A game theoretic approach of the MAC design for infrastructure networks

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***Abstract*—Wireless network operation intrinsically assumes different forms of cooperation among the network nodes, such as sharing a common wireless medium without interfering, relaying frames belonging to other nodes, controlling the transmission power for optimizing spectrum reuse, coding cooperatively multiple frames for improving information redundancy, and so on. For this reason, Game Theory has been extensively employed to model wireless networks. In particular, we propose a game-theoretic approach for defining a generalized medium access protocol for slotted contention-based channels. Contention-based channels are largely adopted in data networks, such as WiFi or WiMax, and even emerging cellular standards. We assume that each node of the network acts as a decision maker or player, and implements a best response strategy on the basis of simple estimators of the network status. When stations are interested in both uploading and downloading traffic, we show that efficient equilibria conditions can be reached. More interesting, these equilibria are reached when all the stations play the same strategy, thus guaranteeing a fair resource sharing. For infrastructure networks, we also propose to exploit the role of the base station to incentive the nodes to operate on the Pareto optimal equilibrium and achieve global optimality and fair performance.**

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: 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.

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 [2].

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 payoff $(J_1, J_2, \ldots, J_n)$, that can be defined according to the network and application scenario, seec [3] also for a literary review.

We propose a game theoretic analysis of DCF in infrastructure networks, when all the stations have a desired ratio between uplink and downlink throughput. Assuming that each station tunes its access probability according to a best response strategy, in [4] and in [5], we derive Nash equilibria and Pareto optimal conditions as a function of the network scenario and we show that efficient equilibria conditions can be naturally reached when stations are interested in both upload and download traffic. Since the utility of each station depends not only on its throughput but also on the AP throughput, no station is motivated to transmit continuously. 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 another station transmits, summarizes the interactions with all the other mobile stations. In presence of downlink traffic, we also assume that the AP contends for 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}.

In particular, as in [5], we consider the following station utility. Assuming that the AP equally shares the downlink throughput among the stations, we can express the uplink throughput S_u^i and the downlink throughput S_d^i for the i-th station as [8]:

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

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

where P is the frame payload which is assumed to be fixed, σ and T are, respectively, the empty and the busy slot duration

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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:

$$J_i = \min\{S_u^i, kS_d\} \quad (3)$$

The rationale of this definition is the assumption that the station applications can require bandwidth on both directions. The coefficient $k \in [0, \infty)$ takes into account the desired ratio between the uplink and the downlink throughput. 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 a *unidirectional traffic* case, in which stations are not interested in downlink throughput and their utility is simply given by the uplink throughput (as assumed in most previous literature). Extensions to an heterogeneous case, where $k = k_i$ is depending on each station is under current research.

In the present paper we define a mechanism design scheme, in which the AP plays the role of arbitrator to improve the global performance of the network, by forcing desired equlibria conditions. We propose to extend current DCF operation by implementing our theoretical best response strategies. To this purpose, we develop some channel monitoring functionalities (similarly to [6], [7]), devised to estimate the network status and to run-time drive the strategy adaptations.

II. Channel access mechanism design

Our previous considerations ([4],[5] about equilibrium conditions and Pareto optimality have shown that the global performance of the distributed access scheme strongly depends on the desired ratio k between downlink and uplink throughput. In fact, the station utility perceived in equilibrium conditions and the maximum social utility depend on k, i.e. on the intersection point between the curves S_u^{hom} and kS_d^{hom}. We recall that $S_u^{hom}(\tau) = S_u(\tau, 1 - (1 - \tau)^{n-1})$ and $S_d^{hom}(\tau) = S_d(\tau, (1 - \tau)^{n-1})$ represent respectively, the uplink and downlink throughput perceived by each station in case of homogeneous outcomes ($\boldsymbol{\tau} | \tau_i = \tau, \forall i$). We can prove the following result.

Proposition 2.1: The social utility is maximized for an homogeneous outcome $(\tau', \tau', \cdots, \tau')$ and such outcome is Pareto Optimal.

