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Adaptive QoS Contrained Priority Scheduling for Cognitive Radio Systems

Mohamed E. Khedr
Electronics and Communication Department
Arab Academy for Science and Technology, Egypt

Rolla Hassan
National Telecom Regulatory Authority, Egypt

Fadel F. Digham
National Telecom Regulatory Authority, Egypt

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 paper, we focus on the packet scheduling in a single cell cognitive radio system, an adaptive downlink scheduling for real time and non-real time applications with the consideration of the primary user activity is proposed. The proposed algorithm satisfies different traffic models based on the QoS level of each traffic type and the spectrum availability. The performance of the proposed algorithm has been evaluated in terms of throughput and delay. This algorithm provides better QoS guarantee for real time traffic and more efficient spectrum utilization for cognitive radio systems.

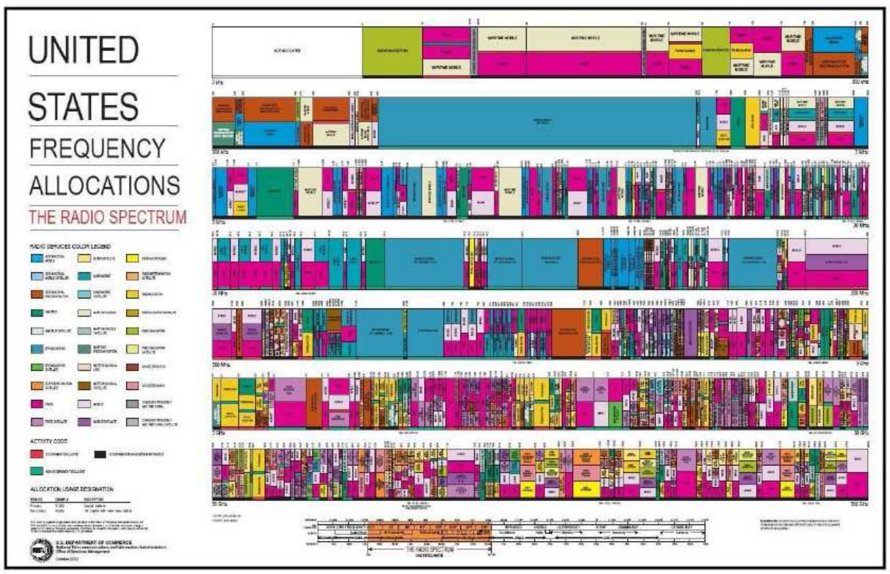
Index Terms: Cognitive radio, Wireless Channel, Resource allocations.

I. 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 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. 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. 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].

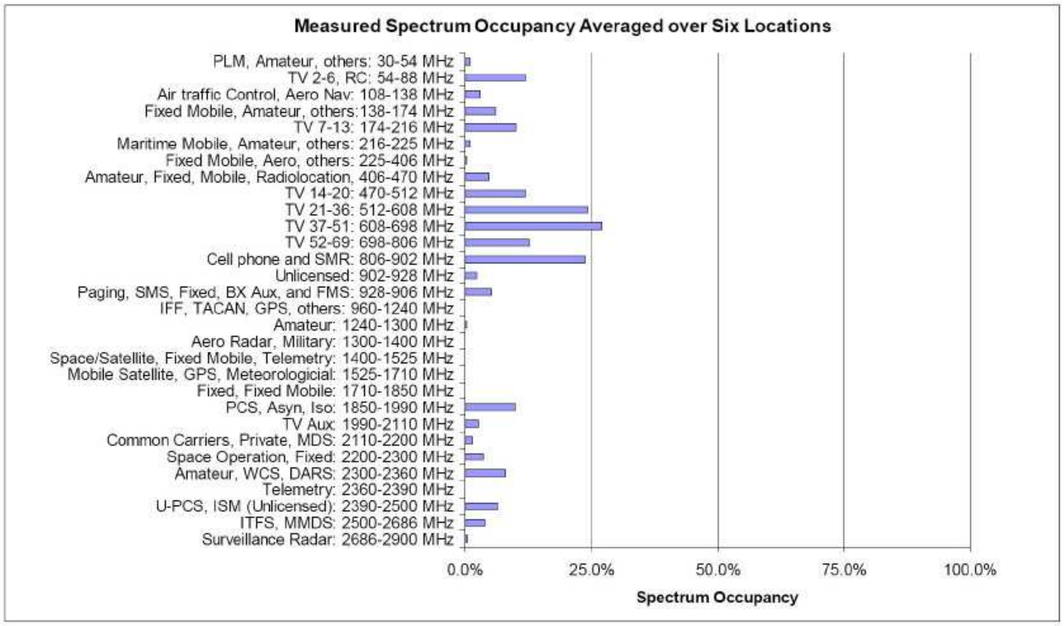
Figure 1: illustration of the frequency allocation chart of FCC [2]



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 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.

The remainder of the paper is organized as follows. Paper motivation and objective is presented in section 2. The literature survey of cognitive radio is presented in section 3 while section 4 presents the resource allocation and scheduling schemes in OFDMA cognitive radio. The proposed model of the CRN, including the network architecture, traffic model and channel model are described in section5. Simulation results are presented in section 6 and conclude the paper in section 7 with conclusions and future work.

Figure 2: Spectrum occupancy in each band averaged over six locations [6]



II. Paper Motivation and Objective

Scheduling is considered the core of spectrum sharing process and plays a crucial role in the network performance. Scheduling schemes decide the order of packet transmission from different users, which in returns will achieve 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.
- The transmission time of CRUs is not fixed, but depends on the activity of the PUs.

Therefore, 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.

The selection of a CRU to use 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, improving the resource utilization to get a high throughput and make a compromise between the system throughput and fairness is an important issue. 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.

III. Cognitive Radio

CR would be realized through the integration of model-based reasoning with software radio and would be trainable in a broad sense, instead of just programmable [8]. The concept of CR emphasizes enhanced quality of information and experience for the user, with cognition and reconfiguration capabilities as a means to this end. Today, however, CR has become an all-encompassing term for a wide variety of technologies that enable radios to achieve various levels of self-configuration, and with an emphasis on different functionalities, ranging from ubiquitous wireless access, to automated radio resource optimization, to dynamic spectrum access for a future device-centric interference management, to the vision of an ideal CR.[8].

CR should be reconfigurable and intelligent in behavior. By intelligent behavior we mean the ability to adapt without being a priori programmed to do this; that is, via some form of learning. For example, a handset that learns a radio frequency map in its surrounding could create a location-indexed RSSI vector (latitude, longitude, time, RF, RSSI) and uses a machine-learning algorithm to switch its frequency band as the user moves. From this it follows that cognitive radio functionality requires at least the following capabilities:

- Awareness of the radio environment in terms of spectrum usage, RF environment, the available node in the network, and the available power [9,10] 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.

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.

