Resource sharing optimality in WiFi infrastructure networks

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***Abstract*— In WiFi networks, mobile nodes compete for accessing a shared channel by means of a random access protocol called Distributed Coordination Function (DCF). Although this protocol is in principle fair, since all the stations have the same probability to transmit on the channel, it has been shown that unfair behaviors may emerge in actual networking scenarios. Assuming that a contending node can dynamically change its strategy, by tuning its contention parameters to non-standard values on the basis of channel observations, we prove that, for infrastructure networks with bidirectional traffic and homogeneous application requirements, selfish access strategies are able to reach equilibrium conditions, which are in many cases also Pareto optimal. Indeed, 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], is addressed by the Distributed Coordination Function (DCF), which is a Medium Access Control (MAC) protocol based on the paradigm of carrier sense multiple access with collision avoidance (CSMA/CA). The basic idea of the protocol is very simple: before transmitting, stations have to sense the channel as idle for avoiding interference with other ongoing transmissions. Whenever the channel is sensed busy, stations have to monitor the channel until it is idle. At this point, rather than immediately transmitting, a further random deferment is considered for avoiding synchronizations with other waiting stations. This random delay, called backoff, is slotted for efficiency reasons. The range in which the delay is extracted, called contention window, is an adaptive parameter which follows a truncated exponential increment law, from a minimum to a maximum value.

The distributed DCF protocol is in principle fair, because the contention window settings should be hard-wired in each station, thus assuring that each node receives in long term the same number of access opportunities. Nevertheless, in actual networks it has been observed that stations may experience heterogeneous performance. In many cases, such unexpected behavior has been recognized as a consequence of selfish settings of the contention windows [2], 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.

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Another problem specifically emerged in infrastructure networks is given by the repartition between uplink and downlink resources. Infrastructure networks are characterized by a star topology, which connects multiple mobile nodes to a common station called Access Point (AP). Since the AP contends as a normal station to the channel, its channel access probability is the same of other mobile stations. This implies that the AP aggregated throughput, i.e. the downlink bandwidth, is equal to the throughput perceived by all the other stations, thus resulting in a per-station downlink bandwidth much lower than the uplink one [3].

The problem of resourse sharing in presence of rational nodes, able to dynamically adapt the contention window settings, can be modeled in terms of non-cooperative games among the nodes. Previous studies have already proposed this modeling approach for the DCF protocol, but they have mainly considered unidirectional traffic flows. In [5], for example, it has been shown that an utility function equal to the node 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 node throughput and costs related to collision rates [5], [6] or to energy consumptions [7] lead to different equilibria, but at the same time they appear less natural.

In this paper we analyze the problem of resource sharing in infrastructure networks. We argue that modeling DCF with rational nodes in infrastructure networks with bidirectional traffic flows is quite different from the unidirectional 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 [8], 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 common applications require both upload and download bandwidth. In these assumptions, nodes are not motivated to transmit continously on the channel in order to leave some resources available to the AP. 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

In an infrastructure network, mobile stations 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 [10] that DCF can be accurately approximated as a persistent slotted access protocol. Indeed, the probability to transmit in a generic channel slot can be approximated by a constant parameter τ (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 τ_i in $[0,1]$[1]. The overall set of strategies in 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. $\boldsymbol{\tau} = (\tau, \tau, ...\tau)$.

Being all the player requirements homogeneous, the equilibria we are going to define are invariant to player permutations. For this reason we define two outcomes $\boldsymbol{\tau^a}$ and $\boldsymbol{\tau^b}$ equivalent if they can be obtained one from the other through an opportune permutation of the indexes and we write $\boldsymbol{\tau^a} \sim \boldsymbol{\tau^b}$. We denote a class of equivalent outcomes as $\{\tilde{\boldsymbol{\tau}}\}$, where $\tilde{\boldsymbol{\tau}}$ is an ordered vector, i.e. a vector with increasing component ($\tilde{\tau}_1 \leq \tilde{\tau}_2 \leq \cdots \tilde{\tau}_n$). If A is a set of ordered vectors, then $\{A\}$ denotes the union of the classes of equivalence of the vectors in A.

Performance perceived by a given station i not only depends on the probability τ_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 (τ_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 τ_{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 [9]:

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

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 a generic couple (τ_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, σ and T are, respectively, the empty and the busy slot duration, 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 apex. 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 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 μs. 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.

[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 $CW^i_{min} = CW^i_{max} = 2/\tau_i - 2$.

