# Performance Analysis of Selfish Access Strategies on WiFi Infrastructure Networks

Laura Giarrè*, Giovanni Neglia+ and Ilenia Tinnirello*
*Università di Palermo, Palermo, Italy +INRIA, Sophia-Antipolis, France

***Abstract*—In this paper we propose a game-theoretic approach for characterizing WiFi network performance in presence of intelligent nodes employing cognitive functionalities. We assume that a cognitive WiFi node is aware of its application requirements and is able to dynamically estimate the network status, in order to dynamically change its access strategy by tuning the contention window settings. We prove that, for infrastructure networks with bidirectional traffic and homogeneous application requirements, selfish access strategies are able to reach equilibrium conditions, which are also Pareto optimal. Indeed, we show that the station strategies converge toward values which maximize a per-node utility function, while maintaining performance fairness.**

## I. Introduction

The problem of resource sharing in WiFi networks [1], [2], is addressed by the Distributed Coordination Function (DCF), which is a well known Medium Access Control (MAC) protocol based on the paradigm of carrier sense multiple access with collision avoidance (CSMA/CA).The distributed DCF protocol is in principle fair. Nevertheless, in actual networks it has been observed that stations may experience heterogeneous performance. In many cases, such unexpected behaviors have been recognized as a consequence of selfish settings of the contention windows [3], whose configuration is made available to end users thanks to open-source drivers. In fact, stations employing lower contention windows gain probabilistically an higher number of transmission opportunities, at the expense of compliant stations. This consideration motivates a game theoretical analysis of DCF, in order to understand the risks or the advantages offered by the possibility to dynamically tune the MAC parameters at each node.

Previous studies have already modeled access to a shared wireless channel in terms of non-cooperative games among the nodes, but they have mainly considered ad hoc mode operation. In [6], for example, it has been shown that an utility function equal to the throughput may lead to a Nash equilibrium in which stations do not perform backoff anymore. This situation creates a resource collapse, because all stations transmit simultaneously thus destroying all packet transmissions. More complex utility functions combining throughput and costs related to collision rates [6], [7] or to energy consumptions [8] lead to different equilibria, but at the same time they appear less natural.

We argue that modeling DCF with rational nodes in infrastructure networks is quite different from the ad hoc case, because infrastructure networks may easily relate individual station performance to overall network performance. This relationship may be artificial, i.e. induced by some punishment strategies implemented by the AP [9], or intrinsic to the traffic scenario. For example, it is likely that each node utility depends on both the node and the AP throughput, since user applications may require bidirectional data transfers.

In this paper we analyze infrastructure networks with rational nodes. We assume that all the stations have uniform application requirements, which are expressed in terms of desired ratio between the uplink and downlink throughput. We formulate an access scheme based on a game theoretic approach, which allows each station to tune its contention parameters according to a best response strategy.

## II. Game theoretic analysis

We model the contention process of intelligent cognitive nodes in an infrastructure network in terms of a non-cooperative game. Contending nodes are involved into two different data streams: on one side, they need to upload traffic to the AP, which is connected to external networks; on the other side, they need to download traffic from the external networks through the AP. The first data stream is referred as uplink data stream, while the second one is referred as downlink data stream. We assume that all the contending stations work in saturation conditions, i.e. they are permanently in a contending state. In fact, non-saturated stations affect the performance of other saturated stations only marginally and regardless to their contention windows.

When all stations are saturated, it has been shown [12] that DCF can be accurately approximated as a persistent slotted access protocol. After each packet transmission originated on the channel, the subsequent channel access is slotted because packet transmissions can be originated only at given time instants, i.e. after an integer number of backoff slots. Moreover, the probability to transmit in a generic channel slot is approximately fixed to a constant parameter $\tau$ (as in persistent protocols), which is related to the backoff expiration rate, i.e. to the contention window settings.

