Packet Dispersion in IEEE 802.11 Wireless Networks

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Abstract—
Packet dispersion techniques have been commonly used to estimate bandwidth in wired networks. However, current packet dispersion techniques were developed for wired network environments and can provide inaccurate results in wireless networks due to wireless capacity variability over short time scales. This paper develops an analytical model to investigate packet dispersion behavior in wireless networks. The packet dispersion model is validated using both an extended ns-2 simulator that includes 802.11 MAC layer rate adaptation and wireless 802.11b testbed measurements. Utilizing the model, this study shows that packet dispersion measures *effective capacity* and *achievable throughput* of wireless networks instead of the maximum capacity as in wired networks. Additionally, mean and variance of packet dispersion in IEEE 802.11 wireless networks is analyzed while considering the impact of channel conditions such as packet size, link rate, bit error rate and RTS/CTS.

I. Introduction

Active bandwidth estimation involves end-host metrics such as capacity, available bandwidth and bulk TCP transfer rate without accessing intermediate routers along the flow path. Internet applications such as peer-to-peer file sharing, overlay networks, Content Distribution Networks (CDN) and multimedia streaming can benefit from accurate bandwidth estimation [1]. However, because current estimation mechanisms were originally developed for wired networks, they can yield inaccurate results in wireless networks where environmental conditions cause wireless capacity variability over short time scales. Wireless mechanisms such as retries with random backoff and dynamic rate adaptation cause bandwidth estimation errors when channel conditions include low reception signal strength or high bit error rate (BER) due to path loss, fading, interference or contention.

The differences in wired and wireless packet dispersion are the major source of wireless bandwidth estimation errors. Thus, reducing measurement errors and improving performance in wireless local area networks (WLANs) requires a better understanding of packet dispersion in wireless networks. While many research models have been developed for wireless networks, few consider WLAN bandwidth estimation. Moreover, current research tends to focus on simplified conditions such as fixed wireless capacities or error free wireless networks [2] to create tractable models. While previous research [3] has demonstrated the impact of IEEE 802.11 packet size and rate adaptation on bandwidth estimation tools, it is difficult to improve the bandwidth estimation tools without an in-depth model of wireless packet dispersion. Therefore, this investigation puts forth both an analytic and a simulation model for WLANs that includes packet dispersion under conditions such as channel contention, fading, BER and dynamic rate adaptation. The analytical model captures WLAN packet dispersion behavior to study the impact of such channel conditions and wireless configuration parameters such as packet sizes, link rate and RTS/CTS on the mean and variance of bandwidth estimation results. Using the packet dispersion model, two wireless packet dispersion measures, *effective capacity* and *achievable throughput* are introduced. This paper also shows that in a saturated WLAN a fluid flow model is not applicable because of the probability-based fairness for channel access across WLAN nodes. The packet dispersion model is validated using network measurements in a wireless 802.11b testbed and an ns-2 simulator modified to include dynamic rate adaptation in the face of challenging environmental conditions. Armed with analytic models, simulation tools and network measurements, this paper is a preliminary study of bandwidth estimation techniques based on a WLAN using packet dispersion and provides insight into possible improvements to WLAN bandwidth estimation techniques.

The paper is organized as follows. Section II summarizes related work in bandwidth estimation using packet dispersion techniques and wireless network modeling. Section III discusses bandwidth estimation in wireless networks and rate adaptation and fading extensions to ns-2. Section IV provides a packet dispersion model for IEEE 802.11 networks. Section V uses the model to analyze packet dispersion issues in wireless networks. Finally, Sections VI presents conclusions and possible future work.

II. Bandwidth Estimation Techniques

Bandwidth estimation techniques focus on end-to-end network capacity or available bandwidth. Capacity, the maximum possible bandwidth that a link or end-to-end path can deliver [1], is usually determined by sending Maximum Transmission Unit (MTU)-sized packets through the IP layer. Available bandwidth, the maximum unused bandwidth at a link or on an end-to-end flow path, is a time-varying metric [1] that depends on link rate and the traffic load. While current active bandwidth estimation techniques include Variable Packet Size (VPS) probing [4], [5], Packet Dispersion, Self-loading Probing [6], [7] and Probe Gap Model (PGM) [8], this investigation focuses on packet dispersion, one of the most simple and mature bandwidth estimation techniques, for wireless networks.

Packet dispersion techniques, including packet pair and packet trains, measure the end-to-end capacity of a network path [9], [10], [11]. Subsequent research and tools, such as *bprobe/cprobe* [12], *nettimer* [13], *pathrate* [14], and *CapProbe* [15] provide enhancements on the basic packet dispersion technique.

Packet pair dispersion sends two equal-sized packets back-to-back into the network. After traversing the narrow link, the time dispersion between the two packets is linearly related to the link with the least capacity.[1] Packet train dispersion extends packet pair dispersion by using multiple back-to-back probing packets. However, the concepts for a packet train are similar to that of a single packet pair.

Figure 1 [1] illustrates the packet dispersion concept. When packets of size L with initial dispersion Δ_{in} go through a link of capacity C_i, the dispersion after the link Δ_{out} becomes [1]:

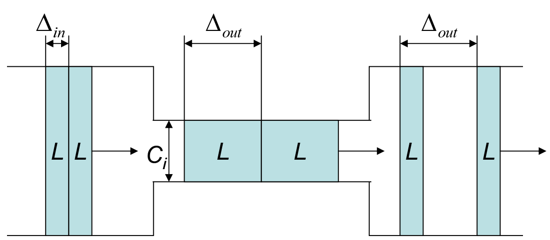

Fig. 1. Packet Dispersion

$$\Delta_{out} = \max(\Delta_{in}, \frac{L}{C_i}) \quad (1)$$

After packets traverse each link on an H hop end-to-end path, the final dispersion Δ_R at the receiver is:

$$\Delta_R = \max_{i=0,\ldots,H}(\frac{L}{C_i}) = \frac{L}{\min_{i=0,\ldots,H} C_i} = \frac{L}{C} \quad (2)$$

where C is the end-to-end capacity. Therefore, the end-to-end path capacity can be estimated by $C = L/\Delta_R$.

