An Optimal Routing in Cognitive Mesh Networks

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Abstract

Cognitive wireless mesh access networks can be used to provide wireless broadband access on under-utilized licensed spectrum. Moreover, wireless mesh network can provide a cost efficient backhaul to the wireless gateway. We study the optimal routing problem covering path selection, resource allocation and interference mitigation. We formulate an optimization problem and use Markov approximation framework to propose an efficient algorithm.

1. Introduction

Cognitive wireless mesh networks are emerging as the key future technology for providing wireless broadband access [1], [2]. In order to fully exploit the aggregate bandwidth available in the radio spectrum, Cognitive Mesh Access Nodes (CMANs) are expected to take advantage of multiple free licensed orthogonal channels, with nodes having the ability to sense the channels and communicate over the channels [1].

A typical CMAN routes the traffic towards wired or wireless gateway nodes that provide the connectivity with the Internet or backhaul. A CMAN architecture is shown in Fig. 1. To increase the available bandwidth, each cognitive WMN node is equipped with multiple radios (NICs). Orthogonal channels are used for each interface of the node which ensures simultaneous communication using all the wireless interfaces without interference. Dynamic channel assignment [1] is required to assign the channels to the network links to ensure the optimum channel usage that can fulfill the routing as well as the bandwidth requirements of the access network. Researchers have identified the strong dependency between the power, routing and the channel assignment. Dynamic channel assignment [1] and efficient routing are critical for ensuring effective utilization of the non-overlapping channels and fulfilling routing as well as the bandwidth requirements.

2. System Model

There are 'F' flows and each flow f_{mn} can choose links to reach from source 'm' to destination 'n'. The objective is to assign flow and channel to each link such that the end-to-end throughput of the flows can be maximized. We assume that paths are not given and the model selects links between source and destination pairs. All links can operate on a single channel selected from multiple channels with different link capacities. In order to define the constraints, we first define the system model. We have a Cognitive WMN consisting of a set of CMAN (or vertices) represented by **V**. The set of links (or edges) between the CMANs are represented by **E** . The set of sub-channels available to the cognitive WMN is represented by **S** . Each node generates a flow which is destined to the gateways where the demand of each source can be represented by d_{mn}. The set of flows is represented by **F**.
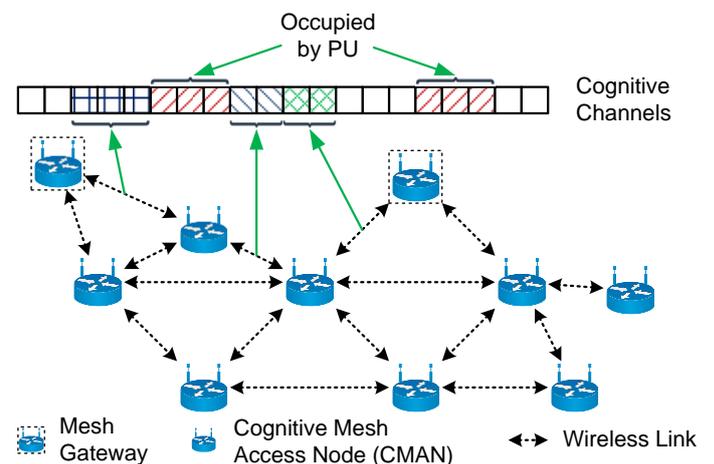

Fig. 1: Network Model

A binary indicator, $x_{ij} \in \{0,1\}$, is used to indicate the active flows on a channel for a source-destination pair. $x_{ij} = 1$ if flow f_{mn} is active on link ij, and $x_{ij} = 0$, otherwise. Similarly, another binary indicator $z_{ij}^k \in \{0,1\}$, is used to indicate whether sub-channel (or RB) k is allocated to link ij. $z_{ij}^k = 1$ if sub-channel k is allocated to link ij, and $z_{ij}^k = 0$, otherwise. Due to the limited channels, complete demand of a source node may not

be fulfilled. Therefore, a fraction of demand can be fulfilled for each flow on each link and is represented by $y_{ij}(f_{mn}) \in [0,1]$. $y_{ij}(f_{mn}) = 1$ represents fulfilling the entirety of the demand request and $y_{ij}(f_{mn}) = 0$ means that the flow request is rejected.

