Meta-heuristic Solution for Dynamic Association Control in Virtualized Multi-rate WLANs

Dawood Sajjadi, Maryam Tanha and Jianping Pan
Department of Computer Science, University of Victoria, Victoria, BC, Canada
Email: {sajjadi, tanha, pan}@uvic.ca

***Abstract*—Chaotic deployment of Wireless Local Area Networks (WLANs) in dense urban areas is one of the common issues of many Internet Service Providers (ISPs) and Wi-Fi users. It results in a substantial reduction of the throughput and impedes the balanced distribution of bandwidth among the users. Most of these networks are managed independently and there is no cooperation among them. Moreover, the conventional association mechanism that selects the Access Points (APs) with the strongest Received Signal Strength Indicator (RSSI) aggravates this situation. In this paper, we present a versatile near-optimal solution for the fair bandwidth distribution over virtualized WLANs through dynamic association control. The proposed scheme is called ACO-PF, which is developed on top of Ant Colony Optimization (ACO) as a meta-heuristic technique to provide Proportional Fairness (PF) among the greedy clients. In fact, it presents a generic and centralized solution for ISPs that are using a common, virtualized or overlapped WLAN infrastructure for serving their customers. We have evaluated the efficacy of ACO-PF through numerical analysis versus popular existing schemes for both downlink and uplink scenarios. Our proposed technique has less complexity in terms of the implementation and running time for large-scale WLANs and it can be easily developed and customized for different objective functions. In addition, it is implemented in a testbed environment to investigate the key challenges of real deployment scenarios.**

***Index Terms*- Dynamic Association Control, Optimization, Virtual Multi-rate WLAN, Ant Colony, Proportional Fairness.**

I. Introduction

According to Cisco visual networking index [1], the amount of cellular traffic that will be offloaded to WLANs is expected to increase from 33% in 2012 to 47% by 2017. This means Wi-Fi networks are becoming drastically dense and chaotic, which is one of the consequences of bandwidth provisioning for highly growing user demands through adding more APs. By increasing the number of APs, theoretically we can promote the Quality of Experience (QoE) for the users through reducing the number of associated users to each AP. Nonetheless, since the number of non-overlapping channels is limited, neighboring APs within the dense areas must operate on the same channel. This fact exacerbates the design complexity of WLANs. Moreover, due to the contention based nature of 802.11 networks and the backoff procedure, there is a considerable throughput degradation in such areas. Also, it is important to note that AP selection based on the strongest RSSI has remained as the most common approach for associating the Wi-Fi users to WLANs; however it cannot reach the maximum network throughput. In addition, the existing 802.11 MAC protocol attempts to give the same chance to all stations that are associated to the same WLAN and it reduces overall network throughput in multi-rate WLANs, significantly. The main reason behind this phenomenon is the unbalanced channel occupancy among the stations with different data rates [2]. Thus, regular fairness provisioning techniques for wired networks such as max-min fairness can not be directly applied to multi-rate WLANs.

Also, it should be noted that although there are a lot of challenges for the management of dense WLANs, there is an opportunity for Wi-Fi stations to associate with the APs which provide them with the highest end-to-end throughput.

In enterprise and community networks of ultra-dense WLANs interconnected by high-speed wired links, the consolidation of distributed APs that belong to different ISPs through a centralized association control not only promotes the customer satisfaction, but also improves the network performance. Since finding the optimal association map of Wi-Fi stations in large-scale WLANs is NP-hard, utilizing centralized solutions on top of the novel technologies, e.g., SDN, is one of the most efficient options. Although the decentralized systems may seem more realistic, the growth of centralized solutions has attracted a lot of attentions due to the feasibility of using efficient algorithms at the controllers. Moreover, distributed schemes impose noticeable convergence latency in large networks and they might miss the near-optimal configuration due to the lack of a holistic view of the system. Hence, by applying cooperative association control schemes, it would be possible to alleviate the impact of drastic interference and throughput degradation in such environments.

Furthermore, sharing a common or overlapped WLAN infrastructure among several ISPs extends the network coverage that facilitates the user connectivity as well as reducing the operational costs. In this situation, since the network capacity is shared within a WLAN infrastructure which is serving the customers of different ISPs, the growth of traffic in one virtual network can lead to the traffic decline in another one. Thus, using an efficient resource sharing scheme through a centralized controller is a necessity for the management of virtualized WLAN infrastructures. Fig. 1 illustrates an example, in which each AP of the virtual WLAN infrastructure broadcasts the SSIDs of three different ISPs. So, the customers of each ISP can be associated to any AP that belongs to the illustrated infrastructure and they will be served based on their service agreements and the total airtime share of their ISPs. All the resource allocation process will be handled by a controller.

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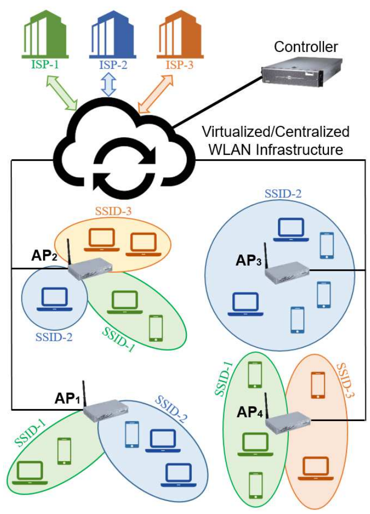


Fig. 1: Virtualized WLAN infrastructure shared among 3 ISPs.

In this paper, we present a meta-heuristic and versatile solution to provide Proportional Fairness (PF) among the clients, which are going to be served by a group of cooperative ISPs over a common WLAN infrastructure. By taking a centralized management approach, all APs can be considered as a single entity and their bandwidth can be shared among customers of diverse ISPs. The proposed scheme is evaluated through extensive numerical analysis in terms of network throughput and fairness. Also, in contrast to most of the prior related work, we arranged a testbed setup to measure the efficacy of our proposed scheme which is Ant Colony Optimization for Proportional Fairness (ACO-PF). Through real testbed scenarios, we have shown the practicality of ACO-PF, which only requires configuration update at APs and software update at stations. It is important to note that we proposed an adaptive and protocol-independent solution for association control on top of the existing products that purposely guarantees backward compatibility and can be extended to all the existing Wi-Fi protocols, e.g. 802.11a/b/g/n/ac.

