A Learning Approach to Wi-Fi Access

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ABSTRACT
We show experimentally that workload-based AP-STA associations can improve system throughput significantly. We present a predictive model that guides optimal resource allocations in dense Wi-Fi networks and achieves 72-77% of the optimal throughput with varying training data set sizes using a 3-day trace of real cable modem traffic.

CCS CONCEPTS
• Networks → Network experimentation;

KEYWORDS
Wi-Fi, load balancing

1 INTRODUCTION
The rapid rise in deployments of connected IoT and AI devices, as well as the continued growth in adoption of mobile devices, has lead to a new surge in Wi-Fi usage. At the same time, more Wi-Fi access points (APs) are appearing to off-load cellular usage, share cellular connections across devices, and to extend signals in mesh networks, or simply to serve more businesses and local stores. Enterprises and large conferences have long battled the problem of serving many stations from a pool of access points efficiently, and it is well known that simply directing stations (STAs) to the closest access points can be suboptimal [15]. The latest 802.11ac and 802.11ax standards help serve this demand by bonding channels and allowing wider bands to improve throughput. The use of wider bands, however, introduces more side lobe interference and leads to fewer orthogonal bands.

A study of a campus WLAN ([4]) concluded that user transfer rates follow a power law, and as a result, load tends to be unevenly distributed across access points. Furthermore, they discovered that which users are active is more significant to the load incurred than how many users are connected. This finding motivates us to look at the problem of load balancing from a STA workload perspective. Many studies have shown that traditional STA to AP association driven by the wireless clients can be suboptimal and that AP-driven central control is beneficial [12, 14, 22].

The problem we are addressing in this paper is the following. When STAs have a choice of which AP to connect to and each AP has a fixed independent capacity constraint on the bandwidth offered, how do we allocate the aggregate bandwidth most efficiently?

Distance to the AP clearly plays a role, but we argue that the characteristics of the workload play an even bigger role in dense deployments. With a very large number of independent random workloads one can expect statistical multiplexing to even out the peaks and valleys in usage and result in little to no unused resources. However, given the limited frequency band widths, having too many stations on the same frequency is inefficient. Stations in general outnumber access points, which use a smaller contention window to adjust the backoff algorithm to serve more stations efficiently. This typically results in two download streams (AP to stations) receiving a higher throughput than mixing an upload and a download stream on the same AP. Similar effects can be seen when mixing low latency applications with high-throughput ones. As a result, dual radio approaches have been suggested [9], to separate out different application streams on different channels.

Our work focuses on performing this separation automatically based on observed workload rates.

Two use cases motivating heterogeneous bandwidth scheduling are community Wi-Fi sharing [18] and channel bonding [19]. These use cases correspond to the backhaul capacity and the airtime bandwidth being scarce (and non-uniform) respectively. Community Wi-Fi is becoming increasingly popular to increase coverage and provide an open alternative to cellular networks, whereas channel bonding is the key strategy (together with multi-antenna solutions like MIMO) that the most recent 802.11 specifications [1, 10] apply to address increased throughput demand.
The key contribution of this paper is an experimental evaluation of workload-aware STA-AP associations in a dense network setting for both backhaul and airtime constrained systems. To the best of our knowledge, this is the first experimental evaluation of such associations, using predictive, demand-exploring algorithms.

2 RELATED WORK
A large body of research has addressed the problem of load imbalance due to suboptimal STA to AP associations. The work can be categorized into: beacon-based decentralized approaches, modifying the protocol of association between the AP and STA; centralized load balancers, making association decisions from a controller with a global view of the network; virtual radios, separating the AP into a dumb radio and a centralized virtual AP that makes association decisions; and finally latency aware approaches, balancing the resources between throughput and latency sensitive applications.

Decentralized Beacons. Measurement Beacons are used in [21] to predict effective throughput before connecting to an AP. [11] extend Beacons with load that STAs can react to. The load information transmitted is aware of the adaptive data rates selected by the AP. The key feature of these approaches is that they are distributed so as to adapt to changes in load gradually. A similar approach using admission control and custom AP load functions is presented in [13]. A cell breathing algorithm, adjusting the power of beacon packets of APs to effectively shrink or grow the cell covered by an AP dynamically based on load was evaluated in [2]. In [3] channel switching to nearby APs during overload is used as a remedy for imbalance whereby AP’s force STAs to switch. [17] implement an AP load balancing strategy that combines controlled channel selection, number of users per AP, and link quality again by extending the information sent in probe responses from APs to STAs. Our approach does not require any modification to the protocols neither on the AP nor the STA side, and can make more informed association decisions thanks to a central view of the network.