### *A. Station strategies*

Let $n$ be the number of saturated contending stations. Since each station $i$ is rational, it can arbitrarily choose its channel access probability $\tau_i$ in $[0, 1]$[1]. The overall set of strategies in

[1] This choice can be readily implemented by tuning opportunistically the minimum ($CW_{min}$) and the maximum ($CW_{max}$) values of the contention windows. By observing that $\tau_i = 1/(1 + E[W]/2)$, where $E[W]$ is the average contention window used by station, a solution is to set $CW^i_{min} = CW^i_{max} = 2/\tau_i - 2$.

978-1-4244-4148-8/09/$25.00 ©2009
This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2009 proceedings.
Authorized licensed use limited to: UR Sophia Antipolis. Downloaded on April 13,2010 at 20:02:27 UTC from IEEE Xplore. Restrictions apply.

the network is then $[0,1]^n$. We define an *outcome* of the game a specific set of strategies taken by the players, then a vector $\boldsymbol{\tau} = (\tau_1, \tau_2, \cdots, \tau_n) \in [0,1]^n$. We also say that an outcome is homogeneous whenever all the stations play the same strategy, i.e. $\boldsymbol{\tau} = (\tau, \tau, ...\tau)$.

Performance perceived by a given station $i$ not only depends on the probability $\tau_i$ to access the channel, but also on the probability that no other station interferes on the same slot. Therefore, from the point of view of station $i$, the vector strategy $\boldsymbol{\tau}$ can be represented by the couple of values $(\tau_i, p_i)$, where $p_i = 1 - \prod_{j \neq i}(1 - \tau_j)$ summarizes the interactions with all the other mobile stations. We also assume that the AP contends to the channel as a legacy DCF station with saturated downlink traffic. Thus, the overall collision probability suffered by station $i$ results $1-(1-p_i)(1-\tau_{AP})$, where $\tau_{AP}$ is the channel access probability employed by the AP. Since the AP is a legacy station, its transmission probability is not chosen by the AP, but is function of the perceived collision probability $p_{AP}$ according to the expression derived in [11]:

$$\tau = f(p) = \begin{cases} \frac{2(1-p^{R+1})}{1-p^{R+1}+(1-p)\sum_{i=0}^{R} p^i W(i)} & 0 \le p < 1 \\ \frac{2(R+1)}{1+\sum_{i=0}^{R} W(i)} & p = 1 \end{cases} \quad (1)$$

where $R$ is the retry limit employed in the network and $W(i)$ is the contention window at the $i$-th retry stage (i.e. $W(i) = \min\{2^i CW_{min}, CW_{max}\}$). We can evaluate the AP collision probability as a function of the vector strategy $\boldsymbol{\tau}$ or as a function of the a generic couple $(\tau_i, p_i)$:

$$p_{AP} = 1 - \prod_{i=1}^{n}(1-\tau_i) = 1-(1-p_i)(1-\tau_i)$$

### B. Station Utility

Assuming that the AP equally shares the downlink throughput among the stations, we can readily express the uplink throughput $S_u^i$ and the downlink throughput $S_d^i$ for the $i$-th station as:

$$S_u^i(\tau_i, p_i) = \frac{\tau_i(1-p_i)(1-\tau_{AP})P}{P_{idle}\sigma + [1-P_{idle}]T} \quad (2)$$

$$S_d^i(\tau_i, p_i) = \frac{1}{n}\frac{\tau_{AP}(1-p_{AP})P}{P_{idle}\sigma + [1-P_{idle}]T} \quad (3)$$

where $P$ is the frame payload which is assumed to be fixed, $\sigma$ and $T$ are, respectively, the empty and the busy slot duration[2], and $P_{idle}$ is the probability that neither the stations, nor the AP transmit on the channel, i.e. $P_{idle} = (1-p_{AP})(1-\tau_{AP})$.