The rest of the paper is organized as follows. In the next section, related work about the PF provisioning in multi-rate and virtualized WLANs is discussed. Then in Section III, the problem formulation for finding the optimal solution is delineated. In Section IV, the proposed scheme is explained. In the succeeding section, the performance assessment procedures for numerical and testbed scenarios are elaborated. Finally, the acquired results are analyzed and justified in Section VI and the concluding statements are presented in the last section.

II. Related Work

Using centralized architectures is considered as an effective strategy for dense deployment and management of WLANs. For instance, in [3] the impact of growing adaptive ISPs on the performance of typical residential APs is investigated and the advantages of utilizing centralized scheme are discussed. In this section, first we introduce some of the related work on centralized PF provisioning. Then, we review the recent publications on the deployment of virtualized WLANs.

A. Proportional Fairness Provisioning

One of the dominant solutions for fairness provisioning in multi-rate WLANs is using PF. The main feature of PF is bandwidth distribution among the stations regarding their physical data rate. Hence, it provides a trade-off between fairness and throughput for maximizing the total allocated bandwidth to all the stations. Note that the objective function of PF provisioning is a non-linear function and finding the optimal solution for AP-station pairs in single association scenarios is NP-hard [4].

In [4], one of the most cited works for PF provisioning in multi-rate WLANs is presented. Two approximation algorithms to achieve optimal proportional fairness through dynamic user association were proposed and evaluated for uniform and hotspot distribution of users. Also, it was assumed that all APs were operating in orthogonal channels and the impact of the interference on effective data rate was overlooked. The authors in [5] showed that PF and airtime fairness are strongly correlated and there is a unique proportional fairness solution for flow rate allocation in any single WLAN. In another work [6], a non-linear approximation optimization algorithm was proposed to find the optimal association matrix for multi-rate Wi-Fi stations. To solve the optimization problem, a compensation function was introduced to fill the integrality gap caused by the relaxation. Also, an online algorithm for optimal association of newly joined users was presented and examined for multi-rate WLANs. The functionality of the presented scheme was only evaluated for downlink traffic which was generated from co-channel saturated APs. In a similar study [7], a centralized collaborative association scheme was introduced that provides PF among the clients of the same upstream ISP. The collaborative association problem was solved for single and multiple AP association scenarios for greedy downlink stations using the same service provider.

In contrast with the mentioned works, ACO-PF presents a less-complex and practical approach to achieve a near-optimal solution for dynamic association control and it has been evaluated for both greedy uplink and downlink scenarios.

B. Virtualized WLANs

In the recent years, virtualization of WLANs has attracted a lot of attention among the researchers. For instance, in [8] a centralized solution for building and management of Virtual APs (VAPs) to achieve finer channel assignment and better load control over WLANs was presented. Considering high density scenarios, a similar framework was introduced in [9] for aggregation of multiple VAPs into a single physical AP. Time Division Multiplexing (TDM) was utilized as the channel access mechanism to avoid collision among the aggregated VAPs and all VAPs had to be placed within the same broadcast domain. In another recent work, a fair strategy for virtualization of WLANs through airtime slicing was formulated [10]. The authors proposed a distributed fair max-min rate allocation algorithm for airtime assignment among multiple ISPs. The offered scheme can be extended from a single WLAN to a shared mesh network among the ISPs as well. It should be noted that since in [10], max-min fairness is considered as the objective function of the formulated problem, achieving an optimal solution for multi-rate WLAN cannot be guaranteed. In other related publications [11] [12], the problem of optimal association and airtime control over multicell WLANs were investigated using monomial approximation. Through numerical analysis, it was shown that by solving the geometric-based optimization problem, network throughput and fairness can be guaranteed among ISPs regardless of the number of ISP users. The main downside of these works is disregarding the impact of interference in dense environments. It was assumed that all APs were functioning in orthogonal channels, which is not reasonable in populated areas. Also, another assumption was that each user had the capability of simultaneous association to multiple APs, which is not a common presumption.

There are some studies to find the best trade-off between the fairness and throughput in multi-rate WLANs using Genetic Algorithms and Simulated Annealing [13] [14] as well, but the presented results were not compared with either the optimal solution or the other schemes. In the next section, the problem formulation to find the optimal solution is explained.

III. Problem Formulation

To evaluate the functionality of our proposed meta-heuristic scheme, at the first step, we need to find a proper estimation of the optimal solution as the baseline. Then, by comparison of the obtained results for the same scenarios, we would be able to perform an accurate performance assessment. In our formulation, we focused on greedy downlink and uplink scenarios which involve many practical applications. Watching HD videos and podcasting the multimedia contents can be considered as the examples of such applications. Therefore, the problem of finding an association map for greedy Wi-Fi stations to maximize the network throughput in a proportionally fair manner can be formulated as follows:

Maximize

$$\sum_{i\in I}\sum_{s\in S_i}\log(\sum_{a\in A} w_s v_{as}\sum_{c\in C} x^c_{as}t^c_{as}r^c_{as}) \tag{1}$$

subject to

$$\sum_{a\in A} x^c_{as} = 1 \qquad \forall i\in I, \forall s\in S_i, \forall c\in C \tag{2}$$

$$\sum_{c\in C} x^c_{as}\ t^c_{as} \le \theta_i \qquad \forall i\in I, \forall s\in S_i, \forall a\in A \tag{3}$$

$$\sum_{s\in S_i} w_s \sum_{a\in A} x^c_{as}t^c_{as} \le \theta_i \quad \forall i\in I, \forall c\in C \tag{4}$$

$$t^c_{as} \le \frac{v_{as}\theta_i}{(\sum\limits_{s'\in S_i} w_{s'}\ x^c_{as'})(\sum\limits_{a'\in A} z^c_{aa'})}\ \forall s\in S_i, \forall a\in A, \forall c\in C \tag{5}$$

$$0\le\theta_i\le 1,\ x^c_{as}, v_{as}, z^c_{aa'}\in\{0,1\}. \tag{6}$$

To find the optimal association map, various parameters such as frequency-reuse constraints, multi-rate transmissions and co-channel interference have to be taken into account. The main goal is maximizing the total allocated bandwidth to the customers of ISPs over the association variable x^c_{as} regarding the predetermined share of each ISP i (θ_i). Since each Wi-Fi station is permitted to associate with any AP of WLAN infrastructure, binary variable x^c_{as} is used to check the association of station s to AP a over channel c. The controller needs to find the values of x^c_{as} for all the stations such that the objective function is maximized. The priority of each station is defined as its weight, which is represented by w_s. Also, the airtime and data rate of the wireless link between station s and AP a on channel c are shown as t^c_{as} and r^c_{as}, respectively. In addition, $\sum\limits_{a\in A} w_s v_{as}\sum\limits_{c\in C} x^c_{as}t^c_{as}r^c_{as}$ is the throughput of station s associated to AP a over the set of all existing channels (C).