However, such a result is based on the assumption that the Access Point behaves as a legacy station. In this section, we explore the possibility to use the Access Point for changing the S_d or S_u functions, in order to force desired equilibrium outcomes. Indeed, since the AP plays the role of gateway to external networks, it can also play the role of arbitrator for improving the global performance of its access network.

A. Tuning of the AP channel access probability

A first solution for changing the uplink and downlink throughput curves is to use the AP channel access probability τ_{AP} as a configuration parameter. Then, τ_{AP} does not depend on $\boldsymbol{\tau}$ according to the following $\tau_{AP} = f(p_{AP})$, where $f()$ has been derived in ([2]):

$$\tau = f(p) = \begin{cases} \frac{2(1-p^{R+1})}{1-p^{R+1}+(1-p)\sum_{i=0}^{R} p^i W(i)} & 0 \le p < 1 \\ \frac{2(R+1)}{1+\sum_{i=0}^{R} W(i)} & p = 1 \end{cases} \quad (4)$$

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. $W(i) = \min\{2^i CW_{min}, CW_{max}\}$).

Now, it is equal to a fixed value, which can be tuned by the AP. The best response solution of the following implicit equation:

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

for all the stations is equal to

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

and the NE in $(0, 1)^n$ becomes $(\tau^+, \tau^+, \cdots \tau^+)$.

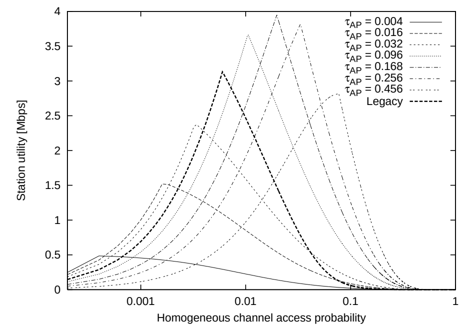

Fig. 1. Station utility at 600 Mbps in case of homogeneous access probability, n=10, k=1, and different τ_{AP} values.

Figure 1 show the effects of the τ_{AP} tuning on the utility perceived for homogeneous outcomes. We considered a scenario with 10 contending stations, a packet size of 1500 byte, and $k = 1$. Each labeled curve refers to a different τ_{AP} setting, as indicated in the legend. For each curve, the NE corresponds to the cuspid point. For comparison, the figures also plot a bold dashed curve for the case in which the AP behaves as a legacy station. Figure 1 has been obtained for an 802.11n PHY layer at the maximum rate (namely, 600 Mbps) and the difference between the NE utility perceived under a legacy AP and under a fixed $\tau_{AP} = 0.168$ is about 0.9 Mbps.

Since each different τ_{AP} setting leads to a different homogeneous NE, given a desired NE it is possible to design the corresponding τ_{AP} value by inverting (6). We can express the utility J^{NE} perceived at the NE as a function of the desired homogeneous NE $(\tau, \tau, \cdots \tau)$. By considering that at

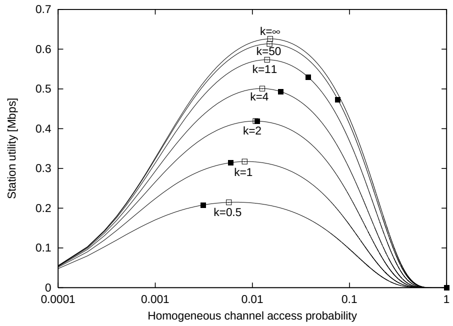

Fig. 2. Station utility at NE as a function of the desired NE outcome, for n=10 and different k values. Maximum station utility under mechanism design (white boxes), station utility at NE under legacy AP (black boxes).

the NE the utility can be expressed as S_u^{hom}, (or equivalently as kS_d^{hom}), after some manipulations it results:

$$J^{NE}(\tau) = \frac{\tau(1-\tau)^n P}{T - (1-\tau)^{n+1}(T-\sigma) + \frac{n-k}{k}T\tau} \quad (7)$$

