A Congestion-Game Based Scheme for Handoff Management in Cognitive Radio Networks

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Abstract—**This paper presents a congestion based game scheme for reactive handoff management in cognitive radio networks. In these networks, Secondary users as the rational decision makers aim to maximize their utility, considering the status of primary channels and the contention regions for each channel. We formulate a multi-objective optimization problem in which the proposed cost function for secondary users considers the quality, price and handoff cost of the selected channel. This type of pricing scheme not only manages the cost, but also avoids the secondary users from all selecting the same set of channels; hence reduces the congestion in high quality channels. The target channel for handoff is selected according to the spatial contention between secondary users. This target channel has the minimum cost in terms of congestion level, financial cost and switching probability. Simulation results are provided to evaluate the performance of the proposed method in two scenarios. The first scenario ignores the pricing method while the second consider the price of each channel in its decision making process These two proposed scenarios have been compared with a recent scheme.**

I. Introduction

Due to insufficient spectrum availability that enforced by regulatory bodies, optimal utilization of the spectrum has known as an important issue in the last decade. The solution for the spectrum scarcity problem uses Dynamic Spectrum Allocation (DSA) instead of Static Spectrum Allocation (SSA) schemes. Cognitive Radio Networks (CRNs) are developed for providing a framework for this purpose. Two types of users have been defined in the hierarchical model of CRNs: Primary Users (PUs) and Secondary Users (SUs). PUs or licensed users have permission to arbitrarily access to their corresponding channels while SUs or unlicensed users can opportunistically exploit the idle channels or white spaces of spectrum [1]. SUs should not incur harmful interference for PUs. Cognitive radio also refers to a new technology that equipped radios with new capabilities like spectrum sensing, behavioral learning, and intelligent decision making. Using these capabilities, CRNs require four functionalities known as Spectrum Sensing, Spectrum Decision, Spectrum Sharing and Spectrum Mobility [1]. Spectrum mobility is a main challenge of CRNs which is less considered in recent literatures.

Due to the preemptive priority of PUs, SUs should vacate the channel as soon as a PU appears on the channel. In this situation, the SU should select a new target channel to resume its transmission. This procedure is called spectrum handoff [1]. As network topology and spectrum availability are changing dynamically, we should handle two main functionalities for spectrum mobility that consist of spectrum handoff and connection management [1]. Spectrum handoff provides monolithic communications in occurrences of link failure or quality degradation. Connection management is required for maintaining the Quality of Service (QoS) or minimizing the quality degradation during spectrum switching [1]. This paper focuses on spectrum handoff without considering connection management. There are two types of spectrum handoff mechanisms known as proactive-decision and reactive-decision spectrum handoff [2]. In the proactive-decision spectrum handoff mechanism, the target channel is determined by long term monitoring of traffic patterns, like PUs' arrival rate, prior to spectrum handoff is requested. In reactive-decision spectrum handoff mechanisms, the target channel is determined after the occurrence of spectrum handoff. Hence, the interrupted SU should explore the spectrum to find the best available channel as its target channel [2]. Both proactive and reactive schemes have their own advantages and disadvantages. Nevertheless, depending on the environment circumstances and capability of SUs we can prefer one against the other. The main disadvantage of proactive approaches is that the preselected target channel may no longer be available at the instant of switching while the main disadvantage of reactive approaches is the delay of sensing. As we assume a negligible period for sensing time, we focus on reactive schemes in this paper rather than proactive schemes.

The rest of this paper is organized as follows: Section II reviews the related works and includes the paper motivation. In section III, the problem statement, assumptions, system model, and notations have been presented. Some background materials on game theory are provided in section IV. The proposed approach using the regional congestion game theory is presented in section V. Simulation results are provided in section VI, followed by the conclusions in section VII.

II. Related Works and Paper Motivation

In [3] a CRN architecture based on spectrum pool is introduced and a spectrum pool structure is proposed to categorize handoff events. These categories are divided

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spectrum mobility management, user mobility management and inter-cell resource allocation. Also, a unified framework for mobility management is defined to support these events. In this paper, the spectrum mobility event is considered and the user mobility and inter-cell resource allocation events are neglected. The spectrum handoff problem in reactive approaches is discussed in [4]. However, the main body of literature on spectrum mobility models the handoff management from a proactive viewpoint.

