Coordinated Channel Access in Cognitive Radio Networks: A Multi-level Spectrum Opportunity Perspective

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***Abstract*—In a cognitive radio network (CRN), spectrum opportunities should be efficiently utilized through careful coordination between cognitive radio (CR) users. In this paper, we formulate the coordinated channel access as a joint power/rate control and channel assignment optimization problem, with the objective of maximizing the sum-rate achieved by all CRs over all channels. The problem is formulated under a generalized multi-level spectrum opportunity framework, which reflects the *microscopic* spatial opportunity available to CRs. A centralized polynomial-time approximate algorithm to the problem is developed. We prove the algorithm's correctness and show its accuracy through numerical examples.**

I. Introduction

Cognitive radio networks (CRNs) have recently received a substantial amount of interest as a means of improving spectrum utilization. Aiming at opening up the under-utilized sectors of the licensed spectrum for secondary reuse, cognitive radios (CRs) can dynamically access a channel, provided that their communications do not cause harmful interference to the licensed users of that channel (a.k.a., the primary radios (PRs)). The operation of a CRN needs to address two essential problems: (1) discovery of spectrum opportunities, i.e., idle channels that can be used by CRs, and (2) efficient reuse of such opportunities. While numerous studies have been dedicated to the first problem based on channel sensing techniques, the second problem remains a challenge in a multi-CR environment. This is because different CRs may sense the same channel and determine it to be available. Therefore, channel access needs to be carefully coordinated between these CRs to avoid collisions and more importantly, ensure efficient utilization of the spectrum opportunity from a network-wide point of view.

In this work, we study the coordinated channel access problem between CRs by formulating it as a joint power/rate control and channel assignment optimization problem. Given the available channels at different CRs, we need to specify for each CR which channels it should transmit on and what powers and rates it should use on these channels. In contrast to previous work that aims at maximizing the information-theoretic capacity of the system, in this work our objective is to maximize the sum-rate achieved by each CR. Unlike the information-theoretic capacity that is defined as a logarithmic function of the received signal-to-interference-plus-noise ratio (SINR), the rate in our setup depends on the PHY-layer implementation. In other words, our problem has a wider scope and can be applied to any arbitrarily given rate-SINR relationship.

Coexistence between PRs and CRs in the same system also gives rise to a new structure for our problem. Two new types of interference need to be accounted for: PR-to-CR interference and CR-to-PR interference. The latter is more critical and should be constrained, because it directly influences PRs' operation. For each CR and each channel, we adopt a *power mask* to describe the maximum transmission power the CR can use without causing unacceptable interference to neighboring PRs. By nature, this power mask is *multi-level*. For example, consider the scenario in Figure 1, where two PR links ($a \to b$ and $c \to d$) and one CR link (CR1 $\to$ CR2) exist in the same vicinity and share the same frequency channel. CR1 can transmit as far as its received power at the closest active PR receiver is smaller than the PR's interference tolerance, for which we assume a small value for all the PRs. So depending on the status (ON/OFF) of the PR links, CR1's power mask takes one of three levels: (PR's interference tolerance)$/h_{1b}$ (Level 1), (PR's interference tolerance)$/h_{1d}$ (Level 2), and $P_{\max}$ (Level 3, the full power supported by the CR's battery), where h_{ij} is the channel gain between nodes i and j, and the circles denote the interference ranges of various levels. Note that this multi-level structure is a generalization of the widely-used *binary* structure, whereby the power mask is 0 if any of the PR neighbors is active, or $P_{\max}$ if none of its PR neighbors is active. We realize that this multi-level structure reflects the *microscopic* spatial opportunity for CRs, and can be potentially exploited to increase the CRN's throughput. So we attempt to accommodate this general form of spectrum opportunity in our optimization. Consequently, our formulation becomes more complicated, because now the same channel may present different levels of availability to different CRs.

