Throughput Maximization in Cognitive Radio Based Wireless Mesh Networks

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***Abstract*—Cognitive radio is a key technology needed to better utilize the available spectrum more efficiently. In this paper, we consider the throughput optimization problem via spectrum allocation in the cognitive radio based wireless mesh networks (CR-based WMNs). Unlike prior research, we consider both the lower layer noncontinuous OFDM features and the physical interference model in designing our solution. We model the problem as a mixed integer nonlinear programming (MINLP) problem and show it to be NP-hard. Both a centralized and a localized approximation solution are provided to the problem. Our solution also includes a power information collection process to mitigate the effects of the propagation gain of power as well as a post-allocation adjustment process. Real world data is used in our evaluations to illustrate the effectiveness of our scheme.**

***Index Terms*—Cognitive radio networks, throughput optimization.**

I. INTRODUCTION

Cognitive radio network (CRN) is promising to be the key technology that enables next generation communication networks [1] which utilize the spectrum more efficiently in an opportunistic fashion without interfering with the primary users. The emergence of cognitive radio technology could be a revolution for those wireless networks requiring large spectrum resources. Wireless mesh networks (WMNs) are among the most urgent ones. Cognitive radios (CRs) are desirable for a WMN in which a large volume of traffic is expected to be delivered, since they are able to utilize available spectrums more efficiently, thus significantly improving the network capacity [1]. However, CRs also introduce additional complexities to bandwidth allocation. In a traditional 802.11-based WMN, a set of homogeneous channels are always available to every mesh router. In a CR-based WMN, each node can access a large number of heterogeneous spectrum bands, which may spread over a wide range of frequencies. Different channels can support different transmission ranges and data rates due to spectrum diversity. This feature will have a significant impact on route and channel selections.

The majority of existing proposals of throughput optimization take an indirect approach: first, simplify physical interference conditions into a set of pairwise constraints (i.e. graph interference model), then distribute spectrum using the graph model [3]. Such simplification, however, comes at a high cost. Radio interference is inherently accumulative and cannot be accurately represented by pair-wise constraints. As a result, decisions made on top of the graph model could lead to inefficient allocation or unwanted interference. Also, regarding to the wide operating spectrum, we must take the character of spectrum diversity into account. Consequently, the physical interference model (SINR model), which accurately modeled the accumulative effect of interference, must be employed.

In this work, we are considering the throughput optimization problem via spectrum allocation. Unlike previous works, we employ the SINR interference model to our problem and propose a comprehensive solution from power measurement to the routing level. In addition, the emergence of non-continuous orthogonal frequency division multiplex (NC-OFDM) technology in cognitive radio enables a node access multiple channels simultaneously. We also take this into consideration in our problem. In summary, a centralized solution with guaranteed performance bound and a localized solution with high efficiency are introduced. Our contributions are summarized as the followings:

- We present and formulate the throughput optimization problem in NC-OFDM CR-based WMN under the SINR model. We formulate the problem as a mixed integer nonlinear programming problem, which is generally NP-hard.
- We propose a centralized comprehensive approximate solution. Based on the collected power information, a centralized solution based on branch-and-bound framework is introduced. The approximate result could be further enhanced by a post-allocation adjustment.
- We also design a low cost localized solution. Only a few rounds of broadcasting and small scale linear programming are required. The simulation shows that for most cases, no more than a few rounds (6 as shown in simulation) are required to converge.
- An extensive simulation study based on a real data set from GoogleWiFi is performed. The results show that our centralized solution could achieve more than 90% of the optimal result in average, while the localized solution achieves 78%.

The remainder of this paper is organized as follows: In Section II, we introduce related papers. The network model and problem definition are presented in Section III. An approximating centralized solution and a localized solution are proposed in Section IV and Section V, consecutively. Section VI is the experiment methods and results. We conclude this paper in Section VII.