The main challenge of reactive spectrum handoff meets its requirement for distributed coordination among SUs after switching for efficient exploitation of white spaces. This challenge can be addressed by game theory because it facilitates developing of distributed mechanisms for channel selection of SUs and mobility management strategies.

A game-based scheme for spectrum sharing in CRNs was presented in [5] where SUs are competing to share the unused bands. The user profit function is defined based on the achieved utility of allocated bandwidth minus the price, which should be paid by the user. We use this pricing idea in our channel selection method. A potential game for the channel selection problem was proposed in [6] in which SUs cooperate with each other. Although this game converges to a Nash Equilibrium (NE), however SUs ought to have a huge message passing, which makes it hardly scalable. Furthermore spectrum mobility management was not considered in [5-6].

A non-cooperative spectrum selection scheme was proposed in [7] to model interactions among SUs which consider the spectrum mobility problem with its system model. A channel switching game was proposed in [8] using a modified minority game where the players try to minimize their cost to find an idle channel. However the spectrum trading didn't consider in [6-8].

As a few works addressed the channel selection and handoff management problem from a reactive viewpoint, this paper has considered a reactive decision-spectrum handoff to evaluate unchallenged discussions of the reactive mode. Game theory is a bag of powerful analytical tools designed to address situations in which the outcome of a decision maker depends not only on its preferences, but also on the choices made by the other interacting decision makers. Hence it is an appropriate framework for modeling the interactions among SUs.

III. System model and Problem Statement

We consider a CRN with N SUs and M channels (M < N) in which each channel assigns to a specific PU. The network environment is a square with a width of D. The system is time slotted in which PUs exploit the channels for some stochastic duration of timeslots. We assume this environment dynamically changes in each timeslot in terms of PU's activities and SU's selected channels but the users are stationary.

The PU_i's traffic is modeled as a 2-state Markov chain, with parameters p_i and q_i which denote the transition probabilities as depicted in Fig. 1.

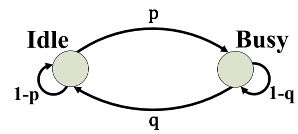

Figure 1. Traffic pattern of PUs

We assume that SUs have data to transmit in all timeslots and the sensing outcomes of SUs are perfect. We assume each user has a specified interference range. While a PU transmits on its own dedicated channel, SUs which are in the range of that PU are not allowed to use the channel. However, SUs located out of this range can use the channel simultaneously. In addition, multiple SUs who are in the range of each other can transmit on a same channel at a same time by the degradation of their QoS. This degradation is due to the increasing the number of interfering SUs. The neighboring concept is defined as follows.

Definition1: SU_i is a neighbor of SU_j if and only if it is located in the interference range of SU_j.

As mentioned above neighboring SUs can transmit on a same idle channel in a same time. This transmitting can be provided through a multiplexing technique like Time Division Multiplexing Access (TDMA). Assuming the same interference range, the neighboring relation is symmetric. This means if SU_i is the neighbor of SU_j, then SU_j is also the neighbor of SU_i.

The goal of this paper is to design a reactive distributed mechanism where each SU is able to select an idle channel considering the required constraints. The challenge is to control channel selection and switch decisions concurrently for SUs in order to minimize the total cost that experienced by all users. SUs should opportunistically access to vacant channels, with the firm constraint to perform handoff whenever the channel gets occupied by its PU. For this purpose, each SU should determine a vector of available channels in each timeslot; we define this vector as feasible channels. Each SU determine this vector through a reactive sensing independently.

Definition2: SU_i's feasible channels are the subset of channels which are available for SU_i, i.e., channels with an inactive or an active PU in which SU_i is out of primary interference range of this active PU.

For the rest of this paper, the term player or user specifically refers to a pair of SU's transmitter and receiver. It is possible that feasible channels and neighboring set are different for a transmitter and receiver of a pair of SU. Hence, in our system model we consider the feasible channels for a pair as the intersection of both transmitter and receiver's feasible channels. In addition, the neighboring SUs for a given pair are the union of both transmitter and receiver's neighbors.

IV. Backgrounds

We model our channel allocation problem as the congestion game first defined by Rosenthal [9]. There is an isomorphic correspondence between a congestion game and a potential game [10]. A definition of the Normal Congestion

Game (NCG) which is based on the congestion model introduced in [9], provide by [11]. For these games we have:

Theorem 1: Every congestion game is a potential game [10].

Theorem 2: Every finite potential game possesses pure-strategy equilibrium [10].