Since packet dispersion provides faster measurement times and induces less network load than other bandwidth estimation techniques, it has been adopted by commercial applications such as Windows Streaming Media where a three-packet train is sent prior to streaming to estimate end-to-end capacity.

III. Packet Dispersion Issues in Wireless Networks

A. Rate Adaptation Simulation

While ns-2[2] provides IEEE 802.11 components such as CSMA/CA, MAC layer retries, contention, propagation and error models, it lacks a rate control algorithm (RCA). Since the 802.11 standard [16] does not specify a specific RCA, each WLAN card manufacturer is free to implement their own RCA. RCAs adjust link rate based on the signal strength or by reacting to accumulated statistics, such as number of retries, packet error rate or throughput [17], [18]. Auto Rate Fallback (ARF) [19], the first commercial RCA implementation, raises the data rate after consecutive transmission successes and lowers the date rate after link layer transmission failures. Under most wired channel conditions, ARF outperforms fixed-rate 802.11, but when transmission failures are caused by wireless link layer congestion, ARF can have a negative impact [20].

Receiver Based Auto Rate (RBAR) [21] uses RTS frame analysis to measure channel quality. RBAR receivers determine the highest feasible frame transmission rate that channel conditions can tolerate and notify the sender of the chosen rate via a CTS frame. Since RTS/CTS messages are sent to the AP, all wireless nodes become aware of the new transmission rate and set their backoff timers accordingly. However, RBAR is not available in basic mode where RTS/CTS is disabled.

Starting with an RBAR simulation module provided by [22] for ns-2 2.1b7,[3] RBAR was re-implemented in NS 2.27. We extended the physical layer parameters using the specifications of the Lucent OriNOCO wireless PC card.[4] Our documented RBAR implementation is available online[5]. Figure 2 provides ns-2 throughput results versus separation distance for two simulated wireless nodes moving away from each other. Average throughput is measured using 1000-byte packets for a single CBR flow with RTS/CTS enabled. The fixed-rate approaches (1, 2, 5.5 and 11 Mbps) have a relatively fixed throughput as the distance increases until the link is dropped when the nodes move out of transmission range. RBAR (labeled "Multiple Rate") dynamically adjusts the rate downward as distance increase.

To more accurately simulate physical condition effects on RCAs, an additional ns-2 extension to model Ricean (or Rayleigh) fading [23] was implemented and imported into NS 2.27. Figure 3 shows simulated effects of Ricean fading for two wireless nodes 390 meters apart where with fading turned off RBAR would fix the data rate at 11 Mbps. The figure tracks RBAR dynamically adjusting the rate between 11, 5.5, 2 and 1 Mbps in response to fading strength variability as a function of time.

B. Issues with Packet Dispersion in Wireless Networks

This section discusses physical layer wireless issues that may cause bandwidth estimation techniques to perform poorly.

Most wireless MAC layers use frame retries or Forward Error Correction (FEC) to recover lost frames. IEEE 802.11 networks retransmit up to a fixed number of times with exponential backoff between retransmissions. While frame retries reduce packet loss, frame retries increase packet delay variance that yields packet dispersion inconsistencies and large variations in time measurements. Namely, dispersion between packet pairs can be compressed or expanded when traversing a wireless AP even without congestion in the network.

Figure 5 depicts a typical network topology for studying packet dispersion in a WLAN. To characterize the effects of wireless traffic on packet dispersion, the wireless network traffic is divided into probing, crossing and contending traffic. *Probing traffic* is the packet pairs or trains sent along the estimated network path through the AP to the client (1). Wireless channel conditions and other traffic may vary the probing traffic dispersion behavior and produce estimation errors.

While *crossing traffic* does not contend with probe packets, crossing traffic does share the bottleneck and thereby strongly impacts bandwidth estimate accuracy on the WLAN. Figure 5 shows crossing traffic coming from the AP to associated clients

[1] Also called the *narrow* link.
[2] The Network Simulator - ns-2. Online at http://www.isi.edu/nsnam/ns/
[3] Downloadable from http://www-ece.rice.edu/networks/.
[4] http://www.agere.com/client/wlan.html
[5] http://perform.wpi.edu/downloads/#rbar

