Achieving fair bandwidth distribution in WiFi Networks: a Game Theoretical Approach

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Abstract: Achieving fair bandwidth distribution among uplink and downlink flows in IEEE 802.11 infrastructure networks is a complex issue, due to the well-known features of the Distributed Coordination Function (DCF) which regulates the access to the shared medium. Indeed, the dynamic adaptation of the contention windows causes phenomena of short-term unfairness, while the use of homogeneous contention parameters among the contending nodes makes the aggregated downlink bandwidth equal to the uplink bandwidth of a single node. We propose a dynamic tuning of the contention parameters used by the nodes, based on simple network monitoring functionalities and rational strategies. Specifically, we propose a game-theoretic analysis of such tuning, devised to guarantee a fair resource sharing among the nodes, while optimizing the per-node uploading and downloading bandwidth.

Keywords: Networks, Game theory, Nash equilibrium, WiFi

1. INTRODUCTION

WiFi infrastructure networks are characterized by a star topology, which connects multiple mobile nodes to a common station called Access Point (AP). On one side, mobile stations can upload traffic to the AP, which is connected to external networks (e.g. to the Internet); on the other side, they can download traffic from the external networks through the AP. The problem of resource sharing in WiFi networks is addressed by the standard 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: sensing the channel before transmitting, and waiting for a random backoff time when the channel is sensed busy. This random delay, introduced for preventing collisions among waiting stations, is slotted for efficiency reason and extracted in a range called contention window. Standard DCF assumes that the contention window is set to a minimum value (CW_{min}) at the first transmission attempt and is doubled up to a maximum value (CW_{max}) after each transmission failure. The distributed DCF protocol is in principle fair,but, since stations experiencing collisions increase their contention windows thus reducing their channel access probability, short-term unfair behaviors can be observed in small time scales. Moreover, the AP contends as a normal station for the channel, then its channel access probability is the same of other mobile stations. This implies that the AP throughput, i.e. the aggregated downlink bandwidth, is equal to the throughput perceived by each of the other stations, thus resulting in a per-station downlink bandwidth much lower than the uplink one.

Indeed, recent extensions of DCF (namely, the EDCA protocol) allow the AP to set heterogeneous contention windows among the stations to give priority to downlink throughput or to delay-sensitive traffic. Thus, nowadays nodes can adapt their contention windows according to the values signaled by the AP for each traffic class. However, there is the risk to exploit this adaptation in a selfish manner, for example by using a contention window value of a higher priority class, as in **?**. Moreover, for a given configuration of the contention parameters employed by the AP and by the nodes, the uplink and downlink bandwidth ratio depends on the number of contending stations and no fixed uplink/downlink bandwidth repartition can be provided.

These considerations motivate a game theoretical analysis of DCF, in order to propose some protocol extensions able to cope with the current resource sharing problems. The problem can be formulated as a non cooperative game, in which the contending stations act as the players of the game. When stations work in saturation conditions, i.e. they always have a packet available in the transmission buffer, DCF can be modeled as a slotted access protocol, while station behavior can be summarized in terms of per-slot access probability, see **?**.

We propose a game theoretic analysis of DCF in infrastructure networks, when all the stations have a desired ratio between uplink and downlink throughput. Let τ_i be the per-slot access probability representing the access strategy of a generic station i. The channel access game can be formulated by considering: n players, the set of strategies $\tau = (\tau_i, i = 1, \ldots, n)$ in $[0,1]^n$, and the station payoffs $(J_1, J_2, \ldots, J_n)$, that can be defined according to the network and application scenario, see **?**.

Previous studies have mainly considered that each node utility is given by the node saturation throughput **?**. In **?**, it has been shown that a utility function equal to the node upload throughput may lead to an inefficient Nash equilibrium in which stations transmit in every channel slot (i.e. play $\tau = 1$). This situation creates a resource collapse, because all stations transmit simultaneously thus destroying all packet transmissions. More complex utility functions combining upload throughput and costs related to collision rates—**??**—or to energy consumptions—**?**—lead to different equilibria, but they appear less natural and implicitly assume that all the nodes have the same energy constraints or collision costs. In some cases, **?**, the utility function does not correspond to any performance metric and so appears completely arbitrary.