We assume that each cognitive channel has S sub-channels (RBs) with bandwidth W. Then, signal to interference plus noise (SINR) on the link ij on RB k is given by:

$$\Gamma_{ij}^k = \frac{h_{ij}^k P_i}{\sum_{m \in \mathbf{V}\setminus\{i\}} h_{mj}^k P_m + W N_0}, \forall \{ij\}, \{mn\} \in \mathbf{E}, \quad (1)$$

where P_i is the transmit power of CMAN i, h_{ij}^k is the path loss between CMANs i and j, and N_0 is the thermal noise for 1 Hz at 20 degree C. The capacity of link ij is calculated as:

$$C_{ij} = \sum_{k \in \mathbf{S}} z_{ij}^k W \log_2(1 + \Gamma_{ij}^k). \quad (2)$$

Next, the rate of a flow passing through link ij is:

$$r_{ij}(f_{mn}) = x_{ij}(f_{mn}) y_{ij}(f_{mn}) d_{mn}, \quad (3)$$

The total flow passing through link ij is calculated as:

$$R_{ij} = \sum_{f_{mn} \in \mathbf{F}} x_{ij}(f_{mn}) y_{ij}(f_{mn}) d_{mn}. \quad (4)$$

3. Problem Formulation

A. **Constraints** for the cognitive WMN are:

Link capacity constraint: The sum of all the flows passing on each link and each channel must be less than or equal to the link capacity, i.e.,

$$R_{ij} \leq C_{ij}, \forall \{ij\} \in \mathbf{E}. \quad (5)$$

Unique flow constraint states that at most one flow can be active between CMAN m and n:

$$\sum_{f_{mn} \in \mathbf{F}} x_{ij}(f_{mn}) \leq 1, \forall f_{mn} \in \mathbf{F}. \quad (6)$$

QoS constraint provides minimum number of required sub-channels (RBs) on link ij:

$$\sum_{k \in \mathbf{S}} z_{ij}^k = \left\lceil \frac{R_{ij}}{W \log_2(1 + \Gamma_{ij}^k)} \right\rceil, \forall \{ij\} \in \mathbf{E}. \quad (7)$$

Spectrum interference constraints: First, given a SINR threshold, Γ_{th}, we define the link conflict and reuse sets as follows:

$$\mathbf{E}_{\text{conflict}} := \{(\{ij\}, \{mn\}) \mid \min\{\Gamma_{ij}^k, \Gamma_{mn}^k\} \leq \Gamma_{th}\}, \quad (8)$$

$$\mathbf{E}_{\text{reuse}} := \{(\{ij\}, \{mn\}) \mid \min\{\Gamma_{ij}^k, \Gamma_{mn}^k\} > \Gamma_{th}\}. \quad (9)$$

(8) states that some links ij and mn causes high interference to each other. Thus, when both links are active, they conflict with each other. On the other hand, (9) states that some links causes low interference to each other and can be active on same sub-channel k. Based on the link conflict and reuse set, we have the following spectrum constraints:

$$z_0^k + z_{ij}^k \leq 1, \forall \{ij\} \in \mathbf{E}, \forall k \in \mathbf{S}. \quad (10)$$

$$z_{ij}^k + z_{ji}^k \leq 1, \forall (\{ij\}, \{ji\}) \in \mathbf{E}, \forall k \in \mathbf{S}. \quad (11)$$

$$z_{ij}^k + z_{mn}^k \leq 1, \forall (\{ij\}, \{mn\}) \in \mathbf{E}_{\text{conflict}}, \forall k \in \mathbf{S}. \quad (12)$$

$$z_{ij}^k + z_{mn}^k \leq 2, \forall (\{ij\}, \{mn\}) \in \mathbf{E}_{\text{reuse}}, \forall k \in \mathbf{S}. \quad (13)$$

where z_0^k is the sensing result. ((10) ensures that no primary user occupied channels is allocated to any link ij. ((12)) ensures that high interference links are not allocated to the same sub-channel k. On the other hand, low interference links are allocated to the same sub-channels given by ((13)).