Cognitive radio should have the ability to sense and be aware of its operational environment, and dynamically adjust its radio operating parameters accordingly. For cognitive radio to achieve this objective, the Physical Layer (PHY) needs to be highly flexible and adaptable. A special case of multicarrier transmission known as OFDM is one of the most widely used technologies in current wireless communications systems and it has the potential of fulfilling the aforementioned requirements of cognitive radios inherently or with minor changes. By dividing the spectrum into sub-bands that are modulated with orthogonal subcarriers, OFDM removes the need for equalizers and thus reduces the complexity of the receiver.

IV. Resource Allocation and Scheduling in OFDMA Wireless Systems

Resource allocation and scheduling are essential components of wireless data systems. Here by resource allocation we refer to the problem of allocating physical layer resources such as bandwidth and power among these active users, scheduling refers to the problem of determining which users will be active in a given time-slot.

Water-filling power allocation principle allows systems to achieve the theoretical capacity offered by a frequency-selective channel. Capacity is operationally defined as the maximum data rate that the channel can support with an arbitrarily low error-rate probability. From an information theoretic perspective, it represents the maximum mutual information between the transmitted data symbols and the received signal vector, where maximization is performed over the probability density function (pdf) of the transmitted data [11, 12].

Assuming perfect timing and frequency synchronization, the output from the receive DFT is expressed by

$$R(n) = H(n)S(n) + W(n), \qquad 0 \le n \le N-1 \tag{1}$$

where $H(n)$ is the channel frequency response over the nth subcarrier, $S(n)$ the corresponding input symbol with power $P_n = E\{|S(n)|^2\}$ and $W(n)$ is white Gaussian noise with zero-mean and variance σ_w^2 Inspection of Eq. (1) indicates that the OFDM channel can be viewed as a collection of parallel independent AWGN sub-channels, one for each subcarrier.

In a practical system, the transmitted power is normally constrained to some value P_{budget}. Mathematically, this amounts to setting

$$\sum_{n=0}^{N-1} P_n \le P_{budget} \tag{2}$$

With $P_n \ge 0$ for n=0,1 …. N-1. It is known that among all input vectors $S=[S(0),S(1), \ldots, S(N-1)]^T$satisfying the overall power constraint Eq. (2), the mutual information $I(S,R)$ between S and the observation vector $R=[R(0),R(1), \ldots , R(N - 1)]^T$ is maximized when the data symbols $\{S(n)\}$ are statistically independent and Gaussian distributed with zero-mean. In this case we have

$$I(S,R) = \sum_{n=0}^{N-1} \log_2\left(1 + \frac{p_n\,|H(n)|^2}{\sigma_w^2}\right) \tag{3}$$

The channel capacity C is obtained by maximizing the right-hand-side of Eq. (3) with respect to $P = [P(0),P(1), \ldots, P(N-1)]^T$, *i.e.*,

$$C = \max_p \left\{\sum_{n=0}^{N-1} \log_2\left(1 + \frac{p_n\,|H(n)|^2}{\sigma_w^2}\right)\right\} \tag{4}$$

The optimum power allocation is found to be

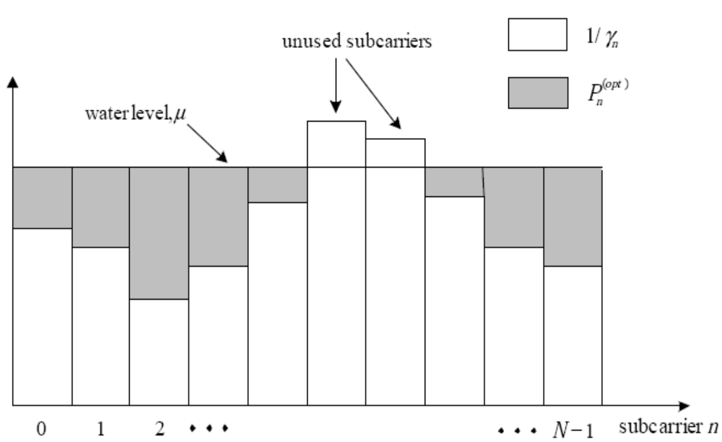
$$P_n^{(opt)} = \left(\mu - \frac{1}{\gamma_n}\right)^{*} \tag{5}$$

where $(x)^+ = \max\{x,0\}$, $\gamma_n = |H(n)|^2/\sigma_w^2$ is the so-called *channel SNR* and μ=1/λ ln 2 is a parameter that must be chosen so as to meet the total transmit power constraint

$$\sum_{n=0}^{N-1} = \left(\mu - \frac{1}{\gamma_n}\right)^{+} = P_{budget} \tag{6}$$

This solution lends itself to an interesting physical interpretation. As depicted in Fig. 3, the quantities $1/\gamma_n$ can be thought of as the bottom of a vessel in which the transmit power P_{budget} is poured similarly to water. In particular, the quantity μ represents the height of the water surface, while $p_n^{(opt)}$ is the depth of the water at subcarrier n. Since the power allocation process resembles the way by which water distributes itself in a vessel, this optimal strategy is referred to as *water-filling* or *water-pouring*.

Figure 3: Water-filling over the available subcarriers



In Single Step Frequency Allocation (SSFA) algorithm, the user requests number of carriers $\boldsymbol{N}_k$, proportional to $\boldsymbol{R}^k_{min}$ which the transmission rate requested by user $\boldsymbol{k}$. The base station first makes a list $\boldsymbol{V}_k$ of favorite subcarriers for each user $\boldsymbol{k}$. In each stage, a subcarrier is allocated to the user with the lowest ratio of allocated to requested carriers, going down the favorites list for the user. For each user $\boldsymbol{k}$, there is also a list $\boldsymbol{A}_k$ of the $\boldsymbol{n}_k$ previously allocated carriers and the $\boldsymbol{N}_k$ - $\boldsymbol{n}_k$ carriers that could still potentially be allocated. When a user requests a carrier that is already allocated, the carrier is given to the user with the highest accumulated relative power loss.

In [14, 15, 16] transmission power and data rate are assigned such that the bit-error-rate (BER) across tones does not exceed a given threshold $p_{e,max}$.

The maximum fairness algorithm aims to allocate the subcarriers and power such that the *minimum* user's data rate is maximized. This algorithm can be referred to as a *max-min* problem, since the goal is to maximize the minimum data rate.

The given problem can be formulated as

$$\max_{P_{k,n} S_k} \min_k \sum_{n(S_k} \frac{B}{N} \log_2 \left(1 + \frac{P_{k,n} h^2_{k,n}}{N_o \frac{B}{N}} \right) \tag{7}$$

where $P_{k,n}$ is the power assigned to user k's sub-channel n, $h_{k,n}$ is the channel gain of user k's subchannel n, S_k is the set of indices of sub-channels assigned to user k, N_o is the power of additive white Gaussian noise (AWGN), B is the total bandwidth. A common approach to solve this equation is to assume initially that equal power is allocated to each subcarrier and then to iteratively assign each available subcarrier to a low-rate user with the best channel on it [13, 17].