By deriving (7), it can be shown that, for $k \neq 0$, the function J^{NE} has a unique maximum in $\tau_o \in (0,1)$. Such desired maximum can be obtained by setting a specific τ_{AP_o} value. Although an exact computation of τ_{AP_o} is in principle possible, by deriving J^{NE} and inverting (6), an approximated optimal tuning can be simply derived, [5]:

$$\hat{\tau}_{AP_o} = \frac{n}{k}\frac{1}{(n+n/k)\sqrt{T/2\sigma}} = \frac{n}{(n+kn)\sqrt{T/2\sigma}}, \quad (8)$$

which leads to the desired NE outcome

$$\hat{\tau}_o = \frac{k}{(kn+n)\sqrt{T/2\sigma} - (n-k)}.$$

Figure 2 visualizes the accuracy of the proposed approximation by plotting the points $(\hat{\tau}_o, J^{NE}(\hat{\tau}_o))$ (white boxes) for different k values. The proposed approximation has an important practical implication. In fact, by simply specifying the application requirements k and estimating the number of contending stations n (as described in section III), the access point can tune its channel access probability to $\hat{\tau}_{AP_o}$, thus forcing the network to the desired equilibrium point. We also report the NE utilities perceived under legacy AP (black boxes). Comparing white and black boxes, it is evident that in many cases the network performance under a legacy AP are suboptimal (i.e. the NE utility is lower than the maximum of the J^{NE} curves.

The figure also plots the limit curve obtained for $k \to \infty$, which represents the system behavior when the application requirements tend to the unidirectional traffic case. In this case, the J^{NE} expression given by 7 tends to the uplink throughput expression. However, this curve is practically unfeasible because for $k \to \infty$ τ_{AP} tends to zero for any desired NE, and cannot be used as a tuning parameter. In other words, although $\hat{\tau}_o$ tends to the finite value $1/(n\sqrt{T/2\sigma}+1)$ maximizing the social utility, the mechanism design cannot be practically performed. When $\tau_{AP} \neq 0$, such as in the legacy case, for $k \to \infty$ the best response of each station tends to 1 (as shown in the black boxes of figure 2).

B. ACK suppression

The mechanism design described in the previous section is unfeasible when $k = \infty$. Moreover, when k is very high (i.e. τ_{AP_o} tends to zero), stations need a long estimation time for correctly evaluate their best response. A solution for controlling the resource repartition in infrastructure networks with negligible (or zero) downlink throughput is a selective discard of the ACK transmissions at the AP side. Since the AP is the common receiver for all stations, suppressing the ACKs at the AP side corresponds to triggering ACK timeouts at the station side, which are interpreted as collisions. Therefore, the ACK dropping can act as a punishment strategy devised to limit the uplink throughput of too aggressive stations. We propose the following threshold scheme: if a generic station i has an access probability τ_i higher than the a given value γ, the AP drops an ACK frame transmission with probability $\min\{\alpha(\tau_i - \gamma), 1\}$.

In this case, by considering $\tau_{AP} = 0$ (i.e. the unidirectional traffic case) or $\tau_{AP} \simeq 0$, the utility function J_i of a given station i can be expressed as:

$$J_i(\tau_i, p_i) = \begin{cases} \frac{\tau_i(1-p_i)}{P_{idle}\sigma + [1-P_{idle}]T} & 0 < \tau_i < \gamma \\ \frac{\tau_i(1-p_i)[1-\alpha(\tau_i-\gamma)]}{P_{idle}\sigma + [1-P_{idle}]T} & \gamma \leq \tau_i < \gamma + 1/\alpha \\ 0 & \gamma + 1/\alpha \leq \tau_i \leq 1 \end{cases} \quad (9)$$

where we recall that $P_{idle} = (1-\tau_i)(1-p_i)$. According to the previous expression, for $\tau_i \leq \gamma$ the utility function J_i is an increasing function of τ_i, while for $\tau_i \leq \gamma$ its slope depends on the α setting. By selecting an α value which corresponds to a negative derivative for $\gamma < \tau_i < \gamma + 1/\alpha$, the utility function is maximized for $\tau_i = \gamma$.

