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FAIR LOAD BALANCING IN WIRELESS NETWORKS

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Abstract-
The traffic load of wireless LANs is often unevenly distributed among the access points (APs), which results in unfair bandwidth allocation among Mobile Users. We argue that the load imbalance and consequent unfair bandwidth allocation can be greatly reduced by intelligent association control. In this paper, we present an efficient solution to determine the user-AP associations for bandwidth allocation. We show the strong correlation between fairness and load balancing, which enables us to use load-balancing techniques for obtaining optimal fair bandwidth allocation. As this problem is NP-hard, we devise algorithms that achieve constant factor approximation. In our algorithms, we first compute a distributed association solution, in which users can be associated with multiple APs simultaneously with variable bandwidth. This solution guarantees the fairest bandwidth allocation in terms of Max-min fairness; we obtain the integral solution from the fractional solution by distributed association algorithm. We also consider time fairness and present a polynomial-time algorithm for optimal integral solution and it is ensure that zero percent data loss.

Keywords- Distributed Association algorithms, IEEE 802.11WLANs, load balancing.

I.INTRODUCTION

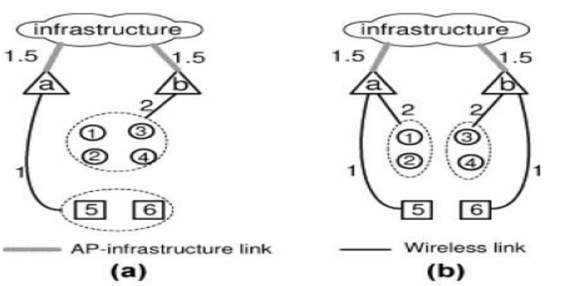
Recent studies on operational Wireless LANS (WLANs)have shown that the traffic load is often distributed unevenly among the access points (APs) for Mobile Users(MU). In WLANs, by default, each user scans all availablechannels to detect its nearby APs and associate itself withthe AP that has the strongest received signal strengthindicator (RSSI), while ignoring its load condition. As usersare, typically, not uniformly distributed, some APs tend tosuffer from heavy load while adjacent APs may carry onlylight load or be idle. Such load imbalance among APs isundesirable as it hampers the network from providing fairservices to its users. As suggested in existing studies theload imbalance problem can be alleviated by balancing theload among the APs via intelligently selecting the user-APassociation, termed association control. Association controlcan be used to achieve different objectives. For instance, itcan be used to maximize the overall system throughput byshifting users to idle or lightly loaded APs and allowingeach AP to serve only the users with maximal data rate.Clearly, this objective is not a desired system behavior fromthe fairness viewpoint. A more desirable goal is to providenetwork-wide fair bandwidth allocation, while maximizingthe minimal fair share of each user. This type of fairness isknown as maxmin fairness. Informally, a bandwidthallocation is max-min fair if there is no way to give more bandwidth to any user without decreasing the allocation of a user with less or equal bandwidth. In this paper, we present efficient user-AP association control algorithms that ensure maxmin fair bandwidth allocation and we show that this goal can be obtained by balancing the load on the APs.

II. REVIEW OF LITERATURE

Load balancing in WLANs has been intensely studied. In [1], association algorithm has been proposed for efficient bandwidth allocation with constant bandwidth. [3]- [4] on operational Wireless LANS (WLANs) have shown that the traffic load is often distributed unevenly among the access points (APs). In WLANs, by default, each user scans all available channels to detect its nearby APs and associate itself with the AP that has the strongest received signalstrength indicator (RSSI), while ignoring its load condition. As users are, typically, not uniformly distributed, some APs tend to suffer from heavy load while adjacent APs may carry only light load or be idle. Such load imbalance among APs is undesirable as it hampers the network from providingfair services to its users. As suggested in existing studies [6]-[7] the load imbalance problem can be alleviated bybalancing the load among the APs via intelligently selecting the user- AP association, termed association control. Association control can be used to achieve differentobjectives. In [7]-[9], different association criteria are proposed. These metrics typically take into account factors such as the number of users currently associated with an AP,the mean RSSI, the RSSI of the new user and the bandwidth a new user can get if it is associated with an AP in [8]. Various WLAN vendors have incorporated proprietary features in the device driver‘s firmware [10], [11]. In these proprietary solutions, the APs broadcast their load conditions to the users via the Beacon messages and each user chooses the least loaded AP. Propose to associate new users with the AP that can provide a minimal bandwidth required by the user. If there is more than one such AP, the one with the strongest signal is selected. Most of these heuristics only determine the association of newly arrived users. Tsai and Lien [8] propose to reassociate users when some conditions are violated. Load balancing in cellularnetworks is usually achieved via dynamic channel allocation (DCA) [12].

