# Available Bandwidth-Based Association in IEEE 802.11 Wireless LANs

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## ABSTRACT

The performance of an IEEE 802.11 station heavily depends on the selection of an AP (Access Point) that the station is associated with to access the Internet. The conventional approach to the AP selection is based on the received signal strength called RSSI (Received Signal Strength Indication) from APs within the transmission range. This approach however, might yield unbalanced traffic load among APs as the station chooses an AP only based on the signal strength, instead of considering the AP load and the level of contention on medium access. Accordingly, the station that is associated with the highest-RSSI AP might suffer from poor network performance. In this paper, we propose a new association metric, *EVA (Estimated aVailable bAndwidth)* with which a station can find the AP that provides the maximum achievable throughput among scanned APs. EVA is designed to estimate the available bandwidth on a channel with respect to a station that is to join a WLAN (Wireless Local Area Network). A station equipped with EVA observes a channel state in a per-slot basis, and yet does not request any external information from nearby APs or neighbor stations. Our estimation mechanism is non-intrusive, fully distributed, and independent of the infrastructure. Through simulation study, we evaluate the accuracy of the estimation and show that EVA-based association yields enhanced throughput performance compared with the legacy scheme.

## Categories and Subject Descriptors

C.2 [**Computer Systems Organization**]:
Computer-Communication Networks
; C.2.1 [**Computer-Communication Networks**]:
Network Architecture and Design
Wireless communication

## General Terms

Algorithms, Measurement



## Keywords

IEEE 802.11 WLANs, Association, Available Bandwidth

## 1. INTRODUCTION

Today, increasing number of users access the Internet via IEEE 802.11 WLANs (Wireless Local Area Networks). We can easily find APs (Access Points) that are in the vicinity at public/municipal places. The selection of the AP that a WLAN station connects with must be done prudently as it determines the performance of the station. In the nomenclature of IEEE 802.11 [1], such AP selection procedure is referred to as *association*.

The most widely used metric for the association of WLAN stations is the received signal power from an AP, known as RSSI (Received Signal Strength Indication). After scanning the channels, a station chooses the AP from which it receives frames with the highest RSSI. As revealed in the literature, however, such an RSSI-based association does not necessarily provide the best throughput performance [2–4]. In addition, the RSSI-based association might result in unbalanced throughput among BSSs (Basic Service Sets). Therefore, a station associated with the highest-RSSI AP might suffer from low throughput that results from the overloaded bandwidth utilization in that BSS.

We propose a new association metric called *EVA (Estimated aVailable bAndwidth)* that is designed to reflect the available bandwidth in a BSS, i.e., the maximum achievable throughput when associated with the target AP. In order to accurately estimate the available bandwidth, *EVA estimator* considers the contention level on a BSS by calculating collision probability and channel idle ratio based on channel state assessment.[1] After searching all accessible channels and, in turn, available APs on scanned channels, a station with the EVA estimator chooses the AP that provides the largest EVA.

In order to make EVA a practical solution, we set the following design goals. First, available bandwidth estimation should be performed in a non-intrusive manner as resource in WLANs is scarce. Second, to avoid the modification of IEEE 802.11 protocol, EVA does not require any extra frame exchanges between stations and APs. Moreover, we do not employ a centralized solution to control a WLAN or estimate available bandwidth. Third, our proposed approach should provide highly accurate estimation in a timely fashion.

[1]For clarity, the term EVA will be used to represent the value of available bandwidth calculated through the proposed EVA estimator.

Through simulation study, we evaluate the accuracy of the proposed EVA estimator on collision probability and available bandwidth in a BSS. We also evaluate the effectiveness of EVA-based association in terms of individual and aggregate throughput performance.

The rest of the paper is organized as follows. Section 2 reviews the related work, and the legacy 802.11 association process is introduced in Section 3. The formulation of EVA is presented in Section 4. Section 5 describes the algorithmic details, and Section 6 shows the accuracy of EVA estimator and the corresponding throughput performance. Finally, the paper concludes with Section 7.

## 2. RELATED WORK

RSSI is commonly used as an association metric in WLANs. This approach is however, well known to have poor network performance when load distribution is highly unbalanced [2–6]. There have been proposals to solve this inefficient network resource usage.

One of these attempts is to receive information from APs. In [2, 4–6], by collecting information such as the number of associated stations or its transmission rate, stations can select an AP with better link quality that is measured by different methods. Such an approach should be accompanied with a protocol modification in the AP side, and is not likely to work with already-deployed WLAN devices.

There are a few centralized solutions [3, 7]. A representative, usually the AP, controls the whole association process. Particularly, the AP decides whether to grant the association of stations. This approach also needs to modify AP's behavior, and brings additional overhead to let the AP be aware of the details of the entire network.

In EVA, on the other hand, the channel state is measured passively. The EVA estimator operates in a distributed manner (working only at the station side) and does not require any modification of a WLAN infrastructure. Furthermore, available bandwidth is predicted when the station searches APs in the 802.11 scanning process and hence, does not incur additional probing overhead.