II. Related Works

Comparing to the traditional wireless network, channel assignment in a CRN has to deal with different scopes of spectrum availability. Thus, various distributed approximations were proposed, which are based on observing local interference patterns [4], or on coordinations between CR nodes that aim at maximizing some system utility [5]. Most recently, the channel assignment problems in a CRN are studied from its dynamic nature. In [3], Y. Yuan et.al. propose a time-spectrum model of the available band. Based on it,a set of distributed assignment algorithms are developed. In [6], Gai et.al. assume the spectrum opportunity is unknown and model it as an arbitrarily-distributed random variable with bounded support, but unknown mean. Under this model, the assignment problem is formulated as a combinatorial multi-armed bandit problem. Different from these works, our target problem is on the global optimization target of throughput under the SINR interference model, thus is much more complex.

The SINR model is widely regarded as a better model for interference characterization. Although such a model is preferred, there are many difficulties in carrying out an analysis with this model due to the computational complexities SINR involves. As a result, there are many previous efforts on single-hop networks, e.g. [7], [8]. For multi-hop networks, some efforts study cross-layer problems involving two layers instead of three layers (physical, link, and network). For example, in [9], Bhatia and Kodialam optimized power control and routing while assuming some frequency hopping mechanism is in place for scheduling, which helps simplify joint consideration of scheduling. These approaches are heuristic at best and cannot offer any performance guarantee. Different from these works, we provide a performance-guaranteed centralized solution along with a fast localized solution.

III. System Model and Problem Definition

A. Network Model

We consider a wireless mesh network with a set of CR mesh routers $\mathcal{N}$ consisting of internet gateway nodes $\mathcal{N}_G$ and non-gateway nodes $\mathcal{N} \setminus \mathcal{N}_G$. Each mesh router is associated with a set of client nodes $\mathcal{C}_i$. Each node $i \in \mathcal{N}$ senses its environment and finds a set of available spectrum bands $\mathcal{M}_i$ for the given time instance (i.e., those bands that are currently not used by primary users), which may not be the same as the available spectrum bands at other nodes. Without loss of generality, we assume that the bandwidth of each spectrum band (channel) is uniformly denoted as W. Denote $\mathcal{M}$ as the union of all spectrum bands among all the nodes in the network, i.e., $\mathcal{M} = \bigcup_{i \in \mathcal{N}} \mathcal{M}_i$, and each band is identically denoted as m. We also denote $\mathcal{M}_{ij} = \mathcal{M}_i \bigcap \mathcal{M}_j$, which is the set of common bands between node i and node j.

B. Interference Model

We apply physical interference model here, for its unique advantage to characterize accumulative feature of interference. In this model, concurrent transmissions are allowed and interference (due to transmissions by non-intended transmitter) is treated as noise.

The key to compute SINR is to compute the values of transmitting and receiving power. We assume that every node sends at constant power of P. Consider a transmission from node i to node j on band m. We use P_{ij}^m to denote the receiving power of node j from node i. When there is interference from concurrent transmissions on the same band, the SINR at node of transmission from node i to node j on band m, denoted as s_{ij}^m, is

$$s_{ij}^m = \frac{P_{ij}^m}{N_0 + \sum_{k \in \mathcal{N}, k \neq i} \sum_{w \in \mathcal{N}, w \neq k, j} P_{kj}^m}. \quad (1)$$

Here, $N_0 = \sigma W$ and σ is the ambient Gaussian noise density.

Once a band $m \in \mathcal{M}_i$ is used by node i for transmission or reception, this band cannot be used again by node i for other transmissions or receptions. Formally, we have

$$\sum_{j \in \mathcal{N}} a_{ij}^m + \sum_{k \in \mathcal{N}} a_{ki}^m \leq 1. \quad (2)$$

Here, $a_{ij}^m \in \{0, 1\}$ denotes whether link ij use band m.

