Fair Bandwidth Allocation in Wireless Mesh Networks With Cognitive Radios

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***Abstract*—Wireless mesh networks (WMNs) are considered to be an economical solution for last-mile broadband Internet access. In this paper, we study end-to-end bandwidth allocation in WMNs with cognitive radios, which involves routing, scheduling, and spectrum allocation. To achieve a good tradeoff between fairness and throughput, we define two fair bandwidth-allocation problems based on a simple max–min fairness model and the well-known lexicographical max–min (LMM) fairness model, respectively. We present linear programming (LP)-based optimal and heuristic algorithms to solve both problems. Extensive simulation results are presented to justify the effectiveness of the proposed algorithms.**

***Index Terms*—Bandwidth allocation, cognitive radios, cross-layer optimization, fairness, lexicographical max–min (LMM) fairness, routing, scheduling, spectrum allocation, wireless mesh networks (WMNs).**

I. Introduction

WIRELESS mesh networks (WMNs) are considered to be a promising solution for the support of low-cost broadband Internet access for large areas [3]. A WMN consists of mesh clients and mesh routers. Mesh routers form the backbone of the network to provide network access for mesh clients, and some of them are *gateways* that are directly connected with the Internet via high-capacity cables. To efficiently deliver a high volume of traffic between the Internet and those nongateway mesh routers over wireless channels, the limited bandwidth needs to be fairly allocated to them.

The proliferation of wireless users motivates new radio technology and new spectrum-access methods since the traditional static spectrum-access method (which assigns a fixed portion of the spectrum to a specific license holder or service for exclusive use) is unable to satisfy the fast increasing demands. With emerging cognitive radios, unlicensed wireless users (a.k.a. secondary users) can opportunistically sense and access the underutilized spectrum bands, even if it is licensed, as long as the licensed wireless users (a.k.a. primary users) in these spectrum bands are not disrupted [2]. This way, interference can be reduced, and network capacity can be improved.

Cognitive radios 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 [2]. However, they 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. However, in a WMN with cognitive radios, each node can access a large number of spectrum bands (channels), which may spread a wide range of frequencies. Different channels can support quite different transmission ranges and data rates, which will have a significant impact on route and channel selections. In addition, a channel is said to be *available* to a cognitive radio only if communications with this channel will not disrupt communications among primary users. Therefore, channel availability depends on the activities of primary users and thus may change over time.

In this paper, we study end-to-end bandwidth allocation in cognitive-radio-based WMNs with the objective of achieving certain fairness among all the nongateway nodes, which involves routing, scheduling, and spectrum allocation. We address fairness based on a simple max–min model that leads to high-throughput solutions with guaranteed max–min bandwidth allocation values, as well as the well-known lexicographical max–min (LMM) model [24]. We formally define the max–min fair maximum throughput bandwidth allocation (MMBA) problem and the LMM fair bandwidth allocation (LMMBA) problem. We first present algorithms to find maximum-throughput bandwidth allocation, which can serve as a benchmark for performance evaluation. Then, we present linear programming (LP)-based optimal and heuristic algorithms for both problems with consideration for channel heterogeneity and dynamic channel availability. To our best knowledge, we are the first to study the joint design of routing, scheduling, and spectrum allocation for fair bandwidth allocation in the context of WMNs and cognitive radios, and we propose provably good solutions.

The rest of this paper is organized as follows: We discuss related work in Section II. The system model is described in Section III. We define the MMBA problem and the LMMBA problems in Section IV. The proposed algorithms are presented in Section V. We present numerical results in Section VI and conclude this paper in Section VII.

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II. Related Work

Maximum throughput and fair resource allocation have been well studied for traditional multiradio WMNs with homogeneous channels. One of the first 802.11-based multichannel multihop WMN architectures was proposed and evaluated in [29]. The authors developed a set of centralized algorithms for channel assignment, bandwidth allocation, and routing. They also presented distributed channel assignment and routing algorithms utilizing only local traffic load information in a later paper [30]. In [31], Tang *et al.* presented a channel assignment algorithm that can be used to compute K-connected and low-interference network topology and an optimal quality-of-service routing algorithm that can be used to find routes for connection requests with bandwidth requirements. A constant-bound centralized approximation algorithm was proposed in [4] to jointly compute channel assignment, routing, and scheduling solutions for fair rate allocation. In [21], the authors studied a similar problem and derived upper bounds on the achievable throughput using a fast primal–dual algorithm. Based on that, they also proposed two channel-assignment heuristics. In [34], Tang *et al.* proposed cross-layer schemes to solve the joint rate-allocation, routing, scheduling, power control, and channel-assignment problems. A joint congestion-control, channel-allocation, and scheduling algorithm was presented in [25], which maximizes the utility function of the injected traffic, while guaranteeing queue stability. In [27], the authors formulated the joint channel-allocation, interface assignment, and the media access control (MAC) problem as a nonlinear mixed-integer network utility-maximization problem. They proposed an optimal algorithm based on exact binary linearization techniques and a simpler near-optimal algorithm based on approximate dual decomposition techniques. Distributed resource-allocation algorithms have also been presented in [9], [12], and [22].

Cognitive radio wireless networks have recently received extensive attention. In [2], Akyildiz *et al.* presented a good state of the art in cognitive radio networks. In [41], Zheng and Peng developed a graph-theoretic model to characterize the spectrum access problem and devised multiple heuristic algorithms to find high throughput and fair solutions. Tang *et al.* introduced a multichannel contention graph (MCCG) to characterize the impact of interference and proposed joint-scheduling and spectrum-allocation algorithms for fair spectrum sharing based on MCCG in [33]. In [39], the concept of a time-spectrum block was introduced to model spectrum reservation, and centralize and distributed protocols were presented to allocate such blocks for cognitive radio users. In [10], a distributed spectrum-allocation scheme based on local bargaining was proposed for wireless ad hoc networks with cognitive radios. Moreover, they presented five spectrum access rules and introduced a distributed spectrum-management architecture in which nodes fairly share spectrum resources by making independent actions following the proposed rules in [11]. In [40], the authors derived optimal and suboptimal distributed strategies for the secondary users to decide which channels to sense and access with the objective of throughput maximization under a framework of partially observable Markov decision process. In a very recent paper [42], Zhou *et al.* have proposed VERITAS, which is a truthful and computationally efficient spectrum auction to support an eBay-like dynamic spectrum market.

