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Etude du niveau d'agrégation des trames dans les réseaux IEEE 802.11 pour l'évaluation du niveau de charge

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Dans cet article, nous nous intéressons à des techniques d'inférence du temps d'occupation du canal fondées sur le taux d'agrégation des trames. Nous proposons un modèle analytique basé sur une chaîne de Markov qui estime le taux d'agrégation théorique pour différents niveaux de charges. Le modèle est confronté à des simulations effectuées sur le simulateur réseau ns-3 et sur un simulateur ad-hoc. Les résultats obtenus montrent que le modèle théorique donne de bonnes approximations du niveau d'agrégation moyen et qu'il peut servir à inférer la charge du réseau.

Mots-clefs : IEEE 802.11n, WI-FI, Frame aggregation, Markov model.

1 Introduction

IEEE 802.11 has become a prominent wireless network access technology. In many situations, a device may attach to several Wi-Fi access points (AP) within the radio range. The operating system makes its choice over metrics that do not take into account the actual available capacity. To fill this gap, several proposals have been made to infer the available bandwidth [MLK08]. In this paper, we focus on estimating the channel busy time fraction (BTF), defined as the proportion of time the wireless medium is sensed busy by an AP. This estimation allows a device to identify the AP that offers the highest availability. However, in the most recent evolutions of 802.11, in particular 802.11n or ac, a frame aggregation mechanism has been introduced. This scheme, which aims to increase the throughput by sending several data packets in a single transmission using a larger aggregated data frame, hurts the accuracy of the available bandwidth tools.

In this paper, we study the possibility to infer the BTF from the level of frame aggregation, defined as the number of packets clustered together in an aggregated frame, of a small probe traffic. We propose two discrete-time Markov chains based analytical models to estimate the theoretical aggregation level of a probe traffic concurrent to a cross traffic. The first is considering a cross traffic that also uses frame aggregation, while the second captures cross traffic without aggregation. Our model is compared to a custom-made simulator and ns-3 simulations, both allowing more generic traffic patterns and realistic scenarios. We show that the mean aggregation level can be an accurate metric to estimate the load of an AP.

2 Model description

First model : Cross traffic aggregates Our system is a wireless network using the IEEE 802.11 Distributed Coordination Function (DCF) to access the radio channel. Two traffics share the capacity :

- Probe traffic is sent by the BTF estimation tool from a client to a server. The server uses the aggregation level of this traffic to estimate the network load. Our model estimates the aggregation distribution of this traffic, defined as the probability for a frame to aggregate n sub-frames for a given BTF. The probe traffic is a constant bit rate (CBR) traffic generated at regular interval d_p. We assume that the buffer and the aggregated frames have a maximum size K_{max}. Consequently, the buffer becomes empty each time a probe traffic frame is sent. The random process describing the number of aggregated sub-frames contained in the n^{th} transmitted frame for this traffic is denoted X_n. It takes its values in the set $\{0,...,K_{max}\}$.

- Cross traffic represents the concurrent traffic between other devices and the AP in the radio range of the node that uses the BTF estimation tool. In our model, this cross traffic is modeled through a unique traffic sent over the channel and managed by a unique queue. It is also a CBR traffic generated each regular interval d_c. The random process that describes the number of packets in the cross traffic buffer at the moment of the n^{th} probe frame transmission is denoted Y_n. The buffer has a maximum size K_{max}. It is emptied when an aggregated frame is sent. The possible states are in $\{0,...,K_{max}\}$.

