Fair Gain Based Dynamic Channel Allocation for Cognitive Radios in Wireless Mesh Networks

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***Abstract*—Wireless mesh networks have the potential to deliver Internet broadband access, wireless local area network coverage and network connectivity at low costs. The capacity of a wireless mesh network is improved by equipping mesh nodes with multi-radios tuned to non-overlapping channels. By letting these nodes utilize the available channels opportunistically, we increase the utilization of the available bandwidths in the channel space. The essential problem is how to allocate the channels to these multi-radio nodes, especially when they are heterogeneous with diverse transmission types and bandwidths. Most of current work has been based on the objective to achieve maximal total bandwidths. In this paper, we propose a new bipartite-graph based model and design channel allocation algorithms that maximize the minimal channel gain to achieve relative fairness. Our model maps heterogeneous network environment to a weighted graph. We then use augmenting path to update channel allocation status and use canonical form to compare the new status with previous status to achieve better fairness. Evaluations demonstrate that our algorithms improve fairness compared with related algorithms.**

***Index Terms*—Dynamic Spectrum Allocation, Cognitive Radio, Mesh Networks**

I. Introduction

RECENT advances in communication technologies and portable computing devices have resulted in the rapid development of wireless network systems. In wireless networks, devices(nodes) are equipped with wireless interfaces and remain connected to the network through wireless links. The critical issue is to provide high bandwidth for nodes to communicate with each other. A wireless mesh network(WMN) is a communication network made up of nodes organized in a mesh topology [1]. WMNs are capable of connecting diverse network nodes such as desktops, laptops, iPads, and smart phones. Heterogeneous networks, e. g., static ad hoc networks, mobile ad hoc networks, and sensor networks, are able to gather together into a WMN network. WMNs have many advantages such as low cost, easy network maintenance, robustness, and reliable service coverage. WMNs have inspired numerous applications due to their advantages over other wireless technologies. A typical wireless mesh network consists of mesh routers and mesh clients [1]. Networks, such as WiFi, 802.15, 802.16 and sensor networks, are integrated into mesh networks through gateways and mesh routers. Mesh clients, either stationary or mobile, can link together, either by themselves or through connections with mesh routers.

WMNs are anticipated to significantly improve the performance of ad hoc networks, wireless local area networks (WLANs), wireless personal area networks (WPANs), and wireless metropolitan area networks (WMANs) [1]. Recent contributions on motion and mobile applications [36] [27] [39] [45] significantly extended various devices to WMNs. An important measurement for the quality of connections in wireless networks is capacity (bandwidth). It is well-known that wireless interference severely limits network capacity in multi-hop settings [2] [54] [37]. Traditionally, a WMN node was equipped with one IEEE radio with one channel. As a result, this single-radio mesh network only provides limited capacity for clients. Fortunately, the physical features of current IEEE radios make it possible for one node to be equipped with multiple network interfaces [3]. Recent research of computer hardware significantly improved the physical characteristics of radios [31] [23] [14]. Therefore, the nodes simultaneously use multiple radios over non-overlapping channels to increase the overall capacity of a wireless mesh network. For example, a mesh node with two interface cards is able to be assigned one 802.11a channel with 5.18G frequency and one 802.11b channel with 2.4G frequency allowing this node to communicate with two other nodes over two different channels simultaneously, thus increasing the overall capacity of the network.

Channel assignment strategies are essential in determining how these channels are used efficiently in various networks [4] [46] [32] [37] [48]. Each node is assigned one or more unused channels. To manage channel assignment properly, appropriate strategies are developed to allocate the existing channels. A basic requirement for channel assignment is to avoid interference because different links or users cannot use the same channel

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within their transmission range at the same time [5] [6]. Static channel allocation algorithms allocate fixed channel slices to each user. This strategy prevents interference, but results in poor utilization and channel holes [7]. To solve the problem, various dynamic assignment solutions have been proposed to allocate channels among heterogeneous users with diverse transmission types and bandwidths. The users sense their available channels and utilize them opportunistically. This becomes possible because lower layer technical innovations equip nodes in wireless mesh networks with multiple radios and enable them to access different channels at different locations and time [8] [9] [10] [50] [43] [51].