Cross-layer schemes have also been proposed for cognitive radio wireless networks. In [35], Wang *et al.* considered the joint design of dynamic spectrum access and adaptive power management. They proposed a power-saving multichannel MAC protocol that is capable of reducing the collision probability and the waiting time in the awake state of a node. In [18], the authors proposed the asynchronous distributed pricing scheme to solve a joint spectrum-allocation and power-assignment problem. In [36], Wang *et al.* presented a joint power- and channel-allocation scheme that uses distributed pricing strategy to improve the network performance. In [38], a novel layered graph was proposed to model spectrum-access opportunities and was used to develop joint spectrum-allocation and routing algorithms. A mixed-integer non-LP-based algorithm was presented to solve a joint spectrum allocation, scheduling, and routing problem in [17]. A distributed algorithm was presented in [28] to solve a joint power control, scheduling, and routing problem with the objective of maximizing data rates for a set of user communication sessions. In [37], the authors presented distributed algorithms for joint spectrum allocation, power control, routing, and congestion control.

The differences between this paper and previous works are summarized as follows: 1) Resource allocation in a cognitive-radio-based WMN with homogeneous channels is quite different from that in a traditional WMN due to its special features, such as dynamic channel availability and channel heterogeneity introduced before. 2) The LMM model is a well-adopted fairness model and a major concern of this paper. However, it has not been well studied in the context of WMNs and cognitive radios. 3) We propose provably good algorithms to solve the formulated problems. However, many related works (such as [10], [18], [35], and [38]) only presented heuristic algorithms that cannot provide any performance guarantees.

III. System Model

We consider a multihop WMN consisting of static mesh routers with their locations known. Each node v_i is equipped with $q_i (q_i > 1)$ cognitive radios. The available spectrums are divided into a set of orthogonal *channels*. Each cognitive radio can dynamically access a channel to deliver its packets but can only work on one of the available channels at one time. The channel availability of a mesh node mainly depends on the activities of primary users in its vicinity. Any existing spectrum-sensing method in the literature [2] can be used to detect locally available channels for each mesh router. These methods can usually guarantee that communications among cognitive radios will not disrupt communications among primary users if every cognitive radio only uses the available channels. Different nodes may have sets of different available channels, and they may change over time. Each radio is assumed to transmit at the same fixed transmission power level, i.e., there are a fixed transmission range (R_h) and a fixed interference range $(I_h < R_h)$ (typically between two and three times R_h) associated with each channel h. In addition, different channels can support

different link capacities and transmission ranges. We consider a scheduling-based MAC layer in which the time domain is divided into timeslots with the same fixed duration. Similar to [7], a spectrum server is assumed to run the proposed bandwidth allocation algorithms to manage resources in the network.

A communication graph $G(V, E)$ is used to model the network, in which every node $v \in V$ corresponds to a mesh router in the network, and there is a link $e = (u, v) \in E$ if there exists a common channel h available for both nodes u and v, and the distance between them $\|u - v\| \leq R_h$. There are n such nodes and m such links. In addition, there are a special virtual sink node z and a directed virtual link from each gateway node to z.

The protocol model [15] is employed to model interference. In a multichannel system, interference is channel dependent. Therefore, we address interference on a link–channel pair basis. All possible link–channel pairs (e, h) can be identified according to the channel availability in every node. Denote the set of link–channel pairs as $\mathcal{A}$. Two link–channel pairs (e, h) and (e', h') ($e = (u, v)$ and $e' = (u', v')$) are said to *interfere* with each other if $h = h'$, and $\|u - v'\| \leq I_h$, $\|u' - v\| \leq I_h$, $\|u - u'\| \leq I_h$, or $\|v - v'\| \leq I_h$. Note that we adopt a symmetric interference model that requires both the receiver and the transmitter to be free of interference, because according to IEEE 802.11 [1], a link layer acknowledgment (ACK) message needs to be sent to the transmitter by the receiver for every data packet.

We introduce the notion *transmission mode* to assist computation. A transmission mode consists of a subset of link–channel pairs that can concurrently be active. A subset of link–channel pairs can be active at the same time if 1) any two link–channel pairs in the subset do not *interfere* with each other ("interfere" is previously defined), and 2) the total number of link–channel pairs *associated with* a node v_i (i.e., the corresponding links are incident to v_i) must be no more than q_i. We have the second condition because the half-duplexing, unicast, and collision-free communications must be ensured for each cognitive radio. Since every element of a transmission mode is a link–channel pair, once a transmission mode is identified, a spectrum allocation can be determined for the set of links contained in those link–channel pairs. We employ a $T \times |\mathcal{A}|$ matrix Γ to represent the set of transmission modes, where T is the number of transmission modes. Each row of the matrix corresponds to a transmission mode, and each column corresponds to a link–channel pair in $\mathcal{A}$. If transmission mode t includes link–channel pair (e_j, h), then $\Gamma^t_{j,h} = 1$. Otherwise, $\Gamma^t_{j,h} = 0$. For ease of presentation, we always append a special all-zero row at the end of Γ, which represents a transmission mode that does not contain any link–channel pair. The average data rate of link e_j can be computed as $\sum_{h=1}^{H} \sum_{t=1}^{T} \Gamma^t_{j,h} c^j_h p_t$, where p_t is the fraction of time that transmission mode t is activated, and c^h_j is the capacity of link e_j on channel h, which is usually a constant. In a wireless system with a scheduling-based MAC layer, a transmission mode is activated for each time slot. The joint scheduling and spectrum-allocation problem is transformed into a problem of finding all the possible transmission modes and the active time fraction for each transmission mode.

