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Scheduling Approach for Reducing Waiting Time in Dynamic Spectrum Allocation in Cognitive Radio Networks

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***Abstract*:** We propose a novel algorithm to reduce average waiting time of secondary user in modeling the dynamic channel allocation problem in cognitive radio networks by applying game theory blended with pricing theory with an effect of past behavior of the channel. Moreover in the proposed work, we define a unique model to stumble on a channel to by Secondary User to minimize the switching of secondary user. The Secondary Users can be considered as selfish users competing with each other for spectrum. These selfish users will try to get more access to the spectrum and achieve higher profits. We propose a scheme to prohibit such users from accessing more bandwidth. Moreover, since the usage of a channel may vary in various time bands, so we allocate a channel to a secondary user based on the utilization history of the channel. In the paper we also propose the scheme to minimize their power requirements.

***Keywords*:** Primary User (PU), Secondary User (SU), xG User, Usage Matrix, xG Network, Game Theory, Signal to Interference-plus-Noise Ratio (SINR)

I. INTRODUCTION

Wireless networks are regulated by a fixed spectrum assignment policy, i.e. the spectrum is regulated by governmental agencies and is assigned to license holders or services on a long term basis for large geographical regions. In addition, a large portion of the assigned spectrum is used sporadically as illustrated in the Figure 1, where the signal strength distribution over a large portion of the wireless spectrum is shown.

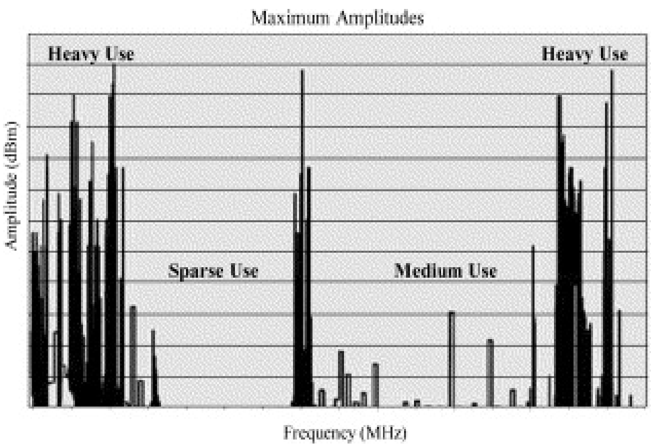

Figure 1: Signal strength distribution wireless spectrum

The spectrum usage is concentrated on certain portions of the spectrum while a significant amount of the spectrum remains unutilized. According to Federal Communications Commission (FCC) [20], temporal and geographical variations in the utilization of the assigned spectrum range from 15% to 85%. Although the fixed spectrum assignment policy generally served well in the past, there is a dramatic increase in the access to the limited spectrum for mobile services in the recent years. This increase is straining the effectiveness of the traditional spectrum policies.

Frequency spectrum is the scarcest resource for wireless communications and may become congested to accommodate diverse types of air interfaces in next-generation wireless networks. The limited available spectrum and the inefficiency in the spectrum usage necessitate a new communication paradigm to exploit the existing wireless spectrum opportunistically. Dynamic spectrum access is proposed to solve these current spectrum inefficiency problems.

Cognitive Radio (CR) is relatively a new technology, which wisely finds a particular segment of the radio spectrum currently in use and chooses unused spectrum quickly without interfering with the transmission of authorized users. Cognitive Radios can find out about current use of spectrum in their operating region, make intelligent decisions, and react to immediate changes in the use of spectrum by other authorized users. The goal of CR technology is to mitigate radio spectrum overcrowding, which actually translates to a lack of access to full radio spectrum utilization. Due to this adaptive behavior, the CR can easily preclude the interference of signals in a crowded radio frequency spectrum. Cognitive radio has emerged as a new design paradigm for next-generation wireless networks that aims to increase utilization of the scarce radio spectrum (both licensed and unlicensed). Learning and adaptation are two significant features of a cognitive radio transceiver.