Scholars have conducted related research [11] [12] [13] [16] [25] based on the objective of achieving maximal total channel utilization. That is, they are focused on maximizing the total channel bandwidths in the channel pool. In many scenarios, although the total bandwidths of assigned channels is maximal, some nodes are assigned very low bandwidth or even starving. Hence the capability of the whole system goes down.

A fairness based dynamic channel allocation algorithm is proposed in this paper. Our algorithm maximizes the minimal assigned channel bandwidth of the nodes and consequently results in the least starvation. We use a bipartite-graph based model to represent availabilities of channels and nodes. And then we use augmenting path and canonical form to find the better matching in the model. The rest of this paper is organized as follows. After reviewing related work in Section II, we describe the problem formulation in Section III. We then present our channel assignment mechanism in Section IV and performance evaluation in Section V. Section VI concludes the paper.

II. Related Work

Recent computer hardware and physical layer have significantly improved the characteristics of network devices and IEEE radios. Shen el at. developed smart grid and renewable energy power stations, which dramatically saved the power of mesh devices [24] [52] [22] [53]. X. Zhang et al. proposed grid model that significantly boost the reliability of hardware and devices. [26] [38] [28]. In addition, intelligence makes the radios cognitive [21] [30] [33] [34] [47] [35]. Moreover, Kunjie et al. significantly contributed to the performance modeling technique [15] [29] [44] [42]. They all provided solid foundation for wireless mesh networks.

The traditional assignment mechanism is to frequently change the channel on the interface [17]. For instance, each packet transmission is based on the current state of the medium. Such a dynamic channel assignment approach requires channel switching at a very fast time scale. The fast channel switching requirement makes the approach unsuitable for user with commodity hardware. Other dynamic channel assignment approaches require specialized MAC protocols or extensions of the MAC layer, making them unsuitable for commodity 802.11, or other wireless network hardware. To use multiple channels with commodity hardware electively, statical channel allocations are investigated in [1] [19]. Such static assignments are not changed when the network scenario changes.

Most dynamic channel allocation mechanisms use heuristic algorithms or graph theory [40] [20] to achieve the goal of increasing total bandwidth utilization. Zheng and Peng [13] proposed a greedy algorithm for dynamic channel allocation. In each step, the algorithm picks the vertex with the highest bandwidth and assigns the channel to its associated user. Then, it cuts the edges that interfere with this user. It repeats these two steps until all the channels are allocated. This algorithm reaches near-optimal total bandwidth utilization without considering any other constraints. But the algorithm may cause low assignment or even starvation for some nodes.

Marina and Das [12] proposed a centralized greedy heuristic algorithm called CLICA for channel allocation. They use degrees of nodes as a guide in determining the order of assignment. Each node is associated with a priority. The model feeds the node with the highest priority and all its adjacent nodes and then update the graph until all the nodes are fed. This algorithm achieves minimal interference and minimal starvation. However, it fails to consider the total bandwidths acquired by each node.

Yang and Fei [37] proposed an algorithm to maximize the total bandwidths of channel allocation for mesh networks. Their approach achieves the maximal total bandwidths. The data structure to save wireless nodes and channels is bipartite graph. It is a novel data structure. In this paper, we use the same data structure to save wireless nodes and channels, but we develop a different algorithm with the objective on maximizing fairness.

Also related is Bhaskaran Raman's work on channel allocation [5]. The paper uses bipartite graph to represent the traffic fraction between a pair of nodes. The traffic fraction from a given node to another is defined as f, and then the traffic fraction in the opposite direction is 1 - f. The objective of the algorithm is to minimize the mismatch, that is, to minimize the difference between the desired match fraction DF and the achieved fraction AF. This method achieves maximal total channel bandwidths but omits the minimal bandwidth among the nodes.