Assuming that each station tunes its access probability using a fixed contention window value, we identify Nash equilibria of the game. We propose to extend current DCF operation by implementing our theoretical best response strategies. To this purpose, we have developed some channel monitoring functionalities in **?**, devised to estimate the network status and to run-time drive the strategy adaptations. Here, we also define a downlink scheduling scheme able to provide a uniform total (uplink and downlink) bandwidth to all the stations.

The rest of the paper is organized as follows. In section 2 we carry out the game theoretic analysis and we find the Nash equilibria; in section **??** we show the MAC scheme implementation and the performance evaluation trough simulations; finally we drew some conclusive remarks in section **??**.

2. CONTENTION-BASED CHANNEL ACCESS: A GAME THEORETICAL APPROACH

We assume that all the stations try permanently to transmit on the channel, i.e. they work in saturation conditions. We have verified that non-saturated stations affect the performance of saturated stations only marginally and regardless of their contention windows. When all stations are saturated, it has been shown in **?** that DCF can be accurately approximated as a persistent slotted access protocol, because packet transmissions can be originated only at given time instants.

2.1 Station strategies

Let n be the number of saturated contending stations. We assume that each station i is rational, and can arbitrarily choose its channel access probability τ_i in $[0,1]$. This choice can be readily implemented by tuning opportunistically the minimum and the maximum values of the contention windows (respectively CW_{min} and CW_{max} for node i). 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 $CW^i_{min} = CW^i_{max} = 2/\tau_i - 2$. This choice also allows to reduce the time-varying fluctuations of the channel access probability experienced in DCF because of the dynamic adaptations of the contention window values. The set of all the strategies in the network is then $[0,1]^n$. We define an *outcome* of the game as 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 define that an outcome is *homogeneous* whenever all the stations play the same strategy, i.e. $\boldsymbol{\tau} = (\tau, \tau, \ldots \tau)$.

The 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 $p_i = 1 - \prod_{j \neq i}(1-\tau_j)$, the probability that at least one other station transmits, summarizes the interactions with all the other mobile stations. Since each contending station can be differently programmed by the users, while the AP is shared among all the stations, we initially assume that the AP behaves as a legacy DCF station with saturated downlink traffic. Thus, the overall collision probability suffered by station i is $1-(1-p_i)(1-\tau_{AP})$, 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}, $\tau_{AP} = f(p_{AP})$, where $f()$ has been derived in **?**:

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

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):

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

2.2 Station Utility

According to the slotted channel model, the random access process can be described as a sequence of slots resulting in a successful transmission (when only one station accesses the channel), in a collision (when two or more stations access the channel), or in an idle slot (when no station accesses the channel). By observing that each slot boundary represents a regeneration instant (see **?**) for the access process, the throughput of each station can be readily evaluated as the ratio between the average number of bits transmitted in each slot and the average duration of each slot, see **?**.

In our study we consider that the AP could allocate a different downlink throughput to each station by implementing a specific scheduling mechanism. For now on we consider that the scheduling rule is given and we denote x_i the fraction of the AP's throughput (S_{AP}) given to station i (clearly $\sum_i x_i = 1$). We can then express the uplink throughput S_u^i and the downlink throughput S_d^i for the i-th station as **?**:

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

$$S_d^i(\tau_i, p_i) = x_i S_{AP}(p_{AP}) = x_i \frac{f(p_{AP})(1-p_{AP})P}{P_{idle}\sigma + [1-P_{idle}]T} \tag{3}$$

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. $P_{idle} = (1-p_{AP})(1-\tau_{AP})$.