Figure 3 plots the station utility perceived in case of homogeneous outcomes, under the ACK suppression scheme, for n=10 and different α values. For $\alpha = 0$, the station utility is simply given by the uplink throughput. In this case, the utility is an increasing function of the channel access probability and the best response of each station is $\tau^{(br)} = 1$. For $\alpha > 0$, the utility function is maximized for $\tau^{(br)} < 1$. Such a maximum corresponds to γ for large enough values of α (in figure, $\alpha = 80$).

We can now give the following result.

Proposition 2.2: The outcome $(\boldsymbol{\tau'} | \tau_i = \tau', \forall i)$ is a Pareto optimal Nash equilibrium of the game, when the ACK suppression scheme indicated above is implemented with

$$\begin{aligned} \gamma &= \tau', \\ \alpha &\geq \frac{1}{\tau'(1+\tau'(-1+\frac{T}{T-(T-s)(1-\tau')^{n-1}}))}. \end{aligned} \quad (10)$$

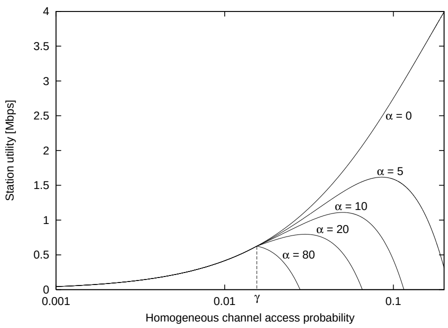

Fig. 3. Station utility in case of ACK suppression, for n=10, k=∞ and different α values.

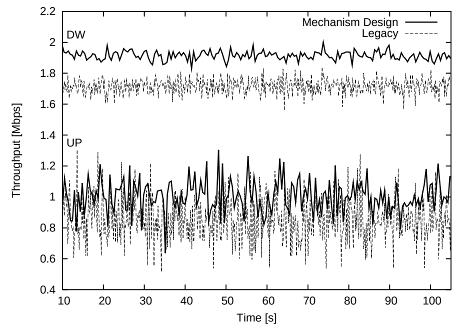

Fig. 4. Uplink and downlink throughput repartition at 11 Mbps under legacy AP (dashed lines) or mechanism design (bold lines), for n=10, k=0.5.

The utility J^{NE} perceived at the NE can be simply expressed as the uplink throughput perceived in case of homogeneous outcome $(\boldsymbol{\tau}|\tau_i = \tau\forall i)$:

$$J^{NE}(\tau) = \frac{\tau(1-\tau)^n P}{(1-\tau)^n\sigma + (1-(1-\tau)^n)T} \tag{11}$$

Therefore, by estimating the number of contending stations n, each AP can implement (as described in section III) an ACK suppression scheme that forces the system to work on the NE $\boldsymbol{\tau_o}$ maximizing the network throughput.

III. 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 enable each contending station to dynamically tune its channel access probability according to a best response strategy. For this purpose, each station needs two estimators for probing the uplink and downlink load conditions. In fact, station best response depends not only on the application requirements (by means of k), but also on the uplink load (by means of n) and downlink load (by means of τ_{AP}).

We consider both the case in which the AP behaves as a legacy station, and the case in which the AP acts as a game designer, for forcing desired equilibrium conditions. In this second case, we assume that also the AP is able to estimate the uplink load (by means of n) and the channel access probability τ_i employed by each station. These estimates are then used for opportunistically tuning the AP channel access probability or the ACK suppression scheme (by means of γ and α).

A. Network load estimators

In contention-based networks, network load can be simply related to channel observations. Considering the slotted channel model due to saturation conditions, a channel observation corresponds to the channel outcome observed into a given slot. Such outcome is given by an idle slot when no station transmits, by a successful slot when a single station transmits, by a collision slot when two or more stations transmit simultaneously.