The network dedicated specially to xG users is called xG or secondary network. The main role for cognitive radios in cognitive networks can be summarized as follows:

A. Spectrum Sensing –

Identifying unused spectrum and sharing the spectrum without destructive interference with other users

B. Spectrum Management –

Capturing the best available spectrum to greet user communication needs;

C. Spectrum Mobility –

Maintaining seamless communication requirements during the switch to better spectrum;

D. Spectrum Sharing –

Providing the fair spectrum scheduling method among contemporaneous cognitive users.

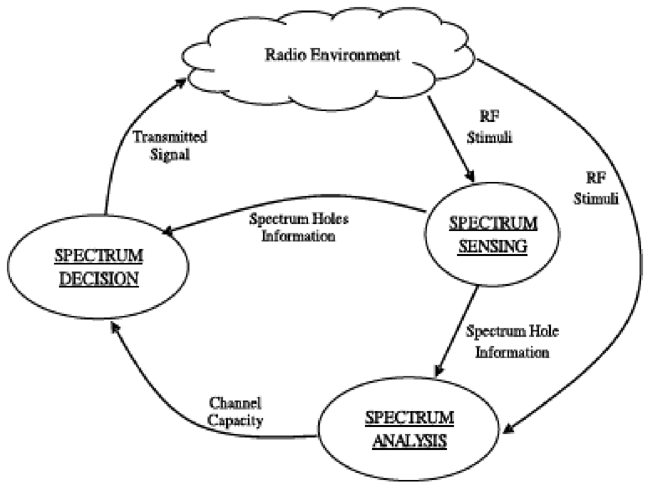

Figure 2: Schematic diagram for cognitive radio process

Section II contains various approaches being used for dynamic channel selection in cognitive radio. Section III contains a brief description of the game theory and justifies the use of game theory in the cognitive radio dilemma. Section IV contains a brief description of the work done in the related field using game theory. Section IV describes the proposed model. Concluding remarks are provided in Section V.

II. APPROACHES FOR DYNAMIC CHANNEL SELECTION

Different techniques and methods are required in a cognitive radio transceiver to realize the processes of dynamic channel selection.

A. Estimation Technique —

Parameter estimation is important for the observation process in a cognitive radio transceiver to obtain information about the ambient network environment. Sophisticated sensing mechanisms are generally required to obtain multiple parameters
(e.g., channel state, traffic load, neighborhood information) simultaneously.

B. Game Theory —

Game theory is a mathematical tool developed to understand competitive situations in which rational decision makers interact to achieve their objectives. The basic concept of game theory is the rationality with which the players of the game will choose their actions based on their interests. The solution of the game is given by the actions through which all the players are satisfied with their received payoffs (i.e., returns). In [19] a game-theoretic adaptive channel allocation scheme was proposed for cognitive radio networks. In particular, a game was formulated to capture the selfish and cooperative behaviors of players.

C. Evolutionary Computation —

Evolutionary computation is a problem solving method based on evolution of biological life in the real world. This could be achieved by simulating evolution behavior of individual structures, which includes the selection and the reproduction processes. The most common technique in evolutionary computation is the genetic algorithm. and it has been applied to cognitive radio [20].

D. Fuzzy Logic —

Fuzzy logic provides a simple way to obtain the solution to a problem based on imprecise, noisy, and incomplete input information. Instead of using complicated mathematical formulation, fuzzy logic uses a human-understandable fuzzy set of membership functions and inference rules to obtain the solution that satisfies the desired objectives. To capture dynamic system behavior, fuzzy logic rules and membership functions need to be adaptive to the changing environment so that the desired solution can be achieved. Fuzzy logic is combined with a learning algorithm (i.e., neuro-fuzzy) that is able to adapt to the changing environment of a cognitive radio system.

E. Markov Decision Process —

Decision theory is required for cognitive radio to choose the best action intelligently in response to environmental stimuli. A partially observable Markov decision process (POMDP) was used for dynamic spectrum access in an ad hoc network [21].