According to Shannon capacity formula, the capacity on the link, from node i to node j, denoted as c_{ij}, will be

$$c_{ij} = \sum_{m \in \mathcal{M}_{ij}} a_{ij}^m W \log_2(1 + s_{ij}^m). \quad (3)$$

C. Problem Definition

We study the problem of throughput optimization in CR-based WMNs. The major traffic travels between the mesh clients associated with $\mathcal{C}_i$ and $\mathcal{N}_G$. $\mathcal{N} \setminus \mathcal{N}_G$ only serve to relay the traffic. Thus, we can model this kind of network as a flow graph $\mathcal{G}$ with $\mathcal{N}_G$ as the source nodes and $\mathcal{C}$ as the flow destination nodes. In graph $\mathcal{G}$, E_{out}^i is the endpoint set of outgoing edges starting with node i, and E_{in}^i is the endpoint set of incoming edges to i. The throughput optimization problem in this situation could be defined as:

Definition 1: Aggregated Throughput Optimization Problem in CR-based WMNs: *given a CR-based WMN $\{\mathcal{N}, \mathcal{N}_G, \mathcal{C}\}$, and available spectrum set $\mathcal{M}_{ij}$ between node i and node j, find a spectrum allocation vector $X = \{a_{ij}^m | i, j \in \mathcal{N}, m \in \mathcal{M}_{ij}, a_{ij}^m \in \{0, 1\}\}$, so that the aggregated throughput between $\mathcal{C}$ and $\mathcal{N}_G$ is maximized.*

In short, we are trying to find a spectrum allocation vector. So that the minimum cut of $\mathcal{G}$ can be maximized.

The aggregated throughput could be formally defined as $\sum_{u \in \mathcal{N}, v \in \mathcal{N}_G} f_{ij}$, and the flow in each link must follow the constraint of

$$f_{ij} \leq \sum_{m \in \mathcal{M}_{ij}} a_{ij}^m W \log_2(1 + s_{ij}^m).$$

Next, we can give the formulation of this problem:

$$\text{Max } F$$

$$\text{s.t. } F = \sum_{u \in E_{in}^{v}, v \in \mathcal{N}_G} f_{uv} \tag{4}$$

$$\sum_{k \in E_{in}^{i}} f_{ki} - \sum_{w \in E_{out}^{i}} f_{iw} = 0,$$
$$\forall i \in \mathcal{N} \setminus \mathcal{N}_G \tag{5}$$

$$f_{ij} \leq \sum_{m \in \mathcal{M}_{ij}} a_{ij}^{m} W \log_2(1 + s_{ij}^{m}),$$
$$\forall i \in \mathcal{N} \bigcup \mathcal{C}, j \in E_{out}^{i} \tag{6}$$

$$\sum_{k \in E_{in}^{i}} a_{ki}^{m} + \sum_{w \in E_{out}^{i}} x_{iw}^{m} \leq 1,$$
$$\forall i \in \mathcal{N}, \forall m \in \mathcal{M}_{ij}, \mathcal{M}_{ij} \neq \emptyset \tag{7}$$

$$s_{ij}^{m} = \frac{P_{ij}^{m}}{N_0 + \sum_{k \in \mathcal{N}, k \neq i} \sum_{w \in \mathcal{N}, w \neq k, j} a_{ij}^{m} P_{kj}^{m}},$$
$$\forall i \in \mathcal{N} \bigcup \mathcal{C}, i \notin \mathcal{N}_G, j \in E_{out}^{i}, m \in \mathcal{M}_{ij} \tag{8}$$

$$s_{ij}^{m} \geq \alpha a_{ij}^{m},$$
$$\forall i \in \mathcal{N} \bigcup \mathcal{C}, i \notin \mathcal{N}_G, j \in E_{out}^{i}, m \in \mathcal{M}_{ij}, \mathcal{M}_{ij} \neq \emptyset \tag{9}$$

$$f_{ij} \geq 0,$$
$$\forall i \in \mathcal{N} \bigcup \mathcal{C}, i \notin \mathcal{N}_G, j \in E_{out}^{i}, m \in \mathcal{M}_{ij}, \mathcal{M}_{ij} \neq \emptyset, \tag{10}$$

where constraint (5) is the flow reservation condition for each relay mesh router. Constraint (10) is the positive flow condition.

