Resource-minimized Channel Assignment for Multi-transceiver Cognitive Radio Networks

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***Abstract*—The advancement of cognitive radio (CR) has uncovered new dynamics in multi-hop, wireless networking. Given the increased agility of a transceiver's frequency assignment, the network topology can be optimized to address end-to-end networking goals. We propose a channel assignment scheme for cognitive radio networks (CRNs) that balances the need for topology adaptation focusing on flow rate maximization and the need for a stable baseline topology that supports network connectivity. We focus on CRNs in which nodes are equipped with multiple radios or transceivers, each of which can be assigned to a channel. First, our approach assigns channels independently of traffic, to achieve basic network connectivity and support light loads such as control traffic, and second, it dynamically assigns channels to the remaining transceivers in response to traffic demand. In this paper, we focus on the traffic-independent (TI) channel assignment with the goal of dedicating as few transceivers as possible to achieving baseline connectivity. By conserving transceivers in the TI assignment, the network is more able to adapt to any traffic demands in a subsequent traffic-driven (TD) assignment. We formulate the problem as a two-stage mixed integer linear program (MILP), with a TI stage and a TD stage. We propose a centralized greedy approach to TI assignment which performs nearly identically to the optimum obtained from the two-stage MILP in terms of the number of transceivers assigned and flow rate in the evaluated scenarios. Subsequently, we propose a distributed greedy TI approach that performs within 9% of the optimum in terms of the number of transceivers assigned and within 1.5% of the optimum in terms of flow rate.**

I. Introduction

Cognitive radio (CR) technologies have enabled increased flexibility in modern communication systems, allowing intelligent reconfiguration of many communication components in software [1]. Cognitive radios have the ability to adjust many radio parameters such as frequency assignment, transmit power, and channel bandwidth, as well as the ability to sense various frequency channels for other radio frequency (RF) activity [2]. These abilities enable dynamic spectrum access (DSA) networks where frequency-agility may be necessary to opportunistically use channels and avoid any licensed spectrum users.

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The advances in CRs also introduce a new set of possibilities in the realm of wireless networking. In [3], it is proposed that nodes make a coordinated effort to adapt the network's elements (possibly including node-radio level parameters) according to end-to-end goals, instead of addressing only link-level goals. We adopt the definition of cognitive radio networks (CRNs) as networks that are able to adapt their operating parameters based on a set of observed stimuli as outlined in [3] and [4]. We promote the idea that a CRN should pursue coordinated, end-to-end networking goals while recognizing the practical needs of the network to maintain stable, underlying network connectivity.

Many works, including [5–11], propose traffic-driven (TD) assignment strategies for maximizing end-to-end flow rate. However, these schemes typically assume a zero-cost control plane enabling basic underlying network connectivity, or these schemes lack consideration of practical CR limitations that may greatly impact network connectivity. These constraints include a limited number of transceivers per node, non-neglible costs in terms of energy associated with enabling and tuning a transceiver to a channel, and non-neglible channel-settling times.

Another set of works focus on traffic-independent (TI) channel assignment strategies that are designed to establish network connectivity with objectives of minimizing interference [12, 13] or maximizing connectivity [14, 15]. See [16] for a comparison of the aforementioned traffic-independent (TI) assignment schemes. Although these schemes address network connectivity needs, these schemes do not conserve any transceivers for any subsequent adaptations to address traffic demands.

As our main contribution, we propose a channel assignment approach to CR node transceivers that addresses both goals of (1) supporting baseline network connectivity and (2) allowing the network to adapt, pursuing end-to-end goals of flow rate maximization. We argue that these two design goals of a channel assignment scheme must be addressed together, since they both access the same pool of resources. An assignment scheme of one type of allocation limits the actions and effectiveness of the other. The objective is to balance the need for a stable baseline topology and the desire to maximize throughput by dynamically adapting the topology to current network conditions. We argue that a network must maintain a stable baseline connectivity to support control traffic generated by multiple layers of the protocol stack.

We propose using a resource-minimized channel assignment (RMCA) scheme for TI channel assignment. The goal is to minimize transceiver and channel usage while meeting basic connectivity and interference requirements, which addresses goal (1). With a resource-minimized scheme, the network keeps some resources in reserve to respond dynamically to traffic stimuli. After forming a connected topology using RMCA, TD channel assignment occurs to maximize the flow rates, which addresses goal (2). Naturally, the fewer transceivers that are assigned while addressing goal (1), the higher the maximum achievable flow rate becomes because there is greater flexibility in the channel assignment, since fewer resources are dedicated to maintaining network connectivity.

We formally present the problem as a two-stage mixed-integer linear program (MILP), which assigns as few transceivers as possible independently of traffic conditions to create an interference-free, connected topology in the first stage. The second stage of assignment follows another MILP of channel assignment (of transceivers not assigned in the first stage) and flow routing to produce the optimal network response to the traffic demands.

We present centralized and distributed approaches to the TI portion of the assignment problem. In addition, we offer simulation results comparing our approaches to approaches ([12–15, 17–19]) from the research literature. We compare all heuristic approaches to the optimum. Since we focus our evaluation on the traffic-independent portion of the assignment problem, we fix the secondary stage of traffic-driven assignment to follow an MILP to produce the optimal channel assignment and flow routing response to the traffic stimuli. Evaluating second-stage algorithms (e.g. those presented in [5–11]) in this framework is the subject of future work.

The remainder of this paper is organized as follows. Section II provides the problem formulation of the optimal resource-minimized channel assignment as well as the optimal traffic-driven channel assignment. Sections III and IV provide our centralized and distributed channel assignment schemes, respectively. Section V outlines other channel assignment algorithms from the research literature and provides a numerical comparison based on simulation. Section VI concludes the paper.

II. Problem Formulation

In this section, we formulate the problem as a two-stage MILP of channel assignment and flow routing. Figure 1 shows the basic idea of the two-stage MILP. The first (TI) stage assigns channels, inducing a topology that does not change based on traffic conditions. The second (TD) stage assigns channels to any unused radios from the first stage, based on traffic conditions, with the goal of maximizing throughput by modifying the topology to be more suited to the current traffic demand. Under changing traffic conditions, the topology can be re-optimized to meet the current traffic demands.

