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Research Article

Cognitive Code-Division Channelization with Admission Control

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We consider the problem of joint resource allocation and admission control in a secondary code-division network coexisting with a narrowband primary system. Our objective is to find the maximum number of admitted secondary links and then find the optimal transmitting powers and code sequences of those secondary links such that the total energy consumption of the secondary network is minimized subject to the conditions that primary interference temperature constraints, secondary signal-to-interference-plus-noise ratio (SINR) constraints and secondary peak power constraints are all satisfied. This is an NP-hard optimization problem which motivates the development of suboptimal algorithms. We propose a novel iterative algorithm to solve this problem in a computationally efficient manner. Numerical results demonstrate that the proposed algorithm provides excellent solutions that result in high energy efficiency and large admitted percentage of secondary links.

1. Introduction

With the explosive demand in wireless service in recent years, radio spectrum has become the scarcest resource for the modern wireless communication industry. Therefore, both spectrum regulation makers and wireless technology specialists endeavor to seek solutions that would increase the amount of available frequency spectrum. With the FCC's report that much of the licensed radio spectrum is highly underutilized [1], the concept of *cognitive radio* was proposed as a solution to the spectrum scarcity problem, where secondary (unlicensed) users can opportunistically access the licensed spectrum provided that they do not cause any "harmful" interference to the primary (licensed) network. From the realization point of view, cognitive radio networking can be realized using two approaches: underlay and overlay [2]. Conventional cognitive radio proposals utilize the overlay approach where secondary users (SUs) detect *spectrum holes* (frequency bands not used by primary users) by sensing the whole spectrum and then transmit over them. In contrast, under the underlay approach, SUs can coexist with the primary users (PUs) as long as interference from SUs does not exceed the tolerable *interference temperature* at the primary receivers. Spread spectrum technology has been proposed as the most promising technology to maximize frequency reuse by exploiting the underlay approach [3]. Spread spectrum technology allows cognitive code-division users to coexist in parallel in frequency and time with primary users. The major challenge is to admit the maximum number of secondary users to access the spectrum and efficiently allocate power and signature to each secondary user.

Admission control and resource allocation problem can be traced back to the 90's. In [4, 5], Foschini and Miljanic proposed a distributed asynchronous power control algorithm under predefined signal-to-interference-plus-noise constraints in conventional cellular systems, which converges to the optimal power allocation solution that minimizes the total transmission power. Furthermore, a distributed power control problem under user-specific signal-to-interference-plus-noise ratio (SINR) and power budget constraints was considered in [6], where distributed constrained power control (DCPC) and asynchronous distributed constrained power control (ADCPC) schemes were developed to maximize the minimum SINR of all users under synchronous and asynchronous power updates, respectively. In [7, 8], admission control problem was studied, and a number of single or multiple transmitter removal algorithms were reported. Among them, stepwise maximum interference removal algorithm (SMIRA) is the most effective one resulting in the smallest outage probability. Recently, interesting research works on admission and power control under the framework of cognitive code-division networks were reported in [9–11]. A centralized algorithm combining geometric programming and tree-pruning method [9] was presented to allow secondary users to share the spectrum under secondary quality of service (QoS) constraints and a primary interference temperature constraint. In [10], a gradient descent algorithm was proposed to solve admission control and power allocation jointly. More recently, in [11], a spectrum underlay cognitive radio network (CRN) was considered, and a low-complexity suboptimal algorithm named interference constraint-aware SMIRA (I-SMIRA) was proposed to maximize the number of admitted SUs. In all the above literature of cognitive code-division networks, no optimization was carried out with respect to code channels (signatures) of secondary users. In contrast, code design for secondary code-division links was considered in [12–14], where SUs coexist with a wideband primary code-division multiple access (CDMA) system. In [12], a single secondary code-divison link is designed such that it achieves the maximum SINR subject to primary SINR requirements [12]. The extension to the design of multiple secondary code-division links is studied in [13, 14]. In practice, there exist many scenarios where the primary (legacy) users communicate with modulated narrowband signals. Under these scenarios, the design of secondary underlay code-division links still remains an open problem.

To the best of our knowledge, this paper presents the first research work on the problem of establishing secondary code-division links coexisting with a primary narrowband system. Since the wideband transmissions of secondary users generally experience multipath fading, the RAKE matched filter is utilized at the secondary receivers (SRs). Our objective is to maximize the number of admitted secondary links and minimize the total power consumption of active secondary links under the following constraints: (1) SINR constraints at secondary RAKE receivers, (2) interference constraints at the primary receivers (PRs), and (3) peak transmission power constraints at secondary transmitters (STs). This optimization problem is an NP-hard problem, which motivates the development of efficient suboptimal algorithms that provide good solutions. We propose an iterative algorithm to solve this problem which produces a suboptimal solution with excellent cognitive networking performance characteristics in terms of the number of admitted SUs and network energy consumption. We provide numerical results to demonstrate that our proposed algorithm outperforms existing signature design and admission control algorithms previously proposed in the literature.

1.1. Contributions. Within this context, our main contributions in this paper can be outlined as the following.

(i) *Uncoordinated Code-Division Spectrum Management.* Unlike traditional frequency division operations, we consider multiple secondary wideband code-division links coexisting with a primary narrowband system, a scenario which has not been previously addressed.

(ii) *Joint Power and Code-Channel Allocation.* Our optimization framework incorporates code sequence design as an additional optimization dimension/resource. This additional dimension is expected to improve spectrum utilization compared to conventional power optimization approaches considered in [6, 9–11].

(iii) *New Removal Criterion.* For the admission control problem, we define a new metric that aggregates only the effective violation (both primary interference and secondary SINR violation) from STs, which is different from and more effective than the one proposed in [11].

The rest of the paper is organized as follows. We present the cognitive code-division network model and formulate the admission control and resource allocation problem in Section 2. The proposed iterative algorithm is described in detail in Section 3. We provide computational complexity analysis in Section 4. In Section 5, simulation results are presented to demonstrate the performance of our proposed algorithm. Concluding remarks are presented in Section 6.

