Capacity-Fairness Performance of an Ad Hoc IEEE 802.11 WLAN with Noncooperative Stations

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Abstract. For an ad hoc IEEE 802.11 WLAN we investigate how the stations' incentives to launch a backoff attack i.e., to configure small minimum and maximum CSMA/CA contention windows in pursuit of a larger-than-fair bandwidth share, affect a proposed capacity-fairness index (*CFI*). We link *CFI* to the network size, "power awareness," a station's perception of the other stations' susceptibility to incentives, and the way of learning how the other stations perceive the other stations' susceptibility to incentives.

1 Introduction

Estimated limits of performance of an IEEE 802.11 WLAN [5] become the more realistic, the richer is the assumed network model; most existing estimates account for PHY-layer bandwidth, MAC and TCP overhead, DATA frame size, number of network stations, station mobility, and channel characteristics. We bring into the picture noncooperative behavior in the form of a backoff attack: each station n is free to configure an arbitrary $w_n = \langle w_{n,\min}, w_{n,\max} \rangle$ (the minimum and maximum CSMA/CA contention windows) in pursuit of a larger-than-fair long-term bandwidth share [1], [3], thus engaging in a noncooperative *CSMA/CA game* [3], [7]. It can be shown that if the *greedy* $\langle 1, 1 \rangle$ configuration is ruled out (the backoff mechanism is mandatory) then the game has a unique Nash equilibrium (NE) [4]. Otherwise, one disincentive to configure $\langle 1, 1 \rangle$ is a certain "power awareness" i.e., fear of another station also configuring $\langle 1, 1 \rangle$, for all the transmission power is then spent on frame collisions. This we assume tantamount to a "penalty" bandwidth share, which leads to multiple Nash equilibria. In the absence of a compelling unique NE we introduce a simple calculus of backoff attack incentives, a form of seeking a best reply to the beliefs as to the other stations' imminent play. We propose a capacity-fairness index (*CFI*), a synthetic performance measure equal to the product of the total goodput (bandwidth utilization) and the Jain index of the stations' bandwidth shares. We link *CFI* to the network size, the stations' "power awareness," a station's perception of the other stations' susceptibility to incentives, and a station's way of learning how the other stations perceive the other stations' susceptibility to incentives. Based on the stations' bandwidth shares b_n obtained from existing models [2], [7] we demonstrate that for small enough networks and "power aware" enough stations, cooperative behavior may ultimately emerge.

2 CSMA/CA Game and Backoff Attack Incentives

To reflect both the total bandwidth utilization $\Sigma_n b_n$ and Jain fairness [6] we use their product i.e., $(\Sigma_n b_n)^3/(N\cdot\Sigma_n b_n^2)$, that we name *capacity-fairness index* (*CFI*). For an N-player CSMA/CA game with payoffs b_n, suppose that x *selfish* stations configure w_s = <2, 2>, y *greedy* stations configure w_g = <1, 1> (i.e., disengage the backoff scheme), and $N - x - y$ *honest* ones stick to a standard-prescribed w_h e.g., <16, 1024>; let the respective payofs be denoted by $b_{s[g,h]}(N, x, y)$. In existing IEEE 802.11 settings, $b_h(N, 0, 0) > 0$ for not too large N and $b_h(N, x > 0, y) \approx 0$. Thus if $x = y = 0$ then $CFI = N\cdot b_h(N, 0, 0)$ (denote this cooperative value by c-*CFI*). Note that $b_G = b_g(N, x, 1)$ is the highest possible payoff, while $b_{s[h]}(N, x, y > 0) = 0$. Let $b_g(N, x, y > 1) = b_C \le 0$, where b_C is a "penalty" payoff, reflecting the fact that a greedy (yet "power aware") station in this case spends all its transmission power to no effect. If $b_C < 0$ [$b_C = 0$] then any configuration profile with $y = 1$ [$y > 0$] is a NE. Thus the game has multiple Nash equilibria; to predict its outcome we calculate backoff attack incentives.