III. Problem Formulation

Mesh networks contain relatively stationary devices such as routers, and mobile devices, such as the mesh clients including smart phones, iPads, laptops and PDAs [6] [37]. Fig.1 gives an example of the topology of a wireless mesh network, in which the mesh routers are equipped with multiple IEEE 802 family radios. The routers need not be equipped with the same number of radios nor do they need to use identical types of radios. The types of the radios and the number of channels depend on the number and physical parameters of their interfaces. At least one router in the mesh is designated as the Channel Assignment Server(CAS), which performs channel allocation. The dotted lines in Fig. 1 illustrate that there could be multiple possible channels assigned to a node.

The channels are heterogeneous in terms of bandwidth and transmission range. The channels within a node's range are available to the node. A particular channel might be available to multiple users, but it can only be allocated to one of them, otherwise there is a conflict. During certain periods of time, nodes are competing for available

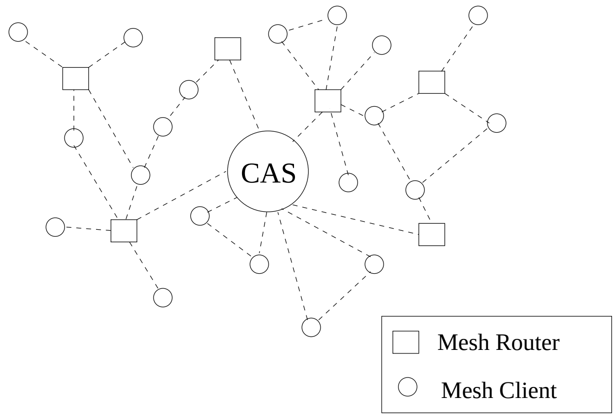

Fig. 1. An example of topology of a wireless mesh network.

channels. In order to achieve fairness, the objective of our assignment strategy is: the minimal gain among the nodes is maximal. The gain of a node is defined as the total bandwidths of channels allocated to the node.

A Bipartite graph [5] is used to model the conflicts and available channels for nodes in this paper. In our model, the vertex set is composed of elements from two subsets, channel set C and node set N. $V = C \cup N$ and $C \cap N = \emptyset$. Edge $e \in E$ is in the form of (c, n) where $c \in C$ and $n \in N$. Edge $e = (c, n)$ means that channel c is available to node n. For each vertex node $n \in N$, there is at least one edge connecting it. Otherwise, we can remove the node from the graph. The same rule holds for channel vertices. We further define a weight function $W : E \rightarrow R^{+}$ over the edge set E. The weight $W(e)$ of edge $e = (c, n) \in E$ is the bandwidth if channel c is assigned to node n.

Figure 2 illustrates a state of the availability and conflict of channels for nodes. For example, c_1 is possible for n_1, n_2 and n_3. The bandwidths are 3,5 and 4 respectively. However, only one of those is available in the allocation result. Otherwise, there is a conflict among the nodes.

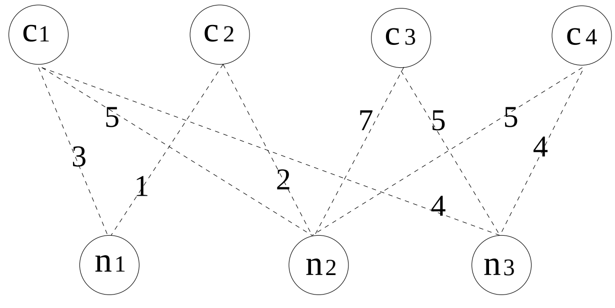

Fig. 2. A bipartite graph to represent availabilities of channels to nodes

Figure 3 shows a possible channel assignment result, in which n_1, n_2 and n_3 have gains 4,5 and 5. The channel assignment problem is to find a subgraph $G' = (V, E')$, where $E' \subseteq E(E'$ is an assignment result), such that the minimal gain among the nodes is maximal. In this paper, dashed lines show the possibility of channels to nodes. Solid lines show channel assignments.

IV. Channel Allocation Algorithms

In this section, we propose the algorithms to solve the channel assignment problem.