The multi-level structure of the power mask makes the widely-used SINR-based approximation unapplicable to our problem. For example, in many existing power/rate control and channel assignment problems, a convex formulation is obtained through the capacity approximation $\log(1+\text{SINR}) \approx \text{SINR}$ if SINR $\ll 1$ (low-SINR regime, e.g., see [9]) or $\log(1+\text{SINR}) \approx \log(\text{SINR})$ if SINR $\gg 1$ (high-SINR regime, e.g., see [11]). However, now a CR is expected to operate over a wide range (low-, mid-, and high-) of SINR regimes over time due to the multiple levels of the power mask. Even at a time instance, different CRs may be operating in different SINR regimes. Therefore, those approximation techniques adopted separately for low- and high-SINR regimes

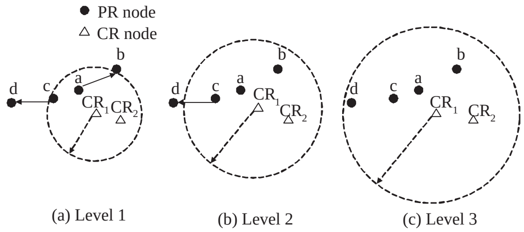

Fig. 1. An example of the multi-level spectrum opportunity.

are no longer appropriate here. A new SINR-independent treatment is needed for the problem.

The contributions of this work are as follows. We first show that the joint power/rate control and channel assignment problem can be formulated as a mixed integer nonlinear programming (MINLP) problem, which is known to be NP-hard. By exploiting the discrete set of rates supported by the CR on each channel, we transform this MINLP to a binary linear programming (BLP) problem that only contains binary variables and linear objective function and constraints. This transformation applies to any given rate-SINR relationship. We then develop a centralized polynomial-time Linear Programming with Sequential Fixing (LPSF) approximate algorithm for the BLP. This algorithm is based on iteratively solving a series of linear programming problems and sequentially fixing the variables to either 1 or 0 in each iteration. In contrast to other sequential-fixing-based algorithms (e.g., [3]), this algorithm guarantees finding of a feasible solution. We prove the correctness of our algorithm. Its accuracy is then verified through simulations. Results show that the performance gap between the approximate and exact solutions is less than 10%.

The rest of this paper is organized as follows. We review the related work in Section II. We describe the models and formulate the optimization problem in Section III. The transformation to BLP formulation and the centralized algorithm are presented in Section IV. Simulations and discussion are provided in Section V, and we conclude the work in Section VI.

II. Related Work

Much of the related work is based on the binary-type spectrum opportunity. Early works provide collision-free channel assignment for CR nodes given a set of available channels at each node. This problem can be described as an interference-graph vertex-coloring problem [15]. To obtain a fast solution, various distributed approximations were proposed, which are based on observing local interference patterns [14], local bargaining [1], or on coordinations between CR nodes that aim at maximizing some system utility [2]. Because of the graph-theoretic nature of these algorithms, they take transmission power as input rather than output, and thus are not applicable to power/rate control problems.

The second body of work considers the sensing/channel access decision-making process from a single CR's viewpoint. This is also termed *MAC-layer sensing*. Existing works include the partially observable Markov decision process (POMDP) model [13], the constrained Markov decision processes (CMDPs) model [12], and the optimal stopping-rule models [5]. Assuming a semi-Markov process for PR traffic, Kim and Shin [6] proposed a sensing-period adaptation algorithm that maximizes the discovery of spectrum opportunities and minimizes the delay in finding an available channel. Based on a similar PR traffic model, the authors in [4] studied a dynamic access scheme subject to a constraint on the CR-to-PR violation rate, but only for a system of one PRN and one CR link. The coordinated use of spectrum opportunities at neighboring CRs has not been considered in these works, and collisions between CR transmissions are resolved using standard CSMA/CA techniques. Such treatment leads to non-optimal performance from a network's viewpoint.

The third type of work simplifies the problem by restricting the treatment to CR nodes only. So the CR-to-PR and PR-to-CR interferences do not appear in their formulation. Within this category, Hou et al. [3] considered the joint optimization of spectrum, scheduling, and routing in a multi-hop software-defined-radio (SDR) network. Yi and Hou [7] [8] studied the joint optimization of power control, scheduling, and routing for a multi-hop SDR network based on a logarithmic rate-SINR relationship assumption.