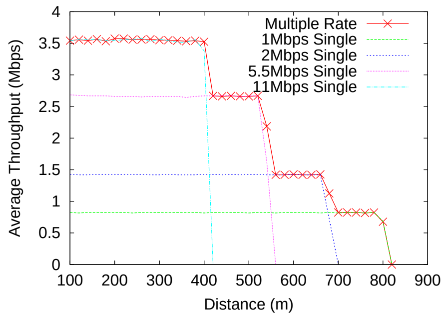

Fig. 2. Throughput comparison as distance increases

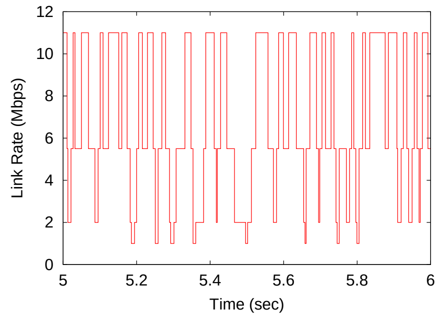

Fig. 3. Link rate adaptation under Ricean fading

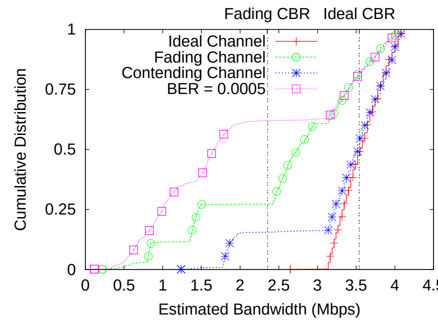

Fig. 4. Capacity estimation using packet Pair techniques in a WLAN

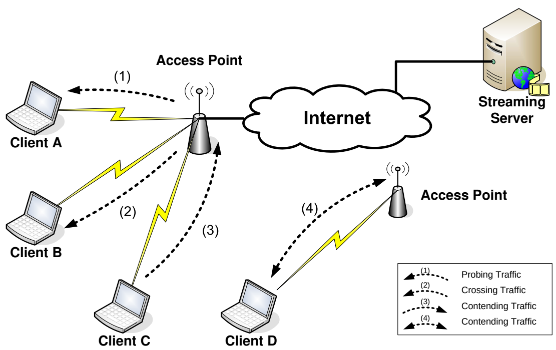

Fig. 5. Probing, crossing and contending traffic in a WLAN

(2). After subtracting contending effects from other wireless traffic, wireless crossing traffic shares the bandwidth with the probing traffic. However, even though statistically contending effects caused by crossing traffic indirectly impact bandwidth estimates, this impact can be captured by packet dispersion techniques. Since several statistical filtering methodologies have been proposed to mitigate the effects of cross traffic [12], [14], crossing traffic effects in WLANs are not considered further in this paper.

Contending traffic accesses the shared wireless channel and competes with probe packets on the estimated path. Figure 5 shows contending traffic sent by clients to the same AP (3) and between other clients and APs (4) within interference range (referred to as co-channel interference). To avoid channel capture, 802.11 uses random backoff between two successive packets from the same node. When packet pairs arrive back-to-back at the AP, the AP delays the second packet by inserting a random backoff time between the packets. Thus, bandwidth estimates using packet dispersion on 802.11 networks are vulnerable to contending traffic that transmits during the delay between the two packets and further delays the second packet in the pair.

Dynamic rate adaptation impedes bandwidth estimation methods because these techniques assume a fixed capacity during the measurement. Figure 3 shows WLAN capacity varying frequently under bad channel conditions. Hence, wireless bandwidth estimation changes with the same granularity. Figure 4 uses ns-2 wireless simulations with RTS/CTS enabled to illustrate the impact of network conditions on packet pair estimation techniques. Each simulation sends continuous packet pairs downstream over a single hop wireless 802.11b network. Both the packet pair and the contending traffic send 1000-byte packets. In all cases, contention is simulated as a 1 Mbps upstream CBR flow. For the ideal channel, simulation errors and fading are disabled. In the fading channel, Ricean propagation from Section III-A is used. For the BER channel, a uniform bit error rate of 5.0×10^{-4} is used. Each CDF curve represents estimates from 1000 packet pairs sent over the wireless network.

In Figure 4, the estimated bandwidth of the ideal channel is uniformly distributed over the range of 3.1 Mbps to 4.1 Mbps due to the random backoff between two successive packets. The multiple mode distribution in the fading channel case is due to dynamic rate adaptation. The strong offset on the capacity estimation at about 1.8 Mbps for the contending channel is due to delay induced by contending packets. The estimated bandwidth results with bit errors yield a continuous cumulative distribution function (CDF) under the 1.8 Mbps range due to frame retries and exponential backoff delay between consecutive retransmissions. However, the step trend between 1.8 Mbps and 3.1 Mbps is similar to the distribution of the contending channel. The 'Ideal CBR' and 'Fading CBR' vertical lines represent average CBR throughputs which approximate average capacity in the ideal and fading channel cases, respectively. Compared to the CBR throughputs, the packet pair estimates are spread over a wide range. This clearly shows the packet dispersion technique is significantly impacted by wireless channel conditions.

IV. Wireless Network Packet Dispersion Model

This section develops an analytical model based on existing IEEE 802.11 wireless network models to explore the relationship between packet dispersion and WLAN conditions.

Capturing packet transmission delay is key to bandwidth estimation techniques that use packet pair (or train) dispersion. The bottleneck (both the narrow and the tight link) on the end-to-end network path is assumed to be the last hop WLAN. While not necessarily true for all flows, this assumption decouples wireless behavior from other issues and simplifies the wireless analysis. To further simplify modeling WLAN packet pair dispersion, no crossing traffic is assumed.

A. Packet Dispersion Model

The model characterizes the dispersion T between two packets in a packet pair in terms of the average, $E[T]$, and the variance, $V[T]$, of packet dispersion for a given wireless network that includes packet size, link rate, BER and access methods.

Our packet dispersion model is built from two Markov chain models: 1) Bianchi [24] uses a Markov model that assumes an idealistic, collision-free channel with a number of stations to analyze DCF operation. To simplify the model, frame retransmissions are considered unlimited such that frames are retransmitted until successful transmission and the 802.11 channel is saturated with each station always having a frame to send. 2) Chatzimisios et al [25] extend this model to include transmission error effects. For a given BER, their model derives the probability τ that a station transmits in a randomly chosen time slot as:

$$\tau = \frac{2(1-2p)(1-p^{m+1})}{W_{min}(1-(2p)^{m+1})(1-p)+(1-2p)(1-p^{m+1})} \quad (3)$$

where W_{min} is the initial contention window size, m is the maximum number of backoff stages, and p is conditional packet error probability:

$$p = 1-(1-\tau)^{n-1}(1-BER)^{L+H} \quad (4)$$

n is the number of stations in the network, L and H are the packet and packet header sizes (physical layer plus MAC layer) in bits. Since the authors prove there exists a unique solution for τ and p from the nonlinear system presented by Equation 3 and 4, these two probabilities can be obtained by numerical techniques.