The standard definition of a congestion game is useful for situations in which there is a competition for a common resource. However, due to the spatial reuse capability of wireless nodes, we have a regional competition. Consider channels as resources where a random user, i^{th} player, only interferes with users which are located in its interference range. Hence, we use a new definition retrieved from [11] as follows:

Definition3: Congestion Game with Resource Reuse (CG-RR) or Spatial Congestion Game (SCG) defined by quintuplet $\Gamma = (\boldsymbol{\mathcal{N}}, \boldsymbol{\mathcal{M}}, (\Sigma_i)_{i\in\boldsymbol{\mathcal{N}}}, \{\boldsymbol{\mathcal{K}}_i\}_{i\in\boldsymbol{\mathcal{N}}}, (c_m)_{m\in\boldsymbol{\mathcal{M}}})$ in which $\boldsymbol{\mathcal{N}} = \{1, 2, \ldots, N\}$ is the set of players or SUs, $\boldsymbol{\mathcal{M}} = \{1, 2, \ldots, \mathrm{M}\}$ is the set of resources or channels, and $\Sigma_i \subset 2^{\boldsymbol{\mathcal{M}}}$ is the strategy space of i^{th} player. Also $\boldsymbol{\mathcal{K}}_i$ is the set of players who are interfering with i^{th} player and $c_m: \mathbb{N} \to \mathbb{Z}$ determine a payoff (or cost) function associated with resource *m*. Selecting resource *m*, the payoff for the i^{th} player is $c_m(x_m^i(\boldsymbol{\sigma}) + 1)$ where $x_m^i(\boldsymbol{\sigma})$ is number of users using resource *m* and interfere with i^{th} player. In mathematical expression, $x_m^i(\boldsymbol{\sigma}) = |\{j: m \in \sigma_j, j \in \boldsymbol{\mathcal{K}}_i\}|$. Note that plus one is due to $\boldsymbol{\mathcal{K}}_i$ is not included i^{th} player. Therefore, total payoff for i^{th} player in a regional congestion game is given by (1).

$$v^i(\sigma) = \sum_{m\in\sigma_i} c_m(x_m^i(\sigma) + 1). \qquad (1)$$

According to the strategy space of i^{th} player which is determined by Σ_i, we can observe that this strategy space is a subset of resources. This means that every player can select more than one resource at each decision stage. However, due to the transceiver constraint, we assume each SU can select only one channel at each decision stage and consequently the strategy space is given by $\Sigma_i = \boldsymbol{\mathcal{M}}$.In other words the strategy space for each player includes *M* separate resources. Therefore, the payoff function for selecting resource *m* with the i^{th} player is given by (2).

$$v^i(\boldsymbol{\sigma}) = c_m^i(x_m^i + 1). \qquad (2)$$

Where $x_m^i(\sigma) = |\{j: m = \sigma_j, j \in \boldsymbol{\mathcal{K}}_i\}|$.We called this game as Regional Congestion Game (RCG). We should note that the payoff function in the RCG is a monotonic increasing function in terms of number of interferers. The cost function of RCG depends on the user. In other words we want to introduce a user specific payoff function in which each player has its preferences; hence we use c_m^i notation instead of c_m in the RCG.

V. Channel Decision Making based on Regional Congestion Game

We can model our channel allocation problem as the outcome of the game in which the players are SUs, their actions or strategies are the feasible channels and their preferences are associated with the quality, price and switching cost of the selected channel.

In this game model the player's objective is to maximize the acquired bandwidth and minimize the procrustean congestion level and switching probability. Congestion level is determined by the number of neighboring users that share the same channel. Hence, a cost function $c_i(.)$ is associated with the decisions of i^{th} player and all of its neighbors. This cost is a function of the channel characteristics. As stated in the definition of RCG, $c_i(.)$ is monotonically increasing in terms of congestion level.

The proposed game can be formally defined as follows:

$$\boldsymbol{G} = < \boldsymbol{\mathcal{N}}, \boldsymbol{\mathcal{M}}, \boldsymbol{\mathcal{M}}, \{\boldsymbol{\mathcal{K}_i}\}_{i\in\boldsymbol{\mathcal{N}}}, \{c_i(\sigma_i, x_i^{\sigma_i})\}_{i\in\boldsymbol{\mathcal{N}}} >$$

Where $\boldsymbol{\mathcal{N}}$, first $\boldsymbol{\mathcal{M}}$ and $\boldsymbol{\mathcal{K}_i}$ is similar to the previous definition and the second $\boldsymbol{\mathcal{M}}$ represent our strategy space. Also σ_i and $x_i^{\sigma_i}$ are the selected strategy of SU_i and the received congestion level for the i^{th} player respectively.