We define the utility function J_i for the mobile station i as:

$$J_i = \min\{S_u^i, k_i S_d^i\} \tag{4}$$

The rationale of this definition is the assumption that the station applications require bandwidth on both directions. The coefficient $k_i \in (0, \infty)$ takes into account the desired ratio between the uplink and the downlink throughput required by station i and we call it the *application requirement* at station i. If $k_i = 1$, station i requires the same throughput in both directions. The limit case $k_i = 0$ corresponds to a user i only interested in the downloading rate S_d^i. In this case it is trivial to determine the user's dominant strategy, that is to not transmit at all in order to avoid any collision with the AP. For this reason, in this paper we exclude the case $k_i = 0$. Conversely, the limit case $k_i = \infty$ corresponds to a user i only interested in the uploading rate S_u^i (as assumed in most previous literature). When $k_i = k$, $\forall i$ we ends up in the uniform application requirements that is studied in **?**, **?**.

2.3 Nash Equilibria

We are interested in characterizing Nash Equilbria (NE) of our game where stations achieve a non-null utility. The inefficient equilibria in which all stations achieve an utility value equal to 0 can be easily found by observing that:

Remark 2.1. In general, station i utility is a function of the whole set of strategies ($\boldsymbol{\tau}$), but it is constant and equal to 0 if a) $p_i = 1$, i.e. if at least one of the other players is transmitting with probability 1 ($\exists j \neq i \mid \tau_j = 1$), or if b) $\tau_i = 0$. We observe also that the AP access probability τ_{AP} depends on τ_i and p_i according to (1) and cannot be equal to 1 for standard contention window values.

Proposition 2.1. The vectors of strategies $\boldsymbol{\tau}$, such that $\exists\, j, l \in 1, 2, \cdots n \mid \tau_j = 1$, $\tau_l = 1$ are NE of the distributed access game in which all stations achieve an utility value that is constant and equals 0.

Proof The result is an immediate consequence of Remark 2.1. If there are at least two stations transmitting with probability 1, then the channel is entirely wasted because of collisions and $S_u^i = S_d^i = 0, \forall i$. In these conditions, $J_i = 0\ \forall i$ and stations are not motivated in changing their strategies.

The following remark will be useful for characterizing more efficient NE.

Remark 2.2. Consider a generic station i and the collision probability $p_i \in (0, 1)$ suffered because of the other station strategies. By derivation, it can be easily proved that $S_d^i(\tau_i, p_i)$ is a monotonic decreasing function of τ_i, starting from $S_d^i(0, p_i) > 0$, and that $S_u^i(\tau_i, p_i)$ is a monotonic increasing function of τ_i, starting from $S_u^i(0, p_i) = 0$.

Let us denote a *best response* strategy of a station i as $\tau_i^{(br)}$. For $k_i = \infty$, the station utility function is equal only to $S_u^i(\tau_i, p_i)$. From Remarks 2.1 and 2.2, it results that the utility is maximized for $\tau_i^{(br)} = 1$ when $p_i < 1$ (then there is a unique best response), and it is constant to 0 when $p_i = 1$ (then any strategy is the best response). For $k_i \neq \infty$ and $p_i < 1$, from Remark 2.2 we can state that the utility J_i is maximized for $\tau_i^{(br)} \in (0, 1)$ such that $S_u^i(\tau_i^{(br)}, p_i) = k_i S_d^i(\tau_i^{(br)}, p_i)$. It follows that, for $p_i < 1$, $\tau_i^{(br)}$ is the solution of the following implicit equation:

$$\tau_i^{(br)} = \frac{k_i x_i \tau_{AP}}{1-(1-k_i x_i)\tau_{AP}} = \frac{k_i x_i f\left(1-(1-p_i)\left(1-\tau_i^{(br)}\right)\right)}{1-(1-k_i x_i) f\left(1-(1-p_i)\left(1-\tau_i^{(br)}\right)\right)} \tag{5}$$