Since the downlink throughput is equal for all the stations, we can avoid the $i$ superscript. We define the utility function $J_i$ for the mobile station $i$ as:

$$J_i = \min\{S_u^i, kS_d\} \quad (4)$$

The rationale of such a definition is the assumption that the station applications require bandwidth on both directions. The

[2] We are implicitly considering a basic access scheme, with EIFS=ACK_Timeout +DIFS, which corresponds to have a fixed busy slot duration in both the cases of successful transmission and collision.

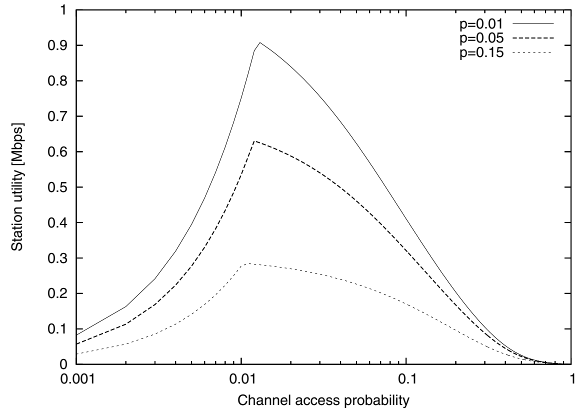


Fig. 1. Utility of a given station $i$, for different $p_i$ values, as a function of the strategy $\tau_i$ ($k = 1$).

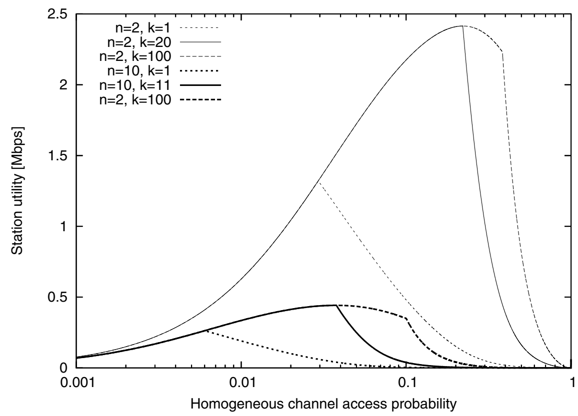


Fig. 2. Station utility in case of homogeneous access probability employed by all the stations and different $k$ values.

coefficient $k \in [0, \infty)$ takes into account the desired ratio between the uplink and the downlink traffic. We assume that the application is the same for all the stations, thus using a fixed $k$ value for all the utility functions. When $k = 1$ all the stations require the same throughput in both directions. Note that $k = \infty$ corresponds to the unidirectional traffic case, in which no station is interested in downlink throughput.

Figure 1 plots the utility of a given station $i$, in case of 802.11b physical layer, $P = 1500$ bytes, a data rate equal to 11 Mbps, and an acknowledgment rate of 1 Mbps. In such a scenario, by including physical preambles, acknowledgment transmissions, MAC headers and interframe times, the $T$ duration is equal to 1667 $\mu s$. Different network conditions, summarized by the $p_i$ probability have been considered. Note that $p_i$ takes into account only the competing mobile stations, so that the actual collision probability is given by $1-(1-p_i)(1-\tau_{AP}(p_i, \tau_i))$. From the figure, it is evident that, for each $p_i$, the utility is maximized for a given best response value (about 0.01 for $p = 0.15$), which slightly decreases as $p_i$ grows.

We also consider the single variable functions $S_u^{hom}(\tau) = S_u(\tau, (1-\tau)^{n-1})$ and $S_d^{hom}(\tau) = S_d(\tau, (1-\tau)^{n-1})$ representing, respectively, the uplink and downlink throughput perceived by each station in case of homogeneous

978-1-4244-4148-8/09/$25.00 ©2009
This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2009 proceedings.
Authorized licensed use limited to: UR Sophia Antipolis. Downloaded on April 13,2010 at 20:02:27 UTC from IEEE Xplore. Restrictions apply.

outcomes $(\boldsymbol{\tau}|\tau_i = \tau, \forall i)$. Figure 2 plots the utility $min\{S_u^{hom}(\tau), kS_d^{hom}(\tau)\}$ of a given station $i$, in case of homogeneous outcomes for $n = 2$ and $n = 10$, and for different $k$ values. In these curves $p_i = (1-\tau)^{n-1}$ is not fixed, because the strategy changes are not unilateral. The optimal strategy, which maximizes the station utility, is function of both $n$ and $k$.

