the other two schemes since it only takes the channel condition into account, making some users with the bad channel conditions always deprived of spectrum resources.

From Figs. 5.1 - 5.3, it can be concluded that the proposed scheme AWSS can achieve a good tradeoff between the system throughput and fairness. Compared with the RAN scheme, it achieves a higher throughput with a slight cost fairness performance. Meanwhile, compared with the OPT scheme, it achieves a much better fairness performance with some sacrifice of throughput.

We also study the impact of the available resources in a CRN when using AWSS on system performance in terms of throughput and service probability, which are shown in Figs. 5.4 - 5.5.

The service probability for CRU i is defined as the probability that CRU i is selected for service at an arbitrary timeslot, which is given by

$$\pi_i = \lim_{n \to \infty} \Pr(\varphi(n) = i) \tag{5.3}$$

where π_i is the service probability of CRU i and $\varphi(n)$ is the index of the selected CRU at the n^{th} timeslot.

We adopt different values of P_{r2} to study performance variations. Here, we set the parameter P_{r2} as 0.2, 0.4, and 0.6 with $P_{r1} = 0.2$, and $\Delta\xi = 10$. Fig. 5.4 shows

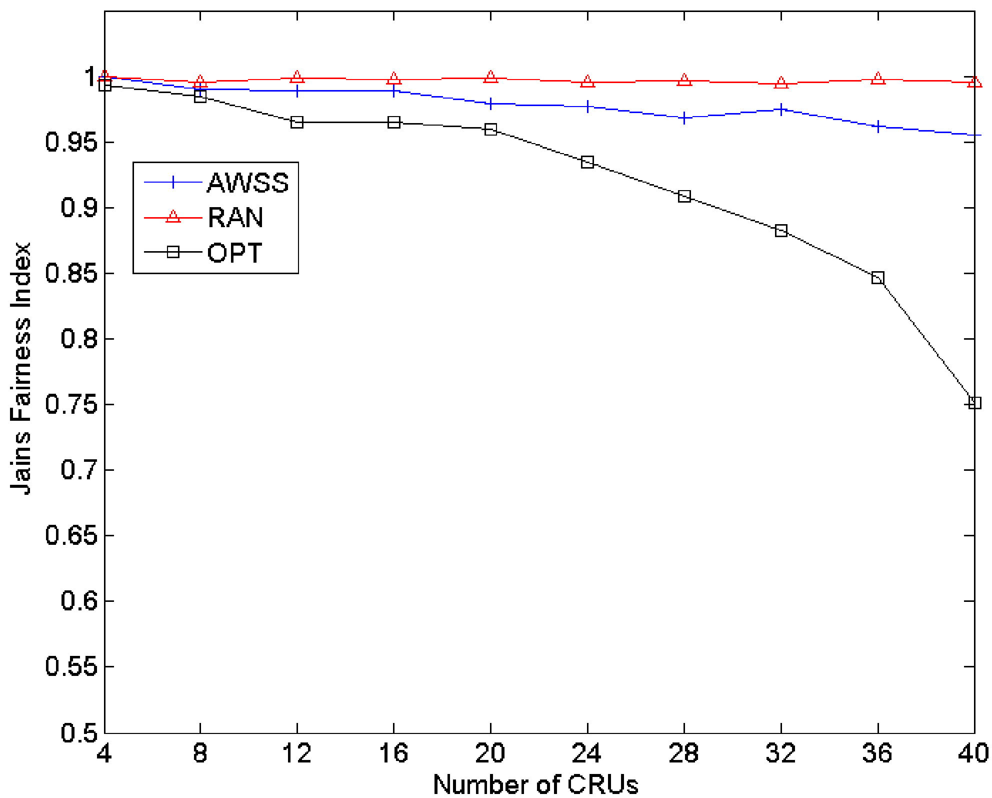

Figure 5.3: The fairness performance versus the number of CRUs ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

