Dynamic Spectrum Access with QoS and Interference Temperature Constraints

Yiping Xing, *Student Member*, *IEEE*, Chetan N. Mathur, *Student Member*, *IEEE*,
M.A. Haleem, *Member*, *IEEE*, R. Chandramouli, *Senior Member*, *IEEE*, and
K.P. Subbalakshmi, *Senior Member*, *IEEE*

Abstract—Spectrum is one of the most precious radio resources. With the increasing demand for wireless communication, efficiently using the spectrum resource has become an essential issue. With the Federal Communications Commission's (FCC) spectrum policy reform, secondary spectrum sharing has gained increasing interest. One of the policy reforms introduces the concept of an interference temperature—the total allowable interference in a spectral band. This means that secondary users can use different transmit powers as long as the sum of these power is less than the interference threshold. In this paper, we study two problems in secondary spectrum access with minimum signal to interference noise ratio (quality of service (QoS)) guarantee under an interference temperature constraint. First, when all the secondary links can be supported, a nonlinear optimization problem with the objective to maximize the total transmitting rate of the secondary users is formulated. The nonlinear optimization is solved efficiently using geometric programming techniques. The second problem we address is, when not all the secondary links can be supported with their QoS requirement, it is desirable to have the spectrum access opportunity proportional to the user priority if they belong to different priority classes. In this context, we formulate an operator problem which takes the priority issues into consideration. To solve this problem, first, we propose a centralized reduced complexity search algorithm to find the optimal solution. Then, in order to solve this problem distributively, we define a secondary spectrum sharing potential game. The Nash equilibria of this potential game are investigated. The efficiency of the Nash equilibria solutions are characterized. It is shown that distributed sequential play and an algorithm based on stochastic learning attain the equilibrium solutions. Finally, the performances are examined through simulations.

Index Terms—Wireless communication, access schemes, constrained optimization, mobile communication systems.

1 Introduction

Enhancing spectrum efficiency is an important task of regulatory authorities worldwide. A number of experimental studies [1] show that spectrum is used inefficiently both in space and time. Low utilization and increased demand for the radio resource suggests the notion of secondary use, which allows unused parts of spectrum owned by the primary license holder to become available temporarily for secondary (nonprimary) users. The dynamic access of spectrum by secondary users is one of the promising ideas that can mitigate unsatisfied spectrum demand, potentially without major changes to incumbents. The wireless device measures RF energy in the channel or the received signal strength indicator to determine whether the channel is idle or not, but this approach has a problem in that wireless devices can only sense the presence of a primary if and only if the energy detected is above a certain threshold. It is true that one cannot arbitrary lower the threshold, as this would result in nondetection because of the presence of noise. In the feature detection approach, which has been used in the military to detect the presence of weak signals [2], the wireless device uses cyclostationary signal processing to detect the presence of primaries. If a signal exhibits strong cyclostationary properties, it can be detected at very low signal-to-noise ratios (SNR) [3]. Then, the question is how to share the available spectrum efficiently and fairly.

The FCC Spectrum Policy Task Force [4] has recommended a paradigm shift in interference assessment; that is, a shift away from largely fixed operations in the transmitter and toward real-time interactions between the transmitter and receiver in an adaptive manner. The recommendation is based on a new metric called the *interference temperature*, which is intended to quantify and manage the sources of interference in a radio environment. The interference temperature is defined to be the RF power measured at a receiving antenna per unit bandwidth. The key idea for this new metric is that, first, the interference temperature at a receiving antenna provides an accurate measure for the acceptable level of RF interference in the frequency band of interest; any transmission in that band is considered to be "harmful" if it would increase the noise floor above the interference temperature threshold as shown in Fig. 1. Second, given a particular frequency band in which the interference temperature is not exceeded, that band could be made available to secondary users. Hence, a secondary device might attempt to coexist with the primary, such that the presence of secondary devices goes unnoticed.

Related work on secondary use of radio spectrum has appeared in [5], [6], [7], [8], [9]. Here, we consider a scenario similar to [9], where secondary users wish to use a local, relatively short-term data service, and all users adopt a

- *The authors are with the Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ 07030. E-mail: {yxing, cnanjund, mhaleem, mouli, ksubbala}@stevens.edu.*

Manuscript received 19 Nov. 2005; revised 16 May 2006; accepted 18 July 2006; published online 15 Feb. 2007.
For information on obtaining reprints of this article, please send e-mail to: tmc@computer.org, and reference IEEECS Log Number TMC-0341-1105.

1536-1233/07/$25.00 © 2007 IEEE Published by the IEEE CS, CASS, ComSoc, IES, & SPS

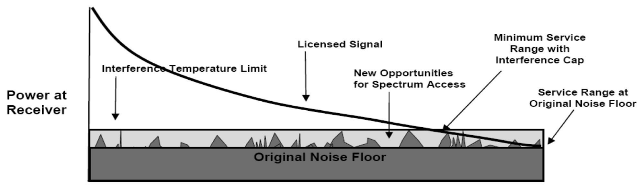


Fig. 1. This figure [21] shows the power that is received from the licensed transmitter as a function of distance. The spectrum agile radio has opportunities represented by the right-hand side box.

spread spectrum signaling format, in which the transmitted power is evenly spread across the entire available band controlled by the manager. A practical realization of this model would be when secondary users (with spread spectrum signaling) and a primary direct-sequence CDMA (DS-CDMA) system coexist in the up-link spectrum band of the primary DS-CDMA system. In the uplink, the interference temperature can be measured at the base station, which is the receiver of the primary system. Hence, the number of measuring points can be significantly reduced. But, of course, our proposed secondary access is definitely not limited to this scenario. The spectrum can be a TV broadcast band, or other emergency band, where the primary transmission will not contribute to the interference temperature. In [9], auction mechanisms for allocating the received power are studied. The logarithmic utilities which are a function of the received Signal-to-Interference Ratio (SIR) are maximized under the constraint of interference temperature. But, without any constraint on the minimum received SIR or maximum transmitting power for the secondary users, the auction-based mechanisms may lead to inefficient solutions. The received SIR for some secondary links may become too low and energy wastage due to several retransmissions will cause interference to other links. It is also possible that the required transmit power for the secondary user may exceed the maximum available transmitting power for the secondary users. An alternative choice would be to completely switch off some of the secondary links when all the secondary users cannot be supported by the system by coordinated control. In this way, the active secondary links are provisioned with QoS in the sense of a guaranteed minimum achievable SIR, and those links switched off at this time period can be awakened when it can be supported with its minimum required SIR.

In our formulation, we take these factors into consideration. We first propose a centralized solution which is a logarithmic utility maximization with constraints. This nonconvex optimization problem can be transformed into a convex optimization, which can be solved by geometric programming efficiently [10], [11].

In this paper, when not all the secondary links can be supported with their minimum SIR requirement, it is desirable to have the spectrum access opportunity proportional to the user priority if they belong to different priority classes. We formulated an operator problem which maximizes the operator revenue. To solve this problem, a centralized reduced complexity searching algorithm is introduced to find the optimal subset of allowable links. Because of the nature of secondary access, distributive algorithms would be desirable. First, we define a secondary spectrum sharing potential game which takes priority classes into consideration, then we propose a sequential play solution which converges to the Nash equilibrium (NE) of the game. Operating at the NE will guarantee that the received power at the measuring point will not exceed the interference temperature constraint and the target SIR for each active link is guaranteed. Besides that, different secondary users with different accessing priorities will have different accessing opportunities with our proposed method. We note that sequential play requires significant information and signalling to operate. To mitigate this drawback, we formulated a stochastic learning automata algorithm, where asynchronous updating is permitted and only local information is needed to complete the probability update.

