

Cross-layer Routing and Dynamic Spectrum Allocation in Cognitive Radio Ad Hoc Networks

Lei Ding, Tommaso Melodia, Stella N. Batalama, John D. Matyjias, and Michael J. Medley

Abstract—Throughput maximization is one of the main challenges in cognitive radio ad hoc networks, where the availability of local spectrum resources may change from time to time and hop-by-hop. For this reason, a cross-layer opportunistic spectrum access and dynamic routing algorithm for cognitive radio networks is proposed, called ROSA (ROUTING and Spectrum Allocation algorithm). Through local control actions, ROSA aims at maximizing the network throughput by performing joint routing, dynamic spectrum allocation, scheduling, and transmit power control.

Specifically, the algorithm dynamically allocates spectrum resources to maximize the capacity of links without generating harmful interference to other users while guaranteeing bounded bit error rate (BER) for the receiver. In addition, the algorithm aims at maximizing the weighted sum of differential backlogs to stabilize the system by giving priority to higher-capacity links with high differential backlog. The proposed algorithm is distributed, computationally efficient, and with bounded BER guarantees.

ROSA is shown through numerical model-based evaluation and discrete-event packet-level simulations to outperform baseline solutions leading to a high throughput, low delay, and fair bandwidth allocation.

Index Terms—Cognitive radio networks, routing, dynamic spectrum allocation, cross-layer design, ad hoc networks.

I. INTRODUCTION

COGNITIVE¹ radio networks [2] have recently emerged as a promising technology to improve the utilization efficiency of the existing radio spectrum. In a cognitive radio network, users access the existing wireless spectrum opportunistically, without interfering with existing users. A key challenge in the design of cognitive radio networks is dynamic spectrum allocation, which enables wireless devices to opportunistically access portions of the spectrum as they become available. Consequently, techniques for dynamic spectrum access have received significant attention in the last few years, e.g., [3] [4] [5] [6] [7].

In addition to this, in cognitive radio networks with multi-hop communication requirements (i.e., cognitive radio ad

hoc networks), the dynamic nature of the radio spectrum calls for the development of novel spectrum-aware routing algorithms. In fact, spectrum occupancy is location-dependent, and therefore in a multi-hop path the available spectrum bands may be different at each relay node. Hence, controlling the interaction between the routing and the spectrum management functionalities is of fundamental importance. While cross-layer design principles have been extensively studied by the wireless networking research community in the recent past, the availability of cognitive and frequency agile devices motivates research on new algorithms and models to study cross-layer interactions that involve spectrum management-related functionalities.

For the reasons above, in this paper we consider interactions between spectrum management and dynamic routing functionalities. With this respect, we propose a distributed algorithm that jointly addresses the routing, dynamic spectrum assignment, scheduling and power allocation functionalities for cognitive radio ad hoc networks. The objective of the proposed algorithm is to allocate resources efficiently, distributively, and in a cross-layer fashion.

We further show how our algorithm can be interpreted as a distributed solution to a centralized cross-layer optimization problem. While the optimization problem is centralized and hard to solve, our algorithm is practically and distributively implementable. We show how a cross-layer solution that solves routing and spectrum allocation jointly at each hop outperforms approaches where routes are selected independently of the spectrum assignment, with moderate computational complexity. Our main contributions can be outlined as follows:

- We derive a distributed and localized algorithm for joint dynamic routing and spectrum allocation for multi-hop cognitive radio networks. The proposed algorithm jointly addresses routing and spectrum assignment with power control under the so-called physical interference model, which computes the interference among secondary users using a SINR-based model. The proposed algorithm considers and leverages the unique characteristics of cognitive radio including the availability of spectrum holes at a particular geographic location and their possible variability with time;
- In the proposed algorithm each cognitive radio makes real-time decisions on spectrum and power allocation based on locally collected information. Nodes can adjust their transmission power to maximize the link capacity on the selected spectrum portion;
- We introduce a notion of “spectrum hole” that considers interference from neighboring secondary as well

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as primary users, and leverage it to optimize resource utilization at a low computational cost;

- We discuss a practical implementation of the proposed algorithm that relies on a dual radio with a common control channel and a frequency-agile data channel;
- We show how the proposed algorithm can be interpreted as a distributed and practical solution to a cross-layer optimal resource allocation problem, whose performance is close to the optimum.

The remainder of this paper is organized as follows. In Section II, we review related work. In Section III, we introduce the system model. In Section IV we propose ROSA, our distributed algorithm for joint routing and dynamic spectrum allocation. Section V addresses implementation details. In Section VI we show how ROSA can be interpreted as a distributed solution to a centralized cross-layer network utility maximization problem for cognitive radio ad hoc networks. Section VII evaluates the performance of the algorithm. Finally, Section VIII concludes the paper.

II. RELATED WORK

Recent work has investigated algorithms and protocols for dynamic spectrum allocation in cognitive radio networks. Proposed approaches to assign spectrum can be broadly classified into *centralized* and *distributed* schemes. For example, the Dynamic Spectrum Access Protocol (DSAP) [8] is centralized, and thus requires a central controller to allocate spectrum. In [7], a distributed spectrum assignment algorithm is proposed, which aims at solving the spectrum allocation problem: which node should use how wide a spectrum-band at what center-frequency and for how long. Our work differs significantly from [7], which assumes mutually exclusive transmissions with zero interference tolerance.

Spectrum band auctions [9][10] have been proposed to allocate wireless spectrum resources, in which bidders obtain different spectrum channels to minimize the interference. In contrast, our proposed solution jointly considers spectrum allocation and routing in a cross-layer fashion, since the available spectrum bands may be different at each hop.

Some recent work has made initial steps in the direction of leveraging interactions between routing and spectrum allocation. In [11], each source node finds candidate paths based on Dynamic Source Routing (DSR) [12] and collects information on link connectivity and quality. For each candidate route, the algorithm finds all feasible spectrum assignment combinations and estimates the end-to-end throughput performance for each combination. Based on this, it selects the route and spectrum assignment with maximal throughput and schedules a conflict-free channel for this route. In [13], a connectivity-based routing scheme for cognitive radio ad hoc networks is proposed, where the connectivity of different paths is evaluated by taking into account primary user activities. The authors in [14] propose a layered graph model, where each layer corresponds to a channel, and find shortest paths based on the layered graph. Both [11] and [14] are channel-based solutions, i.e., the available spectrum is divided into predefined channels, and devices are assigned opportunities to transmit on channels on a relatively long time scale. However, cognitive radio networks

require spectrum allocation on a short time scale since the available spectrum bands will vary continuously based on the activities of primary and secondary users. In addition, the algorithms in [11] and [14] are based on the so-called protocol model [15], in which two links either interfere destructively or do not interfere at all. Although simple, this model fails to capture the cumulative effect of interference. Conversely, our work assumes a richer interference model, which accounts for the fact that advanced transmission techniques, including code-division multiple access (CDMA) [3] [16], allow concurrent co-located communications so that a message from node i to node j can be correctly received even if there is a concurrent transmission close to j .