TABLE I
NOTATIONS

$\mathcal{A}$	The set of link-channel pairs
$\mathbf{B}$	A bandwidth allocation vector
E^{in}_v	The set of the indices of incoming links of node v in G
E^{out}_v	The set of the indices of outgoing links of node v in G
c^j_h	The capacity of link e_j on channel h
$\mathbf{F}$	A link flow allocation vector
H	The total number of channels available in the network
H_i	The set of channels available at node v_i
I_h	The interference range on channel h
n	The number of mesh routers (nodes)
N	The number of non-gateway nodes
N_g	The number of gateway nodes
$\mathbf{P}$	A scheduling vector
q_i	The number of radios at node v_i
R_h	The transmission range on channel h
$\mathbf{R}$	A sorted bandwidth allocation vector
S	The set of non-gateway nodes
S^I	$\{1, 2, \cdots, N\}$
T	The number of transmission modes
Γ	The transmission mode matrix

IV. Problem Definition

Before defining the problems, we will introduce some necessary notations and definitions. Denote the nongateway node set as $S = \{s_1, s_2, \ldots, s_N\}$ and the corresponding bandwidth allocation vector as $\mathbf{B} = [b_1, b_2, \ldots, b_N]$, where b_i is the bandwidth allocated to node s_i in S. The throughput of a bandwidth allocation vector $\mathbf{B}$ is $\sum_{i=1}^{N} b_i$. When a node s_i is allocated a bandwidth of b_i, it can communicate with the Internet with a total bandwidth of b_i, which supports both traffic from node s_i to the Internet and traffic from the Internet to node s_i. We may imagine that the bandwidth b_i is purely used by traffic from node s_i to the Internet and that there is no traffic from the Internet to node s_i. This way, we may imagine that the bandwidth b_i is used by a *flow* from node s_i to sink node z with the understanding that the bandwidth b_i is *physically* used by traffic in both directions. This simplification will not affect the results because of the symmetric interference model. We also want to find a link flow allocation vector $\mathbf{F} = [f_1, f_2, \ldots, f_m]$ (i.e., a routing solution), specifying the amount of traffic f_j routed through link e_j in each time unit, and a scheduling vector $\mathbf{P} = [p_1, p_2, \ldots, p_T]$, specifying time fraction p_t for each transmission mode t. A bandwidth allocation vector is said to be *feasible* if we can find a corresponding scheduling vector, a corresponding link flow allocation vector, and a set of transmission modes that are feasible. The feasibilities of these vectors will be discussed in detail in Section V. All major notations are summarized in Table I.

Now, we are ready to define the optimization problems. As our goal is to achieve certain fairness among all the nongateway mesh routers in terms of bandwidth allocation, we define two problems based on a simple max–min fairness model and the LMM fairness model. Let the network $G(V, E)$, the nongateway node set S, and the available channel set H_i at each node v_i be given.

Definition 1 (MMBA Problem): A feasible bandwidth-allocation vector $\mathbf{B}$ is said to be a feasible max–min fair bandwidth-allocation vector if for any other feasible

bandwidth-allocation vector $\hat{\mathbf{B}}$ we have $\min\{b_i|1 \le i \le N\} \ge \min\{\hat{b}_i|1 \le i \le N\}$. The MMBA problem seeks a feasible max–min fair bandwidth-allocation vector for all nodes in $\mathbf{S}$ along with a corresponding link flow-allocation vector, a corresponding scheduling vector, and a set of transmission modes such that the throughput of this bandwidth-allocation vector is maximum among all feasible max–min fair bandwidth-allocation vectors.

For a bandwidth-allocation vector $\mathbf{B} = [b_1, b_2, \ldots, b_N]$, we will use $\mathbf{R} = [r_1, r_2, \ldots, r_N]$ to denote the sorted version of $\mathbf{B}$ such that $r_1 \le r_2 \le \cdots \le r_N$. Similarly, for bandwidth-allocation vectors $\hat{\mathbf{B}}$, we will use $\hat{\mathbf{R}}$ to denote its sorted version.

Definition 2 (LMMBA Problem): A feasible bandwidth-allocation vector $\mathbf{B}$ is said to be a feasible LMMBA vector if, for any other feasible bandwidth-allocation vector $\hat{\mathbf{B}}$, either $r_i = \hat{r}_i$ for $1 \le i \le N$, or there exists an integer $1 \le j \le N$ such that $r_i = \hat{r}_i$ for $i < j$ but $r_j < \hat{r}_j$. The LMMBA problem seeks a feasible LMMBA vector for all nodes in S along with a corresponding link flow-allocation vector, a corresponding feasible scheduling vector, and a set of transmission modes.

The fairness model behind the MMBA problem is a simple max–min model. The bandwidth-allocation vector obtained by solving the MMBA problem is guaranteed to have the maximum minimum bandwidth value but is not necessarily an LMMBA vector. The LMM model is a well-accepted fairness model [16] because it is believed to be able to provide a very good tradeoff between throughput and fairness.

V. Proposed Algorithms

In this section, we present algorithms that will solve both the MMBA problem and the LMMBA problem. Our algorithms include two phases: In phase 1, identify a set of transmission modes. In phase 2, solve the MMBA problem by solving a corresponding LP problem, and solve the LMMBA problem using an LP-based algorithm. Both the LP formulation and the algorithm will be presented later. If all possible transmission modes are found in the first step, then our two-phase methods can *optimally* solve both problems. Otherwise, if only a subset of all transmission modes are found, then we will end up with suboptimal solutions.

All possible transmission modes can actually be found by using an MCCG presented in [33], which is a multichannel extension of the well-known contention graph [26]. Briefly, in an MCCG, every vertex corresponds to a link–channel pair, and there is an edge between two vertices if the two corresponding link–channel pairs interfere with each other. The importance of the MCCG lies in the fact that a transmission mode corresponds to an independent set in the MCCG. Since our objective is to improve throughput and fairness, we are only interested in transmission modes corresponding to maximal independent sets (MISs). The algorithm presented in [20] that can find all MISs in a graph can be used to identify all possible transmission modes. However, it is well known that the number of all MISs in a graph may exponentially grow with the graph size. If we take all transmission modes as the input for the algorithm in the second phase, then it may take an exponentially long time to solve them. For large cases, the polynomial time-heuristic algorithm in [33] can be used to compute a subset of MISs (transmission modes) in an MCCG with a cardinality of pN_C, where N_C is the number of vertices (link–channel pairs) in the MCCG, and p is a tunable parameter that is usually set to a small integer such as 1 or 2. The algorithm can find a *good* subset of transmission modes, which has been shown to yield close-to-optimal performance by simulation results in [33]. This algorithm starts with every vertex once, which can guarantee that each vertex is covered by at least one transmission mode. It constructs an MIS (transmission mode) in each iteration by keeping to add the vertex (link–channel pair) with the largest weight value, which depends on multiple factors, such as channel capacity and traffic demand. This procedure is repeated p times, which gives a total of pN_C transmission modes. The algorithm we implemented for finding transmission modes in our simulation is slightly different from that in [33]. Our algorithm selects those link–channel pairs with small distances (in terms of hop count) to gateway nodes and breaks ties using the weight function in [33]. We found that it outperforms the original algorithm in [33] for the problems studied here.

