

# A Smart Predictive Link Layer Trigger Algorithm to Optimize Homogenous/Heterogeneous Networks WiFi Handover Decisions

Chunmei Liu  
Clearwire Corp.  
Herndon, VA, USA  
mayliu@alum.mit.edu

Christian Maciocco  
Intel Labs, Circuits and Systems Research  
Hillsboro, OR, USA  
christian.maciocco@intel.com

**Abstract**— In traditional wireless networks, link layer metrics used to trigger handover are mainly signal quality based, such as Received Signal Strength (RSS). While signal quality is one major reason for poor performance in traditional wireless networks, WiFi networks are special in that there is another major reason for poor performance, which is collision. While there exist some metrics to reflect collisions and trigger handover when necessary, such as channel load, this paper explains why these existing metrics, such as channel load, cannot capture the actual collision situation in the network and that one station is experiencing. Based on this observation, this paper proposes a new metric, called station collision probability, as an additional handover trigger metric, and develops a prediction algorithm for this metric. Specifically, for WiFi networks, station collision probability is the probability that a packet being transmitted by a station incurs a collision. A prediction algorithm is developed for station collision probability on unlicensed WiFi networks, which takes the number of collisions between two successful transmissions on the channel as the measurement and predicts the station collision probability by solving a developed equation. The algorithm does not require the station to send any traffic, and applies to real time decisions, including predictive handover decisions to initiate and prepare the handover to reduce latency and service interruption for the end-users. This paper focuses on defining an optimal collision estimation algorithm and the simulation results validates that the algorithm predicts station collision probability and adapts well to the change of network traffic. The predicted station collision probability can then be integrated with the existing signal quality based trigger metrics to trigger handover, which is beyond the scope of this paper and will be the next steps.

**Keywords**- predictive handover trigger; station collision probability; WiFi networks; intra- and inter-technology handover.

## I. INTRODUCTION

In wireless networks, handover is one of the key approaches to ensure user experience and network performance. From user perspective, a user may request handover when it cannot receive quality services from its current access point (AP). From network perspective, an AP may request a group of users to perform handover to balance load. This applies to both homogenous and heterogeneous networks.

Figure 1 illustrates a typical handover architecture based on IEEE 802.21 [1], which is a standard that focuses on

media-independent handover (MIH) method and procedures. The first step in this architecture is link layer trigger, which is also the focus of this paper. The objective of link layer trigger is to provide algorithms to trigger handover when link is not “good”, viewed from data link layer and below. The link layer trigger is then followed by network selection and handover execution.

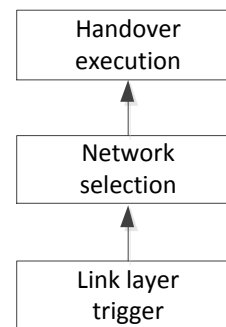


Figure 1. 802.21 based handover architecture.

Link layer trigger consists of the following three portions: 1) trigger metric selection; 2) metric estimation/prediction; 3) metric based trigger algorithm. This paper focuses on the first two: handover trigger metric selection and estimation/prediction. Essentially, this paper considers predictive link layer handover triggers whose purpose is to allow early handover initiation and preparation so that the handover latency and service interruption time can be reduced significantly.

In traditional wireless networks, signal quality related metrics, such as Received Signal Strength (RSS), are typically the metrics of choice used in conventional handover algorithms. Gregory [2] reviews conventional trigger algorithms based on RSS, where RSS used is averaged RSS. Alexe, Vijayan, Zhang, et al. [3][4][5] provide analysis on the handover performance based on these algorithms. Zonoozi et al. [6] further optimizes the parameters including the hysteresis level and signal averaging time.

Signal quality related metrics, such as RSS, captures how good the physical channel is, and gives limits on the max data rate the station can receive, which is directly related to

the station performance. In addition to signal quality, there is another significant aspect that directly impacts station performance, that is, *how much time a station can effectively utilize the physical channel*. The latter is especially important for WiFi networks due to its nature of contention-based MAC, where stations under one AP compete for channel access.