2. System Model and Problem Statement

We consider a primary narrowband system where each primary user holds the license for one of N subbands of the spectrum. We assume that K of N primary users, $1 \leq K \leq N$, are active to transmit from primary transmitters PT_j to primary receivers PR_j, $j = 1, 2, \ldots, K$ in each time slot. A secondary network with M requesting links between secondary transmitters ST_i and secondary receivers SR_i, $i = 1, 2, \ldots, M$, shares the spectrum with the primary system in a spectrum underlay manner. For notational convenience, we number each secondary and primary transmitter-receiver pair by the indices $i \in \mathcal{M} \triangleq \{1, \ldots, M\}$ and $j \in \mathcal{K} \triangleq \{1, \ldots, K\}$, respectively, and refer to them as users. All secondary users are equipped with spread spectrum devices and are expected to simultaneously communicate over the whole spectrum without causing any harmful interference to primary users. Due to the dispersion characteristics of the wireless channel, secondary wideband spread spectrum signals with processing gain L are assumed to propagate over multipath (frequency-selective) fading channels with R resolvable paths.

After carrier demodulation, chip-matched filtering and sampling at the chip rate over the duration of a multipath extended symbol (bit) period of $L + R - 1$ chips, the received signal at SR_i can be represented as

$$\mathbf{r}_i = \sum_{m=1}^{M} \sqrt{E_m} b_m \mathbf{H}_{i,m} \mathbf{s}_m + \mathbf{i}_i + \mathbf{n}, \quad (1)$$

where $E_m > 0$ is the bit energy, $b_m \in \{\pm 1\}$ is the information bit, and $\mathbf{s}_m \in \mathbb{R}^L$ ($\|\mathbf{s}_m\| = 1$) is the normalized signature vector of secondary link m, $m \in \mathcal{M}$; $\mathbf{i}_i$ represents interference induced by all active PUs; $\mathbf{n}$ is additive white Gaussian noise (AWGN) at SR_i with mean $\mathbf{0}$ and covariance $\xi^2\mathbf{I}$. In (1), $\mathbf{H}_{i,m}$ is the multipath channel matrix from ST_m to SR_i given in the form of

$$\mathbf{H}_{i,m} \triangleq \begin{bmatrix} h_{i,m}^{(1)} & 0 & \cdots & 0 \\ h_{i,m}^{(2)} & h_{i,m}^{(1)} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ h_{i,m}^{(R)} & h_{i,m}^{(R-1)} & \cdots & h_{i,m}^{(1)} \\ 0 & h_{i,m}^{(R)} & \cdots & h_{i,m}^{(2)} \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & h_{i,m}^{(R)} \end{bmatrix}_{L+R-1\times L}, \quad (2)$$

where $h_{i,m}^{(r)}$ represents rth resolvable path coefficient modeled as a Rayleigh-distributed random variable. In order to exploit the multipath diversity, we assume that each SR uses a normalized RAKE-matched filter that collects the signal energy from all the received signal paths for the user of interest, that is,

$$\mathbf{w}_{R-MF,i} = \frac{\mathbf{H}_{i,i}\mathbf{s}_i}{||\mathbf{H}_{i,i}\mathbf{s}_i||}. \quad (3)$$

The receiver in this manner achieves the performance of an Rth order diversity communications system. The output of the RAKE filter is given by

$$y_i = \frac{\sqrt{E_i}\mathbf{s}_i^T\mathbf{H}_{i,i}^T\mathbf{H}_{i,i}\mathbf{s}_i b_i}{||\mathbf{H}_{i,i}\mathbf{s}_i||} + \sum_{m=1,m\neq i}^{M} \frac{\sqrt{E_m}\mathbf{s}_i^T\mathbf{H}_{i,i}^T\mathbf{H}_{i,m}\mathbf{s}_m b_m}{||\mathbf{H}_{i,i}\mathbf{s}_i||} + \tilde{n}, \quad (4)$$

where $\tilde{n}$ is the "despread" signal of the narrowband primary interference plus noise, which can be seen as zero-mean AWGN with variance σ^2 [15]. The assumption of AWGN is due to the fact that after despread processing, the power of narrowband primary interference is evenly spread across the broad band of secondary spread spectrum system. The output SINR of the filter $\mathbf{w}_{R-MF,i}$ can be calculated as

$$\begin{aligned} \mathrm{SINR}_i &= \frac{E_i\left(\mathbf{s}_i^T\mathbf{H}_{i,i}^T\mathbf{H}_{i,i}\mathbf{s}_i\right)}{\sum_{m=1,m\neq i}^{M} E_m\left(\left|\mathbf{s}_i^T\mathbf{H}_{i,i}^T\mathbf{H}_{i,m}\mathbf{s}_m\right|^2/||\mathbf{H}_{i,i}\mathbf{s}_i||^2\right) + \sigma^2} \\ &= \frac{\widetilde{E}_i}{\sum_{m=1}^{M}\widetilde{E}_m A_{i,m} + \sigma^2}, \end{aligned} \quad (5)$$

where $\widetilde{E}_i \triangleq E_i||\mathbf{H}_{i,i}\mathbf{s}_i||^2$ denotes the received bit energy at SR_i after its receiver filter and

$$A_{i,m} = \begin{cases} \dfrac{\left|\mathbf{s}_i^T\mathbf{H}_{i,i}^T\mathbf{H}_{i,m}\mathbf{s}_m\right|^2}{||\mathbf{H}_{i,i}\mathbf{s}_i||^2||\mathbf{H}_{m,m}\mathbf{s}_m||^2}, & i \neq m, \\ 0, & i = m. \end{cases} \quad (6)$$

At the primary narrowband receivers, secondary spread spectrum signals are seen as white noise at each licensed narrowband with constant spectral densities [15]. They are also assumed to experience flat fading on each licensed narrow band. In the spirit of cognitive radio, causing no harmful interference can be evaluated by a metric called *interference temperature*, which is defined to be the interference from all SUs measured at PRs.