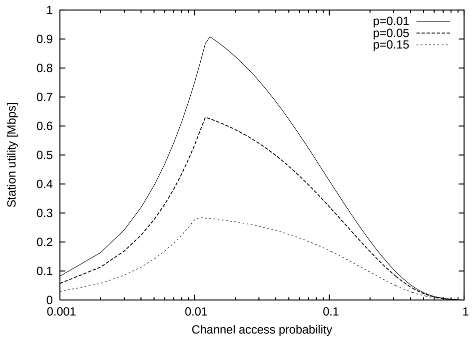

Fig. 1. Utility of a given station i, for different p_i values, as a function of the strategy τ_i ($k = 1$).

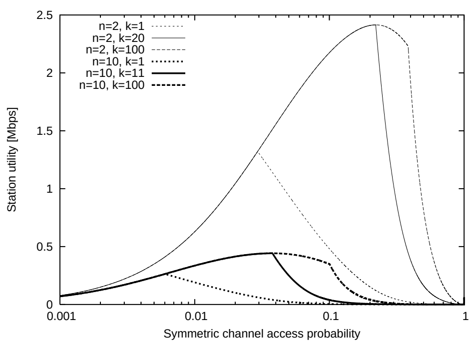

Fig. 2. Station utility in case of homogeneous access probability employed by all the stations and different k values.

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 outcomes ($\boldsymbol{\tau}|\tau_i = \tau, \forall i$). Figure 2 plots the utility of a given station 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

From the utility definition (4), it is evident that the strategies $\{(\boldsymbol{x}, 1), \boldsymbol{x} \in [0,1)^{n-1}\}$ are not Nash Equilibria (NE) as in [5]. In fact, when one station employs a channel access probability equal to 1, the AP collides with probability $p_{AP} = 1$, thus resulting in a downlink throughput S_d equal to 0. Thus, the station is motivated to reduce its transmission probability to a value lower than 1. Conversely, the strategies $\{(\boldsymbol{x}, 1, 1), \boldsymbol{x} \in [0,1]^{n-2}\}$ are still Nash equilibria, because for a given station i the utility function is fixed to 0, regardless of its specific strategy τ_i.

Now, we prove that there is another NE where all the stations achieve a non-null utility. The following remark will be useful to characterize Nash equilibria and Pareto optimality.

Remark 2.1: Consider a generic station i and the collision probability p_i suffered because of the other station strategies. Consider that, for a given $p_i \in (0,1)$, τ_{AP} depends on τ_i according to (1). By derivation, it can be easily proved that $S_d(\tau_i)$ is a monotonic decreasing function of τ_i, starting from $S_d^i(0) > 0$, and that $S_u^i(\tau_i)$ is a monotonic increasing function of τ_i, starting from $S_u^i(0) = 0$.

Remark 2.2: $S_u^{hom}(\tau)$ is not monotonic 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 remark 2.1, 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 τ_i^* is the solution of the following implicit equation:

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

It can be shown that the previous equation has a single solution τ_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, there 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 (5) is the same for all the stations. This excludes the existence of non-homogeneous Nash equilibria. ■

Note that the parameter τ^*, 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: If the solution τ^* of equation 5 for $p_i = (1-\tau^*)^{n-1}$ is lower or equal to τ_x, the NE $(\tau^*, \tau^*, \cdots \tau^*)$ is Pareto optimal.

Proof: First, we observe that, even in presence of the AP downlink flow, the minimum uplink throughput perceived in the network is maximized for a homogeneous outcome. In fact, if $\boldsymbol{\tau}$ is a non-homogeneous outcome in $A = \{\boldsymbol{x}, \boldsymbol{x} \in (0,1)^n\}$, we can prove that the minimum uplink throughput cannot be maximized. Without loss of generality, we consider that $\boldsymbol{\tau}$ is an ordered vector, with $0 < \tau_1 < \tau_2 < \cdots < \tau_n < 1$ and $S_u^1(\boldsymbol{\tau}) = \min_i S_u^i$. Let τ_1' be a new strategy for station 1, such that $0 < \tau_1 < \tau_1' < \tau_2$. For the new outcome $\boldsymbol{\tau'} = (\tau_1', \tau_2, \cdots \tau_n)$, the minimum uplink throughput is still the throughput perceived by station 1. This throughput is higher than the previous one, since $S_u^i(\tau_i)$ is monotonic increasing in τ_i. It follows that $S_u^1(\boldsymbol{\tau'}) = \min_i S_u^i(\boldsymbol{\tau'}) > S_u^1(\boldsymbol{\tau}) = \min_i S_u^i(\boldsymbol{\tau})$.

Second, we observe that when all the station utilities are limited by the downlink throughput, i.e. $S_u^i \geq kS_d \forall i$, S_d is maximized for the homogeneous outcome $\boldsymbol{\tau^*}$. In fact, a non-homogeneous outcome cannot maximize S_d, because it is always possible to increase the AP throughput, by slightly reducing a given channel access probability τ_j while maintaining $S_u^j \geq S_d$ (i.e. while maintaining $\tau_j \geq \tau_j^{br}$). In case of homogeneous outcomes, since $S_d((\tau,\tau,\cdots,\tau))$ is a monotonic decreasing function in τ, the maximum is reached for the minimum τ which guarantees $S_u \geq S_d$, i.e. for $\tau = \tau^*$.