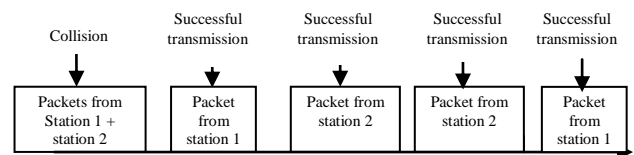
One example of the importance of the latter with respect to station's performance is that, in a WiFi network, even when a station is close to an access point (AP) and the signal quality is excellent, if the network is highly congested, the transmissions from this station will incur collisions coming from other competing stations with high probability. These collisions result in not only packet losses, but also additional backoff stages. All the collision slots and backoff slots are not actually utilized by the station, in that either the transmissions from the station incur collisions and fail (collision slots), or there is no transmission from the station at all (backoff slots). The only effective slots are those that contain successful transmissions. Apparently in this scenario, the time when the station can effectively utilize the physical channel is limited. As a result, although the signal quality is excellent and the channel is excellent, the station experiences significantly deteriorated performance such as low throughput and high delay. Accordingly, in such scenarios, the station should search for handover opportunities, either to another AP within the WiFi network, or to a base station (BS) of another network such as a WiMAX BS.

This paper focuses on the latter aspect, that is, *“how much time can a station effectively utilize the physical channel”*. Specifically, in addition to existing signal quality related metrics, this paper proposes to use station collision probability as a metric to trigger handover from WiFi networks. Station collision probability of a station is defined to be the probability that a packet being transmitted by the station incurs a collision. This probability is the same as the conditional collision probability in Bianchi [7]. Since this probability is to be used as a handover trigger metric, the term station collision probability is used for clarity and to avoid mathematical terms. According to the WiFi backoff mechanism specified in the standard 802.11 [8], once the station collision probability is known, the time that the station can effectively utilize the channel can be calculated from the backoff mechanism. Together with the signal quality, the station performance can then be estimated and a handover can be triggered when necessary.

Note that while currently there do exist some metrics that are somewhat related to MAC collisions and are being used to trigger handover from WiFi networks, such as channel load, they do not reflect collisions. One such an example is when there is only one station transmitting within an AP cell, but the station is saturated, meaning that it always has

packet to transmit. In this case the channel load is high, while there are 0 collisions and the station receives excellent service from the AP. Hence the station should stay with this cell instead of triggering a handover to some other networks.

Also note that since one collision may involve several packets, station collision probability is different from the channel collision probability, which is the probability of a collision among all the transmissions on the channel. Hence station collision probability cannot be estimated by simply computing the percentage of collisions over overall transmissions on the channel. Figure 2 shows an example which illustrates these two probabilities and their differences. It shows that packet collision probabilities for station 1 and 2 are 1/3, respectively, while channel collision probability is 1/5, which does not equal to the station probability of 1/3.



- Station collision probability of station 1 and 2 = 1/3: each station transmitted 3 packets, one of which incurs a collision.
- Channel collision probability = 1/5: the channel sees 5 transmissions, one of which is a collision.
- Station collision probability ≠ channel collision probability

Figure 2. Station collision probability vs channel collision probability.

In addition to propose station collision probability as a handover trigger, this paper develops a prediction algorithm for station collision probability. The algorithm measures number of collisions between two successful transmissions occurring on the channel, computes its average, and then obtains the station collision probability by solving one equation. Since the algorithm uses all channel data, which includes data from other stations instead of data from the considered station only, the algorithm does not require the station to send any traffic. In addition, channel data provides many more samples within a period of time than the station's own data. Hence the proposed algorithm does not require probing, adapts to network traffic changes well, and applies to real-time decisions, including handover decisions.

The predicted station collision probability can then be integrated with the existing RSS based link-layer predictive triggers, such as those described in Huaiyu, Choong, et al. [9][10], to optimize network selection and seamless handover over homogenous or heterogeneous networks. Note that one major difference between the triggers described in Huaiyu, Choong, et al. [9][10] and the triggers proposed in this paper is that the triggers in Huaiyu, Choong, et al. [9][10] are RSS based, while the triggers in the paper focuses on *“how much time can a station*

effectively utilize the physical channel". The integration of the triggers is beyond the scope of this paper and will be our future work.