III.WIRELESS AND WIRED BOTTLENECKS

However, the wireless link is generally considered as the bottleneck. This assumption is not always valid. For instance, consider a WLAN where the APs are connected to the infrastructure



(a) (b)

Fig. 1. Examples of bottlenecks both over the wireless and the wired links. (a) An unfair association. (b) The optimal association.

T1 lines, whose capacity is around 1.5 Mb/s, as illustrated inExample 2. Example 2 demonstrates the need to consider both the wireless and the wired links for load balancing.

Example 2: Consider a wireless system with 2 APs, a and b ,and 6 users, enumerated from 1 to 6, as depicted in Fig. 1. Users 1,2,3 and 4 experience a bit rate of 2 Mb/s from both APs,[A] while users 5 and 6 have a bit rate of 1 Mb/s from both APs. The[B] APs are connected to a fixed network with T1 lines with capacity[C] of 1.5 Mb/s. In the following, we consider two possible associations and we analyze the average bandwidth that they provide to the users.

Case I: A fair user association only from the wireless perspective- Consider the association depicted in Fig. 1(a). Here, the system can allocate a bandwidth of 0.5 Mb/s to each user over the wireless links. However, while AP a can allocate a bandwidth of 0.5 Mb/s to users 5 and 6 on its T1 line, AP b can only provide 3/8 Mb/s to its associated users over its line. In this case, the wireless link of AP is the bottleneck that affects the bandwidth allocation. Meanwhile,the wired link is the bottleneck of AP.

Case II: A fair user association- Consider the association shown in Fig. 1(b). This association provides a bandwidth of 0.5 Mb/s to each user over the wired and wireless channels. Observe that in this case different users may gain different service time on the wireless links and wired backhauls. For instance, user 5 captures 1/3 of the service time of the T1 link of AP, while, it is served 1/2 of the time by its wireless channel. This ensures that user 5, indeed, receives a bandwidth of 0.5 Mb/s.

IV. FAIRNESS AND LOAD BALANCING

In this section, we provide formal definitions of fair bandwidth allocation and load balancing. Additionally, they describe some useful properties that we need for constructing our algorithmic tools. In the following, we consider two association models from this. The first is a single-association model, so-called an integral- association, where each user is associated with a single AP at any given time. This is the association mode used in IEEE 802.11 networks. The second is a multiple-association model, also termed a fractional-association that allows each user to be associated with several APs and to get communication services from them simultaneously. Accordingly, a user may receive several different traffic flows from different APs,and its bandwidth allocation is the aggregated bandwidth of all of them. This model is used to develop our algorithmic tools for the integral- association case. For both association models, we denote by Ua all the users that are associated with AP a ЄA and denotes the set of APs that user u Є U is associated with.

V. DISTRIBUTED ASSOCIATION ALGORITHM

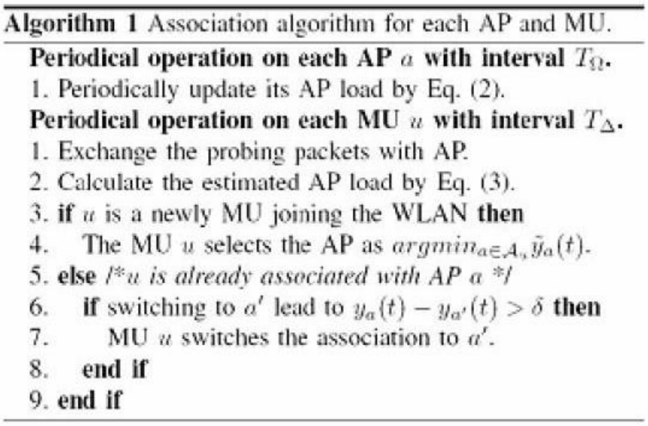
In this section, after exploring the details of distributed AP selection algorithm for APs and MUs, we also analyze the stability and overhead of the proposed algorithm.

A. Association Algorithm for APs and MUs

By exchanging information among MUs and APs, the proposed association scheme can be summarized as Algo.1 as shown in Fig. 2. In legacy IEEE 802.11 standard, the management packets from the AP do not contain any field indicating the AP load information. To realize the proposed scheme, it is required to add one additional field to the beacon and probing packets. Moreover, due to the dynamic nature of the wireless network and the mobility of MUs, the APs should keep updating the AP load by iterative moving average as

$$y_a(t+T_\Omega)=\alpha y_a(t)+(1-\alpha)\sum_{u\in U_a(t)} d_{ua}(t)$$

where $T\Omega$ is the fixed updating interval and $0 \le \alpha \le 1$ is the weighting parameter to tradeoff previously estimated AP load and current value. If a MU is not associated with any AP in the network, it immediately scans all channels by sending probe request messages and receives response packets from the available APs. By detecting the respective RSSI levels to the APs, each MU can determine the most suitable physical data rate for transmitting packets. The proposed AP selection strategy is to let each MU choose the AP with least estimated load by supposing that it will be associated with all available APs. That is, if the newly joining MU u can be served by a subset of APs $Au \in A$, the estimated AP load on $a \in Au$ supposing the association of MU u with AP a will be updated as