Recent work has started investigating cross-layer optimizations for cognitive radio networks. In [17], Hou et al. formulate a cross-layer optimization problem for a network with cognitive radios, whose objective is to minimize the required network-wide radio spectrum resource needed to support traffic for a given set of user sessions. The problem is formulated as a mixed integer non-linear problem, and a sequential fixing algorithm is developed where the integer variables are determined iteratively via a sequence of linear programs. Shi et al. studied the joint optimization of power control, scheduling, and routing for a multi-hop cognitive radio network via a centralized approach [18] and a distributed approach [19]. In [19] the authors developed a distributed optimization algorithm with the objective of maximizing data rates for a set of sessions. The performance of the algorithm is shown to be in average within 88% of the performance of the optimal (centralized) algorithm.

III. SYSTEM MODEL

We consider a cognitive radio network consisting of M primary users and N secondary users. Primary users hold licenses for specific spectrum bands, and can only occupy their assigned portion of the spectrum. Secondary users do not have any licensed spectrum and opportunistically send their data by utilizing idle portions of the primary spectrum.

Let the multi-hop wireless network be modeled by a directed *connectivity* graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{v_1, \dots, v_{N+M}\}$ is a finite set of nodes, with $|\mathcal{V}| = N + M$, and $(i, j) \in \mathcal{E}$ represent a unidirectional wireless link from node v_i to node v_j (referred to also as node i and node j , respectively, for simplicity). Nodes from the subset $\mathcal{PU} = \{v_1, \dots, v_M\}$ are designated as primary users, and nodes from subset $\mathcal{SU} = \{v_{M+1}, \dots, v_{M+N}\}$ are designated as secondary users.

We assume that all secondary users are equipped with cognitive radios that consist of a reconfigurable transceiver and a scanner, similar for example to the KNOWS prototype from Microsoft [20]. The transceiver can tune to a set of contiguous frequency bands $[f, f + \Delta B]$, where ΔB represents the maximum bandwidth of the cognitive radio. We keep the physical layer model general. However, we assume that multiple transmissions can concurrently occur in a frequency band, e.g., with different spreading codes. Among others, our physical layer model could represent orthogonal frequency division multiplexing (OFDM)-based transmission, which is based on a flexible subcarriers pool, and is thus a promising

candidate technology for cognitive radio networks. Alternatively, the considered abstraction could model a multi-channel time-hopping impulse radio ultra wide band system [21].

The available spectrum is assumed to be organized in two separate channels. A *common control channel* (CCC) is used by all secondary users for spectrum access negotiation, and is assumed to be time slotted. A *data channel* (DC) is used for data communication. The data channel consists of a set of discrete minibands $\{f_{min}, f_{min+1}, \dots, f_{max-1}, f_{max}\}$, each of bandwidth w and identified by a discrete index. For example, the interval $[f_i, f_{i+\Delta f_i}]$ represents the (discrete) set of minibands selected by secondary user i between f_i and $f_{i+\Delta f_i}$, with bandwidth $w\Delta f_i$. If we let $w\Delta f_B$ denote the maximum bandwidth of the cognitive radio, where Δf_B denotes the maximum number of minibands, we have $\Delta f_i \leq \Delta f_B$ representing the constraint of maximum bandwidth of the cognitive radio. Each backlogged secondary user contends for spectrum access on the control channel f_{cc} , where $f_{cc} \notin [f_{min}, f_{max}]$. All secondary users exchange local information on the common control channel.

Traffic flows are, in general, carried over multi-hop routes. Let the traffic demands consist of a set $\mathcal{S} = 1, 2, \dots, S$, where $S = |\mathcal{S}|$, of unicast sessions. Each session $s \in \mathcal{S}$ is characterized by a fixed source-destination node pair. We indicate the arrival rate of session s at node i as $\lambda_i^s(t)$, and with $\mathbf{\Lambda}$ the vector of arrival rates.

Each node maintains a separate queue for each session s for which it is either a source or an intermediate relay. At time slot t , define $Q_i^s(t)$ as the number of queued packets of session s waiting for transmission at secondary user i . Define $r_{ij}^s(t)$ as the transmission rate on link (i, j) for session s during time slot t , and \mathbf{R} as the vector of rates. For $\forall i \in \mathcal{SU}$, the queue is updated as follows:

$$Q_i^s(t+1) = \left[Q_i^s(t) + \sum_{k \in \mathcal{SU}, k \neq i} r_{ki}^s(t) - \sum_{l \in \mathcal{SU}, l \neq i} r_{il}^s(t) + \lambda_i^s(t) \right]^+ \quad (1)$$

IV. JOINT ROUTING AND DYNAMIC SPECTRUM ALLOCATION

In this section, we present the distributed joint *ROuting and dynamic Spectrum Allocation* (ROSA) algorithm. We start by introducing the notions of *spectrum hole* and *spectrum utility* in Sections IV-A and IV-B, respectively. Opportunities to transmit are assigned based on the concept of *spectrum utility*, and routes are explored based on the presence of *spectrum holes* with the objective of maximizing the *spectrum utility*. Then, in Section IV-C we outline the algorithm for spectrum and power allocation executed in a distributed fashion at each secondary user. Finally, we present the core ROSA algorithm in Section IV-D.

A. Spectrum Holes

For frequency f , secondary user i needs to (i) satisfy the BER requirement when it transmits to secondary user j , and (ii) avoid interfering with ongoing receivers. Denote $SINR_{PU}^{th}$ and $SINR_{SU}^{th}$ as the SINR thresholds to achieve a target bit error rate BER_{PU}^* for primary users and BER_{SU}^* for secondary users, respectively.

The first constraint can be expressed as

$$\frac{P_i(f) \cdot L_{ij}(f) \cdot G}{N_j(f) + \sum_{k \in \mathcal{V}, k \neq i} P_k(f) L_{kj}(f)} \geq SINR_{SU}^{th}(BER_{SU}^*), \quad (2)$$

where G is the processing gain, e.g., length of the spreading code. $P_i(f)$ represents the transmit power of i on frequency f . $L_{ij}(f)$ represents the the transmission loss from node i to j . The expression $\sum_{k \in \mathcal{V}, k \neq i} P_k(f) L_{kj}(f)$ represents interference at node j . Finally, $N_j(f)$ is the receiver noise on frequency f .