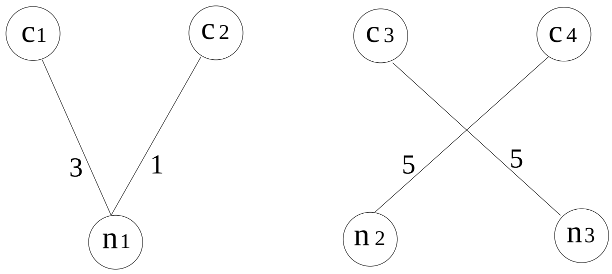

Fig. 3. A possible channel assignment result

A. Augmenting Path

For a given Bipartite graph $G = (V, E)$, a matching M is a subset of E such that any two edges in M are disjoint. The result of channel allocation is an M over G. The vertices adjacent to the edges in M are said to be matched. Based on current matching M, we use the augmenting path approach to find a larger matching M'. If P is a path connecting two unmatched vertices in G and the edges belonging to M and not belonging to M appear in P alternately, then P is an augmenting path based on M [37]. The augmenting path from v_i to v_j has three characteristics:

1) The number of hops in an augmenting path from v_i to v_j is an odd number.
2) Neither v_i nor v_j belongs to M.
3) A larger matching $M^{'}$ can be obtained by M and an augmenting path P based on M. Let $M^{'} = M \oplus P$. That is, the larger matching $M^{'}$ includes the edges that either belong to M or belong to P but do not belong to both M and P.

The $\oplus$ operation is critical in our approach because a channel is only assigned to one node. This $\oplus$ operation avoids multiple assignments. Larger matchings can be defined in various ways, depending on the objectives, such as larger cardinality, larger total weights, larger number of nodes, etc. In our approach, larger matching means the matching with larger minimal gain of the nodes. We use algorithm $FindAugPath(G, M)$ to find an augmenting path in G based on current matching M. We then use $M \oplus P$ to get larger matching. We assume that the channels are c_1, c_2, c_3,..., and the nodes are n_1, n_2, n_3,....

Algorithm 1 finds an augmenting path P in G based on current matching M. The algorithm begins from an unmatched node with least id in C, and try to find an augmenting path with the unmatched node with least id in N. The processing is continued to find an augmenting path. When an augmenting path is found, by $M^{'} = M \oplus P$, a larger matching $M^{'}$ is achieved. For example, in Fig 2, the algorithm selects (c_1, n_1) as the augmenting path, then the matching M contains (c_1, n_1) as shown in Fig 4. Based on this M, c_2 is the least id in C satisfying $(c_2, n_1) \notin M$(unmatched). n_2 is the least id in N satisfying $(c_1, n_2) \notin M$. Then the next augmenting path is $(c_2, n_1), (n_1, c_1), (c_1, n_2)$. By $M = M \oplus P$, the new M will be (c_2, n_1) and (c_1, n_2) in Fig 5.

B. Canonical Form

Fairness is the objective in this paper. We use maximal minimal gain to represent fairness. The gain of a node is

Algorithm 1 *FindAugPath(G,M)*

$P \leftarrow \emptyset$
while an unmatched node in subset C exists **do**
  $c_i \leftarrow$ *the least id in C*
  $n_j \leftarrow$ *the least id in N*
  if $(c_i, n_j) \notin M$ **then**
    $P \leftarrow P \cup (c_i, n_j)$
  end if
  if n_j *is unmatched* **then**
    mark (c_i, n_j) *matched*
    return P
  else
    $c_k \leftarrow$ *the least id in C satisfying* $(c_k, n_j) \notin M$
    $n_l \leftarrow$ *the least id in N satisfying* $(c_i, n_l) \notin M$
    if $(c_k \neq \emptyset$ *and* $n_l \neq \emptyset)$ **then**
      $P \leftarrow P \cup (c_k, n_j) \cup (c_i, n_l)$
      $i \leftarrow k$
      $j \leftarrow l$
    end if
  end if
end while
return P

