

# Rogue Access Point Detection Using Innate Characteristics of the 802.11 MAC

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**Abstract.** Attacks on wireless networks can be classified into two categories: external wireless and internal wired. In external wireless attacks, an attacker uses a wireless device to target the access point (AP), other wireless nodes or the communications on the network. In internal wired attacks, an attacker or authorized insider inserts an unauthorized (or rogue) AP into the wired backbone for malicious activity or misfeasance. This paper addresses detecting the internal wired attack of inserting rogue APs (RAPs) in a network by monitoring on the wired-side for characteristics of wireless traffic. We focus on two 802.11 medium access control (MAC) layer features as a means of fingerprinting wireless traffic in a wired network. In particular, we study the effect of the Distributed Coordination Function (DCF) and rate adaptation specifications on wireless traffic by observing their influence on arrival delays. By focusing on fundamental traits of wireless communications, unlike existing techniques, we demonstrate that it is possible to extract wireless components from a flow without having to train our system with network-specific wired and wireless traces. Unlike some existing anomaly based detection schemes, our approach is generic as it does not assume that the wired network is inherently faster than the wireless network, is effective for networks that do not have sample wireless traffic, and is independent of network speed/type/protocol. We evaluate our approach using experiments and simulations. Using a Bayesian classifier we show that we can correctly identify wireless traffic on a wired link with 86-90% accuracy. This coupled with an appropriate switch port policy allows the identification of RAPs.

**Keywords:** Rogue Access Point Detection, 802.11 MAC Protocol, Rate Adaptation, Distributed Coordination Function.

## 1 Introduction

A dangerous insider attack is one where cheaply available APs are illicitly plugged into the network with the motivation of extending connectivity. Like other insider attacks, the AP stays invisible to a firewall as it is actually behind it, thus making it difficult to detect. Hence, the AP creates a back door for attackers, obviating the need to go through the firewall. This paper presents a practical solution for this attack which can happen in one of two scenarios - wired networks *with* or *without* existing legitimate APs.

The core of our detection scheme is an agent sitting atop a switch, or a separate monitoring device that is connected to the mirror port of a switch, that passively sniffs

passing traffic streams on the wired-side. Using inherent differences in wireless characteristics as compared to wired traffic, this agent is able to deem the originating link as being wired or wireless. This inference is then followed up with a switch port AP authorization policy to differentiate between rogue and legitimate APs.

Though some of the existing methods work with proven efficacy, they do not try to exploit the underlying facets of the wireless MAC protocol to detect RAPs, but instead attempt to classify wireless traffic based on the greater delay observed in network statistics (e.g., round-trip-time (RTT), inter-packet arrival time (IAT)). This is based on an assumption that the wireless link capacity will never reach that of wired. A more general solution is needed as this may not always be the case. Also, since many of the previous algorithms need to be trained on both wired and wireless traffic for a given network, they cannot be used in networks without existing APs as there would be no prior wireless trace available.

As in other wired-side detection approaches from academia<sup>1</sup>, in our method we study the arrival pattern of upstream traffic towards the gateway router (and possibly the Internet) for traces of the 802.11 MAC protocol. Though downstream TCP flows are likely to occupy a significant portion of traffic on the link, our approach is not limited in scope. This is because, as will be shown in Section 4.3, our classifier can work with a minimal input trace. It works with an accuracy ranging from 87% to 91% for upstream data inputs of size ranging from 250 packets to 1000 packets respectively<sup>2</sup>. At any given time, there may be various activities that the RAP is used for in a corporate network, such as, web browsing, email, document uploads to file servers, etc. Web browsing contributes varying levels of upstream data - mostly in the form of HTTP requests - depending on the content and the load of requests. When a web site is crawled by visiting, say five URLs recursively, the amount of upstream data generated varies from 75 data packets (for primarily text based web pages like *www.craigslist.com*) up to 400 packets (for relatively graphic intensive web pages like *www.facebook.com*). Further, it takes about 500 packets to deliver an email of size 750Kb and about 1000 packets to upload a file of 1.5Mb (e.g., saving a file to the company file server). Thus, upstream monitoring is a viable option.

Our first approach exploits the collision avoidance process of the DCF in the 802.11 MAC. To avoid collisions while transmitting, a wireless node has to sense the channel prior to an attempt at sending. Once the channel is clear, the node will wait for a random time period (chosen from 0 time units to a fixed upper bound) before attempting to transmit. If the node senses that the channel is occupied, or in case of a collision, the node has to back-off exponentially before retransmitting (i.e., the fixed upper bound increases exponentially, increasing the probability of choosing a higher back-off value). This procedure, carrier sense multiple access with collision avoidance (CSMA/CA), of the DCF has both fixed components and bounded random components that can be artificially produced and used as a signature for wireless traffic.

The second approach exploits the process of rate adaptation in the 802.11 MAC. Rate adaptation algorithms allow wireless hosts to alter their encoding scheme (transmission rate) to account for channel interference during transmission. When interference is detected, the node adapts its rate and transmits at a slower rate in an

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<sup>1</sup> The wired-side approaches will be discussed in Section 2.

<sup>2</sup> Refer to Figure 8, the details of which will be discussed in Section 4.4.

attempt at reducing packet loss. As the rate adjusts (lower or higher), there are noticeable and unique 'jumps' in the packet IAT. These 'jumps' can be artificially produced and used as a signature for wireless traffic.

For both of the above techniques, we show that the signature created stays intact and can be detected on the wired-side allowing us to deem specific traffic as originating from a wireless node.

Each of the two approaches work best in specific cases. The first approach works best when there is little interference and the transmission rate essentially stays constant. Intuitively, the second approach works best when the network is more volatile as more 'jumps' are produced during that period. Since network stability is unpredictable, we combine the two schemes and present a solution that accounts for realistic, unpredictable network conditions.

The remainder of this paper is organized as follows. Section 2 outlines previous work in RAP detection. In Section 3 we briefly illustrate why magnitude-based approaches are not optimal. An introduction to the 802.11 MAC protocol collision avoidance mechanism and a breakdown of the delay induced by it on wireless traffic is presented in Section 4. A mathematical representation is derived from its inherent mechanism following which we validate the model using a Bayesian classifier. A similar pattern of presentation is taken in Section 5 as in Section 4, where we perform an analysis of the manner in which rate adaptation occurs, followed by accuracy measures of our model. In Section 6, we perform a comparative study of the two techniques in an attempt to come up with a bridged solution. We present the scalability of our techniques in Section 7 and conclude in Section 8.

## 2 Related Work

Current work on RAP detection can be classified into three categories. The first two categories contain techniques that use the magnitude of statistics (mean, median, entropy, etc.) of IATs and RTTs as the primary metrics for classification respectively. The third category contains industry work that primarily make use of radio frequency scanning to discover wireless activity within a network.

