All-Spectrum Cognitive Networking through Joint Distributed Channelization and Routing

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***Abstract*—We consider a secondary multi-hop cognitive radio network with decentralized control that operates cognitively to coexist with primary users. We propose a new spread-spectrum management paradigm, in which, unlike mainstream dynamic spectrum access research, digital waveforms are designed to occupy the entire available spectrum, and to adaptively track the interference profile at the receiver to maximize the link capacity while avoiding interference to primary users.**

In this context, we study the problem of maximizing the network throughput of a multi-hop network through joint routing and spread-spectrum channelization. We first propose a centralized formulation of the network control problem. We then propose an algorithm that can be seen as a distributed localized approximation of the throughput-maximizing policy. We refer to the proposed jointly-designed routing and code-division channelization algorithm as ROCH (Routing and cOde-division CHannelization). Specifically, power and spreading code are jointly selected to maximize the pre-detection secondary SINR **while providing quality of service guarantees to on-going primary and secondary transmissions, while the routing algorithm dynamically selects relays based on the network traffic dynamics and on the achievable data rates on different secondary links. We study the throughput and delay performance of ROCH through a extensive simulation experiments, which demonstrate the appeal of the proposed framework through significant performance gains compared to baseline solutions.**

***Index Terms*—Cognitive radio networks, code-division channelization, routing, power allocation, code-channel allocation, cross-layer design, ad hoc networks.**

I. Introduction

COGNITIVE radio networks [2]-[3] have emerged as a promising technology to improve the utilization efficiency of the existing radio spectrum. Mainstream cognitive radio proposals focus on opportunistic access to the licensed spectrum where the primary users of the band are known a priori and this knowledge can be utilized to detect if the band is occupied by the known signal pattern. Quite the opposite, in the unlicensed band there are potentially many uncoordinated devices, and their signal waveforms and activation statistics are in general unknown. Moreover, in cognitive radio networks with multi-hop communication requirements, spectrum occupancy is location-dependent, and the receiver interference profile may, thus, vary at each relay node.

We therefore propose a new spread-spectrum management paradigm, in which waveforms are designed to occupy the entire available spectrum without generating harmful interference to active primary or secondary users. In this way, the secondary users share the licensed spectrum with the primary users to achieve frequency reuse. At the same time, the dynamic and location-dependent nature of the wireless environment calls for the development of routing algorithms that are aware of the interference profile at each potential relay.

The lack of established infrastructure and the wireless channel dynamics impose an unprecedented set of challenges over spread-spectrum cognitive ad hoc networks. First, secondary users should optimize the spreading code and power to avoid generating harmful interference to primary users. The challenges here arise from the assumption that the spreading codes of primary users are unknown to the secondary users. Second, in a multi-hop network, the spectrum environment varies in time and space depending on the activities of primary users, interference, and fading. The optimal spectrum-spreading channelization may therefore be different at each hop in a multi-hop path. Furthermore, as new secondary links are formed and others vanish, and following network traffic dynamics, routing of data flows from one secondary node to another may frequently change. Therefore, controlling the interaction between routing and code design is of fundamental importance.

In this work, we explore a new framework that captures the interdependencies between spread-spectrum channelization and routing. The throughput optimization is carried out dynamically by all secondary transmitters to continuously adapt to the changing spectrum environment and traffic arrival rates. Specifically, a distributed algorithm for dynamic joint power and spread-spectrum channelization is developed to maximize the pre-detection secondary SINR while guaranteeing the SINR-QoS requirements for on-going transmissions from primary and secondary users. The excellent cognitive network performance characteristics is demonstrated by simulation studies included in this paper.

A motivating example. Through an example, we will try to intuitively highlight the potential benefits of spread-

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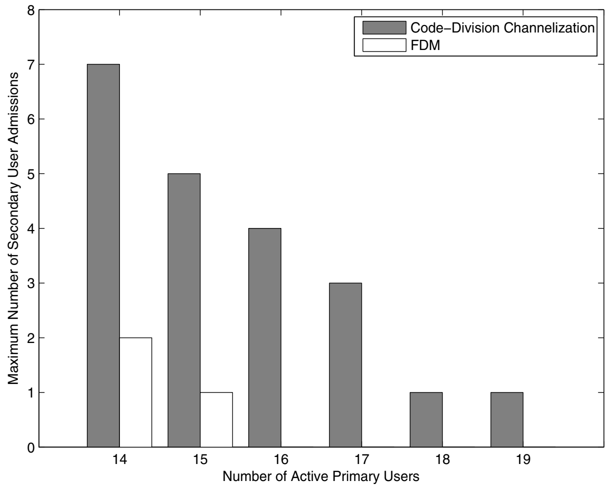


Fig. 1. Comparison between code-division channelization and FDM.

spectrum channelization as compared to traditional frequency-division multiplexing (FDM) for dynamic spectrum access. In code-division channelization, secondary users use spread spectrum signals that occupy the whole spectrum band. In this example, $16-bit$ spreading codes over the real field are assigned to secondary users. In FDM, the whole spectrum band is divided into 16 subbands, and each primary user is assigned with a specific subband. In FDM scenario, secondary users can access a single subband only if the subband is not occupied by primary users or any other secondary users. In the simulation, the transmission SNRs of primary links are all set equal to $15\,dB$; the maximum allowable transmission SNR for secondary links is set to $15\,dB$. All the signature vectors for primary links are generated from a minimum total-squared correlation optimal binary signature set which achieves the Karystinos-Pados (KP) bound [33]-[35] for each $(K, 16)$ pair of values[1], where K is the number of active primary users. Both of code-division channelization and FDM schemes provide the same minimum SINR guarantee $3dB$ for both active primary users and secondary users.

Note that we require that both the code-division channelization and the FDM schemes provide the same minimum SINR guarantee for both active primary users and secondary users. We vary the number of active primary users and evaluate the maximum number of admissions for secondary users with the two different schemes. As shown in Fig. 1, it can be observed that spread spectrum management with code-division channelization allows more secondary users to simultaneously access the spectrum than FDM spectrum management. For example, with 16 subbands and 14 active primary users, only 2 secondary users can access the network with FDM. While up to 7 secondary users can access the network with carefully designed code-division channelization.

Contributions. Within this context, our main contributions in this paper can be outlined as follows:

- **Uncoordinated code-division spectrum management.** Unlike mainstream work on cognitive radio networks, we consider a code-division channelization based secondary network that operates cognitively to coexist with primary users for infrastructure-less cognitive radio ad hoc networks.
- **Distributed joint routing and code-division channelization**. We formulate a joint routing and code-division channelization problem. Given the centralized nature and high computational complexity of the problem, we study localized algorithms for joint dynamic routing and spread-spectrum channelization that are designed to maximize the global objective function of the centralized problem. To the best of our knowledge, no existing algorithm attempts to control the routing and code-division channelization functionalities to jointly maximize the network throughput.
- **Novel low-complexity spread-spectrum channelization algorithms.** We study the problem of designing a joint power and spreading code allocation scheme for the secondary link that maximizes the pre-detection SINR under quality of service constraints for the secondary users. Using semidefinite relaxation, we develop a novel low-complexity suboptimal solution to an otherwise NP-hard problem with excellent performance in practice.

The remainder of this paper is organized as follows. Section II reviews related work. System model is introduced in Section III. We formulate the problem in Section IV. In Section V we propose distributed algorithm for joint routing and code-division channelization. In Section VI secondary power and spreading code allocation solution is proposed. The performance of the proposed distributed solution is evaluated through simulation in Section VI. A few concluding remarks are drawn in Section VII.

II. Related work

Since spectrum occupancy is location-dependent, the spectrum occupancy profile may be different at each relay node in a multi-hop end-to-end path. Therefore, one of the key challenges in the design of cognitive ad hoc networks is to jointly and dynamically allocate routes and portions of the spectrum to each node in the multi-hop network. The authors in [4] proposed a routing algorithm based on a probabilistic estimation of the available capacity of each secondary link. The proposed probability-based routing metric relies on the probability distribution of the interference between primary and secondary users over a given channel. In [5], [6], the authors proposed a connectivity-driven routing algorithm, where paths are measured in terms of their degree of connectivity in a multi-hop cognitive radio network that is highly influenced by the primary user behavior. Route-stability-oriented routing is introduced in [7] based on the concept of route maintenance cost. The maintenance cost represents the effort needed or penalty paid to maintaining end-to-end connectivity. In [8], a distributed and localized algorithm for joint dynamic routing and spectrum allocation for ad hoc cognitive radio networks is proposed. The proposed algorithm jointly addresses routing and spectrum assignment with power control under the physical interference model. In [9], a coordination scheme

[1]When $K <= 16$, the KP-optimal sequences coincide with the familiar Walsh-Hadamard signature codes.

is introduced that allows secondary users to coordinate with primary users. Specifically, secondary users offer their services as an intermediate relay node in an effort to improve throughput of primary users utilizing a 802.11-based channel access mechanism. In return, the secondary user 'piggy-backs' some of its own data while acting as a relay. In [10], the authors propose the CRP routing protocol that considers joint spectrum-route selection and service differentiation in CR routes. The proposed protocol allows for two classes of routes - class I routes that provide better CR network performance, while class II routes aim to achieve a higher measure of protection for the PUs. The authors in [11] proposed a distributed routing algorithm where secondary users minimize their interference to the primary users while keeping the delay along the route low. The reader is referred to [12] and references therein for an excellent survey of the main results in this area.