This problem is modeled in the form of a mixed integer non-linear programming, which is NP-hard in general [10]. As a result, we propose approximation algorithms to solve them.

IV. Centralized Solution

A. Solution Framework

We now give an overview of the solution. The solution performs the following steps in the following order:

- *Initialization*: in this step, we take chances to perform efficient and low cost power measurement to get p_{ij}^{m}. Another step is the construction of the flow graph, so that the variable of E_{in}^{i} and E_{out}^{i} will be ensured.
- *Approximate solving of the optimization problem*: we adopt the branch-and-bound framework to obtain the $(1-\varepsilon)$ approximation result for the MINLP.
- *Post-allocation adjustment process*: after the spectrum allocation, based on the approximate result of the previous result, the nodes cooperatively increase the link capacity locally.

B. Proposed Algorithm

1) Initialization: The SINR model introduces extra complexities over the other model by requiring the transmitting and receiving power at each node. Previous works usually use propagation gain model to estimate the receiving power. However, this model is far from the real condition. The performance gap between optimization based on propagation model and real data could be found in Fig. 1.

Before scheduling, we have to compute all possible SINR values to facilitate scheduling. Therefore, it requires to fetch all the receiving power from all the other nodes in all the shared spectrum to compute all possible SINR values, which is too costly. We cut down the cost in two ways. First, we take advantage of the equation:

$$P_1 - P_2 = 20log(\frac{f_2}{f_1}), \tag{11}$$

to cut down the overhead of transmission in each band to only one transmission in each node. Here, f_1, f_2 are the center frequency of corresponding bands.

On the other hand, now that each node only has to broadcast once, we could take advantage of simultaneous broadcast in each node in different channels. A careful schedule will lead to the least amount of overhead. It could be formalized as:

$$\text{Minimize } T$$
$$\text{s.t. } \sum_{i} x_{i,t}^{m} \leq 1, \tag{12}$$
$$\sum_{m \in \mathcal{M}_{ij}} x_{i,t}^{m} \geq 1, \forall j \in \mathcal{N} \tag{13}$$
$$t \leq T \tag{14}$$

This is a simple LP problem with an optimal solution.

2) Solving the optimization problem: As stated before, both targeting problems are NP-hard. Thus, we have to solve it in an approximate way. We try to follow the branch-and-bound framework [11] and get a $(1-\varepsilon)$-approximate result. This framework requires an upper-bound form of original problem and a lower-bounded one. With both forms, this framework solves the problem by splitting the solution space into multiple small sets and get the best results in all branches. We follow this framework by first trying to relax those non-linear conditions, so that the relaxed form of the problem could serve as the upper-bound in the framework of branch-and-bound. We also find stricter constraints to serve as the lower-bound form of the problem.

There are two non-linear conditions: (7) and (10). For the nonlinear term $log_2(1+s_{ij}^{m}) = \frac{1}{ln_2} ln(1+s_{ij}^{m})$, we employ three tangential supports for $ln(1+s_{ij}^{m})$, which is a convex hull linear relaxation. Suppose that we have the bounds for s_{ij}^{m} , i.e., $(s_{ij}^{m})L \leq s_{ij}^{m} \leq (s_{ij}^{m})_U$. We introduce a variable $t_{ij}^{m} = ln(1+s_{ij}^{m})$ and consider how to get a linear relaxation for t_{ij}^{m} . The curve of $t_{ij}^{m} = ln(1+s_{ij}^{m})$ can be bounded by four segments (or a convex hull). In particular, the three tangent segments are tangential at points $(1+(s_{ij}^{m})L, ln(1+(s_{ij}^{m})L)), ((1+\beta), ln(1+\beta))$ and $(1+P/N_0, ln(1+(s_{ij}^{m})U))$. Clearly, s_{ij}^{m} is upper-bounded by P/N_0 and is lower-bounded by 0. We have:

$$\beta = \frac{[1+P/N_0][ln[(1+P/N_0]]}{P/N_0} - 1, \tag{15}$$

The convex region, defined by the four segments, can be described by the following four linear constraints:

$$t_{ij}^m - s_{ij}^m \leq 0 \tag{16}$$

$$(1+\beta)t_{ij}^m - s_{ij}^m \leq (1+\beta)[ln(1+\beta)-1]+1 \tag{17}$$

$$t_{ij}^m[1+P/N_0] - s_{ij}^m \leq [1+P/N_0][ln(1+P/N_0)-1]+1 \tag{18}$$

As a result, the nonlinear constraint (6) could be rewritten as:

$$f_{ij} \leq W \sum_{m\in\mathcal{M}_{ij}} a_{ij}^m t_{ij}^m. \tag{19}$$

For the SINR constraint, we can rewrite it as:

$$N_0 s_{ij}^m + s_{ij}^m \sum_{k\in\mathcal{N},k\neq i}\sum_{w\in\mathcal{N},w\neq k,j} x_{kw}^m P_{kj}^m - P_{ij}^m = 0. \tag{20}$$

Here, $a_{ij}^m, s_{ij}^m, t_{ij}^m \geq 0$.

Regarding the relaxed form, we put constraints (5), (6), (8), (10), (11), (13)-(18) together to form a convex optimization. Its solution could be noted as $\hat{Z}$ and serve as the upper-bound.

Regarding the lower-bound, we introduce a stricter constraint as

$$N_0 s_{ij}^m + s_{ij}^m \sum_{k\in\mathcal{N},k\neq i}\sum_{w\in\mathcal{N},w\neq k,j} P_{kj}^m - P_{ij}^m = 0, \tag{21}$$

and put constraints(5), (6), (8), (10), (11), (13)-(17), (19) together to form a stricter convex optimization problem. Its solution could serve as the lower-bound in the branch-and-bound framework.

In the standard branch-and-bound procedure, partitioning is done by choosing a variable with the largest relaxation error rate and uses its value in the relaxed solution to divide its value set into two smaller sets. The reason of this approach (with the largest relaxation error rate) is that such a variable is likely to lead to a larger gap between upper and lower-bounds. Thus, we should partition its value set such that the relaxation error rate will become smaller. This division (on value set) also divides the optimization space into two smaller spaces.

As a result, by following the standard branch-and-bound procedure, we get a $(1-\varepsilon)$-approximation result.

3) Post allocation adjustment: Note that both the relaxations have reduced the core variable optimization space, which makes some better allocation vector values exempted. Thus, to get a better result, we have to perform the post allocation adjustment.

The basic idea of this adjustment process is to reallocate the channels among the minimum cut and its neighbor of the network, so that the maximum flow of the existing assignment will be enhanced. This process will be performed for multiple rounds until the flow value can not be increased. This process is also performed centrally, as is depicted in Algorithm 1.

Algorithm 1 Post Allocation Adjustment Algorithm

Require: Available band $\mathcal{M}_i$, $\mathcal{M}_{ij}$
Ensure: Channel Assignment vector $\{a_{ij}^m\}$