F. Pricing Theory —

The pricing mechanism impacts resource allocation in wireless networks since service providers want to maximize revenue and users want to minimize cost for the target quality of service (QoS) performance. Pricing theory can be used for resource management in cognitive radio systems. In [22] a dynamic pricing, resource allocation, and billing method was proposed for cognitive radio users with multiple wireless interfaces. In this system pricing and allocation of radio resources were performed based on an auction mechanism. The system learns the users' bidding strategies by a Bayes optimal classifier, and a multi-unit sealed bid auction is performed to obtain the optimal decision for the service providers and users.

G. Reinforcement Learning —

A reinforcement learning algorithm learns by interacting with the environment. In [23] a reinforcement learning algorithm, Q-learning, was used for dynamic channel assignment in cellular networks. While the amount of traffic in each cell varies, the proposed algorithm learns and adapts the number of channels assigned to each cell so that the call blocking probability can be minimized.

III. GAME THEORY AND COGNITIVE RADIO

Game theory is a natural modeling technique for cognitive radios. A *game* is a model of an *interactive decision process*. An interactive decision process is a process whose outcome is a function of the inputs from several different decision makers who may have potentially conflicting objectives with regard to the outcome of the process. *Game theory* is a collection of models (*games*) and analytic tools used to study interactive decision processes. Every game includes the following components:

A set of *players; Actions* for each of the players; Some method for determining *outcomes* according to the actions chosen by the players; *Preferences* for each of the players defined over all the possible outcomes; *Rules* specific to the model, e.g., the order of play.

In our research work, the basic framework considered is that an operating spectrum is divided into sub-bands or channels. These channels, when not in use by the PUs, are allocated to SUs for enhanced spectrum efficiency. We contribute the following unique features in the spectrum sharing:

Classify the quality of a channel into five different types, depending upon the occupancy of its neighboring channels.

Develop a multi-objective function optimization problem leading to a Game theoretic perspective among cooperative *N* cognitive users in order to allocate channels to these users.

Define idle durations and transmission rate for each channel during which the SUs are permitted to transmit, and develop a game theoretic strategy to allocate single channel to each user, while taking the transmission rate and idle durations into account in defining the reward functions.

In addition, we have considered parameters such as idle duration and transmission time in the context of spectrum sharing. The simple idea behind this approach is that each channel supports its own data transmission rates based on perceived channel conditions and multipath characteristics. During a specific time instant if the idle duration of a particular channel is less than the total transmission time required by the SU, then the channel is not allocated to this particular SU. We show that the spectrum allocation method that does not consider such aspects may lead to inefficient spectrum utilization.

Our proposed spectrum sharing model consists of *M* PUs denoted by *PU*1, *PU*2, …. , *PUM* located in specific channels represented as *Ch*1, *Ch*2, … , *ChM*. Each channel is licensed to a single PU, as is the case of television band where the television transmitters are further away from each other to avoid interference. There are *N* SUs denoted as *SU*1; *SU*2; …., *SUN*. The objective of our spectrum sharing approach is to allocate multiple available channels to an *SUi* based on two factors:

a. The number of packets *SUi* need to transmit
b. The transmission rate of each *Chi*.

Game □□ Cognitive radio network; Player □Cognitive radio; Actions □□ Actions; Utility function □Goal Outcome space □□ Outside world; Utility function arguments □□ Observations/orientation; Order of play □Adaptation timings.

In game theory parlance, a player acting in its own interest (or acting in a way it believes increases its payoff) – no matter how difficult the calculation or fine the distinction in payoffs – is said to be *rational*. We also assume that the radios are acting *autonomously*. With autonomous rationality, we say that a player or its decision rule is autonomously rational.

Depending on the system we are modeling it may be appropriate to assume different device capabilities such as knowledge of the other radios' goals or actions perfect observations and long memories of past behavior. Going from the cognition cycle to a game, every node in a network that implements the decision step of the cognition cycle is a player (making it a decision maker in the interactive decision process). Each radio's available adaptations form the associated player's action set, and the Cartesian product of the radios' adaptations form the action space. The cognitive radio's goal supplies a player's utility function, and the outputs of the cognitive radio's observation and orientation steps are the arguments and valuation for this utility function. Loosely, the observation step provides the player with the arguments to evaluate the utility function, and the orientation step determines the valuation of the utility function.