Central Controllers. Optimal STA to AP association based on estimated wait times on the MAC level were suggested in [6]. AP load balancing based on free airtime measurements and interference from nearby clients and APs were also considered in the DenseAP system presented in [15]. In [5] the authors address the problem of fairness across users accessing a wireless LAN by association control, i.e. which STA is mapped to which AP. They show in simulations that their proposed association algorithm achieves close to optimal load balancing and max-min fairness. Centralized Radio Network Controllers were also explored in [20]. Architecturally, this category of approaches is closest to our work. We extend the existing work by incorporating information about and predicting the workload generated by individual STAs over time. Given the architectural similarity we envision our method to be deployed either as a compliment or a replacement in existing WLAN controllers.

Virtual Radios. In [12] the RF transmission (radio) part of the AP is separated out and the baseband processing is served in a clustered pool of compute resources connected with high-speed fiber. The architecture allows real-time mapping of channels and radios to APs based on traffic load. Similar SDN-based approaches were also exploited in [22] and [14]. These approaches are very similar to the centralized approaches with the main difference being that the central controller has even more information and control over the APs and that handovers can be executed with less overhead. Our approach also relies on smooth handovers and could be deployed as a compliment to virtual radio association algorithms. The additional information in the centralized AP makes it easy to run our STA workload aware algorithm.

Latency Aware. [16] adapt channel width and move stations between channels dynamically based on observed frame rates to allow both latency and throughput sensitive applications to be served at a high QoS concurrently. Similarly [8] optimises low latency streams by using a ping protocol to determine whether delays can be explained by cross-traffic or the station’s own transmission bitrate to avoid backing off too conservatively to avoid congestion. In [7] experiential capacity regions are proposed that represent mixes of STAs that can be admitted into a wireless network based on QoE capacity requirements using a machine learning model. Our work currently focuses on bandwidth scheduling but more general applications to also pack STAs on APs based on latency requirements fits well with our general architecture and is future work.

3 MODEL
The general problem we address is how to best associate STAs (wireless clients) with APs (wireless access points). In this work, the best allocation is the one that yields the highest overall system throughput. Each AP has a fixed transmit and receive capacity, translating to maximum achievable upload and download rates from the STA point of view.

The key variable in this setting is the upload and download rates generated over time by the STAs.
We define an observation window to be one or more time slots in the past for which we know the upload or download rates across all existing STAs.

Similarly we define an allocation window to be one or more time slots in the future for which an allocation is executed.

An allocation here is an instance of an AP-STA association connecting each STA to an AP. We call all feasible allocations (associations where STAs are within reach of APs) the feasible allocation set.

Now, the problem to be solved is the following: Given a set of observations in a historical time window, provide a prediction of the best allocation for the future time window out of the feasible allocation set.

Given that the allocations are enforced in the AP, or a controller, we assume that the feasible allocations are known.

Our proposed model predicts future demand using correlations between observed workload rates and optimal allocations.

We use a set of linear regression models (LR) to predict the throughput of a feasible allocation. Each model uses observed download and upload rates in a particular state of the system. The state is simply defined as the current allocation being enforced. We then define the score, $S$, of a feasible allocation $A'$ given an observed state, $A$, as follows:

$$S_{A,A'} = \sum_{s=1}^{N} w_s r_s^d + w_s r_s^u$$  \hspace{1cm} (1)

where $w$ represents the regression model coefficients to be learned for each station, $s$, of the $N$ stations, $r^d$ the download rates and $r^u$ the upload rates observed during allocation $A$. The score here is the same as the predicted throughput, and hence we pick the allocation $A'$ with the highest score in the current state to enforce, in order to optimize overall system throughput. This means that we train a different model for each allocation used in the observation window, and each model for which we want to predict the throughput. The total number of linear models to train is hence $|A| \times |A'|$. Note, we do not need to observe the same workload demand with all allocation models in each time period in order to train the models. For example, with two allocations $\{a, b\}$ we can observe rates with allocation $a$ in time $t$, then get ground truth throughput in $t+1$, as well as observe the new rates. Then we change to allocation $b$ in time periods $t+2$ and $t+3$ to repeat the procedure, and then finally switch back to allocation $A_a$. In this way we have trained all of our four models $\{S_{a,a}\}$, $\{S_{a,b}\}$, $\{S_{b,b}\}$ and $\{S_{b,a}\}$ in five time steps.