B. **The objective** of MOR is to maximize the end-to-end throughput of the overall system by assigning flow, power and channels. Our objective is to maximize total flow rate for the CMANs. However, the cognitive environment introduce the problem of spectrum scarcity. Hence, we simultaneously maximize total flow rate and minimize the number of channels occupied.

$$U(\mathbf{x}, \mathbf{y}, \mathbf{z}) = \sum_{f_{mn} \in \mathbf{F}} \sum_{ij \in \mathbf{E}} r_{ij}(f_{mn}) - \beta \sum_{ij \in \mathbf{E}} \sum_{k \in \mathbf{S}} z_{ij}^k P_i. \quad (14)$$

where β is the unit price for transmit power, P_i is the transmit power of CMAN i and $\beta \sum_{ij \in \mathbf{E}} \sum_{k \in \mathbf{S}} z_{ij}^k P_i$ represents the total operating cost of the cognitive WMN.

C. **The optimization problem** for Mesh Optimal Routing (MOR) is given as:

maximize: $U(\mathbf{x}, \mathbf{y}, \mathbf{z})$

subject to: (5), (6), (7), (10), (11), (12), (13). (15)

(15) is a combinatorial problem and NP-hard.

4. Markov Approximation

We use Markov approximation framework [3] to solve (15). Let $a = \{\mathbf{x}, \mathbf{y}, \mathbf{z}\}, a \in \mathbf{A}$ be a network configuration where $\mathbf{A}$ is the set of all feasible configurations which satisfy the constraints (5), (6), (7), (10), (11), (12), (13). Further, for ease of presentation, let $U_a = U(\mathbf{x}, \mathbf{y}, \mathbf{z})$. Then, by [3],

$$\max_{a \in \mathbf{A}} U_a \quad \Rightarrow \quad \begin{array}{l} \max_{\mathbf{p} \geq 0} \sum_{a \in \mathbf{A}} p_a U_a \\ \text{s.t.} \quad \sum_{a \in \mathbf{A}} p_a = 1 \end{array} \quad (16)$$

We then apply log-sum-exponential approximation to (16) with the following differentiable function [3], [4]:

$$\max_{a \in \mathbf{A}} U_a \approx g_\beta(U_a) \triangleq \frac{1}{\beta} \log[\sum_{a \in \mathbf{A}} \exp(\beta U_a)] \quad (17)$$

The upper bound of the approximation gap is $\frac{1}{\beta} \log|\mathbf{A}|$ [4]. (17) is the same as the optimal value of the following problem:

$$\begin{array}{l} \max_{\mathbf{p} \geq 0} \sum_{a \in \mathbf{A}} p_a U_a - \frac{1}{\beta} \sum_{a \in \mathbf{A}} p_a \log p_a \\ \text{s.t.} \quad \sum_{a \in \mathbf{A}} p_a = 1 \end{array} \quad (18)$$

where p_a is the proportion of time the configuration a is in use and β is a positive constant. By solving the Karush-Kuhn-Tucker (KKT) conditions [4] of (18),

$$p_a^*(U_a) = \frac{\exp(\beta U_a)}{\sum_{a' \in A} \exp(\beta U_{a'})}, \qquad \forall a \in A. \qquad (19)$$

5. Algorithm Design via Markov Chain

Let each configuration $a \in A$ be the states of a time-reversible ergodic Markov chain with stationary distribution $p_a^*(U_a)$ in (19) [3]. Let $q_{a \to a'}$ be the nonnegative transition rate from state a to state a'. Then the two following conditions are sufficient to allow a large degree of freedom in algorithm design [3]:

1) Any two states are reachable from each other,

2) $p_a^*(U_a)\, q_{a \to a'} = p_{a'}^*(U_{a'})\, q_{a' \to a}$.

