Game Theoretical Analysis of Radio Resource Management in Wireless Networks: A Non-Cooperative Game Approach of Power Control

Nilimesh Halder and Ju Bin Song

Telecomm. Lab, Dept. of Electronic & Radio Eng.,
Kyung Hee University, Korea

Abstract
Radio Resource Management (RRM) is one of the most challenging and one of the most important aspects of modern wireless communication networks. System performance can be improved by applying intelligent radio resource management scheme in wireless networks. So distributed solutions to the resource management are motivated by the need to cope with the complexity in modern wireless communication networks. The purpose of this paper is to analyze the radio resource management problem in a cognitive radio based wireless ad-hoc network from the viewpoint of game theory. The main focus is to model and analyze a distributed power control in cognitive radio based wireless ad-hoc network using non-cooperative games. Using this model, we show a distributed power control scheme that converges to a fixed point for satisfaction of each user in the wireless network. Formulating distributed power control as a non-cooperative game we show the existence and uniqueness of the Nash equilibrium which can be achieved by the application of power control game.
Key words: *power control, radio resource management, cognitive radio, wireless ad hoc networks, game theory, Nash equilibrium.*

1. Introduction

RRM is one of the most challenging and one of the most important aspects of wireless communications. An intelligent radio resource management scheme can significantly improve system performance. For instance, a CDMA (Code Division Multiple Access) system can achieve significant capacity gains relative to a TDMA (Time Division Multiple Access) system. This is not due to any inherent processing advantages provided the Direct Sequence Spread Spectrum (DS-SS) of Frequency Hopped Spread Spectrum (FH-SS) signal. In fact, from an information theory perspective, a CDMA signal has the same capacity as a TDMA signal [1]. Rather, CDMA provides a number of radio resource management advantages not available in a TDMA system. The most notable of these RRM advantages are CDMA's theoretical frequency reuse factor of 1, and an ability to dynamically reallocate bandwidth during voice inactivity [2]. However, a proper understanding of a RRM algorithm often requires an understanding of a number of complex interrelated processes. Thus the number of considerations when analyzing a RRM algorithm can be quite large. This problem is complicated in distributed dynamic RRM algorithms where interactive decision making processes occur. An understanding of these processes is critical as they are a virtual necessity in the increasingly popular cognitive radio based wireless ad-hoc networks and are also encountered to a lesser extent in cellular networks.
In this paper we propose that game theory can be applied to the analysis of these interactive decision processes. Indeed it is anticipated that with a formalized approach of applying game theory to RRM issues and an identification of appropriate game theory models, many of the more difficult RRM problems will be addressed and understood and analyzed within the game theory framework.
The remainder of this document is a discussion of how game theory can be applied to radio resource management in cognitive radio based wireless ad-hoc networks is given. We also show the existence of Nash equilibrium in cognitive radio wireless networks achieved by game theoretical analysis and a description of future research directions.

2. Radio Resource Management in Wireless Networks

RRM can be best understood as a constrained probabilistic optimization problem that can be formulated as follows [2][3][4]:
Given a particular infrastructure deployment (*constraints*), allocate resources (*variables*) in a manner that (ideally) max(min)imize some operational parameter(s) (*objective functions*).
It is important to note that the probabilistic aspect of RRM causes it to differ from most common mathematical optimization problems (linear and nonlinear programming problems). Thus, when evaluating RRM objective functions various statistical measures are frequently used. For instance expected number of dropped calls and the variance in the number of dropped calls are evaluated as

Manuscript received June 5, 2007
Manuscript revised June 20, 2007

opposed to a specific number of outages. RRM is further complicated by the sheer complexity of the interactions of the algorithms under consideration. However like many other optimization problems, RRM also has the complication of having to consider inversely related objectives such as the following:

- Maximize user resources ↔ Maximize coverage/capacity
- Maximize mobility support ↔ Maximize capacity
- Maximize coverage ↔ Minimize cost

However, efficient spectrum use and optimal resource allocation are critical to the network performance. Coverage holes may be left, quality of service guarantees may be left or an excessive amount of spectrum may be lost to overhead.

There are several different aspects to radio resource management. We can divide these schemes into fixed RRM design and dynamic RRM algorithms. In a fixed RRM scheme, resource management decisions are made just once, typically before system deployment. Once this decision is made, to varying extents, these resources cannot be reallocated. If wireless networks were static and deterministic, fixed resource design and allocation would be sufficient. However, mobility is central to wireless networks and expected load distributions, mobile locations, fading profiles, and virtually every other assumption considered during fixed resource design and allocation change during operation. Thus nearly every allocation decision is subject to change in practical wireless networks. This adaptability can significantly improve performance in wireless networks.