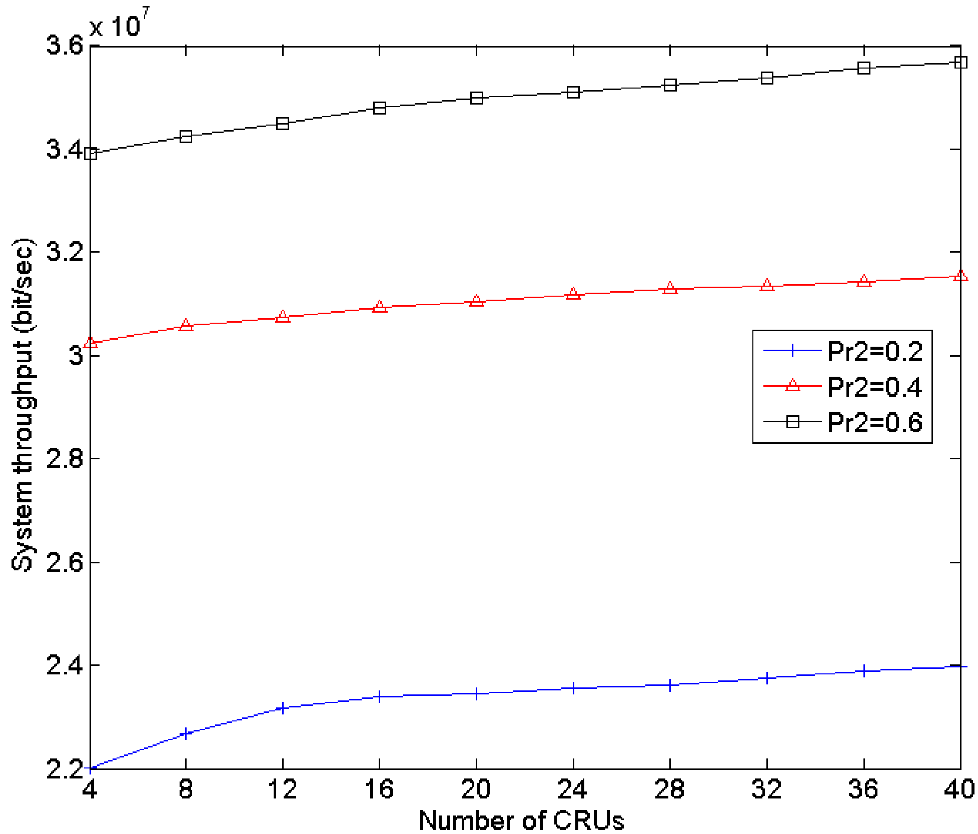

Figure 5.4: System throughput versus the number of CRUs with different P_{r2} ($P_{r2} = 0.2, 0.4$, and 0.6, $P_{r1} = 0.2$, and $\Delta\xi = 10$).

that an increase in P_{r2} corresponds to an increase in the probability of the channel being in an inactive state, and the higher system throughput can be achieved, as well as the service probability, which is shown in Fig. 5.5.

The AWSS performance depends on the parameter $\Delta\xi$, which is the step increment of the weight. Fig. 5.6 shows the system throughput when using the AWSS with the $\Delta\xi = 10, 100$, and 1000.

From Fig. 5.6, we can observe that the larger the $\Delta\xi$, the lower the throughput achieved by the system. This is due to the fact that the proposed AWSS selects the user which has the largest $X_i(n)$ when the channel is inactive. When the $\Delta\xi$ is larger, the user with the worse channel condition has more chances to be selected for transmitting the packets. Therefore, the throughput is decreased in comparison.

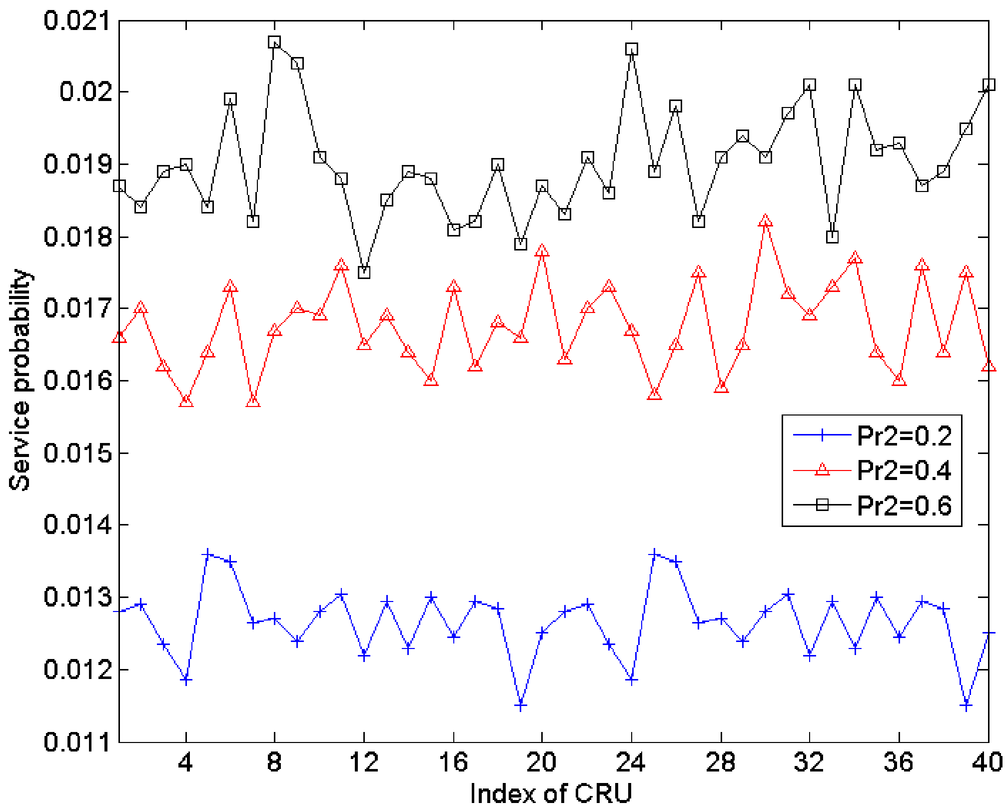

Figure 5.5: Service probability for each CRU with different P_{r2} ($P_{r2} = 0.2, 0.4$, and 0.6, $P_{r1} = 0.2$, and $\Delta\xi = 10$).