2 Secondary Spectrum Sharing Model

Spectrum with bandwidth W is to be shared among M spread spectrum users, where a user refers to a transmitter and an intended receiver pair. For each i, the received SIR is given by

$$\gamma_i = \frac{y_i h_{ii}}{\frac{1}{L}(\sum_{j \neq i} y_j h_{ji}) + \sigma^2}, \quad (1)$$

where L is the normalized spreading sequence length, y_i is user i's transmission power, h_{ij} is the channel gain from user i's transmitter to user j's receiver, and σ^2 is the background noise power that is assumed to be the same for all users. In order to satisfy an interference temperature constraint, the total received power at a specified measurement point must satisfy

$$\sum_{i=1}^{M} y_i h_{i0} \leq B, \quad (2)$$

where h_{i0} is the channel gain from user i's transmitter to the measurement point and $B > 0$ is a predefined threshold. We assume that all the secondary users adopt a spread spectrum signaling format in which the transmitted power is evenly spread across the entire available band. This allows efficient multiplexing of data streams from different sources corresponding to different applications and reduces the combined power-bandwidth allocation problem to a received power allocation problem. Hence, the interference temperature constraint is translated to a total received power threshold B at the measuring point. The system model is shown in Fig. 2.

The model considers only a single measurement point. In practice, it needs to be ensured that the *interference temperature* is not exceeded at any of the primary receivers. A single measurement point cannot ensure this, but our model can be easily extended to scenario where multiple measuring points exist. Under this scenario, multiple interference temperature constraints (Bs) should all be satisfied simultaneously. If a single measurement point is used, the interference temperature limit at this point must be set by a sufficiently large margin lower than the interference temperature actually tolerable by the incumbent receivers.

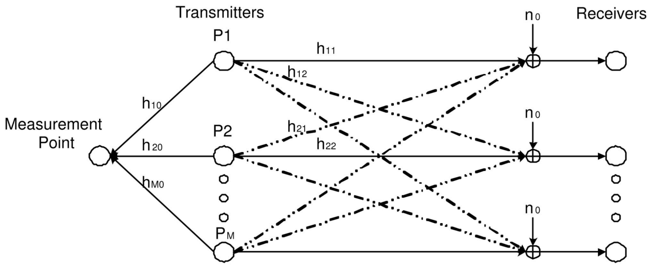


Fig. 2. System model for M transmitter-receiver pairs.

Depending on the propagation environment, the required margin can be 10s of dB.

3 Convex Optimization and Geometric Programming

Convex optimization refers to minimizing a convex objective function over convex constraint sets. We will use a particular type of convex optimization in the form of geometric program [10].

A *monomial* is a function $f : \Re^n \rightarrow \Re$, where the domain contains all real vectors with nonnegative components:

$$f(x) = cx_1^{a_1} x_2^{a_2} \cdots x_n^{a_n}, \quad c \geq 0, \quad \text{and} \quad a_i \in \Re. \tag{3}$$

A *posynomial* is a sum of monomials

$$f(x) = \sum_k c_k x_1^{a_{1k}} x_2^{a_{2k}} \cdots x_n^{a_{nk}}. \tag{4}$$

Posynomials are closed under addition, multiplication, and nonnegative scaling. Monomials are closed under multiplication and division. If a posynomial is multiplied by a monomial, the result is a posynomial; similarly, a posynomial can be divided by a monomial, with the result a posynomial.

A geometric program is an optimization of the form

$$\begin{aligned} \text{minimize} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 1 \\ & h_j(x) = 1, \end{aligned} \tag{5}$$

where f_0 and f_i are posynomials and h_j are monomials. Geometric programs are not (in general) convex optimization problems, but they can be transformed into convex problems by a change of variables and a transformation of the objective and constraint functions. With a change of variables, $y_i = logx_i$ and $b_{ik} = \log c_{ik}$, we can put it into convex form:

$$\begin{aligned} \text{minimize} \quad & \tilde{f}_0(y) = \log\Big(\sum\nolimits_k e^{a_{0k}^T y + b_{0k}}\Big) \\ \text{subject to} \quad & \tilde{f}_i(y) = \log\Big(\sum\nolimits_k e^{a_{ik}^T y + b_{ik}}\Big) \leq 0 \\ & \tilde{h}_i(y) = a_j^T y + b_j = 0. \end{aligned} \tag{6}$$

Since the functions $\tilde{f}_i$ are convex and $\tilde{h}_i$ are affine, this problem is a convex optimization problem.

Convex optimization problems can be solved globally and efficiently through the interior point primal dual method [10], with polynomial running times that are $\mathbf{O}(\sqrt{N})$, where N is the size of the problem.

4 Social Optimization under Interference Temperature Constraint

Secondary user i's valuation of the spectrum is characterized by a utility $v_i(\gamma_i)$, where γ_i is the received SIR at user i's receiver. Similar to the logarithm in Shannon's formula, we define the logarithmic utility $v_i(\gamma_i) = ln(\gamma_i)$. This utility function captures the user's desire for s higher data transmitting rate. With energy consumption and QoS provision considerations, each secondary link has a minimum SIR constraint γ_i^t. Let $\Theta = \{1, 2, \ldots, M\}$ be the set of transmitter and receiver link pairs and let each transmitter's available transmitting power be $y_i \in (0, y_i^{max}], \forall i$.

We can formulate the social rate optimization problem with QoS and interference temperature constraints as follows:

$$\begin{aligned} & \text{maximize} \sum\nolimits_i v_i(\gamma_i) \\ & \text{subject to} \\ & SIR_i \quad \geq \gamma_i^t \quad \forall i \\ & \sum\nolimits_i h_{i0} y_i \quad \leq B \\ & y_i \quad > 0 \quad \forall i \\ & y_i \quad \leq y_i^{max} \quad \forall i. \end{aligned} \tag{7}$$

Maximizing $\sum_i \ln(\gamma_i)$ is equivalent to maximizing $\ln \prod_i \gamma_i$, which is then equivalent to minimizing $\prod_i \frac{1}{\gamma_i}$. Note that the objection function is posynomial and the constraints can also be transformed into posynomial and monomial forms. So, this optimization problem is a convex optimization in geometric program form and can be solved globally and efficiently.

We can define a normalized link gain matrix A with entries $\frac{h_{ij}}{h_{ii}}$ for $i \neq j$ and 0 for $i = j$, and let $H = \gamma^t A$, the normalized noise vector η such that $\eta_i = \frac{n_0}{h_{ii}}$, and vector $\mathbf{c}$ with $c_i = h_{i0}$. Further, we define $\mathbf{y}^{max} = (y_1^{max}, \ldots, y_M^{max})$.