There are two fundamental approaches to dynamic RRM: centralized dynamic RRM and distributed dynamic RRM. In centralized RRM, a single authority, such as a base station, collects information from various nodes in the network, computes a change in resource allocation, and signals this change to the other nodes in the network. In distributed RRM, each of a number of authorities in the network collects information and adjusts the resource allocations within its control. Note that a distributed dynamic RRM algorithm generally incurs less overhead than a centralized dynamic RRM algorithm. However, the operation of distributed algorithms can be difficult to predict as the dynamic actions of one authority can influence the actions of the other authorities in the network. Thus simulations must frequently be used in place of analysis to perform network planning. Additionally, without a convergent state, even more bandwidth might be lost to signaling overhead to accommodate the resource allocation adjustments.

2.1 Power Control

The performance of wireless communications systems is a function of the signal-to-interference-plus-noise-ratio (SINR). While readily apparent at the physical layer, it is also generally true at the higher layers. Optimal network performance is typically achieved only at a unique power vector. In a static network, it would be trivial to assign transmit powers to each node in the network to achieve this power vector. However, wireless systems are generally mobile, or at least operate in a dynamic environment, so that any initial power vector assignment will not maintain its optimality.

For instance, consider a pedestrian in an urban cellular environment who rounds a corner and creates a line-of-sight (LOS) path to his base station. These results in a significant increase in the power received at his base station, significantly improving his performance, but potentially jamming the other users in the network. Clearly this new environment has a different ideal power vector than the original.

In an attempt to maintain the optimum power vector, most modern communications schemes include some form of power control. Power control is a set of real-time algorithms implemented on a network in order to maximize a performance metric. Some common applications of power control include [5][6]:

- Ensuring proper operation in multi- user direct-sequence spread spectrum (DS-SS) systems.
- Trading off system capacity for quality of service.
- Trading off battery life versus quality of service.

Every power control scheme is designed for a particular target application and anticipated devices. These assumptions permit the network planner to maximize QoS while minimizing the use of system resources.

For example consider the following generalization of the reverse-link power control scheme used in IS-95. This scheme is primarily interested in maximizing system capacity while maintaining a minimum QoS, typically measured as a bit-error-rate (BER). For a system operating in the ideal steady-state where all received powers are equal and ignoring out-of-cell interference, [6] gives the relation between system capacity, K desired SINR, $Eb/N0$, spreading gain W/R, signal power S, and noise power η.

$$K = 1 + \frac{W/R}{E_b/N_0} - \frac{\eta}{S} \qquad \dots\dots\dots (1)$$

However, [2] states that if the received powers are instead received with a log normal distribution with a standard deviation of just 2dB, then 60% of the system capacity can be lost. Clearly, power control plays a vital role in the success of a system. It is clear from equation (1) that it is possible to trade off capacity for bit error rate. Thus as the number of users in this system increases, performance can “elegantly” degrade.

2.2 Previous work on Power Control

Previously researchers were engaged to develop some new power control schemes for cellular radio environments. In this section we discuss about some cellular power control schemes specially Yates’s standard interference function model and Goodman’s objective oriented power control schemes.

2.2.1 Yates’s standard interference function model

In [7], Yates represents a novel framework for standard interference function model for uplink power control in cellular radio systems. In this framework, each node, j, attempts to achieve a required SINR, γ_j, with a minimum power consumption, p_j at its node(s) of interest, $\{v_j\}$ (one or more base stations). This model assumes that each node is capable of observing the SINR at $\{v_j\}$ (or alternately, observes the total received power at $\{v_j\}$ and knows its own gains, $h_{j,\{v_j\}}$. Based on these observations, the nodes compute a scenario dependent standard interference function *I*(**p**) formed by the ratio of the target SINR and the effective SINR where **p** is the vector of transmit powers employed in the cell.

The properties of *I*(**p**) are key to the results of the model. *I*(**p**) has the following properties:

- Positivity *I*(**p**) > 0
- Monotonicity If **p** ≥ **p***, then I(**p**) ≥ I(**p***)
- Scalability For all α > 1, αI(**p**) > I(α**p**)

where the convention that **p** > **p*** means that $\mathbf{p}_j > \mathbf{p}^*_j$

In general $I_j(\mathbf{p})$ takes the form shown in equation (2) as the ratio of target SINR and actual SINR. *I*(**p**) is then given by $I(\mathbf{p}) = \times_{j\in N} I_j(\mathbf{p})$.

$$I_j(\mathbf{p}) = \frac{\gamma_j}{\mu_j(\mathbf{p})} \qquad \dots\dots\dots (2)$$