Due to the seamless coverage of APs and using the homogeneous stations and APs, protocol model [15] can be utilized as a simple and efficient choice to model the co-channel interference. Two more binary variables are used in the presented formulation. The first one is v_{as}, which denotes station s either is located or not inside the communication range of AP a. The second one is z^c_{as} that shows the presence of node a within the carrier sensing range of station s over channel c. The main usage of v_{as} is limiting the number of AP candidates for station s to the ones which are placed within its communication range.

Also, there are several constraints that reflect the characteristics of wireless channel and our assumptions. The first one (2), ensures that the customers of each ISP i are allowed to associate to only and only one AP at every unit of time. The second constraint (3) restricts the allocated airtime of every station s from the set of customers of ISP i (S_i) to the predetermined share of the ISP (θ_i) over all the channels. For the scenario in which all stations are the customers of a single ISP, θ_i is equal to 1. The next constraint (4) is similar to (3), but it guarantees that total allocated airtime to all the customers of ISP i over all the WLAN infrastructure is at most equal to θ_i. Also, since it is assumed that all the stations are greedy, i.e. there are always packets for transmission or being received by them, the assigned airtime to the stations of every ISP will be divided equally among them. So, for the downlink scenario, we need to do an equalized bandwidth allocation to all the stations at each AP. This prerequisite is shown by equation (5) using the first term in its denominator. The second term within the denominator counts the number of co-channel APs within the carrier sensing range of AP a that is serving station s over channel c. According to the Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA), the existence of co-channel wireless transmitters within the carrier sensing range of each others while they are attempting to transmit packets causes interference. For the greedy downlink scenario, since the stations are receiving nodes and the APs are transmitters, the number of co-channel APs with the AP that station s is associated with (a) determines the second term of

TABLE I: Parameters utilized in the problem formulation

Symbol	Description
I	the set of Internet Service Providers (ISPs)
A	the set of all Access Points (APs)
S_i	the set of all Stations of ISP i
C	the set of all Channels
θ_i	predetermined share of ISP i
x_{as}^c	1, if station s is associated to a on channel c
r_{as}^c	link data rate between station s and AP a on channel c
t_{as}^c	allocated airtime to station s by AP a on channel c
w_s	the weight (priority) of station s
v_{as}	1, if a is placed within the communication range of s
z_{as}^c	1, if a is placed within the sensing range of s on channel c

the denominator. It should be noted that for the greedy uplink situation, this part has to be replaced with $\sum_{i \in I} \sum_{s' \in S_i} z_{ss'}^c$ which represents the number of co-channel stations with station s from different ISPs. Finally, the last equation represents the range of variable θ_i and the integrality constraints for three binary variables. A brief description of the notations is presented in Table I.

Now, the association problem over a viruralized WLAN infrastructure is formulated as a mixed-integer non-linear program and the key challenge is finding a good approximation of the optimal solution. To solve the described optimization problem, we used the strategy that is introduced in [6]. In that work, the authors presented an approximation of the optimal solution for a similar problem formulation by taking multiple steps. As the first step, they relaxed the integrality constraint of variable x_{as}^c such that each station is allowed to connect to more than one AP at each unit of time. So, by assuming x_{as}^c=1, the optimization problem can be solved in polynomial time. It is important to note that the other presented variables in equation (1) can be obtained prior to solving the problem. For instance, the variables r_{as}^c and v_{as} are the functions of the wireless channel and the distance between station s and AP a. Also, they can be reported by the stations to the APs and subsequently to the controller as the input arguments of the optimization problem. The outcome of the relaxed objective function is called $t_{as}'^c$ which is the input of the next step. By replacing the known $t_{as}'^c$ values in equation (1), we can calculate the fractional association coefficient which is $x_{as}'^c$. Finally, by rounding the estimated $x_{as}'^c$ values to find an integer solution, a good approximation of the optimal association can be acquired. To find the rounded values of $x_{as}'^c$, which represent the final answers ($x_{as}'^c$), the presented algorithm in [16] is one of the most cited techniques. Then, by having the optimal association map, we can easily calculate the airtime and throughput of each Wi-Fi station.

Although by solving the explained formulation we can get a good approximation of the optimal result, its implementation for large-scale virtualized WLAN infrastructures is not efficient in terms of the complexity and running time. Hence, we introduce our meta-heuristic algorithm which is named ACO-PF to achieve a near-optimal solution with less complexity. In the next section, ACO-PF and its components are delineated.

IV. ACO-PF Algorithm

A. ACO Introduction

Since finding the optimal solution for the elaborated problem with large inputs is NP-hard, using the heuristic-based techniques is one of the most efficient approaches to find a near-optimal solution. Ant Colony Optimization (ACO) [17] is one of the well known meta-heuristic schemes that presents a generic probabilistic algorithm to solve computational problems through finding the best route(s) of a given graph. Indeed, it uses a group of ants to explore a large number of possible routes with different costs for finding the route with minimum cost. The best route represents the near-optimal solution, which is a collection of edges of the given graph that constructs the final solution. The beauty of ACO to catch the close answers to the optimal result is using $pheromone$ $trails$ as the key element that builds a cooperative network among the ants. Every ant lays chemical substance which is called $pheromone$ to communicate with others. It also helps each ant to follow the routes that are marked with $pheromone$ laid by other ants. Indeed, $pheromone$ is a historical quality measure that facilitates the search process and each ant shares its experience on finding the best route with the other ants through $pheromone$ $deposition$ and $evaporation$. From an initial random route, the $pheromone$ density varies and the ants follow the route with higher $pheromone$ density. Thus, the $pheromone$ is enhanced by increasing the number of ants that take the same route and it becomes the favored route. At last, among all the taken routes, the favorite ones which are usually the shortest and more efficient ones will be selected. In fact, ACO is a positive feedback-driven mechanism and the system evolves over time for converging to the best solution. This nature-inspired technique is very promising to solve some of the most difficult computational problems in reasonable time and with acceptable accuracy. Due to the page limit, we skip the detailed explanation of the mentioned procedures. More information about ACO can be found in [17].