### C. Nash equilibria

We are interested in characterizing Nash Equilibria and Pareto Optimality of our game model, where all the stations achieve a non-null utility. The following remarks will be useful to such purpose.

*Remark 2.1:* Consider a generic station $i$ and the collision probability $p_i$ suffered because of the other station strategies. For a given $p_i \in (0, 1)$, by taking into account that $\tau_{AP}$ depends on $\tau_i$ and $p_i$ according to 1, $S_d(\tau_i)$ is a monotonic decreasing function of $\tau_i$, starting from $S_d(0) > 0$, and $S_u^i(\tau_i)$ is a monotonic increasing function of $\tau_i$, starting from $S_u^i(0) = 0$.

*Remark 2.2:* When strategy changes are not unilateral (i.e. $p_i = (1-\tau)^{n-1}$ is function of $\tau$), $S_u^{hom}(\tau)$ is not monotonic ($S_u^{hom}(0) = S_u^{hom}(1)$=0) and has a single maximum value $S_u^{hom}(\tau_X)$, with $\tau_X \in (0, 1)$.

Let us consider now the *Best Response*. From the previous remark, we can state that player $i$ utility $J_i$ is maximized for $\tau_i^{(br)} \in (0, 1)$ such that $S_u^i(\tau_i^{(br)}) = kS_d^i(\tau_i^{(br)})$. It follows that $\tau_i^{br}$ is the solution of the following implicit equation:

$$\tau_i^{(br)} = \frac{k\tau_{AP}}{n-(n-k)\tau_{AP}} = \frac{kf\ \ 1-(1-p_i)\ \ 1-\tau_i^{(br)}}{n-(n-k)f\ \ 1-(1-p_i)\ \ 1-\tau_i^{(br)}} . \quad (5)$$

It can be shown that the previous equation has a single solution $\tau_i^*$ in the range $(0, 1)$, which can be numerically solved in a few fixed point iterations.

*Proposition 2.1:* The homogeneous strategy vector $\boldsymbol{\tau}|\tau_i = \tau^* = \frac{kf(1-(1-\tau^*)^n)}{n-(n-k)f(1-(1-\tau^*)^n)}, \forall i$ is the only Nash equilibrium in $[0, 1)^n$ of the game described above.

*Proof:* The strategy vector $(\tau^*, \tau^*, \cdots, \tau^*)$ is a Nash equilibrium as an immediate consequence of (5) for $p_i = (1-\tau_i^*)^{n-1}$. In fact the equation can be read as a mutual best response. Since equation (5) has a single solution, it exists a unique homogeneous NE strategy. Since $(1-p_i)(1-\tau_i) = (1-p_j)(1-\tau_j), \forall i, j$, the right hand of the best response equation is the same for all the stations. This excludes the existence of non-homogeneous Nash equilibria. ∎

Note that the parameter $\tau^*$, which characterizes the Nash equilibrium strategy, only depends on the number of stations $n$ and it is not affected either by the PHY layer parameters (such as backoff slot duration, interframe spaces, etc.) or by the frame length.

*Proposition 2.2:* Given the strategy $\tau_X$ which maximizes the function $S_u^{hom}(\tau)$, if the solution $\tau^*$ of equation 5 for $p_i = (1-\tau^*)^{n-1}$ is lower or equal to $\tau_X$, the NE $(\tau^*, \tau^*, \cdots \tau^*)$ is Pareto optimal.

The proof can be found in [10].