A. Resource-minimized, TI Stage: Problem $\mathcal{RM}$

The first (TI) stage assigns channels independently of traffic conditions to establish connectivity. The objective is to assign as few transceivers (to channels) as possible throughout the network such that a connected, multi-channel topology is established with limited interference. We denote this as problem $\mathcal{RM}$.

Starting with physical layer constraints, we assume the available spectrum is divided into orthogonal channels contained in set $\mathcal{C}$, and each radio occupies a single channel at any given time. Although radios can occupy any channel, we assume the cost of channel switching is too high to incur on a per-packet basis, so nodes cannot receive on one channel and transmit on another with the same radio. Nodes are contained in set $\mathcal{V}$. The objective function is

$$\min \sum_{i \in \mathcal{V}} |\mathcal{C}_i|, \tag{1}$$

where $\mathcal{C}_i$ is the set of channels tuned to by node i with its radios. Each node is equipped with K radios, so each node can occupy up to K channels. That is,

$$|\mathcal{C}_i| \leq K \quad (\forall i \in \mathcal{V}). \tag{2}$$

Also, we define $\mathcal{C}_{ij} = \mathcal{C}_i \cap \mathcal{C}_j$ as the set of channels nodes i and j have in common.

The communication and interference model we adopt for this problem is the double-disk model similar to [12, 14, 16–18]. There are two disks centered at each node. The inner disk, the communication range disk, has a radius of r_{comm} and the outer disk, the interference disk, has a radius of r_{int} ($r_{comm} < r_{int}$). A node i can communicate with any node j within its communication range if $\mathcal{C}_{ij} \neq \emptyset$. If node j is within node i's interference disk and $\mathcal{C}_{ij} \neq \emptyset$, nodes i and j interfere with one another. By definition if two nodes can communicate with each other, they can interfere with each other as well.

We represent the double-disk relationships with sets $\mathcal{CR}_i$ and $\mathcal{IR}_i$ as the set of nodes within communication range and interference range respectively. We also define binary matrices as follows. The interference range matrix is IR, where $IR[i][j] = 1$ if node $i \in \mathcal{IR}_j$ and 0 otherwise. Similarly, we define the communication range matrix $CR[i][j] = 1$ if node $i \in \mathcal{CR}_j$ and 0 otherwise. If $CR[i][j] = 1$, then $IR[i][j] = 1$ by definition.

We define communication graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ where $\mathcal{E}$ is the edge set. An edge e_{ij} exists in $\mathcal{E}$ if $\mathcal{C}_{ij} \neq \emptyset$ and $CR[i][j] = 1$. We define set $\mathcal{P}_{ij}$ as the set of all paths between node i and j where a path p_{ij} is a list i, e_{ik}, k, e_{kl}, l, ... , m, e_{mj}, j of nodes and edges where no node or edge repeats. Since we are trying to achieve basic network connectivity using minimal resources, we stop allocating resources once there is a path between all node pairs in the graph. That is,

$$|\mathcal{P}_{ij}| \geq 1 \quad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}), \tag{3}$$

For the first (TI) stage of the MILP we seek a channel assignment that results with a limited number of interferers (β). That is,

$$\sum_{j \in \mathcal{V}, j \neq i} (IR[i][j] - CR[i][j]) \cdot |\mathcal{C}_{ij}| \leq \beta \quad (\forall i \in \mathcal{V}). \tag{4}$$

Note that under certain parameters (i.e., a low value of β, a particularly awkward node placement, few transceivers, and/or few channels) this constraint can cause the problem to be

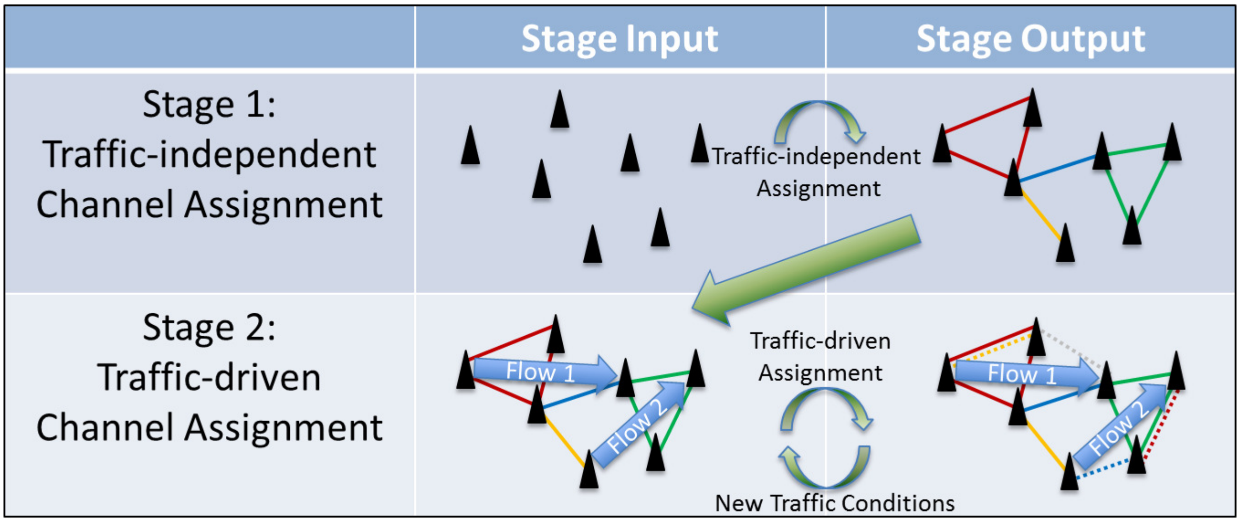

Fig. 1: Two-stage approach: colors represent channels, and solid and dashed lines represent TI and TD links respectively.

infeasible. Although we set $\beta = 0$ in our numerical analysis, we evaluate scenarios where $|\mathcal{C}| = 10$ and $K \geq 2$. This reduces the probability of an infeasible problem, but if this constraint drives the problem to be infeasible, this constraint could be relaxed to allow *some* interferers by setting $\beta > 0$. We found that in all the scenarios we evaluated setting $\beta = 0$ did not make the problem infeasible.