Power levels for each mobile are updated at stage k+1 by the equation (3).

$$p_j(k+1) = p_j(k) I(\mathbf{p}(k)) \qquad \dots\dots\dots (3)$$

Assuming capacity constraints are satisfied, this model is shown to converge to a steady state under the following scenarios:

- Fixed assignment where each mobile is assigned to a particular base station ($|\{v_j\}| = 1$).
- Minimum power assignment where each mobile is assigned to the base station where its SINR is maximized ($|\{v_j\}| = 1$ but v_j changes).
- Macro diversity where all base stations combine the signals of the mobiles ($|\{v_j\}| > 1$)
- Limited diversity where a subset of the base stations combine the signals of the mobiles ($|\{v_j\}| > 1$)
- Multiple connection reception where the target SINR must be maintained at a number of base stations. ($|\{v_j\}| > 1$).

In [7], Yates shows that the standard interference function has the following properties:

- If the algorithm has a fixed point, then that fixed point is unique.
- When *I*(**p**) is *feasible*, a fixed point exists. *I*(**p**) is said to be feasible if there exists some $\mathbf{p} \in \mathbf{P}$ such that $I(\mathbf{p}) \geq \mathbf{1}$
- If *I*(**p**) is feasible, then starting at any **p**(0) other than **p**(0) = **0**, then the algorithm converges to the fixed point when decisions are updated synchronously.

2.2.2 Goodman’s power control schemes

Whereas Yates treated distributed power control as a general fixed point problem, Goodman considers distributed power control as a distributed interactive objective maximization problem [8]. In this formulation the objective function has been expressed as equation (4).

$$u_i(\mathbf{p}) = \frac{R}{p_i} f(\mu_{i,b}) \qquad \dots\dots\dots (4)$$

where R is the data rate, f is the probability of successful bit transmission as a function of a modified SINR, $\mu_{i,b}$. $\mu_{i,b}$ is calculated as follows,

$$\mu_{i,b} = \frac{W}{R} \frac{h_{j,b} p_j}{\sum_{k\in N\setminus j} h_{k,b} p_k + \sigma_b^2} \qquad \dots\dots\dots (5)$$

where W is the transmission bandwidth.

3. Cognitive Radio

Cognitive radio technology is the key technology that enables a wireless network to use spectrum in a dynamic manner. The term, cognitive radio, can formally be defined as follows [9][10][11][12]:

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

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

The cognitive radio concept was first introduced in [13] [14], where the main focus was on the radio knowledge representation language (RKRL) and how the cognitive radio can enhance the flexibility of personal wireless services. The cognitive radio is regarded as a small part of the physical world to use and provide information from environment.

The ultimate objective of the cognitive radio is to obtain the best available spectrum through cognitive capability and reconfigurability as described before. Since most of the spectrum is already assigned, the most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users as illustrated in Fig. 1. The cognitive radio enables the usage of temporally unused spectrum, which is referred to as spectrum hole or white space [10]. If this band is further used by a licensed user, the cognitive radio moves to another spectrum hole or stays in the same band, altering its transmission power level or modulation scheme to avoid interference as shown in Fig. 1.

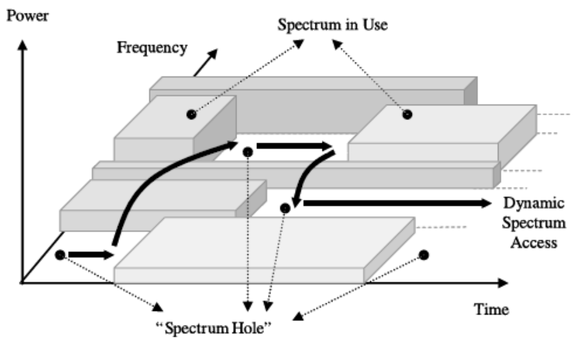

Fig. 1 Spectrum sharing and spectrum hole detection in Cognitive Radio

3.1 Cognitive Functions

The cognitive functions of a cognitive radio enable real time interaction with its environment to determine appropriate communication parameters and adapt to the dynamic radio environment. The tasks required for adaptive operation in open spectrum are shown in Fig. 2, which is referred to as the cognitive cycle [14].