Note that the limit condition $\tau^* = \tau_X$ can be verified for $k = k_x$, since the intersection between the function $S_u^{hom}(\tau)$ and the function $kS_d^{hom}(\tau)$ depends on $k$. Figure 2 shows that the intersection strategy $\tau^*$, for which the utility function has an abrupt slope change, grows as the $k$ value increases. The figure also shows that the limit condition $\tau^* = \tau_X$ is approximately reached for $k_x = 20$ in case of $n = 2$, and for $k_x = 11$ in case of $n = 10$. For smaller $k$ values, the NE is Pareto optimal. For larger $k$ values, stations are mainly interested to the uplink bandwidth and the system tends to the unidirectional case, in which the equilibrium condition is not Pareto optimal.

## III. Best-Response Implementation and Evaluation

Our previous analysis suggests that, in presence of bidirectional bandwidth requirements, stations should be motivated in tuning their contention windows as a function of the AP channel access probability. This is very different from the behavior of current selfish cards, which simply try to maximize their own throughput by using fixed contention windows smaller than the standard ones. Thus, we designed some simple DCF extensions, in order to enable each contending station to dynamically tune its contention windows according to a best response strategy. To this purpose, we also designed two different estimators for probing the network working conditions. In fact, station best response depends not only on the application requirements (by means of $k$), but also on the network load (by means of $n$) and on the other station strategies (by means of $\tau_{AP}$, which in turns depend on the whole outcome $\boldsymbol{\tau}$). This information is not directly available to the contending stations.

### A. Network status estimators

We defined two different estimators for enabling each station to infer about $n$ and $\tau_{AP}$, by independently monitoring the channel activity. The estimators work by filtering some measurements sampled at regular intervals. We express the measurement time intervals in terms of an integer number $B$ of channel slots. Since slot size is uneven (because busy slots last for a $T$ time, while idle slots last only for $\sigma$), the actual time required for a new measurement sample is not fixed.

For measuring the number of stations actually contending on the network, we propose to count the number of different sender addresses observed during the measurement interval. Obviously, for filtering the sender addresses, the monitoring station has to correctly receive the packets. Thus, during the $B$ interval the number of observed packets is not fixed. Let $n^m(t)$ be the load measurement performed during the $t$-th measurement interval by a given station $m$. The estimation $\hat{n}$ of the number of contending stations is then performed as:

$$\hat{n}(t) = \delta\hat{n}(t-1) + (1-\delta)n^m(t) \quad (6)$$

where $\delta$ is the filter memory.

For measuring the AP channel access probability, each station has also to count the number $X$ of transmissions


This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2009 proceedings.
Authorized licensed use limited to: UR Sophia Antipolis. Downloaded on April 13,2010 at 20:02:27 UTC from IEEE Xplore. Restrictions apply.

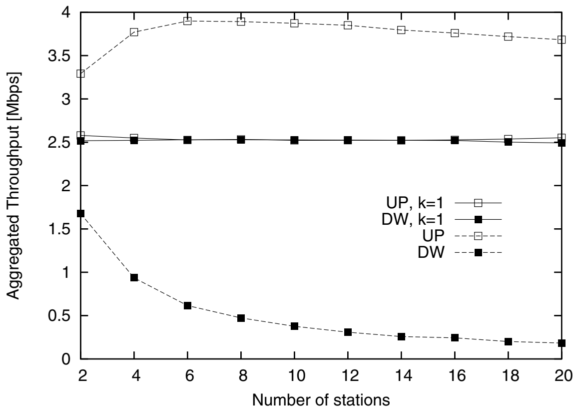


Fig. 3. Aggregated throughput for various number of nodes. Comparison of our scheme ($k = 1$) with standard DCF.