Herein, we consider cognitive networks built around a primary code-division multiplexing (CDM) system. Unlike traditional frequency division operations where cognitive secondary users may transmit opportunistically in sensed spectrum holes/void only, cognitive code-division users may operate in parallel in frequency and time to a primary system as long as the induced spread-spectrum interference remains below a pre-defined acceptable threshold[2]. Power control under an "interference temperature" constraint (total secondary user disturbance power over primary band) was considered [13] in cognitive code-division systems. Furthermore, a joint power allocation and admission control algorithm was proposed in [14] for cognitive CDMA systems to maximize the energy efficiency of secondary users with QoS guarantee for primary and secondary links. In [15], a spectrum underlay (CDM-based) cognitive radio network (CRN) was considered and a low-complexity suboptimal algorithm, named interference constraint-aware stepwise maximum interference removal algorithm (I-SMIRA), was proposed to maximize the number of admitted secondary users by optimizing power and transmission rate. However, no code-channel (signature) optimization was carried out for the secondary users. In contrast, in [16] a secondary code assignment scheme was presented to obtain the binary secondary signature by hard-limiting the code sequence that exhibits the minimum mean-square cross-correlation with the primary received signal. The secondary code set of multiple secondary users was also constructed in an iterative way. Under interference-minimizing code assignments, bit rate and spreading factor adjustments for a secondary CDMA system were considered in [17]. A distributed algorithm for resource allocation of spectral bands, power, and data rates among multiple secondary users for multi-carrier CDMA systems was developed in [18]. The problem of beamforming and power control for CR networks aimed at restricting the interference on PUs has been addressed in [19]. The authors in [20] study the problem of fair spectrum sharing among all SUs in underlay CR networks, subject to certain QoS (in terms of minimum SINR and transmission rate) and outage probability of constraints with imperfect channel state information. A joint admission control and rate/power allocation for secondary users is proposed. In [21], the authors consider the scenario where SUs can adaptively adjust their transmit directions in addition to transmit power according to available channel information. A joint power allocation and phase control solution is proposed subject to interference and power constraints. In [22], the authors study the optimal scheduling problem with the objective to achieve proportional fairness of the long-term average transmission rates among different links in a cognitive ad hoc network with spectrum underlay. Hybrid overlay/underlay CR waveforms were designed to adapt its spectrum to efficiently exploit both unused spectrum holes and underused spectrum bands through OFDM and MC-CDMA in [23].

The common theme of most research in the area of CDMA-based CR networks is to optimize physical layer performance, without modeling in detail how physical layer resource allocation interacts with higher layers of the protocol stack to improve network performance metrics. In comparison with work in this area, our work herein exhibits the following novelties: 1) different from [13], [14], [15], which consider fixed spreading code assignment, we introduce one additional degree of freedom, i.e., we attempt to optimize the spreading codes at the physical layer to further improve the system performance. We develop a novel low-complexity suboptimal solution to an otherwise NP-hard problem with excellent performance in practice; 2) in our work, interference between secondary links is taken into consideration, and the SINR requirement necessary to guarantee a certain level of quality of service for secondary users is also guaranteed. This is different from [16] and [17], where only the interference from secondary to primary users is considered; 3) direct sequence spread spectrum technology is adopted in our work, while [18] and [23] consider CDMA-based multi-carrier modulation; 4) no previous work [13] - [23] considers interactions between the higher layer functionalities of the networking protocol stack (i.e., routing and scheduling) and physical layer resource allocation (i.e., power and spreading code design) in a multi-hop cognitive radio network scenario. In our work, we explore a new framework that captures the interdependencies between spread-spectrum channelization and routing in cognitive radio ad hoc networks. To the best of our knowledge, our work is the first to consider joint code-channel optimization and routing in cognitive ad hoc networks.

III. System Model

We consider a primary spread-spectrum system with processing gain (code sequence length) G. Denote $\mathcal{PU}$ as the set of active primary communication links. Let (l, k) denote the link with transmitter l and receiver k. Note that link (l, k) is distinct from link (k, l). Each primary link is pre-assigned with an unique code sequence, i.e., $\mathbf{s}_{lk}$ for link (k, l). We let $\mathcal{N} = \{1, \cdots, N\}$ represent a finite set of secondary users (also referred to as nodes). Secondary users do not have any pre-assigned code sequence and opportunistically send their data by optimizing code sequence and power.

Traffic flows of secondary users are, in general, carried over multi-hop routes. Let the traffic demands consist of a set $\mathcal{D} = \{1, 2, \cdots, D\}$ of unicast sessions. Each session $d \in \mathcal{D}$ is characterized by the destination node $d, d \in \mathcal{N}$ for the

[2] While early standardization and regulation discussions have begun [24], no conclusive "interference temperature" rules and agreements have been reached yet.

traffic. We indicate the arrival rate of session d at node i as $\mu_i^d(t)$ at time t. Each node maintains a separate queue for each session d for which it is either a source or an intermediate relay. At time slot t, define $Q_i^d(t)$ as the number of queued packets of session d waiting for transmission at secondary user i. Define $r_{ij}^d(t)$ (in packets/s) as the transmission rate on link (i,j) for session d during time slot t, and $\mathbf{R}$ as the vector of rates. Note that $\mu_i^d(t)$ represents the exogenous traffic arrivals at node i, while $\sum_{k\in\mathcal{N},k\neq i} r_{ki}^d(t)$ represents the total endogenous traffic arrivals at node i resulting from routing and transmission decisions from other nodes k.

For $\forall i \in \mathcal{N}$, the queue is updated as follows:

$$Q_i^d(t+1) = \left[Q_i^d(t) + \sum_{k\in\mathcal{N},k\neq i} r_{ki}^d(t) - \sum_{j\in\mathcal{N},j\neq i} r_{ij}^d(t) + \mu_i^d(t) \right]^+ .$$

A. Physical Layer Model

We recall that the secondary cognitive ad hoc network coexists with the primary system over the primary licensed band. In general, the transmitted spread spectrum signal for the link (i,j) is denoted by

$$u_{ij}(t) = \sum_{m=1}^{\infty} \sqrt{E_i} s_{ij}\left(t - mT\right) e^{j(2\pi f_c t + \phi_i)} b_i(m) \quad (1)$$

where $b_i(m) \in \{-1,+1\}$ is the mth data bit (binary phase-shift-keying data modulation), E_i is the total transmission energy, and ϕ_i is the carrier phase with carrier frequency f_c; $s_{ij}(t)$ is the normalized unit-energy user signature waveform with duration T given by

$$s_{ij}(t) = \sum_{g=0}^{G-1} \mathbf{s}_{ij}(g)\psi(t - gT_c) \quad (2)$$

where $\mathbf{s}_{ij}(g),\ g = 0,1,\ldots,G-1$, is the value of the gth chip of the spreading-code vector of the link (i,j), $\psi(t)$ is the chip waveform, and $T_c = \frac{T}{G}$ is the chip period. The combined received signal waveform due to all link transmissions over flat fading channels of impulse response $h_{ij}(t)$

$$y(t) = \sum_{(i,j)\in\mathcal{PU}\cup\mathcal{SU}} h_{ij}(t) u_{ij}(t - \tau_{ij}) + n(t) \quad (3)$$

where $\mathcal{SU}$ is the set of active secondary links, $\tau_{ij} \in [0,T)$ is the relative delay of link (i,j) with respect to the link of interest, and $n(t)$ is a white Gaussian noise process. After carrier demodulation, chip-matched filtering and sampling at the chip rate over the duration of a symbol (bit) period of G chips, the received signal at primary node k over the link of interest (l,k), denoted as $\mathbf{y}_{lk}^{(p)}$, can be represented as

$$\begin{aligned}\mathbf{y}_{lk}^{(p)} =& \sqrt{E_l} L_{lk} \mathbf{s}_{lk} b_l + \sum_{\substack{(m,n)\in\mathcal{PU}\\(m,n)\neq(l,k)}} \sqrt{E_m} L_{mk} \mathbf{s}_{mn} b_m \\ &+ \sum_{(u,v)\in\mathcal{SU}} \sqrt{E_u} L_{uk} \mathbf{c}_{uv} b_u + \mathbf{n}_k. \end{aligned} \quad (4)$$

We note that the superscript "p" in (4) denotes primary node. Similarly, let $\mathbf{y}_{ij}^{(s)}$ denote the secondary signal received at node j over the link of interest (i,j) ,

$$\begin{aligned}\mathbf{y}_{ij}^{(s)} =& \sqrt{E_i} L_{ij} \mathbf{c}_{ij} b_i + \sum_{(m,n)\in\mathcal{PU}} \sqrt{E_m} L_{mj} \mathbf{s}_{mn} b_m \\ &+ \sum_{\substack{(u,v)\in\mathcal{SU}\\(u,v)\neq(i,j)}} \sqrt{E_u} L_{uj} \mathbf{c}_{uv} b_u + \mathbf{n}_j, \end{aligned} \quad (5)$$

where $E_l > 0,\ b_l \in \{\pm 1\}$, and $\mathbf{s}_{lk} \in \mathbb{R}^G,\ \|\mathbf{s}_{lk}\| = 1$, denote bit energy, information bit, and normalized signature vector of primary user l over primary link (l,k), $(l,k) \in \mathcal{PU}$, respectively; $E_i > 0,\ b_i \in \{\pm 1\}$, and $\mathbf{c}_{ij} \in \mathbb{R}^G,\ \|\mathbf{c}_{ij}\| = 1$, denote the bit energy, information bit, and normalized signature vector, respectively, of secondary user i over secondary link (i,j), $(i,j) \in \mathcal{SU}$; $L_{lk},\ (l,k) \in \mathcal{PU}$ and $L_{ij},\ (i,j) \in \mathcal{SU}$ denote the path coefficients for primary link (l,k) and secondary link (i,j), respectively. $\mathbf{n}_k$ and $\mathbf{n}_j$ represent additive white Gaussian noise (AWGN) at primary node k and secondary node j, correspondingly, independent from each other with $\mathbf{0}$ mean and autocovariance matrix $\sigma^2\mathbf{I}$. We note that the superscript "s" in (5) denotes secondary node.