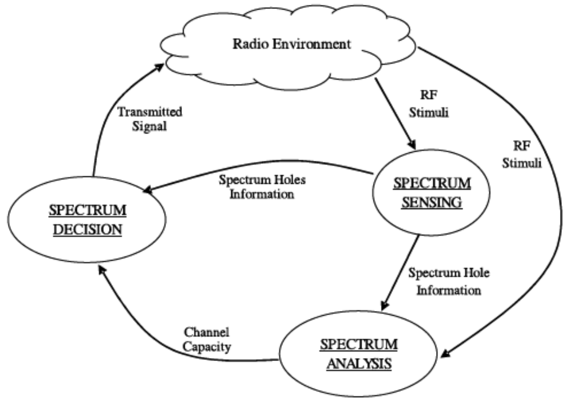

Fig. 2 Cognitive Cycle [14]

The functions of cognitive cycle as shown in Fig. 2 are as follows:

- *Spectrum sensing*: A cognitive radio monitors the available spectrum bands, captures their information, and then detects the spectrum holes.
- *Spectrum analysis*: The characteristics of the spectrum holes that are detected through spectrum sensing are estimated.
- *Spectrum decision*: A cognitive radio determines the data rate, the transmission mode, and the bandwidth of the transmission. Then, the appropriate spectrum band is chosen according to the spectrum characteristics and user requirements.

3.2 Reconfigurable Capabilities

Reconfigurability is the capability of adjusting operating parameters for the transmission on the fly without any modifications on the hardware components. This capability enables the cognitive radio to adapt easily to the dynamic radio environment. There are several reconfigurable parameters that can be incorporated into the cognitive radio [10] as explained below:

- *Operating frequency*: A cognitive radio is capable of changing the operating frequency. Based on the information about the radio environment, the most suitable operating frequency can be determined and the communication can be dynamically performed on this appropriate operating frequency.
- *Modulation*: A cognitive radio should reconfigure the modulation scheme adaptive to the user requirements and channel conditions. For example, in the case of delay sensitive applications, the data rate is more important than the error rate. Thus, the modulation scheme that enables the higher spectral efficiency should be selected. Conversely, the loss-sensitive

applications focus on the error rate, which necessitate modulation schemes with low bit error rate.

- *Transmission power*: Transmission power can be reconfigured within the power constraints. Power control enables dynamic transmission power configuration within the permissible power limit. If higher power operation is not necessary, the cognitive radio reduces the transmitter power to a lower level to allow more users to share the spectrum and to decrease the interference.
- *Communication technology*: A cognitive radio can also be used to provide interoperability among different communication systems.

The transmission parameters of a cognitive radio can be reconfigured not only at the beginning of a transmission but also during the transmission.

4. Game Theoretical Formulation of Transmission Power

The fundamental component of game theory is the notion of a game, expressed in normal form as $G = \langle M, A, \{u_i\} \rangle$, where G is a particular game, M is a finite set of players (decision makers) {1, 2, … …, m}, A_i is a set of action available to player i, $A = A_1 \times A_2 \times ....\times A_m$ is the action space, and $\{u_i\}$ = { $u_1, u_2, ..., u_m$ } is the set of objective functions that the players wish to maximize. For every player i, the objective function u_i, is the function of the particular action chosen by player i, a_i, and the particular action chosen by all other players in the game, a_{-i}. For this model, steady state conditions, known as *Nash Equilibria* are identified wherein no player would rationally choose to deviate from their chosen action as this would diminish their payoff, i.e. $u_i(a) \geq u_i(b_i, a_{-i})$ for all $i, j \in M$. The action tuples (a unique choice of each player) corresponding to the Nash Equilibria are then predicted as most popular outcomes. In a game the steady-state condition (Nash Equilibria) need not to be Pareto Efficient operating point.

The fundamental components of a non-cooperative game can be described as follows [15]:

- *Players*: Players are the decision making entities in the modeled system.
- *Actions*: An action set represents the choices available to a player. Note that these choices may be quite complex and, for instance, may represent a sequence of real world actions. Each player in the game has its own action set and makes its decision by choosing an action from its action set. A choice of actions by all players in the game produces an *action vector* or *action tuple*. All possible action vectors in the game are contained within the game's *action space*. The action space is formed the Cartesian product of every player's action set.
- *Outcomes*: Each action vector produces a well defined and expected *outcome*. Note as an outcome is jointly defined by every player's action choice, there is an interactive relationship. Thus in every game there exists a mapping from the action space to some outcome space. As this mapping is presumed, most game analyses ignore outcomes and focus solely on the actions that produce the outcomes.
- *Preference Relations*: Fundamental to game theory is the concept of *preference relations*. A preference relation describes a comparative preference between two outcomes or action tuples (and thus is a binary operator). The preference operator is normally represented by the symbol $\succeq$. Here, $a \succeq b$ indicates that outcome a is at least as preferable to outcome b. In game theory, the preference relation is assumed to be reflexive, transitive and complete over the action space. In a game, each player is expected to have preference relations defined over all possible outcomes.
- *Utility Functions*: While games can be analyzed based on the ordinal relations implied by preference relations, cardinal relations have a richer tool set and are generally preferred for analysis. Utility functions (objective functions) transform the ordinal relationships of players' preference relationships to cardinal relationships. Generally a utility function is constructed over the action (outcome) space so that if a is preferable to b, then the cardinal value assigned to a will be greater than the cardinal value assigned to b. Thus in light of utility functions, it may be fair to treat the preference operator, $\succeq$, as the greater than or equal to operator, $\geq$.
- *Nash Equilibrium*: An action vector a is said to be a Nash equilibrium (NE) iff $u_i(a) \geq u_i(b_i, a_{-i}) \forall i \in N, b_i \in A_i$ where a is an action tuple, (b_i, a_{-i}) is another action tuple that differs from a only in the component determined by i and u_i is player i's utility function. Restated, a NE is an action vector from which no player can profitably unilaterally deviate. NE corresponds to the steady-states of the game and is then predicted as the most probable outcomes of the game.