A similar approach to ours is presented in [8] and its algorithm works as follows. A station observes a skewed time period of beacon frame receptions to estimate how much bandwidth is available. Although it is a purely non-intrusive operation, it incurs large delay for channel observation and quality estimation as multiple beacon frames must be received – typically, beacons are transmitted every 100 milliseconds.

The estimation of available bandwidth on an 802.11 link is affected by many factors such as retransmissions due to collision or weak signal, corresponding increased backoff interval, busy channel detection due to different system devices, etc. *VMAC* [9] virtually runs MAC process at each station to estimate collision probability and available bandwidth. As it empirically observes the wireless channel, VMAC can estimate the bandwidth that is fluctuating in a time varying manner. The convergence of VMAC estimation however, takes relatively a long time as one estimate sample is collected after finishing every backoff procedure, i.e., taking at least $\frac{CW_{\min}}{2} \cdot tTimeslot$ duration to get a sample on average, where $CW_{\min}$ is the minimum contention window size and *tTimeslot* is the interval of a single backoff timeslot. Meanwhile, the EVA estimator observes the wireless channel in a per-slot basis, thus ensuring to have more number of samples and yielding faster convergence time than VMAC. There could be a tradeoff between convergence time and accuracy. We show that our approach gets more samples and achieves faster estimation convergence without accuracy compromise in Appendix A.

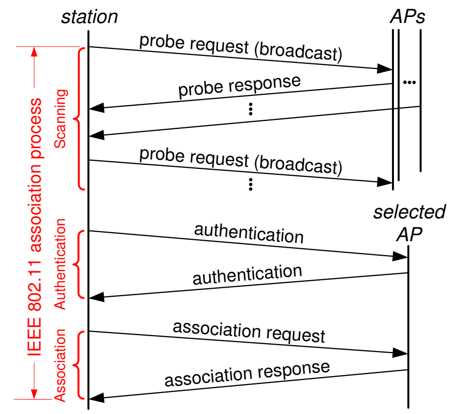



**Figure 1: Frame exchange sequence in the 802.11 infrastructure mode.**

## 3. ASSOCIATION IN 802.11 WLANS

IEEE 802.11 association process is divided into three steps: scanning, authentication, and association, as illustrated in Fig. 1.

The objective of scanning is to select an appropriate AP to be associated with, in all available channels. There are two types of scanning: *active* and *passive*. As the names imply, the station finds APs by listening to periodic beacon frames in the passive mode. The station using active scanning broadcasts a probe request frame on each channel and may receive multiple probe response frames from different APs working on the same channel. Figure 1 shows the frame exchange sequence in the active scanning. Typically for most existing WLAN devices, active scanning is used by default for association.

The criterion that specifies *which channel* should be scanned is addressed in the standard [1]. MAC layer management entity called MLME (MAC sub-Layer Management Entity), initiates scanning channels upon receiving the corresponding request with a list of channels to be scanned, `ChannelList`, from SME (Station Management Entity). Practically, the functional details of SME can be implemented as a form of application software that controls the association of WLAN client, including the `ChannelList`.

Based on the belief that the highest-signal-strength AP would provide the best performance, most commercial devices rely on the conventional association metric, RSSI. Although the 802.11 DCF (Distributed Coordination Function) is designed to offer long-term equal medium access opportunities to all contending stations, RSSI-based AP selection might not provide the desired performance of the station. The AP selection should consider load balancing and fairness among stations as well as throughput.

After scanning, the station attempts to get authenticated and associated with the selected AP by exchanging authentication and association request/response frames as depicted in Fig. 1.

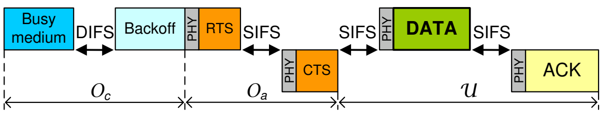



**Figure 2: IEEE 802.11 DCF channel access.**

# 4. METRIC FORMULATION

We first formulate the association metric EVA, starting with its definition. We then describe how to decompose the metric formulation into multiple components that can be separately calculated and estimated.

## 4.1 EVA Definition

The design of EVA aims to estimate available bandwidth on an operating channel, being aware of the contention intensity around the station. We define *available bandwidth* as the maximum achievable bandwidth on the target 802.11 link.

We define the concept of EVA along with the frame exchange sequence of the 802.11 DCF. As illustrated in Fig. 2, after backing off, a station accesses the wireless medium by exchanging RTS (Request-To-Send) and CTS (Clear-To-Send) frames.[2] A data frame transmission then follows and the frame exchange completes by the ACK (Acknowledgement) frame transmission. Keeping the frame exchanges in mind, we define EVA as follows.