Our two-phase algorithms are particularly suitable for cognitive radio networks, in which channels available to each node may change over time. Every time an existing channel becomes no longer available or a new channel becomes available to a mesh node, there is no need to go through the whole two-phase procedure to compute a completely new solution. We can simply eliminate those transmission modes, including the link–channel pair that is no longer available, from the current transmission mode set, or add one or more transmission modes, including the newly available user–channel pairs, to the existing set. Then, a second-phase algorithm can be executed to find a new bandwidth allocation solution. In other words, there is no need to find a completely new set of transmission modes every time when the channel availability changes. This way, a new solution can be obtained based on the updated channel availability in a time-efficient manner. As analyzed in [33], the time complexity of the algorithm in [33] is $O(q^2 N_C + qN_C^3)$. Therefore, this saving could be significant for a network with a large number of nodes and available channels. Of course, the system may experience performance degradation if substantial changes occur after a certain period of time. To guarantee close-to-optimal performance, the algorithms in both phases need to be reexecuted to compute a completely new solution. In addition, channel heterogeneity has been given careful consideration in both the algorithm in [33] and the LP formulations presented later.

Before presenting an LP formulation for the MMBA problem, we give an LP in the following to compute a maximum throughput bandwidth allocation (MBA) vector that can serve as a benchmark. In all these LP problems, we have bandwidth-allocation variables b_i, $1 \le i \le N$, scheduling variables p_t, $1 \le t \le T$, and link flow-allocation variables f_j, $1 \le j \le m$.

$LP1$: MBA

$$\max \sum_{1 \le i \le N} b_i \tag{1}$$

$$\text{s.t.}: \quad \sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = b_i, \qquad 1 \le i \le N \tag{2}$$

$$\sum_{j\in E_v^{\text{out}}} f_j - \sum_{j\in E_v^{\text{in}}} f_j = 0 \qquad \forall v \in V \setminus \left\{S \bigcup \{z\}\right\} \tag{3}$$

$$f_j \le \sum_{h=1}^{H}\sum_{t=1}^{T} \Gamma_{j,h}^{T} c_h^j p_t, \quad 1 \le j \le m \tag{4}$$

$$\sum_{t=1}^{T} p_t = 1 \tag{5}$$

$$p_t \ge 0, \quad 1 \le t \le T \tag{6}$$

$$f_j \ge 0, \quad 1 \le j \le m \tag{7}$$

$$b_i \ge 0, \quad 1 \le i \le N. \tag{8}$$

In this LP, E_v^{in} is the set of the indices of incoming links of node v, and E_v^{out} is the set of the indices of outgoing links of node v in the communication graph G. The *feasibilities* of the bandwidth allocation vector, the link flow allocation vector, and the scheduling vector are ensured by constraints (2)–(5). Specifically, constraint (2) makes sure a bandwidth of b_i is allocated to node $s_i \in S$. Constraint (3) is a general flow-conservation constraint. Constraint (4) guarantees that each link e_j is given enough resources to support the traffic it needs to carry. Constraints (6)–(8) are the constraints for the decision variables. The objective function [see (1)] is to maximize the network throughput. Next, we present an LP formulation for the MMBA problem.

$LP2$: Max–min

$$\max \alpha \tag{9}$$

$$\text{s.t.}: \quad \text{Constraints (2)}-\text{(8)}; \quad b_i \ge \alpha,\ 1 \le i \le N. \tag{10}$$

$LP3(\alpha)$: MMBA

$$\max \sum_{i=1}^{N} b_i$$

$$\text{s.t.}: \quad \text{Constraints (2)}-\text{(7)},\ \text{(10)}.$$

To solve the MMBA problem, we need to solve two LPs sequentially. Note that both LPs include a similar set of constraints as $LP1$ to ensure the feasibilities of those vectors. We first solve $LP2$ and obtain a max–min bandwidth-allocation value α. Because of constraint (10) and the objective function of $LP2$, we can guarantee that for any feasible bandwidth-allocation vector $\hat{\mathbf{B}}$, we have $\min\{\hat{b}_i | 1 \le i \le N\} \le \alpha = \min\{b_i | 1 \le i \le N\}$. Next, we feed α to $LP3$ as a parameter. Constraint (10) in $LP3$ guarantees that in the computed $\mathbf{B} = [b_1, b_2, \ldots, b_N]$, we have $\min\{b_i | 1 \le i \le N\} \ge \alpha \ge \min\{\hat{b}_i | 1 \le i \le N\}$. The objective of $LP3$ is to maximize the throughput. Therefore, solving $LP2$ and $LP3(\alpha)$ together can provide an MMBA solution.

We will present an algorithm for the LMMBA problem by solving a sequence of LPs. Before proceeding with the presentation of the algorithm, we prove an important property—the uniqueness of the feasible LMMBA vector.

Lemma 1: Let $\mathbf{B}^1$ and $\mathbf{B}^2$ be two feasible bandwidth-allocation vectors that are both LMM fair. Then, $b_i^1 = b_i^2$ for $1 \le i \le N$. In other words, the LMMBA vector is unique.

Proof: Let $S_1^1, S_2^1, \ldots, S_K^1$ be a partition of $S^I = \{1, 2, \ldots, N\}$ such that we have the following:

1) For any $1 \le k \le K$ and $i, j \in S_k^1$, we have $b_i^1 = b_j^1$.
2) For any $1 \le k < k' \le K$ and $i \in S_k^1, j \in S_{k'}^1$, we have $b_i^1 < b_j^1$.

Similarly, let $S_1^2, S_2^2, \ldots, S_J^2$ be a partition of the set $\{1, 2, \ldots, N\}$ such that we have the following:

3) For any $1 \le k \le J$ and $i, j \in S_k^2$, we have $b_i^2 = b_j^2$.
4) For any $1 \le k < k' \le J$ and $i \in S_k^2, j \in S_{k'}^2$, we have $b_i^2 < b_j^2$.

Since both $\mathbf{B}^1$ and $\mathbf{B}^2$ are LMMBA vectors, we must have the following.

1) $K = J$.
2) $|S_k^1| = |S_k^2|$ for any $1 \le k \le K$.
3) $b_i^1 = b_j^2$ for any $1 \le k \le K$, $i \in S_k^1$, $j \in S_k^2$.