III. System Model and Problem Formulation

We consider a distributed (ad hoc) CRN that coexists with M legacy (fixed spectrum) PRNs over a finite area. PRN m, $m = 1, \ldots, M$, is licensed to operate over its own frequency channel of bandwidth B_m. In reality, a PRN may occupy more than one frequency channel. Such a network can be easily captured in our model by using multiple (virtual) PRNs that operate over different channels.

Let the number of CR links in the system be N. A CR link refers to a pair of CR sender and a CR receiver. For CR link i, we denote the sender and the receiver by $S(i)$ and $D(i)$, respectively. A CR link can transmit over multiple non-contiguous channels simultaneously. Let the transmission power on channel m be $P_i^{(m)}$. To avoid unacceptable CR-to-PR interference, this transmission power must be constrained below certain power mask $\hat{P}_i^{(m)}$. The value of $\hat{P}_i^{(m)}$ is related to the status of neighboring PRs and thus changes over time. For now, we assume that the value of $\hat{P}_i^{(m)}$s, $i = 1, \ldots, N$ and $m = 1, \ldots, M$, are given in each snapshot as input parameters of the joint power/rate control and channel assignment problem. The calculation of $\hat{P}_i^{(m)}$ is considered in our technical report [10].

We stick to the *protocol model* for the collisions between CRs. We say that CR links i and j are interfering links on channel m if $\hat{P}_i^{(m)} h_{S(i)D(j)} > P_{I,CR}$ or $\hat{P}_j^{(m)} h_{S(j)D(i)} > P_{I,CR}$, where $h_{S(i)D(j)}$ and $h_{S(j)D(i)}$ are the cross-link channel gains of the two links, and $P_{I,CR}$ is a small fixed value, denoting the sensitivity of the CR receiver. Any received power below $P_{I,CR}$ can be deemed as ignorable in terms of interference. We assume that an exclusive channel occupancy policy is used to resolve collision between CRs: For any two interfering CR links on channel m, only one of them can access the channel at any given time.

Treating interference as noise, the rate of CR link i on channel m is given by

$$R_i^{(m)} = B_m f\left(\frac{P_i^{(m)} h_i^{(m)}}{q_{D(i)}^{(m)} + N_0}\right) \quad (1)$$

where f is any arbitrary rate-SINR function decided by the PHY-layer implementation, $h_i^{(m)}$ is the channel gain of link i on channel m, $q_{D(i)}^{(m)}$ is the received interference over channel m at $D(i)$, and N_0 is the AWGN. Because an exclusive channel occupancy policy is used, the interference $q_{D(i)}^{(m)}$ only comes from active co-channel PRs and can be measured by the CR receiver $D(i)$ on line.

For $i = 1, \ldots, N$ and $m = 1, \ldots, M$, define variables

$$x_i^{(m)} \stackrel{\text{def}}{=} \begin{cases} 1, & \text{if channel } m \text{ is used by CR link } i \text{, i.e., } R_i^{(m)} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Our objective is to maximize the sum of rate of all CR links over all channels in current snapshot, i.e.,

$$\text{maximize} \sum_{i=1}^{N} \sum_{m=1}^{M} x_i^{(m)} R_i^{(m)} \quad (3)$$

where the maximization is to be carried out with respect to $x_i^{(m)}$'s and $R_i^{(m)}$'s.

A CR link i should satisfy the following constraints:

C1: CR-to-PR constraint: The transmission power of link i on channel m should not exceed the power mask $\hat{P}_i^{(m)}$. From (1), this constraint can be written in terms of $R_i^{(m)}$ as

$$\frac{1}{h_i^{(m)}}(q_{D(i)}^{(m)} + N_0) f^{-1}(r_i^{(m)}) \leq \hat{P}_i^{(m)}, \quad m = 1, \ldots, M \quad (4)$$

where f^{-1} is the inverse function of f, and $r_i^{(m)} = \frac{R_i^{(m)}}{B_m}$ is the spectrum efficiency of link i on channel m.