*Definition 1.* We consider two sequences of random variables, $\mathcal{T}_i$ and $n_i$: the former is the time duration spent by the station in consideration to transmit a data frame (including both contention delay and frame transmission times as illustrated in Fig. 2) at the station's $i^{\text{th}}$ transmission attempt; and the latter denotes the transmission result at the $i^{\text{th}}$ attempt, i.e., 1 for success and 0 for failure. The subscript $i$ indexes a set of $\mathcal{M}(t)$ transmission attempts of the station by the time $t$. We define EVA as the frame size ($\mathcal{F}$) divided by the fraction of those random sequences:

$$\text{EVA}(t) \triangleq \frac{\mathcal{F}}{\sum_{i=1}^{\mathcal{M}(t)} \mathcal{T}_i / \sum_{i=1}^{\mathcal{M}(t)} n_i}, \tag{1}$$

where the denominator represents the time average of the time spent by the station in order to successfully transmit a data frame over the total observed time interval, $t$.

EVA$(t)$ formulated by a function of random sequences is not useful since its accuracy varies over the size of $\mathcal{M}(t)$. Moreover, EVA$(t)$ does not quickly react to wireless channel variation and contention intensity. The following proposition states that EVA$(t)$ converges to the non-random (probabilistic) mean.

Proposition 1. *Eqs. (1) and (2) are asymptotically equivalent as $t \to \infty$:*

$$\text{EVA} = \frac{\mathcal{F}}{E[\mathcal{T}]/E[n]}, \tag{2}$$

*where $E[\mathcal{T}]$ is the expected frame transmission time and $E[n]$ is the expected number of successfully transmitted data frames at a unit transmission attempt.*

Proof. The random sample (statistical) means of the $\mathcal{M}(t)$ random variables with respect to $\mathcal{T}_i$ and $n_i$ are defined by:

$$\overline{\mathcal{T}}_i = \frac{\sum_{i=1}^{\mathcal{M}(t)} \mathcal{T}_i}{\mathcal{M}(t)}, \quad \overline{n}_i = \frac{\sum_{i=1}^{\mathcal{M}(t)} n_i}{\mathcal{M}(t)}.$$

By the Law of Large Numbers, $\overline{\mathcal{T}}_i \sim E[\mathcal{T}]$ and $\overline{n}_i \sim E[n]$ as $t \to \infty$. In consequence, it follows that EVA $= \frac{\mathcal{F}}{E[\mathcal{T}]/E[n]}$. $\square$

[2]In this paper, we consider RTS/CTS-enabled DCF MAC in EVA formulation. However, the usage of EVA as an association metric is not limited to the RTS/CTS usage, thus being able to change the formulation to be suitable for the access without RTS/CTS exchange.

**Table 1: Notations.**

| Notations | Definitions |
|---|---|
| $\mathcal{O}_{phy}$ | transmission duration for PHY header and preamble |
| $CW_{\min}$ | the minimum contention window |
| $CW_{\max}$ | the maximum contention window |
| *tFrame* | transmission duration for that *Frame* type |
| *tDIFS* | time interval of DIFS (DCF Interframe Space) |
| *tSIFS* | time interval of SIFS (Short Interframe Space) |
| *tBO* | backoff interval |
| *tBusy* | time interval holding medium access due to busy channel |
| *tTimeslot* | unit time interval of a single timeslot |
| $\mathcal{F}$ | frame size |
| $\tau$ | propagation delay |

## 4.2 Frame Exchange Sequence Decomposition

From Proposition 1, EVA can be obtained by calculating $E[\mathcal{T}]$ and $E[n]$. In order to obtain $E[\mathcal{T}]$, we decompose the unit frame exchange sequence, as shown in Fig. 2, into three temporal components:

- $\mathcal{O}_c$ : channel contention overhead,
- $\mathcal{O}_a$ : channel access overhead, and
- $\mathcal{U}$ : unit transmission time required for a data frame transmission.

Therefore, we can revise Eq. (2) as follows:

$$\text{EVA} = \frac{\mathcal{F} \cdot E[n]}{\mathcal{O}_c + \mathcal{O}_a + \mathcal{U}}, \tag{3}$$

and the problem changes to deriving each decomposed components: $E[n], \mathcal{O}_c, \mathcal{O}_a$, and $\mathcal{U}$. Table 1 lists notations of related parameters used in the following derivations.

### 4.2.1 $E[n]$, the expected number of successfully transmitted data frames

Note that $E[n]$ is equal to $P_s$, the probability that a data frame is successfully transmitted in a unit frame exchange. $P_s$ can be presented by:

$$E[n] = P_s = p_s^{rts} p_s^{data}, \tag{4}$$

where $p_s^{rts}$ and $p_s^{data}$ denote the success probabilities of RTS/CTS and data/ACK exchanges, respectively. Note that if we assume no hidden station that is not carrier-sensed by the transmitter, but interferes frame receptions at the designated receiver, a frame collision only happens with the simultaneous transmissions of RTS frames. Accordingly, the collision probability with respect to the transmitting station that estimates EVA can be denoted by $p_c^{rts}$. Therefore, $p_s^{rts}$ and $p_s^{data}$ in Eq. (4) are presented as follows:

$$\begin{cases} p_s^{rts} &= \left(1-p_e^{rts}\right)\left(1-p_e^{cts}\right)\left(1-p_c^{rts}\right), \\ p_s^{data} &= \left(1-p_e^{data}\right)\left(1-p_e^{ack}\right), \end{cases} \tag{5}$$

where $p_e^{Frame}$ is FER (Frame Error Rate) of the specific *Frame* type, such as RTS, CTS, data, and ACK frames.