Combining the objective function and all constraints, problem $\mathcal{RM}$ is as follows.

$$\begin{aligned} &\min \sum_{i\in\mathcal{V}} |\mathcal{C}_i| \\ &\text{subject to} \\ &|\mathcal{C}_i| \leq K && (\forall i \in \mathcal{V}) \\ &|\mathcal{P}_{ij}| \geq 1 && (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}) \\ &\sum_{j\in\mathcal{V}, j\neq i} (IR[i][j] - CR[i][j]) \cdot |\mathcal{C}_{ij}| = 0 && (\forall i \in \mathcal{V}) \end{aligned}$$

B. *Traffic-driven Stage: Problem $\mathcal{FM}$*

After the first (TI) stage is completed, there is a connected, multi-channel topology using as few transceivers as possible. The channels assigned remain unaffected by the traffic induced upon the network. The second (TD) stage then uses the transceivers not assigned in the first stage to assign channels, adapting the topology to maximize flow rate. We denote the set of flows as $\mathcal{F}$. Each flow f has a weighting factor of w_f, which is used to scale the rate of each flow with respect to r. The objective function reads

$$\max \sum_{f\in\mathcal{F}} w_f \cdot r. \tag{5}$$

As in the first stage, we allow each node to occupy up to K (the number of transceivers per node) channels. We define $l_{ij}(c)$ as the physical layer transmission rate from node i to node j on channel c. We assume each transceiver has a maximum rate γ for the sum total of transmission and reception rate per channel. This constraint implies nodes can receive and transmit traffic on each channel/transceiver through some sort of time multiplexing. We also limit the aggregate physical layer link transmission rate on each channel within every interference disk to be γ. This implies that channel sharing (through time multiplexing) is possible among nodes co-located in an interference disk. These constraints read as follows.

$$\sum_{j\in\mathcal{V}, j\neq i} l_{ij}(c) + \sum_{j\in\mathcal{V}, j\neq i} l_{ji}(c) \leq \gamma \quad (\forall i \in \mathcal{V}, \forall c \in \mathcal{C}_i) \tag{6}$$

$$\sum_{j\in V} \sum_{k\in\mathcal{V}, k\neq j} l_{jk}(c) \cdot IR[i][j] \leq \gamma \quad (\forall i \in \mathcal{V}, \forall c \in \mathcal{C}_i) \tag{7}$$

These two constraints help model the basics of a network of transmitters. Each interference disk region is centered at node i, so the aggregate rate of all transmitters, j, within range of i is constrained. Note that these constraints do not enforce a strict scheduling.

We constrain the aggregate communication rate of flows between nodes as:

$$\sum_{f\in\mathcal{F}} t_{ij}(f) \leq \sum_{c\in\mathcal{C}_{ij}} l_{ij}(c) \cdot CR[i][j] \qquad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, j \neq i), \tag{8}$$

where $t_{ij}(f)$ is the data transfer rate for flow f from node i to node j, irrespective of the set of channels involved. The source and destination nodes for flow $f \in \mathcal{F}$ are denoted as $s(f)$ and $d(f)$ respectively. Flow conservation at each intermediate node $i \in \mathcal{V}\backslash\{s(f), d(f)\}$, $f \in \mathcal{F}$ is stated as,

$$\sum_{j\in\mathcal{V}, j\neq i} t_{ij}(f) = \sum_{k\in\mathcal{V}, k\neq i} t_{ki}(f) \qquad (\forall f \in \mathcal{F}, \forall i \in \mathcal{V}, i \neq s(f), d(f)). \tag{9}$$

Flow conservation out of each source node i is stated as,

$$\sum_{j\in\mathcal{V}, j\neq i} t_{ij}(f) = r \quad (\forall f \in \mathcal{F}, i = s(f)). \tag{10}$$

Since there is flow conservation at source and intermediate nodes, there is flow conservation at the destination node. Lastly, we have non-negativity constraints for flow and link rates,

$$t_{ij}(f) \geq 0 \quad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, \forall f \in \mathcal{F}), \tag{11}$$

$$l_{ij}(c) \geq 0 \quad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, \forall c \in \mathcal{C}). \tag{12}$$

Putting together all the constraints and objective function, problem $\mathcal{FM}$ is as follows.

$$\max \sum_{f \in \mathcal{F}} w_f \cdot r$$

subject to

$$|\mathcal{C}_i| \leq K \qquad (\forall i \in \mathcal{V})$$

$$\sum_{j \in \mathcal{V}, j \neq i} l_{ij}(c) + \sum_{j \in \mathcal{V}, j \neq i} l_{ji}(c) \leq \gamma \qquad (\forall i \in \mathcal{V}, c \in \mathcal{C}_i)$$

$$\sum_{j \in V} \sum_{k \in \mathcal{V}, k \neq j} l_{jk}(c) \cdot IR[j][i] \leq \gamma \qquad (\forall i \in \mathcal{V}, \forall c \in \mathcal{C}_i)$$

$$\sum_{f \in \mathcal{F}} t_{ij}(f) \leq \sum_{c \in \mathcal{C}_{ij}} l_{ij}(c) \cdot CR[i][j] \quad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, j \neq i)$$

$$\sum_{j \in \mathcal{V}, j \neq i} t_{ij}(f) = \sum_{k \in \mathcal{N}, k \neq i} t_{ki}(f) \qquad (\forall f \in \mathcal{F}, \forall i \in \mathcal{V}, i \neq s(f), d(f))$$

$$\sum_{j \in \mathcal{V}, j \neq i} t_{ij}(f) = r \qquad (\forall f \in \mathcal{F}, i = s(f))$$

$$t_{ij}(f) \geq 0 \qquad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, \forall f \in \mathcal{F})$$

$$l_{ij}(c) \geq 0 \qquad (\forall i \in \mathcal{V}, \forall j \in \mathcal{V}, \forall c \in \mathcal{C})$$

Table I provides a summary of the notation used in the two-stage MILP defined in this subsection.

III. Centralized RMCA

The running time necessary to solve problem $\mathcal{RM}$ (the optimal TI channel assignment) presented in Subsection II-A grows exponentially with the dimension of the problem's parameters ($|\mathcal{V}|$, K, and $|\mathcal{C}|$). In this section, we present a heuristic approach whose running time grows in polynomial time with the problem's parameters. The goal of this approach, which we denote as centralized RMCA, is the same in that it addresses the problem of resource-minimized, traffic-independent channel assignment with the objective of assigning as few transceivers in the network as possible such that the network is connected and has limited interference.