C2: Power supply constraint: The sum of the transmission powers over all channels should not exceed the maximum power provided by the battery, i.e.,

$$\sum_{m=1}^{M} \frac{1}{h_i^{(m)}}(q_{D(i)}^{(m)} + N_0) f^{-1}(r_i^{(m)}) \leq P_{\max,i}. \quad (5)$$

C3: CR-to-CR collision constraint: If channel m is being used by CR link i, then it cannot be used by another CR link that interferes with link i on channel m, and vice versa:

$$x_i^{(m)} + x_j^{(m)} \leq 1, \quad \forall j \in I_i^{(m)} \quad (6)$$

where $I_i^{(m)} = \left\{j : j \neq i, \hat{P}_i^{(m)} h_{S(i)D(j)}^{(m)} > P_{I,CR}\right\} \cup \left\{j : j \neq i, \hat{P}_j^{(m)} h_{S(j)D(i)}^{(m)} > P_{I,CR}\right\}$ is the set of interfering CR links of link i on channel m.

C1 to C3 are the basic constraints that apply to all CRNs. Additional constraints may exist depending on the CR's PHY-layer implementation, e.g., see [10]. For simplicity, we only include C1 to C3 to our formulation in this paper.

IV. Solutions

A. Transformation to BLP

An observation of the objective function (3) and the constraints C1-C3 shows that this formulation constitutes a *mixed integer nonlinear programming (MINLP)* problem. The solution to such a problem is NP-hard, in general. To make this formulation more amenable for further processing, we exploit the fact that actual communication systems only support a finite set of discrete transmission rates on each channel. Denote this set of rates by $\mathbf{U} = \{0, u_1, u_2, \ldots, u_K\}$ (in b/s/Hz), where $0 < u_1 < \ldots < u_K$. Define $\gamma_k \stackrel{\text{def}}{=} f^{-1}(u_k)$ for $k = 1, \ldots, K$; γ_k is the received symbol energy to interference plus noise density ratio (E_S/I_0) required to support the kth rate under the power-rate relationship defined by (1). Let $C_i^{(m)} \stackrel{\text{def}}{=} \frac{1}{h_i^{(m)}}\left(q_{D(i)}^{(m)} + N_0\right)$ for $i = 1, \ldots, N$ and $m = 1, \ldots, M$. $C_i^{(m)}$ is a known quantity for each CR link on each channel. We further define a new variable $y_{k,i}^{(m)}$ for all $k = 1, \ldots, K$, $i = 1, \ldots, N$, and $m = 1, \ldots, M$:

$$y_{k,i}^{(m)} \stackrel{\text{def}}{=} \begin{cases} 1, & \text{if link } i \text{ is transmitting on channel } m \text{ using rate } u_k \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

In addition, we add the following constraint on $y_{k,i}^{(m)}$:

$$\sum_{k=1}^{K} y_{k,i}^{(m)} \leq 1. \quad (8)$$

which accounts for the fact that a link can use at most one rate on a given channel at a time. It is easy to show that the following relation holds:

$$x_i^{(m)} = \sum_{k=1}^{K} y_{k,i}^{(m)}. \quad (9)$$

Similarly, we can rewrite the spectrum efficiency $r_i^{(m)}$ in terms of $y_{k,i}^{(m)}$ and u_k:

$$r_i^{(m)} = \sum_{k=1}^{K} u_k y_{k,i}^{(m)}. \quad (10)$$

Substituting (9) and (10) into (3) through (6), we get the following equivalent formulation to the original MINLP problem:

$$\begin{array}{lll} & \text{maximize} & \sum_{i=1}^{N}\sum_{m=1}^{M}\sum_{k=1}^{K} B_m u_k y_{k,i}^{(m)} \\ & \text{such that} & \\ \tilde{C}1: & & C_i^{(m)} \sum_{k=1}^{K} \gamma_k y_{k,i}^{(m)} \leq \hat{P}_i^{(m)} \\ \tilde{C}2: & & \sum_{m=1}^{m} C_i^{(m)} \sum_{k=1}^{K} \gamma_k y_{k,i}^{(m)} \leq P_{\max,i} \\ \tilde{C}3: & & \sum_{k=1}^{K} y_{k,i}^{(m)} + \sum_{k=1}^{K} y_{k,j}^{(m)} \leq 1, \quad \forall j \in I_i^{(m)} \end{array} \quad (11)$$

where the maximization is w.r.t. the $y_{k,i}^{(m)}$'s.