As the calculation of Eqs. (4) and (5) is based on the knowledge of FER that depends on $\mathcal{F}$ and the employed modulation and coding scheme, i.e., transmission rate ($r$), an FER estimation method should precede. If we have a predetermined FER vs. SNR (Signal-to-Noise Ratio) table in advance, the problem becomes simple. Such a table can be obtained either from measurement, e.g., [10], or from the vendor's datasheet, e.g., [11]. Upon the reception of frames from an AP, the station measures the average SNR by measuring both RSSI and the observed background noise level, and then FER is obtained from the table.

#### 4.2.2 $\mathcal{O}_c$, the channel contention overhead

From Fig. 2, $\mathcal{O}_c$ can be divided into two time intervals, $tBO$ and $tBusy$, where $tDIFS$ is included into $tBusy$, i.e.,

$$\mathcal{O}_c = E[tBO] + E[tBusy]. \tag{6}$$

Let $\sigma$ denote the *channel idle ratio* during an $\mathcal{O}_c$ period. $\sigma$ is then presented by:

$$\sigma = \frac{E[tBO]}{E[tBO] + E[tBusy]}. \tag{7}$$

By inserting Eq. (6) into Eq. (7), we have $\mathcal{O}_c = E[tBO]/\sigma$ and hence, the problem of $\mathcal{O}_c$ calculation becomes finding $\sigma$ and $E[tBO]$. We will present a way to estimate $\sigma$ in the following section.

In the case of a transmission failure, the backoff procedure updates $CW$ (Contention Window) to $[2 \times (CW+1) - 1]$. Once $CW$ reaches $CW_{\max}$, it remains at this value until finishing the transmission successfully or dropping the frame due to the retry limit, resetting to $CW_{\min}$. The backoff interval of the $i^{\text{th}}$ transmission attempt can be denoted by $tBO_i = \mathsf{rand}\left[0, CW_i\right]$, where $CW_i$ is the size of contention window at the $i^{\text{th}}$ transmission and is written by:

$$CW_i = \mathsf{min}\left[2^{i-1}\left(CW_{\min}+1\right) - 1, CW_{\max}\right]. \tag{8}$$

$\mathsf{rand}[x, y]$ is the operator that randomly draws an integer number from a uniform distribution over the interval $[x, y]$. Accordingly, we can say that $tBO_i \approx CW_i/2$ on average. The average backoff interval per unit transmission, $E[tBO]$ is derived as follows:

$$E[tBO] = \sum_{i=1}^{\gamma} s(i)\frac{CW_i}{2} \cdot tTimeslot, \tag{9}$$

where $\gamma$ is the retry limit and $s(i)$ is the probability that a data frame is successfully transmitted after the $i^{\text{th}}$ transmission attempt, being presented by:

$$s(i) = \left(1-P_s\right)^{i-1} P_s. \tag{10}$$

Accordingly, having the estimate of $p_c^{rts}$ plays a key role in knowing $E[tBO]$, which is similar to the case of $E[n]$.

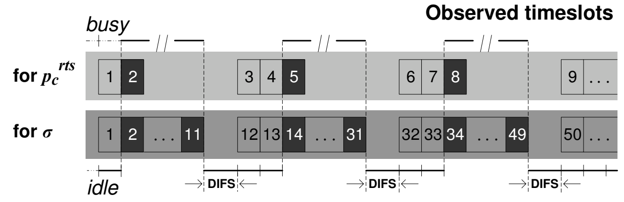



**Figure 3: An illustrative example of channel observation for $p_c^{rts}$, $\sigma$ estimation.**

#### 4.2.3 $\mathcal{O}_a$ and $\mathcal{U}$

As illustrated in Fig. 2, $\mathcal{O}_a$ and $\mathcal{U}$ can be written as:

$$\begin{cases} \mathcal{O}_a &= 2\mathcal{O}_{phy} + tRTS + tSIFS + tCTS + 2\tau, \\ \mathcal{U} &= 2\mathcal{O}_{phy} + tDATA + 2tSIFS + tACK + 2\tau. \end{cases} \tag{11}$$

## 5. ESTIMATION ALGORITHM

We present how to estimate collision probability, $p_c^{rts}$ and channel idle ratio, $\sigma$ with which we can calculate EVA as described in Section 4. We first present an illustrative example and then propose the *EVA estimator*.