Scheduling on the other hand, has two contradictory goals: i) to maximize the overall network throughput, and ii) to guarantee fairness amongst users. Many opportunistic scheduling schemes for time varying channels in the multiple access and multiple antennas have been proposed. In [19], 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 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.

An example is presented in [18], 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 [21], 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 [22] 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 [23], 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.

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 [24], 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 [25], 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 [26], 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 [27]. 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 [28], which uses a probabilistic maximum collision constraint with the primary users. In [29], 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.

V. Adaptive QoS constrained Priority-Based Scheduling Scheme

In this paper, we consider an infrastructure based cognitive radio network providing communication services to secondary users SUs, making use of the available radio resources from licensed networks belonging to primary users PUs. SUs can sense the usage of the channels (i.e, frequency band) licensed to PUs. If a frequency band 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.

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 SUs. 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 SUs.[31]

V.1. Network Architecture

A multi-cell CRN is illustrated in Fig. 4 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 [30]. 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, the cognitive radio system considered in this paper has only one cell as shown in Fig. 5, in which base station (BS) is centrally located and all users are uniformly distributed. As in most cognitive radio systems, the multiple access technique in this system is OFDMA (orthogonal frequency division multiple access). So the basic resource unit for allocation is time-frequency block, which consists of slots in time domain and a sub-channel in frequency domain.

The BS detects the transmission of primary networks, determines the channel availability, and allocates the channel to SUs 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 SU does not share this inactive channel with the other SUs. We focus on the downlink scheduling for transmission from the BS to SUs.

Figure 4: A multi-cell cognitive radio network with centralized control.

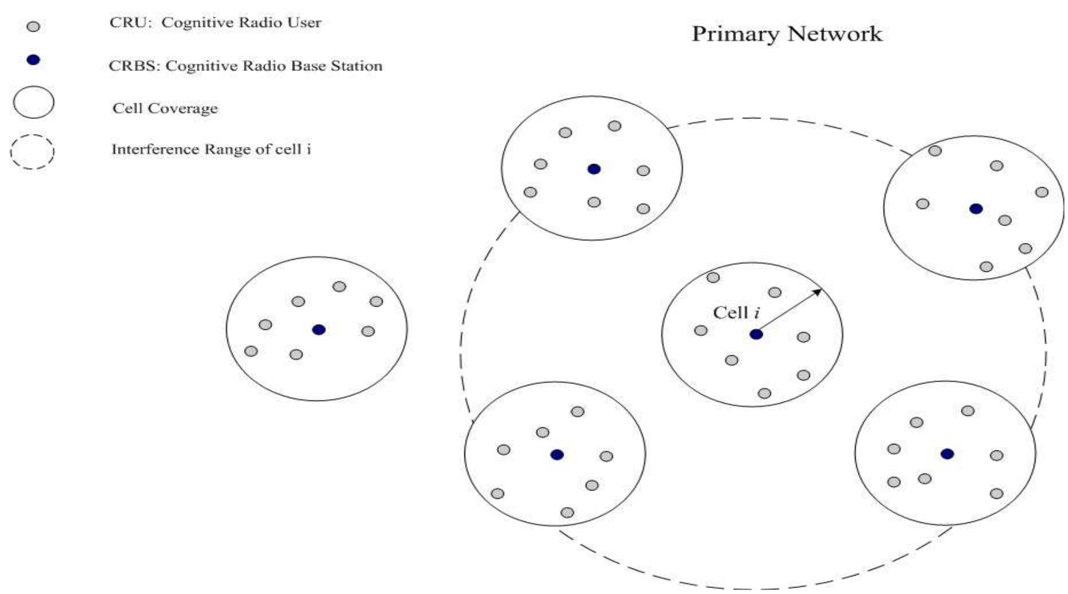
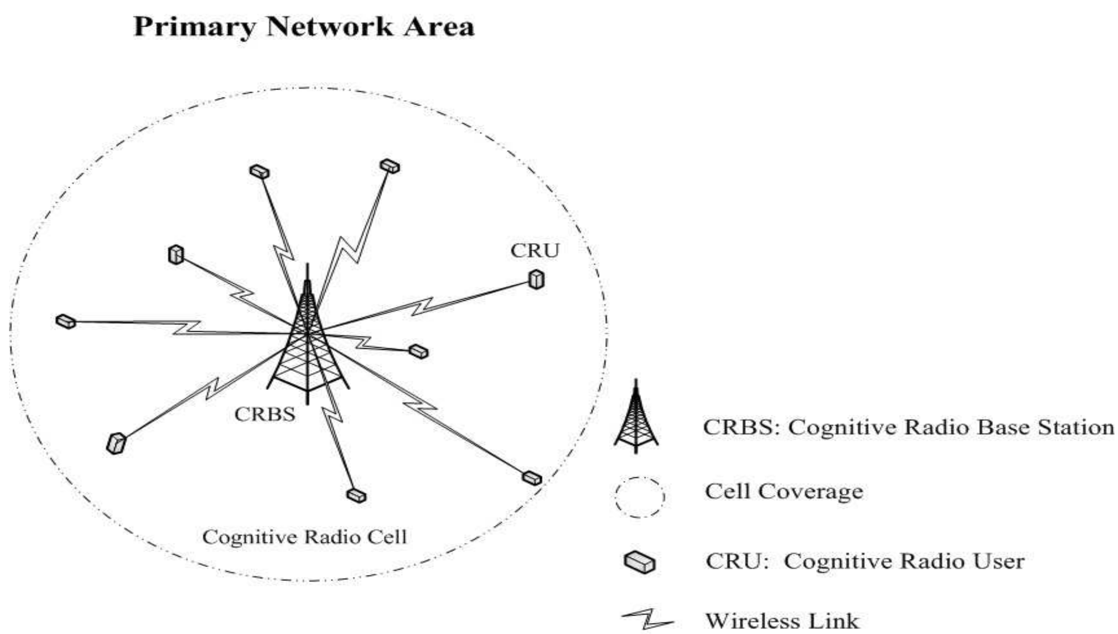


Figure 5: Single cell cognitive radio network with centralized control.



V.2. Traffic Model

There are two main problems for modeling cognitive radio traffic. First, the traffic is based upon a distributed architecture that makes it flexible and adaptable. Second, the growth of the traffic has been difficult to predict. However, Broadband Wireless Access Working Group proposed a set of traffic models suitable for MAC/PHY Simulations of cognitive radio networks. The proposal provides not only the individual traffic models for each service but also the percentages necessary to define the mix of traffic arriving to an access point. The proposal includes three different services: voice, data (HTTP, TCP, and FTP) and streaming [32].