References [1-6] fall in the first category. Beyah R., et al., [1] were among the earliest to suggest the possibility of using temporal characteristics, such as IATs, for RAP detection. They used the IATs of data packets and TCP ACK packets to identify the type of traffic flow. The authors in [2] take a similar approach as that taken in [1] but extend the work by creating an automated classifier. Wei W., et al., in [3-4] present two similar proposals that examine IATs of TCP ACK pairs to identify the type of traffic flow. However, the use of ACK pairs limits this technique to TCP traffic. A noteworthy effort in the area of traffic classification is [5] which attempts to categorize different types of access links using median and entropy of packet IATs. The approach is however not applicable to detecting RAPs because it is active (requires probing) and requires cooperation (probe responses) from malicious nodes. In [6], the authors create a spectral profile for WLANs based on the entropy of IATs. They assume link quality and unpredictability of the wireless medium as the cause for greater wireless 'uncertainty' and do not study the effect of the DCF.

In the second category, [7-9] make use of RTT as a metric for classification. Since these methods rely on RTT, they cannot accommodate traffic streams other than TCP. Though [7] briefly mentions the effect of the DCF, it does not go into detail to study its mechanics. Reference [8] uses a distinctive approach for segregating network types, complete with traffic conditioning to eliminate noise. However, it demarcates wired and wireless traffic with the help of mean and deviation of the RTT dataset which is not advisable as these parameters differ with varying types, speeds, and congestion levels of networks. Their approach is claimed to be non-intrusive. However, since it involves conditioning of traffic it is still, at minimum, pseudo-active. In [9], although for a disparate motive and in a dissimilar context, Cheng L., et al., were among the first to work on identifying wireless traffic for the purpose of access link type recognition. However, their model employs a probing process to gain information about nodes in the network and thus not likely to be of assistance in the RAP problem space for the same reason that [5], as mentioned above, falls short.

The third category includes several industry solutions [10-17], many of which exhibit non-scalability and limited effectiveness because of the use of either radio frequency (RF) scanning and/or MAC address based authentication. The use of RF scanning is not practical as the malicious user can use directional antennas, can adjust the power of the AP as to not be detected, and in large networks it becomes analogous to finding a needle in a haystack. The use of the MAC address as a parameter for authentication is not appropriate because of the ease of spoofing.

Outside of the three categories, [18-20] propose hybrid frameworks consolidating the above mentioned wired and wireless-side detection models and inherit the flaws from each type.

As previous schemes primarily compare the *relative* behavior of traffic on each link, they require traces of each class of network traffic for their scheme to be effective. This approach is limiting, as a network without existing legitimate APs (e.g., government labs) would not be able to easily provide a wireless trace. Further, because many use threshold-based separation metrics, another limiting assumption made is that wireless networks will always be slower than their wired counterparts. As will be shown in subsequent sections, our method is free of each of the aforementioned assumptions.

### 3 Problem with Magnitude-Based Classification

As mentioned in the previous section, many of the existing works focus on the difference, in some form, of the magnitude of the IAT or RTT to differentiate wireless from wired traffic. In this section, we illustrate, via simulation, the challenge with these approaches as wireless speeds begin to approach that of wired traffic.

Simulations were performed using *ns2* [24]. The cumulative distribution functions (CDFs) of the IAT and RTT values are shown in Figures (1a, 1b) and (2a, 2b) respectively. Figures 1a and 2a illustrate why the magnitude-based approaches work when the assumption is that WLANs are slower than LANs ( $\{IAT_{wl}, RTT_{wl}\} > \{IAT_{wb}, RTT_{wb}\}$ ). However, as shown in Figures 1b and 2b, these schemes will breakdown if the WLAN speed reaches that of the LAN ( $\{IAT_{wl}, RTT_{wl}\} \approx \{IAT_{wb}, RTT_{wb}\}$ ).

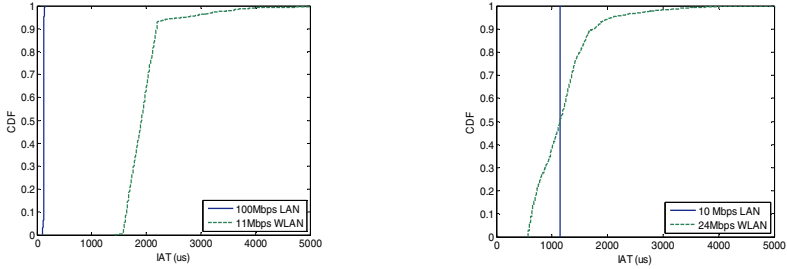


Fig. 1. IAT distribution for (a) slower WLAN, (b) faster WLAN

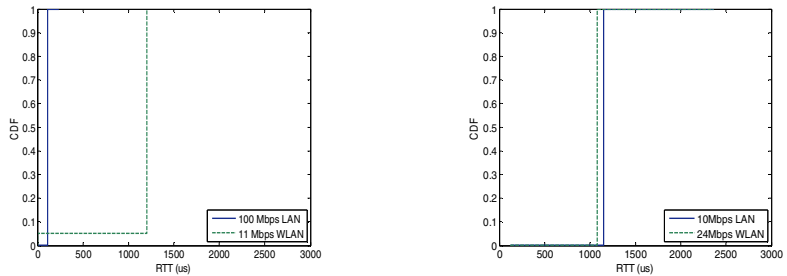


Fig. 2. RTT distribution for (a) slower WLAN, (b) faster WLAN

The results shown in Figures 1 and 2 were obtained from within single trials each of 1000 packets of upstream data for various network type/speeds (LAN - 10Mbps, 100Mbps; WLAN - 11Mbps, 24Mbps). Ethernet and wireless senders were made to send FTP data to a server one hop away on the wired-side. Simulations were performed on a setup similar to the experimental setup that will be described in Section 4.3.

Partially motivated by this argument against threshold based detection, we propose an adaptable solution that makes no assumption about the link speed. In the next section, we introduce our first scheme beginning with an introductory analysis.

### 4 Scheme I – DCF Based Detection

A wireless node’s packet transmission mechanism is regulated by the specifications of the 802.11 MAC layer protocol, the Distributed Coordination Function (DCF). The DCF employs a CSMA/CA distributed algorithm for collision avoidance. In this method, a node that wants to transmit data on a wireless link has to wait for a fixed duration, namely Distributed Inter Frame Space (DIFS) and a bounded random amount of time, called *back-off* ( $\sigma$ ), before using the channel. Upon receiving the data, the node at the other end waits for a fixed period, called the Short Inter Frame Space (SIFS), before answering with a MAC-level acknowledgment (MAC-ACK), and the cycle follows thereon. Further, if the channel is sensed busy or if a collision is detected the originating node backs-off before trying again. The bounded random

delay - Contention window ( $CW$ ) has an exponentially increasing upper bound to reduce the chances of collisions.