Here, we consider joint maximization of the number of admitted SUs and minimization of total energy consumption in the secondary cognitive radio network (CRN). The objective is to find a joint admission control and resource (i.e., power and signature) allocation scheme that maximizes the number of SUs accessing the spectrum and minimizes the total energy consumption. Minimizing total network energy is an important problem especially when the network has a constraint on the interference it can cause to other neighboring networks. Since our goal is to admit as many users as possible and minimize the energy consumption of the network, we initially formulate the problem as a multiobjective optimization problem with three sets of constraints: (1) SINR constraints at the SRs, (2) interference temperature constraints at PRs, and (3) power budget constraints at the STs. We can now formulate problem, referred to as P, as follows:

$$\text{Find} \quad \mathbf{E}, \mathbf{S}$$

$$\text{Maximize} \ \{\|\mathbf{E}\|_0\}, \quad \left\{-\sum_{m=1}^{M} E_m\right\} \quad (7)$$

$$\text{Subject to} \quad \sum_{i=1}^{M} g_{j,i}E_i \leq I_j, \quad \forall j \in \mathcal{K}, \quad (8)$$

$$\mathrm{SINR}_i \geq \mathbf{I}(E_i)\gamma, \quad \forall i \in \mathcal{M}, \quad (9)$$

$$0 < E_i < E_{\max}, \quad \forall i \in \mathcal{M}. \quad (10)$$

In P, $\mathbf{S} \triangleq [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_M]$, $\mathbf{E} \triangleq [E_1, \mathbf{s}_2, \ldots, E_M]$, $\|\mathbf{E}\|_0$ is the zero norm of $\mathbf{E}$ which denotes the number of admitted users, $\mathbf{I}(\cdot)$ is the indicator function for positive real numbers $\mathbb{R}_+$, and $g_{j,i}$ is the path coefficient from ST_i to PR_j. Inequality (8) represents a set of K interference temperature constraints for the PUs. Inequality (9) represents a set of M SINR constraints for the SUs. The SU i will transmit, if and only if the SINR of that link is greater than or equal to the threshold SINR. If the link is not active, that is, if the user is not admitted, the SINR constraint is automatically satisfied.

The problem P is a multiobjective optimization problem (MOP) for which the solution space is represented by a set of Pareto optimal (trade-off) solutions (non-dominated by any other solution) between the two objectives [16]. One technique for solving MOPs is to maximize a (normalized) weighted sum of the objectives where a larger weight represents the objective with higher importance (or priority). However, in our problem, the two objective functions are of different nature, that is, the number of users can only take integer values whereas the total energy can take real values, hence a weighted objective will not be well defined. There are other techniques in the literature to solve MOPs such as evolutionary algorithms [17], but they may be computationally expensive and are not the focus of this work. Our goal in this work is not to find a set of Pareto optimal solutions. Instead, similar to the weighted objective approach, we prioritize our objectives. Let us consider a scenario where the priority is to minimize the energy consumption of the network. Let $\mathcal{S} \triangleq \{(O_1, O_2) | O_1 \in \mathbb{N}, O_2 \in \mathbb{R}_-\}$ denote the set of objective value pairs corresponding to Pareto optimal solutions obtained by solving P. It is easy to see that $(0,0)$ is a trivial Pareto optimal objective pair, that is, $(0,0) \in \mathcal{S}$, since it corresponds to zero (minimum) energy consumption in the network. However, our main goal here is to find a solution that corresponds to a large number of admitted SUs that consume the minimum energy possible. In other words, we assign the first objective in (7) higher importance over the other. Therefore, we divide the problem P into two separate single objective optimization problems and solve them in an iterative manner until convergence is obtained. In the next section and subsections therein, we provide the details of our proposed admission control and resource allocation algorithm.

3. Proposed Admission Control and Resource Allocation Algorithm

Since the objective corresponding to the number of admitted users has higher priority, we start the problem by assuming that all M requesting secondary links are supported. (A set of secondary links is supported if and only if there exists at least one nontrivial (i.e., power greater than zero) resource allocation solution such that all corresponding constraints in (9)-(10) are satisfied.) In this case, the problem is a single-objective joint power and signature allocation problem. Note that this first problem may or may not admit any feasible solutions. After the first problem is attempted to be solved, we define a new single-objective optimization problem for admission control. This second problem is solved only if the previously obtained power and signature allocation solution viloates the constraints of P or if there is no feasible solution to the first problem. We explain the details of our approach in the next subsections.

3.1. Joint Power and Code-Channel Allocation. Under the assumption that there are M SUs that are supported, let P1 denote the new single-objective optimization problem formulated as

$$\begin{aligned} &\text{Find} \quad \mathbf{E}, \mathbf{S} \\ &\text{Minimize} \quad \sum_{m=1}^{M} E_m \\ &\text{Subject to} \quad \text{Constraints in (9) and (10).} \end{aligned} \tag{11}$$