Finally, we prove Pareto optimality when $\tau^* \leq \tau_x$. Let $\boldsymbol{\tau}$ be an outcome different from $\boldsymbol{\tau^*}$, with at least a player better off than in $\boldsymbol{\tau^*}$. This allocation is necessarily non-homogenous, because, being that $\tau^* \leq \tau_x$, $J_i((\tau,\tau,\cdots,\tau))$ is maximized for $\tau = \tau^*$. Let j be the station which perceives the minimum utility. If the minimum utility is determined by the downlink throughput, all the other utilities are also limited by the downlink throughput, and no station can get a better payoff than $kS_d(\boldsymbol{\tau^*})$. If the minimum utility is an uplink throughput, it has to be lower than $S_u^j(\boldsymbol{\tau^*})$, because $\boldsymbol{\tau^*}$ maximizes the minimum uplink throughput. Then, in both the cases player j has a lower utility at $\boldsymbol{\tau}$ than at $\boldsymbol{\tau^*}$. It follows that $\boldsymbol{\tau^*}$ is a Pareto outcome. ■

Note that the intersection between the function $S_u^{hom}(\tau)$ and the function $kS_d^{hom}(\tau)$ depends on k. Let k_x be the value of k for which $\tau^* = \tau_x$. Figure 2 shows that the intersection strategy τ^*, 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.

D. AP optimal strategy

We could argue that the system performance can be further improved by also tuning the AP contention window to a fixed value. In these conditions, since τ_{AP} does not depend on $\boldsymbol{\tau}$ anymore, the best response (5) for all the stations is equal to

$$\tau^+ = \frac{k\tau_{AP}}{n-(n-k)\tau_{AP}} \tag{6}$$

the NE equilibrium point (4) in $(0,1)^n$ becomes $(\tau^+,\tau^+,\cdots\tau^+)$. For $k \neq 0$, by maximizing the NE equilibrium utility as a function of the parameter τ_{AP}, a single optimal τ_{AP}^* can be found, that for $\tau^+ \ll 1$ is approximated as:

$$\tau_{AP}^* = \frac{1}{k\sqrt{2T/\sigma}}. \tag{7}$$

Note that the optimal τ_{AP} is not proportional to $1/n$ as in [9], because the AP downlink throughput corresponds to the aggregation of n flows, whose bandwidths is a fraction of the uplink throughput perceived by each station at the NE point. Such a point corresponds to $\tau^+ = \frac{k}{n\sqrt{2T/\sigma}-(n-1)}$, which depends on both n and the parameters T and σ as in [9].

E. Heterogeneous applications

The generalization to the the case of heterogeneous applications among the nodes is formally immediate. When each node i requires a specific ratio k_i between the uplink and the downlink bandwidth, the station utility function can be defined as:

$$J_i = \min\{S_u^i, k_i S_d\} \tag{8}$$

The best response strategy $\tau_i^{(br)} \in (0,1)$, such that $S_u^i(\tau_i^{(br)}) = k_i S_d^i(\tau_i^{(br)})$, is no longer uniform for all the stations, but depends on k_i:

$$\tau_i^{(br)} = \frac{k_i f(p_{AP})}{n-(n-k_i)f(p_{AP})} \tag{9}$$

Although the general proof is not straightforward, we run several numerical experiments (for different k_1, k_2, $\cdots k_n$ values) and we always found that the best response strategies still converge to a unique stable solution.

Since in most common cases $k_i < 1$ (i.e. nodes require more bandwidth in downlink rather than in uplink) and τ_{AP} is lower than $\frac{1}{CW_{min}/2+1} \ll 1$, equation 9 can be approximated as $\tau_i^{(br)} = k_i\tau_{AP}/n$. Therefore, the ratio between the channel access probability of two different stations i and j is approximately given by the ratio between k_i and k_j, i.e. $\tau_j^{(br)} = k_j/k_i \cdot \tau_i^{(br)}$. With such an approximation, p_{AP} can be expressed as a function of a single strategy $\tau_i^{(br)}$:

$$p_{AP} = 1 - \prod_{l=1}^{n}(1 - k_l/k_i \cdot \tau_i^{(br)}) \tag{10}$$

and equation 9 is an implicit equation with a single unknown parameter $\tau_i^{(br)}$. The uniqueness of the equilibrium conditions can be approximately verified by studying this single-unknown equation.

III. MAC Scheme Design and Evaluation

Our previous analysis suggests that, in the presence of bidirectional traffic 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 τ_{AP}, which in turns depend on the whole outcome $\boldsymbol{\tau}$). This information is not directly available to the contending stations.