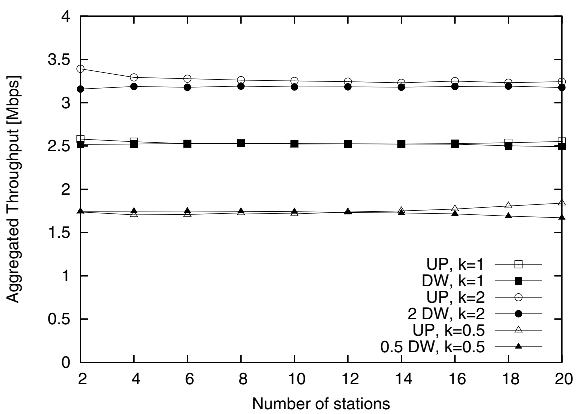


Fig. 4. Aggregated throughput for various number of nodes and $k = 0.5, 1, 2$.

performed by the AP during $B$. Given that stations have no way of understanding which station has transmitted in a collision slot, the station has also to count the total number of collisions $C$ for measuring the $\tau_{AP}^m(t)$ parameter in the $t$-th time interval as $\frac{X}{(B-C)}$. The estimation $\hat{\tau}_{AP}$ of the AP channel access probability is then performed as:

$$\hat{\tau}_{AP}(t) = \gamma\hat{\tau}_{AP}(t-1) + (1-\gamma)\tau_{AP}^m(t) \quad (7)$$

where $\gamma$ is the filter memory.

We can now implement the station best response strategy at time $t$, for a generic station $i$. On the base of (5), station $i$ may update its channel access probability as:

$$\tau^{br}(t+1) = \frac{\hat{\tau}_{AP}(t)}{\hat{n}(t) - (\hat{n}(t) - k)\hat{\tau}_{AP}(t).} \quad (8)$$

### B. Resource repartition

In order to evaluate our scheme effectiveness for approximating the performance of an ideal game in which all stations exactly know the network status, we run some simulations. We developed a custom-made C++ simulation platform, by extending the simulator used in [11]. We considered an 802.11g physical rate, with the data rate set to 6Mbps. The contention windows used by the AP have been set to the legacy values $CW_{min} = 16$ and $CW_{max} = 1024$. All the simulation results have been obtained by averaging 10 different simulation experiments lasting 10s, leading to a confidence interval lower than 3%. Unless otherwise specified, the measurement interval has been set to 500 channel slots (which averagely correspond to 300ms).

Figure 3 compares the behavior of our scheme with standard DCF. Each point refers to a network scenario in which $n$ stations (indicated in the $x$ axis) compete on the channel with an AP. The aggregated uplink throughput (i.e. the sum of the throughput perceived by all the mobile stations) and the aggregated downlink throughput, (i.e. the AP throughput) are indicated by the $y$ axis, respectively by white and black points. From the figure, it is evident that, as the number of contending stations increases, standard DCF gives very poor performance to the downlink throughput. Conversely, our scheme is able to equalize uplink and downlink throughput for each $n$, and even in congested network conditions. Moreover, it is also able to maintain the overall network throughput (i.e. the sum of the aggregated uplink and downlink throughput) almost independent on the network load. For example, for $n = 20$ the sum of the uplink and downlink throughout is about 3.8 Mbps for standard DCF and about 5 Mbps for our scheme.

Figure 4 proves our scheme effectiveness for different application requirements, i.e. for different desired ratio between uplink and downlink throughput. Specifically, we plotted the throughput repartitions obtained for $k = 0.5, 1, 2$ as the number of nodes increases. For sake of presentation, we plotted the aggregated uplink throughput and $k$ times the aggregated downlink one. The figure clearly visualizes that $\sum_i S_u^i = knS_d$ as expected.

### C. Run-time performance

In order to assess our scheme effectiveness in time-varying load conditions, we run several simulation experiments in which we assume that contending stations may activate and deactivate dynamically.