Definition 1: A selfish [greedy] backoff attack incentive is the ratio of the likely payoff upon switching from w_h to w_s [w_g], and the cooperative payoff $b_h(N, 0, 0)$.

A *0-order sophisticated* approach to the "likely" part neglects similar conduct at the other stations: $I_{g,0} = \hat{b}_g(N,0,1)$ and $I_{s,0} = \hat{b}_s(N,1,0)$ (the hats normalize w.r.t. $b_h(N, 0, 0)$). Alternatively, a station forms a model of how the other stations' play is susceptible to the calculated incentives. A *susceptibility map* Φ returns for a (I_s, I_g) pair the probabilities p_s [p_g] of configuring w_s [w_g] at any other station ($p_h = 1 - p_s - p_g$ is the probability of staying at w_h). Intuitively, Φ should be continuous and ensure that p_g increases in I_g, p_s increases in I_s, and p_h decreases in both I_s and I_g. Taking $(p_s, p_g) = \Phi(I_{s,0}, I_{g,0})$, one can calculate the expected normalized payoffs:

$$I_{s[g],1} = \sum_{\substack{x,y,z\ge 0\\ x+y+z\le N-1}} \binom{N-1}{x\ y\ z} p_s^x p_g^y p_h^z \cdot \hat{b}_{s[g]}(N, x+1[x], y[y+1]) \,. \tag{1}$$

This approach can be termed *1-order sophisticated*, as it does account for the other stations also calculating incentive measures, though neglects their use of Φ. Higher-order sophistication consists in re-applying (1) to account for the other stations using Φ, their accounting for the other stations using Φ etc. In the limit Φ is deemed *common knowledge* [4]. Hence, *∞-order sophisticated* incentive measures solve the fixpoint-type equation (where F is defined by (1) with $(p_s, p_g) = \Phi(I_{s,\infty}, I_{g,\infty})$):

$$(I_{s,\infty}, I_{g,\infty}) = F(I_{s,\infty}, I_{g,\infty}) \,, \tag{2}$$

A unique solution of (2) obtains e.g., if Φ is defined as follows:

$$p_s = \varphi^2(I_{s,\infty})/(\varphi(I_{s,\infty}) + \varphi(I_{g,\infty})),\ p_g = \varphi^2(I_{g,\infty})/(\varphi(I_{s,\infty}) + \varphi(I_{g,\infty})) \ . \tag{2}$$

Here, the function φ measures a station's willingness to switch from w_h to w_s [w_g], given (I_s, I_g); it should be continuous and nondecreasing, with $\varphi(0) = 0$ and $\varphi(\infty) = 1$.

If the CSMA/CA game is played, we use the expected value of *CFI* w.r.t. the probabilities of configuring w_g, w_s, and w_h, determined by ∞-order incentives.

Definition 2: The *noncooperative CFI*, denoted n-*CFI*, is defined as

$$\text{c-}CFI \cdot p_{\text{h}}^{N} + p_{\text{g}}(1-p_{\text{g}})^{N-1} b_{\text{G}} + p_{\text{s}} \sum_{x=0}^{N-1} \binom{N-1}{x} p_{\text{s}}^{x} p_{\text{h}}^{N-1-x} (x+1) b_{\text{s}}(N, x+1, 0) \qquad (4)$$

(recall that if all k nonzero payoffs out of N are equal then the Jain index is k/N).

In reality, the other stations' susceptibility to incentives may be learned by playing the CSMA/CA game repeatedly and observing successive configuration profiles. We model this intuition by taking a sigmoid $\varphi(I) = (1-e^{-4I})/(1-e^{-4(I-a)})$ and manipulating its center a. In the i^{th} instance of the game, station n's perception of the other stations' susceptibility is reflected by a_n^i, with the dynamics $a_n^{i+1} = \max\{0, a_n^i + \delta_n(X^i, Y^i)\}$. Here, the function δ_n describes the learning process at station n, and X^i [Y^i] is the number of selfish [greedy] stations in the i^{th} instance, distributed according to p_s, p_g, and $p_h = 1 - p_s - p_g$ as calculated from (3), with the sigmoid φ centered at a_n^i.