- *Best Response Function*: A best response function (correspondence) specifies the action (set of actions) for a particular player, say player i, that produces the largest utility given the action tuple chosen by all remaining players, a_{-i}. Nash equilibriums for a game are equivalent to the fixed points of the multi-player best response correspondence formed from the Cartesian product of all players' best response functions.

A wireless network can be modeled as a game according to Fig. 3. The decision making nodes in the network form the player set of the game, each node's available power levels form the action sets of the players, and the algorithms used by the nodes to modify their behavior form the utility functions and learning processes within the game.

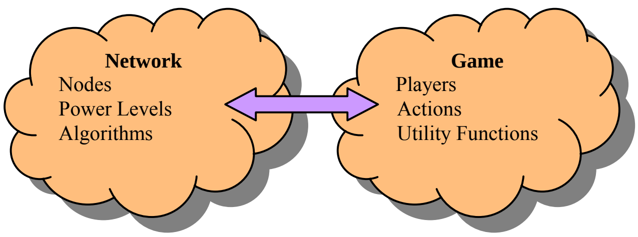

Fig. 3 Network model as a game

Here, we now introduce a more specific game model for distributed transmission power for cognitive radio based wireless ad-hoc networks. The model is based on the following key assumptions:

- Fundamentally, the choice of a power levels are the adaptations that may be adopted at the physical layer by a node of the network.
- From a physical layer perspective, performance is generally a function of the effective signal-to-interference-plus-noise ratio (SINR) at the node(s) of interest.
- Effective SINR is a function of the choice by a node: the transmit power level. The exact structure of this function is also impacted by a variety of factors not directly controllable at the physical layer; the most notable of these factors are environmental path losses and the processing capabilities of the node(s) of interest.
- When the nodes in a network respond to changes in perceived SINR by adapting their signal to SINR changes, a physical layer interactive decision making process occurs.

Based on these assumptions, a game theoretic model for transmission power level of a cognitive radio wireless ad-hoc network can be formed using the parameters listed in Table 1.

Table 1: Power Control Notation

Symbol	Meaning
N	The set of decision making (Cognitive) radios or nodes in the system
i, j	Two different cognitive radios or nodes $i, j \in N$
P_j	The set of power level available to radio or node j
p_i	A power level chosen by j
P	The power space formed by Cartesian product of all P_j. $P = P_1 \times P_2 \times \ldots \times P_n$
p	A power vector from P formed as $p = \{p_1, p_2, \ldots, p_n\}$
$u_j(p)$	The utility that j receives from p. This is the specific function that j is looking to maximize.

Thus the general notation of power game is,

$$G = \langle N, P, \{u_i\} \rangle \qquad \ldots\ \ldots\ \ldots (6)$$

4.1 Power Game Model of Network

In this subsection we describe the power game model of a cognitive radio wireless network.

- *Players*: A set of all decision making nodes in the participating networks. For an example here the set is $N = \{1, 2, \ldots\ \ldots\ \ldots, n\}$ nodes in the networks.
- *Actions*: The set of available power for each node $i \in N$, i.e. $P_i = \{p : p \in [P_{i,\min}, P_{i,\max}]\}$.
- *Utility Functions*: We consider p_i the transmission power of node i and g_i the link gain of i. Then $y_i = p_i g_i$, $i = 1, 2, \ldots\ldots, m$ is the received power of each node i. The quality of service QoS of each node i is measured in terms of the signal to interference plus noise radio (*SINR*) of i .Thus the *SINR* for each node i is given by, $SINR_i = \frac{y_i}{\sum_{j \neq i} y_j + e}$, where e designates external noise power. It is presumed that self-interference is negligible or nonexistent. Each node of interest relays its *SINR* information back to the nodes transmitting to it. Each transmitting node then adapts its transmission parameters as a function of *SINR* at its node of interest constrained by a cost function that models the internal costs for a particular energy / waveform pair (battery life, complexity, distortion) and / or a cost function imposed by a network for a particular energy / waveform pair.