Theorem 1. *If* $\rho(H) < 1$, $(I - H)^{-1}\gamma^t\eta \leq \mathbf{y}^{max}$, *and* $(I - H)^{-1}\gamma^t\eta\mathbf{c} \leq B$, *then there exists power vector* $\mathbf{y}^* > 0$, *which satisfies the above described optimization problem.*

Proof. The dominant (largest) eigenvalue of the matrix H, denoted by $\rho(H)$, is less than one ($\rho(H) < 1$) and $(I - H)^{-1}\gamma^t\eta \leq \mathbf{y}^{max}$ implies that there exists a positive power vector $\tilde{y} = (I - H)^{-1}\gamma^t\eta$ which satisfies the SIR bound and the maximum transmitting power constraints. If, further, $\tilde{y}\mathbf{c} < B$, each user can increase their power by a factor of $B/\sum_i y_i h_{i0}$, which increases the SIR for every user and, hence, will increase the objective function so we can always find another $\tilde{y} \leq \mathbf{y}^* \leq \mathbf{y}^{max}$ which will satisfy the SIR constraints, make the total received power constraint tighter, and maximize the objective function. □

With the total received power constraint B at the measuring point and the QoS constraint, there are some cases when not all the secondary links can achieve their minimum SIR requirement, which raises the problem of system feasibility. Theorem 1 gives the condition under which there will be a feasible power allocation for the secondary users. When the feasibility condition is not satisfied, only a subset of the secondary links can be accommodated. Then, depending on the goal of optimization, the spectrum accessing process will be different. If the goal is still to maximize the total utility which is proportional to the total transmitting rate, the strategy would be to exhaust all the possible active link combinations and then check the feasibility condition and conducting optimization (7) to find the optimal feasible link set and the power allocation. An alternative accessing process that is more fair would be to maximize the number of active secondary links with QoS and interference temperature constraints, which was addressed in [17].

5 Operator Problem with Different Priority Classes

If different users have different contracts defining different priorities or throughput than is perfectly fair, then the operator should provide different throughput for such users. In this case, secondary links, depending on their willingness to pay, belong to L priority classes. Let a_i be the priority parameter for link i. The operator problem is then to maximize the network revenue.

[**Operator Problem**]:

$$\begin{array}{lll} \max \sum_{i\in(i:x_i=1)} a_i. & & \\ \text{subject to} & & \\ SIR_i & \geq \gamma_i^t & \forall i \in (i : x_i = 1) \\ \sum_i h_{i0} y_i & \leq B & \forall i \in (i : x_i = 1) \\ y_i & > 0 & \forall i \in (i : x_i = 1) \\ y_i & \leq y_i^{max} & \forall i \in (i : x_i = 1), \end{array} \quad (8)$$

where x_i is a collection of binary variables and $x_i = 1$ means the ith link transmits; otherwise, $x_i = 0$. By maximizing this revenue, secondary users who pay more will get accessing priority over those who pay less. We model the relation between the price p_i a user paid and the priority parameter a_i as follows:

$$a_i = p_i^{\alpha}, \quad (9)$$

where $0 \leq \alpha \leq 1$ is an operator designable parameter. Small α corresponds to putting more emphasis on system capacity (number of active secondary links), while large α corresponds to putting more emphasis on guaranteeing service to the user paying higher price. Specifically, $\alpha = 0$ corresponds to the problem of maximizing the number of active secondary links (capacity).

6 Optimal Supported Link Subset Searching

It can be proved that the operator problem is NP complete through the steps similar to [16]. In order to reduce the search space and, hence, reduce, the complexity of searching for the optimal supported link subset, we first characterize some properties of the supported link subset.

We say that a power vector $\mathbf{y}$ supports all transmitters at a SIR target γ^t if and only if

$$\mathbf{y} \geq \gamma^t (A\mathbf{y} + \eta). \quad (10)$$

That is, each receiver i has a SIR $\gamma_i \geq \gamma_i^t$. To compute a power vector that satisfies (10) in a distributed fashion, we describe a distributed constrained power control (DCPC) algorithm.

Suppose the power adjustment made by the ith terminal at the nth time instant according to the DCPC is given by

$$\begin{aligned} y_i(n) &= min\left\{ y^{max}, \gamma^t \frac{y_i(n-1)}{\gamma_i(n-1)} \right\} = \\ & min\left\{ y^{max}, \gamma^t \left(\eta_i + \sum\nolimits_{j\in\Theta} y_j(n-1) \frac{h_{ji}}{h_{ii}} \right) \right\}, 1 \leq i \leq M. \end{aligned} \quad (11)$$

It has been shown in [15] that, for any given γ^t, DCPC converges to a unique positive power vector determined by the fixed point solution to

$$\mathbf{y} = min\{\mathbf{y}^{max}, \gamma^t (A\mathbf{y} + \eta)\}. \quad (12)$$

A power vector $\mathbf{y}$ which satisfies the fixed point equations in (12) will be referred to as the stationary power vector. When all transmitters can be supported, DCPC converges to the fixed point solution given by

$$\mathbf{y} = \gamma^t (A\mathbf{y} + \eta). \quad (13)$$

For every subset of transmitters $\Theta_0 \subseteq \Theta$, let $\mathbf{y}^{\Theta_0}$ denote the stationary power vector of a system which consists only of the set Θ_0. Also, let S_{Θ_0} be the subset of transmitters which are supported (at γ^t) under the stationary power vector $\mathbf{y}^{\Theta_0}$ (i.e., in a system where DCPC runs only with the set of transmitters Θ_0). Also, let $\bar{S}$ denote the complement of set S, and let

$$y_i^{\Theta/\Theta_0} = \begin{cases} y_i^{\Theta}, & \text{if} \quad i \in \Theta_0 \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

Theorem 2. *For a link set $\Theta_0 \subseteq \Theta$, if the secondary link system with DCPC consisting of link set Θ_0 is infeasible, the system consisting of set Θ will also be infeasible.*

Proof. Consider two cases:

1. $i \in \Theta_0$ is in the nonsupported set $\bar{S}_{\Theta_0}$.
2. $\bar{S}_{\Theta_0} = \Phi$, i.e., all the links in Θ_0 are supported, but $\sum_{i\in\Theta_0} h_{i0} y_i^{\Theta_0} > B$.

For Case 1,

$$y_i = y^{max}, \forall i \in \bar{S}_{\Theta_0}.$$

Thus, from the fact that the h_{ij}'s are nonnegative and Lemma 2 in [16], which states that $\mathbf{y}^{\Theta_0} \leq \mathbf{y}^{\Theta/\Theta_0}$ (which comes from the fact that using DCPC with an initial power vector $\mathbf{y}^{\Theta/\Theta_0}$ results in a nonincreasing powers sequence which converges to $\mathbf{y}^{\Theta_0}$),

$$\begin{aligned} y_i^{\Theta} \leq y^{max} = y_i^{\Theta_0} &< \gamma^t \left(\eta_i + \sum_{j\in\Theta_0} \frac{h_{ji}}{h_{ii}} y_j^{\Theta_0} \right) \\ &\leq \gamma^t \left(\eta_i + \sum_{j\in\Theta} \frac{h_{ji}}{h_{ii}} y_j^{\Theta} \right). \end{aligned} \quad (15)$$

Thus, i is also in the nonsupported set $\bar{S}_{\Theta}$.

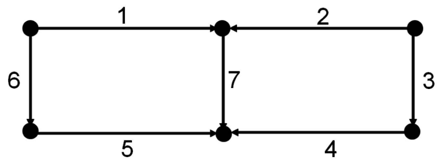


Fig. 3. Example system with seven secondary links.

For Case 2, because we have $\mathbf{y}^{\Theta_0} \leq \mathbf{y}^{\Theta/\Theta_0}$,

$$\sum_{i \in \Theta} h_{i0} y_i^{\Theta} > \sum_{i \in \Theta_0} h_{i0} y_i^{\Theta_0} > B,$$

i.e., the interference temperature bound B is violated. □

Theorem 2 establishes that the tree pruning algorithm [18], which will be described following, is valid for our scenario. Thus, the search for an optimal supported subset of links can be confined to a smaller searching space. This optimization needs all the system information, including all the link gains and the number of secondary links, to conduct the calculation. Therefore, a centralized controller is needed to coordinate the access process.