Characterizing any given MAC layer time slot as either idle, collision, error, or successful, the average length of the slot time is given by:

$$E[slot] = (1-P_{tr})\sigma + P_{tr}P_sT_s + P_{tr}P_cT_c + P_{tr}P_{er}T_{er} \quad (5)$$

where P_{tr} is the probability that there is at least one transmission in the time slot:

$$P_{tr} = 1-(1-\tau)^n \quad (6)$$

P_s is the probability that a transmission occurring on the channel is successful:

$$P_s = \frac{n\tau(1-\tau)^{n-1}}{1-(1-\tau)^n}(1-PER) \quad (7)$$

and PER is the packet error rate, computed from the BER as $PER = 1-(1-BER)^{L+H}$. The probability P_c of a collision when two or more stations simultaneously transmit is:

$$P_c = 1-\frac{n\tau(1-\tau)^{n-1}}{1-(1-\tau)^n} \quad (8)$$

and the probability P_{er} that a packet is received in error is:

$$P_{er} = \frac{n\tau(1-\tau)^{n-1}}{1-(1-\tau)^n}PER \quad (9)$$

In Equation 5, σ is the idle slot time, T_s is the average time the channel is busy because of a successful transmission, T_c and T_{er} are the average time the channel is sensed busy by each station during a collision or packet error, respectively.

Equations 10-13, defined in [24], define T_s^{bas}, T_c^{bas}, T_s^{rts}, and T_c^{rts}, which are T_s and T_c for the basic access and RTS/CTS access, respectively:

$$\begin{aligned}
T_s^{bas} &= H + E\{L\} + sifs + \delta + ack + difs + \delta && (10)\\
T_c^{bas} &= H + E\{L\} + difs + \delta && (11)\\
T_s^{rts} &= rts + sifs + \delta + cts + sifs + \delta + H \\
&\quad + E\{L\} + sifs + \delta + ack + difs + \delta && (12)\\
T_c^{rts} &= rts + difs + \delta && (13)
\end{aligned}$$

rts, cts, ack, H and $E\{L\}$ are the transmission times of RTS, CTS, ACK, packet header (physical layer plus MAC layer) and data packets, respectively. $E\{L\} = L$ for a fixed packet size. δ is the propagation delay. $sifs$ (Short Interframe Space), $difs$ (Distributed Interframe Space) and other specific values for DSSS are defined in the IEEE 802.11 Standard [16]. Since T_{er} assumes only basic access [25], $T_{er} = T_c = T_s$. This is incorrect if RTS/CTS is enabled.

As modeled in [25], the average packet delay $E[D]$ of a packet that is not discarded, is given by:

$$E[D] = E[X] \times E[slot] \quad (14)$$

where $E[X]$ is the average number of slot times required to successfully transmit a packet and is given by:

$$E[X] = \sum_{i=0}^{m}[\frac{(p^i - p^{m+1})\frac{W_i+1}{2}}{1-p^{m+1}}] \quad (15)$$

$(1-p^{m+1})$ is the probability that the packet is not dropped, $(p^i - p^{m+1})/(1-p^{m+1})$ is the probability that a packet that is not dropped at the stage i, and W_i is the contention window size at stage i.

From these previous models, we build a new model for wireless packet dispersion. The dispersion T between two packets in a packet pair is the delay between the arrival times of the first and second packets. Since the model must include both the delay before the transmission of the second packet, $E[D]$, and the time to transmit it, T_s, the dispersion is represented by [26]:

$$E[T] = E[D] + T_s \quad (16)$$

where T_s is modeled by Equation 10 or Equation 12. $E[D]$ is a function of the average slot time length given in Equation 5 and the average number of slot times to transmit a data packet. Since $E[D]$ depends on n (the number of nodes in the contention domain), the wireless link rate C_l and average packet size L, we have:

$$E[D] = d(C_l, L, n) \quad (17)$$

Similarly, to include the impact caused by wireless link rate C_l and the probe packet size L, Equation 10 and Equation 12 are modified as:

$$T_s = t_s(C_l, L) \quad (18)$$

Thus, the packet dispersion estimation C_{est} can be computed as:

$$E[C_{est}] = \frac{L}{E[T]} = \frac{L}{d(C_l, L, n) + t_s(C_l, L)} \quad (19)$$

Note that while C_{est} is the average bandwidth estimate from packet dispersions, it does not equal throughput. Throughput, the average achievable data rate, takes into consideration the probability of transmitting and the probability of successful transmission.

WLAN contending traffic causes extra delay to the probing packets. For packet dispersion techniques, this extra delay can result in an under-estimate of the capacity. The impact caused by contending traffic is more sensitive to the number of nodes in the network than the traffic load at the individual nodes. Assuming each WLAN node always has data to send, $E[D]$ includes the contending traffic based on the number of WLAN nodes.

Wireless channel conditions can be characterized by received signal strength indication (RSSI), SNR, and BER. However, modeling the effects of such channel conditions on packet dispersion is left as future work. Instead, our simplified model only uses BER to characterize the channel condition and assumes the other wireless factors impact BER. As the number of backoffs increases, $E[D]$ increases exponentially until it successfully transmits or until the retry limit has been exceeded.