Each user minimizes its experienced cost function selfishly as follow:

$$\sigma_i^* = arg \min_{\sigma_i \in \boldsymbol{\mathcal{F}_i}} c_i(\sigma_i, x_i^{\sigma_i})$$

The definition of the cost function for SUs depends on the available information. We assume SUs could retrieve the congestion level of selected channel through a common control channel and their RTS/CTS message passing. Also we assume they know the characteristics of each channel.

To have some appropriate criteria we should consider PU's characteristics, channel's characteristics and characteristics of SUs in our cost function.

A. Characteristics of PUs

According to the Markov chain, which depicted in Fig. 1, we define idle and busy periods. Idle (busy) period is the number of consecutive timeslots that a channel is idle (busy) and depends on the value of p^{σ_i} (q^{σ_i}). Smaller value for p^{σ_i} (q^{σ_i}) leads to larger idle (busy) period. The possible values of the Markov chain parameters in TABLE I, extracted from [7]. Also $p^{\sigma_i} - q^{\sigma_i}$ is a measure which indicates the PU's activity.

$$\begin{cases} very\ high\ PU's\ activity & p^{\sigma_i} - q^{\sigma_i} > 0.5 \\ high\ PU's\ activity & 0 < p^{\sigma_i} - q^{\sigma_i} < 0.5 \\ low\ PU's\ activity & -0.5 < p^{\sigma_i} - q^{\sigma_i} < 0 \\ very\ low\ PU's\ activity & p^{\sigma_i} - q^{\sigma_i} < -0.5 \end{cases}$$

Since in the channel selection, SUs sense the channel in a reactive or online approach, the goal could be to select an idle channel with the smallest $p^{\sigma_i} - q^{\sigma_i}$ value.

Based on idle and busy periods we define switching cost in the form of $SC_{ij} = k_j - k_i$. Note that SC_{ij} is the cost of switching from i^{th} channel to j^{th} channel.

TABLE I: Characteristics of PUs and their corresponding channels [7]

	Low PU's activity						**Medium PU's activity**						**High PU's activity**					
	Low opportunity			**High opportunity**			**Low opportunity**			**High opportunity**			**Low opportunity**			**High opportunity**		
No channel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
p	0.2	0.2	0.2	0.2	0.2	0.2	0.5	0.5	0.5	0.5	0.5	0.5	0.8	0.8	0.8	0.8	0.8	0.8
q	0.1	0.1	0.1	0.5	0.5	0.5	0.3	0.3	0.3	0.8	0.8	0.8	0.3	0.3	0.3	0.9	0.9	0.9
BW(KHz)	250	100	70	250	100	70	250	100	70	250	100	70	250	100	70	250	100	70
IBW	1	2.5	3.5	1	2.5	3.5	1	2.5	3.5	1	2.5	3.5	1	2.5	3.5	1	2.5	3.5
Holding Time	5	5	5	5	5	5	2	2	2	2	2	2	1.25	1.25	1.25	1.25	1.25	1.25

Where $k_i = p^{\sigma_i} \times t_{LA}^{\sigma_i}$ and $t_{LA}^{\sigma_i}$ is the time duration from last busy timeslot until now for σ_i. But since $t_{LA}^{\sigma_i}$ is vary from time to time, for the convenience of player's computations we use $\frac{1}{1-(q^{\sigma_i}-p^{\sigma_i})}$ instead of $t_{LA}^{\sigma_i}$, because as mentioned above $q^{\sigma_i} - p^{\sigma_i}$ denotes the activity of PU^{σ_i}. Therefore we have

$$SC_{ij} = \frac{p^{\sigma_j}}{1-(q^{\sigma_j}-p^{\sigma_j})} - \frac{p^{\sigma_i}}{1-(q^{\sigma_i}-p^{\sigma_i})}. \quad (3)$$

B. Characteristics of SUs

In this paper, we assume SUs have the same capabilities, this means that if a channel allocated to some SUs, all of these SUs gain an identical bandwidth. In other words, the proposed game is a type of non-weighted regional congestion game.