The tree pruning algorithm is described below in Algorithm 1, where each secondary link is identified by a unique number; M is the total number of secondary link pairs. In the *Satisfy* procedure, both the interference temperature and the SIR constraints are examined, while set F^{final} contains all the candidate sublink sets. Then, the operator problem described in (8) is transferred to the following problem:

$$arg\max_{k} \sum_{i \in F^{final}(k)} a_i. \tag{16}$$

An instance of the tree pruning algorithm on a seven edge (seven secondary link pairs) example network (Fig. 3) is given in Fig. 4. Initially, every edge in the family is allocated a unique subset. Thus, the initial family comprises as many subsets as the number of edges. For the given example, the initial family is {{1} {2} {3} {4} {5} {6} {7}}. In the next and the following rounds, two fundamental operations take place. The first operation is expansion, where each of the subsets in the family is expanded by including one more unique edge. The uniqueness is in the sense that only edges that have no vertex in common with any of the other edges of the set to be extended are added. This is because it is assumed that a user cannot transmit to nor receive from two other users at the same time. This issue is included in the *Satisfy()* routine. For the given example, the family after first expansion is {{1,3} {1,4} {1,5} {2,4} {2,5} {2,6} {3,5} {3,6} {3,7} {4,6} {6,7} {1} {2} {3} {4} {5} {6} {7}}. The second operation is pruning, where the subsets which are in-turn subsets of larger sets are eliminated from the family. For the given example, the family after first pruning is {{1,3} {1,4} {1,5} {2,4} {2,5} {2,6} {3,5} {3,6} {3,7} {4,6} {6,7}}. These two operations are performed iteratively until expansion stops. For the given example, the final family is {{1,3,5} {1,4} {2,5} {2,4,6} {3,5} {3,6,7} {4,6} {5} {6,7} {7}}.

Algorithm 1 *Tree Pruning*
$i = 1$
$F_i = \{\{1\}\ \{2\} \ldots \{M\}\}$
$F_{i+1} = Extend - Family(F_i)$
while $F_{i+1} \neq \phi$ **do**
  $\forall f_i \in F_i; F_i^{final} = \{f_i : f_i \not\subseteq F_{i+1}(k), \forall k\}$
  $i = i + 1$
  $F_{i+1} = Extend - Family(F_i)$
end while
$F^{final} = \bigcup_i F_i^{final}$
procedure $F_{ext} = Extend - Family(F_{orig})$
$F_{ext} = \{\phi\}$
for $i = 1 : length(F_{orig})$ **do**
  for $j = F_{orig}(i, |F_{orig}(i)|) + 1 : M$ **do**
    if $Satisfy(\{F_{orig}(i)j\})$ **then**
      $F_{ext} = F_{ext} \cup \{F_{orig}(i)j\}$
    end if
  end for
end for

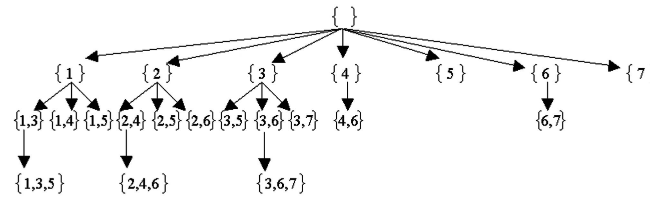


Fig. 4. Instance of tree pruning algorithm on a seven secondary links example system.

7 Potential Games and Secondary Spectrum Sharing

The optimal (centralized) search algorithm described in the previous section gives us the best performance. However, the nature of secondary spectrum sharing is temporary and distributed, a practical secondary spectrum sharing scheme must be distributed. In this section, we develop such a distributed algorithm to solve the operator problem discussed before. This distributed process is composed of two phases. The coordination phase controls the optimal set of active secondary links which can access the spectrum and the power control phase is to allocate transmit power to support the minimum target link SIR γ_i^t given the set of active links.

7.1 Distributed Power Control

Power control plays an important role in dynamic spectrum sharing. Here, secondary nodes maintain their power levels so that the sum of the interference caused by them in a band is below the interference threshold. This allows underlay transmission, thereby maintaining coexistence between primary and secondary users. Clearly, power control in the dynamic spectrum access scenarios has to be distributive in nature. Power control reduces the transmitted power and, hence, the power spectrum density at the measuring point. This improves the efficiency of the spectrum sharing. Besides, power control also reduces the internal interference of the secondary spectrum sharing networks.

When there are M active links, we use the standard DCPC (11) to allocate the transmitting power. This DCPC will make the received SIR converge to the target SIR γ_i^t

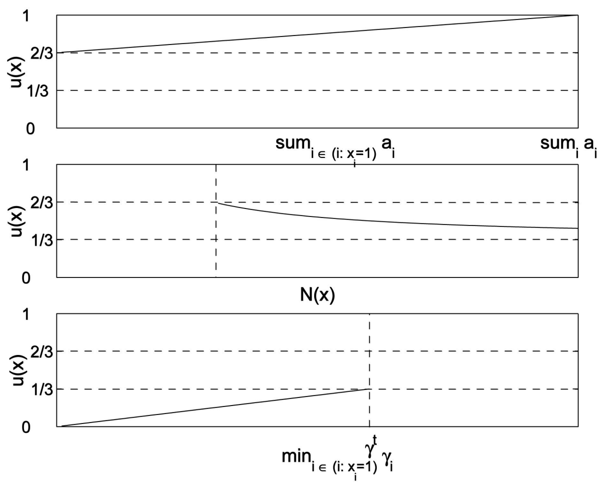


Fig. 5. Utility function $u_i(N(\mathbf{x}))$.

distributively except for cases where maximum transmitting power y_i^{max} is reached.

7.2 Potential Games

Suppose there are M transmitter and receiver link pairs competing for the secondary spectrum access opportunities. Let k be a time (iteration) counter and $N(\mathbf{x}(k))$ be the aggregate received power at the measuring point at time k given by

$$N(\mathbf{x}(k)) = \sum_{i=1}^{M} y_i(k) h_{i0} x_i(k). \tag{17}$$

In order to maximize the network revenue while keeping the aggregated received power at the measuring point under the interference threshold, we define the utility function $u_i(\mathbf{x})$ shown in Fig. 5 for each link pair as follows:

$$u_i(x) = \begin{cases} \frac{\sum_{j \in (j:x_j=1)} a_j}{3\sum_j a_j} + \frac{2}{3}, N(\mathbf{x}(k)) < B, \min_{j\in(j:x_j=1)} \gamma_j > \gamma^t \\ \frac{B}{3N(\mathbf{x}(k))} + \frac{1}{3}, \quad N(\mathbf{x}(k)) \geq B, \min_{j\in(j:x_j=1)} \gamma_j > \gamma^t \\ \frac{\min_{j \in j:x_j=1)} \gamma_j}{3\gamma^t}, \quad \min_{j\in(j:x_j=1)} \gamma_j < \gamma^t. \end{cases} \tag{18}$$

In the secondary spectrum sharing game, each user maximizes its utility function $u_i(\mathbf{x}(k))$ by its choice of being active or not. By maximizing this utility function, the system will reach an operating point where the network revenue is maximized while satisfying QoS and interference temperature constraints. To emphasize that the ith user has control only over its own choice, we use an alternative notation $u_i(x_i, \mathbf{x}_{-i})$, where $\mathbf{x}_{-i}$ denotes the vector consisting of elements of $\mathbf{x}$ other than the ith element, and after each changing of the active link set, the DCPC will be activated to allocate the transmitting power.