V.2.1. Data Traffic

The generation of HTTP, TCP and FTP traffic is based on the superposition of four IPP processes. In an Interrupted Poisson Process (IPP) there are two states as shown in Fig. 6. Data are generated during ON state according to a given distribution and with average rate h bits per symbol. During OFF state, there is no traffic. μ is the average number of transitions from the ON state to the OFF state per unit of time and, similarly, λ is the average number of transitions from the OFF state to the ON state per unit of time. The transitions among ON and OFF state are exponentially distributed whereas the distribution of the inter-arrival time during the active state (ON) gives rise to different types of IPP processes

The instantaneous source rate of an IPP process is:

$$a[n] = \begin{cases} H & \text{if the process is on ON State} \\ 0 & \text{if the process is on OFF State} \end{cases} \tag{8}$$

The effective bandwidth of an IPP is:

$$\alpha_A(v) = \frac{1}{v}\log\left(\frac{\lambda + \mu\varphi(v) + \sqrt{(\lambda + \mu\varphi(v))^2 - 4(\lambda + \mu - 1)\varphi(v)}}{2}\right) \tag{9}$$

Where $\varphi(v)$ is the moment generating function of the interval process during ON state (deterministic, exponential…).

All four processes follow exponential distribution both for transitions among ON and OFF state and among packets during ON state, and different parameters μ^i, λ^i and h^i for representing four different time scale, i=1, … 4.Therefore, the 4-IPP model superimposes for different time scale to generate an accurate representation of data traffic in internet. Table 1 shows the parameters of data traffic, where h^i is expressed in packets per unit of time and μ^i, λ^i are transitions per unit of time .The mean rate of this traffic is $m_A = \sum_{i-1}^{4} h^i \frac{\lambda^i}{\lambda^i + \mu^i}$.

The instantaneous arrival rate $a[n]$ now is the sum of the rates of the four processes

$$a[n] = a^1[n] + a^2[n] + a3[n] + a4[n] \tag{10}$$

Where

$$a^i[n] = \begin{cases} H & \text{if the ith IPP process is on ON State} \\ 0 & \text{if the ith IPP process is on OFF State} \end{cases} \tag{11}$$

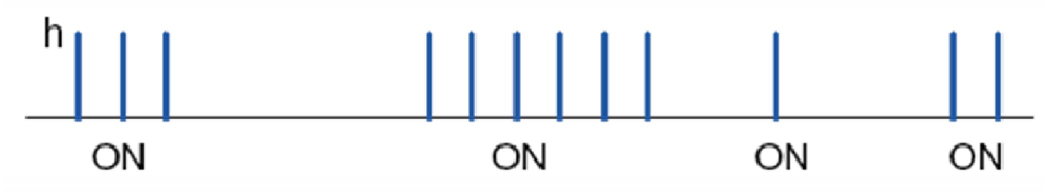
Table 1: Data Traffic Parameters (IEEE 802.16)

Source	$h^{(i)}$	$\mu^{(i)}$	$\lambda^{(i)}$
IPP1	2.679	$4.571*10^{-1}$	3.429*10-1
IPP2	1.698	$1.445*10^{-2}$	$1.084*10^{-2}$
IPP3	1.388	$4.571*10^{-4}$	$3.429*10^{-4}$
IPP4	1.234	$4.571*10^{-1}$	$3.429*10^{-6}$

V.2.2. Voice Traffic

There is a special kind of IPP process in which the rate during ON state is deterministic Therefore, during the ON state the process generates data with fixed rate h and the time spent in ON and OFF states is exponentially distributed with average rate μ and λ, respectively. This model is the classical ON-OFF process, which has been widely used in the literature to model voice traffic. It is also called IDP (Interrupted Deterministic Process).

Figure 6: The ON-OFF process



One IDP represents one voice source, with the parameters shown in the table 2, where h is expressed in packets per unit of time and μ,λ are transitions per unit of time.

They are chosen to match most cited voice model with ON period 352ms and OFF period 650ms, with the appropriate scaling. The instantaneous arrival rate is the same as Eq. (8) The effective bandwidth function of an IDP process is:

$$\alpha_A(v)=\lambda \tag{12}$$

The mean arrival rate of an ON-OFF source is $m_A = h\frac{\lambda}{\lambda+\mu}$ and the EBF yields:

$$\alpha_A(v) = \frac{1}{2v}[h.v - \mu - \lambda + \sqrt{(h.v - \mu - \lambda)^2 + 4.\lambda.\mu}] \tag{13}$$

Table 2: Voice traffic parameters (IEEE802.16)

Source	***h***	μ	λ
IDP1	1.00	$5.682*10^{-2}$	$3.067*10^{-2}$

V.2.3. Video Traffic

Finally, a packet video source is modeled by means of two Interrupted Renewal Processes (2IRP) fitting the most cited video trace in past ten years. This kind of traffic also presents self-similarity. In the IRP the rest time is Pareto distributed rather than exponential and thereby it is not a Markov process anymore. The cumulative distribution function of a Pareto distribution is defined as:

$$F(x) = 1 - (\frac{b}{x})^\alpha \quad x \geq 0 \tag{14}$$

With mean m_x and variance σ_x^2:

$$m_x = \frac{b}{\alpha - 1} \tag{15}$$

$$\sigma_x^2 = \frac{b^2\alpha}{(\alpha-1)^2(\alpha-2)} \tag{16}$$

With the parameters of streaming traffic in Table 3, the model is appropriate, e.g., for MPEG packet video with 25 frames per second with local Hurst parameter ranging from 0.73 to 0.93. The parameter b in the Pareto distribution is set to 1, and α is λ and μ for the ON and OFF period, respectively. Once more, h is expressed in packets per unit of time and λ and μ are transitions per unit of time.

Table 3: Streaming traffic parameters IEEE802.16

Source	***h***	μ	λ
IRP1	44.95	1.14	1.22
IRP2	61.90	1.54	1.28

V.3. Channel Model

Radio waves propagate in free space according to the inverse square law with respect to distance. However, terrestrial radio channels are governed by the various propagation mechanisms such as reflection, refraction, diffraction and scattering [33] manifested in natural and man-made environments. Due to these mechanisms, mobile channels can be characterized by two fading phenomenon: long-term and short term fading. Long-term fading manifests itself in terms of path-loss and shadowing and is slow varying with respect to time and distance, whereas short-term fading varies significantly over few meters and characterized by multipath fading. Long-term fading is modeled by a log-normal distribution [33,p.17]

$$f_{\Omega_{dB}}(\Omega)=\frac{1}{\sqrt{2\pi\sigma_{dB}^2}}\exp\{-\frac{\Omega^2}{2\sigma_{dB}^2}\} \tag{17}$$

Where σ_{dB} is the shadowing standard deviation in dB. The implication of long-term fading on resource allocation technique is to ensure that enough power is transmitted in order to meet the link budget requirements due to path-loss and shadowing. However, due to slow variation of this type of fading, the resource allocation process does not have to be very dynamic.