The impact of the channel condition on the bandwidth estimation is evaluated by modeling the packet dispersion variance, $V[T]$. Assuming the variance is caused by contention and errors, similar to Equation 16:

$$\begin{aligned} V[T] &= V\{D + T_s\} = \sum_{i=0}^{m} \left(\overline{D}_k - E[D]\right)^2 P_i \\ &= \sum_{i=0}^{m} \left[\sum_{k=0}^{i} \frac{E[slot](W_k + 1)}{2} + iT_* - E[D] \right]^2 P_i \end{aligned} \quad (20)$$

where $P_i = (p^i - p^{m+1})/(1 - p^{m+1})$, is the probability that a packet is not dropped at stage i. $\overline{D}_k$ is the average delay for k stage backoff given by $\overline{D}_k = \sum_{k=0}^{i} \frac{E[slot](W_k+1)}{2} + iT_*$, where T_* is the average delay time due to a collision or packet error:

$$T_*^{rts} = \frac{T_c^{rts} P_c^{rts} + \overline{T}_{er}^{rts} \overline{P}_{er}^{rts}}{P_c + \overline{P}_{er}^{rts}} \quad (21)$$

$$T_*^{bas} = T_c^{bas} = T_{er}^{bas} \quad (22)$$

The average delay caused by a packet error for RTS/CTS access method $\overline{T}_{er}^{rts}$ can be modeled as:

$$\overline{T}_{er}^{rts} = \frac{T_c^{rts}(P_{er}^{rts} + P_{er}^{cts}) + T_s^{rts}(P_{er}^{data} + P_{er}^{ack})}{\overline{P}_{er}^{rts}} \quad (23)$$

and the expected overall probability of a packet error for RTS/CTS access $\overline{P}_{er}^{rts}$ can be modeled as:

$$\overline{P}_{er}^{rts} = P_{er}^{rts} + P_{er}^{cts} + P_{er}^{data} + P_{er}^{ack} \quad (24)$$

where the $P_{er}^{rts}, P_{er}^{cts}, P_{er}^{data}, P_{er}^{ack}$ are the probabilities that a packet error occurs in RTS, CTS, DATA and ACK packets, respectively.

Given that the capacity function $C_{est} = L/T$ is twice differentiable and the mean and variance of T are finite, the variance of the estimated capacity can be approximated by the Delta method using second-order Taylor expansions:[6]

$$V[C_{est}] \approx V[T] \left[\left(\frac{L}{T} \right)' \right]_{E[T]}^2 = V[T] \left(\frac{L}{E^2[T]} \right)^2 \quad (25)$$

B. Model Validation

This section provides two distinct sets of validation results for the packet dispersion model. First, the ideal WLAN channel dispersion model with no contending traffic or bit errors is validated via both ns-2 simulations and wireless testbed measurements. Then with contention and BER included in the models, a large set of simulations with randomized wireless nodes are used to validate the more complex packet dispersion model. Table I lists the set of MAC layer parameters used for all instances of the dispersion model and all the reported simulations.

Parameterization for the packet dispersion model required creating programs based on the equations in Section IV to obtain the numerical solutions for p and τ since no closed-form solutions exist. Furthermore, the computation of the times for T_s and T_c was modified to account for the lower transmission rate of the PLCP header [16].

The ideal WLAN scenario consists of an AP and a single wireless client with both basic and the RTS/CTS access methods possible. In this case, since $E[slot]$ is simply the slot time σ and $E[D]$ is the backoff between two successive packets with contention window size W_{min}, the delay model simplifies to:

$$E[D] = \frac{E[slot](W_{min} + 1)}{2} = \frac{\sigma(W_{min} + 1)}{2} \quad (26)$$

The ideal simulations varied the packet size from 100 to 1500 bytes with the wireless capacity set to 11 Mbps. The wireless testbed consisted of a Windows XP PC sending packet pairs over a 100 Mbps channel through a Netgear 802.11b AP/router to a Windows XP laptop wirelessly connected to the AP via a Dell TrueMobile 1300 Mini PCI card. The PC sends at full capacity, packet pairs at the specified packet size. The wireless receiver computes estimations using packet pair dispersion.

Figure 7 graphs the bandwidth estimation results from the models, simulations and measurements for the ideal WLAN scenario. For each packet size in either RTS/CTS or basic access mode (BAS), the simulation results and the error bar in the figure are the average and standard deviation from 500 packet pair estimations. The measurement includes 100 packet pair dispersions with the same packet sizes[7] and channel rate. For basic access, the model, simulation and measurement results all closely match. This indicates that the model and simulation both

[6] http://en.wikipedia.org/wiki/Variance

[7] Due to the Ethernet MTU limit, 1460 bytes are used instead of 1500 bytes as the maximum packet size in the measurement.

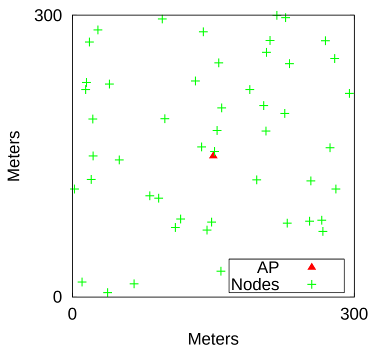

Fig. 6. Randomly generated topology

Parameter	Value
W_{min}	32
W_{max}	1024
MAC header	34 bytes
Phy header	24 bytes
ACK	38 bytes
CTS	38 bytes
RTS	44 bytes
Slot time	20 μsec
SIFS	10 μsec
DIFS	50 μsec

TABLE I
MODEL PARAMETERS

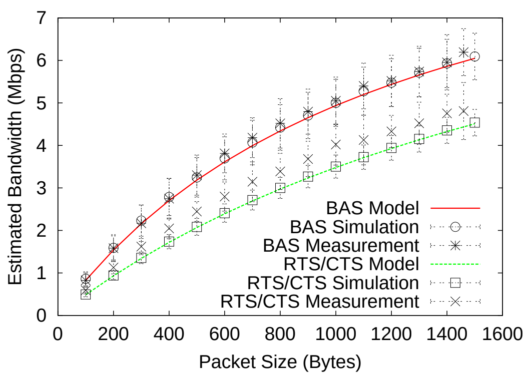

Fig. 7. Bandwidth estimation validation for an ideal WLAN

provide high fidelity compared to real 802.11b networks. With RTS/CTS enabled, the measurement results are slightly higher than the model and simulation. In-depth analysis shows that this difference is because the testbed sends management frames, such as RTS/CTS/ACK at 2 Mbps, which is higher than the 1 Mbps base rate used in the model and simulation.