The previous equation has a single solution τ_i^* in the range $(0, 1)$. In fact, the left side $l(\tau_i^{(br)})$ of (5) is a continuous strictly increasing function of $\tau_i^{(br)}$ with values in $[0, 1]$. For $p_i \neq 1$, the right side $r(\tau_i^{(br)})$ is a continuous strictly decreasing function with values in the same interval (we are going to show it below), and with $r(0) > l(0) = 0$ and $r(1) < l(1) = 1$. Then, there is necessarily a unique solution for $p_i \neq 1$. In order to check our statement about the function on the right side of (5), we can express it as the composition of three functions $h(y) = k_i x_i y/(1-(1-k_i x_i)y)$, $f(x)$, $g(\tau_i^{(br)}) = 1-(1-p_i)(1-\tau_i^{(br)})$. Now $g()$ is strictly increasing for $p_i \neq 1$ and has value in $[0, 1]$. $f()$ is strictly decreasing and has value in $[0, 1]$ (this is evident if we remind that $f(x)$ is the probability to access the channel for a legacy station that experience a collision probability x). $h()$ is strictly increasing in the interval $[0, 1]$ (for all the possible values of $k_i x_i$). Then, the composition $h \circ f \circ g$ is strictly decreasing for $p_i \neq 1$. The solution τ_i^* of (5) can be found numerically in a few fixed point iterations.

Note that, as originally proved in literature and revisited in **?**, if there are stations with only uplink traffic flows, the NE of the distributed access game with non-null utility values are all and only the vector of strategies $\boldsymbol{\tau}$, such that $\exists!\ i \in \{1, 2, \cdots n\} \mid \tau_i = 1$ and $k_i = \infty$.

In this particular case our general utility function leads to the same results of **?**. Conversely, when $k_i \neq \infty\ \forall i$, the next proposition shows that there is a non trivial NE where all players obtain non null utility.

Proposition 2.2. For a given vector $\boldsymbol{k}$ of application requirements $(k_1, k_2, \cdots k_n)$ in $(0, \infty)^n$, and a given vector of downlink throughput coefficients $(x_1, x_2, \cdots x_n)$, it exists a unique NE $\boldsymbol{\tau}$ with non-null utility values.

Proof We already know that all the vectors of strategies such that at least two stations transmit with probability 1 are NE with zero utility. Moreover, an outcome with only one station, say it i, transmitting with $\tau_i = 1$ cannot be a NE because the station would find convenient to unilaterally reduce τ_i to increase its downloading rate. Then we can conclude that a NE with non-null utility values can only exist for $\tau \in [0,1)^n$, or equivalently $p_j < 1$ for all j, so in what follows we consider this case. A NE is an outcome $\boldsymbol{\tau^*}$ of mutual best responses, that can be expressed by (5), being that $p_i < 1$ for all i, i.e. an outcome such that for each i, $\tau_i^* = \frac{k_i x_i \tau_{AP}}{1-(1-k_i x_i)\tau_{AP}}$, with $\tau_{AP} = f(1 - \prod_{i=1}^n (1-\tau_i^*))$. Although the above equations characterize the best responses only for $\boldsymbol{\tau} \in [0,1)^n$, we will first look for solutions with $\boldsymbol{\tau} \in [0,1]^n$, knowing that solutions with one transmission probability equal to 1 are not NE. The conditions can be geometrically represented in the $n+1$ dimensional hypercube $[0,1]^{n+1}$, where the first n dimensions are the strategies $\tau_1, \tau_2, \cdots, \tau_n$ and the last dimension is the AP access probability τ_{AP}. We denote $\boldsymbol{\theta} = (\tau_1, \tau_2, \cdots \tau_n, \tau_{AP})$ a generic vector in this hypercube. Moreover we denote $\mathbf{0}^m$ and $\mathbf{1}^m$ the m-dimensional vectors whose elements are respectively all equal to 0 and to 1.

A solution of the set of equations, if any, corresponds to the intersection of the n-dimensional hypersurface S identified by the equation $\tau_{AP} = f(1 - \prod_{i=1}^n (1-\tau_i))$ with $(\tau_1, \tau_2, \cdots, \tau_n) \in [0,1]^n$, and the one-dimensional curve C, identified by the set of n equations $\tau_i = \frac{k_i x_i \tau_{AP}}{1-(1-k_i x_i)\tau_{AP}}$ with $\tau_{AP} \in [0,1]$.