Based on their knowledge of the game – past actions, future expectations, and current observations – players choose *strategies* – a choice of actions at each stage. These strategies can be fixed, contingent on the strategies of other players, or adaptive to the actions observed in each stage. We denote player *i*'s strategy by the symbol d_i indicating that the strategy of player *i* determines its action in each stage of the repeated game. However, d_i is not only reactive to the current state of the game but it should also consider past states and future expectations.

When players consider future expectations, the players employ utility functions that incorporate the payoff of the most recent stage and a time-discounted expectation of utility received from all future stages. As estimations of future values of u_i may be uncertain, many repeated games modify the original objective functions by discounting the expected payoffs in future stages by the discounting factor δ, where δ ε (0,1] such that the anticipated value in stage *k* to player *i* is given by equation (1) where a_k denotes the action vector played in stage *k*. Note that if δ = 1, then all future payoffs are given equal weight with the present payoff.

(Discounted payoff in stage k)

$$u_i(a^k) = \delta^k u_i(a^k) \quad \ldots(1)$$

Assuming all players' choices of strategies result in the sequence of action vectors (a^k), a player, *i*, that considers future expectations for an infinite horizon would value this sequence as shown in equation 2.

$$u_i(a^k) = \sum_{k=0}^{\infty} \delta^k u_i(a^k) \quad \ldots(2)$$

With players considering their future payoffs, it becomes possible for players to employ strategies designed to punish players in subsequent stages after they deviated from agreed upon behavior in prior stages. When punishment occurs, players choose their actions to reduce the payoff of the offending player.

In the interim between power level updates, each mobile has a probability of□□ of leaving the network and a new mobile enters the network with probability□ If a cognitive radio leaves the network or if a cognitive radio enters the network, the game terminates as the players in the model have changed. So after k iterations the probability that the network is the same as when it began is given by $(1-□)^k(1-□)^k$.

Suppose a network consists of n cognitive radios with each radio, i, free to determine the number of simultaneous frequency hopping channels the radio implements, c_i □[0,□). Guiding this decision, each radio is attempting to maximize the difference between a function of goodput and power consumption as given in equation (3)

$$u_i(c) = P(c)c_i - C_i(c_i) \qquad \ldots(3)$$

Where $P(c)$ is the fraction of symbols that are not interfered with (making $P(c)c_i$ the goodput for radio i) and $C_i(c_i)$ is radio i's cost for supporting c_i simultaneous channels. In general, P decreases as the total number of channels implemented increases and C_i increases with increasing c_i (more bandwidth implies more processing resources implies more power consumption). If we approximate these effects as linear functions, we can rewrite equation (3) as (4).

$$u_i(c) = \left(B - \sum_{k \in N} c_k\right) c_i - K\, c_i \qquad \ldots(4)$$

Where B is the total bandwidth that the waveforms are hopping over, K is the cost of implementing each channel, and N is the set of cognitive radios.

Figure 3 describes the cognition cycle. In the cognition cycle, a radio receives information about its operating environment (**Outside world**) through direct observation or through signaling. This information is then evaluated (**Orient**) to determine its importance. Based on this valuation, the radio determines its alternatives (**Plan**) and chooses an alternative (**Decide**) in a way that presumably would improve the valuation. Assuming a waveform change was deemed necessary, the radio then implements the alternative (**Act**) by adjusting its resources and performing the appropriate signaling. These changes are then reflected in the interference profile presented by the cognitive radio in the **Outside world**. As part of this process, the radio uses these observations and decisions to improve the operation of the radio (**Learn**), perhaps by creating new modeling states, generating new alternatives, or creating new valuations.