Let $\delta_n(x > 0, 0) = -\Delta_n$, $\delta(0, 0) = -2\Delta_n$, and $\delta(x, y > 0) = \Delta_n$, where Δ_n is proportional to station n's initial a_n^0 through a constant Δ (thus relative changes of a are the same at each station). $((a_1^i,...,a_N^i)$, i = 1,2,…) is an N-dimensional random walk with an absorbing state (0,…,0) corresponding to cooperative behavior (the solution of (2) then yields $p_s = p_g = 0$) and another absorbing state (∞,…,∞), with $p_s = p_g = 1/2$ and $p_h = 0$. The capacity-fairness indices at these absorbing states are c-*CFI* and n-$CFI_\infty = (N \cdot b_s(N, N, 0) + b_G)/2^N$, respectively. Define $a_{\max}$ so that the corresponding solution of (2) yields p_s and p_g close to 1/2.

Definition 3: The *noncooperative learning CFI*, denoted nl-*CFI*, is defined as $\pi_N \cdot$c-*CFI* + $(1 - \pi_N)\cdot$ n-CFI_∞, π_N being the probability of reaching the absorbing state (0,…,0) given that each station n selects $a_n^0 \in [0...a_{\max}]$ at random.

Assuming Δ = 0.2, Fig. 1 depicts c-*CFI* and nl-*CFI*. The latter turns out to be distinctly closer to c-*CFI* than n-*CFI* for "power aware" enough stations, as confirmed by numerical experiments whose details are omitted.

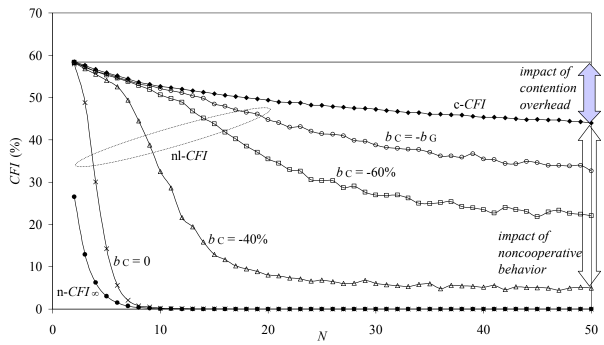

Fig. 1. c-*CFI* and nl-*CFI* for various "power awareness" levels

3 Conclusion

The introduction of w_g and "power awareness" changes the CSMA/CA game into one with multiple Nash equilibria i.e., without a compelling outcome. We envisage that each station then calculates common-knowledge incentives to configure w_s and w_g, and the corresponding probability distribution of imminent configuration profiles. Our study quantitatively illustrates a few intuitions:

- the network's ability to provide high and fair bandwidth shares to all stations diminishes as N increases, partly on account of growing contention overhead, but mostly because of the stations' limited willingness to behave cooperatively; these two factors are illustrated for the $b_C = -40\%$ curve at $N = 50$,
- incentive calculus dictates that the willingness to behave cooperatively grow with "power awareness" for fear of spending all the transmission power without getting any bandwidth share; accordingly, *CFI* improves as b_C goes more negative,
- the predictions depend on a station's perception of the other stations' susceptibility to incentives, reflected by Φ, and the learning process, reflected by δ,
- each of the nl-*CFI* curves lies between the n-CFI_∞ and c-*CFI* ones; its bias towards the latter measures the chance π_N of emergence of cooperative behavior; this is almost certain for small enough N assuming enough "power awareness."

Although the "penalty" bandwidth share b_C was assumed constant across the stations, it is relatively easy to generalize to nonuniform "power awareness" in order to study the coexistence of devices with diverse battery lifetimes.

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