For measuring the number of stations actually contending on the network, we propose to count the number of different transmitters observed during the measurement interval. Each transmitter can be identified by means of its MAC address. Obviously, the monitoring station can identify the transmitter address only when the packet is received correctly. Thus, within B observation slots, the number of successful packets is not fixed. Let $n^m(t)$ be the uplink load measurement performed during the t-th measurement interval by a given station. The estimation $\hat{n}$ of the number of contending stations is then performed as a first order filter.

In order to measure the channel access probability employed by the AP, the monitoring station has to count the number tx_{AP} of successful transmissions performed by the AP during B. Given that there is 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 $\frac{tx_{AP}}{B-C}$. The estimation $\hat{\tau}_{AP}$ is then performed as a first order filter. Further details on the network estimators can be found in [7].

B. Best response performance under AP mechanism design

In order to enable the AP to play the role of game designer, it is necessary to equip this central node with different estimation functions. In case of bidirectional traffic, the AP has to estimate the number of competing stations n for tuning its channel access probability to the optimal value given by (8). For this purpose, the same estimator defined in (III-A) can be used at the AP side. We assume that the application requirement k does not need to be estimated, because it is known a priori (e.g. by means of signaling messages). In turns, each contending station runs an estimator of the AP channel access probability in order to perform a best response strategy adjustment according to (6).

Figure 4 shows an example of uplink and downlink throughput repartition when the AP implements a mechanism design scheme. The simulation refers to an experiment lasting 110 seconds, with 10 competing stations, a packet payload of 1500 byte, an 802.11 PHY layer at 11 Mbps, and $k = 0.5$. For comparison, the figure also plots the throughput repartition perceived under a legacy AP. The figure shows that the mechanism design implementation is effective in improving the downlink and uplink throughput performance. Such an improvement can be obtained despite of the simplicity of the employed load estimators.

When $k \to \infty$, the implementation of the ACK suppression scheme requires that the AP evaluates: i) the γ threshold, which depends on the estimate of n; ii) the α coefficient, which is simply related to γ and to the PHY parameters T and σ; iii) the per-station channel access probability τ_i, $i = 1, 2, \cdots n$, which require n estimators similar to the one used by the stations for evaluating τ_{AP}. During the observation interval B, the AP has to separately count the successful transmissions tx_i performed by each station i, and the number of collisions C, for measuring τ_i^m as $tx_i/(B - C)$. These measurements can be filtered with the usual auto-regressive filter. The implementation of the ACK suppression scheme at the AP side has important implications for preventing users and card manufacturers from using non-standard contention window values.

In order to asses the effectiveness of the ACK suppression implementation as the number of competing stations grows, Figure 5 compares the aggregated network throughput of our scheme with the standard DCF one, for different n values. Each point refers to a network scenario in which n stations (indicated in the x axis) are aware of the ACK suppression risk and employ a consequent best response strategy. Although the variance of the τ_i estimators could imply that in some intervals such a probability passes the threshold value (i.e. there is a non null probability of unnecessary ACK dropping), the figure shows that the aggregated throughput is almost constant regardless of the number of competing stations. This behavior is very different from standard DCF, whose efficiency depends on the number of contending stations and degrades for high load conditions. Therefore, our scheme is able not only to discourage cheating card behaviors, but also to optimize the global network performance.

C. Analisi of the stability of the NE, and quantization effects

In the present appendix, we want we want to model and study: i) the stability of the Nash Equilibrium, with respect to the application requirements k, ii) the quantization effects in the tuning of τ_i, in the case of integer $CW_{min} = CW_{max}$ values, iii) the measurement noise effects on the network equilibria.