This paper is outlined as follows: Section II derives the prediction algorithm for station collision probability. Section III validates the prediction algorithm using OPNET-based simulations. Section IV concludes the paper.

## II. PREDICTION ALGORITHM FOR STATION COLLISION PROBABILITY

### A. Analytical Model

The development of the prediction algorithm for station collision probability is based on the analysis framework proposed in Bianchi [7]. In Bianchi [7], by assuming ideal channel condition, the author considered saturated network and analyzes DCF (Distributed Coordination Function) performance. It is assumed that at each transmission attempt, each packet collides with constant and independent probability. A single station is then modeled as a bi-dimensional Markov chain, with the backoff stage and counter as states, and transition probabilities as functions of assumed constant collision probability. The Markov chain is solved to obtain collision probabilities, saturated throughput, and other parameters. The results show good consistency of the analysis with simulation results.

Two major results obtained in Bianchi [7] are the relationship among the number of saturated stations  $n$ , the probability that a station transmits in a randomly chosen slot  $\tau$ , and station collision probability  $p$ , as follows:

$$\tau = \frac{2(1-2p)}{(1-2p)(W+1) + pW(1-(2p)^m)}, \quad (1)$$

$$p = 1 - (1-\tau)^{n-1}, \quad (2)$$

where  $m$  is the value such that  $CW_{\max} = 2^m CW_{\min}$ ,  $W = CW_{\min}$ ,  $CW_{\min}$  and  $CW_{\max}$  are the minimum and maximum contention window, respectively.

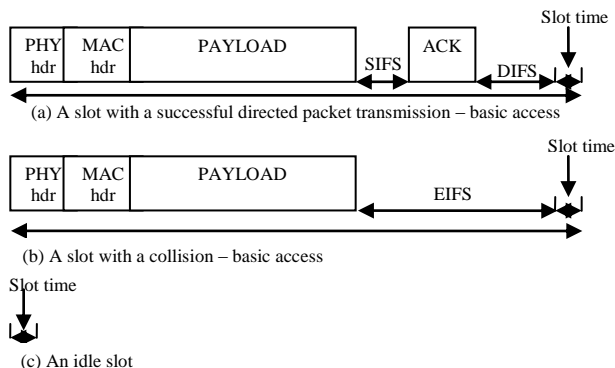


Figure 3. Generic slots in basic access mechanism.

In order to be consistent with the 802.11 standard [8], this paper slightly modifies the format of generic slot used in Bianchi [7] as follows: in Bianchi [7], for basic access, a generic slot that includes a collision consists of PHY and

MAC header plus payload plus DIFS. According to the 802.11 standard [8], a station shall use EIFS, instead of DIFS, before transmission, when it determines that the medium is idle following a collision. Hence the generic slot in this paper is defined as those in Figure 3.

Fortunately, the basic unit of the Markov model in Bianchi [7] is a generic slot, and the Markov model does not change with the format of the generic slot. Hence the analysis in Bianchi [7] can be reused under the new definition of generic slots, and equation (1) and (2) above, which are derived from the Markov model, still holds under the new definition.

### B. Parameter Relationships

Now, let's consider the number of collision slots between two successful transmissions and its expectation, denoted by  $n_c$ , and  $E[n_c]$ , respectively.  $E[n_c]$  will be used later in the proposed prediction algorithm and the predictive trigger.

Let  $P_{tr}$  denote the probability that there are at least one transmission in the considered slot time, and  $P_s$  denote the probability that a transmission occurring on the channel is successful. Then the probabilities that a random slot is an idle slot, a slot with successful transmission, and a slot with collision, are  $1 - P_{tr}$ ,  $P_s P_{tr}$ , and  $(1 - P_s) P_{tr}$ , respectively. Hence, the expectations of  $n_c$  can be represented as follows:

$$E[n_c] = \frac{(1 - P_s) P_{tr}}{P_s P_{tr}} = \frac{1}{P_s} - 1. \quad (3)$$

Moreover, from their definitions,  $P_{tr}$  and  $P_s$  can be represented in terms of  $n$ ,  $\tau$ , and station collision probability  $p$ , as follows:

$$P_{tr} = 1 - (1 - \tau)^n, \quad (4)$$

$$P_s = \frac{n\tau(1-\tau)^{n-1}}{P_{tr}} = \frac{n\tau(1-\tau)^{n-1}}{1 - (1-\tau)^n}. \quad (5)$$