Accordingly, the DCF has both fixed components and bounded random components that can be artificially produced and used as a signature for wireless traffic. The process employed for transmission in a wireless medium and the delay between packet arrivals ( $IAT_{wl}$ ) as observed at the receiver are shown in Figure 3.

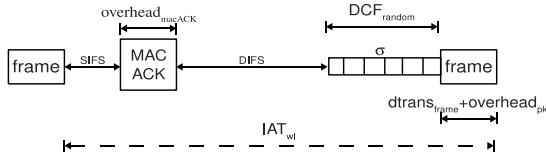


Fig. 3. Illustration of the DCF in 802.11 networks

Drawing from the DCF’s basic mode of operation, we deduce a pattern unique to wireless streams that allows one to anticipate packet arrivals at known intervals. This property enables us to artificially construct packet arrival time series that represent wireless traffic.

### 4.1 Analysis

First, in order to demonstrate the effect of the DCF on the delay, we arrive at representations for the IATs of wired and wireless networks ( $IAT_{wd}$  and  $IAT_{wl}$ ).

In Equations 1 and 2,  $dtrans$ ,  $dprop$  and  $dqueue$  are the transmission, propagation and queuing delays for a network respectively. Since  $dtrans \gg dprop$ , the propagation delay is neglected in our analysis. The queuing delay  $dqueue$  plays an important part in determining the efficacy of wired-side detection. This will be discussed with experimental results in Section 4.3.

$$IAT_{wd} = dtrans_{wd} + dprop_{wd} + dqueue_{wd} \tag{1}$$

$$IAT_{wl} = dtrans_{wl} + dprop_{wl} + dqueue_{wl} \tag{2}$$

$$dtrans_{wd} = dtrans_{frame} + dtrans_{overhead}_{wd} \tag{3}$$

$$dtrans_{wl} = dtrans_{frame} + dtrans_{overhead}_{wl} + DCF_{constant} + DCF_{random} \tag{4}$$

In Equations 3 and 4,  $dtrans_{frame}$  is the transmission time per frame;  $dtrans_{overhead}$  is the overhead incurred in transmitting the packet header in the wired case, and transmitting the packet header and MAC-ACK in the wireless case.

$$dtrans_{overhead}_{wl} = overhead_{pkt} + overhead_{MAC-ACK} \tag{5}$$

Note that  $dtrans_{wl}$  additionally comprises of the waiting time incurred because of the DCF, the constituents of which are shown in Equations 6 and 7.

$$DCF_{constant} = DIFS + SIFS \quad (6)$$

$$DCF_{random} = \sigma \quad (7)$$

The fixed delay element within the DCF contributed delay is a combination of the DIFS and SIFS periods.

The back-off ( $\sigma$ ) is the random period for which the sender has to wait in addition to the DIFS. This is repeated for each unsuccessful transmission attempt. The back-off for the  $i^{th}$  retransmission ( $\sigma_i$ ) is randomly chosen from within the  $CW_i$  which is an increasing function of the number of retransmission attempts and the number of times the channel was sensed as busy by the sender. The DCF uses an exponential algorithm, where for each retry, the  $CW$  size is doubled starting at a lower bound ( $CW_{min}$ ) until a maximum value ( $CW_{max}$ ) is reached.

$$\sigma_i \in (0, CW_i) \quad (8)$$

$$CW_i = \min[2CW_{i-1}, CW_{max}] = \min[2^i CW_{min}, CW_{max}] \quad (9)$$

$$\sigma_i \propto CW_i \propto CW_{min} \quad (10)$$

Hence, arrival times can be predicted as a function of  $CW_{min}$  in the form of a finite random variable. This is an important result which shows that the DCF provides us with an increasing trend for wireless links, one whose base frequency ( $\theta$ ) is given in Equation 11.

$$\theta = 1 / \left( dtrans_{frame} + DCF_{constant} + [0, CW_{min}] \right) \quad (11)$$

Equation 11 forms the basis for our scheme. Specifically, we seek to discover a wireless segment by extracting a basic recurring pattern that exists in all wireless streams. Further, a wireless series can be generated synthetically which spares us from having to train a classifier with real traces.

Since the RAP environment would likely involve a single client node (the malicious intruder), our primary focus is the case where there are minimal collisions as a result of competing traffic in the network, and thus assume that  $\sigma$  varies between 0 and  $CW_{min}$ . We plan to address the scenario where multiple users access the RAP in the future.

This wireless time series is not uniform for different traffic types. In light of Equation 4, it is important to consider two transport protocols - TCP and UDP. Figures 4 and 5 show how the IAT distribution would look for the two different classes.

The frame transmission time for each case would differ as shown in Hypothesis 4.1.

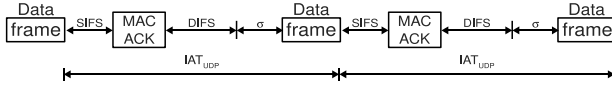


Fig. 4. Packet arrival pattern - UDP

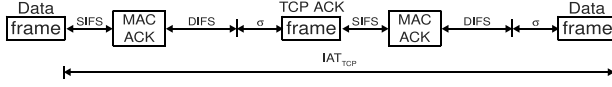


Fig. 5. Packet arrival pattern - TCP

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**Hypothesis 4.1**


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- 1: **if** traffic<sub>UDP</sub> **then**
  - 2:  $dtrans_{frame} = dtrans_{data}$
  - 3: **else if** traffic<sub>TCP</sub> **then**
  - 4:  $dtrans_{frame} = dtrans_{data} + dtrans_{tcpACK}$
  - 5: **end if**
- 

Because of the difference in characteristics, considering an 802.11b network as an example, the transmission delay for the two classes would follow from the information in Table 1 (taken from [21]) as shown in Equations 12 and 13.