Given that each station i corrects its best response according to periodic τ_{AP} estimates, we model the tuning of τ_i as a repeated game. When stations update their τ_i values simultaneously (i.e. the measurement intervals are synchronized) and know the exact τ_{AP} value, we can define a network state $x(t) = \begin{bmatrix} \tau \\ \tau_{AP} \end{bmatrix}$ for a discrete time instant t, and a state model:

$$\begin{cases} x_1(t+1) &= g(x_2(t)) = \frac{kx_2(t)}{n-(n-k)x_2(t)} \\ x_2(t+1) &= h(x_1(t)) = f(1-(1-x_1(t))^n) \end{cases} \quad (12)$$

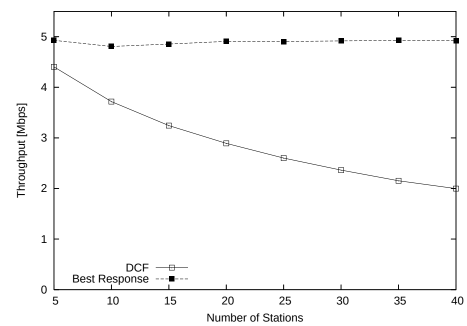

Fig. 5. Unidirectional case ($k = \infty$): aggregated throughput for various number of nodes. Best response is compared with standard DCF.

The model is defined by considering that $g(x2(t))$ is the best response given in (5), and $f(.)$ is the function used in (4) with $p = 1 - (1 - x_1(t))^n$).

We recall that $x \in [0,1]^2$, $g \in [0,1]$ and $h \in [\underline{h}, \overline{h}]$ with $0 < h(1) = \underline{h} \leq \overline{h} = f(0) < 1$. Let $\bar{x} = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \end{bmatrix}$ be the Nash equilibrium, that we have already proven to exist, as the unique intersection of the curve h and g. Linearizing around the equilibrium, the Jacobian is given by

$$J = \begin{bmatrix} 0 & \frac{\delta g}{\delta x_2} \\ \frac{\delta h}{\delta x_1} & 0 \end{bmatrix}$$

and the linearized system eigenavalues are $\lambda_i = \pm j\sqrt{|(\frac{\delta g}{\delta x_2}|_{\bar{x}_2}) * (\frac{\delta h}{\delta x_1}|_{\bar{x}_1})|}$. The latter is true because $\frac{\delta g}{\delta x_2} = \frac{nk}{(n-(n-k)x_2)^2} > 0 \forall x_2$ and $\frac{\delta h}{\delta x_1} < 0 \forall x_1$ [1].

Clearly the local stability of the Nash equilibrium is depending on the amplitude of the eigenvalues, and it is guaranteed only if they are smaller than 1, according to the relative slope of the two curves h and g. In general, it is not possible to assure it, as we have seen in simulations for large k values and different load conditions.

Indeed, in real systems the actual τ_{AP} values are not available and a measurement framework is required. For example, in our simulations, we proposed to filter the τ_{AP} measurements collected at regular time intervals with a simple autoregressive

[1] Although the expression of $\frac{\delta h}{\delta x_1}$ is more complicated, it is intuitive to understand that, as x_1 increases, the AP decreases its channel access probability as a consequence of an higher collision probability (i.e. average contention window value). Being $h(x_1) = f(p(x_1))$ a composite function, $\frac{\delta f}{\delta x_1} = \frac{\delta f}{\delta p}\frac{\delta p}{\delta x_1}$, where the first term is negative and the second is positive (equal to $n * (1 - x_1)^{n-1}$)

filter with memory β. The presence of such a filter affects the relative slope of the curves $h(x_1(t))$ and $g(x_2(t))$, since it changes the system model in:

$$\begin{cases} x_1(t+1) &= g(x_{2f}(t)) \\ x_2(t+1) &= h(x_1(t)) \\ x_{2f}(t+1) &= \beta x_{2f}(t) + (1-\beta)x_2(t). \end{cases} \quad (13)$$

Simulations of the filtered version have shown that it is always possible to choose a β value which guarantees NE stability. Figure 6-a shows the samples $\tau(299)$ and $\tau(300)$ of the repeated game, for $n = 10$, $k \in [0.1, 150]$, and different β values. For $\beta = 0$, i.e. when no filter is applied, the best response converges for $k < 8$ and $k > 130$ and presents a bifurcation in the range $[8, 130]$. The bifurcation range is reduced for $\beta = 0.15$ and disappears for $\beta \geq 0.25$.