By combining equation (2)-(5) and after some manipulations, parameters  $p$ ,  $n$ , and  $\tau$  satisfy the below equation:

$$1 - p - \frac{1}{1 - \tau + n\tau(E[n_c] + 1)} = 0. \quad (6)$$

Furthermore, from equation (2),  $n$  can be represented by  $p$  and  $\tau$  as follows:

$$n = 1 + \frac{\ln(1-p)}{\ln(1-\tau)}. \quad (7)$$

Equations (1), (6) and (7) show that, once we have  $E[n_c]$ ,  $p$ ,  $n$ , and  $\tau$  can be solved by these three equations. This leads to the below prediction algorithm.

### C. Prediction Algorithm

Define function  $f(p)$  as below:

$$f(p) = 1 - p - \frac{1}{1 - \tau + n\tau(E[n_c] + 1)}. \quad (8)$$

where  $\tau$  is given in terms of  $p$  as in equation (1), and  $n$  is given in terms of  $p$  and  $\tau$  as in equation (7).

**Prediction algorithm:**

Choose an arbitrarily small number  $\varepsilon > 0$ . The prediction algorithm for station collision probability is as follows:

Step 1: Upon each successful transmission, collect  $n_c$  and update its average as  $E[n_c]$ .

Step 2: Find  $p \in [0, 1 - \varepsilon]$  such that  $f(p) = 0$  and update  $P_{\text{prediction}} = p$ .

Step 3: Go back to step 1.

**Lemma 1:** for  $E[n_c] \geq 0$  and an arbitrarily small number  $\varepsilon > 0$ , there exists a  $p \in [0, 1 - \varepsilon]$  such that  $f(p) = 0$ .

This lemma can be proved by showing that:

- $f(p)$  is continuous and decreases monotonically with  $p$ ;
- $f(0) \geq 0$ ;
- $f(1 - \varepsilon) < 0$ .

For a), it is straightforward to show that  $f(p)$  is continuous, as below: equation (1) can be alternatively written as below:

$$\tau = \frac{2}{W + 1 + pW \sum_{i=0}^{m-1} (2p)^i} \quad (9)$$

Hence  $\tau$  decreases with  $p$ ,  $\tau \in [\frac{2}{2^m W - 1}, \frac{2}{W + 1}]$ , and  $\tau \leq 1$ . Equation (7) shows that  $n \geq 1$  and by definition,  $E[n_c] + 1 \geq 1$ . Hence  $f(p)$  is continuous by its definition in equation (8).

Monotone can be shown by considering equation (1), (7) and (8) together.

For b), by plugging  $p = 0$  into (1), (7) and (8),  $f(p)$  becomes:

$$f(0) = 1 - \frac{1}{1 + \frac{2}{W + 1} E[n_c]} \quad (10)$$

Since  $W > 0$  and  $E[n_c] \geq 0$ ,  $f(0) \geq 0$ .

For c), since  $\tau \in [\frac{2}{2^m W - 1}, \frac{2}{W + 1}]$  as shown previously, from equation (7),

$$n = 1 + \frac{\ln(1 - p)}{\ln(1 - \tau)} \leq 1 + \frac{\ln(1 - p)}{\ln(1 - \frac{2}{2^m W - 1})}. \quad (11)$$