4 DATA

Given that the model is predictive and should be capable of learning some hidden behavior in the upload and download rates, we collect a real-world trace from a residential deployment with cable modems connected to a cable headend (CMTS) over a HFC network. The data comprise upload and download volumes on a per-second basis for each cable modem that we aggregate into upload and download rates on a minute-by-minute basis. Here, we consider each cable modem trace a proxy for a workload even though it may be a combination of many wireless and wired stations in the home.

Three days of rates were captured from July 5th through July 7th 2017 from 8 cable modems.

The aggregate average upload and download rates with smoothing over a 10min period can be seen in Figure 1 and Figure 2 respectively.

![Figure 1: Aggregate Average Upload Rates over 10min Periods.](image)

The individual traces can be seen in Figure 3.

We note that the workloads are heavily dominated by downloads, but there are periods of high upload traffic in some workloads. To simplify workload replay in our testbed (next section) we only include the rate that is highest (download or upload) in each time slot, and introduce a random noise workload in periods that

\[\text{we have data from 21 modems but only use the top 8 in terms of traffic volume for the primary experiments}\]
have no measured traffic in the order of 100kbps. These, volume-wise, very small adjustments do not change the general patterns of download and upload heavy traffic over time.

Given that our models assume high correlation in rates between subsequent time slots we also verified that autocorrelations are high (0.84) with 1-minute lag as shown in Figure 4.

5 TESTBED
To more accurately capture the effect of different AP-STA associations on system throughput given different workloads, we set up a testbed with 4 APs and 8 STAs powered by Raspberry Pis, in a RF-shielded tent.

The tent is 7x7x7 feet large, and the APs and STAs were positioned in a 4x3 grid with APs in all the corners (see Figure 5).

The APs were set up with hostapd and dusmasq using the internal Raspberry Pi 3 B+ W-Fi card, operating in 802.11ac (VHT) mode with channels 149, 153, 157, and 161 on 20Mhz wide bands. Maximum throughput on a single link were about 70-80Mbps with no significant differences between positions of the APs and STAs in the tent. In other words, all allocations are feasible in the experiments.

Both APs and STAs were configured to transmit at minimal power (1mW) to minimize interference.

The APs limit their upload and download capacities using tc qdisc htb bandwidth shaping. Since shaping on the receiving end is limited to dropping packets which would negatively impact throughput, we always shape on the transmitting end. That is the download capacity is set on the AP side and the upload capacity is set on the STA side (based on the AP that the STA is connected to).

The control plane comprises Ethernet links within a testbed LAN from a fiber switch. Remote control of the testbed is done via a fiber link that is pulled through a tent sleeve to avoid breaking the Faraday property.

A Mini PC NUC connected to the same LAN controls all the experiment runs and the AP and STA configurations over SSH links.

Traffic is replayed using nuttcp with dedicated servers on the APs for each STA, both for the control and data paths. All traffic is using the UDP protocol to achieve max PHY layer throughput.

The minute-by-minute workloads are replayed in parallel across all STAs. A new allocation is enforced for each minute, and each benchmark is run for each minute until the next minute is replayed.

The testbed is in this context used to extract throughput data across many different rate and type (upload, download) combinations as the ground truth. The actual algorithm training and tuning is done offline.

6 BACKHAUL CONSTRAINED EXPERIMENTS
As a first step in evaluating our approach, we constrain the AP backhaul capacities as seen in Table 1.

|   | Upload Limit (Mbps) | Download Limit (Mbps) |
|---|---------------------|-----------------------|
| AP1 (HULD) | 70                  | 1                     |
| AP2 (LUHD) | 1                   | 70                    |
| AP3 (LUHD) | 1                   | 70                    |
| AP4 (HULD) | 70                  | 1                     |

Two APs are given High Upload and Low Download (HULD) capacities and the other two APs are given Low Upload and High Download (LUHD) constraints. The intuition here is that biasing the AP towards serving only one type of heavy workload has been shown to be beneficial as we mentioned in the introduction.