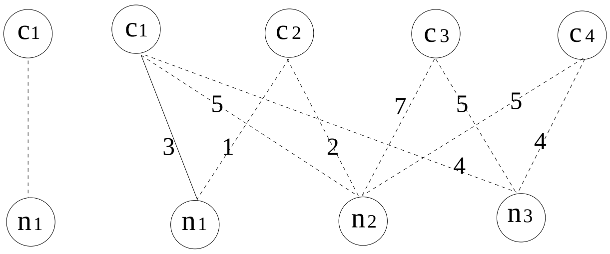

Fig. 4. An augmenting path and matching M

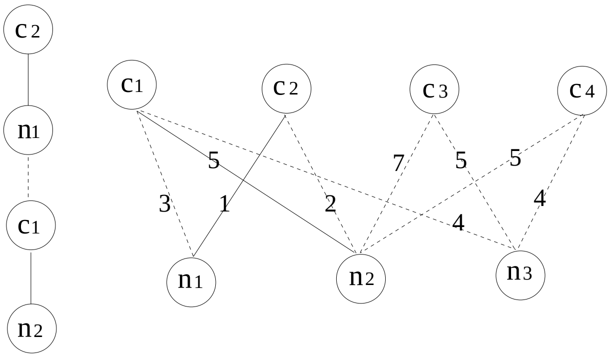

Fig. 5. Another augmenting path and larger matching M

the total bandwidths of the channels assigned to the node. The vector of gains is defined as the gains of all nodes, such as $< 4, 5, 5 >$ in figure 3.

To compare relative fairness between allocations, we define an ordering over gain vectors. It is difficult to compare two vectors if their elements are not ordered. Our idea is that for each vector, we define a canonical form [18] in which the elements are ordered.

Def 1: The canonical form of vector F is denoted as $C(F)$. If $F =< v_1, v_2, ..., v_n >$, then

Algorithm 2 *MaxFairnessMatching(G)*

$GainvectorF \leftarrow < 0, 0, ..., 0 >$
$M \leftarrow \emptyset$
while *unmatched channel node exists* **do**
  $P \leftarrow FindAugPath(G, M)$
  $M = M \oplus P$
  Compute 'F'' *based on* M
  if $F \prec F'$ **then**
    $F \leftarrow F'$
  end if
end while
return M

$C(F) =< u_1, u_2, ..., u_n >$, where $u_1, u_2, ..., u_n$ is a permutation of $v_1, v_2, ..., v_n$, and $u_i \leq u_{i+1}$ for all $1 \leq i \leq n \quad 1$.

Def 2: An ordering $\prec$ over canonical forms.
$< s_1, s_2, ..., s_n > \prec < t_1, t_2, ..., t_n >$ iff there exists an $i (1 \leq i \leq n)$ such that $s_i < t_i$, and for all $1 \leq j < i$, $s_j = t_j$.

Def 3: Two vectors $F_1 \prec F_2$ iff $C(F_1) \prec C(F_2)$.

The goal of $max \quad min$ fair allocation is to maximize the minimal fairness values in the gain vector. With the ordering defined, the optimal solution is the one that maximizes F over the ordering $\prec$. We use the augmenting path approach to find a larger matching based on the current matching. The larger matching is neither the matching with more matched edges, nor the matching with larger total assigned bandwidths, but the larger gain vector over $\prec$. Algorithm 2 achieves fairness channel allocation. The input of the algorithm is a bipartite graph with m channels and n nodes. The output is an allocation(matching) of $max \quad min$ gain over the nodes.

In the algorithm, while there exists an unmatched channel node, the allocation is continued. If the gain vector based on a new matching is larger over canonical form, we update the matching status to the new matching. The processing is repeated until the maximal fairness matching is achieved. Fig 6 shows availabilities between channel and nodes. In the algorithm, (c_1, n_1) is selected as an augmenting path first. The matching is (c_1, n_1) then(Fig 7). The gains of n_1, n_2 and n_3 are 3,0, and 0. So the gain vector is $< 0, 0, 3 >$ in canonical form. Then the algorithm chooses $(c_2, n_1), (n_1, c_1)$ and (c_1, n_2) as augmenting path P. By $M \oplus P$, we get a new matching M: (c_2, n_1) and (c_1, n_2)(Fig 8). The gain vector is $< 0, 3, 4 >$. Since $< 0, 0, 3 > \prec < 0, 3, 4 >$, the gain vector is updated to $< 0, 3, 4 >$. Then based on this M, the algorithm finds an augmenting path $(c_3, n_2), (n_2, c_1)$ and (c_1, n_3). By $M \oplus P$, we get a new matching M: $(c_1, n_3), (c_2, n_1)$ and (c_3, n_2). The gain vector is $< 3, 3, 5 >$. Since $< 0, 3, 4 > \prec < 3, 3, 5 >$, the gain vector is updated to $< 3, 3, 5 >$. The process is repeated until we get the matching of $max \quad min$ gain among the nodes. There are multiple steps to extend the matching. Each latter matching we found must have bigger fairness than the previous one. For example, after the second matching, the better matching can be $(c_1, n_3), (c_2, n_1), (c_3, n_2), (c_4, n_3)$ and (c_3, n_2).