We note that P1 is a nonconvex optimization problem. Our approach in solving P1 starts with optimizing the secondary signature set assuming that the energy associated with each SU, that is, $\mathbf{E}$ is fixed and unknown. The signature set optimization does not require the knowledge of $\mathbf{E}$. We notice that the secondary SINR constraints in (9) can be equivalently written in the form of

$$(\mathbf{I} - \gamma \mathbf{A}) \widetilde{\mathbf{E}} \geq \mathbf{b}, \tag{12}$$

where $\mathbf{b} \triangleq \gamma\sigma^2 \mathbf{1}$, $\widetilde{\mathbf{E}} = [\widetilde{E_1}, \widetilde{E_2}, \ldots, \widetilde{E_M}]^T$, and $\mathbf{A}$ is the matrix of entries $A_{i,j}$ defined in (6), $i, j \in \mathcal{M}$. By the Perron-Frobenius theorem [18], it is well known that there exists a positive vector $\widetilde{\mathbf{E}} > \mathbf{0}$ such that (12) is satisfied with equality if and only if $\rho(\mathbf{A}) < 1/\gamma$, where $\rho(\mathbf{A})$ is the Perron root of $\mathbf{A}$. Note that $\rho(\mathbf{A})$ is an implicit function of secondary signature set $\mathbf{S}$. For a given $\rho(\mathbf{A}) < 1/\gamma$, when (12) is satisfied with equality, it means that the system is using the lowest energy $\widetilde{\mathbf{E}} > \mathbf{0}$ possible to satisfy its SINR constraint. Moreover, smaller $\rho(\mathbf{A})$ means that the system can support a higher SINR requirement. Therefore, intuitively, if we minimize $\rho(\mathbf{A})$, we provide more room to further reduce $\widetilde{\mathbf{E}}$ to satisfy the given SINR requirement in (12) with equality. Therefore, the signature set $\mathbf{S}$ can be optimized to minimize $\rho(\mathbf{A})$ to maximize the energy efficiency of the secondary network. Now, we explain our optimization approach as follows. We note that it is difficult to minimize $\rho(\mathbf{A})$ directly. However, from matrix theory on induced norm, we can write the following:

$$\frac{1}{\sqrt{M}} \sum_{i,j} A_{i,j} \leq \rho(\mathbf{A}) \leq \max_i \sum_j A_{i,j} \leq \sum_{i,j} A_{i,j}. \tag{13}$$

Based on the fact that $\rho(\mathbf{A})$ is lower and upper bounded by multiples of $\sum_{i,j} A_{i,j}$, we define a new cost function $J \triangleq \sum_{i,j} A_{i,j}$ and we optimize the secondary signature by minimizing J using a block coordinate descent algorithm, that is, by iteratively updating one secondary signature at a time. Although J is not a tight bound for $\rho(\mathbf{A})$ in general, it is utilized here for two reasons: (1) minimization of J can be carried out in a tractable manner, (2) the solutions obtained by minimizing J provide good solutions (in fact better solutions than the ones proposed in the literature) as shown by numerical results in Section 5. The signature for secondary link i that minimizes J is given by

$$\mathbf{s}_i^* = \arg\min_{\mathbf{s}_i} \frac{\mathbf{s}_i^T \mathbf{Q}_i \mathbf{s}_i}{\left\|\mathbf{H}_{i,i}\mathbf{s}_i\right\|^2} + \widetilde{Q}_i, \tag{14}$$

where $\widetilde{Q}_i = \sum_{j \neq i} \sum_{m \neq i} A_{j,m}$ and

$$\begin{aligned} \mathbf{Q}_i \triangleq{}& \mathbf{H}_{i,i}^T \left(\sum_{j \neq i} \frac{\mathbf{H}_{i,j}\mathbf{s}_j\mathbf{s}_j^T\mathbf{H}_{i,j}^T}{\left\|\mathbf{H}_{j,j}\mathbf{s}_j\right\|^2} \right) \mathbf{H}_{i,i} \\ &+ \sum_{m \neq i} \frac{\mathbf{H}_{m,i}^T\mathbf{H}_{m,m}\mathbf{s}_m\mathbf{s}_m^T\mathbf{H}_{m,m}^T\mathbf{H}_{m,i}}{\left\|\mathbf{H}_{m,m}\mathbf{s}_m\right\|^2}. \end{aligned} \tag{15}$$

Let $\mathbf{z} \triangleq \mathbf{\Lambda}^{1/2}\mathbf{U}^T\mathbf{s}_i$ where $\mathbf{U}$ and $\mathbf{\Lambda}$ denote eigenvector matrix and diagonal eigenvalue matrix of $\mathbf{H}_{i,i}^T\mathbf{H}_{i,i}$, respectively. If we treat other secondary signatures as fixed parameters, then the optimization (14) takes the equivalent form

$$\mathbf{z}^* = \arg\min_{\mathbf{z}} \frac{\mathbf{z}^T \mathbf{\Lambda}^{-1/2}\mathbf{U}^T\mathbf{Q}_i\mathbf{U}\mathbf{\Lambda}^{-1/2}\mathbf{z}}{\mathbf{z}^T\mathbf{z}}. \tag{16}$$

It is well known that the optimal solution $\mathbf{z}^*$ is the eigenvector of $\mathbf{\Lambda}^{-1/2}\mathbf{U}^T\mathbf{Q}_i\mathbf{U}\mathbf{\Lambda}^{-1/2}$ with minimum eigenvalue. Therefore, the signature $\mathbf{s}_i^*$ that minimizes (14) is given by

$$\mathbf{s}_i^* = \frac{\mathbf{U}\mathbf{\Lambda}^{-1/2}\mathbf{z}^*}{\left(\mathbf{z}^{*T}\mathbf{\Lambda}^{-1}\mathbf{z}^*\right)^{1/2}}. \tag{17}$$

It is straightforward to see that the updated objective J at $\mathbf{s}_i^*$ is no larger than its value evaluated at $\mathbf{s}_i$. In general, repeating the update iteratively for all the signature sets, the secondary signature set converges because the objective function J reduces monotonically after each update and it is lower bounded. In order to deal with ill-conditioned cases where there are multiple stationary (local minimum) points of J with the same value, we stop the iterations if there is no significant improvement in the cost function after a certain number of iterations.