Now, to test the general setup we first look at a sample set of workloads with the behavior shown in Table 2.
Note, we have two STAs each of the classes High Upload (HU), High Download (HD), Low Upload (LU), and Low Download (LD).

We now define three allocations, one that mixes high upload and high download rates on the same AP (HUHD), one that puts high rates and low rates on the same AP and keeps types together (HULU), and finally one that mixes high rates with high rates and keeps types together (HUHU).\footnote{one AP has HUHU the others HDHD, LDLD, and LULU}
Table 2: Sample STA Behavior

| Workload | Type   | Rate (Mbps) |
|----------|--------|-------------|
| 1 (HU)   | Upload | 50          |
| 2 (HD)   | Download | 50        |
| 3 (HD)   | Download | 50        |
| 4 (LU)   | Upload | 0.3         |
| 5 (LU)   | Upload | 0.3         |
| 6 (HU)   | Upload | 50          |
| 7 (LD)   | Download | 0.3       |
| 8 (LD)   | Download | 0.3       |

Table 3 shows the results for these allocations.

Table 3: Sample Workload Results

| Allocation | Throughput (Mbps) | Improvement over HUHD (%) |
|------------|-------------------|--------------------------|
| HUHD       | 103               | 0                        |
| HULU       | 197               | 91                       |
| HUHU       | 123               | 19                       |

As we can see, mapping the right set of workloads to the right AP can have great benefits (91% throughput improvement in this example). Moreover, this example also shows that there could be benefits to collecting the same type of workload on the same AP (20% throughput improvement).

6.1 Trace Prediction

We now move on to experiments with our real workload trace. We evaluate the approach by first fitting the models during a training phase and then executing the models repeatedly during a verification phase.

To be able to cover a longer time period, which is needed to train our model, and to complete the experiment in a reasonable time, we limit the experiment to three alternative allocations. The feasible set of allocations we pick are the same as the ones used with the sample workload. Now, the rates are not static anymore so we rename the allocations to avoid confusion. The HUHD allocation is also the one that allocates the closest AP to each STA so we call it the SINR allocation. The other two we call BENCH1 and BENCH2. Note, the actual allocation is not of interest here, simply that they are different enough to be able to expose different system throughput behavior.

We recall that the workload comprises 72 hours of upload and download rates, so across the 8 workloads a total of 34560 rates are replayed across the three allocation alternatives.

Now after collecting throughput values across all these rates and allocations we evaluate our models as follows.

We train a model to recognize hidden demand and predict the optimal allocation assuming we only have observations from a single allocation. In this case we have a clear split between a test phase where the models are built and an evaluation phase where we execute the model on live data. We hence also study making this split differently, in other words we look at how much training data we need to achieve a certain level of performance in the predictions.

The results are depicted in Figure 6 and summarized in Table 4. With 30% training data we observe 72% of optimal throughput with our method.

Table 4: Percent Improvement over SINR Association

| Model | Test 10% | Test 30% | Test 90% |
|-------|----------|----------|----------|
| Optimal | 27       | 27       | 22       |
| Random  | −10      | −10      | −14      |
| LR      | 16       | 19       | 14       |
7 AIRTIME CONSTRAINED EXPERIMENTS

The next set of experiments test the proposed algorithm in the case of heterogeneous airtime bandwidth capacity on different Wi-Fi channels.

We constrain the AP capacities as seen in Table 5 and set the workload demands according to Table 6.

Table 5: AP Airtime Bandwidth Capacity

| Channel Width (Mhz) | Measured Max (Mbps) |
|---------------------|---------------------|
| AP1 (L)             | 20                  | 48                  |
| AP2 (H)             | 80                  | 144                 |

Table 6: Sample STA Airtime Bandwidth Demand

| Workload | Rate (Mbps) |
|----------|-------------|
| 1 (H)    | 36          |
| 2 (L)    | 12          |
| 3 (H)    | 36          |
| 4 (H)    | 36          |
| 5 (L)    | 12          |
| 6 (L)    | 12          |
| 7 (H)    | 36          |
| 8 (L)    | 12          |

The SINR allocation maps all H workloads to AP1 and all L workloads to AP2, BENCH01 maps all L workloads to AP1 and all H workloads to AP2, and finally BENCH02 maps half of the L workloads and half of the H workloads AP1, and the remaining workloads to AP2.

Table 7 shows the results for these allocations.