Rather than being fixed, the interference between the secondary and primary links varies with the transmit power and spreading code allocation. As modeled in (4) and (5), interference from both primary links and secondary links is considered in our design. Specifically, as shown in (4), which is the received signal at the receiver node k of primary link (l,k), the second term $\sum_{\substack{(m,n)\in\mathcal{PU}\\(m,n)\neq(l,k)}} \sqrt{E_m} L_{mk} \mathbf{s}_{mn} b_m$ represents the interference from other primary links, and the third term $\sum_{(u,v)\in\mathcal{SU}} \sqrt{E_u} L_{uk} \mathbf{c}_{uv} b_u$ represents the interference from secondary links. Similarly, in (5), which is the received signal at receiver node j of secondary link (i,j), the second term $\sum_{(m,n)\in\mathcal{PU}} \sqrt{E_m} L_{mj} \mathbf{s}_{mn} b_m$ represents the interference from primary links, and the third term $\sum_{\substack{(u,v)\in\mathcal{SU}\\(u,v)\neq(i,j)}} \sqrt{E_u} L_{uj} \mathbf{c}_{uv} b_u$ represents the interference from other secondary links.

The linear filters at the primary and secondary receivers that exhibit maximum output SINR [25] can be found to be

$$\mathbf{w}_{max\mathrm{SINR},lk} = c_1 \mathbf{A}_{lk}^{-1} \mathbf{s}_{lk},\ \ (l,k) \in \mathcal{PU},$$
$$\mathbf{w}_{max\mathrm{SINR},ij} = c_2 \mathbf{A}_{ij}^{-1} \mathbf{c}_{ij},\ \ (i,j) \in \mathcal{SU},$$

where $\mathbf{A}_{lk} = \mathbb{E}\{\mathbf{y}_{lk}^{(p)} \mathbf{y}_{lk}^{(p)T}\}$, $\mathbf{A}_{ij} = \mathbb{E}\{\mathbf{y}_{ij}^{(s)} \mathbf{y}_{ij}^{(s)T}\}$, c_1 and c_2 are arbitrary positive constants, i.e., $c_1, c_2 > 0$. Maximum output SINRs at the receiver end for link (l,k) and (i,j) are, respectively, given by

$$\mathrm{SINR}_{lk} = L_{lk}^2 E_l \mathbf{s}_{lk}^T \mathbf{A}_{\setminus(l,k)}^{-1} \mathbf{s}_{lk},\ \ \forall (l,k) \in \mathcal{PU},$$
$$\mathrm{SINR}_{ij} = L_{ij}^2 E_i \mathbf{s}_{ij}^T \mathbf{A}_{\setminus(i,j)}^{-1} \mathbf{s}_{ij},\ \ \forall (i,j) \in \mathcal{SU},$$

where $\mathbf{A}_{\setminus(l,k)}$ and $\mathbf{A}_{\setminus(i,j)}$ are the disturbance autocorrelation matrices at the receiver end for link (l,k) and (i,j), respectively, defined by

$$\mathbf{A}_{\setminus(l,k)} \triangleq \sum_{\substack{(m,n)\in\mathcal{PU}\\(m,n)\neq(l,k)}} L_{mk}^2 E_m \mathbf{s}_{mn} \mathbf{s}_{mn}^T + \sum_{(u,v)\in\mathcal{SU}} L_{uk}^2 E_u \mathbf{c}_{uv} \mathbf{c}_{uv}^T + \sigma^2 \mathbf{I},$$

$$\mathbf{A}_{\setminus(i,j)} \triangleq \sum_{(m,n)\in\mathcal{PU}} L_{mj}^2 E_m \mathbf{s}_{mn} \mathbf{s}_{mn}^T + \sum_{\substack{(u,v)\in\mathcal{SU}\\(u,v)\neq(i,j)}} L_{uj}^2 E_u \mathbf{c}_{uv} \mathbf{c}_{uv}^T + \sigma^2 \mathbf{I}.$$

In our cognitive radio setup, the normalized channel capacity

$\frac{C_{ij}}{W}$ of secondary link (i,j) as a function of SINR_{ij} is given by [26]

$$\frac{C_{ij}}{W} = \log_2(1 + \frac{C_{ij}}{W} SINR_{ij}) \tag{6}$$

where C_{ij} is the channel capacity and W is the bandwidth of the primary licensed band. Given the fixed bandwidth W, the channel capacity C_{ij} can be evaluated by (6) for any instantaneous value of SINR_{ij}.

IV. Problem Formulation

Our goal is to design a distributed cross-layer control algorithm to maximize the secondary network throughput by jointly and dynamically allocating routes, code sequence and transmit power for each secondary link along the path. Denote $\mathcal{SU}(t)$ as the set of secondary links chosen for activation during time slot t, $\mathbf{c}(t) = \{\mathbf{c}_{ij}(t) : (i,j) \in \mathcal{SU}(t)\}$ and $\mathbf{E}(t) = \{\mathbf{E}_i(t) : (i,j) \in \mathcal{SU}(t)\}$ as the sets of code sequences and power allocation decisions for every active secondary link. An ideal throughput-optimal network controller should, at each decision period (i.e. time slot t), find $\mathcal{SU}(t)$, $\mathbf{c}(t)$, and $\mathbf{E}(t)$ to maximize

$$\sum_{i\in\mathcal{SU}} \sum_{j\in\mathcal{SU},j\neq i} C_{ij}(\mathbf{c}(t), \mathbf{E}(t)) \cdot \Delta Q_{ij}(t), \tag{7}$$

where $\Delta Q_{ij}(t) = \max_{d\in\mathcal{D}} \left[Q_i^d(t) - Q_j^d(t)\right]^+$. The transmission rates are then given by

$$r_{ij}^d(t) = \begin{cases} C_{ij}(\mathbf{c}(t), \mathbf{E}(t)) & \text{if } d = d_{ij}^*(t) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where $d_{ij}^*(t) = \arg\max_{d\in\mathcal{D}} \left\{Q_i^d(t) - Q_j^d(t)\right\}$.

The objective function (7) is defined based on the principle of dynamic back-pressure, first introduced in [27]. It can be proven [28] that a control strategy that jointly assigns resources at the physical/link layers and routes to maximize the weighted sum of differential backlogs (with weights given by the achievable data rates on the link) achieves throughput optimality, in the sense that it is able to keep all network queues finite for any level of offered traffic within the network capacity region. Moreover, a desirable solution should enable secondary users to dynamically utilize the available spectrum resource in the code domain to provide SINR guarantees for both primary and secondary users. The problem can be expressed as

$$\begin{aligned}
&\mathbf{P1}: Find: && \mathcal{SU}(t),\ \mathbf{E}(t),\ \mathbf{c}(t) \\
&Maximize: && \sum_{i\in\mathcal{SU}} \sum_{j\in\mathcal{SU}} C_{ij}(\mathbf{c}(t), \mathbf{E}(t)) \cdot \Delta Q_{ij}(t) \\
&Subject\ to: && \\
& && \mathrm{SINR}_{lk} \geq \mathrm{SINR}_{PU}^{th}, \quad \forall (l,k) \in \mathcal{PU}, \\
& && \mathrm{SINR}_{ij} \geq \mathrm{SINR}_{SU}^{th}, \quad \forall (i,j) \in \mathcal{SU}(t), \\
& && \mathbf{c}_{ij}(t)^T \mathbf{c}_{ij}(t) = 1,\ E_i \leq E_{max}, \quad \forall (i,j) \in \mathcal{SU}(t).
\end{aligned}$$

Therefore, ideally, a throughput-optimal policy should continuously (i.e., at each time slot) assign resources on each network link by solving problem $\mathbf{P1}$ to optimality. However, exact solution of $\mathbf{P1}$ requires global knowledge of all feasible allocations and a centralized algorithm to solve a mixed integer non-linear problem (NP-hard in general) such as $\mathbf{P1}$ on a time-slot basis. This is clearly not practical for real-time decision making. This provides the rationale for our distributed algorithm, which is designed to provide an approximate solution to $\mathbf{P1}$ based on real-time distributed decisions driven by locally collected information. Note that, for the sake of simplicity, we will drop all time dependencies.