C. Characteristics of channels

We differ the channels in the cost function by two features called quality and price related to each other. In other words, the channel which has a high quality, imposed a higher price to its users. Indeed price is an increasing function of quality, and quality of each channel determined by its bandwidth. Furthermore the price of a channel has a reverse relation to corresponding PU's activity of this channel.

Therefore the first criterion is the channel's bandwidth that has been expressed in (4). The possible values of the bandwidth parameter in TABLE I, were chosen according to [7].

$$\begin{cases} \beta^i = BW^i & \forall i \in \boldsymbol{\mathcal{M}} \\ \alpha^i = IBW^i & \forall i \in \boldsymbol{\mathcal{M}} \end{cases}. \quad (4)$$

We also define the two criteria of price and channel switching cost as follows.

$$price^m = \left(BW^m \times \left(1 - (p^m - q^m)\right)\right) \forall \in m \in \boldsymbol{\mathcal{M}} \quad (5)$$

$$SCM = \begin{bmatrix} SC_{11} & SC_{11} & \cdots & SC_{1M} \\ SC_{21} & SC_{22} & \cdots & SC_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ SC_{M1} & SC_{M2} & \cdots & SC_{MM} \end{bmatrix}_{M\times M}. \quad (6)$$

Row's indexes are pertaining to σ_i^{old} and column's indexes are pertaining to σ_i^{new}. As the values of p and q are fixed for each PU, SCM is a fixed matrix and we also assume the entries on the major diagonal of this matrix are zero.

Based on these three criteria we introduce the following cost function:

$$cost_i(\sigma_i, \sigma_{-i}) = \sum_{j=1}^{|\mathcal{N}|} \alpha^{\sigma_i} \cdot f^{\sigma}(i,j) + c_i^{\sigma_i}. \quad (7)$$

Where σ_i and $\boldsymbol{\sigma}_{-i}$ are the selected strategy by the i^{th} player and its opponents, i.e., all player excluding i^{th} player, respectively. α^{σ_i} is the characteristic of σ_i, i.e., the inverse of bandwidth (IBW). Also, $c_i^{\sigma_i}$ is the cost of using σ_i for SU_i. This cost is only depends on the requirements of SU_i and its experiments in previous timeslots. As the upper bound of sigma in (7) is the number of SUs, it calculates the number of interferers for i^{th} player.

Also $f^{\sigma}(i,j)$ and $c_i^{\sigma_i}$is computed by (8) and (9) respectively.

$$f^{\sigma}(i,j) = \begin{cases} 1 & \begin{array}{l} i,j\ are\ neighbor\ and\ choose \\ same\ channel\ in\ strategy\ \boldsymbol{\sigma} \end{array} \\ 0 & otherwise \end{cases}. \quad (8)$$

$$c_i^{\sigma_i} = SCM(psc_i, \sigma_i) + price^{\sigma_i}. \quad (9)$$

Where psc_i is the previous selected channel for SU_i Which doesn't depend on the new selected channel. However because the previous selected channel for each SU is variable, as describe in (9), SCM is depending on i^{th} index. In other words each SU has a specific SCM matrix.

It can be shown that the proposed game is a potential game [12]. Therefore, the proposed cost function converges to a NE.

In previous works, the real price of a channel has not considered and channel selection was only depends on the quality of the channels. In this paper we consider both channel's quality and channel's price in the cost function.

In the proposed cost function we define three criteria with different dimensions. Indeed our problem is a multi-objective problem. Therefore for having a meaningful summation in the cost function we use weighted summing in which the weights are the preferences of the users in selecting channels. Therefore we have:

$$cost_i(\sigma_i, \boldsymbol{\sigma}_{-i}) = W_1 \times \sum_{j=1}^{|\mathcal{N}|} \left(\alpha^{\sigma_i} \times f^{\sigma}(i,j)\right)$$
$$+K \times W_2 \times SCM_i^{\sigma_i} + W_3 \times price^{\sigma_i}. \tag{10}$$

Where K is the switching cost effect in which we can evaluate the effect of changing switching cost on some criteria. In other words, for simulation we increase the impact of SCM by K.

Due to precise weights adaptation it is better to normalize three predefine criteria. To this end we divide price and channel switching cost on their maximum value and then we map these two criteria into the range of IBW through a linear mapping.