The second constraint models the condition that receiver l is not impaired by i 's transmission. We can also indicate interference at node $l \in \mathcal{V}, l \neq j$ as $NI_l(f) + \Delta I_{il}(f)$, where $NI_l(f)$ represents noise plus interference at l before i 's transmission, and $\Delta I_{il}(f)$ represents the additional interference at l caused by i 's transmission, i.e., $P_i(f) L_{il}(f)$. This is expressed as

$$\frac{P_l^R(f)}{NI_l(f) + \Delta I_{il}(f)} \geq SINR^{th}(BER^*), l \in \mathcal{V}, l \neq j, \quad (3)$$

where $P_l^R(f)$ represents the signal power being received at receiver l . Since this has to be true for all ongoing transmissions, the constraint can be written as

$$P_i(f) \leq \min_{l \in \mathcal{V}} \frac{\Delta I_l^{max}}{L_{il}(f)} \triangleq P_i^{max}(f) \quad (4)$$

where

$$\Delta I_l^{max}(f) = \begin{cases} \frac{P_i^R(f)}{SINR_{PU}^{th}(BER_{PU}^*)} - NI_l(f), & l \in \mathcal{PU}, \\ \frac{P_i^R(f)}{SINR_{SU}^{th}(BER_{SU}^*)} - NI_l(f), & l \in \mathcal{SU}. \end{cases} \quad (5)$$

The constraint in (2) states that the SINR at receiver j needs to be above a pre-defined threshold, which means that the power received at receiver j on frequency f needs to be sufficiently high to allow receiver j to successfully decode the signal given its current noise and interferences. The constraint in (4) states that the interference generated by i 's transmission on each frequency should not exceed the threshold value that represents the maximum interference that can be tolerated by the most vulnerable of i 's neighbors $l \in \mathcal{V}, l \neq j$. Hence, i 's transmit power needs to be bounded on each frequency. The constraint in (2) represents a lower bound and the constraint in (4) represents an upper bound on the transmit power for each frequency. By combing constraints (2) and (4), we can define for link (i, j) and frequency f

$$S_{ij}(f) = P_i^{max}(f) - P_i^{min}(f), \quad (6)$$

where $P_i^{max}(f)$ is defined in (4) and $P_i^{min}(f)$ is the value of $P_i(f)$ for which equality in (2) holds. Let vectors $\mathbf{P}_i^{max} = [P_i^{max}(f_{min}), P_i^{max}(f_{min+1}), \dots, P_i^{max}(f_{max})]$ and $\mathbf{P}_i^{min} = [P_i^{min}(f_{min}), P_i^{min}(f_{min+1}), \dots, P_i^{min}(f_{max})]$ denote the maximum and minimum transmit power constraints for link (i, j) . Hence, we introduce the following definition.

Definition 1: A *spectrum hole* for link (i, j) is a set of contiguous minibands where $S_{ij}(f) \geq 0$.

Figure 1 illustrates the notion of spectrum hole. As shown in the figure, the spectrum portion $[f_i, f_{i+\Delta f_i}]$ is a possible spectrum hole for link (i, j) .

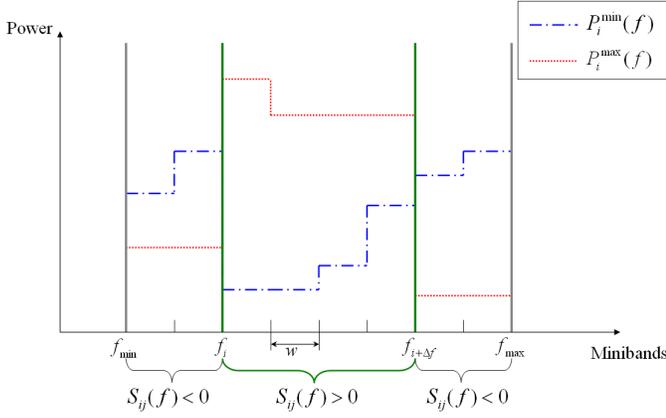


Fig. 1. Illustration of a Spectrum Hole.

B. Spectrum Utility

The control channel is assumed to be time slotted. At each time slot for which node i is backlogged and not already transmitting, node i can evaluate the spectrum utility for link (i, j) , defined as

$$U_{ij}(t) = c_{ij}(t) \cdot \left[Q_i^{s^*}(t) - Q_j^{s^*}(t) \right]^+, \quad (7)$$

where s^* is the session with maximal differential backlog on link (i, j) . The spectrum utility function is defined based on the principle of dynamic back-pressure, first introduced in [22], where the authors showed that a policy 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) is throughput-optimal, in the sense that it is able to keep all network queues finite for any level of offered traffic that is within the network capacity region. As will be discussed in Section VI, the same result can be derived from a cross-layer network utility maximization problem, which can be decomposed into two subproblems. After the decomposition, the solution of the routing and scheduling subproblem requires maximization of a weighted sum of differential backlogs.

Note that, for the sake of simplicity, we will drop all time dependencies in the following. Note also that the notion of spectrum utility is defined for a specific link (i, j) . In (7), $c_{ij}(t)$ represents the achievable capacity for link (i, j) given the current spectrum condition, and is defined as

$$c_{ij}(\mathbf{F}_i, \mathbf{P}_i) \triangleq \sum_{f \in \mathbf{F}_i = [f_i, f_{i+\Delta f_i}]} w \cdot \log_2 \left[1 + \frac{P_i(f) L_{ij}(f) G}{N_j(f) + I_j(f)} \right], \quad (8)$$

where $I_j(f)$ represents the interference at j on f . The achievable values of c_{ij} depend on the dynamic spectrum allocation policy, i.e., spectrum selection vector $\mathbf{F}_i = [f_i, f_{i+\Delta f_i}]$, and power allocation vector $\mathbf{P}_i = [P_i(f)]$, $\forall i \in \mathcal{SU}, \forall f \in \mathbf{F}_i$. The notion of spectrum utility can be thought of as a *differential backlog*, inspired by dynamic resource allocation policies that react to the difference $(Q_i^s - Q_j^s)$ of queue backlogs for a given session [23][24], weighted with dynamic spectrum availability information. Routing with consideration of differential backlog can reduce the probability of relaying data through a congested

relay node. A large queue size at an intermediate node is interpreted as an indicator that the path going through that node is congested and should be avoided, while a small queue size at an intermediate node indicates low congestion on the path going through that node. Therefore, in ROSA nodes with a smaller queue size have a higher probability of being selected as next hop.