### 5.1 An Example

Figure 3 depicts that a station is observing the wireless channel to estimate $p_c^{rts}$ and $\sigma$. The bold horizontal line represents the channel state: upper and lower levels mean busy and idle states of the channel, respectively. Small rectangles are timeslots observed by the station. Upper timeslots enumerated up to 9 is used for $p_c^{rts}$ estimation. Suppose that the channel state changes up and down due to the frame transmissions from other stations, and the observing station, say $\mathcal{A}$, assesses that the channel becomes busy three times (at the $2^{\text{nd}}$, $5^{\text{th}}$, and $8^{\text{th}}$ timeslots). Note that a collision would happen, if $\mathcal{A}$ tried to transmit a frame at these timeslots from which the channel becomes busy. Likewise, $\mathcal{A}$ can estimate its collision probability by counting such collision-induced timeslots out of all elapsed timeslots. In this example, the estimated $p_c^{rts}$ when the $9^{\text{th}}$ timeslot expires becomes $\frac{1}{3}$.

Similarly, we can also estimate $\sigma$ using lower indexed timeslots as follows. $\mathcal{A}$ counts all idle timeslots out of the total observed slots. In this example, the total number of idle timeslots is 5 out of the total elapsed slots, i.e., 50. As a result, $\sigma$ becomes $\frac{6}{50}$ when the latest timeslot expires. Note that the estimation of $p_c^{rts}$ and $\sigma$ can be done concurrently.

### 5.2 EVA Estimator

In order to estimate $p_c^{rts}$ and $\sigma$, we employ the ARMA (Autoregressive Moving Average) estimator [12]. The typical ARMA estimator has the following form:

$$\hat{y}_i = \alpha\hat{y}_{i-1} + \frac{1-\alpha}{K}\sum_{j=0}^{K-1} x_{i-j}, \tag{12}$$

where $\hat{y}_i$ is the target estimate and $x_{i-j}$, with $j = 0, \cdots, K-1$ are the last $K$ timeslot samples. $K$ and $\alpha$ are design parameters that determine the accuracy of the estimator. $K$ plays a role to smooth measurements that are fed to the weighted average; however, as revealed in [13], the selection of $K$ value has little impact on the performance of ARMA estimator, and 10 is used for $K$ in our setting.

On the other hand, the filter memory (or autoregressive weighting factor) $\alpha$ works as a tuner controlling the tradeoff between the estimation accuracy and the response time. In Section 6, we study the impact of $\alpha$ on the performance tradeoff and choose a suitable $\alpha$ based on which station can select the best AP.

At each timeslot, a station assesses the channel state whether it becomes busy or idle. For $p_c^{rts}$ estimation, $x_i$, which is a sample of collision event, is set to 1 if the channel state changes from idle to busy in the $i^{\text{th}}$ timeslot, while $x_i$ is 0 for every idle timeslot. When estimating $\sigma$, $x_i$ means a sample of an idle timeslot. Therefore, for every idle timeslot expiration, $x_i$ becomes 1; otherwise, $x_i$ is 0. Note that for both $p_c^{rts}$ and $\sigma$ estimation, timeslots during which the target station transmits its frames are not considered, since the station only observes per-timeslot channel occupancy taken by other stations, not itself.

A station, say $\mathcal{A}$, which tries to find the best AP to achieve the highest throughput using the EVA metric, runs the following algorithm:

Algorithm 1. ***EVA estimator***

1. *For all tTimeslots, $\mathcal{A}$ assesses the channel state and determines an estimation sample, $x_i$.*
2. *$\mathcal{A}$ runs Eq. (12) with every valid sample, $x_i$, and updates the new estimate, $\hat{y}_i$, i.e., $\hat{p}_c^{rts}$ or $\hat{\sigma}$.*
3. *Going through Eqs. (5), (4), (10), and (9) with the estimated $\hat{p}_c^{rts}$, $\mathcal{A}$ obtains $E[tBO]$.*
4. *$\mathcal{A}$ inserts $E[tBO]$ and the estimated $\hat{\sigma}$ into Eqs. (7) and (6) to get $E[tBusy]$ and $\mathcal{O}_c$.*
5. *EVA is estimated using Eq. (3).*

## 5.3 Implementation Issues

Finding a practical estimation interval for accurate available bandwidth estimation is important. Too short of an estimation interval would result in an inaccurate EVA estimation. A longer estimation interval would yield an enhanced accuracy on the other hand, but might make the estimation useless for the association process because of the long, unaffordable estimation interval.

According to [14, 15], the typical time spent on scanning the 802.11b channels varies from 300 to 500 milliseconds depending on WLAN client devices. Since three to four different channels are used in the 802.11b band, i.e., 2.4 GHz, we can argue that approximately 100 milliseconds is used to scan a single channel.

As addressed previously, the only physically required operation for a station to estimate an EVA value is to observe the changes of wireless medium from busy to idle, or vice versa. Moreover, the channel observation might not incur much overhead and should be done along with the normal 802.11 operations. We will study how accurately the EVA estimator can calculate the available bandwidth within a pragmatic time interval, i.e., 100 milliseconds per each 802.11b channel in Section 6. We will also investigate the appropriate $\alpha$ value in order to achieve an accurate EVA estimation within that time interval.