In the following sections, we first discuss the decentralized solution for joint routing and code-division channelization in Section V. Specifically, we described in detail about how next hops are selected together with physical layer resource optimization in our proposed algorithm. We also discussed how nodes learn about the environment to make distributed decisions on routing based on a combination of physical sensing and of local exchange of information through control packets at MAC layer. Then, we present in detail our power and spreading code allocation algorithm to maximize the SINR for secondary links in Section VI.

V. ROCH: Distributed Joint Routing and Code-Division Channelization

We now present the decentralized joint routing and code-division channelization solution, which aims at maximizing throughput through joint opportunistic routing, dynamic code sequence optimization and transmit power control. In the proposed solution, backlogged nodes i first maximize their local objective function $C_{ij} \cdot \Delta Q_{ij}$ over all feasible next hops j by optimizing $\mathbf{c}_{ij}$ and E_i based on locally collected spectrum information - details are given in what follows. Then, in case of channel access contention, each node will access the channel with a probability that is a monotonically increasing function of its local utility. We now describe the details of the proposed solution. Every backlogged node i performs the following algorithm:

1) Find the set of feasible next hops $\{n_1^d, n_2^d, \cdots, n_k^d\}$ for the backlogged session d, which are neighbors with positive advance towards the destination of d. We say node j has *positive advance* with respect to i iff j is closer to the destination d than i.
2) For each candidate next hop $j \in \{n_1^d, n_2^d, \cdots, n_k^d\}$, maximize link capacity C_{ij} by optimizing $\mathbf{c}_{ij}$ and E_i, using the algorithm proposed in the following Section VI.
3) Schedule the session d^* with next hop j^* with maximal $C_{ij} \cdot \Delta Q_{ij}$. Hence, routing is performed in such a way that lightly backlogged nodes with higher link capacity receive most of the traffic.
4) Once the next hop and corresponding code sequence and power allocation have been determined, the probability of accessing the medium is calculated based on the value of $C_{ij} \cdot \Delta Q_{ij}$. Nodes with higher $C_{ij} \cdot \Delta Q_{ij}$ will have a higher probability of accessing the medium and transmit. Note that links with higher differential backlog may have higher spectrum utility, and thus have higher probability of being scheduled for transmission. This is implemented by varying the size of the contention window at the MAC layer. The transmitting node i generates a backoff counter BC_i chosen randomly (with

a uniform distribution) within the interval $[1, 2^{CW_i - 1}]$, where CW_i is the contention window of transmitter i, whose value is a decreasing function $\Phi()$ of $C_{ij} \cdot \Delta Q_{ij}$ as below

$$CW_i = -\theta_1 \cdot \frac{C_{ij} \cdot \Delta Q_{ij}}{\sum_{k \in \mathcal{N}_i, k, l \in \mathcal{V}} (C_{kl} \cdot \Delta Q_{kl})} + \theta_2, \quad (9)$$

where $\theta_1 > 0, \theta_2 > 0$ and the denominator represents the objective value of neighboring competing nodes. Note that sender i collects the utility values of its neighbors by overhearing control packets coded by a common spreading code.

Algorithm 1 ROCH Algorithm

1: At backlogged node i
2: **for each** backlogged session d **do**
3: **for** $j \in \{n_1^d, n_2^d, ..., n_k^d\}$ **do**
4: Calculate link capacity C_{ij} by optimizing $\mathbf{c}_{ij}$ and E_i using algorithm 2 proposed in the following Section VI.
5: **end for**
6: **end for**
7: Schedule $(d^*, j^*) = \arg\max (C_{ij} \cdot \Delta Q_{ij})$
8: Set contention window $CW_i = -\theta_1 \cdot \frac{C_{ij} \cdot \Delta Q_{ij}}{\sum_{k \in \mathcal{N}_i, k, l \in \mathcal{V}} (C_{kl} \cdot \Delta Q_{kl})} + \theta_2$
9: Return $[s^*, j^*, CW_i]$

Note that only the second step involves solving a real optimization (maximization) problem (with low complexity). Specifically, in step 2, the user needs to solve the optimal power and spreading code allocation problem by performing the algorithm discussed in Section VI (which has polynomial complexity). In step 3, the user simply selects the next hop (and the associated session) with maximal utility by comparing utility values of all candidate next hops. In step 4, the user simply calculates the contention window size based on (9) for MAC layer.

The algorithm calculates the next hop j opportunistically depending on queueing and spectrum dynamics, according to the objective function $C_{ij} \cdot \Delta Q_{ij}$. The combination of opportunistically selected next hops leads to a multi-hop path. The multi-hop path discovery terminates when the destination is selected as the next hop. If the destination is in the transmission range of the transmitter (either a source or an intermediate hop for that session), the differential backlog between the transmitter and the destination is no less than the differential backlogs between the transmitter and any other nodes, because the queue length of the destination is zero. With this scheme, lightly-congested nodes (as indicated by a smaller differential backlog) have a higher probability of being selected as intermediate relays. Links with larger differential backlogs result in smaller contention window size at the medium access control, and therefore have higher probability of accessing the channel to reserve resources. Ultimately, heavily backlogged nodes with potential high-data rate opportunities to transmit have a higher probability of accessing the channel.

The algorithm is implemented through a MAC protocol that uses a three-way handshake between source and destination. The three-way handshake is carried out via exchange of Request-to-Send (RTS), Clear-to-Send (CTS) and Data Transmission reServation (DTS) packets. Backlogged nodes contend for spectrum access on a common control channel that operates in parallel to the data channel through a common spreading code. Each node makes adaptive decisions based on local information collected through RTS/CTS/DTS packets coded with a common spreading code. The DTS packet is used to announce the information on spreading code, transmit power allocation and queueing information to neighboring nodes. We include queuing information in the control packets to allow the nodes to make routing decisions. The set of feasible next hops can be obtained by requiring only the neighborhood geographical information (can be obtain by GPS for example) and an estimate of the destination's position. Geographical information, together with the queue information, are encapsulated in the control packets (i.e., RTS/CTS/DTS) to allow nodes to exchange their information.

VI. Cognitive Secondary Power and Spreading Code Allocation

We now come to the spread-spectrum channelization problem, which is a crucial component of our spectrum management framework and is executed at step 2 of the algorithm described in the previous section. We would like to dynamically and adaptively generate digital waveforms that span the whole available spectrum band to maximize the capacity of the link, and that at the same time avoid interfering with existing users (what we refer to as spread-spectrum channelization). Each secondary user optimizes the waveform to be used based on the current interference condition at the secondary receiver and on the interference receiver profile to maximize the overall network throughput, as described in Section V. We present the secondary code-channel optimization formulation in Section VI-A. The formulated problem is NP-hard with complexity exponential in G. In Section VI-B, we develop a realizable suboptimal solution with polynomial complexity.

A. Cognitive Spread-spectrum Channelization Formulation

In order for a cognitive radio network to efficiently share the licensed band with the primary network, the secondary transmitter has to guarantee the SINR QoS of all primary users and ongoing secondary users and, simultaneously, maximize the secondary SINR of link (i, j) at its receiver end. We first assume that the secondary link (i, j) is activated with the transmission bit energy E_i and (normalized) signature vector $\mathbf{c}_{ij}$. In this spirit, our objective is to find the pair $(E_i, \mathbf{c}_{ij})$ that maximizes SINR_{ij} under the constraints that SINR_{lk}, $\forall (l, k) \in \mathcal{PU}$, and SINR_{uv}, $\forall (u, v) \in \mathcal{SU} - \{(i, j)\}$, are all above the prescribed thresholds SINR_{PU}^{th} and SINR_{SU}^{th}, respectively, i.e.

$$(E_i, \mathbf{c}_{ij})^{opt} = \underset{E_i > 0, \mathbf{c}_{ij} \in \mathbb{R}^G}{\arg\max} \; E_i \mathbf{c}_{ij}^T \mathbf{A}_{\backslash (i,j)}^{-1} \mathbf{c}_{ij} \quad (10)$$

$$\text{s.t. } E_l L_{lk}^2 \mathbf{s}_{lk}^T \mathbf{A}_{\backslash (l,k)}^{-1} \mathbf{s}_{lk} \geq \mathrm{SINR}_{PU}^{th}, \; \forall (l,k) \in \mathcal{PU},$$
$$E_u L_{uv}^2 \mathbf{c}_{uv}^T \mathbf{A}_{\backslash (u,v)}^{-1} \mathbf{c}_{uv} \geq \mathrm{SINR}_{SU}^{th}, \; \forall (u,v) \in \mathcal{SU} - \{(i,j)\},$$
$$\mathbf{c}_{ij}^T \mathbf{c}_{ij} = 1, \; E_i \leq E_{max},$$

where E_{max} denotes the maximum allowable bit energy for the secondary user.

The optimization task of maximizing a quadratic objective function ($\mathbf{A}^{-1}_{\backslash(i,j)}$ is positive definite) subject to the constraints in (10) is, unfortunately, a non-convex NP-hard optimization problem [30]. In the following, we delve into the details of the problem and develop a realizable solution.