Table 7: Sample Airtime Results

| Allocation | Throughput (Mbps) | Improvement over SNR (%) |
|------------|-------------------|--------------------------|
| SNR        | 95                | 0                        |
| BENCH01    | 170               | 80                       |
| BENCH02    | 140               | 48                       |

We can see that we can improve the SNR allocation throughput with about 80% with perfectly matched workloads to capacities.

7.1 Trace Prediction

We now replay our 3-day trace and assume that we only have access to the throughput values observed with an SINR allocation in the previous time slot to make an allocation decision for the next time slot. Recall that each time slot is one minute. To saturate the airtime capacity we aggregate data from 21 modems into 8 streams, only use two APs, and artificially increase the traffic volume by a factor of 5. This ensures that airtime is under contention while not changing the dynamics of the trace. Furthermore, we only consider download replay, as uploads are insignificant compared to the airtime used by downloads.

The resulting workload can be seen in Figure 7.

![Figure 7: Aggregate Average Download Rates over 10min Periods for Airtime Experiments.](image)

The results with training data portions of 10-90% are shown in Figure 8 and summarized in Table 8.

Table 8: Percent Improvement over SNR Association

| Model | Test 10% | Test 30% | Test 90% |
|-------|---------|---------|---------|
| Optimal | 13      | 14      | 18      |
| Random  | 3       | 3       | 9       |
| LR    | 8       | 11      | 14      |
It takes more data to make the model perform and the benefit is slightly less compared to the optimal improvement compared to the backhaul experiment results. With 30% training data we observe 77% of optimal throughput with our method.

8 OPPORTUNITY SIMULATION

We have shown that we can train our predictive models to perform close to the optimal allocation. But what is the potential improvement in throughput of an optimal allocation?

To find out we compare our experiment results to a simulation replicating the network configuration of the airtime experiment. The simulator was implemented in ns3 and use the exact same workload data as the experiment as input. As in the testbed, two orthogonal channels, 20Mhz and 80Mhz, were configured. The 20Mhz channel was configured with standard 80211g and the MinstrelWifiManager and the 80Mhz channel with the 80211ac standard, ConstantRateWifiManager and DataMode and ControlMode HtMcs7. The 8 STAs are, like in the experiments, mapped uniformly to the two APs and the 4 STAs assigned to an AP are positioned equidistance in a 2m radius cicle around the AP with the ConstantPositionMobilityModel. The distance was set to allow each individual STA to transfer at the max PHY rate to the AP (if none of the other STAs transmit at the time).

We now evaluate the potential improvement in throughput by picking the most optimal allocation in each time period, a random allocation in each time period, and the static allocation across all periods that performs best in aggregate.

We compare the experiment result with the simulation result, and we also add more allocations to the simulations to get closer to the true optimal allocation. Recall that the experiment only picked 3 different allocations. In theory there are \( \binom{8}{4} = 70 \) possible balanced allocation permutations. To restrict the permutations further we also filter out the allocations that are reflections of each other (same groups of STAs allocated to the APs but just on different APs). The resulting number of permutations are then 35. So the simulation experiment that measures the opportunity for an optimal allocation tests 35 allocations for each time step.

The experiment results are denoted with EXP, the simulation that uses 3 allocations like the experiment with SIM and the simulation using all 35 allocations with SIM35. The metrics used are BEST, denoting the improvement over the best performing static allocation, and RAND, denoting the improvement over a method picking a random allocation in each time period. The latter is implemented as a round robin allocator to yield deterministic simulation results, but the semantics is the same. Both of these measures are computed as \( \frac{V - M}{M} \) where V is the studied throughput value and M is the corresponding value for the measure (BEST or RAND).

The throughput improvements are summarized in Table 9.

|        | BEST | RAND |
|--------|------|------|
| EXP    | 0.10 | 0.12 |
| SIM    | 0.20 | 0.26 |
| SIM35  | 0.23 | 0.37 |

The absolute throughput values between the experiment and the two simulations cannot be compared directly as the settings are not identical, but we can compare the simulations that only differ in the number of allocations used. Although the improvement over the best allocator is slightly bigger in the case with only 3 possible allocations, the improvement in absolute throughput values when using 35 allocations is about 8%. We also note that the improvement over the best
static allocation is a theoretical value as you would not know what the best allocation is before you know the future workload rates. The number is just used to indicate that there is an opportunity to dynamically change the allocation over time even for already associated streams. The random allocation improvement is a better indicator of the true improvement opportunity. Similarly choosing a random allocation out of a large number of potential allocations is a better indicator of the true opportunity. Hence, the conclusion from these simulations is that we can see up to 37% improvement in average per-minute throughput with a density of 4 STAs per AP when load balancing across two APs using a realistic 3-day-long cable modem trace by simply moving individual STAs between APs based on their traffic.