# 6. PERFORMANCE EVALUATION

We present our simulation study to evaluate the effectiveness of the proposed EVA association metric. We first describe the simulation environment and identify the performance tradeoff between accuracy and responsiveness of the EVA estimator. Finally, we evaluate the throughput performance based on the proposed association metric, EVA.

## 6.1 Simulation Setup

We enhance the 802.11 DCF module in the *ns*-2 simulator [16] to support the proposed EVA-based association. The 802.11b is considered as the PHY module [17], and the highest transmission rate, i.e., 11 Mbps, is employed by all stations. Each station transmits 1028-byte frames with 20 dBm power and all stations are static. We use the empirical BER (Bit Error Rate) vs. SNR curves provided by Intersil[3] to estimate the FER (Frame Error Rate) [11]. The background noise level is set to –96 dBm. We use a log-distance path-loss model with the path-loss exponent of four to simulate the indoor office environment [18].

As addressed in Section 5, we set the number $K$ of samples for moving average process to 10, and vary $\alpha$, the weighting factor for autoregressive process from 0.99 to 0.9999 to study its impact on the estimation accuracy and responsiveness tradeoff in the ARMA estimator.

## 6.2 Accuracy and Responsiveness

In order to evaluate the accuracy of the EVA estimator, we compare the estimation results with those of simulation and analytic models. We run the estimator by varying the filter memory of $\alpha$ ($0.99 \leqslant \alpha \leqslant 0.9999$), while observing the performance tradeoff. The compared simulation result is obtained based on the setting that a station in consideration is associated and communicates with an AP in an infinite backlogged condition. For the analytical result, we employ the Markov chain-based analysis model proposed in [19].

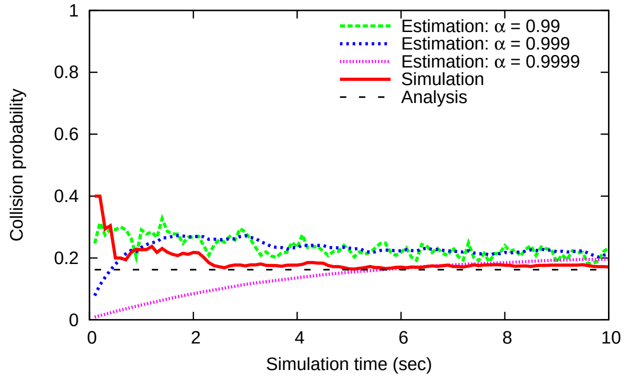
We consider two different scenarios: (1) when a station that estimates EVA tries to associate with an AP; (2) and when a station tries to change its association to another AP to achieve a better throughput performance, i.e., the station is already associated with an AP. The corresponding results are shown in Figs. 4 and 5, respectively. In both scenarios, the number of stations is set to 10 including the station of our interest, and each station is associated with a single AP. Note that only the first scenario represents the case for the initial association attempt of a station.

As shown in both Figs. 4 and 5, the target station observes the channel for ten seconds and estimates $p_c^{rts}$ and EVA. Both cases show the similar trends in the convergence and fluctuation tradeoff when $\alpha$ varies. Larger $\alpha$ shows less estimation fluctuation, but takes longer to converge.

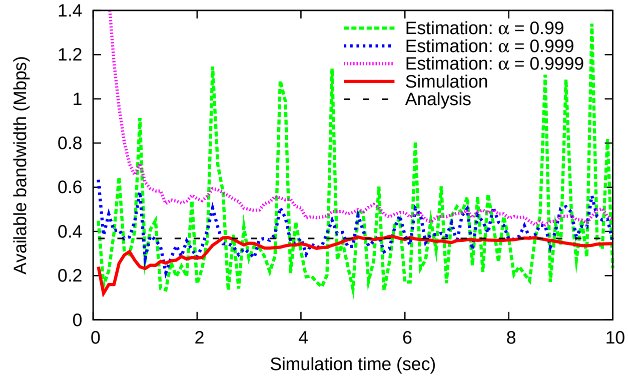
[3]The BER curves in [11] were measured in an AWGN (Additive White Gaussian Noise) environment.