B. ACO-PF: Using ACO for PF Provisioning

In this subsection, it is shown how ACO has been applied to our predefined objective function for maximizing PF over a WLAN infrastructure. First, we explain our proposed scheme to find a near-optimal association map for the customers of a single ISP. Then, we clarify how it can be extended for being applied to the scenarios, including multiple ISPs.

Since the online algorithms make decisions without considering the future and it may result in unfairness and starvation [4], we designed ACO-PF as an offline periodic-based algorithm. The ACO-PF algorithm is illustrated in Algorithm 1. As the inputs, we have a set of APs (A) and greedy stations (S). At the first phase, we need to calculate the rate matrix r_{as}^c for all the Wi-Fi stations. This matrix represents the maximum achievable data rate between each station and all the existing APs within the WLAN infrastructure. The data rate values for each pair of $(AP, station)$ can be estimated based on the channel parameters such as shadowing factor, path loss exponent, and the distance between the AP and the station. Furthermore, according to equation (5), we consider the impact of co-channel interference for either downlink or uplink scenarios on this matrix. For instance, if the link data rate between AP a and downlink greedy station s is 54 Mbps, and there are three co-channel APs within the carrier sensing range of AP a, the maximum achievable data rate of station s is 18 Mbps, while station s is the only associated station to AP a. Otherwise, 18 Mbps should be divided by the number of associated stations to AP a to find the downlink data rate of station s. In addition to the data rate matrix, ACO control factors (α, β) and evaporation rate (ρ) have to be set before running the algorithm. Also, three matrices including heuristic (η), pheromone trails (τ) and cost (C) need to be initialized.

In the next phase, regarding the predetermined number of iterations and ants, a $Path\ Construction$ function is called to build the path with minimum cost. The final outcome of this function represents the near-optimal solution and it contains a collection of determined APs for serving the Wi-Fi stations. The main body of $Path\ Construction$ is shown in Algorithm 2. The input arguments comprise the sets of stations (S) and APs (A) and three matrices $(C,\ \eta,\ \tau)$. At each iteration of ACO-PF, a group of ants attempt to find the best path according to the illustrated process in Algorithm 2. At the first step, each ant creates an AP Candidates List (ACL_s) for every station s. ACL_s contains the APs that are located within the communication range of station s. Next, the stations will be sorted in increasing order regarding the length of their $ACLs$. Thus, the users that have fewer choices for association will be explored first. Every ant traverses the list of Wi-Fi stations (S) and associates each station s to AP a as a member of its ACL. This association is shown as adding AP a to the constructed $Path$ regarding the computed transition probability p^j_{as}. The probability of associating AP a to station s by ant j that is known as transition probability is defined as follows:

$$p^j_{as} = \frac{\tau^{\alpha}_{as}\eta^{\beta}_{as}}{\sum_{a \in ACL_s} \tau^{\alpha}_{as}\eta^{\beta}_{as}} \tag{7}$$

The nominator of equation (7) calculates the attractiveness of adding AP a to the set of selected APs $(Path)$ and its denominator estimates the desirability of selecting all existing APs in ACL_s for station s. The key elements in the equation are τ^{α}_{as} and η^{β}_{as} which are the pheromone trail level and heuristic of selecting AP a for station s, respectively. The parameters α and β define the relative influence of the $pheromone\ trail$ and the $heuristic$ information. For calculating the mentioned variables, we need to estimate the allocated bandwidth (BW) to station s according to the association map of the stations that have been placed already inside the constructed $Path$. Then, the logarithm of BW will be added to $TotalBW$ that denotes the sum of allocated bandwidth to all the stations. This variable that is the representative of our objective function (1) is the key metric to compute the cost of constructed path by each ant.

After AP assignment to all the stations of inside $Path$, $TotalBW$ can be utilized as the heuristic of the newly created path. It means the routes with larger amount of $TotalBW$ has more attractiveness for the ants and the final solution will be converged to them. Also, since the main goal of ACO is finding the route with minimum cost, the cost function is defined as the inverse of $TotalBW$. By calculation of $TotalBW$ after adding every station s to $Path$, the corresponding rows of heuristic and cost matrices for this station have to be updated. Next, according to the new values, the transition probabilities are estimated. The aforementioned process is carried out for all the stations of WLAN infrastructure and at the final step, the minimum value of cost matrix C and its respective $Path$ are returned to the main algorithm. The returned $Cost$ is compared with the $BestCost$ value so far and if it is smaller, then the value of the returned $Cost$ and its corresponding $Path$ are stored. It is important to note that at the end of each iteration, the matrix of pheromone trail levels (τ) should be updated. This is one of the most necessary steps to ensure that ants have not been converged to a local optimum. Finding the $BestPath$ provides the near-optimal association map of all stations that maximizes PF of our network and can be used to calculate the share of each station from the network capacity.

For the scenarios with multiple ISPs, we need to define a vector of $TotalBW$. Every element i of this vector $(TotalBW_i)$ represents the allocated portion of $TotalBW$ to ISP i based on its predefined share (θ_i). Hence, during the estimation of $TotalBW$ at $Path\ Construction$ function, by fulfilling the following conditions, we ensure that the customers of ISP i are constrained to the predetermined share θ_i over the common WLAN infrastructure. Equation (8) represents the explained conditions for the set of given ISPs (I) and their respective shares (θ_i).

Algorithm 1 ACO-PF Algorithm.