We need to prove that $S_k^1 = S_k^2$ for any $1 \le k \le K$. We will use a simple fact related to *convex set* [6]. Since $\mathbf{B}^1$ is a feasible bandwidth allocation vector, there must exist a corresponding link flow-allocation vector $\mathbf{F}^1$ so that $\mathbf{B}^1$ and $\mathbf{F}^1$ satisfy the linear constraints (2)–(8). Similarly, since $\mathbf{B}^2$ is a feasible bandwidth-allocation vector, there must exist a corresponding link flow-allocation vector $\mathbf{F}^2$ so that $\mathbf{B}^2$ and $\mathbf{F}^2$ satisfy the linear constraints (2)–(8). Let $\mathbf{B}^3 = (\mathbf{B}^1 + \mathbf{B}^2/2)$, and let $\mathbf{F}^3 = (\mathbf{F}^1 + \mathbf{F}^2/2)$. Since the set of feasible bandwidth-allocation vectors and corresponding link flow-allocation vectors satisfying the set of linear constraints (2)–(8) form a convex set [6], $\mathbf{B}^3$ is a feasible bandwidth-allocation vector, with $\mathbf{F}^3$ as a corresponding link flow-allocation vector.

It follows from the definition of $\mathbf{B}^3$ and the partitions $S_1^1, \ldots, S_K^1$ and $S_1^2, \ldots, S_K^2$ (note that $K = J$). We know the following conditions.

1) If i is an index such that $i \in S_k^1 \cap S_k^2$ for some $1 \le k \le K$, then $b_i^3 = b_i^1 = b_i^2$.
2) If i is an index such that $i \in S_j^1 \cap S_k^2$ for some $1 \le j < k \le K$, then $b_i^1 < b_i^3 < b_i^2$.

Let α_k be the common value for the elements in S_k^1 for $k = 1, \ldots, K$. From the foregoing facts, we know that

$$b_i^3 \begin{cases} = \alpha_1, & \text{for } I \in S_1^1 \cap S_1^2 \\ < \alpha_1, & \text{otherwise.} \end{cases} \tag{11}$$

Since $\mathbf{B}^1$ and $\mathbf{B}^2$ are both LMM fair, we must have $S_1^1 = S_1^2$ (otherwise, $\mathbf{B}^3$ becomes a better bandwidth-allocation vector in the sense of LMM fairness).

Suppose we have proved that $S_k^1 = S_k^2$ for $k = 1, 2, \ldots, K_1$, where $1 < K_1 < K$, and $K_2 = K_1 + 1$. We will have

$$b_i^3 \begin{cases} = \alpha_k, & \text{for } I \in S_k^1 \cap S_k^2,\ 1 \le k \le K_1 \\ = \alpha_{K_2}, & \text{for } I \in S_{K_2}^1 \cap S_{K_2}^2 \\ < \alpha_{K_2}, & \text{otherwise.} \end{cases} \tag{12}$$

This proves that we must have $S_{K_2}^1 = S_{K_2}^2$. Repeating this process, we have $S_k^1 = S_k^2$ for $k = 1, 2, \ldots, K$. ■

Note that the basic idea used in the preceding proof (the midpoint of two points in a convex set is also in the convex set) is similar to that used for proving the lemma [8, Lemma 3.1]. We present the proof here for the completeness of this paper. Hou *et al.* [16] considered LMM fair rate allocation under a lifetime constraint in wireless sensor networks. They proved the uniqueness of the LMM fair rate-allocation vector for their

problem using parametric analysis and duality properties of LP [5]. Our proof of the uniqueness of the LMMBA vector is different and simpler.

Since the feasible LMMBA vector is unique, we may denote the partition $S_1^1, S_2^1, \ldots, S_K^1$ of $\{1, 2, \ldots, N\}$ as $S_1, S_2, \ldots, S_K$ and use α_k to denote the LMMBA value for nodes in S_k for $k = 1, 2, \ldots, K$.

The optimal algorithm for the LMMBA problem is formally presented as Algorithm 1. The basic idea of the algorithm is to solve $LP4(k)$ iteratively. For $k = 1, 2, \ldots, K$, the algorithm computes the bandwidth allocation values (α_k, as defined in the proof of Lemma 1) and identifies the set $S_k \subseteq S^I$ such that $b_i = \alpha_k$ if and only if $i \in S_k$.

In Algorithm 1, δ_k, b_i, f_j, and p_t are variables of $LP4(k)$, and β_i, b_i, f_j, and p_t are variables of $LP5(k, \bar{S}, \beta)$. Clearly, during the execution of the algorithm, for every node $i \in S_k$, we must have $b_i = \alpha_k$. However, there may be some node $i \notin \bigcup_{l=1}^{k} S_l$ but $b_i = \alpha_k$. In $LP5(k, \bar{S}, \beta)$, β is a small and tunable parameter, and it was set to 0.01 in the simulation. The purpose of having constraint (18) is to force nodes not belonging to S_k (i.e., nodes whose bandwidth values can further be improved) out of $\bar{S}$ in each iteration. Note that there are no constraints (15) or (20) when $k = 1$. In short, $LP4(k)$ is used to identify S_k, and the corresponding bandwidth-allocation value α_k for $k = 1, 2, \ldots, K$ and $LP5(k, \bar{S}, \beta)$ is used to determine the *actual* S_k.