Thus the objective function u_i can be described in terms of *SINR* as follows,

$$u_i = \left(\sqrt{i \times SINR_i}\right) - c_i\left(p_i\right) \quad \dots\dots\dots (7)$$

$$u_i = \left(\sqrt{i \times \left(\frac{y_i}{\sum_{j \neq i}^{M} y_j + e}\right)}\right) - c_i(p_i) \dots\dots\dots (8)$$

Here $c_i\left(p_i\right)$ is the cost function of each node i which can be described in unit price of power p', i.e. $c_i\left(p_i\right) = p' * p_i$. In this power control game each node will try to increase its utility by choosing a power from available power vector rationally and finally reach a steady state condition i.e. *Nash Equilibria*.

4.2 Existence of Nash Equilibrium

In this section we describe the Nash Existence Theorem and apply this theorem we show the Nash Equilibrium (NE) for our modeled power game.

4.2.1 Nash Existence Theorem

A strategic game $G = \langle N, A, R \rangle$ has at least one NE if $\forall i \in N$ the following condition holds

- The set A_i of actions is non empty, compact and convex subset of a Euclidean space.

The terms from set theory used in this theorem are concisely defined in [16].

4.2.2 NE for Power Game

The power game described in previous section has at least one Nash Equilibrium (NE). In order to prove this we apply Nash Existence Theorem to power game.

- *Proof*: The action sets P_i are non empty and convex, by definition. Each P_i is closed since it includes the boundary levels $P_{i,\min}$ and $P_{i,\max}$. All power levels in P_i lie within the boundary, thus it is bounded. Therefore the P_i's are compact.

Thus the power game must have Nash Equilibrium point.

4.3 Nash Equilibrium Solution Method

The objective of this power game for each node can be stated as: for each node $i \in N$, given the action tuples of the remaining players, i.e. $\left(P_j\right)_{j \in N \setminus i}$ find an action P_i that maximize the utility function u_i. This motivates a distributed solution approach which proceeds as an iterative optimization problem of a scalar objective function. The iterative step is defined as follows:

- *Step*: For each node $i \in N$, given $\left(P_j\right)_{j \in N \setminus i}$, find the maximum utility from equation (9).

$$P_{i,eqm} = \max_{P_i}\left[u_i\left(P_i, P_{-i}\right)\right], \forall i \in N \quad \dots\dots\dots (9)$$

This iterative procedure continues until all nodes in the network find that their utilities do not change between iterations and the change in their power levels is less than a pre-defined bound or an upper limit on the number of iterations is reached.

5. Simulation and Results

We consider a cognitive radio wireless ad-hoc network where the number of nodes N = 17, external noise e = 0.001 and unit power price = 0.5. We assume the available received power space P is a set of any real number between 0 to 10. At every iteration each node asynchronously in a random order decides its individually optimal strategies i.e. transmission power to achieve its utility. By applying power game model each node reaches a steady state i.e. Nash Equilibria point after some iteration. In Fig. 4 each node converges at a fixed power level to meet Nash Equilibria as well as maximizes its utility.

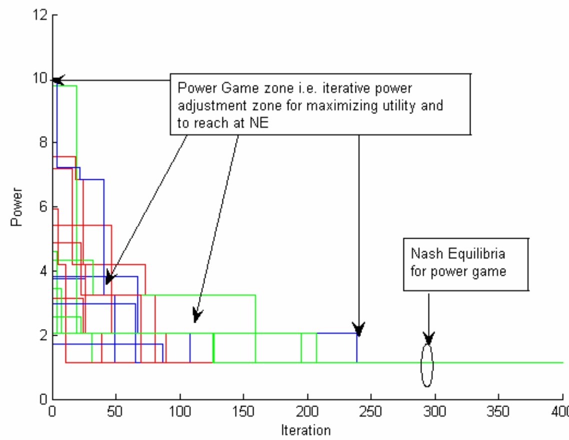

Fig. 4 Power of each node meets the NE

In Fig. 5 we show the utility of each node. Each mobile reaches its maximum utility after playing power game and shows its Nash Equilibrium point.