B. Cognitive Secondary Channel Design

Using the matrix inversion lemma on $\mathbf{A}^{-1}_{\backslash(l,k)}$ and $\mathbf{A}^{-1}_{\backslash(u,v)}$, respectively, we can express the key quadratic constraint expressions in (10), respectively, as

$$\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{\backslash(l,k)}\,\mathbf{s}_{lk} = \frac{\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk}\mathbf{s}_{lk}}{1 - E_l L^2_{lk}\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk}\mathbf{s}_{lk}}, \forall(l,k) \in \mathcal{PU}, \quad (11)$$

$$\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{\backslash(u,v)}\,\mathbf{c}_{uv} = \frac{\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv}\mathbf{c}_{uv}}{1 - E_u L^2_{uv}\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv}\mathbf{c}_{uv}}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\}, \quad (12)$$

where we recall that $\mathbf{A}_{lk} = \mathbb{E}\{\mathbf{y}^{(p)}_{lk}\mathbf{y}^{(p)T}_{lk}\}$ and $\mathbf{A}_{uv} = \mathbb{E}\{\mathbf{y}^{(s)}_{uv}\mathbf{y}^{(s)T}_{uv}\}$. Then, the primary SINR constraints in (10) become

$$\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk}\mathbf{s}_{lk} \geq \frac{\mathrm{SINR}^{th}_{PU}}{E_l L^2_{lk} + \mathrm{SINR}^{th}_{PU} E_l L^2_{lk}} \triangleq \alpha_{lk},\ \forall(l,k) \in \mathcal{PU}, \quad (13)$$

while the secondary SINR constraints are given by

$$\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv}\mathbf{c}_{uv} \geq \frac{\mathrm{SINR}^{th}_{SU}}{E_u L^2_{uv} + \mathrm{SINR}^{th}_{SU} E_u L^2_{uv}} \triangleq \gamma_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\}. \quad (14)$$

The optimization problem (10) can be rewritten as

$$\begin{aligned} (E_i, \mathbf{c}_{ij})^{opt} = &\ \underset{E_i>0, \mathbf{c}_{ij}\in\mathbb{R}^G}{\arg\max}\ E_i\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{\backslash(i,j)}\,\mathbf{c}_{ij} \quad (15)\\ \text{s.t.}\ & \mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk}\mathbf{s}_{lk} \geq \alpha_{lk}, \quad \forall(l,k) \in \mathcal{PU},\\ & \mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv}\mathbf{c}_{uv} \geq \gamma_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\},\\ & \mathbf{c}^T_{ij}\mathbf{c}_{ij} = 1,\ E_i \leq E_{max}. \end{aligned}$$

Using the matrix inversion lemma on $\mathbf{A}^{-1}_{lk}$ and $\mathbf{A}^{-1}_{uv}$ this time, we can express the optimization constraints as explicit functions of signature vector of the secondary link $\mathbf{c}_{ij}$, i.e.

$$\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk}\mathbf{s}_{lk} \geq \frac{E_i L^2_{ik}\mathbf{s}_{lk}\mathbf{A}^{-1}_{lk\backslash(i,j)}\mathbf{c}_{ij}\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{lk\backslash(i,j)}\mathbf{s}_{lk}}{1 + E_i L^2_{ik}\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{lk\backslash(i,j)}\mathbf{c}_{ij}} + \alpha_{lk}, \quad \forall(l,k) \in \mathcal{PU}, \quad (16)$$

$$\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv}\mathbf{c}_{uv} \geq \frac{E_i L^2_{iv}\mathbf{c}_{uv}\mathbf{A}^{-1}_{uv\backslash(i,j)}\mathbf{c}_{ij}\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{uv\backslash(i,j)}\mathbf{c}_{uv}}{1 + E_i L^2_{ik}\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{uv\backslash(i,j)}\mathbf{c}_{ij}} + \gamma_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\}. \quad (17)$$

For notational simplicity, define the $G \times G$ matrices

$$\mathbf{B}_{lk} \triangleq L^2_{ik}\mathbf{A}^{-1}_{lk\backslash(i,j)}\mathbf{s}_{lk}\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk\backslash(i,j)} - \beta_{lk}L^2_{ik}\mathbf{A}^{-1}_{lk\backslash(i,j)} \quad (18)$$

$$\mathbf{B}_{uv} \triangleq L^2_{iv}\mathbf{A}^{-1}_{uv\backslash(i,j)}\mathbf{c}_{uv}\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv\backslash(i,j)} - \beta_{uv}L^2_{iv}\mathbf{A}^{-1}_{uv\backslash(i,j)} \quad (19)$$

where

$$\beta_{lk} \triangleq \mathbf{s}^T_{lk}\mathbf{A}^{-1}_{lk\backslash(i,j)}\mathbf{s}_{lk} - \alpha_{lk}, \quad \forall(l,k) \in \mathcal{PU}, \quad (20)$$

$$\beta_{uv} \triangleq \mathbf{c}^T_{uv}\mathbf{A}^{-1}_{uv\backslash(i,j)}\mathbf{c}_{uv} - \gamma_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\}. \quad (21)$$

Then, the optimization problem in (15) can be rewritten -for one more time- as

$$\begin{aligned} \mathbf{x}^{opt} = &\ \underset{\mathbf{x}\in\mathbb{R}^G}{\arg\max}\ \mathbf{x}^T\mathbf{A}^{-1}_{\backslash(i,j)}\,\mathbf{x} \quad (22)\\ \text{s.t.}\ & \mathbf{x}^T\mathbf{B}_{lk}\mathbf{x} - \beta_{lk} \leq 0, \forall(l,k) \in \mathcal{PU},\\ & \mathbf{x}^T\mathbf{B}_{uv}\mathbf{x} - \beta_{uv} \leq 0, \forall(u,v) \in \mathcal{SU} - \{(i,j)\},\\ & \mathbf{x}^T\mathbf{x} \leq E_{max} \end{aligned}$$

where $\mathbf{x}$ is the amplitude-including signature vector of secondary link (i,j), $\mathbf{x} \triangleq \sqrt{E_i}\mathbf{c}_{ij}$. From the perspective of computational effort, however, (i) $\mathbf{B}_{lk}$ and $\mathbf{B}_{uv}$ are not necessarily positive semidefinite, hence the problem in (22) is in general a non-convex quadratically constrained quadratic program (non-convex QCQP), and (ii) the complexity of a solver of (22) is exponential in the dimension G (NP-hard problem).

Using the commutative property of trace, we are able to represent the optimization problem in (22) as

$$\begin{aligned} \mathbf{X}^{opt} = &\ \underset{\mathbf{X}\in\mathbb{R}^{G\times G}}{\arg\max}\ Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}\} \quad (23)\\ \text{s.t.}\ & Tr\{\mathbf{B}_{lk}\mathbf{X}\} \leq \beta_{lk}, \quad \forall(l,k) \in \mathcal{PU},\\ & Tr\{\mathbf{B}_{uv}\mathbf{X}\} \leq \beta_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\},\\ & Tr\{\mathbf{X}\} \leq E_{max},\ \mathbf{X} \succeq \mathbf{0},\ rank(\mathbf{X}) = 1. \end{aligned}$$

where $\mathbf{X} \triangleq \mathbf{x}\mathbf{x}^T$ and $\mathbf{X} \succeq \mathbf{0}$ denotes that the matrix $\mathbf{X}$ is positive semidefinite.

To effectively attack the problem anyway, the problem in (23) is relaxed to a semidefinite program by dropping the rank constraint, i.e.

$$\begin{aligned} \mathbf{X}' = &\ \underset{\mathbf{X}\in\mathbb{R}^{G\times G}}{\arg\max}\ Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}\} \quad (24)\\ \text{s.t.}\ & Tr\{\mathbf{B}_{lk}\mathbf{X}\} \leq \beta_{lk}, \quad \forall(l,k) \in \mathcal{PU},\\ & Tr\{\mathbf{B}_{uv}\mathbf{X}\} \leq \beta_{uv}, \quad \forall(u,v) \in \mathcal{SU} - \{(i,j)\},\\ & Tr\{\mathbf{X}\} \leq E_{max},\ \mathbf{X} \succeq \mathbf{0}. \end{aligned}$$

Then, (24) is a convex problem that can be solved using semidefinite programming within the error ϵ in $O(G^4 \log 1/\epsilon)$ time. The solution $\mathbf{X}''$ returned by semidefinite programming makes the objective function $Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}\}$ attain a value within $(Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}'\} - \epsilon, Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}'\})$. Of course, because of the constraint relaxation itself the objective function evaluated at the optimum point $\mathbf{X}'$ in (24) is just an upper bound on the value of the objective function evaluated at the optimum point of interest $\mathbf{X}^{opt}$ of (23), $Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}^{opt}\} \leq Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}'\}$. Since $\mathbf{X}'$ is not available, we have $\mathbf{X}''$ with $Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}''\} \in (Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}'\} - \epsilon, Tr\{\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{X}'\})$. So far, for the cognitive design of a code-division secondary link, first, for the given primary and secondary SINR-QoS thresholds $\mathrm{SINR}^{th}_{PU} > 0$ and $\mathrm{SINR}^{th}_{SU} > 0$, we test whether β_{lk}, $\forall(l,k) \in \mathcal{PU}$ and $\beta_{uv}, \forall(u,v) \in \mathcal{SU} - \{(i,j)\}$ are all greater than zero. If this is not true, then the SINR-QoS constraints cannot be satisfied and outright no secondary transmission is allowed. Otherwise, we solve the problem (24) by semidefinite programming with the return $\mathbf{X}''$. If the rank of $\mathbf{X}''$ is 1 with eigenvalue, eigenvector pair $(\lambda_1, \mathbf{v}_1)$, then we already have our secondary link design with signature $\mathbf{c}_{ij} = \mathbf{v}_1$ and transmission bit energy $E_i = \lambda_1$. If the rank of $\mathbf{X}''$ is not 1, further work is needed as described below.