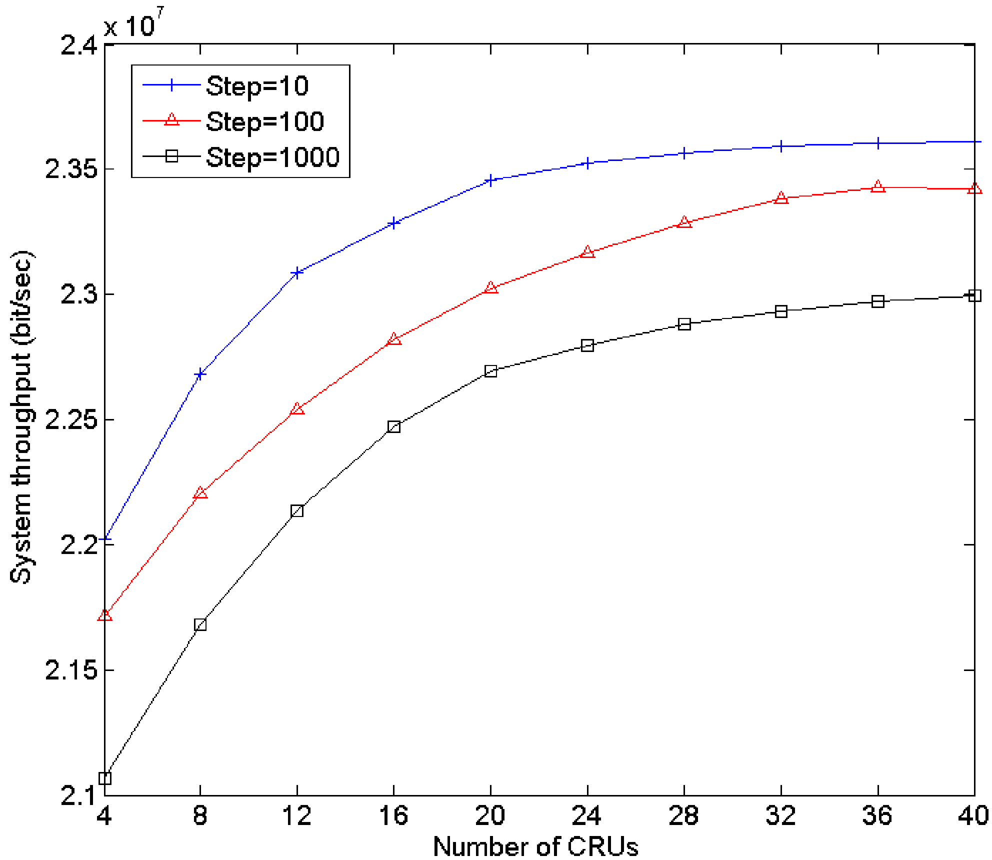

Figure 5.6: System throughput versus the number of CRUs with different $\Delta\xi$ ($\Delta\xi = 10, 100,$ and 1000, $P_{r2} = 0.2$, and $P_{r1} = 0.2$).

5.2.2 Non-Saturated Traffic Simulation Results

Non-saturated traffic simulation results are discussed in this section. We assume that non-saturated traffic at each node uses Poisson call arrivals and a Weibull file size whose parameters are given in Table 5.1. The simulation time is 120000 timeslots (2400 seconds). Each of the simulation results represents an average of 10 random runs.

Fig. 5.7 shows the system throughput versus the number of CRUs for the three scheduling schemes. It can be observed that, with an increased number of CRUs,