**Table 2: RMS error of the estimated values.**

| | Not associated | | Associated | |
|---|---|---|---|---|
| $\alpha$ | $p_c^{rts}$ | EVA | $p_c^{rts}$ | EVA |
| 0.99 | 0.112 | 0.214 | 0.097 | 0.239 |
| 0.999 | 0.028 | 0.141 | 0.038 | 0.190 |
| 0.9999 | 0.144 | 1.109 | 0.146 | 1.275 |

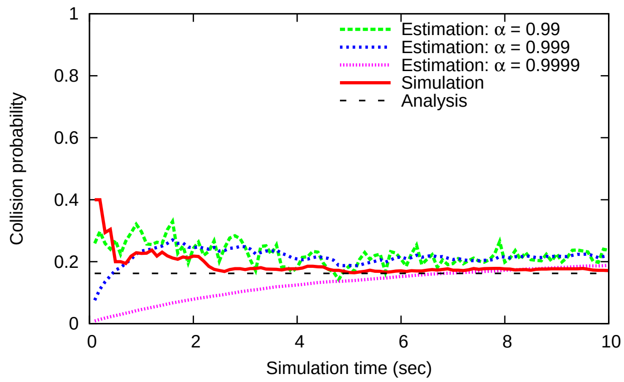



(a) Collision probability ($p_c^{rts}$).

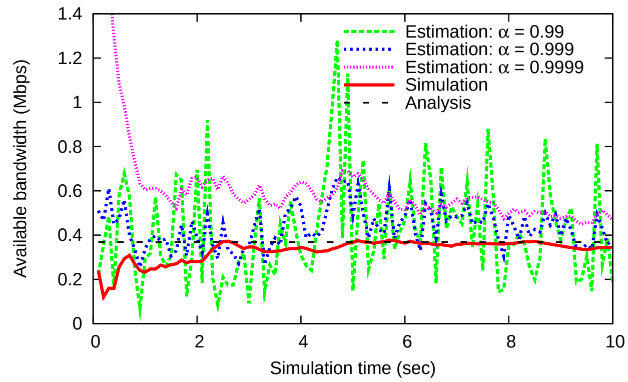



(b) Estimated available bandwidth (EVA).

**Figure 4: Comparison of estimated results with the simulated and analyzed when *not* associated.**

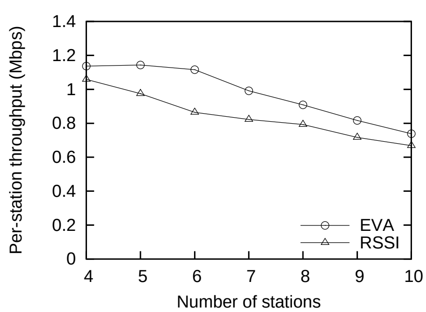



(a) Collision probability ($p_c^{rts}$).

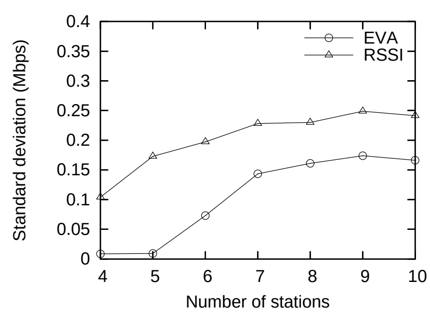



(b) Estimated available bandwidth (EVA).

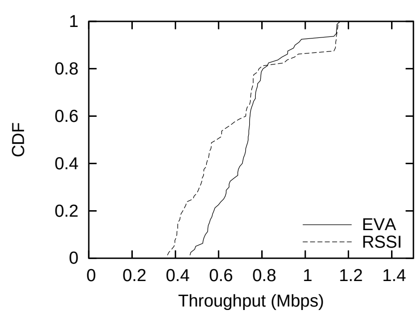
**Figure 5: Comparison of estimated results with the simulated and analyzed when associated.**




(a) Average per-station throughput.




(b) Standard deviation of achieved throughput among contending stations.




(c) Cumulative fraction of achieved throughput of each contending station when the number of stations is 10.

**Figure 6: Performance comparison of EVA and RSSI-based association processes.**

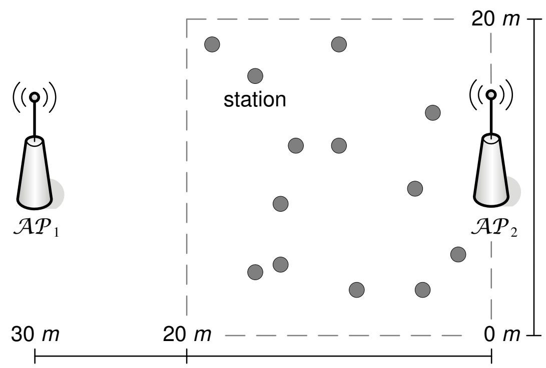



**Figure 7: The topology of simulation.**

To further investigate the effect of $\alpha$, we calculate RMS (Root-Mean-Square) errors of all estimates. We collect 100 random samples of $p_c^{rts}$ and EVA at 100 milliseconds, and derive ensemble averages to find which $\alpha$ value yields the smallest estimation error for both estimates. Table 2 shows the RMS errors calculated for all $\alpha$ values. For all $\alpha$ values and whether associated or not, we observe that $\alpha = 0.999$ shows the minimum RMS error. Therefore, we fix the value of $\alpha$ and the estimation interval to 0.999 and 100 milliseconds, respectively, for the following simulation environment.