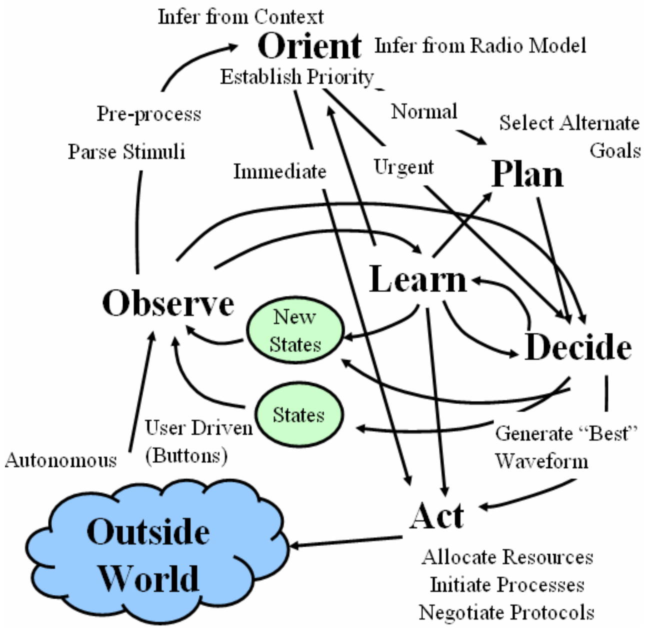

Figure 3 – The Cognitive Cycle

IV. RELATED WORK

Spectrum sensing is key for effective spectrum management as it enables SUs to detect PUs in the operating channels.

All the existing channel allocation algorithms concentrate on user request priorities or channel conditions, joint user requests and channel priorities can be predicted in formulating power efficient channel allocation to support Quality of Service *QoS* among SUs. Two main characteristics of the cognitive radio can be defined [4,5]: *Cognitive capability* - It refers to the capability of the radio technology to capture or perceive the information from its radio environment; *Reconfigurability* - It enables the radio to be dynamically programmed according to the radio environment.

In [6], spectrum decision rules are presented, which are focused on fairness and communication cost. However, the method assumes that all channels have comparable throughput capacity. In [8], an opportunistic frequency channel skipping protocol is proposed for the search of superior quality channel, where this channel decision is based on Signal to Noise Ratio (SNR). In order to consider the primary user activity, the number of spectrum handoff, which happens in a specific spectrum band, is used for spectrum decision [7].

In [9] [10], the authors investigated whether spectrum efficiency and fairness can be obtained by modeling the spectrum sharing as a repeated game. The authors in [11] proposed local bargaining to achieve distributed conflict-free spectrum assignment that adapted to network topology changes. In [12], a no-regret learning algorithm using the correlated equilibrium concept to coordinate the secondary spectrum access was considered. Various auction and pricing approaches were proposed for efficient spectrum allocation, such as auction games for interference management [13] [14], the demand responsive pricing framework [15], and pricing for bandwidth sharing between WiMAX networks and WiFi hotspots [16]. A belief assisted distributive double auction was proposed in [17] that maximized both primary and secondary users' revenues, and a game-theoretical overview for dynamic spectrum sharing was presented in [18]. Although the approaches listed above have boosted the spectrum efficiency, most of them are based on the assumption that the players (e.g., wireless users/devices) are honest and will not cheat. Nevertheless, selfish players aim only to maximize their own interests; if they believe their interests can be further increased by cheating, the users will no longer behave honestly, which usually results in a disastrous outcome for the spectrum sharing game. Therefore, designing a robust spectrum sharing scheme that can suppress cheating behaviors of selfish users is of critical importance.

V. THE PROPOSED MODEL

We propose a mechanism for design-based dynamic spectrum access approaches in two scenarios: spectrum sharing in unlicensed bands and licensed bands. Here is the difference:

The strategy space of secondary users in open spectrum (xG network) sharing may include the transmission parameters they want to adopt, such as the transmission powers, access rates, time duration, etc.; while in licensed spectrum trading, their strategy space includes which licensed bands they want to rent, and how much they would pay for leasing those licensed bands.