Since there are a lot of intermediated steps, we ignore portion of them. By the algorithms proposed in this paper, the matching is: $(c_1, n_1), (c_2, n_1), (c_3, n_2), (c_4, n_3)$ and (c_5, n_2)(Fig 9).The gain vector is $< 6, 7, 8 >$. The algorithm maximizes minimal gain. Hence starvation is avoided.

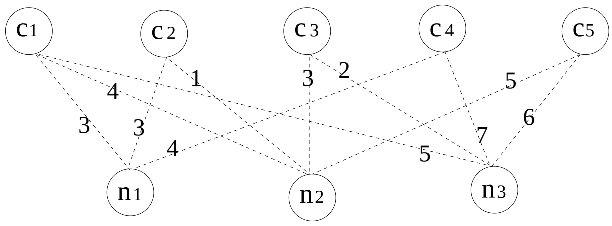

Fig. 6. Availabilities between channel and nodes.

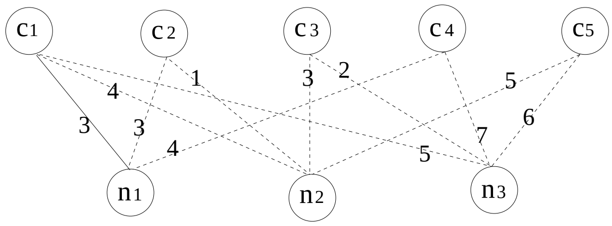

Fig. 7. The first matching.

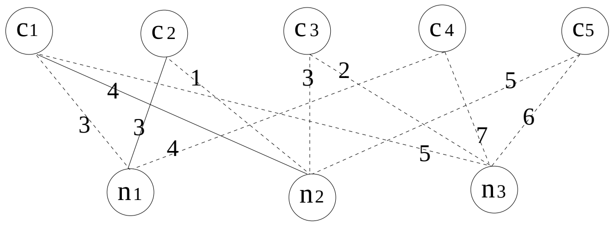

Fig. 8. The second matching.

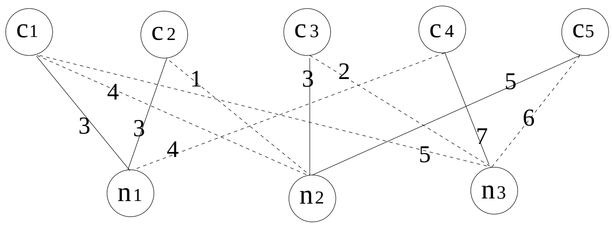

Fig. 9. Final max-min matching.

We assume that the vertex number is $|V|$ and the edge number is $|E|$ in all algorithms. The objective of algorithm 1 is to find the augmenting path. The time complexity is $O(|V| * |E|)$ to find the augmenting path [37] [41]. Algorithm 2 is to find the maximal fairnes matching satisfying that each node is assigned at most one channel. This algorithm needs $O(|V|)$ iterations. And algorithm 1 is called in each iteration. Since the time complexity of algorithm 1 is $O(|V|*|E|)$, the complexity of Algorithm 2 is $O(|V|^2 * |E|)$. This algorithm will be repeated at most $O(|E|)$ times. Hence the time complexity of $MaxFairnessMatching$ algorithm is $O(|V|^2 * |E|^2)$.

The Channel Assignment Server(CAS) periodically checks the topology change of the network and calls the algorithms upon the changing of the top.