An examination of (11) shows that the former MINLP problem has been transformed into a binary linear program (BLP) that contains only binary variables and linear objective function and constraints. A nice property of (11) is that the rate levels u_k, $k = 1, \ldots, K$, and the corresponding γ_k's are fed into the BLP formulation as tuples (u_k, γ_k). In other words, the BLP formulation does not rely on the specific functional relationship between u_k and γ_k, and thus can accommodate any arbitrary rate-power relation (e.g., a staircase-like function that characterizes practical multi-rate systems).

B. LPSF Centralized Algorithm

A BLP is a combinatorial problem. Its solution, in general, is NP-hard. A typical algorithm to approximately solve this problem is the so-called *branch-and-bound* algorithm, whose worst-case time complexity is exponential.

Instead of employing a branch-and-bound algorithm, we develop polynomial-time approximate algorithms by exploiting the special structure of the problem. An observation of (11) indicates that if we relax $y_{k,i}^{(m)}$'s from their binary values and allow them to take real values between 0 and 1, then the formulation becomes a linear program (LP) that is solvable in polynomial time. In addition, the constraint $\tilde{C}3$ dictates that if for some m, k, and i, $y_{k,i}^{(m)} = 1$, then $y_{h,i}^{(m)} = 0$ for all $h \neq k$ and $y_{l,j}^{(m)} = 0$ for all $j \in I_i^{(m)}$ and $1 \leq l \leq K$. In other words, a strong dependence exists between the $y_{k,i}^{(m)}$'s that belong to the same interfering CR link set. The main idea behind our fast approximate solution is to fix the values of $y_{k,i}^{(m)}$'s sequentially through solving a series of relaxed LP problems, with at least one $y_{k,i}^{(m)}$ finalized to a binary value at each iteration.

Our approximation algorithm, called LP with sequential fixing (LPSF), is described in Table I. In the first iteration, we append the constraint $0 \leq y_{k,i}^{(m)} \leq 1$ to (11) and relax all $y_{k,i}^{(m)}$'s to real values between 0 and 1. We refer to the resulting formulation as LP$^{(1)}$, which must have a feasible solution according to Lemma 1. The solution to LP$^{(1)}$ is an upper bound on the optimal solution to (11), because the feasibility region of the BLP is a subset of that of LP$^{(1)}$. However, the solution of LP$^{(1)}$ is, in general, not a feasible solution to the original BLP problem, because the $y_{k,i}^{(m)}$'s can now take values between 0 and 1. Among all $y_{k,i}^{(m)}$'s, we pick the one that has the largest value, and we denote this $y_{k,i}^{(m)}$ by $Y_{k,i}^{(m)}$ for ease of identification. We set $Y_{k,i}^{(m)} = 1$. Accordingly, all $y_{h,i}^{(m)}$'s for $h \neq k$ and all $y_{l,j}^{(m)}$'s for $j \in I_i^{(m)}$ and $1 \leq l \leq K$ must now be set to 0. Substituting these $y_{k,i}^{(m)}$'s with their fixed values into the LP$^{(1)}$, we get a new LP, called LP$^{(2)}$, whose variables do not include those that have been fixed after the execution of LP$^{(1)}$ (such variables have been replaced by their binary values). A feasibility check is then conducted on LP$^{(2)}$. If the feasible region of LP$^{(2)}$ is empty, that means the first fixing in this iteration, i.e., $Y_{k,i}^{(m)} = 1$, is not correct. So we reset $Y_{k,i}^{(m)}$ to 0. This change means all those variables that belong to the same interfering CR link set as $Y_{k,i}^{(m)}$ and whose values have been fixed to 0 in this iteration must now become variables. The revised fix, i.e. $Y_{k,i}^{(m)} = 0$, is then substituted into LP$^{(1)}$, giving rise to LP$^{(3)}$. LP$^{(3)}$ must be feasible (see Lemma 2). In a nutshell, at this point we either have a feasible LP$^{(2)}$ or have a feasible LP$^{(3)}$. In either case, the new feasible formulation is renamed as LP$^{(1)}$ and a new iteration starts following the same process above. The process is repeated until all $y_{k,i}^{(m)}$'s are set to either 0 or 1. The final rate allocation of each link on each channel is calculated according to (10).