There is a strong dependency between the processes X_n and Y_n. When an aggregated frame is sent, its length impacts the transmission duration, and consequently, the number of packets received in the probe and cross traffic buffers. The two processes have to be considered conjointly. The Markov chain is thus defined as the couple $(X_n,Y_n)_{n\geq 0}$. It is assumed homogeneous. We consider the transition probability $P_{(i,j)(l,m)}$ from state (l,m) to state (i,j) defined as : $P_{(i,j)(l,m)} = \mathbb{P}\left((X_{n+1},Y_{n+1}) = (i,j) | (X_n,Y_n) = (l,m)\right)$. The transition probabilities are determined by the time between two consecutive probe traffic transmissions. As both probe and cross traffics are deterministic, this time sets the number of packets that arrived in each buffer and that will be sent in the aggregated frame. Figure 1 shows an example of possible events between two probe transmissions. Let assume that the current state of the Markov chain at step n is (l,m). First, the probe traffic frame is sent. its transmission duration is $f(l)$. The funtion $f(.)$ counts the time to access the medium (Distributed Inter-Frame Space (DIFS) and the backoff), the physical and the MAC headers, the payload and the Frame Check Sequence (FCS), the shortest Inter-frame Space (SIFS), and the Ack or BlockAck.

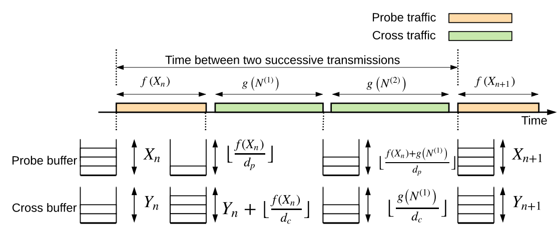
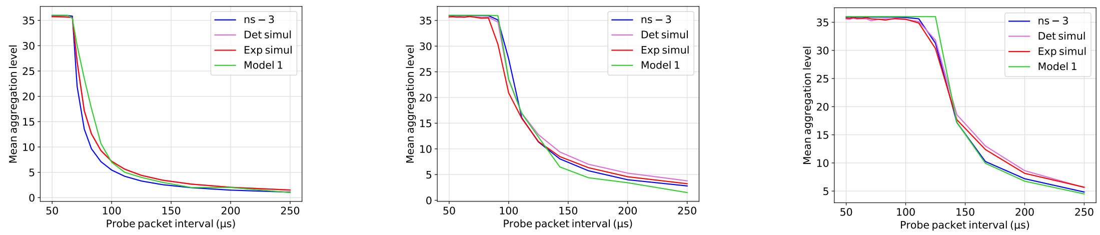


FIGURE 1: Possible events between two successive probe transmissions. $f(X_n)$.

At the end of this transmission, the probe traffic buffer contains $\lfloor \frac{f(l)}{d_p} \rfloor$ packets, and the cross traffic buffer contains $N^{(1)} = m + \lfloor \frac{f(l)}{d_c} \rfloor$ packets. Then, several successive transmissions of cross traffic may occur. Let $N^{(k)}$ be the number of packets in the cross traffic buffer at the time when the cross traffic tries to access the medium for the k^{th} time. $N^{(1)}$ has already been computed. If the cross traffic succeeds to access the medium, an aggregated frame composed of $N^{(1)}$ packets is sent. During this transmission, $N^{(2)}$ packets arrived in the cross traffic buffer with : $N^{(2)} = \left\lfloor \frac{g(N^{(1)})}{d_c} \right\rfloor$, where $g(.)$ is the duration of the transmission of the cross traffic aggregated frames. The only difference with $f(.)$ is the physical transmission rate and the packet size that can be different from the probe traffic. More generally, $N^{(k)} = \left\lfloor \frac{g(N^{(k-1)})}{d_c} \right\rfloor$. The probability that k cross traffic packets are sent successively is denoted $\mathbb{P}\Big(Q(l,m) = k\Big)$, where m and l denote the buffer states and $Q(l,m)$ is the number of successive times that the cross traffic accesses the medium. $k = 0$ means that the cross traffic does not access the medium between two successive probe traffic transmissions, due to an empty buffer or because the probe traffic wins the access. The probability that the cross traffic accesses the medium successively k times, given that probe and cross traffics have a non-empty buffers, is $p(k)$. This probability depends on the contention window. We get : $\mathbb{P}\Big(Q(l,m) = 0\Big) = \mathbb{1}_{m+\frac{f(l)}{dc}<1} + (1-p(1)) \cdot \mathbb{1}_{m+\frac{f(l)}{dc}\geq 1}$. For $k>0$, we get, $\mathbb{P}\Big(Q(l,m) = k\Big) = p(k) \cdot \prod_{q=1}^{k} \mathbb{1}_{N^{(q)}\geq 1} \cdot \Big(\mathbb{1}_{N^{(k+1)}=0} + (1-p(k+1))\mathbb{1}_{N^{(k+1)}>0}\Big)$, where the product corresponds to the probability that the cross traffic has a non-empty buffer during each of the k successive transmissions and in the $k+1$ access, it loses the access or it has an empty buffer. Considering that the probe traffic is CBR, we obtain the following transition probabilities.