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Algorithm 1 Association algorithm for each AP and MU.
Periodical operation on each AP $a$ with interval $T_\Omega$.
1. Periodically update its AP load by Eq. (2).
Periodical operation on each MU $u$ with interval $T_\Delta$.
1. Exchange the probing packets with AP.
2. Calculate the estimated AP load by Eq. (3).
3. if $u$ is a newly MU joining the WLAN then
4.     The MU $u$ selects the AP as $argmin_{a \in A_u} \tilde{y}_a(t)$.
5. else /*$u$ is already associated with AP $a$ */
6.     if switching to $a'$ lead to $y_a(t) - y_{a'}(t) > \delta$ then
7.         MU $u$ switches the association to $a'$.
8.     end if
9. end if
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Fig. 2. The distributed algorithm for load balancing in WLANs.

$$\tilde{y}_a(t) = y_a(t) + d_{ua}(t) \quad (\forall a \in A_u).$$

Then the MU will select an AP as argminaϵAuỹa(t). After the MU joins the WLAN, it will keep periodically (with period $T\Delta$) detecting the load information from the neighboring APs and change its association if the AP loads can be further decreased. This operation is not only necessary to reduce the effect introduced by the joiningorder of MUs but also required for the MU to be adaptive to the dynamic wireless environment and topology changes. The period $T\Delta$, configured to be more than 10 seconds, is much longer than the load-updating period $T\Omega$ on the AP.

B. Association Algorithm for APs and MUs

In dynamic WLANs, the association of MUs should vary with the network conditions. However, it is not intuitively obvious that the proposed distributed algorithm is self- stabilizing for static networks. That is, MUs continually looking to balance the AP loads will eventually converge toa stable result in static topology. Here we can show that indeed this process does stabilize.

Theorem 1: For a fixed population WLAN with APs and static MUs that implement the above distributed association algorithm with $\delta = 0$, the switching operations of the MUs inAlgo. 1 reaches a stable state where MUs cease changing associated APs2.

Proof: The core part of the proof is that a monotonic property of global lexicographic ordering [15] decrement holds whenever one MU switches its association.Lexicographic order, a concept borrowed from economics, can be used to compare the extent of fairness between two vectors. Given two vectors A and B; the method to determine the lexicographic order is to compare the corresponding values index by index after sorting the original vectors. According to Algorithm 1, assuming one MU switch from AP a to AP b, the AP loads of them are denoted as ya, yb, y‘ a, and y‘ b , respectively. Straightforwardly, we will have yb < ya, y‘ b < ya, and y‘ a < ya, where the lexicographic order has been decreased. Since the lexicographical order cannot be infinitely decreased, we can conclude that the Algo. 1 will stop after finite number of operations.

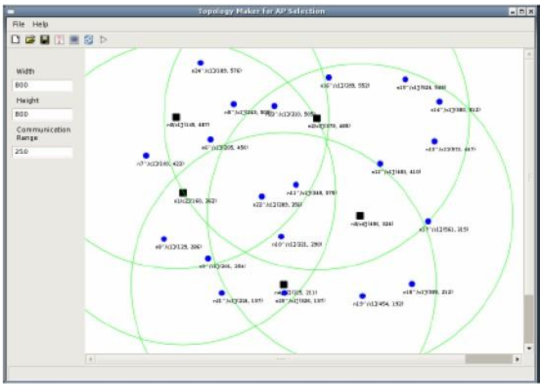
The introduced overhead by the proposed algorithm on the AP is straightforwardly low. On each MU, the most time consuming operation is the periodically probing process in every $T\Delta$ seconds. However, this probing process only takes around 300ms according to measurements. Comparing with the interval $T\Delta$, the overhead is almost negligible.

VI. PERFORMANCE EVALUATION

In this section, we first introduce the numerical evaluation based on the developed simulation program. The program is able to simulate dynamic and large-scale topology to clearly show the achievable benefits of the proposed scheme. We then provide NS2 [16] simulation results for a medium-size topology with suddenly roaming clients. Finally, we also explain our prototype implementation on a testbed built withnormal computers. To measure the performance, we use total throughput Σ u Є U Ɵu as the metric to measure the overall efficiency and Jain‘s fairness index [17] to denote the degree of load balancing in the network.

$$\frac{(\sum_{u\in U}\theta_u)^2}{|U|\sum_{u\in U}\theta_u{}^2}$$

$^2\delta = 0$ is the loosest condition to activate the switching operation.