Note that a similar algorithm was suggested in [3] to solve a different problem. From a methodology's standpoint, the major difference between our algorithm and the one in [3] is that there is no guarantee that an feasible solution can be found at the termination of the algorithm in [3]. Our algorithm improves upon [3] by adding a revised-fixing component when any intermediate fixing leads to infeasibility, such that a feasible solution can always be found. We now prove the correctness of our algorithm.

STEP 0: Get LP$^{(1)}$ by appending $0 \leq y_{k,i}^{(m)} \leq 1$ to (11) and relaxing all variables to real values.
STEP 1: Solve LP$^{(1)}$.
STEP 2: Pick $Y_{k,i}^{(m)} \Leftarrow \max\left\{y_{l,j}^{n}, l \in (1,\ldots,K), j \in (1,\ldots,N), n \in (1,\ldots,M)\right\}$.
STEP 3: Get LP$^{(2)}$ by substituting $Y_{k,i}^{(m)} = 1$, $y_{h,i}^{(m)} = 0$ for $h \neq k$ and $y_{l,j}^{(m)} = 0$ for $\forall j \in I_i$ and $1 \leq l \leq K$ into LP$^{(1)}$.
STEP 4: If LP$^{(2)}$ is feasible
  LP$^{(1)} \Leftarrow$ LP$^{(2)}$
 else
  Get LP$^{(3)}$ by substituting $Y_{k,i}^{(m)} = 0$ into LP$^{(1)}$.
  LP$^{(1)} \Leftarrow$ LP$^{(3)}$
 End-if
STEP 5: If all variables are fixed, then **Terminate**; otherwise go to **STEP 1**.

TABLE I
LPSF ALGORITHM.

Theorem 1: The LPSF algorithm can correctly determine the binary values of all $y_{k,i}^{(m)}$'s in no more than NMK iterations.

The proof of Theorem 1 is based on the following lemmas.

Lemma 1: In the first iteration, LP$^{(1)}$ has an optimal solution.

Proof: It is easy to show that at least $y_{ki}^{(m)} = 0$ for all $k = 1,\ldots,K$, $i = 1,\ldots,N$, and $m = 1,\ldots,M$, is a feasible solution to the original BLP. Thus it is also a feasible solution to LP$^{(1)}$. Note that all variables are bounded between [0, 1], therefore Lemma 1 holds. ■

Lemma 2: In the first iteration, LP$^{(3)}$ has an optimal solution.

Proof: According to Lemma 1, LP$^{(1)}$ in the first iteration must have optimal solution, therefore $Y_{ki}^{(m)} \geq 0$ must holds before the fix. When $Y_{ki}^{(m)}$ is fixed to 0 to get LP$^{(3)}$, its value is changed from no less than 0 to 0, leading to a non-increase in the required transmission power. So no R.H.S. of C1' through C3' could be violated by this non-increasing action on the L.H.S. of C1' through C3'. Therefore LP$^{(3)}$ must have at least one feasible solution. Noting that all variables are bounded between [0, 1], Lemma 2 holds. ■

Lemma 3: LP$^{(1)}$ and LP$^{(3)}$ have optimal solutions in all iterations.