9 CALIBRATION SIMULATION

The preceding experiments showed that we can train a model to accurately predict the best STA-AP associations based on observed rates. Given that we need to train or calibrate a large number of models, and that the performance during calibration will not be better than a random allocation, it is instrumental that the calibration is as efficient as possible, i.e. the calibration periods are minimized while allowing the model to be reused as long as possible.

To quantify the model performance under calibration we run simulations, where we train 9 models (each of the three benchmark allocations both as observed allocation and allocation to predict). The calibration cycles through a set of calibration allocations, as follows:

\[ CC = [1, 1, 2, 1, 3, 2, 2, 3, 3, 1] \]

where \( CC \) is a single calibration cycle of allocations. When running the system through these 10 states we are able to train each of the 9 models with a single feature list and prediction pair.

Now the question is how many cycles do we need to train with before getting a significant improvement in throughput and at what point does the throughput deteriorate as the calibration time performance degrades the overall benefit of the predictions.

The results can be seen in Figure 9.

We note that the system reaches its optimal around 100 calibration cycles. The model trained can then be used for the remainder of the data set without training (total dataset has about 420 cycles). The LEARN TRAINED curve shows the model performance after the model was trained. Here we see an optimal point around 160 cycles. This indicates that there is a potential to get further improvements if the calibration is shortened or the reuse of the model increased.

![Figure 9: Throughput as a ratio of optimal throughput given different calibration cycle lengths.](image)

Table 10 summarizes the results.

| Model | Cycles | 10 | 100 | 170 |
|-------|--------|----|-----|-----|
| Random |        | 80 | 80  | 80  |
| Overall Learned |        | 79 | 86  | 80  |
| Learned after Training |        | 79 | 92  | 93  |

In summary, the simulation shows that the calibration overhead only reduces the improvement by 6-7 percent points compared to the maximum improvement during the trained regime.

10 IMPLEMENTATION

We implement the proposed method using the hostapd socket control protocol. For two APs the DISASSOCIATE command is used to move STAs between APs. For more than two APs BSS_TM_REQ could be used to allow candidate lists to steer the STA to the correct AP. Upload and download rates are collected using STA-FIRST and STA-NEXT iterations. These rates are used both to train the STA workload predictors as well as

3https://w1.fi/wpa_supplicant/devel/hostapd_ctrl_iface_page.html
4BSS Transition Management Requests as defined in 802.11v
to measure the aggregate system throughput. Python REST (Flask) servers deployed on the APs use the local hostapd socket protocol and exposes a JSON interface to the central controller. The central controller is also implemented in Python and uses the scikit-learn linear models package to create models, fit models to data, and finally to predict optimal allocations (throughputs) with the fitted models.

The controller implements the following steps:

1. **Generate candidate set of allocations.** Given the number of APs and STAs available in the system we can enumerate all possible allocation permutations \( (a^s) \). Where \( a \) is the number of APs and \( s \) the number of STAs. To limit the potential candidate set we could filter out allocations that are not balanced, or in the case of two APs are reflections of each other. We could filter the candidate set further by only considering STAs with a traffic volume or SNA above a certain threshold. As an example, if we have two APs and we only want balanced allocations we will have \( \binom{a^s}{2} \) possible allocations. Now, given all these permutations we randomly select a subset. The size of this subset is a configuration parameter. The more samples the more likely the predicted allocation is to improve throughput, but the longer it takes to calibrate.

2. **Create calibration cycle of allocation transitions.** Next, we create a calibration cycle comprised of an ordered list of candidate allocations from the previous set. The goal is to train \( A^2 \) models, where \( A \) is the number of candidate allocations. The calibration cycle starts with training the model \( 0, 0 \), i.e. the observed rates are taken from the first candidate allocation and the throughput is measured in the next time step with the first allocation. All possible transitions are then enumerated while minimizing the overall size of the calibration cycle. This would typically result in a list that has \( A^2 + 1 \) elements.