Width
800
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Communication Range
250

Fig. 3. The snapshot of developed numerical simulator.

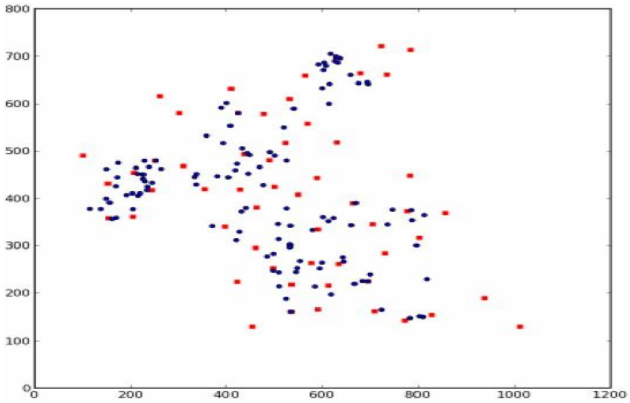

Fig. 4. A realistic scenario with measured mobility for numerical simulation. The red squares denote the APs and the blue circles denote the MUs at the beginning of simulation.

VII. NUMERICAL SIMULATION FOR REALISTIC SCENARIO

In order to evaluate the proposed scheme for large-scale topologies, we have developed a discrete-event simulator based on SimPy [18], which is a Python framework for discrete-event simulation applications. Users can manually place the APs and MUs in the GUI (Graphic User Interface).The generated scenario can also be saved and loaded for future use. The snapshot of the program interface is capturedand shown in Fig. 3. To accelerate the simulation, the complex behavior of IEEE 802.11 MAC is simplified and the throughput is calculated by the throughput model given in [12]. We use a set of measured trace files provide by [19],which collected the 20 minutes measurement data by capturing the realistic mobility patterns of the MUs in the campus of Dartmouth University. From the measurement results, we pick up 56 APs and 126 MUs with their mobility placed in a rectangle topology of size 1100×1000m2 as shown in Fig. 4.

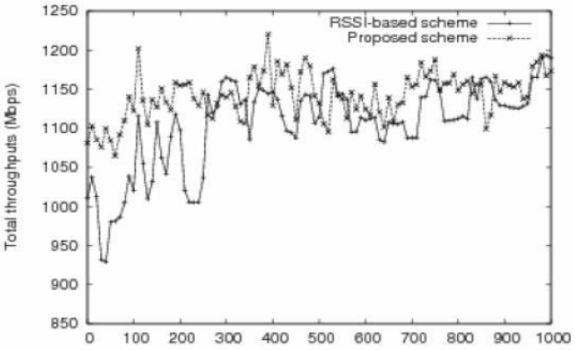

Fig. 5. The throughput difference between RSSI-based scheme and proposed scheme w.r.t simulation time for the realistic topology shown in Fig. 5.

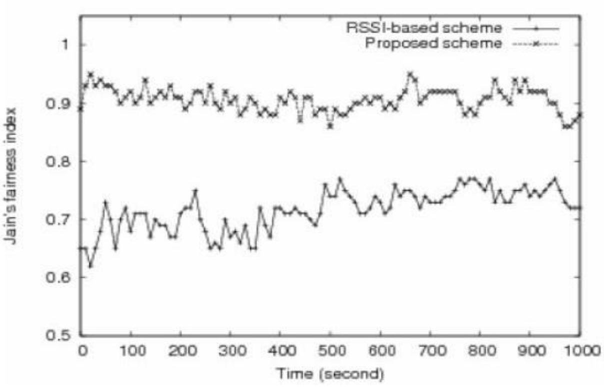

Fig. 6. The Jain‘s fairness value difference between RSSI- based scheme and proposed scheme w.r.t simulation time for the realistic topology shown in Fig. 5.

According to Fig. 5 and Fig. 6, we can observe that the total throughput achieved by the proposed scheme is generally the same or sometimes higher than that of the default RSSI based scheme. However, the value of fairness metric has been apparently (between 20%-30%) improved after applying the proposed scheme. On the other hand, we also find that it mostly takes only one probing and reassociation operation for the MUs to reach a steady state when they move around in the topology.

VIII. CONCLUSION

In this paper, we have explored the load balancing schemeto guarantee the throughput fairness among the MUs. To achieve this, we have proposed a distributed and self- stabilized association scheme for the MUs in the multi-rate WLANs. The proposed scheme gradually balances the AP loads in a distributed manner. With extensive simulations,we can observe that it can significantly improve, or sometimes nearly double, the extent of throughput fairness among the MUs with low overhead. To show the feasibility of the proposed scheme, we have implemented a prototype on normal computers by modifying open source wireless driver software packaged Our research is oriented for practical WiFi products and can be implemented with small additional modification to achieve apparent load balancing in deployed WLANs.

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