We let \mathbf{A} indicate active links of secondary users on the data channel, i.e., $a_{ij} = 1$ indicates that link (i, j) is active, while $a_{ij} = 0$ indicates that the link is not active. Similarly, we denote \mathbf{A}^P as the link status of primary users, i.e., $a_{ij}^P = 1$ indicates that link between primary users i and j is active (input to the problem). Thus, at each time slot the global objective is to find global vectors $\mathbf{P} = [\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_N]$, $\mathbf{F} = [\mathbf{F}_1, \mathbf{F}_2, \dots, \mathbf{F}_N]$, \mathbf{A} (and, implicitly, \mathbf{C}) that maximize the sum of spectrum utilities over the activated links, under given BER and power constraints. This is expressed by the problem below.

$$\begin{aligned} \mathbf{P1} : \text{Given} : & \quad \text{BER}_{SU}^*, \mathcal{G}(\mathcal{V}, \mathcal{E}), P^{Bgt}, \mathbf{Q}, \mathbf{A}^P \\ \text{Find} : & \quad \mathbf{P}, \mathbf{F}, \mathbf{A} \\ \text{Maximize} : & \quad \sum_{i \in \mathcal{SU}} \sum_{j \in \mathcal{SU}, j \neq i} U_{ij} \cdot a_{ij} \quad (9) \\ \text{Subject to} : & \end{aligned}$$

$$\text{SINR}_{kl}^f \geq \text{SINR}_{PU}^{th}(\text{BER}_{PU}^*) \cdot a_{kl}^P, \quad \forall k, l \in \mathcal{PU}, \forall f \in \mathbf{F}_k \quad (10)$$

$$\text{SINR}_{ij}^f \geq \text{SINR}_{SU}^{th}(\text{BER}_{SU}^*) \cdot a_{ij}, \quad \forall i, j \in \mathcal{SU}, \forall f \in \mathbf{F}_i \quad (11)$$

$$\sum_{f \in \mathbf{F}_i} P_i(f) \leq P^{Bgt}, \quad \forall i \in \mathcal{SU}, \quad (12)$$

$$0 \leq \Delta f_i \leq \Delta f_B, \quad \forall i \in \mathcal{SU}. \quad (13)$$

In the problem above, we denote SINR_{ij}^f as the SINR for link (i, j) . Constraint (10) indicates that primary user transmissions should not be impaired. Constraint (11) imposes that secondary user transmissions should also satisfy a given BER performance, while sharing the spectrum with other secondary users. In (12), P^{Bgt} represents the instantaneous power available at the cognitive radio. Constraint (13) imposes a limit on the bandwidth of cognitive radios. In addition, $\sum_{i \in \mathcal{SU}} (a_{ij} + a_{ji}) \leq 1, \forall j \in \mathcal{SU}$ must hold.

Solving the problem above requires global knowledge of feasible rates, is centralized and its complexity is worst-case exponential. This provides the motivation for our distributed algorithm, whose objective is to maximize (9) under the constraints introduced by cognitive radio networks in a distributed fashion. In addition, we show how the distributed algorithm can be implemented in a practical protocol.

C. Spectrum and Power Allocation

In this section we present the spectrum and power allocation algorithm executed in a distributed fashion at each secondary user to maximize the link capacity given the current spectrum condition. Maximizing the capacity of link (i, j) means selecting spectrum $\mathbf{F}_i = [f_i, f_{i+\Delta f_i}]$ and corresponding transmit power $P_i(f)$ on each frequency to maximize the Shannon capacity.

$$\begin{aligned} \mathbf{P2} : \text{Given} : & (i, j), \mathbf{I}_j, \mathbf{N}_j, \mathbf{L}_{ij}, \mathbf{P}_i^{\min}, \mathbf{P}_i^{\max}, P^{Bgt} \\ \text{Find} : & [f_i, f_{i+\Delta f_i}], \mathbf{P}_i \\ \text{Maximize} : & c_{ij} \end{aligned} \quad (14)$$

$$\text{Subject to :} \quad P_i^{\min}(f) \leq P_i(f) \leq P_i^{\max}(f), \forall f \in [f_i, f_{i+\Delta f_i}]; \quad (15)$$

$$\sum_{f \in [f_i, f_{i+\Delta f_i}]} P_i(f) \leq P^{Bgt}, \forall i \in \mathcal{SU}; \quad (16)$$

$$0 \leq \Delta f_i \leq \Delta f_B, \forall i \in \mathcal{SU}, \quad (17)$$

where $\mathbf{I}_j = [I_j(f_{\min}), I_j(f_{\min+1}), \dots, I_j(f_{\max})]$, $\mathbf{N}_j = [N_j(f_{\min}), N_j(f_{\min+1}), \dots, N_j(f_{\max})]$, and $\mathbf{L}_{ij} = [L_{ij}(f_{\min}), L_{ij}(f_{\min+1}), \dots, L_{ij}(f_{\max})]$ with $i, j \in \mathcal{SU}$.

The objective of the problem above is to find the spectrum hole with maximal capacity, given spectrum condition and hardware limitations of the cognitive radio. Note that constraint (15) imposes the presence of a spectrum hole, and constraints (16) and (17) indicate the hardware restrictions.

For a fixed contiguous set of minibands $[f_i, f_{i+\Delta f_i}]$, we can obtain a solution to the problem above by relaxing constraints (15) and (16). Hence, we can express the dual objective function as

$$\begin{aligned} g(\mathbf{P}_i, \mathbf{\Upsilon}) = & \sum_{f \in [f_i, f_{i+\Delta f_i}]} w \cdot \log_2 \left[1 + \frac{P_i(f)L_{ij}(f)G}{N_j(f) + I_j(f)} \right] + \\ & \sum_{f \in [f_i, f_{i+\Delta f_i}]} [v_{\min}^f (P_i^{\min}(f) - P_i(f)) + v_{\max}^f (P_i(f) - P_i^{\max}(f))] \\ & + v^{Bgt} \left(\sum_{f \in [f_i, f_{i+\Delta f_i}]} P_i(f) - P^{Bgt} \right), \end{aligned} \quad (18)$$

where

$$\mathbf{\Upsilon} = [v_{\min}^{f_i} v_{\min}^{f_{i+1}} \dots v_{\min}^{f_{i+\Delta f_i}} v_{\max}^{f_i} v_{\max}^{f_{i+1}} \dots v_{\max}^{f_{i+\Delta f_i}} v^{Bgt}] \quad (19)$$

is the vector of Lagrange multipliers, $\mathbf{\Upsilon} \succeq 0$.

Algorithm 1 Spectrum and Power Allocation.

Inputs: (i, j) , \mathbf{I}_j , \mathbf{N}_j , \mathbf{L}_{ij} , \mathbf{P}_i^{\min} , \mathbf{P}_i^{\max} , P^{Bgt} .