After computing the secondary signature set, we consider the constraints in (10) and (12) together and follow the ADCPC algorithm proposed in [6] to update the transmission bit energy for each secondary link in an iterative manner. The energy update at each iteration t is given by

$$E_i(t) = \min\left\{E_{\max}, \frac{\gamma E_i(t-1)}{\mathrm{SINR}_i(t-1)}\right\}. \tag{18}$$

Following [6], it can be shown that the iterative update in (18) converges to a unique vector determined by the fixed-point solution

$$\mathbf{E}^{\mathcal{M}} = \min\left\{E_{\max}\mathbf{1}, \gamma\mathbf{W}^{-1}\mathbf{A}\mathbf{W}\mathbf{E}^{\mathcal{M}} + \mathbf{W}^{-1}\mathbf{b}\right\}, \tag{19}$$

where $\mathbf{W} \triangleq \mathrm{diag}(\|\mathbf{H}_{1,1}\mathbf{s}_1\|^2, \|\mathbf{H}_{2,2}\mathbf{s}_2\|^2, \ldots, \|\mathbf{H}_{M,M}\mathbf{s}_M\|^2)$, $\mathcal{M}$ is the set of active secondary links and $\mathbf{E}^{\mathcal{M}}$ is the solution of (19), referred to as *stationary bit-energy vector*. In [6], it was also shown that if the stationary bit-energy vector $\mathbf{E}^{\mathcal{M}}$ by (18) meets all secondary SINR constraints in (9), then the secondary SINR constraints are satisfied with equality. The solution $\mathbf{E}^{\mathcal{M}}$ of (19) is optimal in terms of energy efficiency provided that all the constraints in (9), (10) of the problem P1 are satisfied.

We should note here that there is a possibility of not having a feasible solution for P1, since it may not be feasible for all M secondary links to transmit at the same while satisfying their SINR constraints. In this case, the fixed energy point $\mathbf{E}^{\mathcal{M}}$ in (19) will have at least one SU that uses its maximum energy $E_{\max}$. Whether there is a feasible solution for P1 or not, the admission control procedure which is explained in the next section needs to be followed, since P1 does not incorporate primary interference temperature constraints.

3.2. Admission Control. When the network is dense and the number of requesting secondary links is high, it becomes difficult to support all requesting secondary links simultaneously, that is, the constraints in (8), (9), and (10) may not be simultaneously satisfied for all requesting secondary links. In this case, the problem becomes an admission control problem where the objective is to find the subset of requesting secondary links with the maximum size while satisfying all the constraints in (8), (9), and (10). We now attempt to solve the admission control problem denoted by P2 formulated as

$$\begin{aligned} &\text{Find} \quad \mathbf{E}, \mathbf{S} \\ &\text{Maximize} \quad \|\mathbf{E}\|_0 \\ &\text{Subject to} \quad \text{Constraints in (8), (9) and (10).} \end{aligned} \tag{20}$$

The problem of admission control, that is, maximizing the number of admitted SUs was shown to be NP-hard in [11]. The NP-hardness of this problem motivates the development of effective and computationally efficient heuristic algorithms that provide good suboptimal solutions. In fact, not surprisingly, all the admission control algorithms developed in the literature so far are based on such heuristics [7–11]. For P2, rather than using the conventional admission control procedure proposed in [8], we propose a new removal criterion that effectively incorporates primary interference temperature constraints. We start with following the notations originally proposed in [8]. For every bit-energy vector $\mathbf{E}$ and subset $\mathcal{M}_0 \subseteq \mathcal{M}$, let us define

$$\alpha_i(\mathbf{E}) \triangleq \frac{\gamma\left(\widetilde{E}_i \sum_{j\neq i} A_{j,i} + \sigma^2\right)}{\left\|\mathbf{H}_{i,i}\mathbf{s}_i\right\|^2} - E_i, \tag{21}$$

$$\beta_i(\mathbf{E}) \triangleq \frac{\gamma\left(\sum_{j\neq i} A_{i,j}\widetilde{E}_j + \sigma^2\right)}{\left\|\mathbf{H}_{i,i}\mathbf{s}_i\right\|^2} - E_i, \tag{22}$$

$$D^{\mathcal{M}_0}(\mathbf{E}) \triangleq \sum_{i\in\mathcal{M}_0} \beta_i(\mathbf{E}). \tag{23}$$

We note that $\alpha_i(\mathbf{E})$ indicates the excess interference power caused by ST_i; $\beta_i(\mathbf{E})$ indicates the excess interference power measured at SR_i; $D^{\mathcal{M}_0}(\mathbf{E})$ indicates the total excess interference power which all the SRs in the subset $\mathcal{M}_0$ experience. From the results in [8], we note that

$$\begin{gathered} \beta_i(\mathbf{E}) \geq 0, \quad i \in \mathcal{M}, \\ D^{\mathcal{M}}(\mathbf{E}) = \sum_{i\in\mathcal{M}} \beta_i(\mathbf{E}) = \sum_{i\in\mathcal{M}} \alpha_i(\mathbf{E}) \geq 0. \end{gathered} \tag{24}$$

We also see that $D^{\mathcal{M}}(\mathbf{E}^{\mathcal{M}}) = 0$ if and only if all M secondary links are supported.

The basic idea behind our admission control algorithm is that we iteratively remove the link which violates the constraints in (8), (9), and (10) the most until all the constraints are satisfied. We now explain the algorithm more formally. Due to the fact that the stationary bit-energy vector $\mathbf{E}^{\mathcal{M}}$ already satisfies power budget constraints in (10), we consider admission control in three different scenarios.

Scenario 1. The stationary bit-energy vector $\mathbf{E}^{\mathcal{M}}$ satisfies all the primary interference constraints in (8), whereas it violates some of the secondary SINR constraints in (9).

Scenario 2. The stationary bit-energy vector $\mathbf{E}^{\mathcal{M}}$ satisfies all the secondary SINR constraints in (9), whereas it violates some of the primary interference constraints in (8).

Scenario 3. The stationary bit-energy vector $\mathbf{E}^{\mathcal{M}}$ violates some of the primary interference constraints in (8) and some of the secondary SINR constraints in (9), simultaneously.