In open spectrum sharing, the utility function for the secondary users is often defined as a non-decreasing function of the Quality of Service (QoS) they receive by utilizing the unlicensed band; in licensed spectrum trading, the utility function for the users often represents the monetary gains (e.g., revenue minus cost) by leasing the licensed bands.

Let there are *nc* number of channels and same is the count of PU licensed to one individual channel; nt is the count of time slots; ns is the count of secondary users. Following matrices are maintained at each base station:

A. *pUsage Matrix α :*

It is a *nt x nc* matrix keeping track of count of usages by a PU of its licensed channel in various time slots.

B. *sUsage Matrix β:*

It is a *nt x ns* matrix keeping a record of count of requests by SU in various time slots.

C. *tRemaining Matrix ξ:*

It is a one dimensional matrix of size *nc*. We allocate a time burst of b unit time to a PU or SU. As soon as a channel is allocated to PU or SU, the entry is done for that channel of the burst time. This value is decreased by 1 after each unit time. A zero entry reflects that the channel is free.

D. *allocation Matrix ζ:*

It is a *nt x nc x ns* size matrix. *ζ[i,j,k]* represents the that SU_k is allocated channel *j* in the time slot *i*.

These can be summarized as shown in Figure 4.

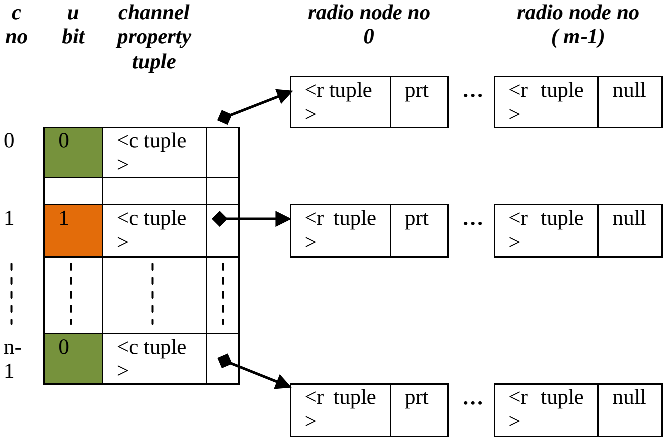

Figure 4 – The data structure to be maintained at each base station

a. c no – channel number
b. u bit – channel lock bit (0-free; 1- occupied)
c. channel tuple – for just pervious m allocations (using LRU scheme). It contains count of radios preempted, average utilization time span for PU, average utilization time span for SU, total utilization time, average bid price the PU is getting, average SINR
d. radio node tuple– each for one cognitive radio. It contains radio id *r*,SU / PU bit (in case of xG network it is invalid), duration of previous use t_p, to decide the punitive action, duration of total use t_u, to decide the punitive action, duration of total time in the range of the base station t_t, minimum offered bid price p_m, actual bid price p_a,the transmit power p_i,data rate *R*, the packet length *L*, the bandwidth of the transmitted signal *W*, the gain of the cognitive radio to the base station *g*, noise power at the base station *σ*.

The nodes of one radio are also connected in the form of a linked list. As soon as, a radio is out of the range of a base station, its entries are deleted from the database.

Cognitive radio networks can be characterized as asynchronous decision timings. In a power control game, radios adjust their power levels in an attempt to maximize some utility function, typically some function that balances SINR or throughput against power consumption or battery life. A cognitive radio will try to maximize its utility function given in equation (5).

$$u_i = \frac{R}{p_i}(1-e^{-0.5\gamma_i})^L \qquad \ldots(5)$$

Where p_i is the average transmit power of i^{th} radio. In this expression, throughput is a function of the data rate, *R*, the packet length, *L*, and the received SINR of player *i's* signal, γ_i, where γ_i is calculated as shown in equation (6).

$$\gamma_i = \frac{W}{R}\frac{g_i\, p_i}{\sum_{k\in N} g_k\, p_k + \sigma} \qquad \ldots(6)$$

where, *W* is the bandwidth of the transmitted signal, g_k is the gain of the k^{th} cognitive radio to the base station, p_k is the average transmit power of radio *k* and σ is the noise power at the base station.