Figure 5 shows a simulation example lasting 300 seconds, in which we start with 5 contending stations, add 5 more stations after 100 seconds and switch 3 stations off at 200 seconds. In the figure we plot the throughput perceived by a given reference station (namely, station labeled as station 1) and the aggregated throughput perceived by the AP. The figure also plots the number of active stations estimated by station 1 on the basis of the load filter defined in (6), for $\delta = 0.7$ and $B = 500$ slots. We can draw some interesting observations. First, the average AP throughput is basically independent on the number of stations contending in the network. This behavior is very different from the standard DCF behavior, according to which the AP behaves as a normal station. Second, the station throughput is approximately equal to the desired ratio, i.e. to $1/n$ the downlink throughput. Note also that our scheme is different from a classical prioritization scheme, such as the schemes defined in the EDCA extensions. Indeed, by giving lower contention windows to the AP, we are not able to perform a desired resource repartition between uplink and downlink which is also load independent. Finally, the load estimator gives quite stable results, because the number

978-1-4244-4148-8/09/$25.00 ©2009
This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2009 proceedings.
Authorized licensed use limited to: UR Sophia Antipolis. Downloaded on April 13,2010 at 20:02:27 UTC from IEEE Xplore. Restrictions apply.

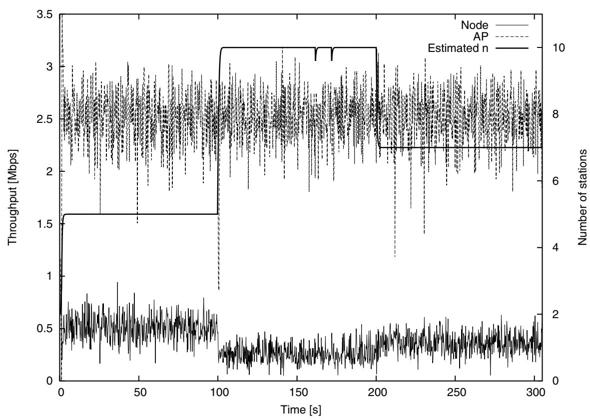


Fig. 5. Effects of best response strategies ($k = 1$) on AP aggregated throughput and a given node throughput in dynamic load conditions.

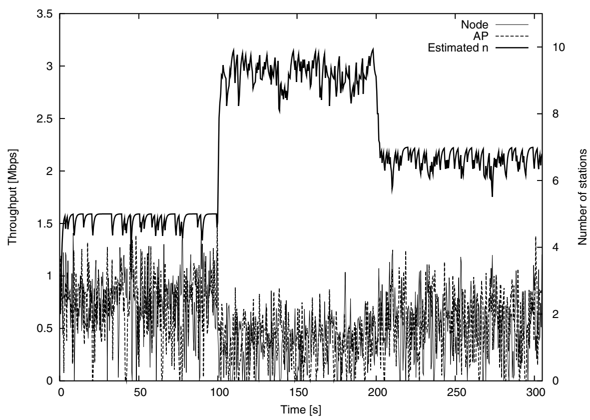


Fig. 6. AP aggregated throughput and a given node throughput for standard DCF in dynamic load conditions.

of different stations listened in each temporal window $B$ is always equal to the total number of contending stations. We can see that only in the interval between 100 and 200 seconds, during which we have a number of contending stations equal to 10, the estimator gives a number of contending stations lower than the actual times for two times. In fact, since we are monitoring a fixed number of slots, as the number of stations in the network grows, it is more likely that in some intervals some stations do not succeed in transmitting on the channel.

Figure 6 shows, for the same simulation experiment described in the previous figure, the AP and the reference station performance perceived under standard DCF. We can clearly see that the AP behavior is identical to the reference station, since DCF is not able to differentiate the AP performance. Therefore, it degrades as the number of contending stations increases. Although we are using standard DCF, we also run the load estimators at each station, by using the same window value $B = 500$ slots (even if not necessary). These estimations allow somehow to probe the short term unfairness of standard DCF, since they measure the number of different stations transmitting in small time scales. From the figure, we see that the load estimations exhibit some evident fluctuations, thus proving that show-term unfairness emerges in time scales comparable with our observation window. Since for the same time window the estimations carried out under our scheme does not suffer of similar fluctuations, we can also conclude that our scheme improves the protocol short-term fairness.