In Scenario 1, the admission control problem can be equivalently converted into the problem considered in [8]. In this case, SMIRA in [8] can be used to remove the most violated secondary link one after one until all the constraints in (8), (9), and (10) are satisfied. According to the definition of violation measure in (21), (22), and (23), the removal criterion of SMIRA is to reduce $D^{\mathcal{M}}(\mathbf{E})$ the most by removing the secondary link indexed by i_{remove} given as

$$i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{\max(\alpha_i(\mathbf{E}), \beta_i(\mathbf{E}))\}. \tag{25}$$

Intuitively, secondary link i_{remove} is the one that causes the most interference to other secondary links or receives the most interference from other links.

For Scenarios 2 and 3, we define a new metric that quantifies the excess interference power caused by ST_i and measured at PRs as

$$\eta_i(\mathbf{E}) \triangleq \sum_{j\in\mathcal{M}}\left[E_i - \frac{1}{g_{j,i}}\left(I_j - \sum_{k\neq i} g_{j,k}E_k\right)\right]x_{j,i}, \tag{26}$$

where

$$x_{j,i} = \begin{cases} 1, & \sum_{k\in\mathcal{M}} g_{j,k}E_k - I_j > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{27}$$

We note that $\eta_i(\mathbf{E})$ represents aggregate effective violation caused by ST_i at the PRs for which the primary interference constraints are violated. Note that this metric different than the one proposed in [11] which incorporates all the effects (even including negative (non)violation effects) from primary transmitters. In Scenario 2, some of the primary interference temperature constraints are violated. Therefore, we remove the secondary link in Scenario 2 as follows:

$$i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{\eta_i(\mathbf{E})E_i\}. \tag{28}$$

In the last scenario (Scenario 3), we have to aggregate the violation effects of both secondary SINR constraints and primary interference constraints. We propose the following removal criterion for Scenario 3:

$$i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{[\max(\alpha_i(\mathbf{E}), \beta_i(\mathbf{E})) + \eta_i(\mathbf{E})]E_i\}. \tag{29}$$

In fact, $[\max(\alpha_i(\mathbf{E}), \beta_i(\mathbf{E}))+\eta_i(\mathbf{E})]E_i$ denotes the comprehensive excess interference power of secondary link i weighted by its transmitting power. By using this criterion, intuitively, the network would potentially reserve the maximum number of secondary links that consume the minimum total energy.

After removing one link at a time, we return to P1 again and attempt to solve P1 and repeat the procedure in an alternating manner. We note that removing one link at a time does not necessarily solve P2, but the whole iterative algorithm solves P1 and P2 jointly as explained in the next section.

3.3. Joint Admission Control and Resource Allocation. The steps of our iterative joint admission control and resource allocation algorithm are summarized as follows.

(1) At iteration $t = 0$, set $\mathbf{E}(0) = c\mathbf{1}$ (c is a small constant).

(2) Solve P1 using the proposed method in Section 3.1 and go to step 3. If there is no feasible solution for P1, go to step 3 (Note that the number of admitted SUs M is updated at each iteration (see Section 3.1).).

(3) If the constraints of P (or P2) are violated, remove one link using the proposed method in Section 3.2, set $t = t + 1$, set $M = M - 1$ and go to step 2. Else stop.

Note that the convergence of this iterative algorithm is guaranteed, because, at step 3, the SUs that were previously removed are not reconsidered. In this case, the solution will be suboptimal, however the iterations will eventually converge in the worst case to the point corresponding to the objective pair $(0, 0)$, that is, the solution that has zero admitted users. Therefore, the maximum number of iterations required for convergence is M. The details regarding the steps of our proposed joint admission control and resource allocation algorithm are explained in Algorithm 1.

4. Computational Complexity

The computational cost is evaluated in terms of "FLOP", which is defined by an additive or a multiplicative operation. The computational complexity of the signature set optimization is dominated by the complexity of the eigen-decomposition for Q_i, $i \in \mathcal{M}$, which is $\mathcal{O}(ML^3)$. Given the optimized signature set, the power allocation is carried out by the iterative procedure in (18) using DCPC and ADCPC algorithms. The complexity of this procedure is of order $\mathcal{O}(M^2L^2)$. Then, we test whether the constraints (9) and (8) (equivalently, (12) and (8)) are satisfied. If the constrains are all met, this pair $(\mathbf{E}, \mathbf{S})$ is output as the optimal solution. Otherwise, the admission control procedure is followed, whose complexity is of order $\mathcal{O}(ML)$. We repeat the procedure of joint power and code-channel allocation and the procedure of admission control in an alternating manner until all the aforementioned constraints are satisfied (see Algorithm 1). As noted, the maximum number of iterations required for convergence of Algorithm 1 is at M. This is due to the greedy nature of the algorithm. At each iteration, one secondary user is removed from the network and that user is not admitted again in the following iterations. Therefore, the total complexity of Algorithm 1 is of order $\mathcal{O}(M^2L^3 + M^3L^2)$. For comparison purposes, consider the alternative algorithms that use our optimized signature set along with SMIRA and I-SMIRA. The former and the latter have computational complexities of order $\mathcal{O}(M^3L^2)$ and