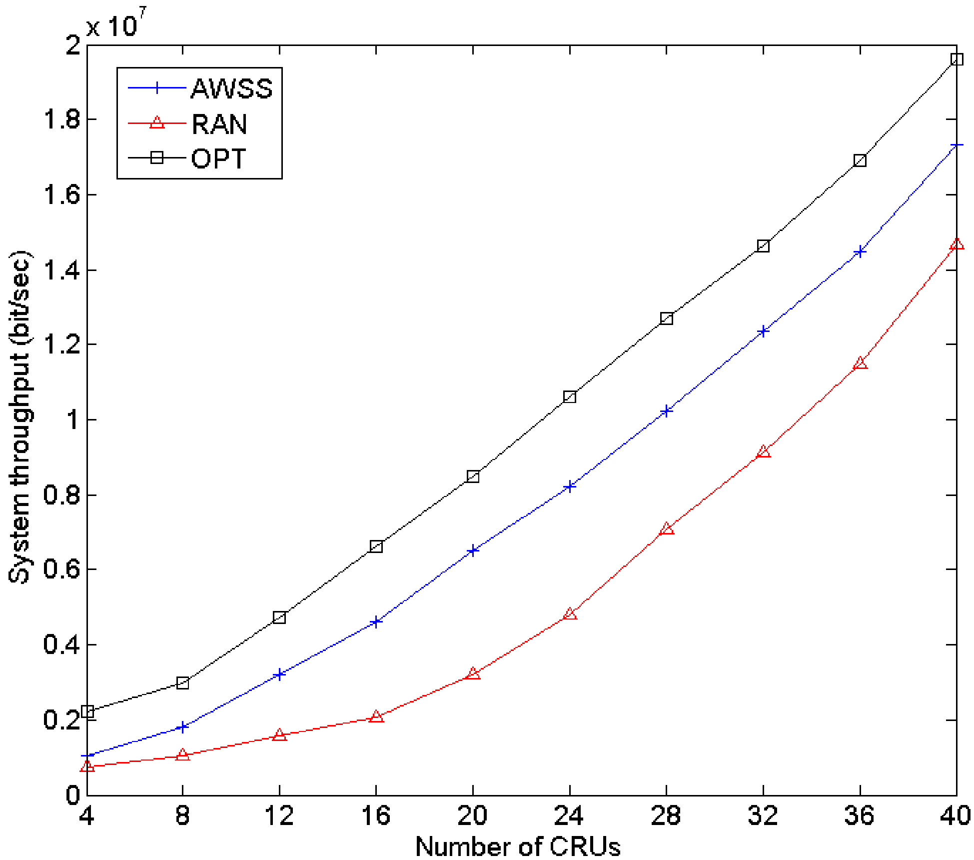

Figure 5.7: System throughput versus the number of CRUs in non-saturated traffic ($\lambda = 10$, $P_{r1} = 0.2$, and $P_{r2} = 0.2$, $\Delta\xi = 10$).

the system throughput increases sharply. The effect of the channel-diversity gain is very distinct in the non-saturated traffic case.

Through Fig. 5.8, we can observe that the fairness in non-saturated traffic leads to the same conclusions as that found in the saturated traffic case with regards the propose scheme when compared to the other two schemes. According to the adjustment of the weight of the CRUs, the proposed AWSS scheme could obtain almost ideal fairness performance. However, the OPT scheme, which solely considers the channel condition, has the worst fairness performance.

From Fig. 5.7 - 5.8, the AWSS scheme can achieve a good tradeoff between the throughput and fairness. Compared with the RAN scheme, it achieves a higher

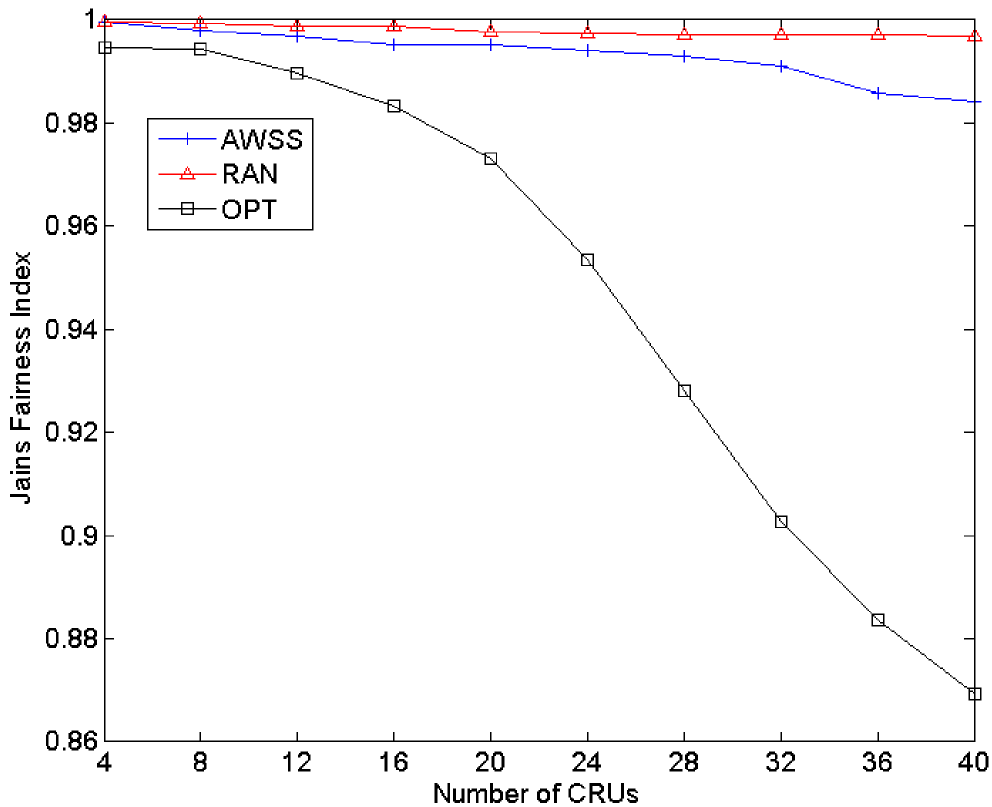

Figure 5.8: The fairness performance versus the number of CRUs in non-saturated traffic ($\lambda = 10$, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

throughput at the cost of slightly degraded fairness performance. Meanwhile, compared with the scheme OPT, it achieves a much better fairness performance with some sacrifice of throughput. This is the same conclusion as in the saturated traffic case.

The call arrive rate λ is an important parameter to indicate the traffic load, which affects the system performance. We study the impact of this parameter on system throughput and fairness in the CRN as shown in Figs. 5.9 - 5.11, where the λ value is set from 0.1 to 500.

Fig. 5.9 demonstrates that the larger the value of λ, the more traffic of each user has in the queue, the higher system throughput.

From Fig. 5.10, with the increase of the λ, the system throughput increases. When the λ is large enough, the throughput is almost equal to the throughput with saturated traffic. Since the queue is unlikely to be empty when the λ is big enough, the non-saturated traffic approaches to the saturated traffic.

Fairness performance can also be affected by the traffic parameter λ. Fig. 5.11 shows that, with the increase of the λ value, the fairness index is decreased.