Statistically on the other hand, multipath channel can be characterized by a power delay profile $c(\tau)$ [33,p.70] , which gives the expected value of the power as function of the time-delay spread τ of the channel. The received envelope can be statistically characterized by the scattering environment of the mobile terminal. Due to the motion of the mobile travelling at some velocity $v(^m/_s)$, the position of the scatterers with respect to the mobile varies with time and arriving multipath waves experience a doppler shift in their frequencies.

The Doppler shift of the n^{th} reflected wave f_n is determined by the angle of arrival α_n as $f_n=f_m \cos(\alpha_n)$, where $f_m=\frac{v}{\lambda_c}, \lambda_c=\frac{c}{f_c}$ is the wavelength of the carrier wave [33,p.37]. if the environments has scatteres that are isotropically placed with no line-of-sight (LOS), then α_n can be modeled as being uniformaly distributed in the interval $[-\pi,\pi]$. The received envelope is correlated with the following autocorrelation function:

$$\varphi(\tau)=\frac{\rho}{2}J_0(2\pi f_m\tau) \tag{18}$$

where J_0 is the zero-order Bassel function of the first kind [33,p.40]. The received envelope $r(t)$ is given by a Rayleigh distribution.

$$f_R(r)=\frac{2r}{\rho}\exp\left\{-\frac{r^2}{\rho}\right\} \tag{19}$$

Where $\overline{P}$ is the expectation of the received power. The recievd power $p(t)=r^2(t)$ can be modeled as exponential distribution [33,p.47]

$$f_p(p)=\frac{1}{p}\exp\left\{-\frac{p}{\rho}\right\} \tag{20}$$

It can be observed from the above equation that the variation of the short-term fading is dependent on the mobile velocity, and even for low speed mobile terminals, the fluctuations can be drastic over short period of time. This implies that the resource allocation technique needs to adapt to the time-varying channel conditions very quickly in order to gain in terms of spectrum efficiency.

V.4. The Proposed Algorithm

Compared to conventional wireless communication systems, the uncertain availability of the channel is a unique feature of CRNs.

The channel state information available to the secondary users is described by a probability vector $P_n^{(f)} = [P_1^{(f)}, P_2^{(f)}, \ldots P_N^{(f)}$ where $P_n^{(f)}$ is the probability that channel n is free. We assume that this information is obtained either by sensing the channel, or through knowledge of the traffic statistics of the primary users, or a combination of both.

Let N be the total number of the available sub-channels, M the number of sub-channels during one scheduling period ($M=T_{sp}/L$) where T_{sp} is the scheduling period and L is the time slot length, $r(n)$, n=1,2, … N the number of remaining free slots of sub-channel n (at the beginning of each scheduling period $r(n)=M$), K the total number of SUs, and $q(i,j)$ the traffic queue of user i and traffic class j. Table 4 lists the notations used in this paper.

Table 4: List of Notations

Notation	
$p(i,j)$	the priority function of user i of traffic queue j
c_j	adaptive service coefficient
α_j, β_j	weights for balancing the impact of delay and throughput priority terms
$W_{i,j}$	the waiting time of the user i of traffic queue j
T_j, r_j	maximum packet delay bound and expected packet throughput of traffic class j
$q(i,j)$	traffic queue of user i and class j
$b_{in}^{(j)}$	the number of bits for each user i with traffic class j using sub-channel n
$P_n^{(f)}$	the probability that channel n is free
$r(n)$	the remaining free slots of sub-channel n
R_j	the target bit rate
L	the time slot length
M	the number of sub-channels during one scheduling period
N	the total number of the available sub-channels
$\overline{n}$	the number of non-real time traffic classes

The proposed algorithm has the following steps:

- serving priority calculation;
- best sub-channel search; and
- Modulation and coding scheme selection.

Stage 1: Priority Calculation

In the first step, the priority function is calculated in order to sort the traffic queue based on the QoS of the class it belongs to and the type of traffic whether it is real-time or non-real time. The priority of user i requesting traffic class j is expressed as follows:

$$P(i, j) = c_j \exp[\alpha_j \frac{w_{ij}(t) - T_j}{T_j} - \beta_j \frac{\overline{b}_{ij}}{R_j L}] \tag{21}$$

Where c_j is the adaptive service coefficient, α_j and β_j are weights for balancing the impacts of the delay and throughput of the traffic class j ($\alpha_j + \beta_j$=1), T_j and R_j are respectively the maximum packet delay bound and the target bit rate of traffic class j, L is the time slot length, w_{ij} (t) is the waiting time user i with traffic class j has incurred since its arrival until being served at time t, $\overline{b}_{ij}$ is the target number of bits to be transmitted by user i for traffic class j. The priority function in Eq.(21) has a similar structure to that used in [34] with the following distinctions identifying our contributions:

c1 In [34], the priority function is proportional to the deviation of the achievable rate from the target bit rate. This criterion then requires ongoing calculation throughout the scheduling period and more importantly does not account for the actual data payload requirements. In this paper, the priority function is modified to be inversely proportional to the number of time slots needed, i.e., more weight is giving to short payloads in an attempt to accommodate as many users as possible so long as the rate and waiting time targets are still fulfilled. From another perspective, given the opportunistic access of the SUs and the stochastic activity of the PUs, the less time a channel can be utilized, the more likely the transmission succeeds. The average number of time slots is calculated as $\frac{\overline{b}_{ij}}{R_j L}$ as per the priority function in Eq. (21)

c2 As in [34], the coefficient c_j is introduced to assure special consideration of the real-time traffic. While c_j in [34] takes on two values only, we rather make it inversely proportional to the ratio between the total number of free channels and the number of non real-time classes, i.e.,

$$c_j = \begin{cases} 1 + e^{-N/\overline{n}} & j \text{ is real - time} \\ 1 & j \text{ is non - real time} \end{cases} \tag{22}$$

where $\overline{n}$ is the number of non-real time traffic classes (MPEG and FTP).

Stage 2: Channel Selection

The second stage now is to find the best sub-channels that have the best channel conditions for the top priority traffic queue q(i,j). The channel transfer function of the unknown data symbols are then determined by interpolation. The number of pilots, placement and the type of interpolation will greatly influence the quality of the channel estimation.

The LS (Least Square) estimator is a suitable and efficient technique for a broadband wireless system. The fading channel can be considered as a 2D lattice in the time-frequency plane. It is shown that the estimator of H for LS is given by [36, 37]:

$$\hat{H}_{LS} = \frac{Y(k)}{X(k)} = H(k) + \frac{W(k)}{X(k)} \tag{23}$$

Where- Y(k)- received OFDM signal.

X(k)- transmitted OFDM signal.

W(k)- noise(AWGN).