VI. Simulation Results

We consider an environment with size 500×500 by 20 SUs and 9 PUs in which each channel is dedicated to a PU randomly. Interference range for PUs and SUs set to 300 and 200 respectively.

To evaluate the effect of channel selection in switching, we run our game in the 10 timeslot iteratively and evaluate three metrics.

1- Utility: The multiplication of the bandwidth and holding time divided by number of interferers for a selected channel.

2- Price: The sum of the prices associated with SUs.

3- Switching probability: the ratio of a number of switching to total number of decision stages.

We consider both price based and without pricing scenarios in simulations. The weighting parameters for price based scenario are $W_1 = 0.8$, $W_2 = 0.15$ and $W_3 = 0.05$. Also these weights for the ignoring price scenario are $W_1 = 0.9$, $W_2 = 0.1$ and $W_3 = 0$. These settings are based on the environmental features like dimension, number of players and a number of resources as well as the player's characteristics like transmitting rate and resource's features like PU's activity.

We compare the results of simulation with the original cost function which introduced in [7]. It is significant to notice that in all simulations we use a unique evaluation metric.

The utility of these three approaches is depicted in Fig. 2. The proposed schemes with pricing and without pricing outperform the results of [7].

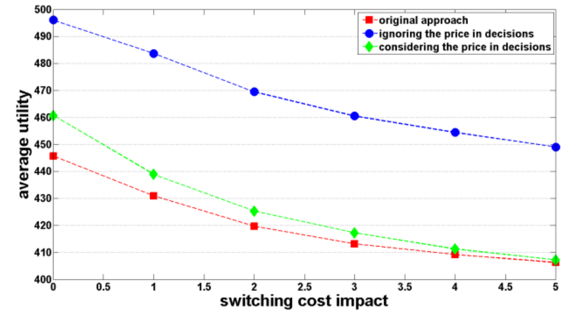

Figure 2. Average utility of SUs

The increasing impact of switching cost leads to decrease the average utility in all three schemes because the incentive of SUs for switching to better channel would be reduced.

As we expected, considering the price in the cost function cause to decrease the utility, because choosing a better channel leads to paying higher prices.

We also evaluate price in terms of switching cost, as depicted in Fig. 3. Increasing switching cost leads to decrease the price for SUs, because they have no incentive to choose a better channel and since selecting a better channel has a higher price, the imposed price would be decreased.

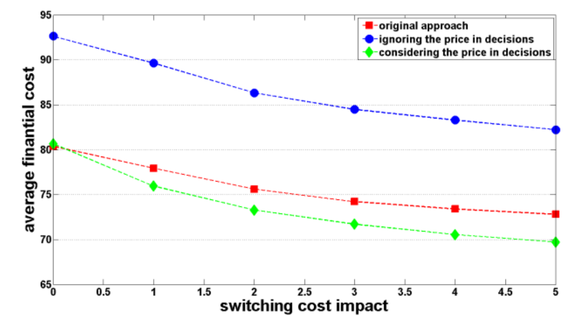

Figure 3. Average imposed price of SUs

The switching probability of the free pricing scheme is almost same as [7]. However, by adjusting the weights in the price-based scheme we can obtain better results as depicted in Fig. 4.

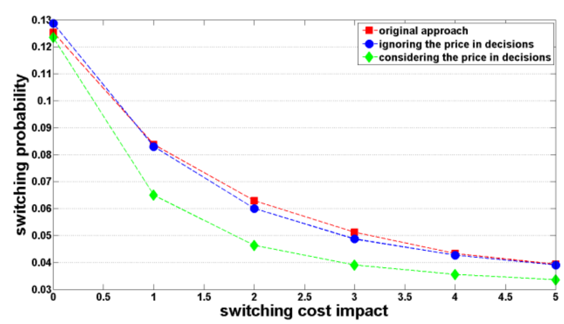

Figure 4. Switching probability of SUs during all timeslots

Only the impact of channel selection on delay has been considered in the evaluation and the delay of coordination or multiplexing has been neglected because these delays are same for all SUs.

VII. CONCLUSIONS

We propose a reactive scheme for spectrum handoff and channel selection problem in cognitive radio networks using regional congestion game theory. Developing a price based utility function for each secondary user we derive the results of the game and compare it with a recent similar scheme. The proposed scheme has the capability of adjusting in different conditions. Simulation results are provided to evaluate the performance of the proposed scheme in terms of achieved average utility, imposed price and switching probability.

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