When $\mathbf{X}'$ of (24) (or in practice $\mathbf{X}''$) is of rank 2 or more, we can not find the direct mapping from $\mathbf{X}'$ of (24) to $\mathbf{x}^{opt}$ in (22). Under this case, we may switch the search for an optimal vector in (22) to a search for an optimal probability density function (pdf) of vectors that maximizes the average objective function subject to average constraints, i.e.

$$\begin{aligned} f^{opt}(\mathbf{x}) = \max_{f(\mathbf{x})} \ & \mathbb{E}\{\mathbf{x}^T \mathbf{A}^{-1}_{\backslash(i,j)} \mathbf{x}\} \qquad (25)\\ \text{s.t.} \ & \mathbb{E}\{\mathbf{x}^T \mathbf{B}_{lk} \mathbf{x}\} \le \beta_{lk}, \forall (l,k) \in \mathcal{PU},\\ & \mathbb{E}\{\mathbf{x}^T \mathbf{B}_{uv} \mathbf{x}\} \le \beta_{uv}, \forall (u,v) \in \mathcal{SU} - \{(i,j)\},\\ & \mathbb{E}\{\mathbf{x}^T \mathbf{x}\} \le E_{max} \end{aligned}$$

where $f(\mathbf{x})$ denotes the probability density function of $\mathbf{x}$ and $\mathbb{E}\{\cdot\}$ denotes statistical expectation. Using the commutative property between trace and expectation operators, the pdf optimization problem in (25) takes the equivalent form

$$\begin{aligned} f^{opt}(\mathbf{x}) = \arg\max_{f(\mathbf{x})} \ & Tr\{\mathbf{A}^{-1}_{\backslash(i,j)} \mathbb{E}\{\mathbf{x}\mathbf{x}^T\}\} \qquad (26)\\ \text{s.t.} \ & \mathbf{B}_{lk} \mathbb{E}\{\mathbf{x}\mathbf{x}^T\} \le \beta_{lk}, \forall (l,k) \in \mathcal{PU},\\ & \mathbf{B}_{uv} \mathbb{E}\{\mathbf{x}\mathbf{x}^T\} \le \beta_{uv}, \forall (u,v) \in \mathcal{SU} - \{(i,j)\},\\ & \mathbb{E}\{\mathbf{x}\mathbf{x}^T\} \le E_{max}. \end{aligned}$$

We can show that $f^{opt}(\mathbf{x})$ is in fact Gaussian with $\mathbf{0}$ mean and covariance matrix $\mathbf{X}'$, $f^{opt}(\mathbf{x}) = \mathcal{N}(\mathbf{0}, \mathbf{X}')$. With $\mathbf{X}''$ as a close approximation of $\mathbf{X}'$, we can draw now a sequence of samples $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_P$ from $\mathcal{N}(\mathbf{0}, \mathbf{X}'')$. We test all of them for "feasibility" on whether all constraints of (22) are satisfied and among the feasible vectors (if any) we choose the one, say $\mathbf{x}^{(0)}$, with maximum $\mathbf{x}^T \mathbf{A}^{-1}_{\backslash(i,j)} \mathbf{x}$ objective function value. We could have suggested at this time a cognitive secondary link design with $\sqrt{E_i}\mathbf{c}_{ij} = \mathbf{x}^{(0)}$. Instead, we will use $\mathbf{x}^{(0)}$ as an initialization point to an iterative procedure below that will lead to a improved link design vector. First we express $\mathbf{A}_{\backslash(i,j)}$ as

$$\mathbf{A}_{\backslash(i,j)} = \mathbf{S} \Sigma \mathbf{S}^T + \sigma^2 \mathbf{I} \qquad (27)$$

where $\mathbf{S} \triangleq [\{\mathbf{s}_{lk}, \forall (l,k) \in \mathcal{PU}\}, \{\mathbf{c}_{uv}, \forall (u,v) \in \mathcal{SU} - \{(i,j)\}]$ denotes the matrix with columns the signatures of the primary users and ongoing secondary users; $\Sigma \triangleq \text{diag}(\{E_l L^2_{lj}, \forall (l,k) \in \mathcal{PU}\}, \{E_u L^2_{uj}, \forall (u,v) \in \mathcal{SU} - \{(i,j)\})$. Using the matrix inversion lemma,

$$\mathbf{A}^{-1}_{\backslash(i,j)} = \frac{1}{\sigma^2}\mathbf{I} - \frac{1}{\sigma^4}\mathbf{S}(\Sigma^{-1} + \frac{1}{\sigma^2}\mathbf{S}^T\mathbf{S})^{-1}\mathbf{S}^T. \qquad (28)$$

Substitution of (28) in the objective function of (22) leads to

$$\mathbf{x}^T \mathbf{A}^{-1}_{\backslash(i,j)} \mathbf{x} = \frac{1}{\sigma^2}\mathbf{x}^T\mathbf{x} - \frac{1}{\sigma^4}\mathbf{x}^T \mathbf{Q}\,\mathbf{x} \qquad (29)$$

where $\mathbf{Q} \triangleq \mathbf{S}(\Sigma^{-1} + \frac{1}{\sigma^2}\mathbf{S}^T\mathbf{S})^{-1}\mathbf{S}^T$. In (29), the first term $\frac{1}{\sigma^2}\mathbf{x}^T\mathbf{x}$ is a convex function while the second term $-\frac{1}{\sigma^4}\mathbf{x}^T\mathbf{Q}\,\mathbf{x}$ is a concave function (which implies that $\frac{1}{\sigma^4}\mathbf{x}^T\mathbf{Q}\,\mathbf{x}$ is convex). Based on the first-order condition of convex functions, we have

$$\mathbf{x}^T\mathbf{x} \ge 2\mathbf{x}^{(0)T}\mathbf{x} - \mathbf{x}^{(0)T}\mathbf{x}^{(0)} \qquad (30)$$

where $\mathbf{x}^{(0)}$ denotes an initial feasible vector. Then, we combine (29) and (30) and form an optimization problem that maximizes the following concave function

$$\frac{2}{\sigma^2}\mathbf{x}^{(0)T}\mathbf{x} - \frac{1}{\sigma^4}\mathbf{x}^T\mathbf{Q}\,\mathbf{x} - \frac{1}{\sigma^2}\mathbf{x}^{(0)T}\mathbf{x}^{(0)} \qquad (31)$$

that leads to a *suboptimum* solution for our original problem in (22). To maximize (31) in view of our constraints in (22), we restrict all non-convex constraints into convex sets (linearization). In particular, we consider the non-convex constraints

$$\mathbf{x}^T\mathbf{B}_{lk}\,\mathbf{x} \le \beta_{lk}, \quad \forall (l,k) \in \mathcal{I}^{(p)}_{nc}, \qquad (32)$$

$$\mathbf{x}^T\mathbf{B}_{uv}\,\mathbf{x} \le \beta_{uv}, \quad \forall (u,v) \in \mathcal{I}^{(s)}_{nc}, \qquad (33)$$

where $\mathcal{I}^{(p)}_{nc}$ and $\mathcal{I}^{(s)}_{nc}$ denote sets of all pairs $(l,k) \in \mathcal{PU}$ and $(u,v) \in \mathcal{SU} - \{(i,j)\}$ for which the quadratic constraint is non-convex function, respectively. Then, we decompose the matrices $\mathbf{B}_{lk}$ and $\mathbf{B}_{uv}$ into its positive and negative parts that are positive semidefinite, i.e. $\mathbf{B}_{lk} = \mathbf{B}^+_{lk} - \mathbf{B}^-_{lk}$, where $\mathbf{B}^+_{lk} = L^2_{lj}\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{s}_{lk}\mathbf{s}^T_{lk}\mathbf{A}^{-1}_{\backslash(i,j)}$, $\mathbf{B}^-_{lk} = \beta_{lk}L^2_{lj}\mathbf{A}^{-1}_{\backslash(i,j)}$; $\mathbf{B}_{uv} = \mathbf{B}^+_{uv} - \mathbf{B}^-_{uv}$, where $\mathbf{B}^+_{uv} = L^2_{uj}\mathbf{A}^{-1}_{\backslash(i,j)}\mathbf{c}_{uv}\mathbf{c}^T_{uv}\mathbf{A}^{-1}_{\backslash(i,j)}$, $\mathbf{B}^-_{uv} = \beta_{uv}L^2_{uj}\mathbf{A}^{-1}_{\backslash(i,j)}$. Therefore, the original non-convex constraints can be written as