Algorithm 1 LMMBA

Step_1 $k := 1$; $\alpha_0 := 0$; $S_0 := \emptyset$;
Step_2 Solve $LP4(k)$; $\alpha_k := \alpha_{k-1} + \delta_k$;
Step_3 $\bar{S} := S^I \setminus \bigcup_{l=0}^{k-1} S_l$;
Step_4 Solve $LP5(k, \bar{S}, \beta)$; $Y := \emptyset$;
  forall ($i \in \bar{S}$ such that $\beta_i < 0$) do
    $Y := Y \bigcup \{i\}$;
  endforall
Step_5 **if** ($Y \neq \emptyset$)
    $\bar{S} := \bar{S} \setminus Y$; goto Step_4;
  else
    $S_k := \bar{S}$;
    if ($\bigcup_{l=0}^{k} S_l = S^I$)
      return;
    else
      $k := k + 1$; **goto** Step_2;
    endif
  endif

$LP4(k)$

$$\max \delta_k \tag{13}$$

s.t. : Constraints (3)−(8);

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = \alpha_{k-1} + \delta_k \quad \forall i \in S^I \setminus \bigcup_{l=0}^{k-1} S_l \tag{14}$$

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = \alpha_l \quad \forall i \in S_l, 1 \leq l < k. \tag{15}$$

$LP5(k, \bar{S}, \beta)$

$$\max \sum_{i \in \bar{S}} \beta_i \tag{16}$$

s.t. : Constraints (3)−(8)

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = \alpha_k + \beta_i \quad \forall i \in \bar{S} \tag{17}$$

$$0 \leq \beta_i \leq \beta \quad \forall i \in \bar{S} \tag{18}$$

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = \alpha_k \quad \forall i \in S^I \setminus \left\{ \bar{S} \bigcup_{l=0}^{k-1} S_l \right\} \tag{19}$$

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j - \sum_{j \in E_{s_i}^{\text{in}}} f_j = \alpha_l \quad \forall i \in S_l, \quad 1 \leq l < k. \tag{20}$$

Theorem 1: Algorithm 1 correctly computes the feasible unique LMMBA vector $\mathbf{B}$ in polynomial time if the cardinality of the given transmission mode set is polynomial.

Proof: When we solve $LP4(1)$, we obtain the max–min bandwidth allocation value α_1, together with a bandwidth allocation vector $\mathbf{B}$, such that $\alpha_1 = \min\{b_i | 1 \leq i \leq N\}$. Note that $i \in S_1$ implies $b_i = \alpha_1$. However, $b_i = \alpha_1$ does not imply $i \in S_1$. That is to say, by simply solving $LP4(1)$, we can only obtain a superset of S_1. To obtain the *actual* S_1 from $\overline{S}$, we solve $LP5(k, \overline{S}, \beta)$, which maximizes the sum of the bandwidth values of the nodes in $\overline{S}$, while keeping the bandwidth allocated to nodes that have been decided not in $\overline{S}$ at α_1. Clearly, $\overline{S}$ is a proper superset of S_1 if and only if there exists a bandwidth-allocation vector $\mathbf{B}$ so that

$$b_i \geq \alpha_1, \qquad 1 \leq i \leq N \tag{21}$$

$$\sum_{i \in \overline{S}} b_i < |\overline{S}| \times \alpha_1. \tag{22}$$

This means that when $\overline{S} \neq S_1$, by using $LP5(k, \overline{S}, \beta)$, we can always identify at least one node $i \in \overline{S}$ with $\beta_i < 0$ such that $i \notin S_1$ and move it out of $\overline{S}$. Clearly, in at most $(N - |S_1|)$ iterations, we will have $\overline{S} = S_1$. This shows that we have computed S_1 and the bandwidth value for S_1 (α_1) correctly.

For general k ($1 < k \leq K$), the algorithm first computes a superset $\overline{S}$ of S_k and then iteratively removes from $\overline{S}$ the nodes that do not belong to S_k. Eventually, we have $\overline{S} = S_k$. This proves the correctness of the algorithm.

To analyze the time complexity of the algorithm, we note that, in the worst case, the running time of the algorithm is dominated by solving a sequence of $LP5(k, \overline{S}, \beta)$ in each iteration. For each value of k, we need to solve $O(N)LP5(k, \overline{S}, \beta)$. This gives an upper bound of $O(N^2)LP5(k, \overline{S}, \beta)$, each of which has $O(m + T)$ variables and $O(m + T)$ constraints. It is well known that an LP problem with polynomial numbers of constraints and variables can be solved in polynomial time [5]. Therefore, the proposed algorithm is a polynomial time algorithm if T is polynomial. This completes the proof. ■

If we employ the parameter-analysis technique [16] in Algorithm 1, then the number of LPs to be solved may be reduced. However, we choose the current approach since it has a more intuitive analysis and has a polynomial time complexity. We notice that Algorithm 1 can quickly compute a feasible LMMBA vector in practice since there are efficient algorithms for solving LP problems [5]. Algorithm 1 can provide a link flow-allocation vector $(\mathbf{F})$ that gives the *aggregated* flow value for each link. However, we may also want to have a node-specific flow allocation that gives the flow value corresponding to each nongateway node on each link. This can be done by using arc chain decomposition [14] or by simply solving $LP6(\mathbf{B}, \mathbf{F})$, as defined in the following. In this LP, f_j^i is a node-specific flow variable and indicates the flow routed through link e_j for traffic between node $s_i \in S$ and sink node z. Since we only want to have a feasible solution, it does not matter what the objective function is.

$LP6(\mathbf{B}, \mathbf{F})$: Node-Specific Link Flow Allocation

$$\max f_1^1 \tag{23}$$

$$\text{s.t.}: \quad \sum_{i=1}^{N} f_j^I = f_j, \quad 1 \le j \le m \tag{24}$$

$$\sum_{j \in E_{s_i}^{\text{out}}} f_j^I - \sum_{j \in E_{s_i}^{\text{in}}} f_j^I = b_i, \quad 1 \le i \le N \tag{25}$$

$$\sum_{j \in E_v^{\text{out}}} f_j^I - \sum_{j \in E_v^{\text{in}}} f_j^I = 0 \qquad \forall v \in V \setminus \left\{ S \bigcup \{z\} \right\} \quad 1 \le i \le N \tag{26}$$

$$f_j^I \ge 0, \quad 1 \le i \le N, \quad 1 \le j \le m. \tag{27}$$

VI. Numerical Results

In this section, we use numerical results to illustrate the performance of the proposed bandwidth-allocation algorithms. The LP problems were solved by CPLEX 10.1 [13]. As mentioned before, the algorithm described in Section V was used to find a subset of all transmission modes. In our simulation, we considered cognitive radio WMNs with n stationary nodes randomly located in a region. The number of radios (q) in each node was set to 2. The total number of available channels (H) was set to 24. Different channels support different link capacities and transmission ranges. For each channel, the interference range was set to twice the corresponding transmission range. We also randomly placed 12 primary users in the region. Each of them randomly chose a working channel that became unavailable for the cognitive radios within its interference range. Bandwidths allocated to each nongateway node, network throughput, and the well-known Jain's fairness index [19] $(f(b_1, b_2, \ldots, b_N) = ((\sum_{i=1}^{N} b_i)^2 / N \sum_{i=1}^{N} (b_i)^2)$ were employed as performance metrics. In addition, nongateway nodes were sorted in nondescending order of their bandwidth values.