This difference must be factored in when modeling the traffic behavior.

$$\begin{aligned}
 IAT_{wl_{UDP}} &\cong dtrans_{wl_{UDP}} \\
 &= DCF_{constant} + DCF_{random} + dtrans_{frame} + dtrans_{overhead_{wl}} \\
 &= DCF_{constant} + DCF_{random} + dtrans_{data} + dtrans_{overhead_{wl}} \\
 &= 60 + \sigma + 1018 + 215 + 10 \\
 &= 1303 + \sigma
 \end{aligned} \tag{12}$$

$$\begin{aligned}
 IAT_{wl_{TCP}} &\cong dtrans_{wl_{TCP}} \\
 &= 2DCF_{constant} + 2DCF_{random} + dtrans_{frame} + 2dtrans_{overhead_{wl}} \\
 &= 2DCF_{constant} + 2DCF_{random} + dtrans_{data} + dtrans_{tcpACK} \\
 &\quad + 2dtrans_{overhead_{wl}} \\
 &= 120 + 2\sigma + 1018 + 30 + 2(215 + 10) \\
 &= 1618 + 2\sigma
 \end{aligned} \tag{13}$$

Note that TCP does not always have to wait for an ACK before transmitting the next packet. In fact, when a node is transmitting TCP traffic with a congestion window size  $W$  greater than one (that is,  $W > 1$ ), it is likely to exhibit UDP-like behavior (in the



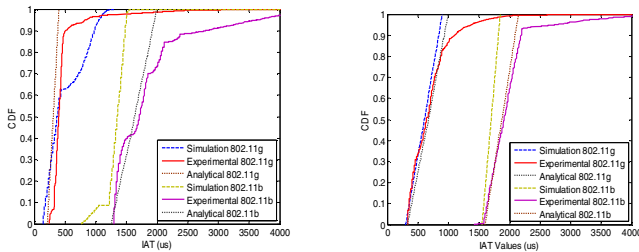
form of multiple sequential packets) except for the time when it is waiting for ACKs. In fact, in the case of upstream TCP traffic to the Internet, a node is highly likely to transmit in bursts. Thus, TCP’s IAT distribution would resemble that of UDP for the most part. Hence, having taken into account the frequency of packet arrivals for both UDP in Equation 12 and the extreme-case TCP (that is,  $W = 1$ ) in Equation 13, our model is scalable for all traffic types.

As part of our groundwork, we used the expression from Equation 4 - which repeats with the frequency shown in Equation 11, combined with the expected values for each type of WLAN (for example, the data from Table 1 was imported for a 802.11b WLAN) to artificially build a profile set. We used values for  $DCF_{constant}$  from the 802.11 standard. Also, we used a pseudo random number generator to emulate  $DCF_{random}$ , where random values were generated from within a range equivalent to the initial  $CW$ , that is,  $(0, CW_{min})$ .

**Table 1.** 802.11b MAC Transmission Overhead

Variable	Parameter	Time ( $\mu s$ )	Formula
$DCF_{constant}$	DIFS	50	$2 * \text{slot time} + \text{SIFS} = 50$
	SIFS	10	SIFS
$DCF_{random}$	Average $\sigma$	310	$(\# \text{ of slots} * \text{slot time})/2 = (31 * 20)/2 = 310$
$dtrans_{frame}$	$dtrans_{data}$	1018	Packet size/data rate = $(1400 * 8)/11 = 1018$
	$dtrans_{TCP-ACK}$	30	TCP-ACK/data rate = $(40 * 8)/11 = 30$
$dtrans_{overhead}$	$overhead_{pkt}$	215	$(\text{Preamble} + \text{PLCP hdr.})/\text{data rate} + \text{MAC hdr.}/\text{data rate} + \text{MAC CRC bits}/\text{data rate} = (144 + 48)/11 + (30 * 8)/11 + (4 * 8)/11 = 192 + 21 + 2 = 215$
	$overhead_{MAC-ACK}$	10	MAC-ACK/data rate = $(14 * 8)/11 = 10$

Figures 6a and 6b display the CDF of the IAT of TCP and UDP flows generated via experimentation and simulation, as well as those constructed artificially using Equations 12 and 13. The figures illustrate how closely the experimental and simulated delay distributions follow the ones artificially created.



**Fig. 6.** (a) CDF of IAT for UDP. (b) CDF of IAT for TCP.

Also from Figure 6b, while more than 90% of the sample set follows a uniform random dispersal over the window size, a fraction of the flow tends to deviate out of bounds. We attribute this to the overhead in the network caused by  $dprop_{wl}$ , possible link-layer retransmissions and packet collisions during transmission.

To arrive at the results in Figure 6, separate TCP and UDP experiments and simulations were performed individually for the 802.11b and 802.11g configurations. For each transport protocol and each WLAN speed setting, 1000 data packets were sent from the wireless client using a socket program to the wired-side server and the IATs were recorded on the wired-side. Correspondingly, the artificial profiles each comprise of 1000 IAT values.

The experiments that produced part of the results in Figure 6 were performed in a lab testbed that will be discussed in Section 4.3. The simulations associated with Figure 6 were performed in a similar setup as the lab testbed using *ns2*.

In this sub-section, we showed that it is possible to independently conjecture how a wireless stream would behave in different types of networks. To demonstrate the accuracy of the technique, a Bayesian classifier is used to compare incoming streams' IAT distributions with the training IAT profile set. The foundation for this classification is presented in the next sub-section.

## 4.2 Classification Scheme

We use a Naïve Bayes classifier which bins the IAT datasets (the artificial profiles and experimental/simulation traces used for the purpose of testing the system), calculates for each dataset the number of occurrences in each bin, compares the bin frequencies of each profile with those of the trace and predicts the trace as being akin to the profile whose frequency distribution closest resembles that of the trace. The Chi-square Goodness of Fit test is employed to determine the fit between each profile and the unknown trace.

The inputs are binned into ' $b$ ' number of bins, where  $b$  depends on the bin width and input data size. For both the bin width and input data size, different values are tried with the goal of optimizing ' $b$ ' to furnish maximum accuracy. Details about these experiments will be discussed in Section 4.4.

Profiles  $f_i$  are compared with an unknown sample  $f_x$  based on the frequency of occurrences in each bin. The Bayes theorem is based on the conditional probability model, where the posterior probability is a function of the prior probability and the likelihood.

Because the nature of incoming traffic cannot be predicted, prior probability is unknown and is assumed equally distributed over the  $n$  profiles.

$$\text{PriorProbability } P(f_i) = 1/n \quad (14)$$

Likelihood (measure of how similar the unknown trace is to a given profile) is calculated for each profile using a two-sample Chi-square test which is run independently on all sample-profile bin frequency pairs.

$$\text{Likelihood } P(f_x | f_i) \quad (15)$$

Posterior probability (measure of how likely a profile is the closest match for the unknown) is calculated as follows:

$$\text{Posterior Probability } P\langle f_i | f_x \rangle = P\langle f_x | f_i \rangle \cdot P(f_i) \tag{16}$$

Since  $f_x$  is a random variable  $\{x_1, x_2, \dots, x_d\}$ ,

$$P\langle f_i | f_x \rangle = P\langle (x_1, x_2, \dots, x_d) | f_i \rangle \cdot P(f_i) \tag{17}$$

$$P\langle f_i | f_x \rangle = P(f_i) \cdot \prod_{k=1}^d P\langle x_k | f_i \rangle \tag{18}$$

Since the prior probability is constant, the posterior probability essentially depends on the likelihood measures. It is derived by aggregating the Likelihood measures, each of which is calculated using the Pearson's Chi-square test. This test estimates the probability that an unknown distribution fits a Chi-square distribution given a null hypothesis. This null hypothesis is rejected (or accepted) based on the probability of the unknown trace's fit to the Chi-square distribution. This probability is determined as a function of the Chi-square statistic which is obtained as follows:

$$\chi^2 = \sum_{i=1}^k \left( (X_i - P_i)^2 / P_i \right) \tag{19}$$

$X_i$  and  $P_i$  are the bin frequencies of bin  $i$  of the two samples to be compared - the unknown and a profile. Note that the profile  $P$  is the null hypothesis. In our case,  $P$  is the synthetically created wireless profile. The Chi-square statistic is calculated over the bin frequencies of  $k$  bins.