A. Graph Connectivity Metric

Before describing the approach, we define a non-traditional graph-theoretic metric for graph connectivity. The usual graph-theoretic metric for graph connectivity is k-node-connectivity, where k is the minimum number of node-disjoint paths over all node pairs. We denote the number of node-disjoint paths between nodes i and j as P_{ij}^{ND}, which equals the cardinality of the maximum-sized subset of $\mathcal{P}_{ij}$ whose elements, which are paths, have no nodes in common other than nodes i and j. The drawback with the k-node-connnectivity metric is that, in some cases, it is dominated by the single worst node-pairing. We suggest a more granular metric k', where k' is k plus the proportion of all node pairs $\{(i,j) : i,j \in \mathcal{V}, i \neq j\}$ with more than k node-disjoint paths $P_{ij}^{ND} > k$. This is written as

$$k' = \frac{1}{|V| \cdot (|V|-1)} \cdot \sum_{i \in V} \sum_{j \in V, j \neq i} \min(P_{ij}^{ND}, k+1). \tag{13}$$

Note that expression $\min(P_{ij}^{ND}, k+1) \in \{k, k+1\}$ so k' is in the interval $[k, k+1)$.

We utilize the higher granularity of this connectivity metric (as compared to traditional k-node-connectivity) to guide the channel assignment to reach a graph connectivity of $k \geq 1$ using as few channels as possible.

Symbol	Definition
$\mathcal{V}$	Set of nodes
$\mathcal{E}$	Set of edges
$\mathcal{C}$	Set of channels
$\mathcal{C}_i$	Set of channels assigned to node i
$\mathcal{C}_{ij}$	Set of channels assigned to i and j ($\mathcal{C}_i \cap \mathcal{C}_j$)
K	Number of transceivers per node
γ	Maximum capacity of transceivers, links, and interference disks
$IR[i][j]$	Binary interference range matrix, 1 if i and j are in interference range of each other
$CR[i][j]$	Binary communication range matrix, 1 if i and j are in communication range of each other
β	Maximum number of interferers allowed: $\beta = (IR[i][j] - CR[i][j]) \cdot \|\mathcal{C}_{ij}\|$
$\mathcal{P}_{ij}$	Set of all paths from i to j
$l_{ij}(c)$	Transmission rate on link i to j on channel c
$\mathcal{F}$	Set of all network flows
$s(f), d(f)$	Source and destination nodes of flow $f \in \mathcal{F}$
$t_{ij}(f)$	Node-to-node transfer rate of flow f from i to j
r	Base flow rate
w_f	Weight of flow f

TABLE I: Summary of Two-stage MILP Notation

B. The Centralized RMCA Algorithm

We outline the algorithm in this subsection and provide pseudocode in Algorithm 1. Starting with an empty channel assignment at all nodes, the basic idea of this approach is to iteratively assign channels to node transceivers with each assignment yielding the highest increase in the graph's k'-connectivity ($\Delta k'$). Essentially, we greedily maximize k' with each assignment, and there is an intelligent process for handling the situation where no increase in k' is possible. Since the objective is to connect the network using as few transceivers as possible, the algorithm terminates once $k \geq 1$ (or an equivalent stop condition is $k' \geq 1$). Although we focus on reaching $k \geq 1$, the algorithm can be easily extended to target greater values of k or k'.

First, we score the potential assignment of each channel at each node, with the score being the change in the graph's k'-connectivity ($\Delta k'$) due to the assignment if the channel is eligible. At node $i \in \mathcal{V}$, the channel eligibility set $\mathcal{C}_i^e$ is defined as $\mathcal{C} \backslash \{\mathcal{C}_i \cup \bigcup_{j \in \mathcal{IR}_i \backslash \mathcal{CR}_i} C_j\}$. This results in a $|\mathcal{V}|$ x $|\mathcal{C}|$ matrix of scores. A negative score, indicating an ineligible assignment, is given to all channels at a node if the node has no free transceivers, and a negative score is given for any channel at nodes which introduce any interference, which enforces the interference constraint in equation (4). Also, if the node is already assigned a particular channel a negative score is given, preventing subsequent assignment of the same channel. Second, if the maximum node-channel score is greater than zero, the channel assignment corresponding to the entry is performed with any ties broken by selecting the lowest indexed node and channel. The process repeats starting with another scoring of the channels.

Oftentimes, the maximum score will equal zero (e.g. the first assignment in the network), so we provide the following procedure for assigning a channel when this is the case. First, two conditions are tested sequentially. If both conditions are false, there is a default assignment. Note that if all scores are negative, no channel assignment occurs and the algorithm terminates (since no channel assignment is eligible).

Condition 1: *There exists a node $i \in \mathcal{V}$ that has a degree equal to k ($k = 0$ in this case) and $|\mathcal{C}_i^e| > 0$.* If the condition is true the lowest-indexed eligible channel is assigned at the node of degree k. If multiple nodes have a degree of k, select the lowest-indexed node. The point is that we are trying to reach a connectivity of $k + 1$, and since k is bounded by the minimum node degree in the network graph, denoted $\delta(\mathcal{G})$, we must ensure that every node has degree of at least $k + 1$ before we can achieve a connectivity of $k + 1$.

Condition 2: *There exists a source-destination node-pairing (i, j) such that P_{ij}^{ND} equal to k and $|\mathcal{C}_i^e| + |\mathcal{C}_j^e| > 0$ (either i or j has an eligible channel).* If the condition is true, we assign an eligible channel to either node i or j. If both have an eligible channel, we select the node with the lower node degree: $\text{argmin}(|\mathcal{E}_i|, |\mathcal{E}_j|)$, where $\mathcal{E}_i$ is the set of edges at node i. If nodes i and j have equal node degree and at least one eligible channel, we select the node with the lower index. The motivation is that in order for the network to reach a connectivity of $k + 1$ all node pairings (i, j) must have $P_{ij}^{ND} \geq k + 1$, so we attempt to increase any P_{ij}^{ND} that is equal to k.

Default: If conditions (1) and (2) are false, we select the node with the least number of channels assigned and an eligible channel to assign and assign that node an eligible channel. As before, all ties are broken by choosing the lowest indexed channel or node index.