Packet delay is defined as the difference in end-to-end delay between received packets in a flow, which is given by

$$PD_{sys} = \frac{1}{M \cdot S} \sum_{i=1}^{M} \sum_{j=1}^{S} (DT_{ij} - AT_{ij} + TT_{ij}) \tag{5.4}$$

where PD_{sys} is the system packet delay, DT_{ij} is the packet j's departure timeslot of CRU i, AT_{ij} is the packet j 's arrival timeslot of CRU i, TT_{ij} is the packet j's transmission time of CRU i, S is the number of the departure packet and M is the number of CRUs.

Fig. 5.12 shows the system packet delay versus the number of CRUs for the three scheduling schemes. It can be observed that, with an increased number of CRUs, the system packet delay increases.

Fig. 5.13 demonstrates that the larger the value of λ, the more traffic of each

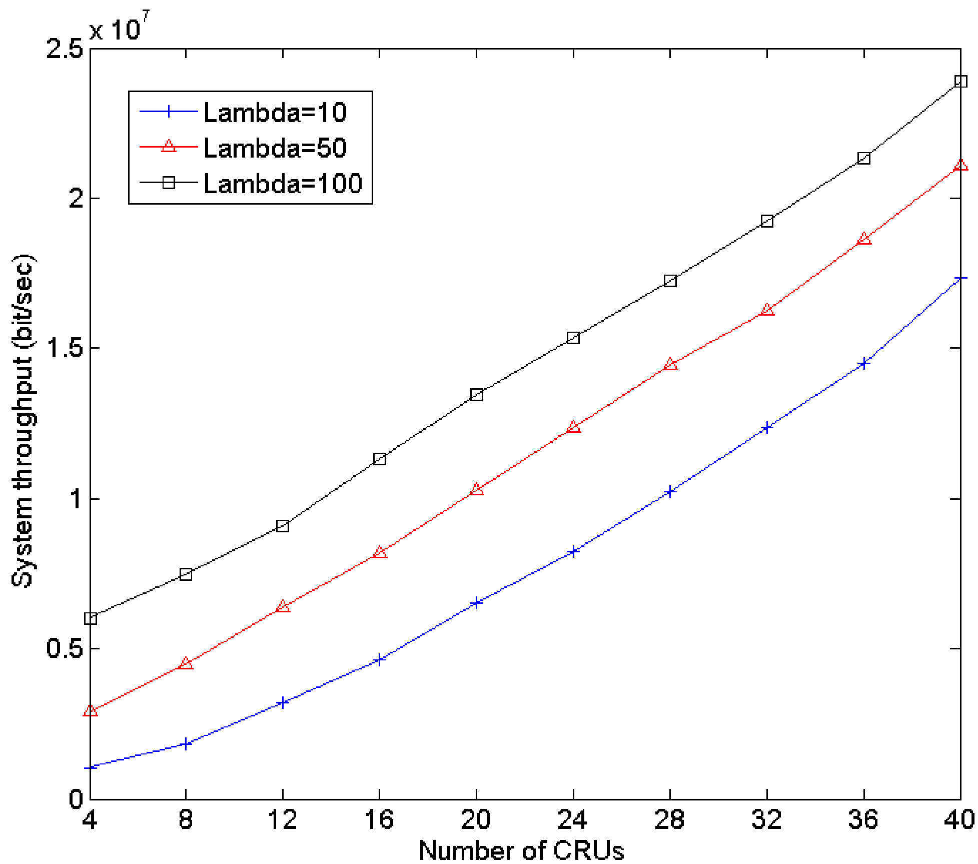

Figure 5.9: System throughput versus the number of CRUs with the different λ in non-saturated traffic ($\lambda = 10, 50$, and 100, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