$Input$. A set of greedy users (S) and APs (A).
$Output$. Maximizing Proportional Fairness.
Create the $Rate$ matrix (r^c_{as}).
Initialize ACO parameters, i.e., α, β, ρ.
Initialize η, τ, and C matrices.
for $i = 1 : Iterations$ **do**
  for $j = 1 : Ants$ **do**
    $[Cost, Path] = PathConstruction(S, A, C, \eta, \tau)$
    if $Cost < BestCost$ **then**
      $BestPath \leftarrow Path$
      $BestCost \leftarrow Cost$
    end if
  end for
  Update the pheromone trails (τ).
end for
Update station association list w.r.t. the $BestPath$.
Estimate the stations throughput w.r.t. association map.

Algorithm 2 Path Construction Function.

$Input.$ sets of S & A and matrices C, η, τ.
$Output.$ Estimated $Cost$ and $Path$ for the given inputs.
$Path \leftarrow \phi$
for s = 1 : $|S|$ **do**
  while ACL_s is not empty **do**
    TotalBW $\leftarrow 0$
    Add AP a to the constructed $Path$ w.r.t. p^j_{sa}.
    for k = 1 : $|Path|$ **do**
      $BW \leftarrow$ Estimate stations k's bandwidth.
      $TotalBW \leftarrow TotalBW$ + $log(BW)$
    end for
    $\eta_{sa} \leftarrow TotalBW$
    $C_{sa} \leftarrow \frac{1}{TotalBW}$
    Recalculate all transition probabilities p_{sa}.
  end while
end for
$Cost \leftarrow C_{|S||ACL_s|}$
return $Cost$, $Path$

$$\frac{TotalBW_i}{TotalBW} \leq \theta_i, \quad \sum_{i \in I} \theta_i = 1, \quad \forall i \in I \tag{8}$$

In the next section, we elaborate the selected scenarios to evaluate the functionality of the proposed solution.

V. Performance Evaluation

We have evaluated the functionality of ACO-PF through numerical analysis and testbed experimentation. Prior to explaining the conducted experiments, we describe our presumptions.

A. Key Assumptions

For all the scenarios, it is assumed that the stations are greedy with the same priority and each one communicates directly with only one AP over an extended period of time. So, each station is placed within the coverage of at least one AP and each AP has at least one associated station. Also, our proposed scheme is evaluated under a stable network condition, i.e., no new station joins or leaves our WLANs. We have utilized multi-rate APs in our experiments that serve different stations with diverse link data rates according to the signal strength. It is supposed that all APs are using omni-directional Single-Input Single-Output (SISO) antennas to ensure that the data rate of each station is a non-zero value just over one channel [7]. Table II summarizes the utilized parameters. It should be noted that most of these assumptions are based on the prior works [7] [6]. In addition, we have conducted the testbed experiments from the macroscopic point of view to reduce the complexity and considering the overhead of the control traffic between the stations and the controller. Moreover, due to the intermittent nature of wireless channels and bursty characteristic of traffic, we used physical data rate instead of instantaneous data rate as a proper measure that reflects channel conditions over a long time interval [4]. Also, it should be noted that in the proposed algorithm, $log(0)$ is assumed to be 0 and all data rate values that are equal to 0, have been removed from the objective function.

TABLE II: Values of the key parameters

Parameter	Value	Parameter	Value
α	0.1	$TX\ Power$	20 dBm
β	1.9	$TX/RX\ Gain$	4 dBi
ρ	0.1	$Frequency$	2.4 GHz
$\lvert Ants \rvert$	30	$Comm.\ Range$	110 m
$Iterations$	300	$Sensing\ Range$	220 m

B. Numerical Analysis

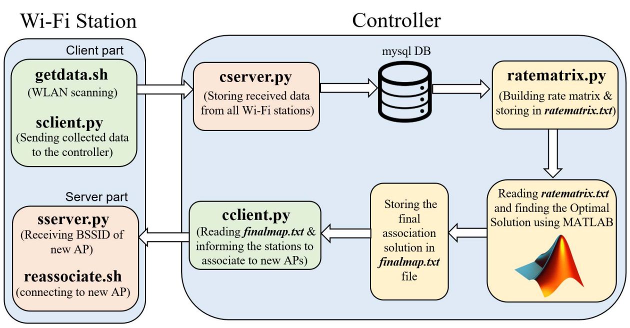
In this part, the performance of ACO-PF for different scenarios is compared with the following association schemes:

- RSSI-based Association (RSSI): It picks the AP with the strongest received signal strength, which is a function of the environment and distance between AP and stations.
- Least Loaded AP First (LLF): In this scheme, each station associates to the AP in its communication range that has the smallest number of associated users [18].
- Approximated Optimal (A-OPT): We have used the approximation algorithm introduced in [6] to find an estimation of the optimal solution for the problem formulation presented in Section III.

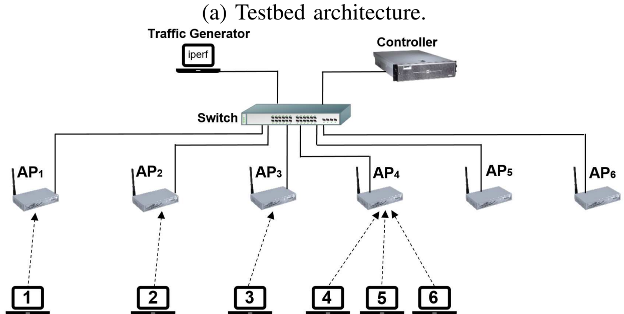
We have assumed a grid of 20 APs placed within a 300 m $\times$ 400 m area. The inter-AP distance is 100 m. The experiments are conducted for two cases with uniformly distributed stations. The first case involves distributing the stations inside the entire defined area and the second is the distribution of stations in a square-shaped hotspot at the center of the area. To model the wireless channel, we apply the indoor path loss calculation in [19] to our scenarios. All APs are working at 2.4 GHz and the data rates of 802.11g standard are used for the experiments. The aggregate (total) and per-user throughput as well as Jain's Fairness Index (JFI) [20] are calculated for all the scenarios to measure the performance of different association schemes. Also, each scenario is carried out for three sets of 50, 100, and 200 stations. We have considered both co-channel and orthogonal APs in the arranged topology to run our scenarios. The testbed setup and the map of APs with orthogonal channels are shown in Fig. 2b and Fig. 2c, respectively. For running the experiments of this section, MATLAB and CVX are utilized.