According to [38] the pilots inserted whether along the frequency or time should follow the Nyquist rate. The channel is estimated only at the pilot positions in the frequency-time grid. The channel at the data positions are then determined using interpolation algorithms which will be discussed later. Another channel estimator technique is the LMMSE (Linear Minimum Mean Square Error). The LMMSE is a widely used channel estimator technique for OFDM as it optimum in minimizing the MSE of the channel estimates in the presence of AWGN. The LMMSE uses additional information of the channel like the SNR and other statistically data which makes it more complex. The LMMSE also uses the correlation between subcarriers [38].

$$\hat{H}_{LMMSE} = R_{H_p H_p}\left(R_{H_p H_p} + \frac{\beta}{SNR}\right)^{-1} \hat{H}_{LS} \tag{24}$$

$$\beta = E\left\{|X(k)|^2\right\} E\left\{1/|X(k)|^2\right\}$$

Where:

RHpRHp - Autocorrelation between pilot subcarriers.

As seen from the previous equation that the LMMSE estimator uses the estimation obtained from the LS estimator for determining the channel estimation at different pilot locations.

Three different types of interpolation techniques [39] were used. The constant coefficient, where the channel response of the pilot remains the same for all data after the pilot until another estimation is determined. The 2D-Averaging algorithm averages the estimated channel for pilot subcarriers and uses it for the data in between. This algorithm is mainly suitable for slow fading channels. The 2D-Linear Interpolator, which is widely used, does 1D-interpolation across the samples in the horizontal and vertical direction (i.e. time & frequency) in order to estimate the channel for the data symbols. This is more or like fitting straight lines between samples.

Stage 3: Modulation and Coding Selection

Based on the knowledge of the received SNR range, the corresponding modulation and coding rate can be determined yielding the number of achievable bits on the corresponding sub-channel (selected in stage 2). Table 5 lists the received SNR ranges along with the corresponding achievable number of bits b_{in}.

Table 5: Modulation and Coding Scheme [8]

Received SNR range (dB)	Modulation	Coding rate	b_{in}
<10	QPSK	1/2	45
10~15	QPSK	3/4	68
15~17	16-QAM	1/2	90
17~20	16-QAM	3/4	135
20~23.5	64-QAM	2/3	180
>23.5	64-QAM	3/4	203

Our 3[rd] contribution is the execution of stages 2 and 3 jointly while accounting for the variations in channels availability. In particular, our criterion for channels selection/ordering is based on both channels quality and availability. Namely, based on the received SNR (a measure of the channel quality), we get the corresponding b_{in} (as in Table 5) and then order the currently available channels for each user based on the effective number of bits the channel can support, expressed as $b_{in}\, P_n^{(f)}$ where $P_n^{(f)}$ denotes the probability of channel n being free. If $b_{in}^{(j)}$ denotes the number of achievable bits by user i with traffic class j using sub-channel n, we should select the best channels that can achieve the target number of bits ($\overline{b}_{ij}$) using

$$\overline{b}_{ij} = \sum_{n=1}^{N} b_{in}^{(j)} P_n^{(f)} \tag{25}$$

Pseudo Code

Input: $\alpha_j, \beta_j, T_j, R_j, b_{ij}, L, P_n^{(f)}$

Initialization:

- Users' SNR generation (across a circular area given path losses and fading effects)
- Initiate the arrival processes
- $r(n)=M$
- Calculate c_j as per Eq. (4)

Scheduling:

1. For each i (user index) and j (service index)
   - compute the waiting time
   - compute the priority as per Eq. (21)
2. Given the top priority:
   - given the SNR, find b_{in} (Table 5)
   - rank channels available based on $b_{in} P_n^{(f)}$
3. serve the lower priority classes given available resources

End

VI. Numerical Results

The performance of the proposed algorithm is investigated in this section. The simulation parameters of the WRAN system specified in IEEE802.22 are shown in table 6:

Table 6: Parameters of the WRAN system specified in IEEE802.22 [35]

Parameter	Value
Cell radius	33km
Transmitting antenna highest of BS	100m
Receiving antenna height of users	10m
EIRP of BS	100w
Bandwidth of sub-channel	0.214MHz
Number of sub-channel	64
Length of a scheduling period	20ms
Length of a slot	0.317ms

The channel model used in the simulation consists of three models: large-scale path loss model, the shadow fading model and the multipath fading model. [35, 36]

The traffic model consists of three types: VoIP, MPEG and FTP. The traffic models parameters are given in the following table 7:

Table 7: Simulation parameters of the simulation

Traffic model	VoIP	MPEG	FTP
Simulation model	IDP	2IRP	4IPP
Distribution of the ON/OFF duration time	Exponential	Pareto	Exponential
Distribution of the interval between two packets	Constant	Exponential	Exponential
Packets rate (packets/s)	17.6	126.3	6.5
Packet size (bits)	528	1504	1536
Bit rate (kbps)	9.3	190	10

The algorithm parameters α_j and β_j (the weights for balancing the impacts of delay and throughput priority of traffic class *j*) are listed in the following table 8:

Table 8: Algorithm parameters

Parameters	VoIP	MPEG	FTP
α_j	0.5	0.9	0.7
β_j	0.5	0.1	0.3

Fig. 7 shows the estimation techniques used in our algorithm and the minimum square error value as a function of SNR [20]. As shown in the figure, as the channel conditions changes the algorithm will alter the type of estimator and interpolator used.

Figure 7a: Rayleigh channel (4 paths), AWGN, Doppler frequency= 50Hz,

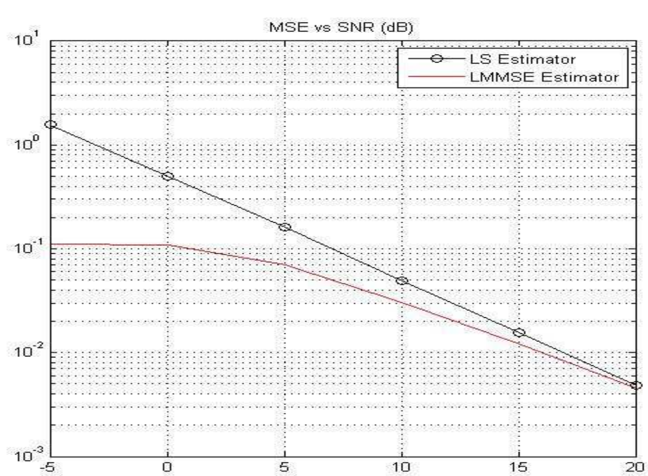


Figure 7b: Rayleigh channel (4 paths), AWGN, Doppler frequency= 50Hz, interpolation= 3,3