Perform a maximum flow algorithm on the assigned flow network G_f and get the maximum flow value f_v and the minimum cut set S_{min}
for $\forall ij \in S_{min}$ **do**
  $\rho_i = |\sum_{k\in E_{in}^i} c_{ki} - \sum_{w\in E_{out}^i} c_{iw}|$
  $\rho_j = |\sum_{w\in E_{out}^j} c_{jw} - \sum_{k\in E_{in}^j} c_{kj}|$
  for $\forall m \in \mathcal{M}_{ij}$ and $a_{ij}^m = 0$ **do**
    Backup original value and let $x_{ki}^m = 0, x_{lj}^m = 0, x_{it}^m = 0, x_{jw}^m = 0, \forall k \in E_{in}^i, w \in E_{out}^j, t \in E_{out}^i, l \in E_{in}^j$ and $a_{ij}^m = 1$
    Recompute $c'_{ki}, c'_{jw}, c'_{it}, c'_{lj}, \forall k \in E_{in}^i, w \in E_{out}^j, t \in E_{out}^i, l \in E_{in}^j$
    $\rho'_i = |\sum_{k\in E_{in}^i} c'_{ki} - \sum_{w\in E_{out}^i} c'_{iw}|$
    $\rho'_j = |\sum_{w\in E_{out}^j} c'_{jw} - \sum_{k\in E_{in}^j} c'_{kj}|$
    if $\rho'_i + \rho'_j \geq \rho_i + \rho_j$ **then**
      Restore the original value of $a_{ij}^m, x_{ki}^m, x_{lj}^m, x_{it}^m, x_{jw}^m$, $\forall k \in E_{in}^i, w \in E_{out}^j, t \in E_{out}^i, l \in E_{in}^j$
    end if
  end for
end for
Perform a maximum flow algorithm on the assigned flow network G_f with new $\{a_{ij}^m\}$ and get the maximum flow value f'_v and the minimum cut set S_{min}
if $f'_v > f_v$ **then**
  $f_v = f'_v$
  goto 2;
end if

V. Localized Solution

We use a local heuristic which maximizing the total flow traveling through. The most sophisticated part of local channel assignment is to resolve the conflict locally. We manage to do this via an iterative neighbor consensus process. The localized algorithm consists of two phases, initialization and optimization, respectively.

A. Initialization

In the initialization phase, we first perform the power information collection algorithm and flow graph construction. In this way, each node i is able to get the $P_{wi}^m, \forall w \in \mathcal{N}, m \in \mathcal{M}_i$ and E_{in}^i, E_{out}^i. Then, each node shares the information of E_{in}^i, E_{out}^i and $\{P_{wi}^m\}$ with its one-hop neighbor set (v_1^i) by performing one round of broadcasting. After this, each node is able to compute the value of $\widehat{s_{ki}^m}, \forall k \in v_1^i$, which is defined by the following equation:

$$\widehat{s_{ki}^m} = \frac{P_{ki}^m}{\sum_{w\in\mathcal{N}} P_{wi}^m + \sigma W} \tag{22}$$

Then, each node broadcasts the $\{\widehat{s}_{ki}^m\}$ to its neighbor. After this process, each node i is able to compute its probability to use channel m in any outgoing edges, denoted by u_i^m, defined by the following equation:

$$u_i^m = min(1, max(\{\widehat{s_{iw}^m}/\alpha, w \in E_{out}^i\})) \quad (23)$$

u_i^m will also be shared by neighbors. The expected throughput of each channel is formally defined as:

$$\widehat{c_{kl}^m} = \frac{P_{kl}^m}{\sum_{w\in v_1^l} u_w^m P_{wl}^m + \sum_{w\in\mathcal{N}\setminus v_1^l} P_{wl}^m + \sigma W} \quad (24)$$

Another broadcast of $\widehat{c_{kl}^m}$ is required so that each node will get the expected throughput of each channel in all its incoming and outgoing edges.

B. Adjustment

In the adjustment process, each node uses the collected information to solve the following local optimization problem, denoted as LP_1:

$$\text{Max} \quad min(\textstyle\sum_{k\in E_{in}^i} f_{ki}, \sum_{w\in E_{out}^i} f_{iw}) \quad (25)$$

$$\text{s. t.} \quad f_{kl} = \textstyle\sum_{m\in\mathcal{M}_{kl}} a_{kl}^m \hat{c_{kl}^m} \quad (26)$$

$$\textstyle\sum_{k\in E_{in}^i} a_{ki}^m + \sum_{w\in E_{out}^i} a_{iw}^m \le 1 \quad (27)$$

This is a linear programming problem, thus, it can be solved efficiently. After grabbing the assignment results in node i, denoted as a_{ij}^{mi}, each assignment should be the consensus result of both endpoints. Formally, $a_{ij}^m = a_{ij}^{mi} * a_{ij}^{mj}$. This requires another broadcast of the assignment results.