We also show the effects of using integer $CW_{min} = CW_{max} = CW$ values (for tuning the τ values) on the Nash equilibrium. To model this effect, that has been implemented in the real simulations, at each step the contention window is chosen according to $CW(t) = \lfloor \frac{2}{g(x_2(t))} \rfloor - 2$ and the model is updated as:

$$\begin{cases} x_1(t+1) &= \frac{1}{0.5\lfloor \frac{2}{g(x_2(t))} \rfloor - 1} \\ x_2(t+1) &= h(x_1(t)) \\ x_{2f}(t+1) &= \beta x_{2f}(t) + (1-\beta)x_2(t). \end{cases} \quad (14)$$

We verified in simulation that the quantization has a marginal effect on system stability. Figure 6-b visualizes such an effect for the same configurations described in the previous figure. As can be noticed, the effect of the quantization is affecting the convergence values only when k is very large.

Finally, by neglecting the noise on the n measurements, the noise on the τ_{AP} measurements can be included by considering the following state model:

$$\begin{cases} x_1(t+1) &= g(x_{2f}(t)) \\ x_2(t+1) &= h(x_1(t)) \\ x_{2f}(t+1) &= \beta x_{2f}(t) + (1-\beta)(x_2(t) + r(t)) \end{cases} \quad (15)$$

where $r(t)$ can be approximated by a random Gaussian variable, with zero mean and variance equal to $x_2(t)(1-x_2(t))/B$. Figure 6-c shows the average values and the fluctuation range of the best response x_1, for different k values. Again, for small k values the noise effects are negligible.

IV. Conclusions

The proliferation of MAC-level programmable WiFi cards can potentially create serious coexistence problems, since some stations can implement greedy access policies for increasing their bandwidth share at the expenses of compliant users. For this reason, we proposed a game-theoretic analysis of persistent access schemes for WiFi infrastructure networks, in order to characterize equilibria conditions and to design disincentive mechanisms for inefficient behaviors.

We proposed some extensions to standard DCF, recalling that contention-based channels are largely adopted in data networks, such as WiFi or WiMax, and even emerging cellular standards, in order to i) estimate the network status, and ii) emulate an access scheme based on best response strategies and AP mechanism design. We proved the effectiveness of our solutions for controlling the resource sharing in WiFi networks in various network scenarios. We are currently investigating on the prototyping of our solutions in actual WiFi cards and APs. While the estimate and best response modules can be simply implemented at the driver level, the ACK dropping scheme requires a hardware/firmware update.

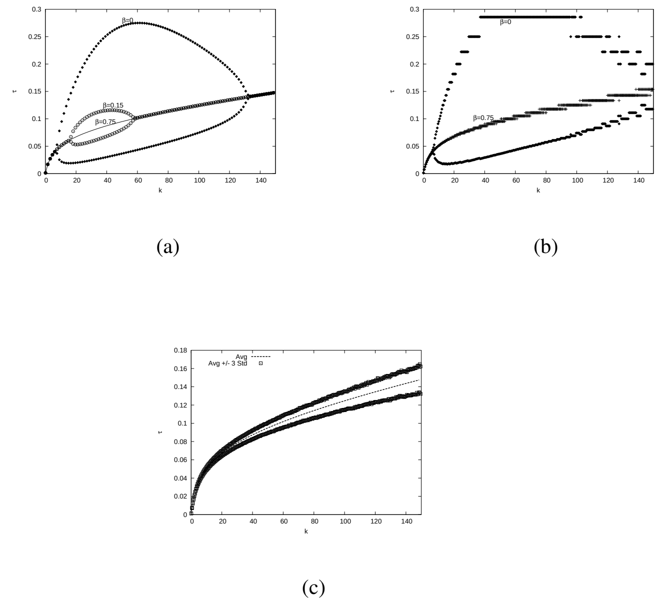

Fig. 6. Stability (a), quantization effects (b) and measurement noise effects (b) on stations best response, for $k = 0.1 : 150$.

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