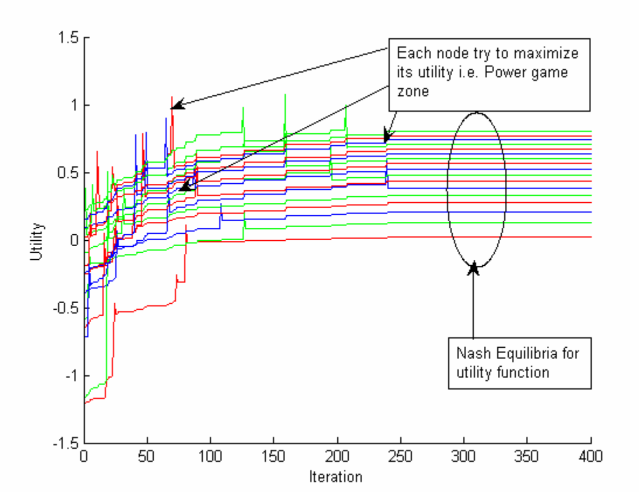

Fig. 5 Utility of each node and its NE

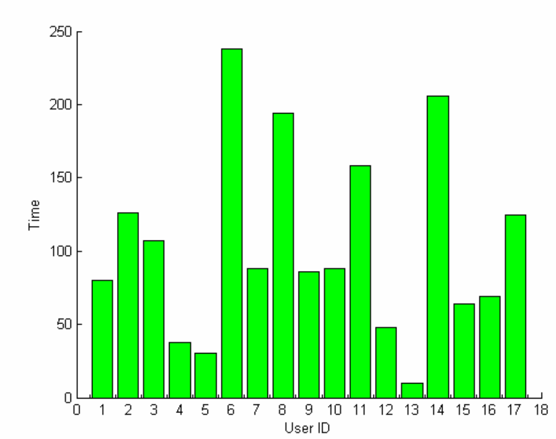

Fig. 6 Time required by each node to reach its NE

Fig. 6 shows the required iteration time of each node to reach the stead state situation i.e. NE point.

Now we show the simulation results of another utility function that is derived from the current action sets and *SINR*. We introduce the logarithmic approach of utility function. Then the desired utility function is,

$$u_i = \log_{10}\left(i * SINR_i\right) - c_i\left(p_i\right) \qquad \dots \dots \dots (10)$$

$$u_i = \log_{10}\left(i * \left(\frac{y_i}{\sum_{j \neq i}^{M} y_j + e} \right) \right) - c_i(p_i) \qquad \dots \dots \dots (11)$$

Here we modify the cost function as $c_i\left(p_i\right) = p' * p_i^q$ to punish more the node which rationally uses more power. Applying the same power game and same parameters, we find the existence of Nash Equilibrium for this utility function. Fig. 7 and Fig. 8 show the existence of Nash Equilibria for power and utility respectively.