The localized algorithm could be summarized as follows:

1) Share the assignment result with two-hop neighbors via two rounds of broadcasting.
2) Each node recomputes the expected throughput of each unassigned channel m in each of the incoming links.

$$\tilde{c}_{kl}^m = \frac{P_{kl}^m}{\sum_{w\in v_1^l \bigcup v_2^l} a_{wl}^m P_{wl}^m + \sum_{w\in\mathcal{N}\setminus(v_1^l \bigcup v_2^l)} P_{wl}^m + \sigma W} \quad (28)$$

3) Recompute the aggregated throughput of node i under the current assignment $\{a_k^i, k \ge 1\}$, which is $min(\sum_{k\in E_{in}^i} f_{ki}, \sum_{w\in E_{out}^i} f_{iw})$. If the aggregated throughput is not increased, use $\{a_{k-1}^i\}$ as the final assignment of node i and terminate the algorithm.
4) Based on the $\tilde{c}_{kl}^m$, resolve the optimization problem LP_1 again for all the unassigned channel m, without modifying the existing assignment where $a_{ij}^m = 1$.
5) Make a consensus for the assignment from both endpoints.
6) If no more links are assigned, the algorithm terminates; otherwise, go to step 1.

Because each node has limited channels and each round will make at least one assignment, this algorithm will eventually converge.

VI. Evaluation

A. Simulation Settings

For one set of network settings, we have to give out the mesh node set $\mathcal{N}$, gateway node set $\mathcal{N}_G$, the available channel set $\mathcal{M}_i$ in each node, and finally, the receiving power from node i to node j in band m as P_{ij}^m.

Our network settings are based on GoogleWiFi Trace. Clearly, this data set is not cognitive radio data. However, we can use the power and position information to generate our network scenarios.

Generally, we extract network scenarios in this way: Randomly pick n number of nodes from GoogleWiFi Trace. We also set the total operating bandwidth to approximately $2.4GHz$, with m number of orthogonal channels of $20MHz$, which is the general settings in IEEE 802.11. We use the trace data to generate $\{P_{ij}^m\}$. We assume that the trace data of the RSSI (Receiving Signal Strength Index) in node j from node i in band l is P_{ij}^l, where l is the band centered at $2.4GHz$. In WiFi, the RSSI is enclosed in the packet. Thus, we are not able to get P_{ij}^l when a packet transmitted from node i to node j cannot be decoded.

The available channels in each node are constrained by the PU nodes. We randomly deploy a certain number of PU nodes with assigned working channels. All the nodes within the communication range of PU could not share the same channels.

In this way, one simulation scenario is generated. We generate 200 scenarios to perform a statistical performance comparison evaluation.

B. Simulation Results

Based on the generated scenarios, we perform a statistic evaluation on the performance and cost of our algorithms.

1) Effectiveness of Power Collection: Compared to pervious work, the major difference is that we use a power information collection procedure instead of the power propagation model to measure the interference. We conduct a statistical evaluation of its effectiveness over the propagation model based on the positions. The cumulative results are shown in Fig. 1. From this figure, we can tell that the power information collection procedure helps the centralized solution to enhance its performance and mitigate the performance degradation introduced by the inaccurate model of power propagation gain model.

2) Effectiveness and Overhead of Post-Allocation Adjustment: To evaluate the effectiveness of our proposed post-allocation adjustment, we also compare the performance of centralized solution without adjustment, and also the one with adjustment. Both algorithms are conducted upon all scenarios. The results are shown in a CDF form in Fig. 3. We can see that the post-allocation adjustment indeed improves the overall throughput.