IV. Distributed RMCA

In this section, we present a distributed scheme to the problem of resource-minimized, traffic-independent channel assignment, which is adapted from our prior work in [16]. A distributed channel assignment algorithm may be necessary when centralized control is not possible (e.g., ad hoc networks).

Algorithm 1 Centralized RMCA Algorithm

$\mathcal{C}_i \leftarrow \emptyset, \forall i \in \mathcal{V}$
while $k < 1$ **do**
  for all $i \in \mathcal{V}$ **do**
    for all $c \in \mathcal{C}$ **do**
      if $C_i \cup \{c\}$ is eligible **then**
        score$[i][c] \leftarrow \Delta k'$ of $\mathcal{G}$ with $\mathcal{C}_i \cup \{c\}$
      else
        score$[i][c] \leftarrow -1$
      end if
    end for
  end for
  $(i^*, c^*) \leftarrow \text{argmax}_{i \in \mathcal{V}, c \in \mathcal{C}}(\text{score}[i][c])$
  if score$[i^*][c^*] > 0$ **then**
    $C_{i^*} \leftarrow C_{i^*} \cup \{c^*\}$
  else if score$[i^*][c^*] = 0$ **then**
    if Condition 1 is true **then**
      $i^* \leftarrow \text{argmin}_{i \in \mathcal{V}}(\delta(\mathcal{G})) : |\mathcal{C}_{i^*}^e| > 0$
      $c^* \leftarrow \text{argmax}_{c \in \mathcal{C}}(\text{score}[i^*][c])$
    else if Condition 2 is true **then**
      $(i^*, j^*) \leftarrow \text{argmin}_{i \in \mathcal{V}, j \in \mathcal{V} \backslash i}(P_{ij}^{ND}))$
      if $(|E_{j^*}| < |E_{i^*}|$ and $|\mathcal{C}_{j^*}^e| > 0)$ or $(\mathcal{C}_{i^*}^e = \emptyset)$ **then**
        $i^* \leftarrow j^*$
      end if
      $c^* \leftarrow \text{argmax}_{c \in \mathcal{C}}(\text{score}[i^*][c])$
    else
      $i^* \leftarrow \text{argmin}_{i \in \mathcal{V}}(|\mathcal{C}_i|) : |\mathcal{C}_{i^*}^e| > 0$
      $c^* \leftarrow \text{argmax}_{c \in \mathcal{C}}(\text{score}[i^*][c])$
    end if
    $C_{i^*} \leftarrow C_{i^*} \cup \{c^*\}$
  else
    Terminate, no channel assignment is eligible
  end if
end while

A. Assumptions

Each node uses local information to assign channels. We assume that through some local neighbor discovery process nodes are aware of all other nodes within reliable communication range, which at node i is denoted as set $\mathcal{CR}_i$. Also, through some channel sensing mechanism, we assume that nodes can sense interference on a channel, which is defined as the presence of another node on a channel where the other node is outside of communication range but within interference range.

Any two nodes that are within communication range of each other and have at least one channel in common are neighbors. The set of neighbors at node i is defined as $\mathcal{N}_i = \{j \in \mathcal{CR}_i \mid \mathcal{C}_{ij} \neq \emptyset\}$. We assume that neighboring nodes can become aware of each other's 1-hop neighbors, making nodes aware of all 2-hop neighbors. This is possible through standard control messages (e.g. HELLO messages). The set of all nodes in the 2-hop neighborhood of node i is defined as $\mathcal{N}_i^2 = \{k \in \mathcal{N}_j \mid j \in \mathcal{N}_i, k \neq i\}$.

B. The Distributed RMCA Algorithm

We outline the algorithm in this subsection and provide pseudocode in Algorithm 2. The algorithm starts with no channels assigned to any transceivers and assigns channels until achieving a local connectivity of $\mathcal{CR}_i \subset \mathcal{N}_i^2, \forall i \in \mathcal{V}$, meaning that all nodes in communication range of each other become either 1- or 2-hop neighbors with the hope that this local connectivity translates in to a global k-connectivity greater than or equal to 1.

This algorithm starts with no channels assigned ($\mathcal{C}_i = \emptyset, \forall i \in \mathcal{V}$), and nodes take turns selecting channels in a round-robin fashion for a total of K rounds. In the RMCA algorithm, the channel with the highest number of additional neighbors at node i without any interference is selected. Channels are selected until $\mathcal{CR}_i \subset \mathcal{N}_i^2, \forall i \in \mathcal{V}$.

If at node i, $\mathcal{CR}_i \not\subset \mathcal{N}_i^2$, and all channels in $\mathcal{C} \setminus \mathcal{C}_i$ do not yield any new neighbors, an unoccupied, interference-free channel (if one exists) is selected by node i. By selecting this channel, node i intends to motivate other nodes in $\mathcal{CR}_i \setminus \mathcal{N}_i^2$ to subsequently join node i on the channel. Although it is possible for this algorithm to terminate without establishing a connected network due to the strict interference constraint, we remain consistent with the problem formulation defined in Subsection II-A. See [16] for details on how to relax the interference constraint of this algorithm.

Algorithm 2 Distributed RMCA Algorithm

$\mathcal{C}_i \leftarrow \emptyset, \forall i \in \mathcal{V}$
for $t = 1$ to K **do**
  for $i \in \mathcal{V}$ **do**
    if $\mathcal{CR}_i \not\subset \mathcal{N}_i^2$ **then**
      for $c \in \mathcal{C}$ **do**
        if no interference sensed on channel c **then**
          score[c] $\leftarrow |\{j \in \mathcal{CR}_i \setminus \mathcal{N}_i^2 \mid c \in \mathcal{C}_j\}|$
        else
          score[c] $\leftarrow -1$
        end if
      end for
      $c^* \leftarrow \mathrm{argmax}_{c \in \mathcal{C}}$(score[$c$])
      if score[c^*] ≥ 0 **then**
        $C_i \leftarrow C_i \cup \{c^*\}$
      end if
    end if
  end for
end for

V. Performance Evaluation

In this section, we present the numerical analysis parameters and results in various scenarios. We also present other approaches from the research literature. We evaluate the characteristics of the traffic-independent topology generated. Subsequently, we show how the traffic-independent topology affects the network's ability to dynamically respond to changing traffic conditions.