We observe that S is continuous, and it divides the hypercube in three regions: the surface S itself, the region R_b of the points "below the surface", i.e. $R_b = \{\boldsymbol{\theta} | \tau_{AP} < f(1 - \prod_{i=1}^n (1-\tau_i))\}$, and the region R_a of the points "above" it, i.e. $R_a = \{\boldsymbol{\theta} | \tau_{AP} > f(1 - \prod_{i=1}^n (1-\tau_i))\}$. Note that the point $\mathbf{0}^{n+1}$ belongs to R_b, because $f(p_{AP}(\mathbf{0}^n)) > 0$, and the point $\mathbf{1}^{n+1}$ belongs to R_a because $f(p_{AP}(\mathbf{1}^n)) < 1$. The one-dimensional curve is also continuous and it connects $\mathbf{0}^{n+1}$ (for $\tau_{AP} = 0$) and $\mathbf{1}^{n+1}$ (for $\tau_{AP} = 1$), then it necessarily intersects the surface. This proves that it exists an intersection point.

Moreover, it is easy to check that, for each i, $\frac{\partial \tau_{AP}}{\partial \tau_i}|_{\boldsymbol{\tau} \in S} < 0$ and $\frac{\partial \tau_i}{\partial \tau_{AP}}|_{\boldsymbol{\tau} \in C} > 0$. Then there can be a unique intersection point.

Finally, we observe that this intersection point has to belong to $(0,1)^{n+1}$, because the sign of the derivatives for the point in C imply that all the points of C lie in $(0,1)^{n+1}$ but $\mathbf{0}^{n+1}$ and $\mathbf{1}^{n+1}$, neither of which can be the intersection point because we have shown that they do not belong to S. Then, the intersection point is indeed a NE and moreover the corresponding nodes' utilities are all non-null.

Figure **??** shows some examples of equilibrium conditions in terms of surface and parametric curve intersections for two stations (hence in a 3-dimensional space) and for different k_1 and k_2 values.

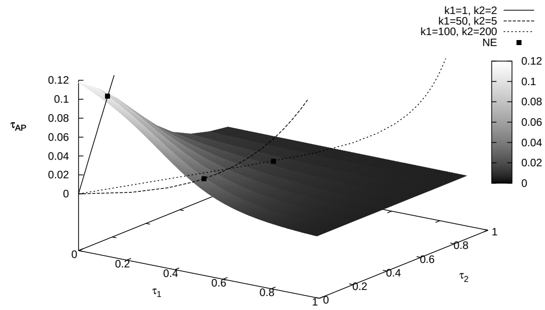

Fig. 1. Geometric interpretation of the Nash equilibrium for heterogeneous application requirements

2.4 Downlink Scheduling Scheme

For evaluating the ratio x_i of the downlink throughput to be assigned to each station, the AP can employ different policies. If the AP is not aware of the application requirements of each station, a possible solution is to equally share the downlink throughput among the stations (i.e. $x_i = 1/n$ $\forall i$). Under this policy , called *Application-Agnostic (AA)* scheduling, since each station i tries to get an uplink throughput equal to $k_i S_d^i = k_i/nS_{AP}$, the total uplink and downlink throughput perceived by each station at the NE is $(1+k_i)/nS_{AP}$. This implies that stations requiring large k_i values will consume a large fraction of the network resources.

Whenever the AP is able to estimate the application requirement of each station (by monitoring the ratio between the uplink and downlink throughput perceived by each station), it can implement a different downlink scheduling policy devised to improve the network fairness. For example, by imposing that the total per-node bandwidth $S_u^i + S_d^i = (1+k_i)x_i S_{AP}$ is equal for each station, with the constraint $\sum_i x_i = 1$, it results:

$$x_i = \frac{\frac{1}{k_i+1}}{\sum_{j=1}^n \frac{1}{k_j+1}} \tag{6}$$

We refer to this policy as an *Application-aWare (AW)* scheduling policy. When multiple stations have the same application requirements, we can group these stations into applications classes, each identified by a specific k_i value. Stations belonging to the same classes will receive the same downlink ratio x_i.

Note that the AA scheduling policy guarantees a uniform utility for all the stations, while the AW scheduling policy equalizes the total per-station bandwidth, thus resulting in heterogeneous utilities. Therefore, we could argue that a different utility definition, based on the total per-station bandwidth, could be considered. However, such a definition does not capture the bidirectional nature of the considered applications and could lead to situations in which the uplink or downlink bandwidth is null.