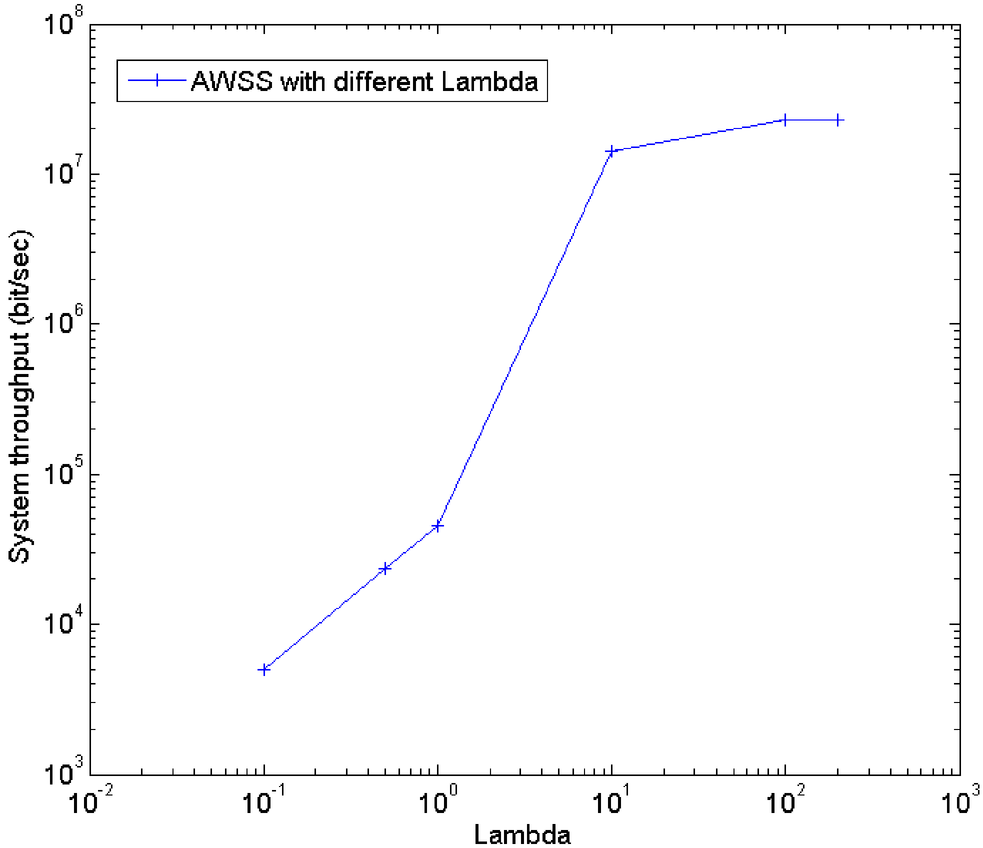

Figure 5.10: System throughput of the AWSS with the different λ in non-saturated traffic ($\lambda = 0.1, 0.5, 1, 10, 100$, and 200, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

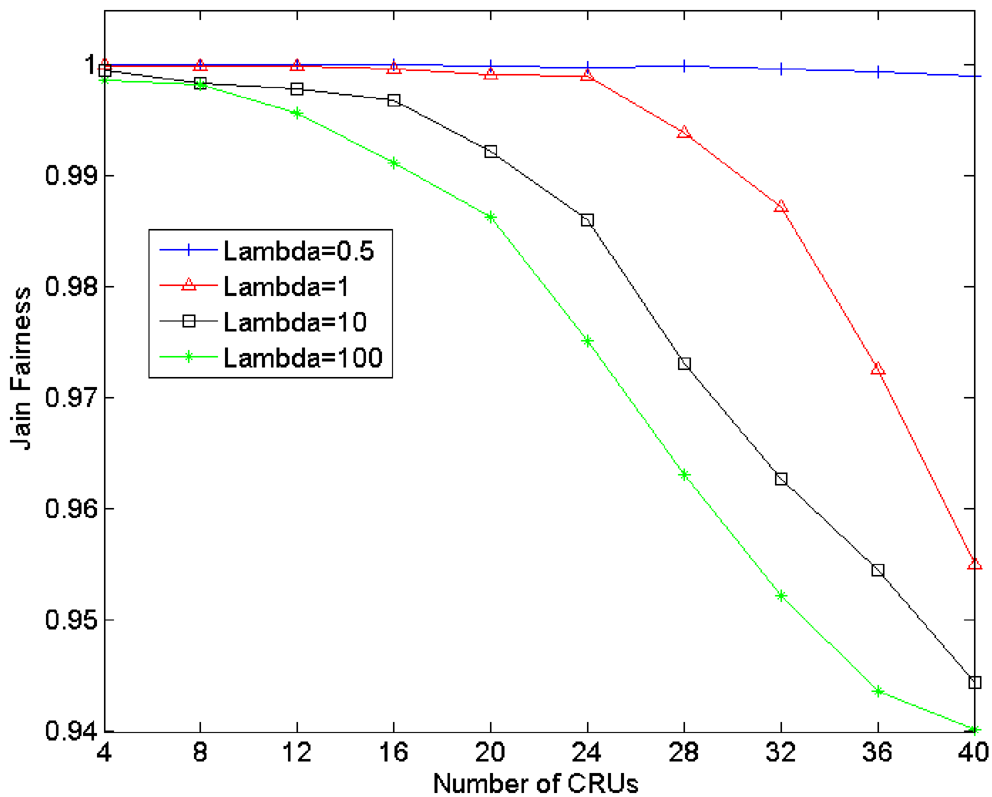

Figure 5.11: The fairness performance versus the number of CRUs with the different λ in non-saturated traffic ($\lambda = 0.5, 1, 10,$ and 100, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