Furthermore, if we let $\exp(-\alpha)\,(q_{a \to a'} + q_{a' \to a}) = 1$, we obtain the following symmetric transition rates as:

$$q_{a \to a'} = \exp(-\alpha)\,(1 + \exp[\beta(U_a - U_{a'})])^{-1} \qquad (20)$$

$$q_{a' \to a} = \exp(-\alpha)\,(1 + \exp[\beta(U_{a'} - U_a)])^{-1} \qquad (21)$$

where α is a constant.

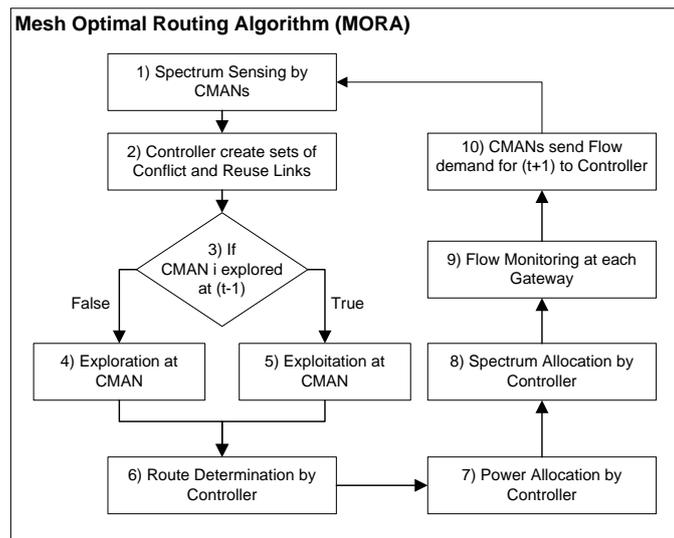Based on (20) and (21), we designed the Mesh Optimal Routing Algorithm (MORA) as shown in Fig. 2.

Fig. 2: Mesh Optimal Routing Algorithm (MORA).

6. Simulation Results

We performed experiments to test convergence of the proposed unsupervised learning algorithm (MORA). Fig. 3 shows the total flow rate achieved for the CMANs for centralized and distributed implementation of MORA are shown. Initially, we can see large fluctuations in the total flow rate. As the time wore on, the exploration rate of CMANs is reduced and the fluctuations become smaller. Finally, MORA converges around 700 iterations. Fig. 4 shows the total incurred cost for the cognitive WMN. Our objective is to maximize total flow rate for the CMANs. However, the cognitive environment introduce the problem of spectrum scarcity. Hence, we simultaneously maximize total flow rate and minimize

the number of channels occupied. Thus, there is a trade-off between total flow rate and total incurred cost and MORA find the balance using unsupervised learning.
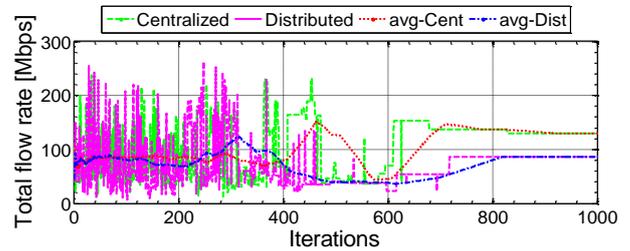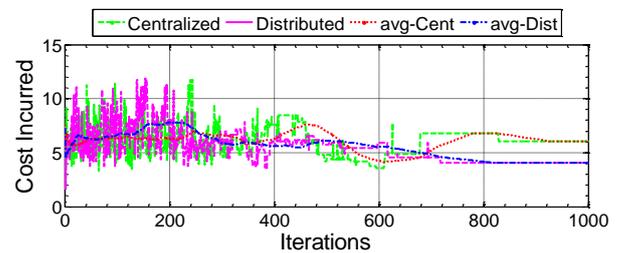
Fig. 3: Total flow rate versus iterations

Fig. 4: Total incurred cost versus iterations.

7. Conclusion

In this paper, we study optimal routing in cognitive mesh access network. First, we propose an optimization formulation for mesh optimal routing. Second, we apply Markov approximation framework to arrive at mesh optimal routing algorithm (MORA). Finally, we perform numerical analysis to validate our proposal.

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