### 4.3 Experimental Setup and Validation of Wired-Side Approach

In this sub-section, we discuss: (i) preliminary experiments that were performed to validate the general idea behind our wired-side approach and (ii) the outline of the experimental test plan we used to evaluate the system's accuracy.

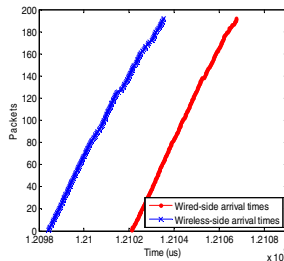


Fig. 7. Packet arrival times on wired and wireless sides

An experimental testbed was built using three Lenovo laptops, three Dell desktops, a Netgear 10/100 Mbps Fast Ethernet switch and a Linksys 2.4Ghz 802.11b-g AP. The laptops were made to connect to a server on the wired-side through the AP and switch. A desktop was set up as a sink server to receive data from both LAN and WLAN senders. The classifier resides on a desktop connected to the switch immediately linking the AP to the LAN.

To ensure that our technique for wired-side detection is viable, we first determined whether the temporal characteristics of the IAT observed on the wireless link were intact on the wired-side. It is important to check if the DCF induced delay is carried over to the Ethernet backbone with minimal additional overhead delay added to it. In a single hop scenario, the overhead is primarily a function of the router queuing delay and processing delay.

The results shown in Figure 7 are a representative sample of the arrival times of about 200 packets extracted from a trace of a total of 10,000 packets of upstream TCP data sent from a wireless-side sender using a socket program to the wired-side server. The arrival times on the wired-side were recorded at the receiver node. On the wireless side, a laptop acting as a sniffer was used in promiscuous mode to capture traffic from the wireless sender. We observed that the arrival rates were retained albeit with a uniformly witnessed lag (as a result of router queuing) as shown in Figure 7.

Given the simple one-hop path from the WLAN to the classifier on the wired-side, a switch with minimal traffic load exhibits a nearly constant queuing delay ( $d_{queue}$ )<sup>3</sup> which is illustrated by the nearly fixed distance between the lines in Figure 7. In Section 7, we discuss how the model scales to networks where the classifier is placed several hops away from the AP.

#### 4.4 Accuracy Measures

Having visually shown why it is likely that the packet IAT from the wireless side is carried over to the wired-side, we evaluate the scheme's accuracy in extracting the DCF imposed delay to determine the packet's originating link.

First, we tuned the bin width and input data size to find the optimal pair - one that maximizes True Positive Rate (TPR) and minimizes False Positive Rate (FPR). This is followed by additional testing with the chosen optimal parameters to obtain the system accuracy.

The classifier was tested on traces from both wired and wireless TCP/UDP data transfers. Sample trials on the LAN were used to measure the FPR and trials on the WLAN to measure the TPR. Trials were performed on the WLAN for both 802.11b and 802.11g specifications by configuring the AP to operate in the required mode. For each network type (WLAN/LAN) and protocol (TCP/UDP), 50 sets of data were fed into the classifier. The detections from the 50 trials were used in determining TPR/FPR measures for the classifier. This process was repeated for different bin width and input data size combinations. The results shown in Figure 8 are an average of the results from the TCP and UDP trials.

An optimal bin width of  $500\mu s$  and input size of 1000 packets were chosen, as the pair gives the minimum FPR of 2% and maximum TPR of 91%. On testing the system

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<sup>3</sup> Refer to Equations 1 and 2 for the definition and Section IV.A for a discussion on  $d_{queue}$ .

with the chosen parameters (Bin width = 500us, Input size = 1000 packets, and FPR = 2%) for a total of 10 additional trials, it was observed that the technique is accurate in detection approximately 92% of the time for UDP and 89% of the time for TCP traffic, as can be seen from Figure 9.

In the RAP attack scenario, the attacker would likely often hop on the connection for short bursts of time to avoid detection. Given the attacker's short-lived stay online, it is important that the classifier be able to work on a minimum amount of data. Also, considering the relatively negligible portion of WLAN traffic occupied by upstream data (in comparison with TCP downstream data), the classifier might not have much to work with and hence, must be trained accordingly.

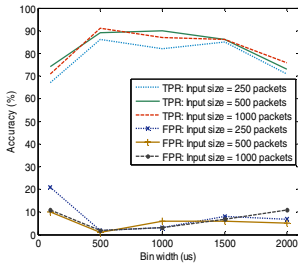


Fig. 8. Parameter tuning

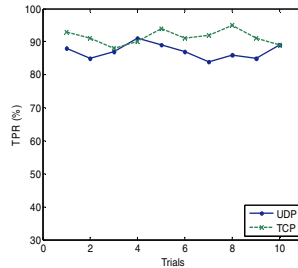


Fig. 9. TPR for chosen bin width and FPR

Each input data size may correspond to different application data on the RAP because each application (e.g., web browsing, email, file upload) contributes different amounts of upstream traffic to the classifier. Accordingly, the results shown in Figure 8 provide a sample of the system's accuracy for different classes of applications - each pertaining to a different input size. For a bin width of 500us, the system exhibits maximum accuracy that ranges from 87% to 91% for input sizes varying from 250 packets to 1000 packets. As a result, the attacker is slightly more likely to be detected if he were uploading a file of 1Mb than if he were reading the news at say, *www.cnn.com*, because the former would contribute the sufficient amount of data faster than the latter.

In this section, we discussed our first scheme of detection. In this method, our classifier is trained artificially on IAT signatures individually for different network speeds and different transport protocols for both the LAN and WLAN. We also showed the accuracy measures from lab experiments. This scheme is optimal when there is no interference on the channel and the link is stable. As will be shown in Section 6, its performance degrades as rate adaptation occurs in response to poor link quality. Therefore, in the next section we present a scheme that thrives during rate adaptation.