A random simulation topology was created (see Figure 6) to study the packet dispersion model with contention and bit errors. Since all the nodes are within transmission range of each other, there are hidden terminals in this topology. Bandwidth estimation is computed with $L/\overline{T}$, where $\overline{T}$ is the average dispersion time from 500 packet pairs.

The number of sending nodes is increased from 2 to 50 to increase the contention level in the models. By assuming every node always has traffic to send, the model estimates packet dispersion under saturation conditions. To simulate saturation, an upstream 10 Mbps CBR flow is sent from each wireless node to the AP, while the packet pair traffic is sent downstream from the AP to a single node. The wireless data rate is fixed at 11 Mbps and both the CBR flows and the packet pair probes send 1500-byte packets. To avoid severely impacting the estimation results, packet pairs are sent at a lower rate of 100 Kbps.

All the contention simulations without errors were repeated with bit error rates of 1×10^{-5}. With B_{mod} and B_{sim} as the modeled and simulated bandwidth estimations, respectively, the relative error E for each topology from 2 to 50 nodes is defined as:

TABLE II
ERRORS IN THE BANDWIDTH ESTIMATION MODEL COMPARED WITH SIMULATIONS

	Error Free		$BER = 10^{-5}$	
	RTS/CTS	Basic	RTS/CTS	Basic
Mean Error	8.05%	4.90%	9.40%	7.67%
Stdev	6.72%	4.28%	5.30%	3.82%

$$E = \frac{|B_{sim} - B_{mod}|}{B_{sim}} \tag{27}$$

and the mean and standard deviation of error are defined as the average and standard deviation of the E values. Table II summarizes the dispersion model with contention validation results performed under different channel conditions and shows a close match between the model and simulations for both ideal and bit error channels. Further model parameter tests comparing modeled throughput to simulated throughput generally yield a close match. Additional details of the parameter validation process are in [27].

V. ANALYSIS

A. Packet Dispersion in 802.11

Since the model developed does not extend over the whole network path, the analysis focuses on a WLAN with the assumptions that all packet dispersion occurs at the AP and that there is no crossing traffic in the downstream direction.

Understanding packet dispersion in wireless networks, requires separating the non-saturated and saturated scenarios. Given a non-saturated WLAN with low BER where the probability of packet pair dispersion due to contending traffic is relatively low, the packet pair dispersion estimate represents the maximum channel capability for forwarding traffic for a given packet size. However, this capability includes overhead caused not only by packet headers, but also by the random delay between successive packets, MAC layer contention backoff, MAC layer retries and basic two way hand-shake (DATA/ACK) or four hand-shake (RTS/CTS/DATA/ACK). Emphasizing this difference, the term *effective capacity* indicates the maximum capability of the wireless network to deliver network layer traffic. Unlike in wired networks, wireless dynamic rate adaptation alters effective capacity by adjusting the packet transmission rate. Therefore, effective capacity is defined as a function of time and packet size:

$$C_e = \frac{\int_{t_0}^{t_1} \frac{L}{\overline{T}(t)} dt}{t_1 - t_0} \tag{28}$$

where $\overline{T}(t)$ is the average packet pair dispersion at time t. Moreover, given discrete packet pair samples, the effective capacity is:

$$C_e = \frac{\sum_{i=1}^{n} \frac{L}{T(i)}}{n} \tag{29}$$

where n is the number of samples from packet pair measurements and $T(i)$ is the dispersion of the nth packet pair.

However, in a wireless network with considerable contending traffic or BER, MAC layer retries due to bit errors and collisions

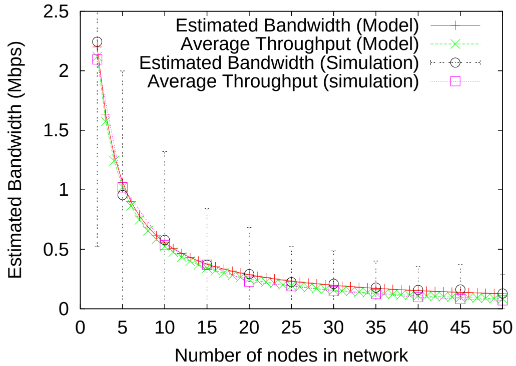

Fig. 8. Packet pairs estimations and CBR throughput

between the probing traffic and contending traffic add delay to packet dispersion. Hence, average packet pair dispersion represents the average time used to forward one single packet. This represents the traffic the network can forward given the contending traffic and BER. This average packet pair dispersion rate is not the available bandwidth because it includes the impact of the contending traffic. This metric, referred to as *achievable throughput* for the current level of contending traffic, is:

$$A_t = \frac{L}{\frac{1}{n}\sum_{i=0}^{n} T(i)} \tag{30}$$

MAC layer retries caused by contention and BER are major sources of achievable throughput degradation. Achievable throughput is greater than available bandwidth because it aggressively takes bandwidth from the crossing traffic and it represents the average throughput along the same direction as the probing traffic. Therefore, the following relationship exists among the available bandwidth (A), achievable throughput (A_t) and effective capacity (C_e): $A \leq A_t \leq C_e$. Moreover, in a non-saturated WLAN that has available bandwidth for new traffic, the achievable throughput can be modeled using a fluid model because contending effects can be ignored if total throughput in the wireless network is less than the effective capacity.

A saturated wireless network is caused by multiple non-responsive traffic sources, such as UDP flows, transmitting above the flow's fair-share bandwidth. However, in a saturated wireless network no bandwidth is available, and each node contends with other traffic to access the wireless channel. Overall throughput is reduced by contending effects and achievable throughput represents the fair share of the effective capacity for all the active contending nodes.