1: Select an arbitrary initial signature set for M requesting secondary links.
2: Calculate $\mathbf{Q}_i$ by (15).
3: Obtain $\mathbf{U}$ and $\mathbf{\Lambda}$ through eigendecomposition of $\mathbf{H}_{i,i}^T\mathbf{H}_{i,i}$.
4: Update $\mathbf{s}_i$ using (17).
5: Repeat Step 2–4 until the secondary signature set converges.
6: Calculate the matrix $\mathbf{A}$ by (6).
7: $t = 0$; initialize $\mathbf{E}(0)$ with $c\mathbf{1}$, where c is a small constant.
8: $t = t + 1$.
9: **for** $i = 1, 2, \ldots$ **do**
10: Update $E_i(t) \leftarrow \min\{E_{\max}, \gamma E_i(t-1)/\mathrm{SINR}_i(t-1)\}$
11: **end for**
12: Repeat Step 6–11 until $\mathbf{E}$ converges to a stationary bit-energy vector.
13: Calculate $\alpha_i(\mathbf{E})$, $\beta_i(\mathbf{E})$ and $\eta_i(\mathbf{E})$ by (21), (22) and (26), respectively.
14: **if** $\sum_{i\in\mathcal{M}} g_{j,i}E_i \le I_j \quad \forall j = 1, 2, \ldots, K$ **then**
15: **if** $(\mathbf{I} - \gamma\mathbf{A})\widetilde{\mathbf{E}} \ge \mathbf{b}$ **then**
16: Flag_constraints_satisfied $\leftarrow 1$
17: **else**
18: Remove the secondary link $i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{\max(\alpha_i(\mathbf{E}), \beta_i(\mathbf{E}))\}$.
19: **end if**
20: **else**
21: **if** $(\mathbf{I} - \gamma\mathbf{A})\widetilde{\mathbf{E}} \ge \mathbf{b}$ **then**
22: Remove the secondary link $i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{\eta_i(\mathbf{E})E_i\}$.
23: **else**
24: Remove the secondary link $i_{\text{remove}} = \arg\max_{i\in\mathcal{M}}\{[\max(\alpha_i(\mathbf{E}), \beta_i(\mathbf{E})) + \eta_i(\mathbf{E})]E_i\}$.
25: **end if**
26: **end if**
27: Repeat Step 1–26 until Flag_constraints_satisfied = 1.

Algorithm 1: Proposed joint admission control and resource allocation algorithm.

$\mathcal{O}(M^3L^2 + M^2L)$, respectively. This suggests that if M is equal or close to L, then both three algorithms have the same order of computational complexity.

5. Simulation Results

In this section, we provide some simulation results to evaluate the performance of the proposed algorithm. We consider a primary narrowband system with $K = 5$ active transmission links and a secondary code-division network with M requesting links and processing gain $L = 16$. We assume that each secondary transmission between secondary transmitters and receivers propagates over a multipath channel with $R = 3$ resolvable paths where the corresponding channel coefficients are taken to be the magnitude of independent complex Gaussian random variables with mean 0 and variance 1. The channels between secondary transmitters and primary receivers follow a path loss model with the path-loss exponent of 4, that is, $g_{j,i} = C/d_{j,i}^4$, where $d_{j,i}$ denotes the distance between ST_i and PR_j drawn i.i.d. from a uniform distribution over $[2, 2.5]$, and C is a constant set to 1/3 [10]. The SINR threshold and maximum allowable bit energy for secondary links are set to $\gamma = 10$ dB and $E_{\max} = 17$ dB, respectively. The maximum tolerable interference temperatures at the K primary receivers are all set to $I_j = 3$, $j = 1, \ldots, K$. The variance ξ of AWGN in (1) is set to 1. We assume that each primary transmitter creates 5 dB (≈ 3.2) interference on their corresponding (narrow)bands at the secondary receivers. Furthermore, each primary user is assumed to occupy $1/L$ of the whole available bandwidth. Under these assumptions, the total primary interference power at a given secondary receiver equals 1. As a result, the total primary interference plus noise after RAKE filtering ("despreading") becomes zero-mean AWGN with variance $\sigma^2 = 2$ [15]. Our simulations are based on 1000 Monte Carlo random channel realizations.

We compare the performance of the proposed joint resource allocation and admission control algorithm (Section 4) with the following benchmarks. (i) Proposed optimized secondary signature set by (17) with SMIRA; (ii) Proposed optimized secondary signature set by (17) with I-SMIRA; (iii) Karystinos-Pados (KP) bound equality binary signature set [19–21] with I-SMIRA (The binary signature set that achieves KP bound is minimum total-squared correlation optimal. For $L = 16$, when $M \le L$ the KP-optimal sequences coincide with the familiar Walsh-Hadamard signature codes.).

In Figure 1, we plot the admitted percentage of secondary links as a function of the SINR threshold γ of secondary links. We assume that there are $M = 16$ requesting secondary links in the network. It is clear from the figure that the proposed optimized secondary signature set results in significant performance improvement with respect to the KP bound equality signature set. Furthermore, the proposed joint resource allocation and admission control algorithm outperforms other three algorithms including the ones using

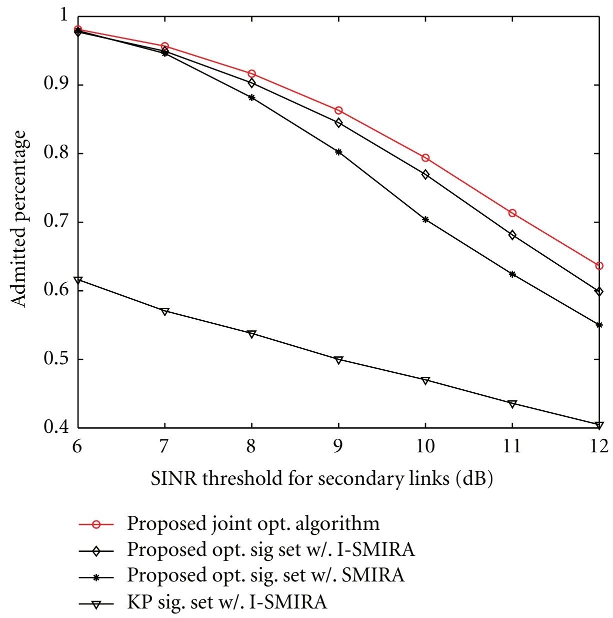

Figure 1: Admitted percentage of secondary links as a function of the SINR threshold for secondary links.