Proposition 1. *The secondary spectrum sharing game is a potential game and has a pure strategy (deterministic) equilibrium.*

This proposition comes from the fact that we can define a potential function $\Phi = u(\mathbf{x})$ which satisfies $\triangle\Phi = \triangle u_i(\mathbf{x})$. Hence, we can start from an arbitrary deterministic strategy vector $\mathbf{x}$, and at each step, one player increases its utility. That means that, at each step, Φ is increased identically. Since Φ can accept a finite amount of values, it will eventually reach a local maxima. At this point, no player can achieve any improvement, and we reach a Nash equilibrium (NE). A practical method to achieve the NE would be to use sequential play where each player maximizes its own utility function sequentially while other players' strategies are fixed.

To achieve this sequential play, a simple random access scheme similar to [22] can be introduced where each user makes the update with probability $P_a = 1/N$. More specifically, at the beginning of each time slot, each user flips a coin with probability P_a and, if successful, makes a new decision based on the current values for the utility function value; otherwise, the user takes no new action. This scheme ensures that, on average, exactly one user makes decisions at a time, but of course has a nonzero probability that two or more users take actions simultaneously. But, as reported in [22], this will not destroy the potential function's upward monotonic trend. Of course, one way to reduce the collision would be to decrease P_a, but this will also decrease the convergence speed.

Theorem 3. *The sequential play will never converge to a solution where the total received power at the measuring point exceeds the interference temperature bound.*

Proof. Suppose $\mathbf{x}^0$ is a Nash equilibrium solution of the game and suppose, at this point, $N(\mathbf{x}^0) > B$. Then, by the definition of the utility function (18), we know that one of the link pairs with $x_i = 1$ can always increase its payoff $u_i(x_i, \mathbf{x}^0_{-i})$ by changing its strategy to $x_i = 0$; hence, this point $\mathbf{x}^0$ can never be a Nash equilibrium. We know that the sequential play will never converge to a point which is not a Nash equilibrium. Hence, the above theorem. □

Theorem 4. *The sequential play will always converge to a solution where all the active links are supported with their target SIR.*

Proof. Similar to the previous proof, suppose $\mathbf{x}^0$ is a Nash equilibrium solution of the game and, at this point, let $\gamma_i < \gamma^t$. Then, by the definition of the utility function (18), the link $j = \arg\min_{j\in(j:x_j=1)} \gamma_j$ can always increase its payoff by changing its strategy to $x_j = 0$; hence, this point $\mathbf{x}^0$ can never be a Nash equilibrium. □

To characterize the efficiency of the Nash equilibrium point achieved by the sequential play, let $\mathbf{x}^o$ be the Nash equilibrium strategy profile. This point has the property that either

$$\min_{j\in(j:x^o_j=0)} N(x_j = 1, \mathbf{x}^o_{-j}) > B, \tag{19}$$

which means, at the Nash equilibrium point, if any single secondary link j with $x_j = 0$ changes its choice to $x_j = 1$ unilaterally, the total received power at the measuring point would exceed the interference temperature threshold B or, if adding one more link, some of the active links will not achieve their target SIR. We note that multiple Nash equilibria may exist in this game. Finally, sequential play does not allow asynchronous updates by individual users. This may cause signaling and other overhead. To overcome this issue, we consider a stochastic learning-based distributed solution that is described next.

7.3 Learning Automata

The stochastic learning technique has been successfully used in wireless packet networks for online prediction, tracking, and discrete power control [19], [20]. It is shown to be computationally simple and efficient. The learning algorithm determines probabilistic strategies for players by considering the history of play. The probability updating algorithm used by each of the user is as given below:

1. Set the initial probability $p_i(0)$.
2. At every time step k, the ith user chooses $x_i(k) = 1$ or 0 (to transmit or not) according to its action probability p_i.
3. After the distributed power control (DCPC) phase, each player obtains a feedback $u_i(\mathbf{x}(k))$ based on the set of all actions $\mathbf{x}$.
4. Each player (i) updates its action probability according to the rule:

$$\begin{aligned} p_i(k+1) &= p_i(k) + bu_i(k)(1-p_i(k)) \quad & x(k)=1 \\ p_i(k+1) &= p_i(k) - bu_i(k)p_i(k) \quad & x(k)=0, \end{aligned} \tag{20}$$

where $0 < b < 1$ is the step size and $u_i(k)$ is utility function which lies in the interval (0,1).

5. If p_i converges, stop. Otherwise, go to Step 2.

The probabilistic update used in (20) is a stochastic learning automata updating known as linear reward-inaction (L_{R-I}) [12].

To characterize the proposed learning automata algorithm, we first define the expected payoff for player i as g^i, given by

$$\begin{aligned} g^i(p_1,\dots,p_M) &= E[u_i \mid jth\ player\ employs\ strategy \\ p_j, 1 \le j \le M] &= \sum_{x_1,\dots,x_M} u_i(x_1,\dots,x_M) \prod_{s=1}^{M} p_{sx_s}, \end{aligned} \tag{21}$$

where $p_{sx_s} = p_s$ if $x_s = 1$ and $p_{sx_s} = 1 - p_s$ if $x_s = 0$.

Definition 1. *The N-tuple of strategies $(p_1^o,\dots,p_M^o)$ is said to be a Nash equilibrium, if, for each i, $1 \le i \le M$, we have*

$$\begin{aligned} & g^i(p_1^o,\dots,p_{i-1}^o,p_i^o,p_{i+1}^o,\dots,p_M^o) \\ & \ge g^i(p_1^o,\dots,p_{i-1}^o,p_i,p_{i+1}^o,\dots,p_M^o) \quad \forall p_i \in [0,1]. \end{aligned} \tag{22}$$

In general, each p_i^o above will be a mixed strategy and we refer to $(p_1^o,\dots,p_M^o)$ satisfying (22) as a Nash equilibrium in *mixed* strategies. A Nash equilibrium is said to be in *pure* strategies if $(p_1^o,\dots,p_M^o)$ is a Nash equilibrium with each p_i^o being either 0 or 1. Nash equilibrium is a profile of strategies such that each player strategy is an optimal response to the other players' strategies.

Theorem 5. *The proposed learning automata algorithm converges to one of the Nash equilibria of the game.*

Proof. For any choice of pure strategies, payoffs are the same for all players (users), i.e.,

$$u_i(\mathbf{x}) = u_j(\mathbf{x}), \forall i,j \in M, \forall \mathbf{x} \in \{0,1\}^M.$$

So, we identify this game as a coordination game where at least one Nash equilibrium in pure strategies exists. And further, at least one Nash equilibrium must be Pareto efficient. When considering a game with common payoff, under the L_{R-I} learning algorithm, the automata team converges to one of the Nash equilibria [13]. □

Theorem 6. *The proposed learning automata algorithm will never converge to a point where the total received power at the measuring point exceeds the interference temperature bound.*

Theorem 7. *The proposed learning automata algorithm will always converge to a point where all the active links are supported with their target SIR.*

These two theorems can be proved through the same argument as Theorem 3 and Theorem 4 with the fact that it is known that the stochastic learning algorithm with common payoff games always converges to a pure strategy rather than to a mixed strategy [13]. So, we will only consider pure equilibria.