In terms of the cost of the post-allocation adjustment, we examine the number of iterations for the adjustments conduced. The results can be found in Fig. 6. We can see

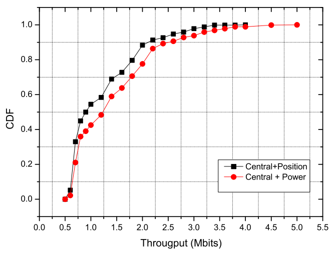

Fig. 1. Power information collection vs. propagation model.

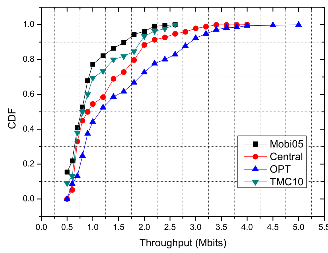

Fig. 2. Centralized solution vs. the optimal solution and others.

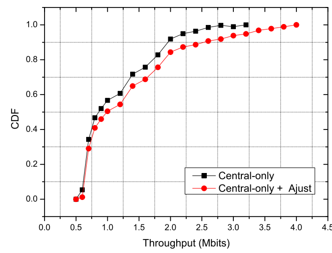

Fig. 3. Without adjustment vs. With adjustment.

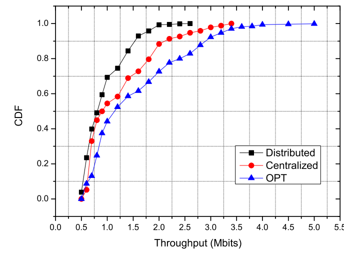

Fig. 4. Localized solution vs. centralized and optimal solution.

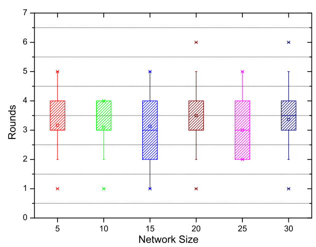

Fig. 5. Cost of localized solution.

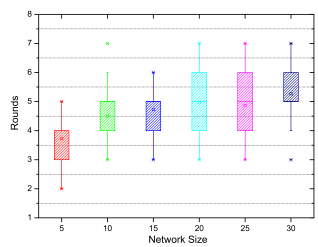

Fig. 6. Cost of post-allocation adjustment.

that, regardless of the network size, the adjustment will be terminated in no more than 7 rounds. Especially, for most of the cases, the adjustment will be finished around 3-6 rounds.

3) Performance of Centralized Solution: To better understand the performance of our comprehensive centralized solution, we compare our algorithm not only with the optimal results, but also with the algorithms introduced in the last section. They are denoted as Mobi05 [12] and TMC10 [13], respectively. To obtain the optimal results, this group of experiments is not conducted upon scenarios with over 20 nodes. The results in Fig. 2 show that our algorithm outperforms both algorithms in the control group. There is still a margin between ours and the optimal results.

4) Performance and Overhead of Localized Solution: We evaluate our localized solution by comparing it with the centralized solution and the optimal results. They are all conducted in scenarios with less than 20 nodes. We can see the results in Fig. 4. The average result shows that the localized solution achieves approximately 78% of optimal results.

Regarding the overhead of the localized solution, we measure its convergence speed in terms of the number of iterations. The results are in Fig. 5. The convergent iteration is surprisingly as good as no more than 6. For most of the cases, despite the size of the network, the algorithm will terminate within 4 rounds.

VII. Conclusion

We study the throughput optimization problems via spectrum allocation in CR-based WMNs under the physical interference model. This problem has been modeled as a mixed integer non-linear programming problem. Both centralized and localized solutions are proposed to solve it, approximately. The centralized solution follows the branch-and-bound framework, thus, providing $(1-\varepsilon)$-approximate results. Along with solving the MINLP, a power collection procedure to replace the propagation gain model and a post-allocation adjustment process are proposed to form a comprehensive solution. We propose a localized solution to this problem as well. A comprehensive statistical evaluation based on real data is conducted. The simulation results illustrate the effectiveness of our proposed solutions.

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