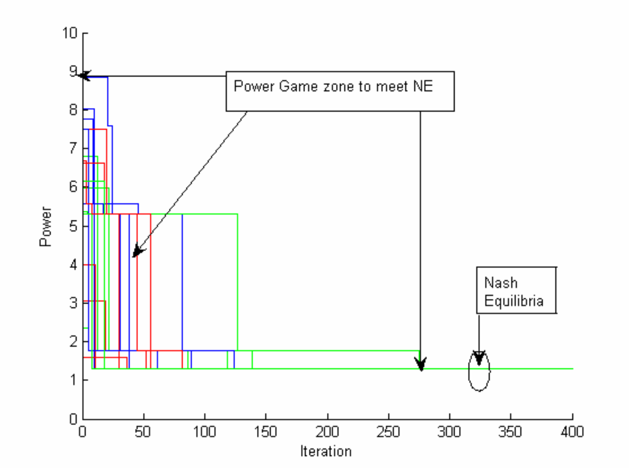

Fig. 7 Nash Equilibrium for power game

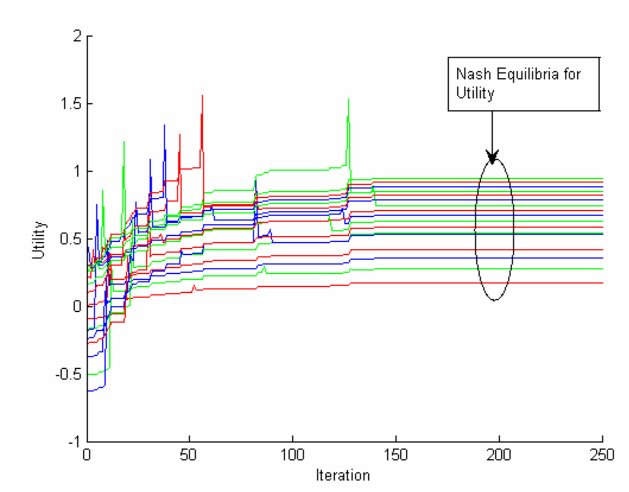

Fig. 8 Nash Equilibrium for logarithmic utility

6. Conclusion

Radio resource management is a challenging task in cognitive radio wireless networks because all nodes are communicating one another in a distributed manner. In this paper we introduced game theoretical techniques for radio resource management especially power management in cognitive radio wireless ad-hoc networks. We showed that by applying non-cooperative game theoretical techniques we got Nash Equilibrium for these networks and all participating nodes in the networks showed steady state condition. Our future approach will be to extend this work to rate control as well as throughput maximization of a large self-organizing network.

References

[1] T. Cover and J. Thomas, *Elements of Information Theory*, John Willey & Sons, Inc, New York City, 1999.

[2] Magnusson, P., Lundsjo, J., Sachs, J., Wallentin, P**., "**Radio resource management distribution in a beyond 3G multi-radio access architecture", *Global Telecommunications Conference, 2004.* Vol-6, Page(s):3472 - 3477

[3] Taesoo Kwon, Dong-Ho Cho, "Adaptive radio resource management based on cell load in CDMA-based hierarchical cell structure", *Vehicular Technology Conference, 2002*, Vol-4, Page(s): 2337-2341.

[4] Hills, A., Friday, B., "Radio resource management in wireless LANs", *IEEE Communication Magazine, 2004*, Vol-42, Page(s): 9-14.

[5] Cameron, Rick and Brian Woerner. "Performance Analysis of CDMA with Imperfect Power Control," *IEEE Transactions on Communications*, Vol-44, July 1996, pp. 777-781.

[6] K. Gilhousen, I. Jacobs, R. Padovani, A. J. Viterbi, L. Weaver, C. Wheatley III, "On the Capacity of a Cellular CDMA System" *IEEE Transactions on Vehicular Technology*, vol. 40, May 1991, pp. 303 – 312.

[7] R. Yates, "Uplink Power Control in Cellular Radio Systems," *IEEE Journal on Selected Areas in Communications*, Vol. 13, No 7, September 1995, pp. 1341-1347.

[8] D. Goodman and N. Mandayam., "Power Control for Wireless Data," *IEEE Personal Communications*, April, 2000, *IEEE Personal Communications*, pp. 48 – 54.

[9] J. Mitola, Ed., "Special issue on software radio," in *IEEE Commun. Mag.*, May 1995.

[10] S. Haykin, "Cognitive radio: brain-empowered wireless communications", *IEEE Journal on Selected Areas in Communications*, 23 (2) (2005) 201–220.

[11] R.W. Thomas, L.A. DaSilva, A.B. MacKenzie, "Cognitive networks", *Proc. IEEE DySPAN 2005*, November 2005, pp. 352–360.

[12] F.K. Jondral, "Software-defined radio-basic and evolution to cognitive radio", *EURASIP Journal on Wireless Communication and Networking*, 2005.

[13] J. Mitola III, "Cognitive radio for flexible mobile multimedia communication", *Proc. IEEE International Workshop on Mobile Multimedia Communications (MoMuC)*,1999, November 1999, pp. 3–10.

[14] J. Mitola III, "Cognitive radio: an integrated agent architecture for software defined radio", *PhD Thesis*, KTH Royal Institute of Technology, 2000.

[15] D. Fudenberg and J. Tirole, *Game theory*, MIT Press, Cambridge, MA, 1991.

[16] Osborne, M.J., Rubinstein, A., "*A Course in Game Theory*", MIT Press, 1994.

Nilimesh Halder is currently a PhD student and a member of Telecom. Lab in the Dept. of Electronic and Radio Eng. at Kyung Hee University. He received the B.S. degree in Computer Science and Engineering from Khulna University, Bangladesh in 2005. His research interests include wireless communications, ad-hoc mobile networks, radio resource management, power control & management, self-organizing networks, cognitive radio and game theory.

Ju Bin Song is currently a professor in the Dept. of Dept. of Electronic and Radio Eng., Kyung Hee University, from 2003.He received BS and MS degree in 1987 and 1989, respectively and PhD degree in the Department of Electronic and Electrical Eng., University College of London, UK in 2001. He was senior researcher in ETRI from 1992 to 1997 and a research fellow in UCL, 2001. He was a professor in Hanbat National University from 2002 to 2003. His research interests include telecommunications, mobile multi-hop networks, radio resource management and next generation communications. He is a member of IEEE, KICS and KIEE.