C. Experimentation Testbed

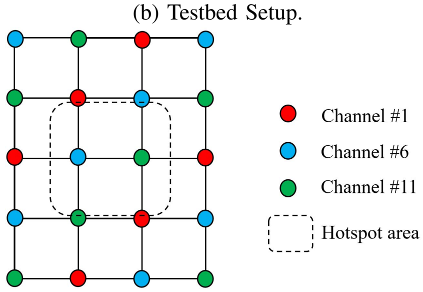
To investigate the basic operation of ACO-PF versus the most popular association scheme (RSSI), we arranged a testbed setup as illustrated in Fig. 2b. We utilized six Wi-Fi stations, six APs, one controller and one traffic generator to build an indoor WLAN scenario. Detailed information on the utilized equipment and network setup can be found in [21] [22]. In this design, each station runs two background programs which are in charge of sending the channel information to the controller (*sclient.py*) and receiving association control commands from the controller (*sserver.py*). The transmitted data by each station contains the RSSI values from all nearby APs which are aggregated in a database at the controller for building the $rate\ matrix$. As mentioned earlier, this matrix shows the data rate values for all pairs of $(AP, station)$ in our WLAN. To find each pair of this matrix, first we need to calculate the Signal to Interference plus Noise Ratio (SINR) of each wireless link at the receiver side. Then, it is feasible to map the calculated SINR values to the corresponding data rates according to the table presented in [6]. All the required data for doing this operation are provided by $ath9k$ driver. Also, by using the restart-mode of Atheros chipsets, the drastic impact of hidden terminals is addressed during the experiments [23]. The computed $rate\ matrix$ is passed to a MATLAB program that runs the ACO-PF algorithm. The outcome of this algorithm determines the final association map of Wi-Fi stations, and is handed over to $cclient.py$. Eventually, the stations are informed for associating to the new APs which results in the enhancement of the network throughput and fairness. The explained process is illustrated in Fig. 2a. We have conducted a downlink scenario for UDP and TCP traffic.



(a) Testbed architecture.



(b) Testbed Setup.



(c) Arranged topology for numerical analysis.

Fig. 2: Experiment setup and architecture.

VI. Results and Discussion

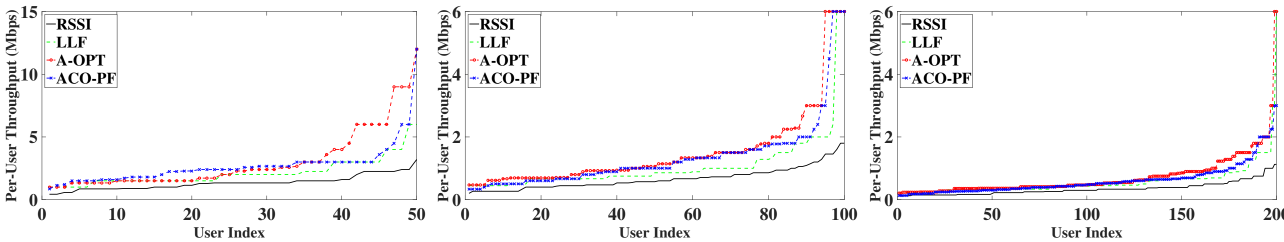
In this section, due to space constraints, the selected acquired results for the defined scenarios are delineated.

A. Numerical Results

Fig. 3 illustrates the first set of results for hotspot downlink scenarios. It shows the measured user throughputs for different number of users when APs are using orthogonal channels. Each graph displays the downlink throughput of the stations from the smallest to the largest values. As illustrated, ACO-PF achieves better bandwidth distribution among the users which is consistent with the JFIs presented in Fig. 4b. Fig. 4 and Fig. 5 represent aggregate throughput and fairness index for orthogonal (Fig. 4a and 4b) and co-channel (Fig. 5a and 5b) APs in hotspot downlink scenarios, respectively. It can be seen that although A-OPT for all cases and different number of users has the largest aggregate throughput, its fairness index in some situations is lower than the others. This result shows the existence of a trade-off between the aggregate throughput and fairness index. The acquired results for ACO-PF are quite close to A-OPT while ACO-PF can achieve such results with less complexity. Also, it is clear that using three orthogonal APs improves the aggregate throughput over co-channel APs around four times. It should be noted that for both co-channel and orthogonal APs, the aggregate throughput of ACO-PF is at least two times of the RSSI-based association scheme. This improvement is achieved by associating the edge users, i.e., users at the coverage boundary of multiple APs, to the APs that either have no or fewer number of associated users.

For the scenarios that the users are uniformly distributed, there is no significant difference between the aggregate throughput of RSSI scheme and sub-optimal solutions. This is due to the greedy nature of the user traffic and the utilization of all the APs by all the stations. Similar explanation applies to the downlink scenarios with orthogonal (Fig. 6a and 6b) and co-channel (Fig. 7a and 7b) APs. In co-channel hotspot uplink scenarios, increasing the number of the stations worsens the destructive impact of interference and it leads to the substantial reduction of aggregate throughput for all the schemes. However, according to Fig. 8a and Fig. 8b, ACO-PF can achieve better results in terms of both throughput and fairness. Also, uniformly distributed stations in uplink co-channel scenario achieve similar results (Fig. 9a and 9b). This similarity comes from the reduction of the aggregate throughput due to the impact of interference by increasing the number of stations. It is important to note that aggregate throughput for uniform user distribution in co-channel uplink scenario is by far larger than the hotspot uplink cases. For the hotspot scenario, the small distance between the stations aggravates the influence of interferers and it leads to significant decrease of aggregate throughput in comparison to the previous scenarios.

Also, to evaluate the functionality of our proposed scheme for resource allocation among the customers of two ISPs over a common WLAN infrastructure, we conducted another experiment for the hotspot scenario and 50 users. In this scenario, it is assumed that we have two ISPs with equal bandwidth share

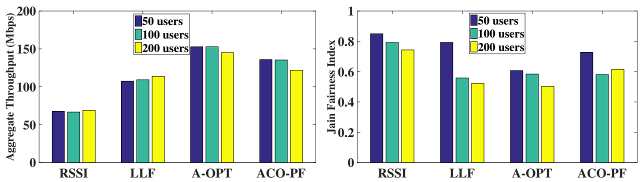


(a) 50 users.