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1:  $[f_i^*, \Delta f_i^*] = \emptyset$ ,  $\mathbf{P}_i^* = \mathbf{0}$ 
2: for  $\Delta f_i \in [0, \Delta f_B]$  do
3:    $m = 1$ ,  $\Delta = \infty$ ,  $c_{ij} = 0$ 
4:   for  $f_i \in [f_{\min}, \dots, f_{\max} - \Delta f_i]$  do
5:     while  $\Delta > \Delta^{th}$  do
6:        $m = m + 1$ 
7:       for  $f \in [f_i, \dots, f_{i+\Delta f_i}]$  do
8:         Assign  $P_i^m(f)$  as in (20)
9:       end for
10:      Update Lagrange Multipliers
11:       $\mathbf{\Upsilon}(m) = [\mathbf{\Upsilon}(m-1) + \frac{1+\epsilon}{m+\epsilon} \mathbf{\Gamma}(m)]^+$ 
12:       $\Delta = |\mathbf{\Upsilon}(m) - \mathbf{\Upsilon}(m-1)|_2$ 
13:    end while
14:    Calculate  $c_{temp}$  as in (8)
15:    if  $c_{temp} > c_{ij}$  then
16:       $c_{ij} = c_{temp}$ 
17:       $[f_i^*, \Delta f_i^*, \mathbf{P}_i^*] = [f_i, \Delta f_i, \mathbf{P}_i]$ 
18:    end if
19:  end for
20: Return solution as  $[f_i^*, \Delta f_i^*, \mathbf{P}_i^*, c_{ij}]$ 

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A solution to problem **P2** is obtained as described in Algo-

gorithm 1, which provides a dual-based iterative solution to the problem. Specifically, for a given spectrum window between frequency f_i and $f_{i+\Delta f_i}$, at each iteration m the algorithm assigns power $P_i^m(f)$ sequentially for each frequency as in (20). Equation (20) is obtained by setting $\frac{dg(\mathbf{P}_i, \mathbf{\Upsilon})}{dP_i(f)} = 0$. Then, Lagrange multipliers are updated following a gradient descent algorithm. In Algorithm 1, Δ^{th} represents a target precision, while ϵ is a small constant used in the gradient stepsize $\frac{1+\epsilon}{m+\epsilon}$. Finally, $\mathbf{\Gamma}(m)$ represents a suitable gradient at step m , i.e.,

$$\begin{aligned} \mathbf{\Gamma}(m) = & [(P_i^{\min}(f_i) - P_i^{m-1}(f_i)) \dots (P_i^{\min}(f_{i+\Delta f_i}) - P_i^{m-1}(f_{i+\Delta f_i})) \\ & (-P_i^{\max}(f_i) + P_i^{m-1}(f_i)) \dots (-P_i^{\max}(f_{i+\Delta f_i}) + P_i^{m-1}(f_{i+\Delta f_i})) \\ & \left(\sum_{f \in [f_i, f_{i+\Delta f_i}]} P_i^{m-1}(f) - P^{Bgt} \right)]. \end{aligned} \quad (22)$$

D. Routing and Dynamic Spectrum Allocation Algorithm

We now present the cross-layer ROuting and dynamic Spectrum Allocation algorithm (ROSA), which aims at maximizing throughput through joint opportunistic routing, dynamic spectrum allocation and transmit power control, while performing scheduling in a distributed way.

Every backlogged node i , once it senses an idle common control channel, performs the following joint routing and scheduling algorithm:

- 1) Find the set of feasible next hops $\{n_1^s, n_2^s, \dots, n_k^s\}$ for the backlogged session s , which are neighbors with positive advance towards the destination of s . Node n has *positive advance* with respect to i iff n is closer to the destination than i . Calculate c_{ij} for each link (i, j) , where $j \in \{n_1^s, n_2^s, \dots, n_k^s\}$, using Algorithm 1.
- 2) Schedule s^* with next hop j^* such that

$$(s^*, j^*) = \arg \max(U_{ij}^s). \quad (23)$$

Note that U_{ij}^s depends on both the capacity and the differential backlog of link (i, j) . Hence, routing is performed in such a way that lightly backlogged queues with more spectrum resource receive most of the traffic.

- 3) Once spectrum selection, power allocation and next hop have been determined, the probability of accessing the medium is calculated based on the value of $U_{ij}^{s^*}$. Nodes with higher $U_{ij}^{s^*}$ will get a higher probability of accessing the medium and transmit. Note that U_{ij}^s defined in (7) is an increasing function of $(Q_i^s - Q_j^s)$, i.e., links with higher differential backlog may have higher spectrum utility, thus have higher probability of being scheduled for transmission.

This probability is implemented by varying the size of the contention window at the MAC layer. The transmitter i generates a backoff counter BC_i chosen uniformly from the range $[0, 2^{CW_i-1}]$, where CW_i is the contention window of transmitter i , whose value is a decreasing function $\Phi()$ of the optimal spectrum utility $U_{ij}^{s^*}$ as below

$$CW_i = -\alpha \cdot \frac{U_{ij}^{s^*}}{\sum_{k \in \mathcal{SU}, (k,l) \in \mathcal{E}} U_{kl}^s} + \beta, \quad \alpha > 0, \beta > 0 \quad (24)$$

where $\sum_{k \in \mathcal{SU}, (k,l) \in \mathcal{E}} U_{kl}^s$ represents the total spectrum utility of the competing nodes. Note that sender i col-

$$P_i^m(f) = \frac{wL_{ij}(f)G \log_2 e - (N_j(f) + I_j(f))(v_{min}^{f,m} + v_{max}^{f,m} - v^{Bgt,m})}{L_{ij}(f)G(v_{min}^{f,m} + v_{max}^{f,m} - v^{Bgt,m})} \quad (20)$$

lects the spectrum utilities of its neighbors by overhearing the control packets on the common control channel as discussed in Section V. Nodes with smaller values of the backoff counter will have higher priority in allocating resources for transmission than nodes with larger value of the backoff counter. With this mechanism, heavily backlogged queues with more spectrum resources are given higher probability of transmitting.

Algorithm 2 ROSA Algorithm.

```

1: At backlogged node  $i$ 
2:  $U_i = 0$ ,  $[f_i^*, \Delta f_i^*] = \emptyset$ ,  $\mathbf{P}_i = \mathbf{0}$ 
3: for each backlogged session  $s$  do
4:   for  $j \in \{n_1^s, n_2^s, \dots, n_k^s\}$  do
5:     Calculate  $c_{ij}$ ,  $[f_i, \Delta f_i]$  and  $\mathbf{P}_i$  using Algorithm 1
6:      $U_{temp} = c_{ij} \cdot (Q_i^s - Q_j^s)$ 
7:     if  $U_{temp} > U_i$  then
8:        $U_i = U_{temp}$ 
9:        $[s^*, j^*, U_{ij}^s, f_i^*, \Delta f_i^*, \mathbf{P}_i^*] = [s, j, U_i, f_i, \Delta f_i, \mathbf{P}_i]$ 
10:       $a_{ij}^* = 1$ 
11:    end if
12:  end for
13: end for
14: Set contention window  $CW_i = \Phi(U_{ij}^{s^*})$ 
15: Generate backoff counter  $BC_i \in [0, 2^{CW_i-1}]$ 
16: Return  $[s^*, j^*, BC_i, U_{ij}^{s^*}, f_i^*, \Delta f_i^*, \mathbf{P}_i^*, a_{ij}^*]$ 

```

The details are shown in Algorithm 2.