To illustrate achievable throughput in a saturated wireless network, packet pair results are compared with CBR throughput using the simulation topology in Figure 6. Achievable throughput is computed from the dispersion time of 500 packet pairs with a sending rate of 100 Kbps and a 10 Mbps CBR flow. The contending traffic at each node is 10 Mbps, and the packet size for packet pairs, contending traffic and CBR traffic are all 1500 bytes. Figure 8 shows that the packet pair estimates are nearly the same as the average CBR throughput for both the model and simulations. In this saturated scenario, CBR throughput represents achievable throughput.

Packet train techniques apply the same packet dispersion ideas to packet pair dispersions. However, the large number of packets in a train make it more vulnerable to contending traffic. Therefore, packet train dispersion in wireless networks does not measure the effective capacity, but rather indicates the achievable throughput.

Wireless networks are a mixture of contending, bit errors and rate adaptation conditions. It is difficult to distinguish packet dispersion results that are impacted by MAC layer retries from results due to WLAN rate adaptation. Even though the achievable throughput can be estimated, it can be difficult to determine the effective capacity from the estimation results in such mixed channel conditions. Therefore, other techniques may be needed to remove MAC layer retries caused by contention and BER to get more accurate effective capacity estimates.

B. *Analysis of the Estimation Results*

As discussed in [28], packet size significantly impacts the measurement of wireless network throughput because of the wireless overhead. Similarly, probe packet size effects estimation results dramatically. Generally, as packet size increases relative overhead due to headers is reduced. For example, Figure 7 depicts the effective capacity of an ideal channel at 11 Mbps, with both basic and RTS/CTS access methods. To effectively estimate bandwidth, probing packet size must be close to the packet size of the applications that use the bandwidth estimation. For example, streaming video should use a probing packet size close to the video packet size to pick an effective streaming rate.

MAC layer rate adaptation impacts the effective capacity significantly. However without knowing wireless channel conditions and the vendor-implemented rate adaptation algorithm, it is difficult to model the practical effects of rate adaptation. Figure 9 illustrates the relationship between effective capacity and the channel rate in a ideal condition with 1500 byte packets for both basic and RTS/CTS access methods. Although the adaptation algorithm and channel conditions may vary the result of rate adaptation, the relationship between the channel rate and the effective capacity still holds because of the statistical nature of the model. Therefore, the model can be used to predict the effective capacity by using the average channel rate instead of a fixed date rate.

Bit errors reduce achievable throughput in wireless networks because MAC layer retries reduce the efficiency of the wireless network. Moreover, packet drops due to exceeding MAC layer retry limits also directly reduce the achievable throughput in wireless networks. Figure 10 shows the packet dispersion results of the model and simulation for 1500-byte packets sent on a 5-node wireless basic access network with BER ranging from 1×10^{-7} to 1×10^{-3}. Achievable throughput decreases as the BER increases. As the BER reaches approximately 1×10^{-3}, the wireless network gets almost no achievable throughput.

The RTS/CTS four-way handshake lowers the impact of hidden terminals by reducing the cost of collisions while introducing considerable WLAN overhead. Without considering the hidden terminal problem, RTS/CTS can still improve the network average throughput under high traffic load conditions. Figure 11 uses the model to illustrate the crossover point for 1500-

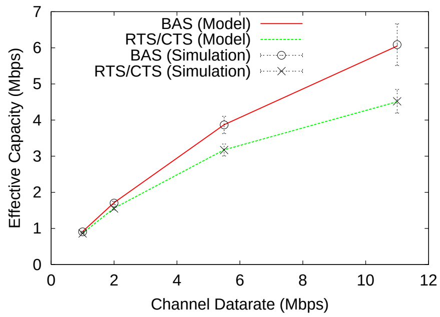

Fig. 9. The impacts of channel datarate

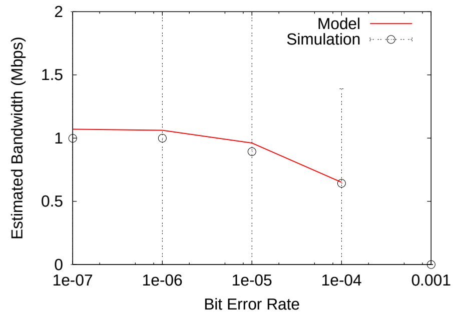

Fig. 10. The impacts of channel bit error rate (BER)

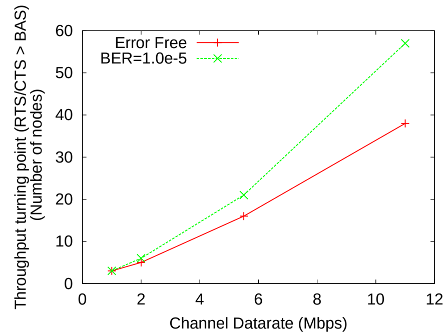

Fig. 11. Compare RTS/CTS with basic access on achievable throughput

byte packets where RTS/CTS gets higher achievable throughput compared to basic access for different link rates. The crossover point is measured as the number of fully loaded nodes in the wireless network. The higher the link data rate, the more likely basic mode will have a higher throughput than RTS/CTS. For example, RTS/CTS will only have a higher throughput if there are more than 57 fully loaded nodes in an 11 Mbps network. Moreover, BER increases the crossover point where RTS/CTS achieves higher throughput than basic access. This figure demonstrates why RTS/CTS is disabled in most wireless networks.

C. *Analysis on the Variance of the Bandwidth Estimation*

The packet dispersion model provides the variance and standard deviation of the bandwidth estimates. Figure 12 shows the standard deviation of the estimations from the model and simulations with 1500-byte packets and basic access. The standard deviation of the simulated estimation is computed based on 500 packet pair dispersions. As the traffic load increases, the standard deviation decreases because more contending sources more evenly distribute backoff delay across multiple estimates. However, for less than five nodes, the modeled standard deviations do not match the simulation results. This is because the variance of a randomly selected number of backoff time slots in the contention window is not included in Equation 20. With high traffic load, the variance from multiple random backoff time slots can be safely ignored because it is relatively small compared to the variance due to the number of retries. However, retry probability is low for the network with fewer than five nodes. Thus the time slot variance dominates the overall variance and causes the mismatch between the model and simulation.