The learning automata algorithm needs less information and control signalling to operate than the sequential play. The sequential play requires that each player updates its strategy one by one. And, at the time of decision, in order to compute the utility function, the information required includes all active users' SIRs, priorities, and the current interference temperature. Significant control signalling is also required to accomplish this process distributively. An alternative choice would be to run this sequential play at a central controller. For the learning automata, asynchronous updating is permitted. The only information needed is a feedback of the current utility function value. To compute this utility function, each active user should report its SIR and priority parameter to the measurement point which acting also as a central controller. But the trade-off is that learning automata converges much slower than the sequential play. The information needed by these algorithms can be distributed through a common control channel which has been assumed in many similar literatures in this area.

One assumption in this paper is that the interference temperature remains constant during the secondary use of the spectrum. With mobile users, the interference temperature may vary. One solution to account for this variance would be that the secondary access algorithm is triggered periodically. A short period would ensure that, when the interference temperature is violated, the system would recover quickly.

8 Numerical Results

In this section, we first present some numerical examples for a simple secondary sharing system with only three transmitting and receiving pairs. The target SIR is selected to be $\gamma^t = 12.5$, and the noise power is $\sigma^2 = 5 \times 10^{-13}$, which approximately corresponds to the thermal noise power for a bandwidth of 1 MHz. We consider low rate data users using a spreading gain of $L = 128$. Path gains are obtained using the simple path loss model $h_j = K/d_j^4$, where $K = 0.097$. This gives the following gain matrix:

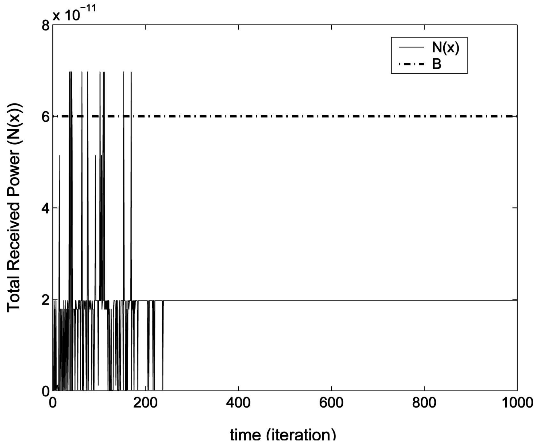


Fig. 6. Evolving of the total received power $(N(x))$ over time for the learning automata algorithm.

$$H' = 10^{-7}\begin{bmatrix} 0.0097 & 0.1552 & 0.0148 \\ 0.0019 & 0.0034 & 0.0066 \\ 0.0748 & 0.0237 & 0.0307 \end{bmatrix}. \quad (23)$$

When the interference temperature bound and noise ratio is $B/\sigma^2 = 200$ (We use these ratios only to illustrate clearly how the system works. Of course, we can use a lower ratio by reducing the target SIR), this three secondary link pair system is feasible. Using the geometric programming optimization method, we find that the maximum aggregate utility is 8.3567, with $\gamma_1 = 12.5$, $\gamma_2 = 12.5$, $\gamma_3 = 27.2541$, $y_1 = 0.0164\text{W}$, $y_2 = 0.0988\text{W}$, and $y_3 = 0.0107\text{W}$ for each link. When $B/\sigma^2 = 60$, the social optimization is infeasible, but we can resort to our proposed potential game. Under equal priority case $\mathbf{a} = [1, 1, 1]$, when using sequential play, after convergence, only link subsets {1,3} or {2,3} can coexist with $\gamma = 12.5$. When the learning automata algorithm is used, the evolution of the total received power $N(\mathbf{x})$ is shown in Fig. 6. As discussed, we see that the total received power converges to a value below the interference temperature threshold B. The evolution of the choice probability p is shown in Fig. 7. After convergence, only links 2 and 3 are active with equal probability initialization. The optimal link subset searching results in the same optimal link subset {1,3} and {2,3}. It can be observed in Fig. 6 that, during the settling phase, $N(x)$ exceeds B. So, depending on the application, there should be some predefined extra margin to accommodate the fluctuation during the settling phase. But, this may reduce the capacity of the secondary system.

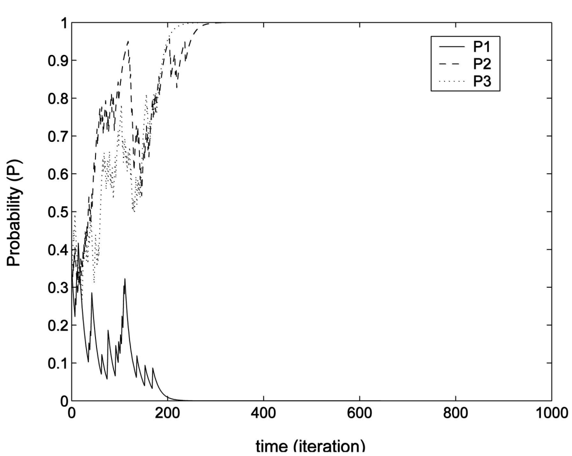


Fig. 7. Choice probability p of the activation strategy over time for learning automata algorithm.

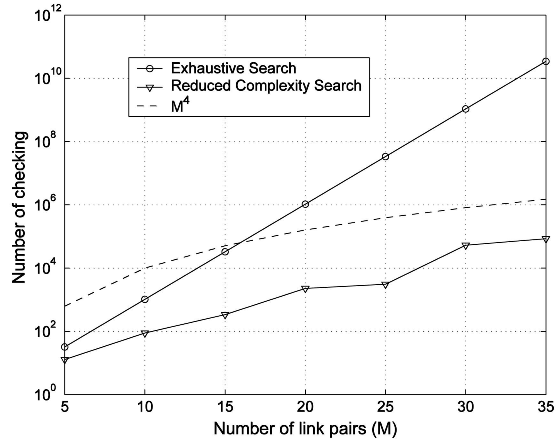


Fig. 8. The reduced complexity search algorithm (tree pruning) versus the naive exhaustive search.

The proposed optimal supported link subset searching algorithm can significantly reduce the searching space, as shown in Fig. 8. Each point in the curve for the reduced complexity search algorithm (tree pruning) results from an averaging over 10 random secondary link geometric distributions with M link pairs, $B/\sigma^2 = 60$ and $\gamma_t = 12.5$. The naive exhaustive search algorithm needs to check 2^M subsets to find the optimal supported secondary link set, while it can be seen that the search complexity for the reduced complexity search in this typical scenario is bounded by M^4, which is polynomial complexity. It is obvious in the worst case when both the target SIR and the interference temperature bounds are absent when the reduced complexity search is similar to exhaustive searching.

Despite the suboptimal nature of the sequential play algorithm, the convergence speed is dramatically reduced, as shown in Fig. 9. It can be seen that, even with 35 total secondary link pairs, the sequential play converges within 100 iterations.

As we have previously mentioned, the actual utility results after convergence depend on the initial starting point for the sequential play. In Fig. 10, we illustrate the variation in the utility obtained with various initializations (100 trials are considered) for an secondary spectrum sharing scenario with 10 link pairs, $B/\sigma^2 = 960$ and $\gamma_t = 12.5$. The priority vector is set to be $\mathbf{a} = [10, 10, 5, 5, 5, 1, 1, 1, 1, 1]$. We can see that considerable utility improvements can be achieved if the algorithm is run repeatedly with different initializations and the best configuration is selected.