A. Algorithms

Prior to discussing the numerical procedure we outline selected algorithms from the research literature and how they are used in our evaluation. In [18], an approach called Interference-Aware Topology Control (IA-TC) is proposed. In the first step of IA-TC, the authors propose a topology control scheme called Minimal Interference Survivable Topology Control (INSTC) that selects a threshold of minimal conflict weight where the set of edges below the threshold connect the graph and will subsequently be assigned channels. In decreasing order of conflict weight, the edges are greedily assigned the least used channels in interference range. Depending on the problem parameters, some nodes may have unassigned transceivers. In [18], these unassigned transceivers are assigned the least used channel in the node's interference range in the last step; however, we adapt this last step by assigning any unassigned transceivers in response to traffic conditions to more fairly compare the work in [18] to our work.

In [17], a channel assignment algorithm titled Connected Low Interference Channel Assignment (CLICA) is proposed. The algorithm takes as input a graph (with edges assigned channels). Similar to IA-TC the edges are assigned channels that are in minimal use within interference range; however, the order in which edges are assigned adapts based on how many transceivers remain at each node. The nodes with only a single unassigned transceiver are given the highest priority to be assigned next. The resulting channel assignment assigns channels to all edges and may leave nodes with unassigned transceivers. In our performance analysis, we denote two algorithms following the approach of CLICA with different input graphs. The first approach, denoted CLICA, takes as input the *colorless* communication graph with edges existing between nodes that are within communication range of each other. The second approach, denoted INSTC-CLICA, takes as input the subgraph of the *colorless* communication graph following the INSTC procedure. Refer to [18] for details on IA-TC and INSTC and to [17] for details on CLICA.

In addition to analyzing our channel assignment schemes against IA-TC, CLICA, and INSTC-CLICA, which minimize resources allocated independently of traffic conditions to a degree, we analyze our proposed schemes against other channel assignment schemes that allocate all resources independently of traffic conditions [12–15, 19]. The proposals in [15] and [14], which are labeled Maximum Clique and CogMesh, respectively, maximize network connectivity subject to a limited interference. The proposals in [12] and [13], which are labeled DGA and COSAP, respectively, adopt a dual approach of minimizing aggregate interference subject to a level of network connectivity. Another approach called SAFE is proposed in [19], where all but one of each nodes' transceivers are assigned a random channel with the last one tuned to a channel in common with all other nodes in communication range. The reason for including these purely traffic-independent allocation schemes is to illustrate that our approach uses fewer transceivers to maintain connectivity and is able to support significantly higher flow rate, further motivating our proposed

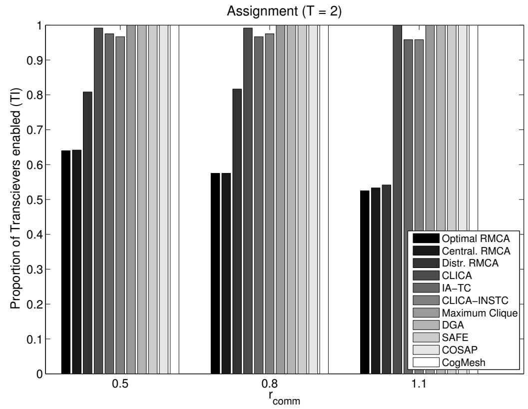

Fig. 2: Proportion of Network Transceivers Assigned ($T = 2$)

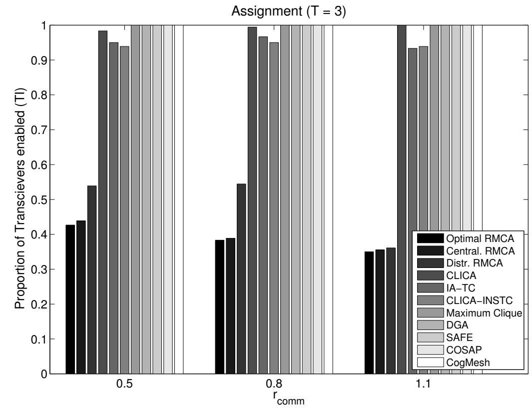

Fig. 3: Proportion of Network Transceivers Assigned ($T = 3$)

two-stage assignment.

B. Numerical Procedure

The numerical procedure follows the approach presented in Fig. 1 where the TI assignment forms a connected topology in the first stage, and in the second stage the topology adapts to maximize flow rate. We use MATLAB and CPLEX to solve the problems. We vary the approaches to channel assignment in the first stage, and the second stage is the solution of problem $\mathcal{FM}$, as presented in subsection II-B, using any unassigned transceivers from the first stage.

We run multiple simulations to characterize the flow rates using each approach. We set the number of nodes, $|\mathcal{V}|$, to 20. Nodes are placed in a rectangular area with edges of length 2 and 0.5, and we vary r_{comm} to be 0.5, 0.8, and 1.1, with $r_{int} = 1.75 \cdot r_{comm}$. The variation in communication range causes the network diameter to vary from 2 to 6 hops. Using a rectangle, as opposed to a square, allows us to see 6-hop network diameters without increasing the number of nodes too much. We also vary the number of transceivers per node from 2 to 4.

In Figures 2 - 4, we count the number of transceivers assigned independently of traffic conditions. We see that the centralized RMCA algorithm performs identically to the optimal approach (the solution to problem $\mathcal{RM}$) in the scenarios evaluated. The distributed RMCA algorithm assigns slightly more transceivers than does the optimal approach, but it assigns as little as one third fewer transceivers than the other approaches. Also, as r_{comm} increases, the distributed RMCA algorithm performs close to optimal. Averaging all the scenarios together, the distributed RMCA algorithm performed within 9% of the optimal approach. As the number of transceivers per node increases, the gap between the other approaches and the optimal grows. However, this is not true for the centralized and distributed RMCA algorithms. Reducing the number of transceivers allocated independently of traffic conditions reduces the energy consumption since there is a non-negligible cost in enabling and operating a transceiver.