$$P_{(i,j)(l,m)} = \sum_{k=0}^{\infty} \mathbb{P}\Big(Q(l,m) = k\Big) \cdot \mathbb{1}_{d_p \cdot i \leq f(l) + \sum_{q=1}^{k} g(N^{(q)}) < d_p \cdot (i+1)} \cdot \mathbb{1}_{N^{(k+1)} = j} \tag{1}$$

As the Markov chain is irreducible and has a finite number of states, it exists a unique stationary distribution. Let us denote μ the matrix corresponding to this stationary distribution : $\mu = (\mu_{i,j})_{0\leq(i,j)\leq K_{max}}$. The stationary distribution π of the sub-chain (X_n) is given by $(0 \leq i \leq K_{max})$: $\pi_i = \sum_{j=0}^{K_{max}} \mu_{i,j}$. The mean aggregation level



(a) 0 BTF (b) 0.375 BTF (c) 0.625 BTF

FIGURE 2: Mean aggregation level versus BTF

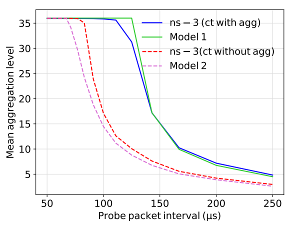


FIGURE 3: Mean aggregation level for model 1 and model 2, 0.625 BTF

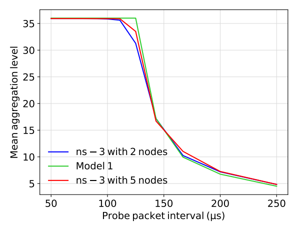


FIGURE 4: Mean aggregation level for model 1 with 5 nodes, 0.625 BTF

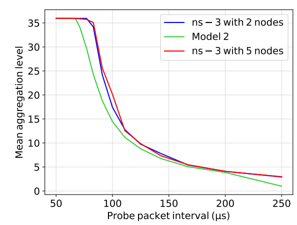


FIGURE 5: Mean aggregation level for model 2 with 5 nodes, 0.375 BTF

for the probe traffic is then computed as : $MeanAgg = \sum_{n=1}^{K_{max}} n \cdot \pi_n$.

Second model : Cross traffic does not aggregate A slight simplification of the model can capture cross traffic without frame aggregation. By lack of space, we do not present the calculus.

A limitation of these models is that they assume a perfect MAC layer and buffers of size K_{max}.

3 Numerical results and Discussion

We validate the model against two simulators. A custom-made simulator that follows the same principle as the Markov chain. It allows us to simulate more general patterns of cross traffic. The ns-3 simulations allow us to compare our simplified model to realistic scenarios capturing the complexity of the whole network stack. The network topology is composed of an AP, a station sending the probe traffic, and a second one for the cross traffic. Under ns-3, we also considered a more generic scenario composed of an AP and five nodes. A node for the probe traffic and four nodes for the cross traffic.