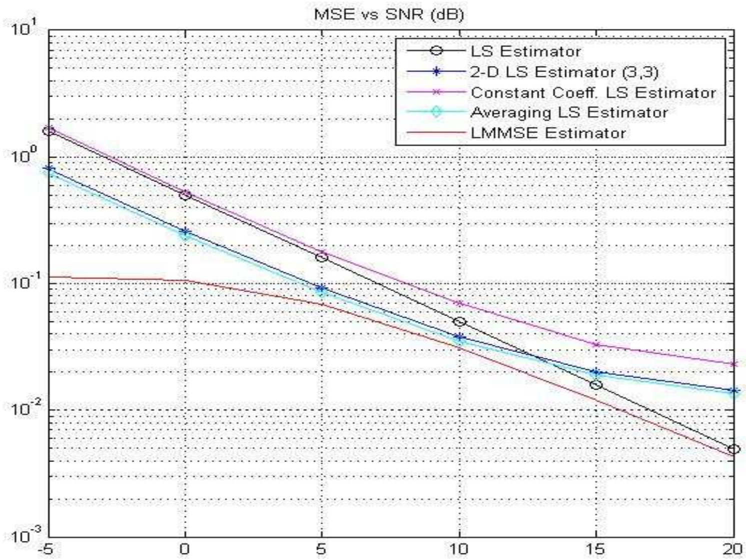
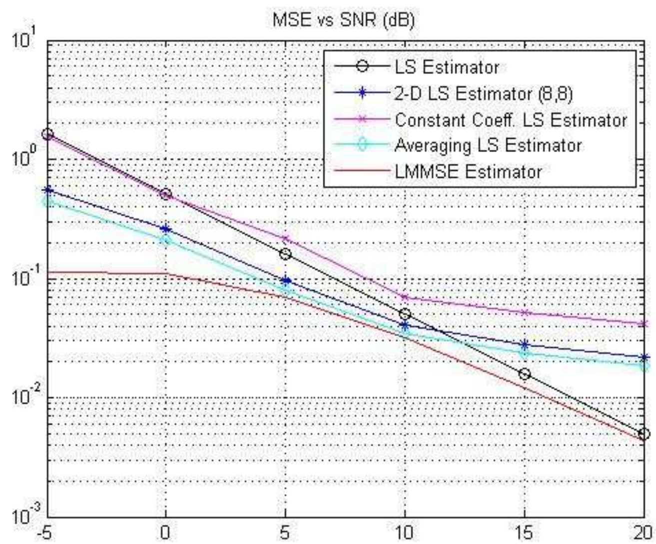


Figure 7c: Rayleigh channel (4 paths), AWGN, Doppler frequency= 50Hz, interpolation 8,8



We evaluate the performance of the proposed algorithm by comparison with the adaptive packet scheduling algorithm in [34]. The simulation results for K=100 users are given to illustrate the performance of the different algorithms.

We use APS-F-ref to denote the reference Adaptive Packet Scheduling Algorithm in [83] which the priority is based on frequency unit allocation. As for APS-T-ref it denotes the reference Adaptive Packet Scheduling Algorithm in [34], but is based on time unit allocation while APS-F-prop is used to denote our proposed algorithm which the priority is based on frequency unit allocation and APS-T-prop denotes the proposed algorithm based on time unit allocation.

Fig. 8 compares the throughput of our proposed algorithm (APS-F-prop) to that of the reference one (APS-F-ref). As shown, our proposed scheme yields a relative gain of almost 20% as the number of users increase. This is mainly due to the priority nature of our proposed algorithm where the priority function is inversely proportional to the number of time slots needed, yielding more weight to short payloads in an attempt to accommodate as many users as possible so long as the rate and waiting time targets are still fulfilled.

Figure 8: Throughput comparison between APS-F-ref and APS-F-prop

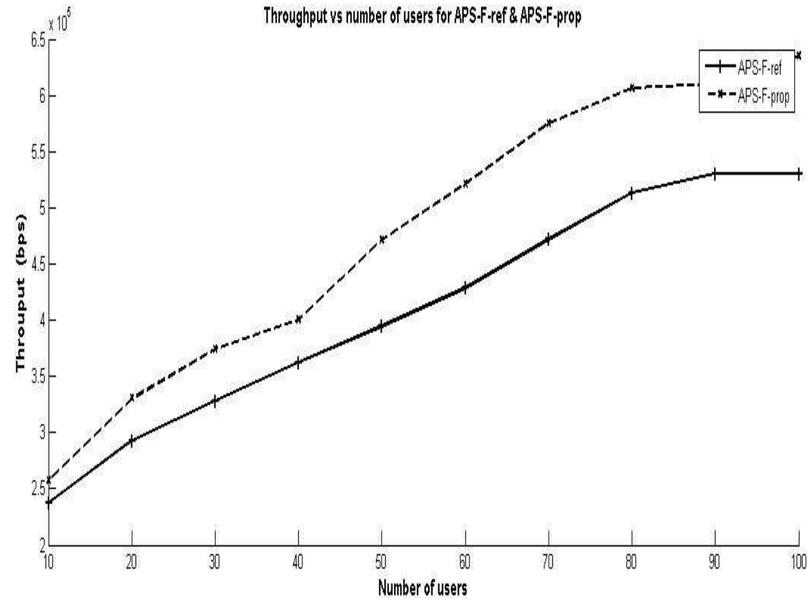


Fig. 9 compares the throughput of our proposed algorithm (APS-T-prop) to that of the reference one (APS-T-ref). As shown, our proposed scheme yields a relative gain of almost 10% as shown in Fig. 9. The figure also shows that throughput is not proportionally increasing with allocated time slots to users, on the contrary, it is to a great extend almost constant due to the limitation on the maximum number of time slots that can be assigned to users.

Figure 9: Throughput comparisons between APS-T-ref and APS-T-prop

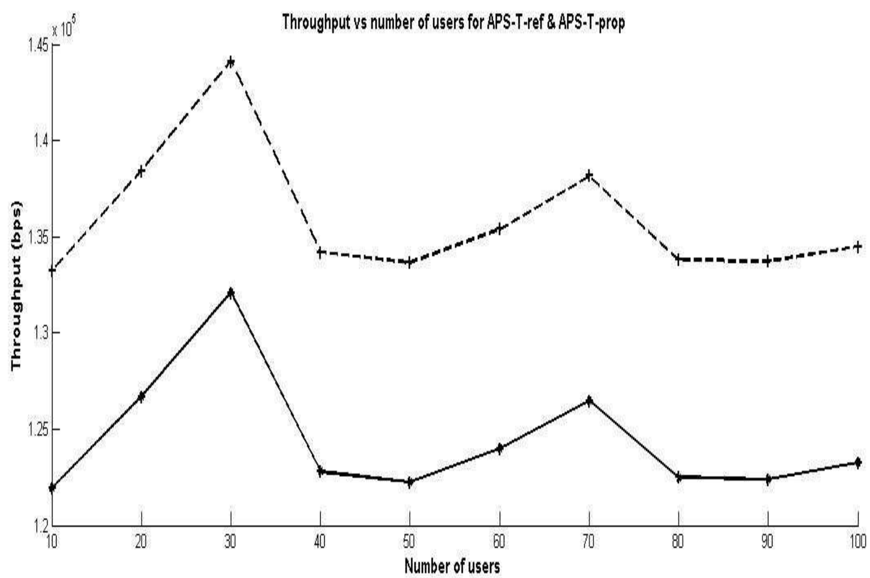


Fig.10 compares the two proposed algorithms s throughput versus number of users. Relative gain is nearly same with few numbers of users but as the number of users increases the APS-F-ref shows superior advantage over APS-T-ref.