Hence from equation (8),

$$\begin{aligned} f(1 - \varepsilon) &\leq 1 - (1 - \varepsilon) - \frac{1}{1 - \frac{2}{W + 1} + n \frac{2}{W + 1} (E[n_c] + 1)} \\ &\leq \varepsilon - \frac{1}{1 - \frac{2}{W + 1} + \left(1 + \frac{\ln(1 - p)}{\ln(1 - \frac{2}{2^m W - 1})}\right) \frac{2}{W + 1} (E[n_c] + 1)} \\ &\leq \varepsilon - \frac{1}{c_0 - c_1 \ln \varepsilon} \end{aligned}$$

where  $c_0$  and  $c_1$  are constants and  $c_0 = 2 - \frac{2E[n_c]}{W + 1}$ ,

$$c_1 = -\frac{E[n_c] + 1}{\ln(1 - \frac{2}{2^m W - 1})} \frac{2}{W + 1} \geq 0.$$

Further processing the above equation shows that

$$f(1 - \varepsilon) \leq \frac{c_0 \varepsilon - c_1 \varepsilon \ln \varepsilon - 1}{c_0 - c_1 \ln \varepsilon} \leq 0, \quad (12)$$

where the last inequality holds since the numerator is less than 0 for arbitrarily small  $\varepsilon$ , and the denominator comes from  $1 - \frac{2}{W + 1} + n \frac{2}{W + 1} (E[n_c] + 1)$ , which is greater than 0 as  $n \geq 1$  and  $E[n_c] + 1 \geq 1$  as shown previously.

**Lemma 2:** The computation complexity of the proposed algorithm is upper bounded by  $\log_2 \frac{1}{\delta}$ , where  $\delta$  is the given tolerance.

The computation complexity of the algorithm depends on the number of iterations needed for solving  $f(p) = 0$  in step 2. If the bisection method is employed, the complexity is  $\log_2 \frac{1}{\delta}$ . Hence the computation complexity of the estimation algorithm is upper bounded by  $\log_2 \frac{1}{\delta}$ .

Note that this lemma says that if the tolerance is  $10^{-2}$ , then at most 7 iterations are enough. This shows the low computation complexity of the proposed algorithm.

### III. SIMULATION RESULTS

The proposed algorithm is simulated by OPNET. The scenario simulated is shown in Figure 4, where station 1 to 9 has saturated traffic with destination being station 0, and the physical channel is set to be perfect to exclude the effects of channel losses. Station 1 to 9 start packet transmissions at a random time between 0s and 5s after the start of the simulation, and prediction of station collision probability starts at 5s.

For station 5, Figure 5 plots the comparison between predicted station collision probability and actual percentage of packets that incurred collisions, where the blue curve is

the actual percentage and the red curve is the predicted station collision probability. The transient period of the blue curve at the beginning of the simulation is due to the random start time of all stations' traffic.

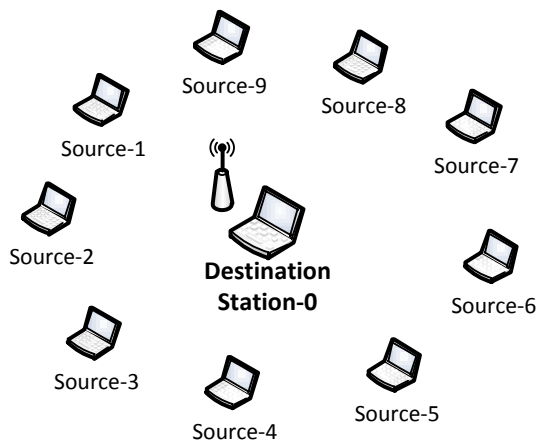
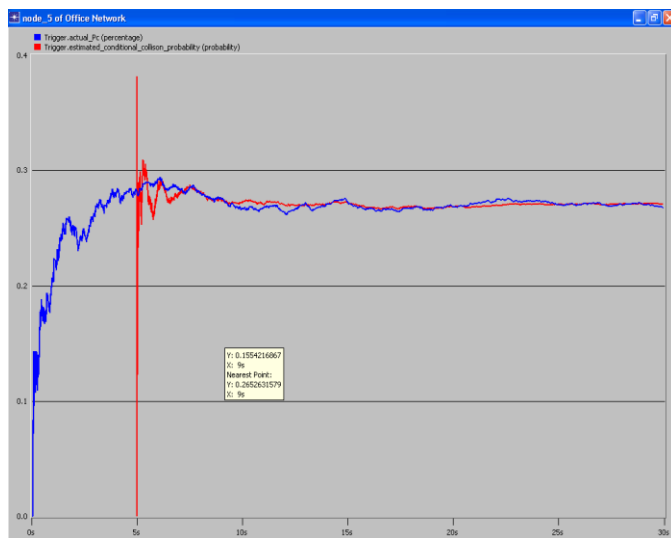


Figure 4. OPNET simulation scenario with ten stations.