ROSA calculates the next hop opportunistically depending on queueing and spectrum dynamics, according to the spectrum utility function in (7). Hence, each packet will potentially follow a different path depending on queueing and spectrum dynamics. Hence, packets from the same session may follow different paths. At every backlogged node, the next hop is selected with the objective of maximizing the spectrum utility. The combination of 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 relay node 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. Hence, the destination has a higher probability of being selected as next hop than any other neighboring node of the transmitter. Note that the transmitter may still select a node other than the destination as the next hop even if the destination is in the transmission range. This can happen, for example, if there is no available miniband (low interference) between the transmitter and destination, or if the interference on all minibands at that time is high, which results in low link capacity between the transmitter and the destination.

V. COLLABORATIVE VIRTUAL SENSING IN ROSA

As discussed earlier, we assume that each node is equipped with two transceivers, one of which is a reconfigurable transceiver that can dynamically adjust its waveform and

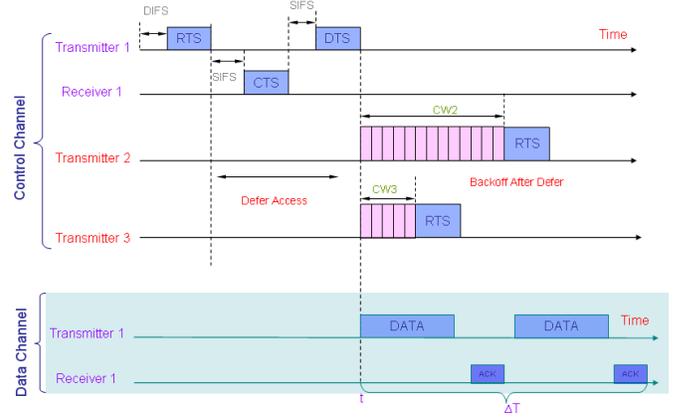


Fig. 2. ROSA's Medium Access Control.

bandwidth for data transmission². The other is a conventional transceiver employed on the common control channel. Handshakes on the CCC are conducted in parallel with data transmissions on the data channel.

We propose a new scheme called *Collaborative Virtual Sensing* (CVS), which aims at providing nodes with accurate spectrum information based on a combination of physical sensing and of local exchange of information. Scanner-equipped cognitive radios can detect primary users transmissions by sensing the data channel. In addition, collaborative virtual sensing is achieved by combining scanning results and information from control packets exchanged on the control channel that contain information about transmissions and power used on different minibands.

ROSA's medium access control logic is illustrated in Fig. 2. Similar to the IEEE 802.11 two-way RTS (request-to-send) and CTS (clear-to-send) handshake, backlogged nodes contend for spectrum access on the CCC. In particular, backlogged nodes must first sense an idle control channel for a time period of Distributed Inter-Frame Spacing (DIFS), and then generate a backoff counter. The values of backoff counter are determined under the objective that nodes with higher spectrum utility should have a higher channel access probability.

The sender informs the receiver of the selected frequency interval $[f_i, f_{i+\Delta f}]$ using an RTS packet. On receiving the RTS packet, the receiver responds by using a CTS packet after the Short Inter-Frame Space (SIFS) and tunes its transceiver for data transmission on the frequency specified in the RTS packet. As in [7], an additional control packet, DTS (Data Transmission reReservation), is needed for the transmitter to announce the spectrum reservation and transmit power to its neighbors. Here, we modify the RTS/CTS/DTS packets and include channel allocation information to allow the nodes to make adaptive decisions. The control packets carry address fields of the sender and the receiver, the spectrum reservation

²Implementations of ROSA that rely on a single transceiver are also possible, for example by letting the reconfigurable transceivers periodically tune to the common control channel to exchange control information. This is the subject of ongoing research.

$[f_i, f_{i+\Delta f}]$, reservation duration field $(t_0, t_0 + \Delta t)$, information on queue length \mathbf{Q} , and power constraints $\mathbf{P}^{\max}, \mathbf{P}^{\min}$, all of which are input parameters of ROSA. Based on the collected information, each node learns the spectrum environment and queue length information from its neighborhood. Each backlogged node performs ROSA to adaptively select the portion of the spectrum to be used and the next hop. Note that Δt is the reservation time for the data channel, and includes the time needed for transmitting all the remaining data in the scheduled queue $\Delta Q_i^s / c_{ij}$, plus the time needed to ACK packets. By actively collecting RTS, CTS, and DTS packets transmitted on the CCC, each node learns spectrum and queue information of its neighborhood.

Once RTS/CTS/DTS are successfully exchanged, sender and receiver tune their transceivers to the selected spectrum portion. Before transmitting, they sense the selected spectrum and, if it is idle, the sender begins data transmission without further delay. Note that it is possible that the sender or the receiver find the selected spectrum busy just before data transmission. This can be caused by the presence of primary users, or by conflicting reservations caused by losses of control packets. In this case, the node gives up the selected spectrum, and goes back to the control channel for further negotiation. During the RTS/CTS/DTS exchange, if the sender-selected spectrum can not be entirely used, i.e., the receiver just sensed primary user presence, the receiver will not send a CTS. The sender will go back to the control channel for further negotiation once the waiting-for-CTS timer expires and the RTS retransmission limit is achieved. When data are successfully received, an ACK will be sent by the receiver. The transaction is considered completed after the ACK is successfully received.

VI. INTERPRETATION OF ROSA AS A NUM SOLVER

In this section, we show how ROSA can be interpreted as a distributed dual-based solution to a cross-layer network utility maximization problem for cognitive radio ad hoc networks under the system model described in the previous sections. A joint congestion control, routing, and dynamic spectrum allocation problem for cognitive radio networks can be formulated as follows.

$$\begin{aligned} \mathbf{P3} : \text{Given} : & \quad BER_{SU}^*, BER_{PU}^*, \mathcal{G}(\mathcal{V}, \mathcal{E}), P^{Bgt}, \mathbf{A}^P \\ \text{Find} : & \quad \mathbf{A}, \mathbf{R}, \mathbf{C} \\ \text{Maximize} : & \quad \sum_{i \in SU} \sum_{s \in \mathcal{S}} U_i(\lambda_i^s); \quad (25) \\ \text{Subject to} : & \end{aligned}$$

$$\lambda_i^s + \sum_{k \in SU, k \neq i} r_{ki}^s = \sum_{l \in SU, l \neq i} r_{il}^s, \quad \forall i \in SU, \forall s \in \mathcal{S} \quad (26)$$

$$\sum_{s \in \mathcal{S}} r_{ij}^s \leq c_{ij}, \quad \forall i \in SU, \forall j \in SU \setminus i. \quad (27)$$