The matrix *ξ* is used for deciding the allocation to reduce the power requirement. In practice, some free channels are preferred over others for an SU. For example, a free band in between two bands with PUs is less preferred than a free band with adjacent unused bands. The possible option s are given in Figure 5. Each SU has a spectral mask on the maximum transmission power admissible in each channel. Therefore, this results in a low signal-to noise-ratio (SNR). This compels us to delve into the different configurations of the free bands with adjacent PUs while focusing on a specific free channel, *Chi*. The channels are assumed to be orthogonal to each other. This assumption enables us to consider that adjacent channels do not interfere.

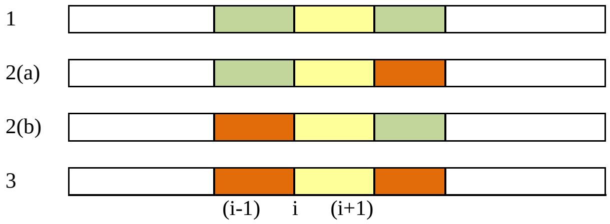

Figure 5 – Possible option of a free channel

The channel i is free and is under consideration for allocation to SU. There are two adjacent channels (i-1) and (i+1). We consider three various configurations:

a. Both adjacent channels are free.
b. and (b) only one of the adjacent channels is free.
c. Both adjacent channels are occupied.

Hence, the priority of the allocation will be case 1> case 2 > case 3. To incorporate this aspect, we modify the equation (5) as below:

$$u_i = \frac{R}{s * p_i} (1\text{-}e^{-0.5\gamma i})^L \qquad \ldots(7)$$

Where s is a factor decided as below:

s = 1; when both adjacent channels are fre

= 2; when any one of the adjacent channels is free and another is occupied

= 3; when both adjacent channels are occupied

The usage of time slice by an SU is obtained from *sUsage matrix β*. One SU is allocated one time slice *t* at one time. If a SU occupies more time slices in continuation, it will be susceptible for punitive action, in the sense that if there are *n* SU's competing *m* numbers of channels, then in the next time slice:

a. if n>m, then the SU's has to wait in the queue
b. if n=m, then the SU will get low quality channel

Graphs representing this scenario are shown in Figure 6 and 7.

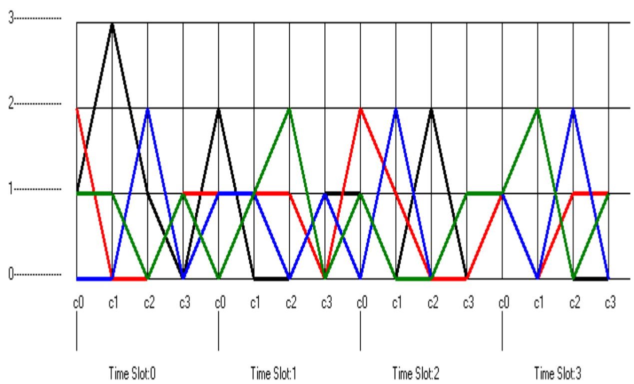

Figure 6 - Graph for channel allocation for secondary user

With an idea of including pricing theory, let η is the pricing factor, defined as:

η = price offered by SU / price demanded by PU

We incorporate a factor η in the equation (7) and modifying it to equation (8).