Note that, our scheme performance also depends on the time window $B$. This interval has to be carefully tuned, in order to guarantee a reasonable probability to catch all the contending stations in each measurement interval. To this purpose, we propose to run two different $\hat{n}$ estimators in parallel, based on two different measurement intervals (e.g. $B$ and $2B$), and to adaptively increase or decrease the $B$ value according to the comparison between the two estimates. For space reason, we omit the details of such a dynamic tuning.

## IV. Conclusions

In this work we propose some extensions to standard DCF, in order to emulate an access scheme based on best response strategies. We consider infrastructure networks, where user utility functions depend on both the uplink and the downlink throughput. We prove that, in this scenario, node strategies can easily converge to a Nash equilibrium which maximizes the global utility and opportunistically shares the total downlink and uplink bandwidth. More interesting, such equilibrium strategies are not affected by physical layer parameters and only depend on the number of contending stations and application requirements. Numerical experimental results show how the best response mechanism provides the desired throughput repartitions among the stations, converging to the Pareto optimal strategies and improving the protocol short-term fairness.

## References


[1] IEEE Standard 802.11 - 1999; Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications; November 1999.

[2] Wi-Fi Alliance, www.wi-fi.org

[3] G. Bianchi, A. Di Stefano, C. Giaconia, L. Scalia, G. Terrazzino, I. Tinnirello, "Experimental assessment of the backoff behavior of commercial IEEE 802.11b network cards", *Proc. of IEEE Infocom 2007*, May 2007, Anchorage, pp. 1181-1189.

[4] S.W. Kim, B.S. Kim, Y. Fang, "Downlink and uplink resource allocation in IEEE 802.11 wireless LANs", *Proc. of IEEE Conf. on Vehicular Technology*, Jan. 2005, Dallas, vol. 54, pp. 320-327.

[5] IEEE 802.11e Supplement to Part 11: Wireless Medium Access Control (MAC) and Physical Layer Specification: Medium Access Control (MAC) Enhancements for Quality of Service (QoS)", October 2005.

[6] M. Cagalj, S. Ganeriwal, I. Aad, J.P. Hubaux, "On selfish behavior in CSMA/CA networks", *Proc. of IEEE Infocom*, March 2005, Miami, vol. 4, pp. 2513-2524.

[7] L. Chen, S.H. Low, J. Doyle, "Contention Control: A Game-Theoretic Approach", *Proc. of IEEE Conf. On Decision and Control*, Dec. 2007, New Orleans, pp. 3428-3434.

[8] G. Zhang, H. Zhang, "Modelling IEEE 802.11 DCF in wireless LANs as a dynamic game with incompletely information", *Proc. of Conf. on Wireless, Mobile and Multimedia Networks*, Jan. 2008, Mumbai, pp. 215-218.

[9] L. Giarré, G. Neglia and I. Tinnirello. The Role of the Access Point in Wi-Fi Networks with Selfish Nodes. GameNets, Instanbul, 2009, also in INRIA Technical Report N. RR6737, 2008.

[10] L. Giarré, G. Neglia and I. Tinnirello, "Resource Sharing Optimality in WiFi Infrastructure Networks", *Proc. of IEEE CDC*, Dicember 2009, Shangai.

[11] G. Bianchi, "Performance Analysis of the IEEE 802.11 Distributed Coordination Function", *IEEE Journal of Selected Areas in Communication*, vol. 18, no. 3, pp.535-547, March 2000.

[12] G. Bianchi, I. Tinnirello "Remarks on IEEE 802.11 Performance Analysis", *IEEE Communication Letters*, Vol. 9, no. 8, August 2005.


978-1-4244-4148-8/09/$25.00 ©2009
This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2009 proceedings.
Authorized licensed use limited to: UR Sophia Antipolis. Downloaded on April 13,2010 at 20:02:27 UTC from IEEE Xplore. Restrictions apply.