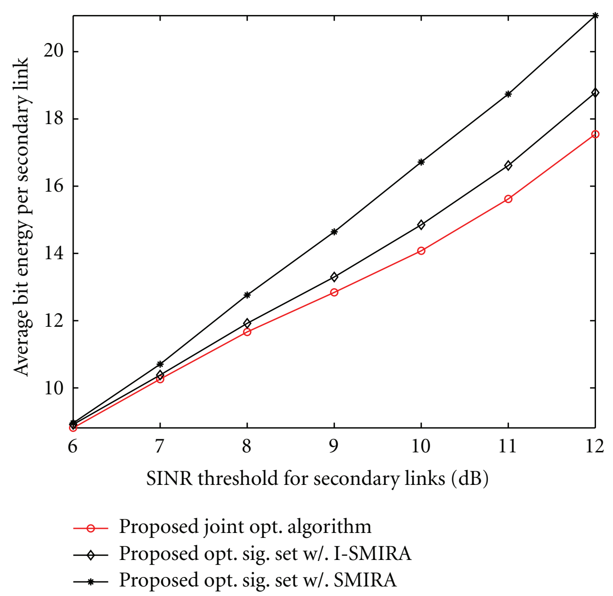

Figure 2: Average bit energy per secondary link as a function of the SINR threshold for secondary links.

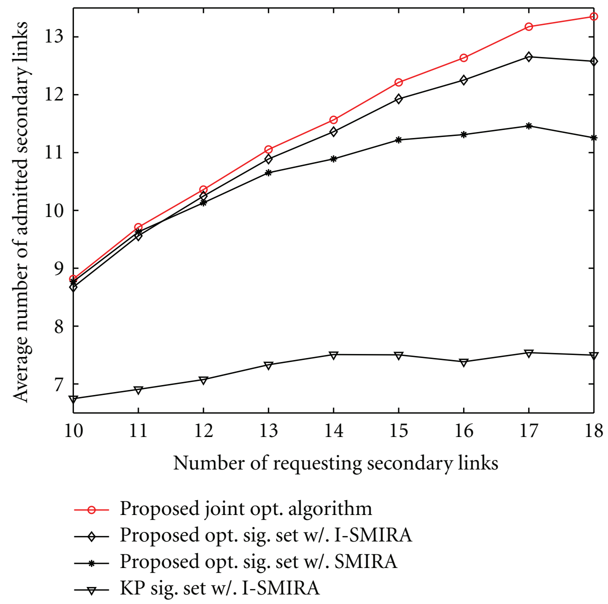

Figure 3: Average number of admitted secondary links versus the number of requesting secondary links averaged over 1000 random channel realizations.

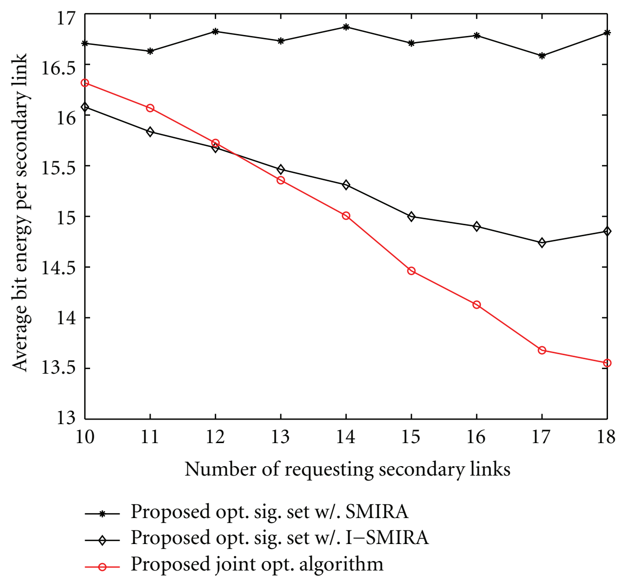

Figure 4: Average bit energy per secondary link versus the number of requesting secondary links.

our optimized signature sets with SMIRA and I-SMIRA admission control strategies. The improvement achieved by the proposed algorithm becomes more significant as secondary SINR threshold increases, that is, as secondary QoS requirement becomes more stringent. In Figure 2, we investigate the energy efficiency of the secondary network. Here, we do not include the KP bound equality signature set with I-SMIRA in the comparison due to its relatively low admission rate of secondary links. The proposed algorithm again achieves the highest energy efficiency compared to its counterparts.

Figures 3 and 4 demonstrate the impact of the number of requesting secondary links on the secondary network performance. We fix the secondary SINR threshold to 10 dB and vary the number of requesting secondary links from 10 to 18. Figures 3 and 4 show the average number of admitted secondary links and the average bit energy per secondary link, respectively, versus the number of requesting secondary links. Similarly, the proposed joint resource allocation and admission control algorithm achieves visible improvement against the other two algorithms. We should mention that, when the number of requesting secondary links is small, the performance of the optimized signature set with I-SMIRA is slightly better than the proposed algorithm in terms of average bit energy consumption as seen in Figure 4. This is due to the fact that the proposed algorithm supports more secondary links than I-SMIRA which in turn increases the relative average energy cost when the number of requesting secondary links is small. As the number of secondary requests increases, it is clear that the proposed joint algorithm results in better energy efficiency outperforming other algorithms.

6. Conclusions

We studied the problem of cognitive code-division networking where secondary users coexist with a narrowband primary system. We formulated the problem as the search for the powers and signatures of secondary links to maximize the number of admitted secondary links and minimize the total power consumption of secondary links under primary interference temperature constraints, secondary SINR constraints, and maximum peak power constraints. We proposed an iterative joint admission control and resource allocation algorithm for this NP-hard optimization problem which provides excellent results by allowing a large number of active secondary links while improving the energy efficiency of the network as shown in the simulation results.

Depending on the operation mode of the primary system (narrowband or wideband), the proposed solution in this paper can be combined with a primary system identification technique followed by an adaptive selection of secondary operation mode between the proposed solution herein and the solution proposed in [12]. Such an adaptive operation mode will ensure that the secondary links can efficiently and effectively share the licensed band in a dynamically changing environment.

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