(b) 100 users.

(c) 200 users.

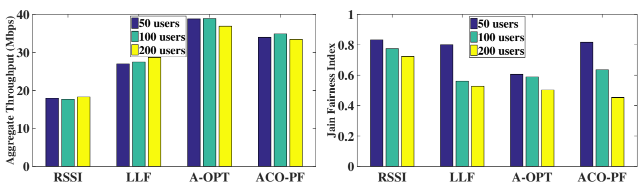
Fig. 3: Obtained user throughputs for hotspot downlink scenario with orthogonal APs.



(a) Throughput, orthogonal.

(b) Fairness, orthogonal.

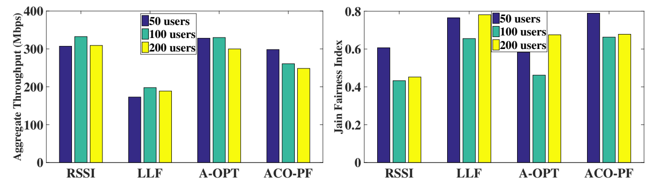
Fig. 4: Results for hotspot downlink orthogonal scenarios.



(a) Throughput, co-channel.

(b) Fairness, co-channel.

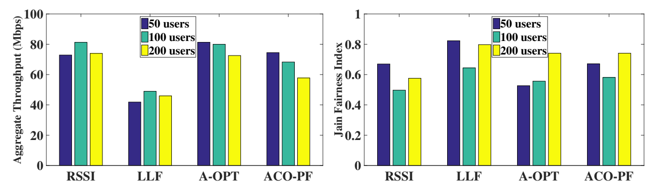
Fig. 5: Results for hotspot downlink co-channel scenarios.



(a) Throughput, orthogonal.

(b) Fairness, orthogonal.

Fig. 6: Results for uniform downlink orthogonal scenarios.



(a) Throughput, co-channel.

(b) Fairness, co-channel.

Fig. 7: Results for uniform downlink co-channel scenarios.

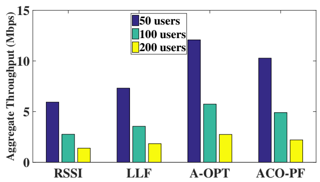
and different number of customers. We measured the aggregate throughput of RSSI and ACO-PF schemes for different ratio of ISP-1 customers to the total number of customers. According to the presented results for the RSSI scheme in Fig. 10a, although both ISPs shall have an equal bandwidth share, the only way to improve the aggregate throughput of ISP-1 is increasing the number of its customers. On the other hand, as shown in Fig. 10b, ACO-PF guarantees the predetermined share of each ISP and provides a fair load sharing for both of them regardless of the number of their customers. It should be noted since the experiments are carried out for deterministic topologies, there is no need to calculate confidence intervals for RSSI, LLF and A-OPT schemes that do not depend on random variables. Also, since confidence intervals for ACO-PF are negligible, they have not been displayed.

B. Experimentation Results

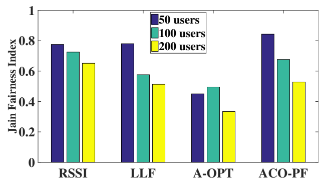
The testbed experiments are conducted on the illustrated topology in Fig. 2b. The average measured user throughput for greedy UDP and TCP downlink flows are illustrated in Fig. 11a and 11b. The presented results are the average of 5 runs, each of which is 5 minutes long. The shown graphs substantiate that in spite of the existence of co-channel APs around our testbed setup, using ACO-PF improves the aggregate throughput, significantly. After replacing the RSSI-based association scheme by ACO-PF, we see the overall network throughput for both UDP and TCP traffic have been improved more than 25% and 30%, respectively. Moreover, fairness index is increased from 0.88 to 0.99 for UDP traffic and remained intact (0.97) for TCP flows. Also, as it can be seen in the figure, the measured throughput values for all the stations except the first two have increased. The throughput reduction of the first two stations after switching to ACO-PF is due to the interference caused by the external APs, which is a function of the positions of the stations as well as the channel activity.

VII. Conclusion

The considerable throughput reduction and unbalanced distribution of bandwidth among the users in WLANs, particularly in populated areas underscore the need for more efficient association control mechanisms. In this paper, ACO-PF as a dynamic association control for virtualized WLAN infrastructures is introduced and evaluated through extensive numerical analysis and testbed experimentation. The proposed scheme is developed on top of ACO, and provides a practical and flexible

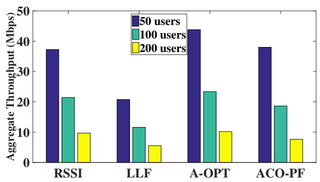


(a) Throughput, hotspot.

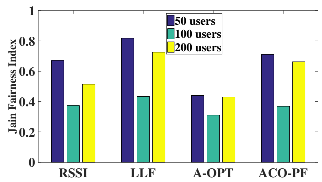


(b) Fairness, hotspot.

Fig. 8: Results for hotspot uplink co-channel scenarios.

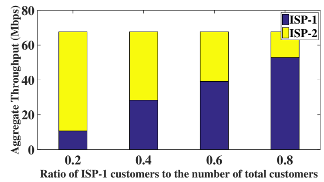


(a) Throughput, uniform.

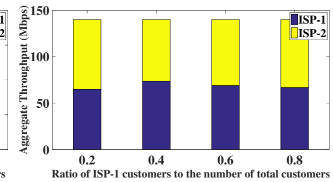


(b) Fairness, uniform.

Fig. 9: Results for uniform uplink co-channel scenarios.

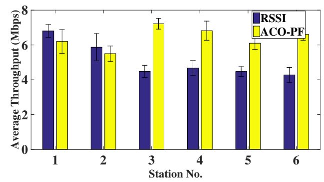


(a) RSSI scheme.

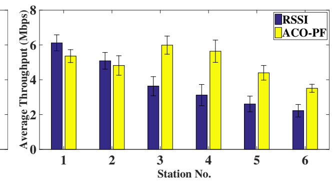


(b) ACO-PF scheme.