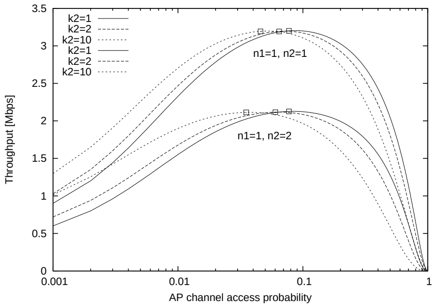

Fig. 2. Per-station total bandwidth, for different service classes ($k_1 = 1$, $k_2 = 1, 2, 10$) and approximated maximum values (empty boxes).

2.5 Tuning of the AP channel access probability

In order to improve the downlink short-term fairness and the overall network performance, we can use the AP channel access probability τ_{AP} as a tuning parameter. In this case, τ_{AP} does not depend on $\boldsymbol{\tau}$ according to (1), but it is equal to a fixed value c, which can be tuned by the AP. The best response (5) for each station i is equal to

$$\tau_i^+ = \frac{k_i x_i \cdot c}{1 - (1 - k_i x_i)c} \tag{7}$$

and the NE in $(0, 1)^n$ becomes the intersection between an hyperplane $\tau_{AP} = c$ and the parametric curve C identified by the best response equations. Let $J_i^{NE}(c)$ and $S_{AP}^{NE}(c)$, respectively, the station i utility and the AP throughput perceived at the NE for each different c value selected by the AP. When $x_i \neq 0 \ \forall i$, the utility value J_i^{NE} of each station is proportional to the AP throughput. Therefore, all the utilities can be maximized by maximizing the same function S_{AP}^{NE}:

$$\max_c J_i^{NE}(c) = k_i x_i \cdot \max_c S_{AP}^{NE}(c).$$

Figure **??** shows the effects of the τ_{AP} tuning on the total bandwidth perceived by $n1$ and $n2$ contending stations belonging to two different service classes. Specifically, $n1$ stations have an application requirement $k_1 = 1$ and $n2$ stations have an application requirement k_2, equal to $1, 2, 10$ in Figure **??**. The figure has been obtained for a packet size of 1500 bytes, under the AW scheduling policy. From the figure, it is evident that the per-station bandwidth can be maximized for a given τ_{AP_o} value. Although a closed form expression for such a maximum is not trivial, we verified that an excellent approximation for $k_i > 1 \ \forall i$ is given by:

$$\tau_{AP_o} = \frac{1}{(1 + \sum_i k_i x_i)\sqrt{T/2\sigma}} \tag{8}$$

The approximation is based on the result shown in **?**, according to which the optimal channel access probability that for a network with n competing stations is given by $\frac{1}{n\sqrt{T/2\sigma}}$. In our scenario, at the NE outcome, the AP behaves as a single contenting station, while all the others require an uplink throughput equal to $k_i x_i$ times the AP one. Figure **??** shows (empty boxes) the bandwidth perceived when τ_{AP} is tuned to the approximated value (**??**). The points are quite close to the actual maximum values (as we also verified numerically).

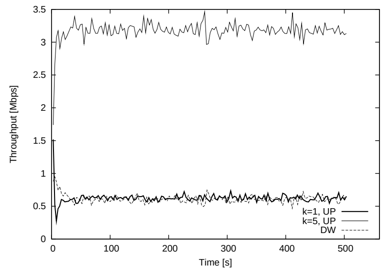

Fig. 3. Throughput repartition in case of heterogeneous application requirements ($k_1 = 1$,$k_2 = 5$) for two contending stations under the AA downlink scheduling.