Analysis of variance of the bandwidth estimations is helpful for designing new bandwidth estimation algorithms, such as to decide the number of packet pairs in an estimate or the length of a packet train. Furthermore, packet dispersion variance also provides additional information for inferring network conditions, such as the traffic load and the bit error rate.

Packet size also affects the variance in the bandwidth estimations. Larger packet sizes yield a relatively larger variance. Figure 13 depicts the standard deviation of packet pair estimations in a basic access, 5-node wireless network, with no errors and $BER = 10^{-5}$. The BER curve shows a higher standard deviation than the error free channel for the same packet size. This is because packet error rate increases with BER, and this raises the probability of MAC layer retries which produces more packet pair estimation variance.

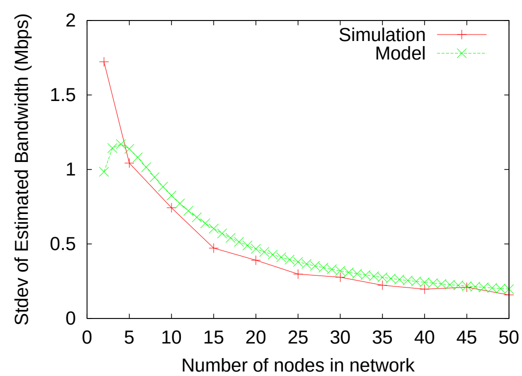

Fig. 12. Simulating and modeling standard deviations of estimation

Figure 14 shows the standard deviation of packet pair estimations with 1500-byte packets in a 5-node wireless network with no errors and $BER = 10^{-5}$. The variance of bandwidth estimations increases as the channel datarate increases. This implies that the higher the link datarate, the higher the relative error in the estimation. Compared to the channel without errors, the channel with errors has a higher variance for all datarates. This is because the bit errors cause more MAC layer retries and more variance in the estimation results.

Bit errors impact not only the packet dispersion result in wireless networks, but also its variance. Figure 15 shows the standard deviation for 1500-byte packets on a 5-node 11 Mbps wireless network with BER ranging from 1×10^{-7} to 1×10^{-3}. For BERs less than 10^{-5}, the standard deviation of the bandwidth estimations increases as the BER increases. The variance starts to decrease as BER increases over 10^{-5}. This is because the number of retries reaches the retransmission limit, therefore reducing the variance in the backoff delay across multiple packet pairs. In fact, for a BER higher than 10^{-4}, the packet drop rate is so high that only a few packets get through the network (with a large number of retries). Note, the RTS/CTS access method has a lower standard deviation than the basic method in all cases.

VI. Conclusion

This paper presents an analytic model to investigate packet dispersion behavior in IEEE 802.11 wireless networks. The

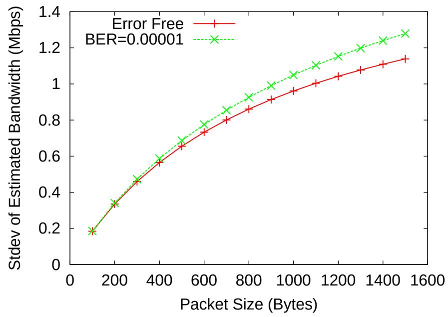

Fig. 13. The impact of packet sizes on the standard deviation of bandwidth estimation

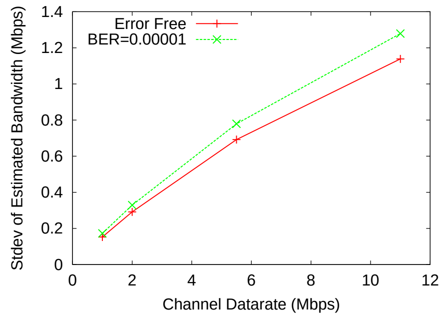

Fig. 14. The impact of channel datarate on the standard deviation of bandwidth estimation

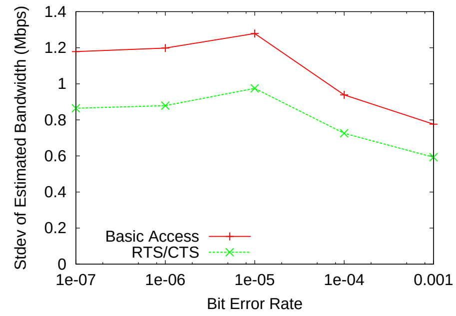

Fig. 15. The impacts of BER on the standard deviation of bandwidth estimation

packet dispersion model is validated by an extended ns-2 simulator and with wireless 802.11b testbed measurements. Utilizing the packet dispersion model, the following observations can be made:

1. Packet dispersion measures the *effective capacity* and the *achievable throughput* of a wireless network instead of the capacity as in a wired network. Effective capacity, defined as a function of packet size and time, represents the ability of a wireless network to forward data over a given time period. Achievable throughput is the maximum throughput that a node can achieve when contending with other existing traffic on a wireless network.

2. Wireless channel conditions, such as and RTS/CTS access method impact the bandwidth estimation results and the variance of the results. The packet size and link rate have positive correlation with both the bandwidth estimations and variances of the estimations. The BER of the channel has a negative correlation with the bandwidth estimations and a positive correlation with variances of the estimations. RTS/CTS reduces estimated bandwidth and the variance of the estimations.

Our ongoing work involves further evaluation of the packet dispersion model in a wireless testbed under a variety of network conditions that includes saturation, contention and wireless rate adaptation. Other possible future work may include the improvement to bandwidth estimation techniques by utilizing the model in actual wireless networks.

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