Fig. 10: ISP load sharing for RSSI and ACO-PF schemes.



(a) UDP throughput.



(b) TCP throughput.

Fig. 11: Testbed results for UDP/TCP downlink scenario.

solution to achieve near-optimal network aggregate throughput and improving the fairness index. Also, it guarantees the predetermined share of all service providers that are using a shared WLAN infrastructure. One of the main features of the presented work is its independence from the underlying MAC and network protocols and it can be applied to WLANs by updating the AP configuration and Wi-Fi stations. For the future work, we intend to investigate the same problem for the heterogeneous traffic pattern as well as its integration with multi-hop community Wi-Fi mesh networks. In this case, the best route for the network flows can be approximated through solving the multi-commodity optimization problem.

Acknowledgment

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References

[1] Cisco, "Cisco visual networking index: forecast and methodology, 2015-2019," Cisco, Tech. Rep., 2015. [Online]. Available: http://goo.gl/ockPWc

[2] M. Heusse, F. Rousseau, G. Berger-Sabbatel, and A. Duda, "Performance anomaly of 802.11b," in *INFOCOM 2003. 22nd Annual Joint Conference of the IEEE Computer and Communications*, vol. 2, March 2003, pp. 836–843.

[3] A. Baid and D. Raychaudhuri, "Understanding channel selection dynamics in dense Wi-Fi networks," *Communications Magazine, IEEE*, vol. 53, no. 1, pp. 110–117, January 2015.

[4] L. Li, M. Pal, and Y. R. Yang, "Proportional fairness in multi-rate wireless LANs," in *INFOCOM 2008. The 27th Conference on Computer Communications. IEEE*, April 2008.

[5] A. Checco and D. J. Leith, "Proportional fairness in 802.11 wireless LANs," *IEEE Comm. Letters*, vol. 15, no. 8, pp. 807–809, August 2011.

[6] W. Li, S. Wang, Y. Cui, X. Cheng, R. Xin, M. A. Al-Rodhaan, and A. Al-Dhelaan, "AP association for proportional fairness in multirate WLANs," *IEEE/ACM Trans. on Networking*, vol. 22, no. 1, pp. 191–202, 2014.

[7] O. Karimi, J. Liu, and J. Rexford, "Optimal collaborative access point association in wireless networks," in *INFOCOM, 2014 Proceedings IEEE*, April 2014, pp. 1141–1149.

[8] Y. E. Lin and T. M. Tsai, "Creation, management and migration of virtual access points in software defined WLAN," in *2015 International Conference on Cloud Computing and Big Data*, 2015, pp. 313–320.

[9] T. Nagai and H. Shigeno, "A framework of AP aggregation using virtualization for high density WLANs," in *Intelligent Networking and Collaborative Systems (INCoS)*, Nov 2011, pp. 350–355.

[10] A. Checco and D. J. Leith, "Fair virtualization of 802.11 networks," *IEEE/ACM Trans. on Networking*, vol. 23, no. 1, pp. 148–160, 2015.

[11] M. Derakhshani, X. Wang, T. Le-Ngoc, and A. Leon-Garcia, "Airtime usage control in virtualized multi-cell 802.11 networks," in *2015 IEEE Globecom Workshops*, Dec 2015, pp. 1–6.

[12] M. Derakhshani, X. Wang, T. Le-Ngoc, and A. Leon-Garcia, "Virtualization of multi-cell 802.11 networks: Association and airtime control," *arXiv preprint arXiv:1508.03554*, 2015.

[13] M. Al-Rodhaan, Q. Ma, and A. Al-Dhelaan, "Genetic algorithm based approach to enhance network performance in multi-rate WLANs," *Trans. on Networks and Comm.*, vol. 3, no. 6, p. 44, 2016.

[14] Q. Ma, A. Al-Dhelaan, and M. Al-Rodhaan, "Improving tradeoff between fairness and throughput in multi-rate WLANs: Simulated annealing approach," *BRIS Journal of Advances in Science and Technology*, vol. 2, no. 3, pp. 127–137, 2014.

[15] K. Jain, J. Padhye, V. N. Padmanabhan, and L. Qiu, "Impact of interference on multi-hop wireless network performance," *Wireless networks*, vol. 11, no. 4, pp. 471–487, 2005.

[16] D. B. Shmoys and É. Tardos, "An approximation algorithm for the generalized assignment problem," *Mathematical Programming*, vol. 62, no. 1-3, pp. 461–474, 1993.

[17] M. Dorigo, M. Birattari, and T. Stützle, "Ant colony optimization," *Computational Intelligence Mag., IEEE*, vol. 1, no. 4, pp. 28–39, 2006.

[18] O. Ekici and A. Yongacoglu, "A novel association algorithm for congestion relief in IEEE 802.11 WLANs," in *Proceedings of the 2006 international conference on Wireless communications and mobile computing*. ACM, 2006, pp. 725–730.

[19] ITU, "Recommendation ITU-R P.1238," ITU, Tech. Rep., 1997. [Online]. Available: https://goo.gl/YdtlHf

[20] R. Jain, D.-M. Chiu, and W. R. Hawe, *A quantitative measure of fairness and discrimination for resource allocation in shared computer system*. Eastern Research Laboratory, Digital Equipment Corporation Hudson, MA, 1984, vol. 38.

[21] D. Sajjadi, F. Hashim, K. H. Kwong, D. Chieng, S. C. Ng, and M. Tanha, "An adaptive rate allocation system to mitigate starvation dilemma in multi-radio multi-hop wireless mesh networks," *Wireless Personal Communications*, vol. 84, no. 4, pp. 2881–2912, 2015.

[22] D. Sajjadi, M. Tanha, and J. Pan, "A comparative study of channel switching latency for conventional and SDN-based routing in multi-hop multi-radio wireless mesh networks," in *13th IEEE CCNC*, January 2016, pp. 330–334.

[23] P. C. Ng and S. C. Liew, "Throughput analysis of IEEE 802.11 multi-hop ad hoc networks," *IEEE/ACM Trans. on Networking*, vol. 15, no. 2, pp. 309–322, April 2007.