$$\mathbf{x}^T\mathbf{B}^+_{lk}\,\mathbf{x} - \beta_{lk} \le \mathbf{x}^T\mathbf{B}^-_{lk}\,\mathbf{x}, \quad \forall (l,k) \in \mathcal{I}^{(p)}_{nc}, \qquad (34)$$

$$\mathbf{x}^T\mathbf{B}^+_{uv}\,\mathbf{x} - \beta_{uv} \le \mathbf{x}^T\mathbf{B}^-_{uv}\,\mathbf{x}, \quad \forall (u,v) \in \mathcal{I}^{(s)}_{nc}, \qquad (35)$$

where both sides of the inequalities are convex quadratic functions. Linearization of the right-hand side of (34) around the vector $\mathbf{x}^{(0)}$ leads to

$$\mathbf{x}^T\mathbf{B}^+_{lk}\,\mathbf{x} - \beta_{lk} \le \mathbf{x}^{(0)T}\mathbf{B}^-_{lk}\,\mathbf{x}^{(0)} + 2\mathbf{x}^{(0)T}\mathbf{B}^-_{lk}\,(\mathbf{x} - \mathbf{x}^{(0)}), \quad \forall (l,k) \in \mathcal{I}^{(p)}_{nc}, \qquad (36)$$

$$\mathbf{x}^T\mathbf{B}^+_{uv}\,\mathbf{x} - \beta_{uv} \le \mathbf{x}^{(0)T}\mathbf{B}^-_{uv}\,\mathbf{x}^{(0)} + 2\mathbf{x}^{(0)T}\mathbf{B}^-_{uv}\,(\mathbf{x} - \mathbf{x}^{(0)}), \quad \forall (u,v) \in \mathcal{I}^{(s)}_{nc}. \qquad (37)$$

In (36) and (37), the right-hand side is an affine lower bound on the original function. It is thus implied that the resulting constraints are convex and more conservative than the original ones, hence the feasible set of the linearized problem is a convex subset of the original feasible set. Thus, by linearizing the concave parts of all constraints, we obtain a set of convex constraints that are tighter than the original non-convex ones. Now, the original optimization problem takes the form

$$\mathbf{x}^{(1)} = \arg\max_{\mathbf{x}\in\mathbb{R}^L} \ \frac{2}{\sigma^2}\mathbf{x}^{(0)T}\mathbf{x} - \frac{1}{\sigma^4}\mathbf{x}^T\mathbf{Q}\mathbf{x} - \frac{1}{\sigma^2}\mathbf{x}^{(0)T}\mathbf{x}^{(0)} \qquad (38)$$

$$\begin{aligned} \text{s.t.} \ & \mathbf{x}^T\mathbf{B}^+_{lk}\,\mathbf{x} - \mathbf{x}^{(0)T}\mathbf{B}^-_{lk}\,(2\mathbf{x} - \mathbf{x}^{(0)}) \le \beta_{lk}, \ \forall (l,k) \in \mathcal{I}^{(p)}_{nc},\\ & \mathbf{x}^T\mathbf{B}_{lk}\mathbf{x} \le \beta_{lk}, \quad \forall (l,k) \in \mathcal{PU} - \mathcal{I}^{(p)}_{nc},\\ & \mathbf{x}^T\mathbf{B}^+_{uv}\,\mathbf{x} - \mathbf{x}^{(0)T}\mathbf{B}^-_{uv}\,(2\mathbf{x} - \mathbf{x}^{(0)}) \le \beta_{uv}, \ \forall (u,v) \in \mathcal{I}^{(s)}_{nc},\\ & \mathbf{x}^T\mathbf{B}_{uv}\mathbf{x} \le \beta_{uv}, \quad \forall (u,v) \in \mathcal{SU} - \mathcal{I}^{(s)}_{nc} - \{(i,j)\},\\ & \mathbf{x}^T\mathbf{x} \le E_{max}. \end{aligned}$$

The problem in (38) is a convex QCQP problem and can be solved efficiently by standard convex system solvers [31] to produce a new feasible vector $\mathbf{x}^{(1)}$. The objective function $\mathbf{x}^T\mathbf{A}^{-1}_{\setminus(i,j)}\mathbf{x}$ in (22) evaluated at $\mathbf{x}^{(1)}$ takes a value that is larger than or equal to its value at $\mathbf{x}^{(0)}$. Repeating iteratively the linearization procedure, we can obtain a sequence of feasible vectors $\mathbf{x}^{(0)}, \mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(N)}$ with non-decreasing values of the objective function in (22). As demonstrated by experimental results in [32], it is observed that eight or nine iterations are enough for effective convergence. After numerical convergence, the secondary link (i,j) is suggested with signature $\mathbf{c}_{ij} = \mathbf{x}^{(N)}/\|\mathbf{x}^{(N)}\|$ and bit energy $E_i = \|\mathbf{x}^{(N)}\|^2$. If the secondary transmission bit energy and signature vector returned by our algorithm satisfy the constraint $E_iL^2_{i,j}\mathbf{c}^T_{ij}\mathbf{A}^{-1}_{\setminus(i,j)}\mathbf{c}_{ij} \geq \mathrm{SINR}^{th}_{SU}$, the secondary link (i,j) with E_i and $\mathbf{c}_{ij}$ is considered as candidate for transmission. Otherwise, transmission over the path (i,j) is not allowed.

Our proposed scheme is summarized in Algorithm 2.

Algorithm 2 Cognitive Code-division Channelization.

```
if β_lk ≥ 0, ∀(l,k) ∈ PU and β_uv ≥ 0, ∀(u,v) ∈ SU − {(i,j)}
then
    Run SDP optimizer
    if Rank(X″)=1 then
        Obtain (λ_1, v_1) from eigen decomposition of X″
        Assign E_i ← λ_1 and c_ij ← v_1
    else
        Draw x_1, x_2, ..., x_P from N(0, X″)
        if Any feasible sample x_p, p ∈ {1, ..., P} that satisfies
        x_p^T B_lk x_p ∀(l,k) ∈ PU & x_p^T B_uv x_p ∀(u,v) ∈ SU − {(i,j)}
        then
            x^(0) ← feasible x_p with maximum x_p^T A^{-1}_{\(i,j)} x_p value
            Run iteratively linearized optimizer with convergence
            point x^(N)
            Assign E_i ← ||x^(N)||^2 and c_ij ← x^(N)/||x^(N)||
        else
            No feasible solution by assigning E_i ← 0 and c_ij ← 0
            Return
        end if
    end if
    if E_i L^2_{i,j} c_ij^T A^{-1}_{\(i,j)} c_ij ≥ SINR^th_SU then
        Output the solution E_i and c_ij
    else
        No feasible solution by assigning E_i ← 0 and c_ij ← 0
    end if
else
    No feasible solution by assigning E_i ← 0 and c_ij ← 0
end if
Return the link design (E_i, c_ij) as candidate for transmission.
```

The complexity of the optimization in the physical layer (i.e. optimizing the secondary transmission bit energy and signature vector) is dominated by the complexity of solving the semidefinite program in (24). The computation complexity of the algorithm for the physical layer is $\mathcal{O}(G^4 \log 1/\epsilon)$. [32] gives more detailed complexity analysis on the optimization in the physical layer. For any of the K feasible next hops, each node executes ROCH, which clearly has polynomial complexity in the number of $\mathcal{O}(G^4 \log 1/\epsilon)$. Conversely, the centralized algorithm of this family of schedule and routing has worst-case exponential complexity [29].

Here, we demonstrate the effective convergence of proposed algorithm through simulation studies. In the simulation, the transmission SNRs of primary links are all set equal to $15\,dB$. The number of active primary users is set to 16 (fully loaded). All the signatures for primary links are generated from a minimum total-squared correlation optimal binary signature set which achieves the Karystinos-Pados (KP) bound [33]-[35]. The SINR threshold is set to $3\,dB$ for both primary and secondary users. In Fig. 2, we plot the secondary receiver *average* SINR for the experimental instants of $rank(\mathbf{X}'') > 1$ as a function of the iteration of the optimizer initialized at the point/design $\mathbf{x}^{(0)}$ that is the best out of $P = 20$ samples drawn from the $\mathcal{N}(\mathbf{0}, \mathbf{X}'')$ pdf. It is pleasing to observe that eight or nine iterations are enough for effective convergence and the improvement is more than $5\,dB$.

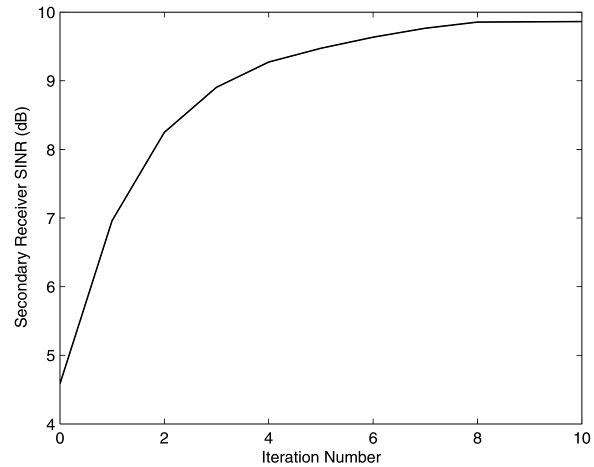


Fig. 2. Secondary receiver SINR as a function of the iteration step of the linearized optimizer initialized at the best feasible sample out of $P = 20$ drawings from the $\mathcal{N}(\mathbf{0}, \mathbf{X}'')$ pdf.