We designed eight scenarios for performance evaluation. In scenarios 1–4, all the channels have the same transmission range of 250 m, but they have different capacities. We divided them into three groups with eight channels each. The first group of channels has a capacity of 11 Mb/s, the second group has a capacity of 36 Mb/s, and the third group has a capacity of 54 Mb/s. All of the nodes in these scenarios were placed in a region with a size of 1300×1300 m^2. In scenarios 5–8, the channels have different transmission range and capacities. We divided them into three groups with eight channels each as well. The first group of channels has a capacity of 11 Mb/s and a transmission range of 500 m. The second group has a capacity of 36 Mb/s and a transmission range of 250 m. The third group has a capacity of 54 Mb/s and a transmission range of 100 m. All of the nodes in these scenarios were placed in a region with a size of 2500×2500 m^2. The network size (n) and the number of gateway nodes (N_g) varied in different scenarios.

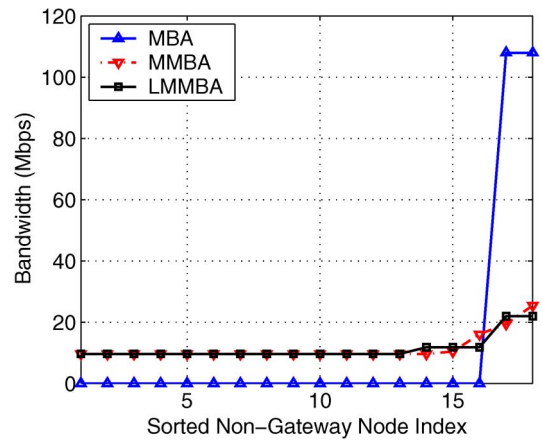

Fig. 1. Scenario 1. $N = 20$, $N_g = 2$, and 1300×1300 m^2.

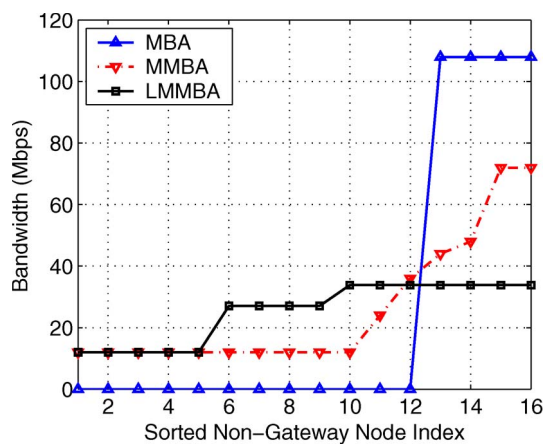

Fig. 2. Scenario 2. $N = 20$, $N_g = 4$, and 1300×1300 m^2.

Figs. 1–8 show the bandwidth allocated to each nongateway node given by the three algorithms in different scenarios. Figs. 9 and 10 show the throughput and fairness index values given by the three algorithms in different scenarios, respectively. In these figures, we use "MBA," "MMBA," and "LMMBA." We make the following observations from the results.

1) According to Fig. 9, the average throughputs given by the MMBA and LMMBA algorithms are 92% and 88% of the maximum throughput, respectively. The MMBA algorithm performs slightly better than the LMMBA algorithm in terms of throughput.

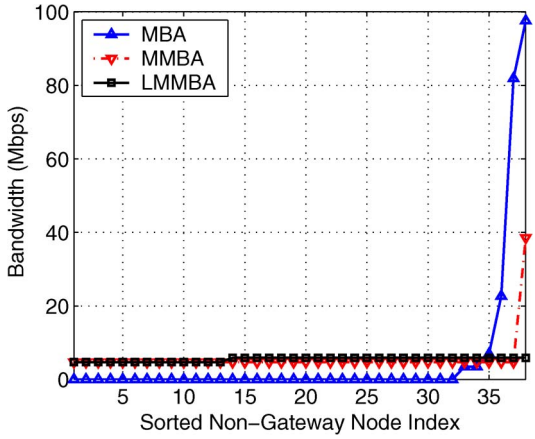

Fig. 3. Scenario 3. $N = 40$, $N_g = 2$, and $1300 \times 1300\ \mathrm{m}^2$.

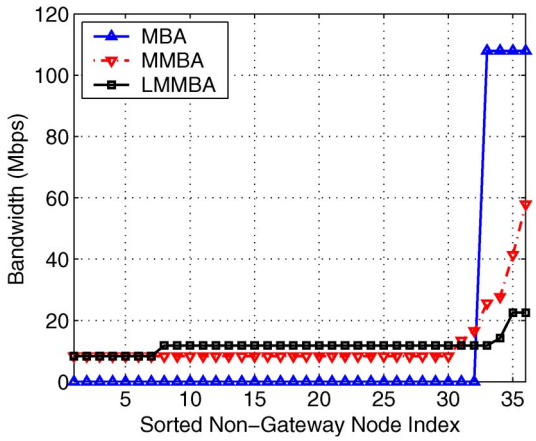

Fig. 4. Scenario 4. $N = 40$, $N_g = 4$, and $1300 \times 1300\ \mathrm{m}^2$.

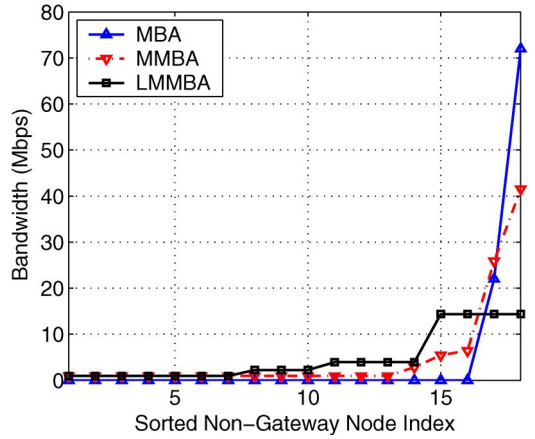

Fig. 5. Scenario 5. $n = 20$, $N_g = 2$, and $2500 \times 2500\ \mathrm{m}^2$.