In addition to saving energy, in Figures 5 - 7, our proposed RMCA algorithms greatly outperform the approaches from the research literature in terms of flow rate in almost all of the scenarios evaluated. Given that the centralized RMCA algorithm matched the optimal approach in the number of transceivers assigned, we expect the flow rate to also match the optimal since the centralized RMCA algorithm conserves as many transceivers as the optimal approach does, allowing the centralized RMCA network to adapt as much as the optimal approach.

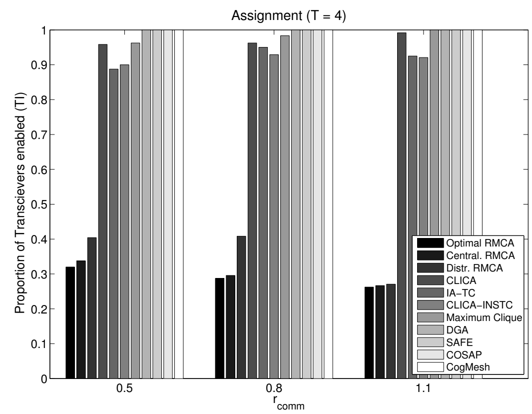

Fig. 4: Proportion of Network Transceivers Assigned ($T = 4$)

Although the distributed RMCA algorithm achieves within 9% of the optimum in terms of the number of transceivers assigned independently of traffic conditions, it achieves within 3.5% of the optimum in terms of maximum achievable flow rate averaged over all evaluated scenarios. The slight suboptimality of the distributed RMCA algorithm in terms of the number of traffic-independently assigned transceivers only slightly hinders the maximum achievable flow rate because there are enough transceivers conserved to address traffic demands.

In the scenarios with $r_{comm} = 0.5$, the difference between the optimal flow rate and the other approaches is smaller, especially in the scenario with four transceivers per node. When $r_{comm} = 0.5$, nodes have a lower node degree than when r_{comm} is higher, so there are fewer possible adaptations, leading to less improvement with a TD channel assignment. In the scenario with four transceivers per node, the TI assignment of the other schemes assigns channels to many of the possible communication links over multiple channels, leaving less room

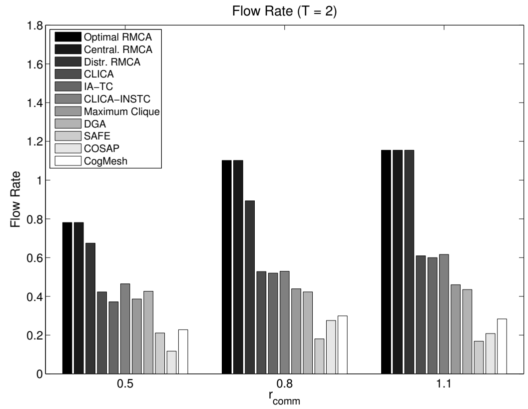

Fig. 5: Flow Rate (2 Transceivers per Node)

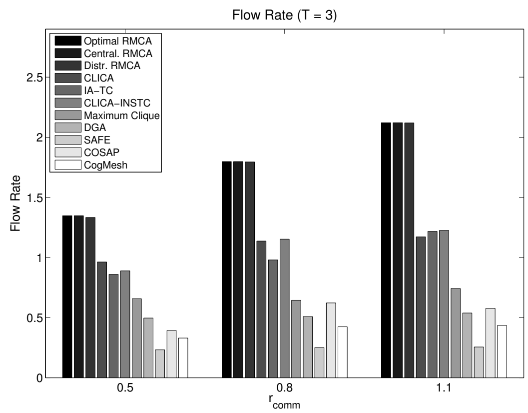

Fig. 6: Flow Rate (3 Transceivers per Node)

for improvement in flow rate with a TD assignment.

In comparing Figure 6 to Figure 7, there is not a significant gain in flow rate with our proposed schemes going from 3 to 4 transceivers per node. The reason is that the number of transceivers is not limiting performance when there are 3 transceivers per node. The number of channels is limiting the performance when there are 3 transceivers per node. We set the problems' parameters to allow for these two different scenarios (one where the number of transceivers is limiting the performance and another where the number of channels is limiting performance). Also, increasing the number of channels makes the problem much more difficult to solve in terms of computing power.

Although the maximum achievable flow rates are similar in the scenario with $r_{comm} = 0.5$ and four transceivers per node, the cost is shown in Figure 4, where other schemes allocate almost three times the number of transceivers in the TI stage of channel assignment. The higher the number of TI transceivers, the higher the cost is in terms of energy consumption and, potentially, network lifetime. Lastly, we see that schemes that assign transceivers purely independently of transceivers yield a significantly lower flow rate than all the other schemes that include any traffic-driven assignment. This result further justifies our two-stage approach to channel assignment.

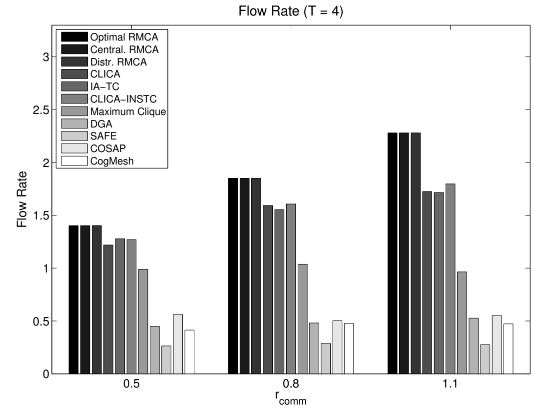

Fig. 7: Flow Rate (4 Transceivers per Node)

VI. Conclusion

The central motivation for this work is to find an effective strategy for channel assignment in a cognitive radio network in which nodes have multiple transceivers. Such a channel assignment scheme should achieve connectivity, exhibit minimal interference, and be adaptive to the network's dynamic traffic demands. We show a two-stage approach to channel assignment. The first, traffic-independent (TI), stage allocates resources as to maintain a connected, multi-channel topology, which is able to support light traffic demands (e.g., network control traffic). We propose that the TI channel assignment allocate as few resources as possible in order to make subsequent traffic-driven (TD) assignment in the second stage. The second, TD, stage of assignment allocates resources as to maximize the end-to-end flow rate. It is imperative that the TI stage use as few resources as possible, enabling the TD stage to more aptly respond to changing traffic demands and maximize flow rate.