Red curve - predicted station collision probability  
Blue curve - actual percentage of packets from station 5 that incurred collisions.

Figure 5. Comparison between actual percentage of collisions and predicted station collision probability.

For other stations, the comparison between predicted station collision probability and actual percentage of collided packets is similar, which is not shown here due to limited space. Figure 5 clearly shows that the estimated station collision probability converges to the actual percentage of collisions very fast. In addition, the prediction starts during the transient period, and the predicted station collision probability reaches its “steady state” value faster than the actual percentage of collided packets. Hence this algorithm indeed predicts future station collision probability and adapts to the change of network traffic well.

Detail data analysis shows that the estimation errors differ from station to station. The largest estimation error is

7.5%, and the smallest is 1.2%, which validates the accuracy of the proposed prediction algorithm.

#### IV. CONCLUSION

For wireless stations, it is key to detect and react rapidly to link condition changes as they directly affect the station connectivity and application performance.

In this paper, in addition to the commonly used signal quality based triggers, we proposed a novel smart predictive handover trigger algorithm based on mobile station collision probability once an issue has been detected with the current network. A prediction algorithm is developed to predict station collision probability, which does not require the station to send any traffic, has low computation complexity, and applies to real time decisions. Simulation results show that the predicted value matches well with the actual value. The predicted station collision probability hence provides the basis for a predictive handover trigger that based on not only signal quality, but also potential collisions one station may experience, which captures the actual performance the station may expect.

As a next step we are integrating the described station collision probability with RSS to investigate how to select the most appropriate ones under various conditions and the resulting handover performance for WiFi wireless station.

#### REFERENCES

- [1] IEEE P802.21/D01.00, March 2006, “Draft IEEE Standard for Local and Metropolitan Area Networks: Media Independent Handover Services”.
- [2] Gregory P. Pollhi, “Trends in Handover Design”. IEEE Communications Magazine, pp. 82-90, March 1996.
- [3] Alexe E. Leu and Brian L. Mark, ” A Discrete-Time Approach to Analyze Hard Handoff Performance in Cellular Networks”. IEEE Transactions on Wireless Communications, pp. 1721-1733, Sept. 2004.
- [4] R. Vijayan and J. M. Holtzman, “A model for analyzing handoff algorithms,” IEEE Trans. Veh. Technol., vol. 42, pp. 351–356, Aug. 1993.
- [5] N. Zhang and J. M. Holtzman, “Analysis of handoff algorithms using both absolute and relative measurement,” in Proc. Veh. Technol. Conf., 1994, pp. 82–86.
- [6] M. Zonoozi, P. Dassanayake, M. Faulkner, "Optimum Hysteresis Level, Signal Averaging Time and Handoff Delay". IEEE 47th VTC, May 1997, USA, pp. 310-313.
- [7] G. Bianchi, “Performance analysis of the IEEE 802.11distributed coordination function,” IEEE J. Select. Areas Commun., vol. 18, no. 3, pp. 535-547, 2000
- [8] IEEE P802.11, Jun. 2007, “IEEE Standard for Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications”.
- [9] Huaiyu Liu, Christian Maciocco, Vijay Kesavan, and Andy Low, “Energy Efficient Network Selection and Seamless Handovers in Mixed Networks”. IEEE World of Wireless Mobile and Multimedia Networks, 2009
- [10] K.N. Choong, Vijay Kesavan, S.L. Ng, Francisco de Carvalho, Andy Low and Christian Maciocco, “SIP-based IEEE 802.21 Media Independent Handover – A BT Intel Collaboration”. IEEE Springer, BT Technical Journal Vol 25 N0 2, pp. 219-230, April 2007.