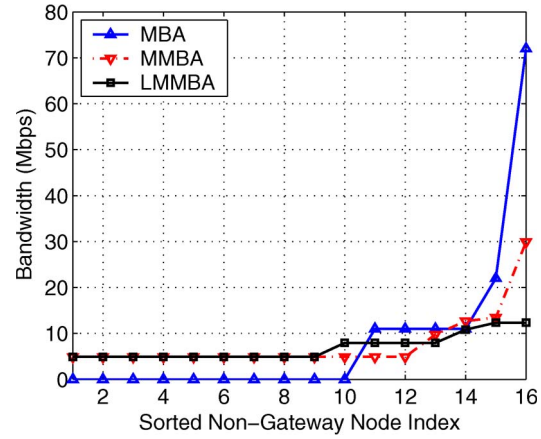

Fig. 6. Scenario 6. $n = 20$, $N_g = 4$, and $2500 \times 2500\ \mathrm{m}^2$.

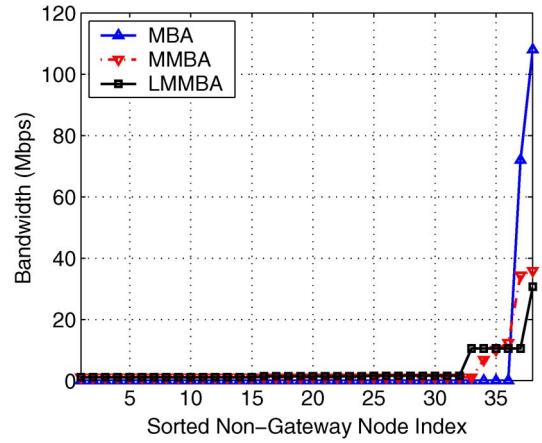

Fig. 7. Scenario 7. $n = 40$, $N_g = 2$, and $2500 \times 2500\ \mathrm{m}^2$.

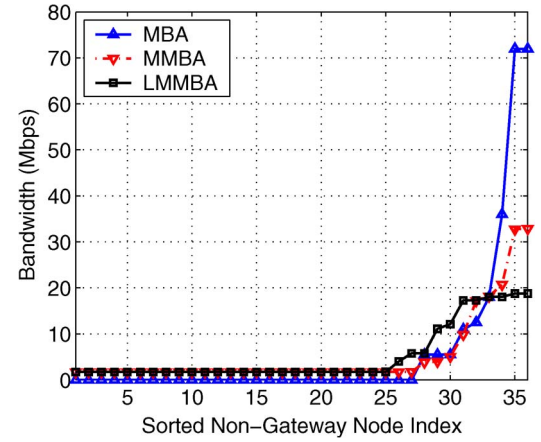

Fig. 8. Scenario 16. $n = 40$, $N_g = 4$, and $2500 \times 2500\ \mathrm{m}^2$.

2) As expected, the LMMBA algorithm performs best in terms of fairness. If every nongateway node gets the same bandwidth-allocation values, then Jain's fairness index is equal to 1.0. The larger the fairness index, the fairer the bandwidth allocation. According to Fig. 10, the average fairness indexes given by the MBA, MMBA, and LMMBA algorithms are 0.13, 0.48 and 0.72, respectively. The MBA algorithm leads to serious unfairness, which can also been observed from Figs. 1–8. For example, there are a total of 18 nongateway nodes in Fig. 1. Sixteen of them obtain a bandwidth of 0; however, two of them obtain a bandwidth of 108 Mb/s. Similarly, in Fig. 2, 14 nongateway nodes obtain a bandwidth of 0; however, four nodes obtain a bandwidth of 108 Mb/s. Both MMBA and LMMBA algorithms can guarantee certain minimum bandwidth allocation. However, the difference between

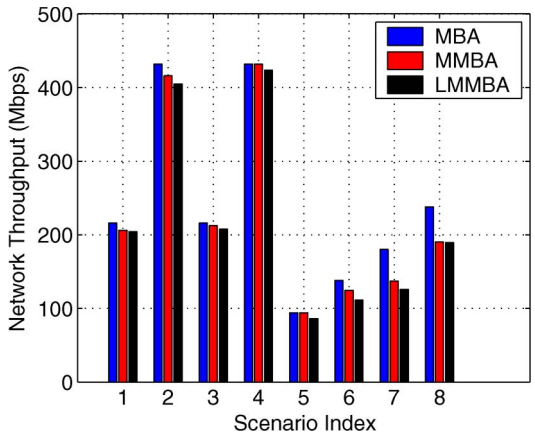

Fig. 9. Network throughput.

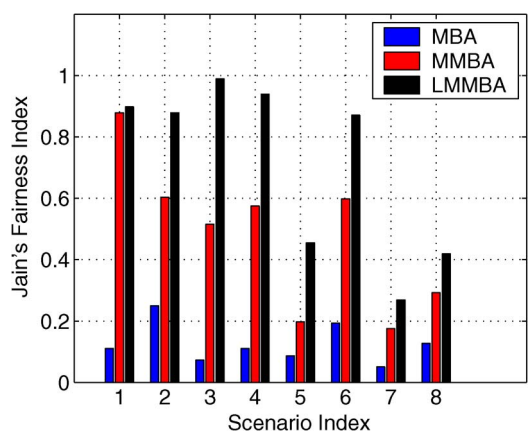

Fig. 10. Jain's fairness index.

the maximum and minimum bandwidth values may be significant. For example, in Fig. 2, this difference is more than 60 Mb/s. The LMMBA algorithm gives the same minimum bandwidth-allocation values as the MMBA algorithm. Moreover, it always partitions nongateway nodes to several groups (usually, the number of groups is very small), and within each group, all nodes allocate exactly the same amount of bandwidth.

3) The number of gateway nodes significantly affects the network throughput. From Figs. 1 and 2, we can see with the increase of gateway nodes (from 2 to 4) that the maximum network throughput is doubled.

VII. Conclusion

In this paper, we have studied end-to-end bandwidth-allocation problems in cognitive radio WMNs with the objective of achieving a good tradeoff between fairness and throughput. We formally defined two fair bandwidth-allocation problems, namely, the MMBA problem and the LMMBA problem. We presented LP-based optimal and fast heuristic algorithms for both problems. It has been shown by numerical results that the throughput given by the MMBA and LMMBA algorithms are very close to the corresponding maximum achievable throughput on average, and the LMMBA algorithm achieves the fairest bandwidth allocation in terms of Jain's fairness index.

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