Note that if \mathbf{C} is the feasible set of the physical rates, values of $c_{ij} \in Co(\mathbf{C})$, i.e., they are constrained to be within the convex hull of the feasible rate region [24][25]. The feasible set of the physical rates is expressed by

$$c_{ij} \triangleq \sum_{f \in [f_i, f_{i+\Delta f_i}]} w \cdot \log_2 \left[1 + \frac{P_i(f) L_{ij}(f) G}{N_j(f) + I_j(f)} \right] \quad (28)$$

$$\begin{aligned} SINR_{kl}^f & \geq SINR_{PU}^{th} (BER_{PU}^*) \cdot a_{kl}^P, \quad \forall k, l \in \mathcal{PU}, \forall f \in [f_k, f_{k+\Delta f_k}] \quad (29) \\ SINR_{ij}^f & \geq SINR_{SU}^{th} (BER_{SU}^*), \quad \forall i, j \in SU, s.t. \sum_{s \in \mathcal{S}} r_{ij}^s \geq 0, \forall f \in \mathbf{F}_i \quad (30) \end{aligned}$$

$$\sum_{f \in [f_i, f_{i+\Delta f_i}]} P_i(f) \leq P^{Bgt}, \quad \forall i \in SU, \quad (31)$$

$$0 \leq \Delta f_i \leq \Delta f_B, \quad \forall i \in SU. \quad (32)$$

In the problem above, the objective is to maximize a sum of utility functions $U_i(\lambda_i^s)$, which are assumed to be smooth, increasing, concave, and dependent on local rate at node i only [26]. Constraint (26) expresses conservation of flows through the routing variables r_{ij}^s , which represent the traffic from session s that is being transported on link (i, j) . Finally, constraint (27) imposes that the total amount of traffic transported on link (i, j) is lower than the capacity of the physical link.

By taking a duality approach, the Lagrange dual function of $\mathbf{P3}$ can be obtained by relaxing constraint (26) through Lagrange multipliers $\mathbf{Q} = [Q_i^s]$, with $i \in SU$ and $s \in \mathcal{S}$.

$$\begin{aligned} L(\mathbf{Q}) = \max_{\mathbf{A}} & \left\{ \sum_{i \in SU} \sum_{s \in \mathcal{S}} (U_i(\lambda_i^s) - Q_i^s \lambda_i^s) \right\} + \\ & + \max_{\mathbf{R}, \mathbf{C}} \left\{ \sum_{i \in SU} \sum_{j \in SU, j \neq i} \sum_{s \in \mathcal{S}} r_{ij}^s (Q_i^s - Q_j^s) \right\}, \quad (33) \end{aligned}$$

where variables indicating data rates are still constrained to be $c_{ij} \in Co(\mathbf{C})$, and \mathbf{C} is defined by constraints (28)- (32).

In the above decomposition, the first term of (33) represents the congestion control functionality (which can be carried out independently), while the second term represents routing, scheduling, and physical rate allocation. Let $\mathbf{A}^*(\mathbf{Q}), \mathbf{R}^*(\mathbf{Q}), \mathbf{C}^*(\mathbf{Q})$ be the vectors of optimum values for a given set of Lagrange multipliers \mathbf{Q} . While $\lambda_i^{s,*}(\mathbf{Q})$ can be computed locally at each source i of session s , $\mathbf{R}^*(\mathbf{Q}), \mathbf{C}^*(\mathbf{Q})$ require global knowledge and centralized algorithms.

To solve the above problem, the following actions need to be performed at each time slot t :

- Update the congestion control variables. For each session s and for each source node i :

$$\lambda_i^s(t) = \sup_{\lambda_i^s} \{U_i(\lambda_i^s) - Q_i^s \lambda_i^s\} \quad (34)$$

- Scheduling and Routing. For each link (i, j) , choose the session that maximizes the differential backlog between transmitter and receiver:

$$s_{ij}^* = \arg \max_s \{Q_i^s - Q_j^s\} \quad (35)$$

Then, set $r_{ij}^{s_{ij}^*}(t) = c_{ij}(t)$. Assign link rates $c_{ij}(t)$ to maximize the weighted sum of the link rates of the network, where the weights correspond to differential backlogs:

$$\mathbf{C}(t) = \arg \max_{\mathbf{C}} \left\{ \sum_{i \in SU} \sum_{j \in SU, j \neq i} c_{ij} (Q_i^{s_{ij}^*} - Q_j^{s_{ij}^*}) \right\} \quad (36)$$

Note that the maximization above is analogous to the

dynamic backpressure algorithm in [24][22].

- Update Lagrange multipliers (queues) as

$$Q_i^s(t+1) = \left[Q_i^s(t) + \epsilon \left(\sum_{k \in SU, k \neq i} r_{ki}^s(t) - \sum_{l \in SU, l \neq i} r_{il}^s(t) + \lambda_i^s(t) \right) \right]^+ \quad (37)$$

Note that the Lagrange function is always convex, and thus the multipliers can be computed using a subgradient algorithm.

Clearly, the bottleneck of the above solution lies in the routing and scheduling component in (36). Solving (36) requires global knowledge of feasible rates and centralized algorithm. It has been shown that the complexity of this family of schedule problems is worst-case exponential [22][27]. Exact distributed solution of (36) is thus infeasible. However, it can be shown that the closer a policy gets to maximizing (36), the closer the policy gets to the capacity region of the network [24]. This provides the rationale for our distributed algorithm, whose objective is to maximize (36) under the constraints expressed by (30) and (31), together with (32) for cognitive radio ad hoc networks.

VII. SIMULATION RESULTS

To evaluate ROSA, we have developed an object-oriented packet-level discrete-event simulator, which models in detail all layers of the communication protocol stack as described in this paper. We first concentrate on evaluating the network throughput, delay, and fairness. Then, we compare the performance of the proposed distributed algorithm and the centralized algorithm. In all simulation scenarios, we considered a common set of parameters. A grid topology of 49 nodes is deployed, in a 6000 m x 6000 m area. We initiate sessions between randomly selected but disjoint source-destination pairs. Sessions are CBR sources with a data rate of 2 Mbit/s each. We set the available spectrum to be 54 MHz - 72 MHz, a portion of the TV band that secondary users are allowed to use when there is no licensed (primary) user operating on it. We restrict the bandwidth usable by cognitive radios to be 2, 4 and 6 MHz. The bandwidth of the CCC is 2 MHz. The duration of a time slot is set to 20 microseconds. Parameters α and β in (24) are set to 10 and 10 respectively. A Larger CW can reduce the collision rate but may lead to lower utilization of the control channel caused by backoff. These values are implicitly optimized based on the network size in the paper. The SU SINR threshold is 9 dB, and the PU SINR threshold is 19 dB in the simulation.

We average over multiple trials to obtain a small relative error (within 10% of the average value). The data rate is a step-wise approximation of (8), which can model, among others, different modulation schemes available for different $SINR$ values. Fig. 3(a) illustrates the network throughput achieved by ROSA with time as the number of active sessions varies. With a higher number of active sessions, ROSA achieves higher overall network throughput by adaptively adjusting bandwidth to enable concurrent parallel transmissions.