Fig. 11 depicts the performance of the sequential play results with respect to the optimal subset searching results. Each point in the sequential play solution curve represents an averaging over 10 trials with an secondary spectrum sharing scenario with 10 link pairs, $B/\sigma^2 = 960$ and $\gamma^t = 12.5$. The priority vector is set to be the same as before.

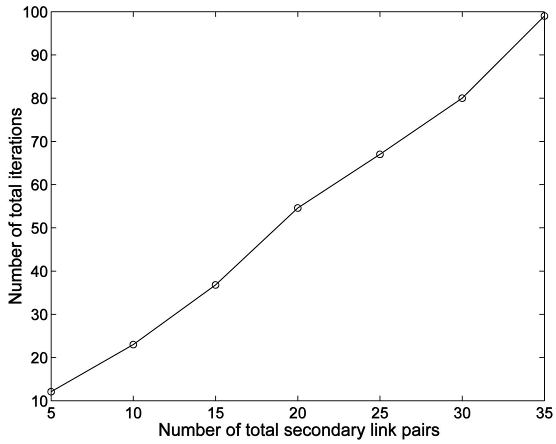


Fig. 9. Convergence of the sequential play.

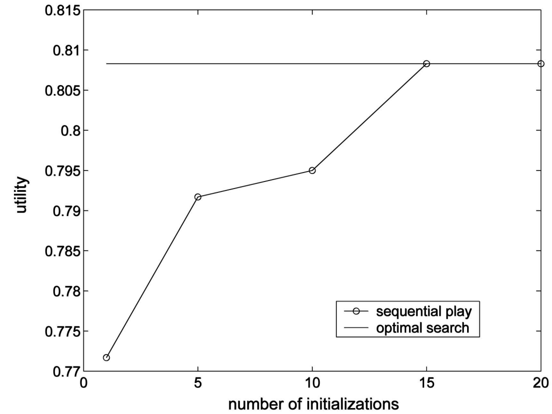


Fig. 11. Optimal subset searching versus sequential play with different initializations.

Even though the sequential play converges to local optimal solutions, it can be seen from Fig. 11 that, as we increase the number of different initializations, the sequential play converges to the optimal solution.

The capacity of the network is evaluated as the total number of active link pairs in our context. When the utility function is concerned, to maximize the capacity corresponds to setting $\alpha = 0$ in the utility function, where $0 \leq \alpha \leq 1$ is an operator designable parameter. Small α corresponds to putting greater emphasis on system capacity (number of active secondary links), while large α corresponds to putting greater emphasis on guaranteeing service to the user paying a higher price. Specifically, with $\alpha = 0$, we can get a similar graph as Fig. 11 with $a = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]$. It can be observed that, as the number of initializations increases, the sequential play converges to the optimal capacity solution.

The converged solution of the sequential play algorithm depends on the initialization which is chosen from the two strategies: active or inactive with equal probability when all the links have equal priority. Hence, on average, when not all the secondary links can be active at the same time, under a long run, they will have the same chance to be active under the condition that they are in the Nash equilibria solution set. This property provisions the sequential play with fairness.

Further, we compared our proposed sequential play algorithm with a Transmit Power Control (TPC) scheme that limits the aggregate interference to the transceiver presented in [5]. In the TPC scheme, the primary transceiver system can control the interference from the Cognitive Radio (CR) devices by broadcasting a beacon signal, containing a parameter α (relevant to the interference it can tolerate). The resulting interference levels at the primary receiver caused by the individual CR devices are equal. This scheme ([5]) did not consider the QoS issues, therefore resulting in degraded performance. As in Fig. 12, there are 10 secondary CR link pairs. The target SIR is 12.5. These links are randomly deployed. As can be observed under the TPC scheme, only one link pair will achieve the target SIR, while under our proposed scheme, there are five links which achieved the target SIR. Hence, under the interference temperature constraint, our proposed scheme efficiently utilized the spectrum for data transmission.

9 Conclusions

We have considered spectrum sharing among a group of spread spectrum users with a constraint on the total interference temperature at a particular measurement point and a QoS constraint for each secondary link. A social

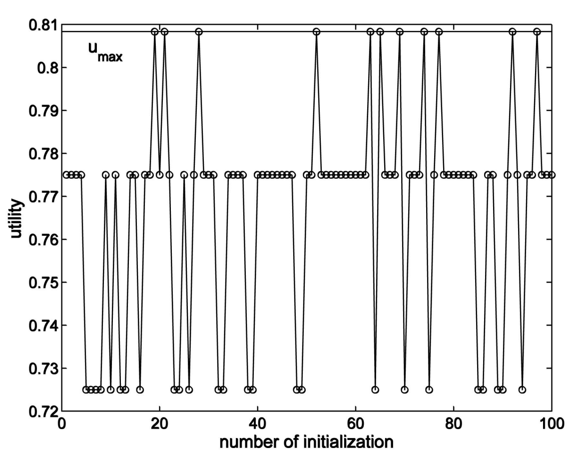


Fig. 10. Utility for different initializations of the sequential play.

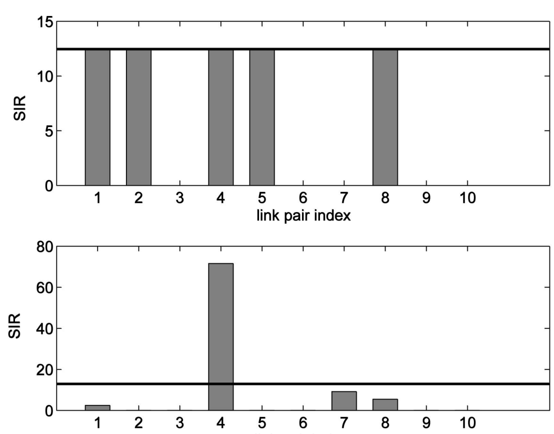


Fig. 12. Sequential play versus TPC scheme.

optimization set-up of this problem is formulated which is solved efficiently by using a geometric programming method. There are cases when this system with all secondary links active will be infeasible. A reduced complexity optimal link subset searching is introduced to find feasible subsets of links which can significantly reduce the searching space compared with naive searching. Then, we define the secondary spectrum sharing problem as a potential game which takes different priority classes into consideration. First, this game is solved through sequential play. The sequential play is shown to converge to the Nash equilibria with acceptable speed but with relatively significant controlling signal and operating information. Then, a learning automata algorithm is introduced which only requires feedback of the utility value to converge to the Nash equilibria, but the drawback is the low convergence speed. The achieved Nash equilibrium is characterized to be a point with a good trade-off between the efficiency and the complexity.

ACKNOWLEDGMENT

This work is supported in part by the US National Science Foundation under grant NSF CAREER 0133761. The authors would like to thank the anonymous reviewers for their constructive comments which led to a significant improvement of the manuscript.

REFERENCES

[1] http://www.sharedspectrum.com/?section=measurements, 2007.

[2] R. Kolodziejski and J. Betz, "Detection of Weak Random Signals in IDD Non-Gaussian Noise," *IEEE Trans. Comm.*, vol. 48, no. 2, Feb. 2000.

[3] N. Sai Shankar, C. Cordeiro, and K. Challapali, "Spectrum Agile Radios: Utilization and Sensing Architectures," *Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN '05)*, 2005.

[4] Federal Comm. Commission, Spectrum Policy Task Force, Report ET Docket no. 02-135, Nov. 2002

[5] J.C. Haartsen, L. Wieweg, and J. Huschke, "Spectrum Management and Radio Resource Management Considering Cognitive Radio Systems," *Proc. XXVIIIth Int'l Union of Radio Science (URSI) General Assembly*, Oct. 2005.