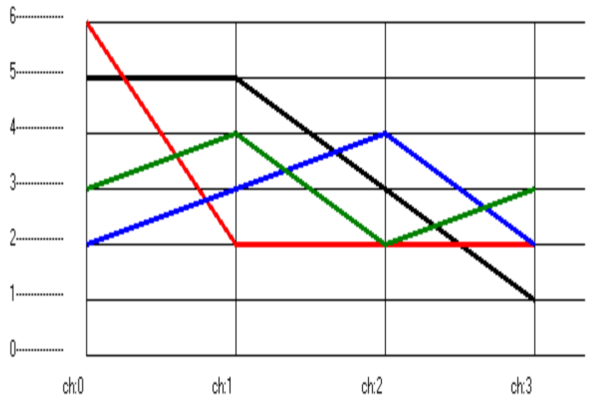

Figure 7 - Graph for total channel allocation

$$u_i = \frac{\eta * R}{s * p_i} (1\text{-}e^{-0.5\gamma i})^L \qquad \ldots(8)$$

For a normal scenario, η = 1; but is the SU is ready to pay more for the sake of quality, then η >1.

Graphs representing this scenario are shown in Figure 8 and 9.

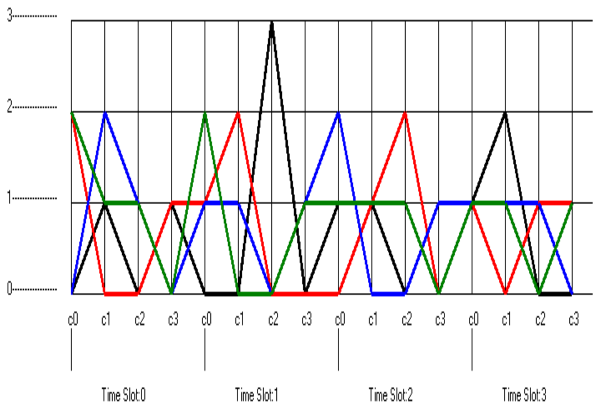

Figure 8 - Graph for channel allocation for secondary user

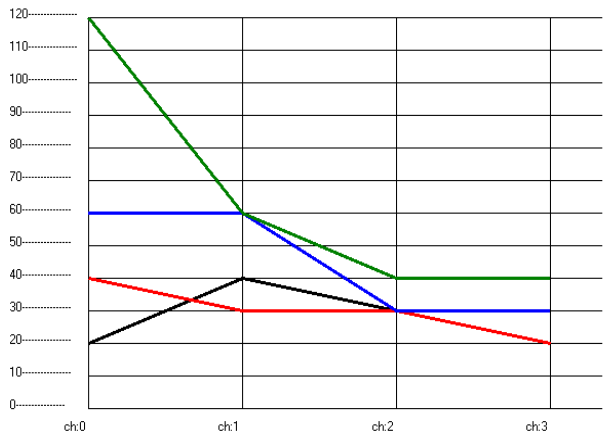

Figure 9 - Graph for total channel allocation

There is a clear improvement in switching between the channels.

In a repeated game, the overall payoff is represented as a normalized discounted summation of the payoff at each stage game.

$$U_i = (1-\delta)\sum_{n=0}^{+\infty}\delta^{n} u_i[n] \qquad \ldots(9)$$

where $u_i[n]$ is user i's payoff at the n-th stage, $\delta(0<\delta<1)$ is the discount factor which indicates that a user values the current stage payoff more than the payoffs in future stages, and $(1-\delta)$ can be viewed as a normalization factor. As $u_i[n]$ is assumed to be a finite value, U_i is well-defined in the repeated game. If δ is close to 1, we say that the user is patient; if δ is close to 0, we say that the user is myopic. In general, the spectrum sharing in unlicensed bands lasts for a long time, and we can assume that δ is close to 1. Because the users care about not only the current payoff but also the rewards in the future, they have to constrain their behavior in the present to keep a good credit history; otherwise, a bad reputation may cost even more in the future.

VI. CONCLUSION AND FUTURE WORK

We have proposed a novel algorithm to model the dynamic channel allocation problem in cognitive radio networks. In this paper, we investigated a game-theoretical mechanism design methods for channel selection by incorporating the usage history simultaneously trying to minimize the transmit power requirement. The proposed work is unique as no other approach takes into consideration the priorities for both the SUs as well as the channels in the operating spectrum along with the past usage data and power requirement. As the future work we are trying to integrate the cost demanded by the PU of the channels.

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