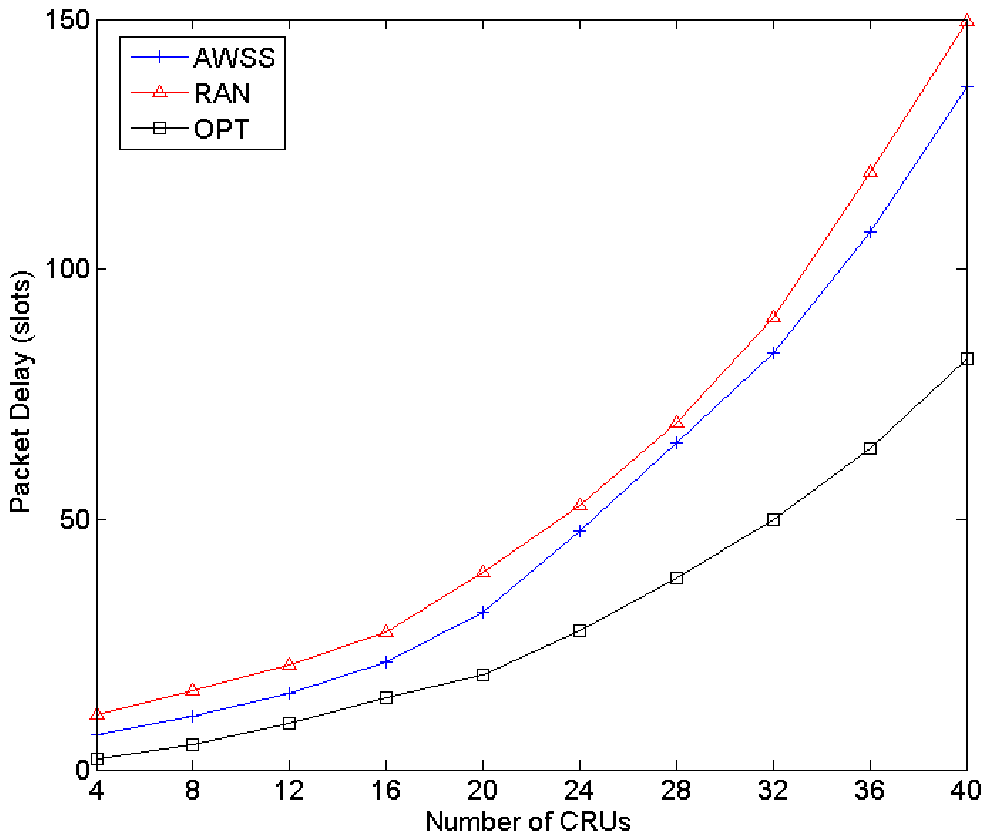

Figure 5.12: The system packet delay versus the number of CRUs in non-saturated traffic ($\lambda = 10$, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

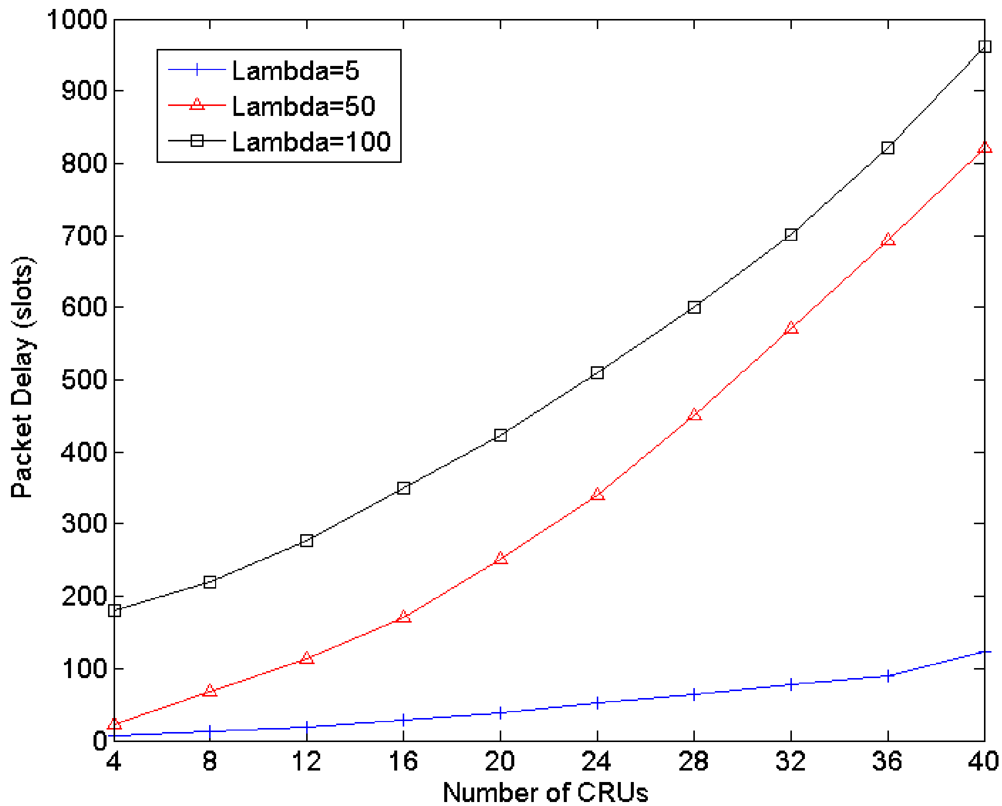

Figure 5.13: The system packet delay versus the number of CRUs the different λ in non-saturated traffic ($P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

user has in the queue, the higher the packet delay. At the same time, with the increase of the CRUs in the system, the packet delay increases.

From Fig. 5.14 , with the increase of the λ, the system packet delay increases. At the beginning, since the traffic load is low, the packet delay has almost the same lower value. When the λ is higher, the arrival number of the packets is much larger than the departure number of the pakcets in the system, the packet delay increases sharply. The larger the λ, the higher the delay a packet will experience.