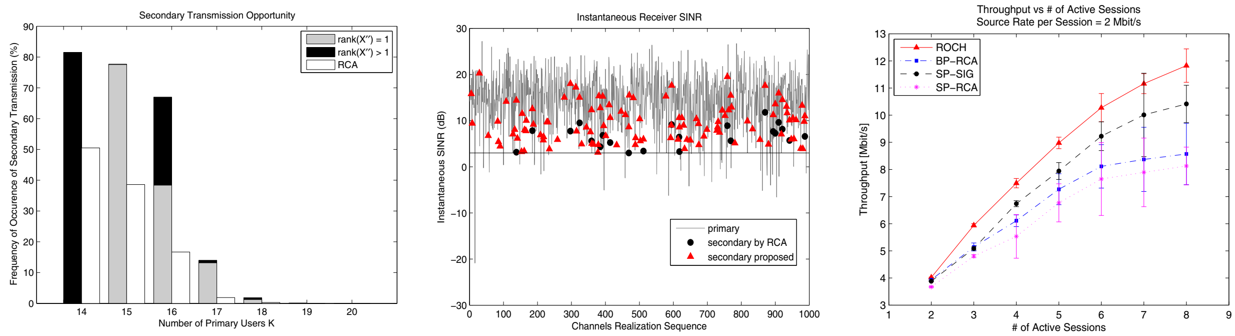
VII. Performance Evaluation

In this section, we evaluate the performance of ROCH in a multi-hop cognitive radio network. We have developed an object-oriented packet-level discrete-event simulator, which models in detail all layers of the communication protocol stack, including routing, medium access control and spread-spectrum channelization as described in this paper.

A. Performance of Secondary Dynamic Spectrum Access

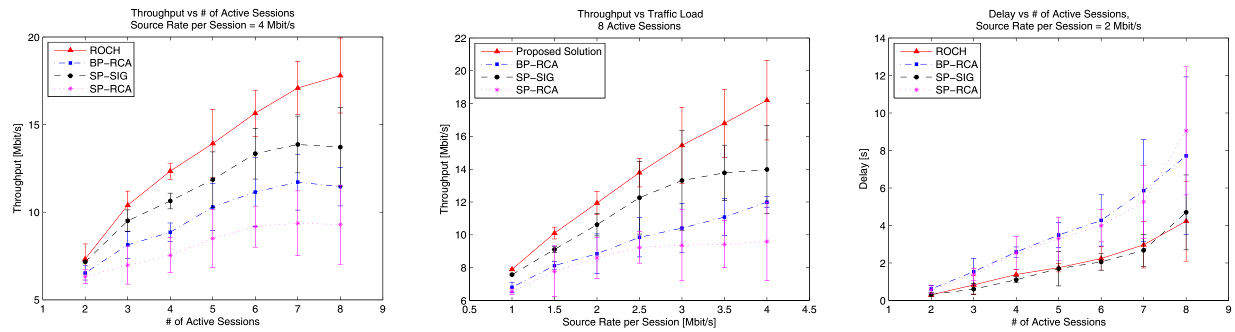
We consider K active links (including primary and secondary links) with signature length (system processing gain) $G = 16$. We are interested in establishing a secondary code-division transmitter/receiver pair when K varies from 14 to 20. All link signatures are generated from a minimum total-squared-correlation optimal binary signature set which achieves the Karystinos-Pados (KP) bound for each (K, G) pair of values[3]. The transmission SNRs of K active links are all set equal to $\frac{E_i}{\sigma^2} = 15\,dB$, $i = 1, 2, \ldots K$; the maximum allowable transmission SNR for the secondary link is set to $\frac{E_{max}}{\sigma^2} = 15\,dB$. The channels are modeled as

[3]For $G = 16$, when $K \leq G$ the KP-optimal sequences coincide with the familiar Walsh-Hadamard signature codes.



(a) (b) (c)

Fig. 3. (a) Secondary transmission percentage as a function of the number of active links under Cases $rank(\mathbf{X}'') = 1$ and > 1 (the study includes also the random code assignment scheme); (b) Instantaneous output SINR of a primary signal against primary SINR-QoS threshold SINR_{PU}^{th} (thick line) and instantaneous output SINR of secondary signal; (c) Throughput vs. Number Active Sessions.



(a) (b) (c)

Fig. 4. (a) Throughput vs. Number Active Sessions; (b) Throughput vs. Traffic Load; (c) Delay vs. Number Active Sessions.

Rayleigh fading. The channel coefficients are taken to be the magnitude of independent complex Gaussian random variables with mean 0 and variance 1. The receiver SINR thresholds for primary and secondary links are set to $\text{SINR}_{PU}^{th} = 3\,dB$ and $\text{SINR}_{SU}^{th} = 3\,dB$, respectively. When random vector drawing is necessary, $P = 20$ test vector points are generated.

In Fig. 3(a), we plot, as a function of the number of active links K, the percentage of times that one more secondary link is enabled directly under the proposed algorithm in Section V as well as the random code assignment (RCA) scheme where the candidate signature is randomly generated with unit norm and transmission bit energy is set to be the maximum allowable value E_{max}. We observe that our proposed algorithm in Section VI offers more opportunities for cognitive secondary transmission than RCA.

In Fig. 3(b), to gain visual insight into operation of the network we plot the *instantaneous* receiver SINR of a primary active link and the candidate secondary link for the case $K = 17$ over an experimental data record sequence of 1000 Rayleigh fading channel realizations. Missing secondary signal SINR values indicate instances when no feasible solution was returned. The proposed scheme highly increases the probability of secondary transmission compared to RCA. When secondary transmissions do occur for both schemes, joint power and sequence optimization executed by the proposed scheme results in superior SINR performance for the secondary receiver over RCA.

B. Network Performance Evaluation

A grid topology of 49 secondary nodes and 14 active primary links is deployed in a 5000 m $\times$ 5000 m area. The spreading code length is set to 16 for both primary and secondary users. Active primary links use pre-assigned code sequences as described in the previous section. We initiate CBR traffic sessions between randomly selected but disjoint source-destination pairs among the 49 nodes. Parameters θ_1 and θ_2 in (9) are set to 5 and 10, respectively. Rayleigh fading channel is used and the path loss exponent is set to four. We compare the performance of ROCH with three alternative schemes. All alternative schemes rely on the same knowledge of the environment as ROCH. In particular, we consider the solution SP-SIG where routing is based on the shortest path with dynamic signature and power allocation (as proposed in Section VI). The other two solutions use RCA with fixed power allocation. We consider BP-RCA as the solution where routing is based on the same utility function as ROCH but with random code assignment, and SP-RCA as the solution where routing is based on the shortest path with random code assignment.

We compare the four solutions by varying the number of sessions injected into the network and plot the network throughput (sum of individual session throughputs). Figures 3(c) and 4(a) show the impact of the number of sessions injected into the network on the network throughput. The traffic load per session is set to 2 Mbit/s and 4 Mbit/s. As shown in both figures, ROCH achieves the highest throughput. The improvement obtained by ROCH is more visible when the number of active sessions increases. Solutions with adaptive signature design, i.e., the proposed solution ROCH and SP-SIG, outperform RCA-based solutions, i.e., BP-RCA and SP-RCA. With the same signature optimization algorithm, ROCH outperforms SP-SIG since SP-SIG restricts packets forwarding to the receiver that is the closest to the destination, even if the link capacity is very low or the receiver is heavily congested.

Fig. 4(b) shows the impact of source data rate per session on the performance of throughput. We evaluate the throughput performance as the traffic load per session increases from 1 Mbit/s to 4 Mbit/s. As shown in Fig. 4(b), ROCH obtains a significant throughput gain.

Fig. 4(c) shows the delay performance for the four solutions with traffic load 2 Mbit/s per session. In general, solutions with adaptive signature design (ROCH and SP-SIG) outperforms RCA-based solutions (BP-RCA and SP-RCA) in terms of delay, and the delay performance gap between the two grows as the number of sessions increases.

VII. Conclusions

We studied and proposed a decentralized algorithm for joint dynamic routing and code-division channelization in cognitive radio ad hoc networks. We considered the general problem of maximizing the network throughput through joint routing and spread-spectrum channelization. We proposed an algorithm that can be seen as a distributed localized approximation of the throughput-maximizing policy. The proposed algorithm requires solution of a code-division channelization problem as the search for the secondary amplitude, code transmission pair that maximizes the secondary link output SINR subject to the condition that all primary signal output SINR values are maintained above a given SINR-QoS threshold value. The formulated constrained optimization problem is non-convex and NP-hard in the code vector dimension. Simulation results show that the proposed algorithm considerably outperforms baseline solutions.

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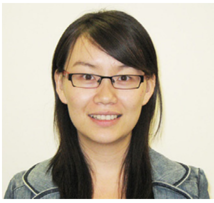

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