## 5 Scheme II – Rate Adaptation Based Detection

The 802.11 MAC protocol provides wireless entities with the ability to change their encoding scheme (data transmission rate) when the need arises. Using automatic rate fallback (ARF), when a node reaches a threshold of not receiving MAC-layer ACKs,

it reduces its rate to one that corresponds to a stronger encoding algorithm in order to ensure more robust transmission.

As shown in [21], rate adaptation occurs regularly in WLANs because signal and link-layer interference are common phenomena. Given that rate adaptation occurs regularly, we seek to exploit this property that is specific to wireless streams to distinguish them from their wired counterparts. Particularly, the switching of the physical-layer data rate creates a variation in throughput and packet delay in a wireless transmission that is rarely found in wired traffic. We exploit the unique behavioral characteristics at the time of rate switching to identify wireless traffic.

In this section, we first examine the behavior of the IAT during switches in data rate. Based on this, we derive an artificial profile for the IATs during such shifts in data rate. The artificial profiles are incorporated into a classifier, which is then evaluated for accuracy.

### 5.1 Analysis

In this sub-section, we illustrate the effect of rate adaptation on a series of packets. Specifically, we show that there exists an IAT pattern that is exhibited only during rate adaptation and not when a pair of successively transmitted packets is sent at a constant physical layer data rate.

First, we visually illustrate how rate adaptation alters the arrival periods of packets transmitted at different data rates. Figure 10 is an example representation of the expected packet arrival sequence for a sample wireless transfer. In Figure 10, note that the IATs vary for each rate  $R_i$  because slower rates trigger greater packet delays.

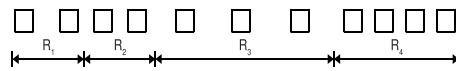


Fig. 10. Packet arrivals during rate adaptation

The probability  $P_i$  of the event  $R_i$  occurring depends on what we call the *channel interference index* ( $\Omega$ ) which has a range  $\{0 \leftrightarrow 1\}$ .

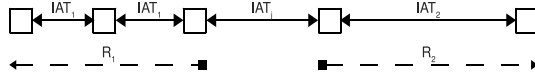
$$IAT_{wl} = \sum_i IAT_i P_i \tag{20}$$

$$\begin{aligned} \text{If } (i < k \wedge \Omega \rightarrow 0) P_i &\leq P_k \\ \text{If } (i < k \wedge \Omega \rightarrow 1) P_i &\geq P_k \end{aligned} \tag{21}$$

In other words, the probability of occurrence of a lower transmission rate (in Equation 21, rate  $i$  is lower than rate  $k$ ) is inversely proportional to signal interference and collisions. Our model safely assumes that the measure of interference  $\Omega$  is not known prior and hence  $P_i$  is unknown.

This being the case, unlike Scheme I which assumes minimal to no rate adaptation, we choose to focus not on sets of  $IAT_i$  (that is, the IAT of two packets transferred at same rate) but instead on  $IAT_j$  (that is, the IAT of two packets transferred at different rates).

Having abstractly shown the influence of rate adaptation on the IATs and having settled on the idea that the inference model should be based on the IAT behavior during the transition in data rate ( $IAT_j$ ), we proceed to study  $IAT_j$ .



**Fig. 11.** IAT pattern during a rate switch

As shown in Figure 11,  $IAT_j$  is the delay during the ‘jump’ from one rate to the next. Note that in Figure 11,  $IAT_j$  is of a different magnitude than  $IAT_i$ , where  $IAT_i$  is the IAT during rate  $R_i$  and  $i = \{1,2\}$ . Accordingly, in our classifier, we associate  $IAT_{wl}$  with  $IAT_j$ . To determine which link type the test data (that exhibits  $IAT_x$ ) belongs to, we use the basic premise given in Hypothesis 5.1.

To illustrate the behavior of the jumps, an initial set of experiments were performed on an 802.11b WLAN; IATs for packet pairs transmitted at the same rate as well as different rates were extracted. In the absence of notable real channel interference, to simulate rate adaptation in a simple lab testbed, the experiments were performed in the presence of a running microwave. A laptop was used as a sniffer on the wireless-side to collect the data rates corresponding to the packets within a transmission.

A sample of the IATs from a two minute upstream data transfer is shown in Figure 12. Although the interference resulting from the microwave usage was strong enough to invoke rate switches down to 2Mbps and sometimes 1Mbps, for the purpose of the current argument, the aggregated IATs of packets transmitted at 11Mbps, 5Mbps and

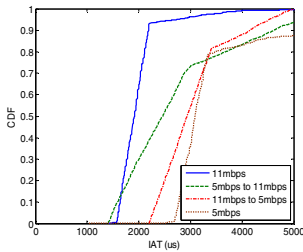
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**Hypothesis 5.1**

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- 1: if  $IAT_x \approx IAT_j$  then
- 2: Report *Wireless*
- 3: else
- 4: Report *Wired*
- 5: end if

---



**Fig. 12.** IAT behavior during a rate switch – TCP

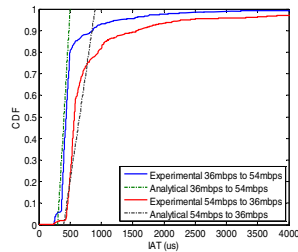
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**Hypothesis 5.2**

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- 1: if  $R_i < R_{i+1}$  then
- 2:  $IAT_i > IAT_j > IAT_{i+1}$
- 3: else
- 4:  $IAT_i < IAT_j < IAT_{i+1}$
- 5: end if

---



**Fig. 13.** TCP Analytical vs. Experimental Signatures – 802.11g WLAN

packets transmitted immediately after changes in data rate both ways are the only IATs shown in Figure 12.

It can be seen in Figure 12 that the IAT distributions of the jumps fall in between those of the stable rate phases before and after. This leaves us with Hypothesis 5.2.

The rationale behind this (as shown in Figure 14) is that during the transition from  $R_1$  to  $R_2$ , the MAC-level ACK is transmitted at  $R_1$  and the subsequent data frame at  $R_2$ . That is, a node which decides to reduce its data rate transmits the next data packet at the new rate but the MAC ACK for the previous data packet would still be sent from the AP at the old rate. Also, as can be seen from Figure 12, because of the difference in frame and MAC ACK sizes, the IAT distribution during the jump ( $IAT_j$ ) is biased towards that corresponding to the rate following the jump. That is, since the frame size  $\gg$  MAC ACK size and because the data frame is sent at the new rate,  $IAT_j$  is closer to the IAT associated with the new rate.