3. **Train models.** Next, we simply loop through the calibration cycle a given number of iterations, adding one new feature and response pair to each model for each iteration. The number of cycles can be seen as the memory of the models, and again the more cycles the longer the calibration takes, but the more accurate the predictions might be.

4. **Predict next allocation.** After the calibration is done we are ready to start predicting the optimal allocation in the next time step using our models. The currently enforced allocation as well as the STA rates are collected and fed into all the models that have the allocation as the starting state. The model corresponding to the allocation with the highest predicted throughput is then selected and enforced. The newly enforced allocation then becomes the starting state for the next prediction.

5. **Update models.** Every time we make a prediction we also collect the ground truth of the obtained throughput given an observed state with one allocation and an enforced allocation. The model corresponding to this state transition is then updated by simply popping the oldest feature and response pair and adding the new one, to maintain the length of the memory from the calibration. Alternatively and arbitrary memory size may be specified where popping does not start until a threshold is reached. The purpose of that would be to allow predictions before the system is fully calibrated, but the downside is that there may then be an uneven number of training data points (memory) in the different models during an interim period.

The first three steps are typically only done during a bootstrap phase or after there has been a significant change in the stations associated with the APs, and we hence refer to them as the calibration phase.

Now, what happens if a new STA enters the system or an old one drops out? In the first case we could simply ignore the new STA in our models and just have the newly measured throughput be an indirect indicator of a new STA impacting the optimal allocation. However, in that case we cannot move the new STA which may or may not be an issue. Alternatively, we could add the new STA to all the existing trained models and simply add a 0 for the historical rates of the new STA. If a STA drops out the rates would just naturally all become 0 and the impact of the STA in the model will gradually diminish. The STA would however still have a model parameter that consumes computer memory and, hence it could similarly to the new STA at some point also be explicitly deleted from the model. To make this work, we not only keep the fitted model in memory but also the feature and response arrays so we can easily refit modified feature arrays.

## 11 ANALYSIS

To improve our intuition why the proposed method works, we illustrate with the simplest possible case of two APs and two STAs. Let’s also assume that the first AP has higher bandwidth capacity than the first AP, e.g. uses a wider band or a higher frequency.
The total number of permutations is $2^2 = 4$ and the number of balanced allocations are $\binom{2}{2} = 2$. The allocations are $A_1 = 1, 2$ and $A_2 = 2, 1$, i.e. put $s_1$ on $a_1$ and $s_2$ on $a_2$ or $s_1$ on $a_2$ and $s_2$ on $a_1$. The calibration cycle then becomes $[1, 1, 2, 2, 1]$ to capture all transitions and train all four linear models, which are (we remove intercept and error terms for clarity):

$$\begin{align*}
m_{A_1, A_2} &= k_1r_1 + k_2r_2 \\
m_{A_1, A_2} &= k_3r_1 + k_4r_2 \\
m_{A_2, A_1} &= k_5r_1 + k_6r_2 \\
m_{A_2, A_2} &= k_7r_1 + k_8r_2
\end{align*}$$

(2)

where $m_{A_1, A_2}$ is the model predicting the throughput of allocation $A_2$ given rates $r$ observed with allocation $A_1$, and $k$ represents the model coefficients to be fit.

Now, given that $a_1$ has more bandwidth than $a_2$, and that we are currently in a state $A_1$, we can expect that the throughput for $s_1$ would stay the same or drop in a transition to $A_2$, and vice versa, the throughput for $s_2$ would increase or stay the same in a transition to $A_2$.

So if the average observed $r_1$ is higher in state $A_1$ than in $A_2$ then $k_1 > k_3$. Similarly if the average observed $r_2$ is lower in state $A_1$ than in $A_2$ then $k_2 < k_4$. Hence, $m_{A_1, A_1}$ should yield a higher throughput than $m_{A_1, A_2}$ for an observed rate of $r_1$ and $r_2$, and in other words the optimal next allocation is to put $s_1$ on $a_1$ and $s_2$ on $a_2$, which corresponds to intuition.

12 CONCLUSIONS

In summary, we have verified experimentally with real workload traces that different associations of STAs with APs based on transmission rates can improve throughput significantly compared to SINR associations in a dense Wi-Fi network.

A simple linear regression ensemble model shows good performance when learning hidden demand and predicting optimal allocations in future time periods.

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