Fig. 11 and 12 shows the average waiting time versus number of users for APS-F and APS-T from point of view of our algorithm and reference model. Fig.11 and 12 shows that there is no difference in the average waiting time in APS-prop and APS-ref.

Figure 10: Gain relative for APS-F-prop and APS-T-prop

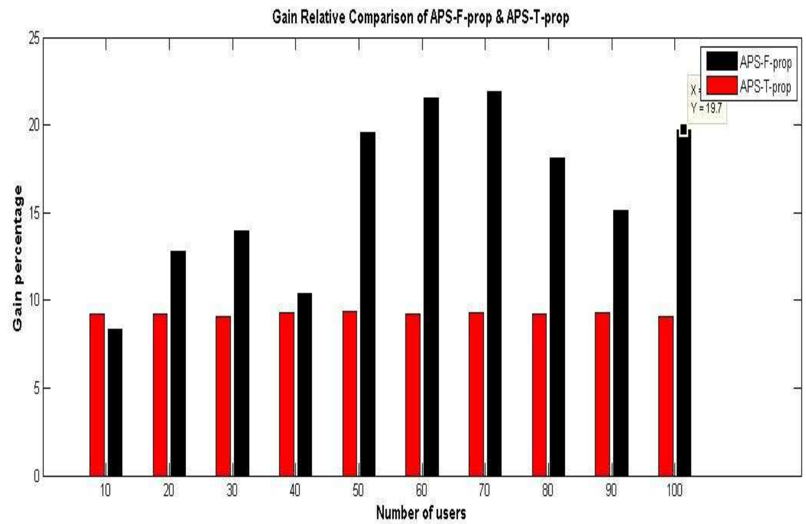


Figure 11: Waiting time comparison between APS-T-ref and APS-T-prop

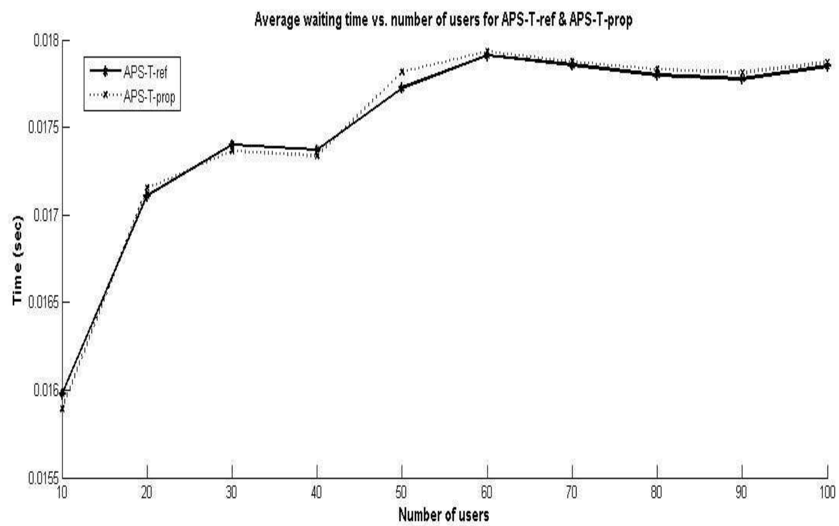
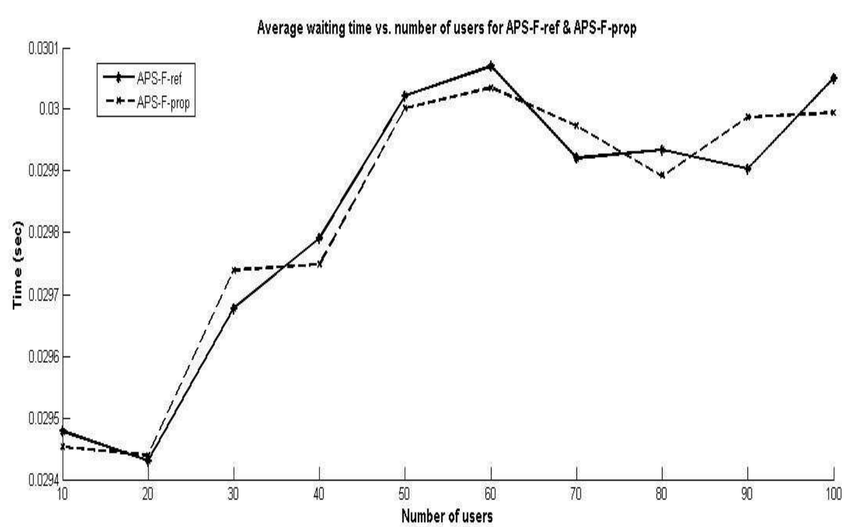


Figure 12: Waiting time comparison between APS-F-ref and APS-F-prop



VII. Conclusion and Future Work

In this research, a priority based scheduling is developed with the aim to achieve a better performance tradeoff in terms of throughput and waiting time and achieving flexible and fair scheduling for traffic in the cognitive radio network. In the scheduling algorithm, a priority function is introduced in order to sort the traffic queue based the QoS of the class it belongs to and type of traffic whether it real-time or non-real time. This scheduling scheme also addresses the unfairness problem faced by other scheduling scheme by giving more weight to short payload in order to accommodate as many users as possible so long as the rate and waiting time targets are still fulfilled From another perspective, given the opportunistic access of the SUs and the stochastic activity of the PUs, the less time a channel can be utilized, the more likely the transmission succeeds. The performance of proposed algorithm exhibits higher relative throughput gain compared to existing schemes while maintaining the same waiting time values.

Since the cognitive radio network is a very dynamic environment, design and performance evaluation of the spectrum allocation and power adaptation algorithms, which are capable of learning dynamically, is of prime importance. In future, the objective is to extend our approach to the dynamic spectrum allocation problem and to design algorithms that are capable of learning and evolving. Another goal of future research will be to develop efficient auction mechanisms which are useful when there is a central server distributing the resources without sharing the information of users amongst each other. Typically in such scenario users bid to obtain the resources with respect to their physical constraints and utilization limits. An important goal of development of such algorithms is not only maintaining fairness but also maximizing overall system throughput. There are many issues that should be further investigated in scheduling for cognitive radio networks. The research work in this paper 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 is important and poses 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.

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