[6] S. Haykin, "Cognitive Radio: Brain-Emprowered Wireless Communications," *IEEE J. Selected Areas in Comm.*, vol. 23, no. 2, Feb. 2005.

[7] J.M. Peha and S. Panichpapiboon, "Real-Time Secondary Markets for Spectrum," *Telecomm. Policy*, vol. 28, nos. 7-8, pp. 603-618, Aug. 2004.

[8] A. Tonmukayakul and M.B.H. Weiss, "Secondary Use of Radio Spectrum: A Feasibility Analysis," *Proc. Telecomm. Policy Research Conf. (TPRC '04)*, Oct. 2004.

[9] J. Huang, R. Berry, and M.L. Honig, "Auction-Based Spectrum Sharing," *ACM/Springer Mobile Networks and Applications J. (MONET)*, vol. 11, no. 3, June 2006.

[10] S. Boyd and L. Vandenberghe, *Convex Optimization.* Cambridge Univ. Press, 2004.

[11] D. Julian, M. Chiang, D. O'Neill, and S. Boyd, "QoS and Fairness Constrained Convex Optimization of Resource Allocation for Wireless Cellular and Ad Hoc Networks," *Proc. INFOCOM*, pp. 477-486, June 2002.

[12] K.S. Narendra and M.A.L. Thathachar, *Learning Automata: An Introduction.* Prentice Hall, 1989.

[13] P.S Sastry, V.V. Phansalkar, and M.A.L. Thathachar, "Decentralized Learning of Nash Equilibria in Multi-Person Stochastic Games with Incomplete Information," *IEEE Trans. Systems, Man, and Cybernetics*, vol. 24, pp. 769-777, May 1994.

[14] D. Fudenberg and J. Tirole, *Game Theory.* MIT Press, 1991.

[15] S.A. Grandhi, J. Zander, and R. Yates, "Constrained Power Control," *Wireless Personal Comm.*, vol. 1, no. 4, 1995.

[16] M. Andersin, Z. Rosberg, and J. Zander, "Gradual Removals in Cellular PCS with Constrained Power Control and Noise," *Wireless Networks*, vol. 2, no. 1, pp. 27-43, 1996.

[17] Y. Xing and R. Chandramouli, "QoS Constrained Secondary Spectrum Sharing," *Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN '05)*, 2005.

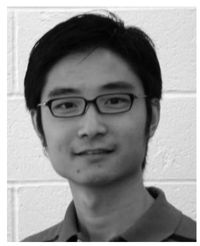
[18] C.N. Mathur, M.A. Haleem, R. Chandramouli, and K.P. Subbalakshmi, "Complexity of Channel Assignment Problems with Constraints in Multi-Hop Wireless Networks," technical report, 2005.

[19] S. Kiran and R. Chandramouli, "An Adaptive Energy Efficient Link Layer Protocol Using Stochastic Learning Control," *Proc. IEEE Int'l Conf. Comm. (ICC '03)*, 2003.

[20] Y. Xing and R. Chandramouli, "Distributed Discrete Power Control for Bursty Transmissions over Wireless Data Networks," *Proc. IEEE Int'l Conf. Comm. (ICC '04)*, 2004.

[21] P. Kolodzy, "Spectrum Policy Task Force: Findings and Recommendations," *Proc. Int'l Symp. Advanced Radio Technologies (ISART '03)*, Mar. 2003.

[22] N. Nie and C. Comaniciu, "Adaptive Channel Allocation Spectrum Etiquette for Cognitive Radio Networks," *Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN '05)*, Nov. 2005.



Yiping Xing (S'03) received the BS degree from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2001 and the ME degree from the Stevens Institute of Technology, Hoboken, New Jersey, in 2004, both in electrical engineering. He is currently working toward the PhD degree in the Department of Electrical and Computer Engineering at the Stevens Institute of Technology. His current research interests include radio resource management for cellular and ad hoc networks, access control for cognitive radios, and game theory for wireless networks. He received the Outstanding Research Award in 2005 and the Graduate Fellowship Award in 2006 from the Stevens Institute of Technology. He is also the recipient of the IEEE CCNC '06 best student paper award. He is a student member of the IEEE.

Chetan N. Mathur received the BE degree in computer science from the Visveshwaraiah Institute of Technology, Bangalore, India, in 2002 and the MS degree in computer engineering from the Stevens Institute of Technology, New Jersey. Part of his MS thesis was patented by the Stevens Institute of Technology. He is currently pursuing the PhD degree in computer engineering at the Stevens Institute of Technology, New Jersey. In the past few years, he has published several research papers in the fields of cryptography, coding theory, and dynamic spectrum access. He has also received numerous awards, including the IEEE best student paper award presented at IEEE Consumer Communications and Networking Conference (CCNC '06) and the IEEE student travel grant award presented at the International Conference on Communications (ICC '05). He is an active student member of the IEEE and is on the advisory board of Tau Beta Pi, the national organization of engineering excellence.

M.A. Haleem (S'94-M'03) received the BSc Eng degree with specialization in electrical and electronic engineering from the University of Peradeniya, Kandy, Sri Lanka, in 1990, the MPhil degree in electrical and electronic engineering from the Hong Kong University of Science and Technology, Hong Kong, in 1995, and the PhD degree in electrical and computer engineering from the Stevens Institute of Technology, Hoboken, New Jersey, in 2005. Dr. Haleem was with the Wireless Communications Research Department, Bell Laboratories, Lucent Technologies Inc., Crawford Hill, Holmdel, New Jersey, from 1996 to 2002 as a consultant and a member of the technical staff. He was with the Department of Electrical and Electronic Engineering, University of Peradeniya, Sri Lanka, from 1990 to 1993 and held the position of lecturer. He is currently a postdoctoral researcher in the Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, New Jersey. He is a member of the IEEE.

R. Chandramouli (M'00) is an associate professor in the Electrical and Computer Engineering (ECE) Department at the Stevens Institute of Technology. His research in wireless networking, cognitive radio networks, wireless security, steganography/steganalysis, and applied probability is funded by the US National Science Foundation, US AFRL, US Army, ONR, and industry. He has served as an associated editor for the *IEEE Transactions on Circuits and Systems for Video Technology* (2000-2005). Currently, he is the founding chair of the IEEE Technical Sub-Committee on Cognitive Networks, technical program vice chair of the IEEE Consumer Communications and Networking Conference (2007), and chair of the Mobile Multimedia Networking Special Interest Group of the IEEE Multimedia Communications Technical Committee. He is a senior member of the IEEE.

K.P. Subbalakshmi is an assistant professor in the Electrical and Computer Engineering Department at the Stevens Institute of Technology. Her research interests include multimedia security, wireless security, and joint source channel coding. Her research is funded through grants from the US National Science Foundation, US Air Force Research Laboratory, US Army, ONR, and industry. She has served as a guest editor for the *IEEE Journal on Selected Areas of Communications* special issue on cross-layer optimized wireless multimedia communication. Currently, she serves as the secretary of IEEE Multimedia Communications Technical Committee and the chair of the Security Special Interest Group of the IEEE Multimedia Communications Technical Committee. She is involved in organizing/chairing several IEEE symposia and conferences, including the IEEE Symposium on Network and Information Systems Security, GLOBECOM '06. She is a senior member of the IEEE.