Proof: The situation in the first iteration is proved by Lemma 1 and Lemma 2. In the second iteration, LP$^{(1)}$ comes from either a feasible LP$^{(2)}$ or a feasible LP$^{(3)}$ of the first iteration. So LP$^{(1)}$ must be feasible in the second iteration. Given LP$^{(1)}$ is feasible in the second iteration, the rational used in proving Lemma 2 also applies here to prove the feasibility of LP$^{(3)}$ in the second iteration. This induction repeats itself in all iterations. Noting that all variables are bounded between [0, 1], Lemma 3 holds. ■

The proof of Theorem 1 is straightforward: Iteratively applying Lemmas 1 to 3, it is guaranteed that in each iteration at least one $y_{ki}^{(m)}$ is fixed to either 0 or 1 and a new feasible LP$^{(1)}$ is generated for the next iteration. For the last iteration, if fixing $y_{ki}^{(m)}$ to 1 does not lead to a feasible BLP solution, then

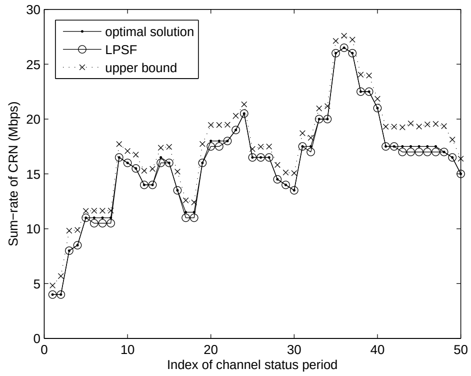

Fig. 2. Trace of the CRN's sum-rate.

changing its value to 0 must lead to a feasible BLP solution (due to the same reason as in the proof of Lemma 2). ■

Based on Theorem 1, it is easy to show that the time complexity of the LPSF algorithm is bounded by the complexity of the LP solver times NMK. Because a LP solver has polynomial complexity, the complexity of the LPSF is also polynomial. In addition, the performance gap between the approximate solution and the actual optimum can be explicitly evaluated by comparing against the upper bound of the optimal solution, which is the the solution to $\text{LP}^{(1)}$ in the first iteration. Lemma 1 has guaranteed the existence of this upper bound. We will shortly show by simulation that this gap is very small (below 10%), and in most cases it is zero.

V. Simulation Results

We consider a 1000×1000 meter^2 region, where 5 PRNs (5 channels) coexist with 5 CR links. The numbers of PRs over each channel are 25, 10, 15, 20, and 25, respectively. Each channel has 1 MHz of bandwidth. We assume the following rate-SINR relationship: $R_i^{(m)} = B_m \log_2(1 + \text{SINR}/8)$ and $r_i^{(m)} \in \{0, 1/2, 1, 3/2, 2\}$ bits/second/Hz for all i and m. The locations of the PR and CR transmitters and receivers are randomly selected. A path loss model with exponent of 4 is assumed for the channel gain between any two points. We assume the PRs on all channels follow the same 2-state Markov activity model, i.e., durations of ON/OFF states are exponentially distributed, with average ON and OFF periods set to 1 s and 10 s, respectively. The transmission power of a PR is 500 mW. $P_{\max}$ for a CR is 1 W. We take the interference tolerance $P_I = 2P_{I,CR} = 0.12346$ μW. The power masks of all CRs are calculated periodically according to the SB scheme described in [10]. A CR is capable of using all 5 channels at one time. We compare the sum-rate of all CR links achieved in each reporting period under an exhaustive-search algorithm that finds the optimal solution and our polynomial-time LPSF algorithm.

A sample trace of the CRN sum-rate is plotted in Figure 2 for 50 consecutive periods. The upper bound generated in the first iteration of the LPSF algorithm is also shown. It is clear that the LPSF algorithm gives near-optimal solutions. In all cases, these solutions are within 5% from the optimal solution, and are often optimal. The upper bound provided by the LPSF algorithm is reasonably tight. In all simulations, the gap between this bound and the optimal solution does not exceed 10%. So this bound provides a useful reference to evaluate the accuracy of the approximate solution in large networks when the optimal solution is computationally difficult to obtain.

VI. Conclusions

In this paper, we developed a centralized algorithm to solve the joint power/rate control and channel assignment problem for the coordinated channel access in CRNs. The problem is formulated under a multi-level spectrum opportunity framework that reflects the microscopic spatial opportunity available to CRs. Currently, our work only applies to single-hop ad hoc CRNs. Our future efforts will address multi-hop environments.

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