Figure 2 shows the mean aggregation level for the probe traffic when the aggregation is enabled for the cross traffic. Simulations are thus compared to the Markov chain (Model 1). The probe packet interval varies from $50\mu s$ to $250\mu s$ and the cross traffic is set in order to have a BTF equals to 0, 0.375, and 0.625 corresponding to three load levels. Two types of cross traffic distributions are emulated in the ad-hoc simulator : exponential and deterministic. According to these results, it appears that the model and the ad-hoc simulator follow closely the pattern of the ns-3 simulations for all the levels of cross traffic. Deterministic and exponential cross traffic give similar results.

Figure 3 provides the probe mean aggregation when frame aggregation is enabled or disabled for the cross traffic. We compare the results of the Markov chains (Model 1 and 2) to ns-3 simulations (with or without agg). The aggregation level is lower when cross traffic aggregation is disabled. Indeed, each cross traffic frame is sent independently, with shorter transmission times. Consequently, the probe traffic receives fewer packets to aggregate between two consecutive medium accesses. Also, cross traffic reaches saturation faster (as it sends fewer frames on average). As soon as it has always a frame to send, its buffer state does not impact the probe aggregation level.

In the model, the cross traffic is sent by a single queue. Figures 4 and 5 compare ns-3 scenarios where the cross traffic is generated by 4 concurrent nodes, with or without frame aggregation. The results show that the number of concurrent nodes has a negligible impact on the probe traffic aggregation level. Despite the complexity brought by the network stack layers (beacon frames, congestion, random backoff, etc) and the different number of deployed stations, our approach is not affected in the considered scenarios.

Discussion

Frame aggregation for load estimation We now discuss the feasibility to consider the mean aggregation level to estimate the BTF. A method could consist of sending probe packets with increasing interval time from a client to a server. Then the server estimates the mean aggregation level. The computation of the error between the measured aggregation level and the theoretical ones derived from our model can then be used to infer the BTF. The inferred BTF would be the one that minimizes the error between the measured and theoretical aggregation levels for a set of probe traffic intervals. Our simulation results indicate that this method should work perfectly, at least for ns-3 simulations : there are very small differences between the simulations and the models. Besides, the results with or without aggregation are significantly separated, which makes it possible to identify if the cross traffic is aggregated or not.

Experiments and limitations A part of the experiments has been conducted. Our experimental environment was set up as follows. A probe application was executed on a laptop and a cross traffic application on an Android phone. Another computer, configured as an AP, was used as a client for the cross traffic and server for the probe. The physical transmission rate was 144.4 Mbps (i.e., MCS index 15 in 802.11n). Also, we deployed a sniffer which contains a specific Wireless NIC that allowed us to estimate the BTF. To compute the aggregation level, we used the sniffer that captures frames sent through the network. The aggregation level is then computed according to the frame identifier. This method gives results that match well with our simulations and models. However, it may be difficult to deploy it because it requires special features and configurations of the Wi-Fi card : it has to be in monitor mode, Wi-Fi security options must be disabled, etc. A computation method implemented at the application level is thus preferable. We have tested a threshold-based method introduced in WBest+[AFG14] and AIWC [SS17] to estimate the aggregation level : if an inter-arrival time is below a given threshold, the two packets are considered as aggregated. Our test on Linux Ubuntu shows that this technique is inefficient due to the different waiting times introduced by the operating system. Being able to detect frame aggregation at the application level on the server side is a technical challenge that still need to be tackled.

4 Conclusion

In this paper, we study the possibility to consider the frame aggregation level to infer the BTF. We propose two Markov chains to estimate the theoretical aggregation level for a specific scenario where a probe traffic concurrent to a cross traffic. Available bandwidth estimation works are based on empirical observation, and to our knowledge, there was no theoretical analysis of the aggregation level for this particular context. We have shown through a large set of simulations performed with ns-3 and a custom-made simulator that the model allows an accurate estimation of the aggregation level. For the considered scenarios, the results show that the aggregation level could be an accurate metric to infer the network load. Our approach has been implemented in a testbed. However, we faced problems to capture the aggregation level at the application layer. An open issue is thus to propose techniques that estimate precisely the aggregation level at this layer.

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