V. Performance Evaluation

The performance evaluation was conducted in a simulated noiseless radio network environment, where the nodes are distributed in a given area and each may have a different transmission range and bandwidth. We are focused on the comparison of fairness between our results and the outputs generated by other allocation approaches. We map this network to a weight graph $G = (V, E)$, where the weight represents the bandwidth. We test both a sparse and a relatively dense network scenario; the numbers of nodes are 20 and 50 respectively. In each case, we let the number of channels vary from 100 to 400 with increments of 50. We set the bandwidths of channel distributed from 1 to 9. The channels in a network are arbitrarily available to the nodes. For the sparse network with 20 nodes, we randomly generate 10 graphs and conduct the experiment 10 times based on the graphs. We get the fairness value of each graph and then calculate the average value. For the relatively dense network with 50 nodes, we do the same experimentation.

The metric to evaluate the performance is the maximal minimal gain among the nodes. We compare our solution with three other approaches. The first one is NMSB (Non-collaborative-Max-Sum-Bandwidth). In each step, this approach picks the vertex with the highest bandwidth and assigns it to its associated user. Then the algorithm removes the edges that interfere with this user until all the channels are allocated. The second one is CMSB (Collaborative-Max-Sum-Bandwidth). This approach picks up the vertex with the highest label, defined as the bandwidth of a channel divided by the number of users interfering with each other with regard to this channel. The process is repeated until all channels have been allocated. The third approach is MAX-TOTAL, which tries to allocate the channels with larger weights to users and avoid starvation the same time.

In Fig. 10, we evaluate the fairness of these approaches based on 20 nodes. The results show that the minimal gain generated by our approach(FAIRNESS) is higher than other approaches. It is about 10% higher than MAX-TOTAL, 15% higher than CMSB and 18% higher than NMSB.

In Fig. 11, our evaluation is based on 50 nodes. The results indicate that the minimal gain generated by our approach(FAIRNESS) is higher than other approaches. It is about 10% higher than MAX-TOTAL, 15% higher than CMSB and 19% higher than NMSB.

VI. Conclusion

In this paper, we presented a bipartite graph based mechanism to assign channels to wireless network devices that can opportunistically utilize its available spectrum. The objective is to consider fairness issue. We developed a bipartite-graph based model, and compared gains by canonical forms. Our algorithm dynamically allocates channels to nodes in a heterogeneous wireless network environment. It dramatically reduced starvation

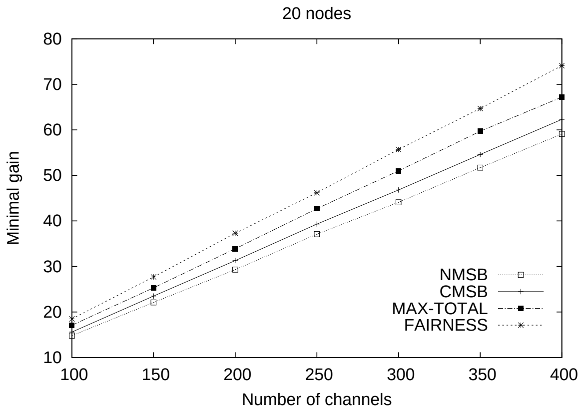

Fig. 10. Ratio of allocation

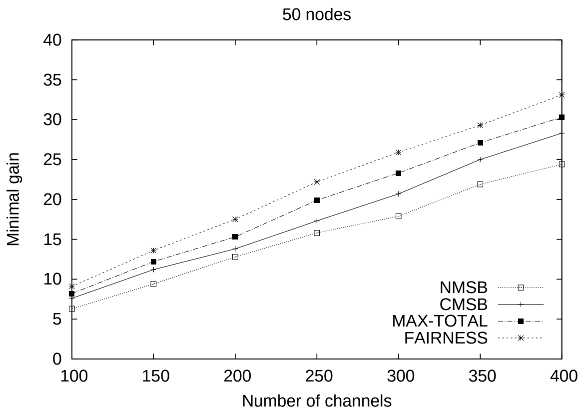

Fig. 11. Total bandwidth of allocated channels

and significantly improved fairness compared with related algorithms in dynamic channel allocation environment. Simulations demonstrate that our approach results in significant performance benefits over related approaches.

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