In summary, the simulation results demonstrate the efficiency and effectiveness of the proposed AWSS scheme in terms of important performance metrics, including the service probability, packet delay, and throughput, as well as fairness. The AWSS scheme achieves a good tradeoff between the system throughput and fairness in the

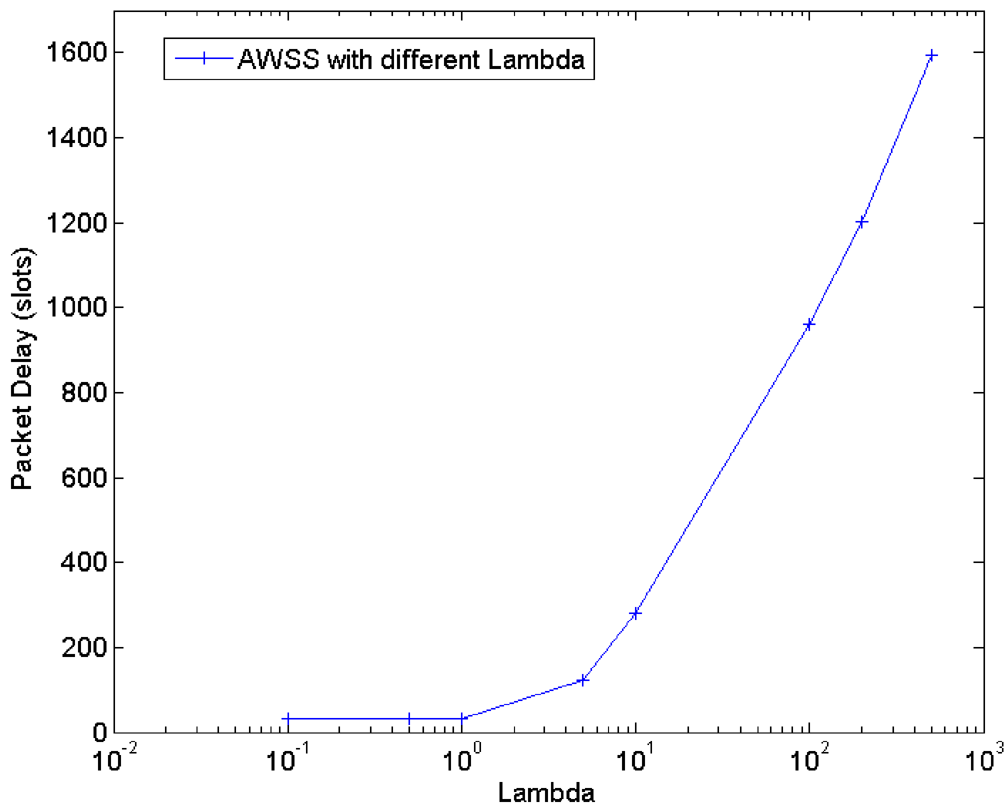

Figure 5.14: System packet delay of the AWSS with the different λ in non-saturated traffic ($\lambda = 0.1, 0.5, 1, 5, 10, 100, 200, 500$, $P_{r1} = 0.2$, $P_{r2} = 0.2$, and $\Delta\xi = 10$).

cognitive radio network.

Chapter 6

Conclusion and Future Work

6.1 Conclusions

In this research, an adaptive weighted scheduling scheme is developed with the aim to achieve a better performance tradeoff in terms of throughput and fairness. Based on the network model under considerations, the link-layer frame structure is proposed. A simply but efficient adaptive weighted scheduling scheme is then proposed for achieving flexible and fair scheduling for data traffic in the cognitive radio network.

In the scheduling scheme, an AWF is introduced to adjust the priority of different CRUs to be selected for service. By jointly considering the instantaneous channel conditions, adaptive weighted factor and the channel availability which is a unique feature of the CRN, this scheduling scheme addresses the unfairness problem faced by traditional PF scheduling schemes, where the use of PF schemes in a CRN directly can lead to the spectrum resource deprivation of a user for extended periods of time in the scenario where the user experiences a poor channel condition when the channel is available and experiences a good channel condition when the channel is unavailable. By adaptively weighting the priority of different CRUs based on this combined analysis approach, CRUs with poor channel conditions also have a chance to be selected for data transmission and hence fairness amongst users can be improved.

The performance of proposed scheme is studied under two traffic scenarios (the saturated traffic case and non saturated traffic case) in terms of the system throughput and fairness. The impacts of weights and channel conditions on performance metrics are studied. Simulation results demonstrate the effectiveness and efficiency of the proposed scheme in fair resource allocation and high resource utilization.

6.2 Future Work

There are many issues that should be further investigated in scheduling for cognitive radio networks. The research work in this thesis focuses on the scheduling in a single cell system with a single channel. Besides the single cell mode, other more practical system models such as multi-cell scenario and ad hoc networks are important and pose more challenging issues.

In multi-cell wireless networks, the resource allocation and scheduling should be designed from the perspective of the whole network. Channel allocation, power allocation, and load balance in multi-cell scenarios need to be addressed for improving the network-resource utilization, decrease the regional congestion by alleviating the intra- and inter-cell interference and adaptively adjusting BS association. How to extend our work in the multi-cell wireless systems for achieving flexible and efficient resource allocation deserves further investigation.

Compared with the networks with centralized control, ad hoc networks have agile infrastructures for communication and its communication range can be expanded easily. There is no need for any fixed radio base station or router. Such a network is self-organizing and adaptive. At the same time, the availability of channels varies widely from the one place to the other places. If the network operates in an ad hoc mode, a CRU can set up direct connections with its neighbors. Therefore, the characteristics of an ad hoc network lead to some new challenges for scheduling in distributed cognitive radio networks.

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