3. GAME-BASED MAC SCHEME: IMPLEMENTATION AND EVALUATION

On the basis of the results discussed in the previous sections, we propose some simple DCF extensions devised to i) enable each contending station to dynamically tune its channel access probability according to a best response strategy; ii) enable the AP to act as a game designer for forcing desired equilibrium conditions. Being n the number of stations associated to the AP, we assume that the AP maintains n independent downlink queues. For each station i, uplink and downlink transmission queues are always saturated, apart from the case $k_i = \infty$ in which the i-th downlink queue is empty. We also assume that each station is aware of its application requirements k_i, while the AP is aware of the number of associated stations n involved in the contention process. In actual networks, for implementing a best response strategy, each station needs to estimate the AP channel access probability τ_{AP}. Moreover, for implementing the mechanism design and scheduling policies described in the previous sections, the AP needs to estimate the channel access probability τ_i employed by each station and the per-station application requirements k_i. It is possible to simply filter some channel status observations (idle slots, busy slots and successful transmissions) for providing run-time estimations as described in **?**. We consider both the case in which the AP behaves as a legacy station, and the case in which the AP can adaptively tune its channel access probability.

We extended the custom-made C++ simulation platform used in **?**. 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%. The measurement interval considered for run-time estimations has been set to 400 channel slots.

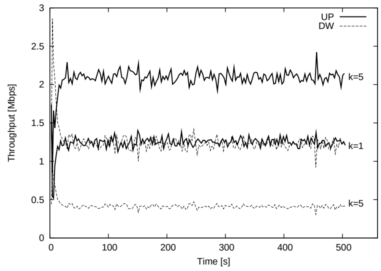

Fig. 4. Throughput repartition in case of heterogeneous application requirements ($k_1 = 1$,$k_2 = 5$) for two contending stations under the AW downlink scheduling.

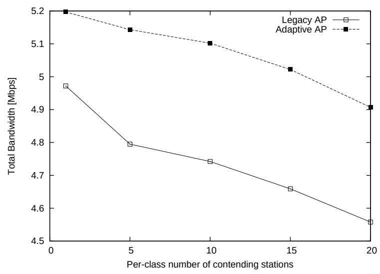

Fig. 5. Total bandwidth available in the network under the AW downlink scheduling, for two service classes ($k_1 = 1$, $k_2 = 10$) compared with a legacy AP.

Figures **??** and **??** shows the time-varying uplink and downlink throughput perceived by two contending stations in case of heterogeneous application requirements (namely, $k_1 = 1$ and $k_2 = 5$). Under the AA scheduling, the two stations perceive the same average downlink throughput (for sake of presentation the figure shows one curve only), while the uplink one is proportional to the per-station k_i value. This means that station 2 employing $k_2 = 5$ gets an overall bandwidth much higher than station 1, **although the utility perceived by the two stations (i.e. the minimum uplink and downlink throughput) is the same**. Conversely, under the AW scheduling, station 1 perceives a higher downlink throughput than station 2, thus leading to a total bandwidth (uplink and downlink) of about 1.4+1.4 Mbps. Station 2 still perceives an uplink throughput equal to $k_2 = 5$ times the downlink one, but thanks to the downlink throughput reduction, its overall bandwidth is comparable with station 1.

Figure **??** plots the overall bandwidth (i.e. $\sum_{i=1}^{n} S_u^i + S_d^i$) available in the network under the AW scheduling policy, in case of two service classes ($k_1 = 1$ and $k_2 = 10$), as a function of the per-class number of stations $n_1 = n_2$. The τ_{AP} tuning has been implemented according to the approximated optimal value given in (**??**). For $n_1 = n_2 = 20$, the bandwidth available under legacy AP is 10% lower than the one available in case of adaptive τ_{AP} tuning.

4. CONCLUSIONS

Resource sharing in WiFi networks has been modeled via game theory. Analysis of the contention based channel access has been presented and Nash equilibria has been proved, when a bidirectional heterogeneous traffic is considered. The Access Point is used to tune the downlink traffic in order to achieve fairness in bandwidth distribution. Two scheduling algorithms, AA (Application Agnostic) and AW (Application Aware), are presented. Both the algorithms induce the stations to work along their best response access probability, ensuring a uniform utility (AA) and a total per-station bandwidth. The proposed game-based MAC scheme has been implemented and evaluated in simulations, showing the increased bandwidth perceived by the stations when the tuning is applied.

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