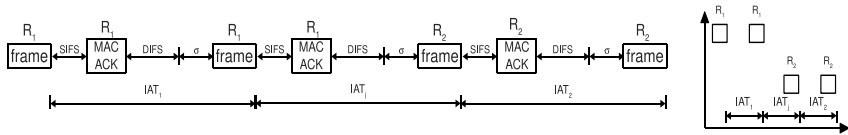


Fig. 14. DCF behavior during a rate switch

This difference in behavior during a rate switch can be exploited by studying how it reflects on individual delay components of the corresponding IATs, as shown below:

$$dtrans_{wl(1,2)} = dtrans_{frame(1,2)} + DCF_{constant} + DCF_{random} + overhead_{MAC-ACK(1,2)} + overhead_{pkt(1,2)} \tag{22}$$

$$dtrans_{wl_j} = dtrans_{frame_2} + DCF_{constant} + DCF_{random} + overhead_{MAC-ACK_1} + overhead_{pkt_2} \tag{23}$$

Using Equation 23 as the base for our synthetic profiles, substituting jump-specific  $dtrans_{frame}$  and  $dtrans_{overhead}$  values, our classifier can be trained as shown in Figure 13. Similar to the synthetic IAT profiles shown for the (36Mbps, 54Mbps) pair in Figure 13, multiple such *jump* signatures were constructed for different data rate pairs as training sets for the classifier. Additionally, the training sets included IAT signatures for 10Mbps and 100Mbps LANs.

### 5.2 Classification Scheme

The classifier used for this method is similar to the one explained in Section 4.2, with appropriate changes made to incorporate the fact that only the IAT values during *jumps* in rates are considered for training and testing as opposed to the values during a stable rate period. In the Bayesian classifier, instead of comparing the entire trace of IAT readings with the profiles, individual values are inspected for possible *jumps*. That is, a comparison of two datasets (training and testing sets) is not required;



instead, it is sufficient to check individual incoming IAT values to see which IAT jump signatures they are closest to.

### 5.3 Experimental Setup and Validation of Wired-Side Approach

The experimental setup used to validate the scheme is similar to that used for Scheme I discussed in Section 4.3. As in [21], we use a synthetic means (microwave interference) to force rate switching to investigate Scheme II. One of the laptops is used as a sniffer on the wireless side, while another laptop is used to transfer data to the wired-side desktop sink server.

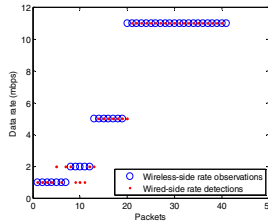


Fig. 15. Rate detection on wired and wireless sides

To determine whether a node is switching rates when capturing packets on the wireless side is simple, as its physical layer header contains the actual transmission rate. However, the rate in the wireless frame is not carried over to the wired-side. Accordingly, on the wired-side, we have to infer the rate by observing the packets' IAT pattern. We verified that this approach is viable by capturing traffic both on the wireless-side and the wired-side, and comparing the data rate observations made on the wireless-side with the data rate predictions made by the classifier on the wired-side. We observed packets that switch rates on the wireless side with a laptop acting as a sniffer capturing promiscuously (by looking at the *radiotap* header in the wireless frame) and concurrently on the wired-side by feeding captured IATs of the same packets into the classifier. From this, we were able to determine that specific IAT values on the wired-side correlated to confirmed rate adaptations on the wireless side.

Figure 15 gives a representative sample of the rates of the packets extracted on the wireless side and the rates inferred by the classifier on the wired-side, illustrating the correlation of rates of the same packets observed at both points. A total of 6000 upstream TCP data packets were transmitted with 81% of the rates predicted correctly. It is important to note that though the accuracy of classification of the data rates on the wired-side was 81%, the classifier is accurate in access link type classification up to an average TPR of 97% for UDP and 91% for TCP (refer to Figure 18). This is because even the IATs corresponding to the incorrectly inferred rates are closer to the synthetic *jump* IAT profiles that the classifier was trained on as opposed to the Ethernet IAT signatures.

The accuracy measures of the classifier used to test Scheme II are shown in the next sub-section.

## 5.4 Accuracy Measures

As in Scheme I, to validate the system, the bin width used in the Bayesian binning approach was first tuned to determine an optimum value for the classifier. Note that Scheme II operates independent of the input size as it does not compare the dataset as a whole with the profiles and instead studies the input trace a packet at a time.

For each bin width, ten trials were performed, in each of which the classifier was tested on TCP/UDP data packet pairs of upstream Ethernet and WLAN traffic. TPR/FPR were generated as a function of the fraction of the input trace accurately classified each time (Figure 16).

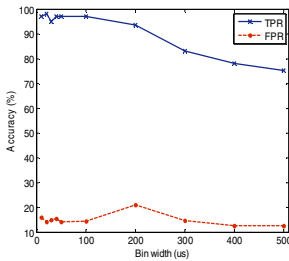


Fig. 16. Bin width tuning

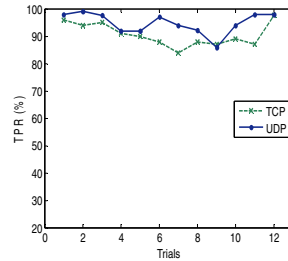


Fig. 17. TPR for chosen bin width and FPR

In order to optimize the effectiveness of this technique, we calculate what we call the Effective Accuracy and find the optimum value that maximizes this difference between TPR and FPR in an attempt to make a balanced trade-off between the two metrics. For the chosen parameters (Bin width =  $20\mu\text{s}$  and FPR = 14%), 12 additional trials are run to observe the TPR distribution (Figure 17).

Note that the accuracy measures shown in Figure 17 hold for WLANs with considerable rate adaptation. As will be shown in the next section, the accuracy of this scheme increases as a function of the amount of interference on the network and thus the method is not suitable for networks with minimal rate adaptation. In the next section, we propose a technique that bridges the strengths of the two schemes discussed so far in an effort to arrive at a comprehensive solution for normal networks (i.e., networks with varying levels of interference).

## 6 Consolidated Model

While Scheme I compares input sample traces as a whole with each of the profiles, Scheme II checks individual packet pairs within a trace for a switch in data rate. This implies that since the input sample trace to be compared may encompass several rates, Scheme I's accuracy is likely to subside with increased rate adaptation. Conversely, Scheme II will not accurately classify wireless traffic in the absence of a minimum degree of rate adaptation.

### 6.1 Analysis

In an effort to present a general solution that works both when the link is stable as well as when rate adaptation occurs, we revisit the *channel interference index* ( $\Omega$ )<sup>4</sup> defining it as follows:

$$\Omega \propto \frac{Accuracy_{SchemeII}}{Accuracy_{SchemeI}} \tag{24}$$

Equation 24 essentially captures the inverse relationship between Schemes I and II. Scheme I works better when there is little to no interference, while Scheme II works better during interference. Thus, it is important to consolidate the pros of the two approaches in a way that the resulting system is effective regardless of the link stability.