## 6.3 AP Selection by EVA

We now evaluate the effectiveness of the proposed EVA association metric by comparing it with the legacy scheme, RSSI-based association. The considered topology is shown in Fig. 7, where two APs and multiple stations are deployed. Two APs (denoted as $\mathcal{AP}_1$ and $\mathcal{AP}_2$) are separated by 30 $m$ from each other, and stations are randomly located in the area of $20 \times 20$ $m^2$, which is shifted toward $\mathcal{AP}_2$ as shown in Fig. 7. In this topology, we expect that more stations associate with $\mathcal{AP}_2$ than $\mathcal{AP}_1$ if the RSSI metric is employed. Meanwhile, stations working with EVA might associate with $\mathcal{AP}_1$ in spite of lower RSSI value, since each station estimates its maximum achievable throughput and selects the highest-throughput AP. Different frequency channels are assigned to each AP thus having no inter-channel interference. The carrier sense range is set to 80 $m$, so that all stations and APs can see frame transmissions from others in this topology. The offered load of each station is set to 1.14 Mbps during simulation runs.

Figure 6(a) shows the per-station throughput of both EVA and RSSI-based association. All results are averaged over 10 runs. We observe that the proposed EVA-based association shows about 16.2 % enhanced throughput gain over the legacy association.

We also show the standard deviation of the achieved throughput of all contending stations in Fig. 6(b). While EVA-based association presents smaller standard deviation (i.e., at most 0.17 Mbps when the number of stations is 9), the legacy scheme shows larger standard deviation for all the cases, which means that the achieved throughput among stations is often highly unbalanced.

In the case of 10 contending stations, we present the cumulative fraction of the achieved throughput of each contending station in Fig. 6(c). EVA-based association (the solid line) shows steeper slope of curve, meaning that most stations achieve throughput evenly. We also count the number of associated stations with different APs. With RSSI, 3.125 stations (out of 10) associate with $\mathcal{AP}_1$ on average, while the number of stations that are associated with $\mathcal{AP}_2$ is 6.875. On the other hand, stations with the EVA estimator are more evenly distributed between two APs: 4.25 stations with $\mathcal{AP}_1$ and 5.75 with $\mathcal{AP}_2$. As the result indicate, we can achieve better balanced throughput share as well as higher individual/aggregate throughput performance with the proposed EVA-based association.

# 7. CONCLUSION

We presented a new association metric called EVA (Estimated aVailable bAndwidth) for IEEE 802.11 stations. EVA is designed to enhance the throughput performance of an individual station by estimating the available bandwidth provided by multiple APs and selecting the best one to associate with.

We first showed the accuracy of the proposed estimation method by comparing our estimation of collision probability and available bandwidth with the simulation and analytic models. We compared EVA-based association with the legacy scheme in terms of individual and aggregate throughput performance. We showed that EVA-based association increases the per-station throughput, balances the load of the APs, and consequently, enhances the aggregate network throughput. Moreover, the EVA estimator does not require any extra probing overhead.

As future work, we plan to extend the formulation of EVA to incorporate the impact of hidden stations into the available bandwidth estimation. Moreover, we plan to apply the usage of EVA to the handoff decision criterion so as to enhance the throughput performance of mobile stations.

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# APPENDIX

## A. COMPARISON OF CONVERGENCE TIME OF EVA AND VMAC ALGORITHMS

PROPOSITION 2. *Every timeslot considered as a valid one for the estimation of EVA has the same probability to be sampled in the VMAC algorithm.*

PROOF. Let $p_n$ be the probability that the $n^{\text{th}}$ timeslot is chosen by a VMAC station to get an estimation sample, $\ell$ be the total number of contention window stages, i.e., $\ell = \log_2(\frac{CW_{\max}+1}{CW_{\min}+1}) + 1$, and $q_{n,i}$ be the probability that the contention window size is $CW_i$ when deriving $p_n$. The probability that an estimation sample is chosen at the $(n+1)^{\text{th}}$ timeslot is written by:

$$p_{n+1} = \sum_{i=1}^{\ell} q_{n+1,i} \sum_{j=0}^{CW_i} \mathsf{Prob}[BC = j | CW_i] \cdot p_{n-j}, \qquad (13)$$

where $BC$ is a backoff counter selected by the VMAC algorithm out of $[0, CW_i]$.

Suppose that each VMAC station joins a WLAN in a random manner. At the very first sampling attempt, the probability that a VMAC station obtains an estimation sample in an arbitrary timeslot should be the same with those for all other timeslots to be chosen. In other words, $p_{n-j}$ in Eq. (13) becomes identical for $\forall j$. Consequently, Eq. (13) reduces to: $p_{n+1} = p_n$, which means that any timeslot used in the EVA estimator can be an estimation sample with the same probability in a VMAC station. $\square$

Based on Proposition 2, both EVA and VMAC algorithms should have the similar estimation accuracy. However, the convergence time of EVA should be shorter than that of VMAC as EVA collects more samples for a given time duration.