We compare the performance of ROSA with two alternative schemes, both of which rely on the same knowledge of the

environment as ROSA. In particular, we consider Routing with Fixed Allocation (RFA) as the solution where routing is based on differential backlog (as in Section IV) with pre-defined channel and transmit power, and to Routing with Dynamic Allocation (RDA) as the solution where routing is based on shortest path with dynamic channel selection and transmit power allocation without considering differential backlog.

We compare against the three solutions by varying the number of sessions injected into the network and plot the network throughput (sum of individual session throughput) in Fig. 4(a), which shows that ROSA outperforms RFA and RDA. When there are a few active sessions, e.g., 2 or 4, ROSA, RDA and RFA obtain similar throughput performance. However, with more active sessions, ROSA and RDA perform much better than RFA since they use the best among possible spectrum allocations and routes adaptively. RDA restricts packets forwarding to the receiver that is closest to the destination, even if the link capacity is very low or the receiver is heavily congested. In contrast, ROSA, by considering both the link capacity and the differential backlog, is more flexible and may route packets along paths that temporarily take them farther from the destination, especially if these paths eventually lead to links that have higher capacity and/or that are not as heavily utilized by other traffic. The improvement obtained by ROSA is more visible when the number of active sessions increases.

Fig. 4(b) shows the delay performance for the three solutions. RFA, on average, delivers a larger delay than the other two solutions. The above delay performance gap grows as the number of sessions increases. As shown in Fig. 4(b), ROSA provides very low and stable delay performance as the number of sessions increases. ROSA and RDA yield almost the same delay performance.

Fig. 4(c) shows the impact of source data rate per session on the performance of throughput and delay. We evaluate the throughput and delay performance as the traffic load per session increases from 100 Kbit/s to 8 Mbit/s. As shown in Fig. 4(c), the throughput achieved by ROSA increases linearly as the load per session increases. As the load increases, ROSA obtains a significant throughput gain.

Fig. 3(b) shows Jain's fairness index, calculated as $(\sum r_s)^2 / S * \sum (r_s)^2$, where r_s is the throughput of session s , and S is the total number of active sessions. As shown in the figure, the overall fairness among competing sessions is improved by ROSA using prioritized channel access scheme. When the sessions are dynamic, the protocol is supposed to be stable since the algorithm adaptively adjusts channel selection and power allocation according to the current transmissions.

We compare the performance in terms of network spectrum utility defined in (9) of **P1** between our distributed algorithm and the centralized algorithm. We consider a cognitive radio network with 10 nodes. We assume that there are 7 secondary users and 3 primary users associated with 3 different minibands. Every primary user holds a license for one specific miniband, and can only occupy its assigned miniband. We activate sessions between randomly selected but disjoint source-destination pairs among the 7 secondary users. Fig. 3(c) shows that even though ROSA uses only local information and has low complexity, the performance

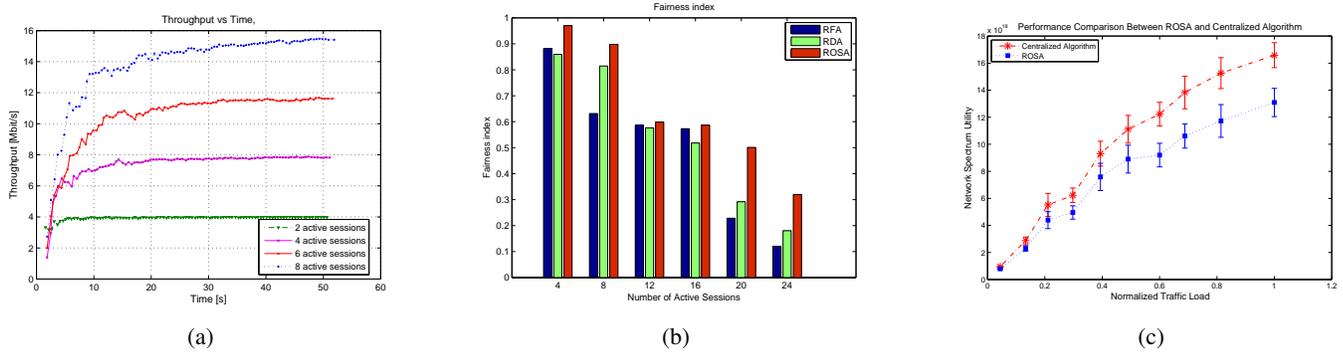


Fig. 3. (a): Throughput for Different Number of Active Sessions; (b): Fairness Index; (c): Performance Comparison Between ROSA and Centralized Algorithm

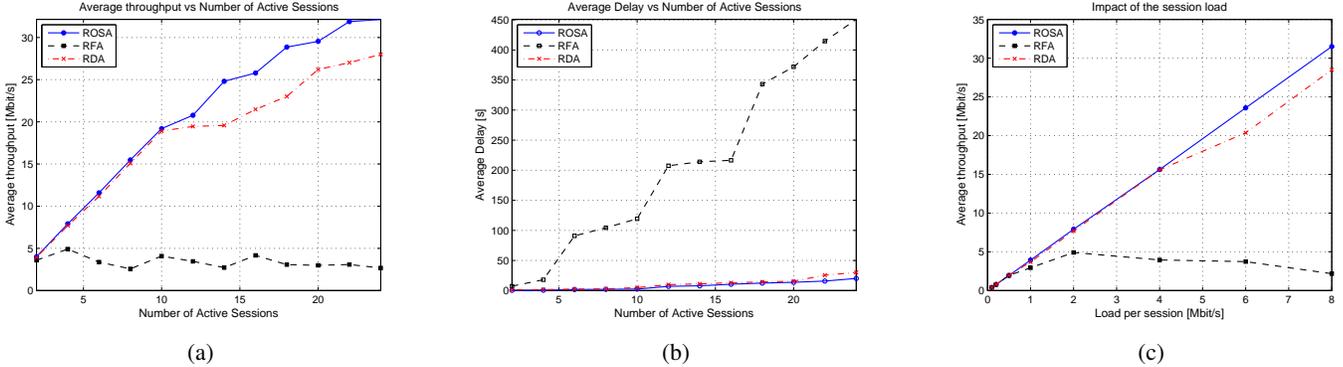


Fig. 4. (a): Throughput vs Number of Active Sessions; (b): Delay vs Number of Active Sessions; (c): Impact of Source Data Rate per Session on Throughput

is within 75% of the optimal (centralized) solution. However, the centralized solution is obtained with global information and has exponential computational complexity.

VIII. CONCLUSIONS

We proposed, discussed and analyzed ROSA, a distributed algorithm for joint opportunistic routing and dynamic spectrum access in multi-hop cognitive radio networks. ROSA was derived by decomposing a cross-layer network utility maximization problem formulated under the constraints of cognitive radio networks. Through discrete-event simulation, ROSA was shown to outperform simpler solutions for inelastic traffic. Future work will aim at deriving a theoretical lower bound on the performance of ROSA. In addition, we are currently implementing ROSA on a software defined radio platform based on an open source platform built on GNU radio and USRP2.

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