### 6.2 Classification Scheme

To combine the two schemes, we partition the input data set into blocks of a constant size with the expectation that each block will be comprised of data at a specific rate. Of course this need not be the case. So, in addition to this, we exploit the fact that Scheme I detects the access link types of stable rate periods well and Scheme II detects the *jumps* well. For the combined solution, the input trace is fed into the classifier one block at a time. Scheme I contributes the network type/speed observation for each of the partitions and Scheme II points out where two stable rate periods intersect (that is, the *jumps* in data rate), the aggregation of which gives us the temporal distribution of rates for a series of packet pairs. This technique is illustrated in Figure 18, where *x* and *y* are the inferred data rates. Based on the inferred rates, the combined scheme determines the access link type of the individual partitions. The final access link type classification decision for the whole block of data is made as a function of the WLAN-to-Ethernet classification ratio of individual partitions. That is, the classifier decides between WLAN and Ethernet based on which link type is classified in majority of the partitions. The general idea behind this unified model is that if one of the two schemes fail, a healthy net effect is maintained as the other scheme chips in.

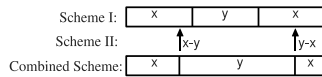


Fig. 18. Depiction of combined scheme

### 6.3 Experimental Setup

The experimental setup used to test the first two schemes is employed to validate the combined scheme. A block size of 250 packets is chosen. Accordingly, in our experiments, each input trace of 1000 packets is partitioned into four blocks of 250 packets each.

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<sup>4</sup> Note that this metric was previously introduced in Section V.A.

In the next section, we evaluate the accuracy of the combined scheme (in comparison with that of the first two schemes) as a function of  $\mathcal{Q}$  by testing against data sets that differ in the number of times rate adaptation is invoked.

#### 6.4 Accuracy Measures

The accuracy measures of the consolidated system (in comparison with those of the other two schemes) are shown in Figures 19.

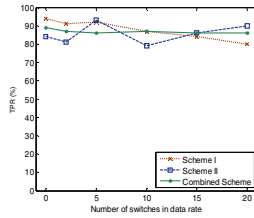


Fig. 19. Scheme accuracy comparison

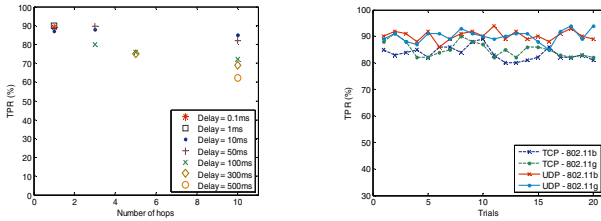
A total of 14 trials were performed to assess how the TPR varies with an increase in the degree of rate adaptation. This testing set comprised of 2 trials each for the 7 different degrees of rate adaptation. The degree of rate adaptation is devised as a function of the number of switches in data rate invoked within the 1000 packet input data set. Figure 19 shows the results of such experiments performed individually for each of the three schemes. Results shown in Figure 19 are an average of the outcomes from separate TCP and UDP trials. Note that the combined scheme's accuracy is not as high as that of Scheme I. However, this technique is nonetheless effective and unlike the initial two schemes, the combined technique is realistic as it makes no assumption about the link quality.

## 7 Measure of Robustness and Scalability

In this section, we discuss how the system's performance scales to larger, more realistic networks. We evaluate the system's scalability in two scenarios - (i) a network where the classifier is placed multiple hops away from the AP via simulation, and (ii) a real network (as opposed to a lab testbed).

First, to test the combined scheme's scalability as a function of the classifier's distance from the AP, simulations were performed where detection takes place several hops upstream instead of the switch immediately connecting the AP to the LAN. This is important because the AP to be detected may not always be one hop away from the classifier node. We consider the effect of different fixed access-link and bottleneck delays at each hop, including the best-case ( $1ms$ ,  $10ms$ , and  $50ms$ ) as well the worst-case ( $300ms$  and  $500ms$ ) delays. The measurements observed indicate that despite a decrease in accuracy with an increase in the distance, the system averages a worst-case accuracy of above 60%, average-case accuracy of above 75% and best-case accuracy of

above 85% (Figure 20a). The results shown in Figure 20a were obtained from simulations done using *ns2* and varying the number of hops between the AP and the classifier node. The TPR measurements shown in the figure are an average of results from 10 trials - each of 10,000 upstream data packets - performed separately for each delay value and tested individually for a given number of hops. The 10 trials comprised of 5 TCP and 5 UDP trials. The trace of 10,000 packets in each trial was fed into the classifier 1000 packets at a time.



**Fig. 20.** Multi-hop accuracy: (a) Simulation, (b) Experiment

Next, we conducted experiments on a real network to arrive at the accuracy measures of the classifier when tested with traces from a real environment. Trials were performed on a multi-hop fiber-optic university backbone. A wireless node was made to connect via an AP from a classroom building to the wired-side server three blocks away in the Computer Science Department. The accuracy of the combined scheme was measured over a total of 20 trials performed individually for TCP/UDP data transfers and for 802.11b/g network configurations. In each trial, the classifier was tested on a 10 minute long trace for TPR measures. As shown in Figure 20b, the classifier is accurate up to approximately 90% of the time for UDP and 85% of the time for TCP.

## 8 Conclusion and Future Work

The proposed method detects RAPs by extracting characteristics unique to a wireless stream from network traffic. It makes use of two 802.11 MAC specifications to fingerprint wireless attributes from the wired-side making the process simple and scalable.

In this paper, we have studied the working and validated the accuracy of our detection techniques in several environments. This method is immediately deployable and is shown to scale well to realistic scenarios outside of a lab testbed. In the future, we will continue in this direction and further test the system for robustness to other use cases.

We plan to extend this work by scaling it to networks of greater traffic density by taking into consideration the effect of collisions in the network as a result of multiple users on the RAP. To this end we will study various error models and incorporate the traffic behavior during each of these into our design. Further, we intend to study the effect of link delay on the accuracy of the system in an attempt to derive a metric that the classifier shall be tuned for when placed multiple hops away from the AP. Also,

we will test the system's robustness using different real network traces from publicly available archived sources (e.g., CRAWDDAD).

Further, looking ahead in RAP detection, we must assume that the misfeasor could be tech savvy and aware of RAP defenses. To this end, we will analyze possible options that an attacker has to evade detection by cleverly altering his transmission pattern. Threat strategies that an attacker may employ include reducing or increasing his packet delay and interleaving his wireless transmissions with other types of traffic to bypass the classifier's signatures. Note that the DCF parameters can be manipulated in open source 802.11 drivers.

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