In order to evaluate the impact of the TI assignment on the maximum achievable flow rate, we formulate flow maximization problem $\mathcal{FM}$, which follows an MILP of channel assignment (of transceivers not dedicated traffic-independently to maintaining network connectivity) and flow routing. To fairly compare each TI scheme's impact on flow rate, problem $\mathcal{FM}$ is solved to assign any transceivers not assigned traffic-independently to maximize flow rate. We find that our proposed approaches are able to achieve a higher maximum flow rate than other approaches due to using fewer transceivers for TI channel assignment. Furthermore, our proposed approaches achieve within 3.5% of the optimal (the solutions of both $\mathcal{RM}$ and $\mathcal{FM}$) flow rate averaged across all evaluated scenarios.

A. Dynamic Channel Availability

Much of the research literature on cognitive radio and dynamic spectrum access (DSA) discusses how cognitive radios can be used to handle situations where channel availability may be dynamic. The two-stage network resource allocation scheme we propose is applicable to this scenario by making use of channel availability characteristics. Specifically, we propose identifying the degree of each channel's availability (e.g. expected length of the duty cycle of each channel's availability), and consider the most available channels for the TI assignment given the desire to maintain network connectivity without interruption. The remaining channels, with potentially more dynamic or less predictable availability, would be considered for assignment to meet dynamic traffic demands. The point is to conserve the channels with the most availability for the TI assignment, and if necessary, the TI assignment could be repeated if network connectivity is disrupted.

We hope to build upon these ideas by developing a practical TD allocation algorithm that assigns available channels dynamically in response to traffic demands. Specifically, in the future, we will evaluate a resource-minimized channel assignment complemented with a TD allocation protocol that seeks to allocate the appropriate available channels based on the current channel availability and traffic conditions.

References

[1] J. Reed, *Software radio: a modern approach to radio engineering*. Prentice Hall Professional, 2002.

[2] B. Le, T. Rondeau, and C. Bostian, "Cognitive radio realities," *Wireless Communications and Mobile Computing*, vol. 7, no. 9, pp. 1037–1048, 2007.

[3] R. Thomas, D. Friend, L. DaSilva, and A. MacKenzie, "Cognitive Networks: Adaptation and Learning to Achieve End-to-end Performance Objectives," *IEEE Communications Magazine*, vol. 44, no. 12, pp. 51–57, 2007.

[4] Q. Mahmoud, *Cognitive Networks*. Wiley Online Library, 2007.

[5] L. Tassiulas and A. Ephremides, "Stability Properties of Constrained Queueing Systems and Scheduling Policies for Maximum Throughput in Multihop Radio Networks," *IEEE Transactions on Automatic Control*, vol. 37, no. 12, pp. 1936–1948, 1992.

[6] M. Alicherry, R. Bhatia, and L. Li, "Joint Channel Assignment and Routing for Throughput Optimization in Multi-Radio Wireless Mesh Networks," in *Proceedings of ACM International Conference on Mobile Computing and Networking (MOBICOM)*, p. 72, ACM, 2005.

[7] M. Neely and R. Urgaonkar, "Optimal Backpressure Routing for Wireless Networks with Multi-receiver Diversity," *Ad Hoc Networks*, vol. 7, no. 5, pp. 862–881, 2009.

[8] Y. Shi and Y. Hou, "A Distributed Optimization Algorithm for Multi-hop Cognitive Radio Networks," in *Proceedings of IEEE International Conference on Computer Communications (INFOCOM)*, pp. 1292–1300, IEEE, 2008.

[9] R. Urgaonkar and M. Neely, "Opportunistic Scheduling with Reliability Guarantees in Cognitive Radio Networks," *IEEE Transactions on Mobile Computing*, vol. 8, no. 6, pp. 766–777, 2009.

[10] J. Deaton, S. Ahmad, U. Shukla, R. Irwin, L. DaSilva, and A. MacKenzie, "Evaluation of Dynamic Channel and Power Assignment for Cognitive Networks," *Wireless Personal Communications*, vol. 57, pp. 5–18, 2011.

[11] R. Irwin and L. DaSilva, "Channel Assignment Based on Routing Decisions (CARD): Traffic-Dependent Topology Control for Multi-Channel Networks," in *Proceedings of IEEE International Conference on Communications (ICC) CogNet Workshop*, 2009.

[12] A. P. Subramanian, H. Gupta, S. R. Das, and J. Cao, "Minimum Interference Channel Assignment in Multi-radio Wireless Mesh Networks," *IEEE Transactions on Mobile Computing*, vol. 7, no. 12, pp. 1459–1473, 2008.

[13] A. Plummer Jr, T. Wu, and S. Biswas, "A Localized and Distributed Channel Assignment Framework for Cognitive Radio Networks," in *First International Workshop on Cognitive Wireless Networks*, ACM, 2007.

[14] T. Chen, H. Zhang, G. Maggio, and I. Chlamtac, "CogMesh: A Cluster-based Cognitive Radio Network," in *Proceedings of IEEE Dynamic Spectrum Access Networks (DySPAN)*, pp. 168–178, 2007.

[15] G. Jakllari, S. Ramanathan, J. Redi, D. Coffin, W. Tetteh, J. Burgess, and R. Irwin, "Distributed Assignment of Frequency Channels to Transceivers over Dynamic Spectrum," Sept. 16 2010. US Patent App. 20,100/232,372.

[16] R. Irwin, A. B. MacKenzie, and L. DaSilva, "Resource-Minimized Channel Assignment for Multi-transceiver Wireless Networks," in *Proceedings of IEEE Global Communications Conference (GLOBECOM)*, 2011.

[17] M. Marina, S. Das, and A. Subramanian, "A Topology Control Approach for Utilizing Multiple Channels in Multi-radio Wireless Mesh Networks," *Computer Networks*, 2010.

[18] J. Tang, G. Xue, and W. Zhang, "Interference-aware Topology Control and QoS Routing in Multi-channel Wireless Mesh Networks," in *Proceedings of ACM International Symposium of Mobile Ad Hoc Networking and Computing (MOBIHOC)*, pp. 68–77, ACM, 2005.

[19] M. Shin, S. Lee, and Y. ah Kim, "Distributed Channel Assignment for Multi-radio Wireless Networks," in *Proceedings of IEEE Mobile Adhoc and Sensor Systems (MASS)*, pp. 417–426, 2006.

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