A. Best response Implementation and Estimation

We defined two different estimators for enabling each station to infer about n and τ_{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

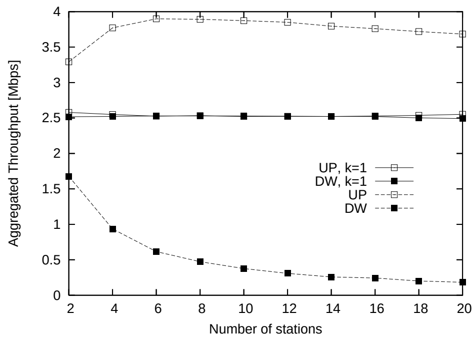

Fig. 3. The aggregated throughput is showed for various number of nodes. The standard DCF (dotted line) is compared with our scheme for $k = 1$ (continuous line).

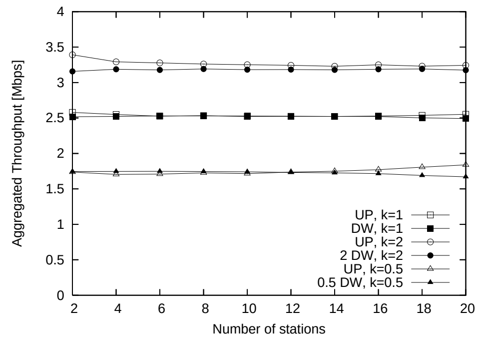

Fig. 4. Aggregated throughput for various number of nodes and $k = 0.5, 1, 2$.

B of channel slots. Since slot size is uneven (because busy slots last for a T time, while idle slots last only for σ), the actual time required for a new measurement sample is not fixed.

The estimation of the number of stations actually contending on the network is implemented by counting the number of packet senders observed during the measurement interval. Obviously, to filter 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 performed with a first order autoregressive filter.

$$\hat{n}(t) = \delta\hat{n}(t-1) + (1-\delta)n^m(t) \tag{11}$$

where δ is the smoothing coefficient. For measuring the AP channel access probability, each station has also to count the number tx of transmissions 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 $\tau^m_{AP}(t)$ parameter in the t-th time interval as $\frac{tx}{(B-C)}$. The estimation $\hat{\tau}_{AP}$ of the AP channel access probability is then performed via filtering.

$$\hat{\tau}_{AP}(t) = \gamma\hat{\tau}_{AP}(t-1) + (1-\gamma)\tau^m_{AP}(t) \tag{12}$$

where γ is the smoothing coefficient.

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:

$$\tau^{br}(t+1) = \frac{\hat{\tau}_{AP}(t)}{\hat{n} - (\hat{n}(t) - k)\hat{\tau}_{AP}(t).} \tag{13}$$

B. Resource repartition

We show how our scheme is approximating the performance of the ideal game in which all stations exactly know the network status. We developed a custom-made C++ simulation platform, by extending the simulator used in [9]. 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 $k = 0.5, 1, 2.$ and increasing number of nodes. For sake of presentation, we plotted the aggregated uplink throughput and k times the aggregated downlink one. The figure clearly visualizes that $\sum_i S^i_u = knS_d$ as expected.

Finally, we analyzed the resource repartitions obtained for $k = 0.5, 1, 2$ when also the AP implements a best response strategy (instead of working as a legacy station). In this case, for easily implementing the solution of the best response equation, we tuned the AP channel access probability according to the approximated expression given in (7). Since this expression does not depend on n but only on the application requirements k, we assumed that this tuning is performed just once, at the beginning of the simulation. From the figure, we notice that the payoffs obtained by the stations are comparable with the previous case. As the number of

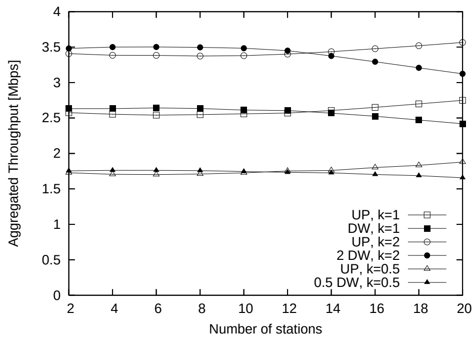

Fig. 5. Aggregated throughput for various number of nodes and $k = 0.5, 1, 2$.

station grows, the throughput repartition is slightly different from the desired one, because we are using an approximated τ_{AP}^{br} expression.

IV. Conclusions

In this work we propose some extensions to standard DCF, in order to emulate an access scheme based on best response strategies for infrastructure networks. 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 bandwith. Such equilibrium strategies are not affected by physical layer parameters and only depend on the number of contending stations and application requirements.

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