

Resource Control for the EDCA Mechanism in Multi-Rate IEEE 802.11e Networks*

Vasilios A. Siris

Institute of Computer Science, FORTH and
Department of Computer Science, Univ. of Crete
P. O. Box 1385, 711 10, Heraklion, Crete, Greece
vsiris@ics.forth.gr

Costas Courcoubetis

Department of Informatics
Athens Univ. of Economics and Business
47A Evelpidon & 33 Lefkados, 113 62, Athens, Greece
courcou@aueb.gr

Abstract

We investigate the problem of efficient resource control for elastic traffic in IEEE 802.11e's Enhanced Distributed Channel Access (EDCA) mechanism. Our approach considers an economic modelling framework based on congestion pricing that captures how various factors, such as the probability of attempting to transmit a frame, the use of the basic CSMA/CA or the RTS/CTS procedure, and the physical layer transmission rate, contribute to congestion. We discuss the application of the framework for achieving class-based throughput differentiation, for performing explicit congestion notification (ECN) marking based on the level of congestion in the wireless channel, and for modelling the performance of TCP congestion control over EDCA. In these application scenarios we discuss how to estimate the optimum minimum contention window and the congestion prices based on the 802.11e parameters and actual measurements, in order to achieve efficient channel utilization.

1 Introduction

The number of users accessing the Internet and enterprise intranets through wireless networks will continue to grow with the proliferation of wireless hotspots and enterprise wireless LANs based on the IEEE 802.11 standard. The IEEE 802.11b standard can support transmission rates up to 11 Mbps, whereas the newer standards 802.11a/g support transmission rates up to 54 Mbps. Hence, the available bandwidth in wireless LANs is at least one order of magnitude smaller than the capacity typically available in wired networks. Moreover, emerging multimedia services over wireless networks will have different bandwidth and delay requirements. For all the above reasons, resource control and service differentiation in wireless LANs based on IEEE 802.11 will become increasingly important.

Resource control procedures are required to be fair and adaptive to different network loads, and achieve efficient utilization of the shared wireless channel. One approach for developing such procedures is based on economic mod-

elling, which has been successfully applied to both wired and wireless, e.g. CDMA networks [1, 2]. A key feature of economic models is the efficient utilization of network resources through a decentralized control approach, and encoding of user preferences using utility functions. The work presented in this paper is, to the authors' knowledge, the first application of economic modelling that takes into account the specific characteristics and operation of the contention-based EDCA mechanism in multi-rate IEEE 802.11e networks.

The model proposed in this paper can be applied in a class-based service differentiation framework, where the wireless LAN's access point estimates the optimum minimum contention window for different service classes, based on the level of congestion; this has high practical significance, since the IEEE 802.11e standard defines how the minimum contention windows for various classes are communicated to the wireless stations, but not how they should depend on the network load and traffic characteristics in order to achieve efficient channel utilization. Another application of our model is to achieve efficient utilization of the wireless channel through a decentralized scheme, using explicit congestion notification (ECN) for signalling the level of congestion in the 802.11 network. Finally, by considering utility functions for encoding end user and application preferences, the proposed framework can be used to investigate the performance of transport protocols over EDCA. Although the p-persistent approximation that we consider does not capture the exponential backoff behavior of 802.11, our experiments indicate that it is accurate in the range of values that are of interest to us, which are the values that maximize the aggregate utility or throughput; this suggests that more detailed throughput models would provide very few additional practical advantages.

The rest of the paper is organized as follows. In Section 2 we present a brief overview of IEEE 802.11e's EDCA mechanism. In Section 3 we discuss an analytical throughput model for multi-rate 802.11e networks. In Section 4 we present our framework for efficient resource control. In Section 5 we discuss the application of the framework, and in

*This work has been supported by British Telecom, UK.

Section 6 we present experimental results that demonstrate and evaluate its use. Finally, in Section 7 we present a brief overview of related work, and in Section 8 we conclude the paper identifying related and future research directions.

2 IEEE 802.11e and EDCA

IEEE 802.11's DCF (Distributed Coordination Function) is based on CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance). According to the collision avoidance mechanism of CSMA/CA, before initiating the transmission of a frame, a station selects a random backoff period from the interval $[0, CW - 1]$, where CW is referred to as contention window. The station waits for the channel to be idle for a total time equal to this backoff period, after which it senses the channel to see if it is idle for a DIFS interval, in which case it can transmit a data frame with the basic CSMA/CA procedure, or an RTS frame with the RTS/CTS procedure. CW has an initial value CW_{min} , and is doubled when a collision occurs, up to the maximum value CW_{max} .

The IEEE 802.11e standard supplement addresses the issue of QoS support in wireless LANs. The MAC protocol of 802.11e is the Hybrid Coordination Function (HCF), which supports both contention-based and controlled channel access. Contention-based access is supported by the Enhanced Distributed Channel Access (EDCA) mechanism, which is an extension of the DCF mechanism that enables distributed differentiated access to the wireless channel with the support of multiple access categories (ACs). A higher priority access category has a smaller minimum contention window CW_{min} , thus has a higher probability to access the channel. Additionally, different access categories can have a different maximum contention window CW_{max} and interframe spacing interval (IFS).

3 Throughput model for EDCA

Several analytical studies have approximated the congestion avoidance procedure of 802.11 with a p-persistent model [3, 4]. In a p-persistent model, the probability p that a station tries to transmit in a time slot is independent of previous transmission attempts. The p-persistent model closely approximates the throughput of the actual congestion avoidance procedure when the average backoff is the same [3]; moreover, the saturation throughput has a small dependence on the exact backoff distribution [5].

If $E[CW]$ is the average contention window, then the approximate p-persistent model has transmission probability $p = \frac{2}{E[CW]+1}$ [3]. If the probability of a frame being involved in more than one collision is very small, then $E[CW] \approx CW_{min}$ [4]. In IEEE 802.11e, different wireless stations can have a different minimum contention window, hence using the same arguments as above [4], the corresponding transmission probability of station i is

$$p_i = \frac{2}{CW_{min,i} + 1}. \quad (1)$$

802.11's MAC layer operation can be viewed in time as involving three different types of time intervals: a successful transmission interval, a collision interval, and an idle interval. We denote the length of the first two interval types as T^{suc} , T^{col} , and assume they are normalized to the duration of the idle interval. The duration of these time intervals depends on the physical layer encoding and the MAC layer operations. The average throughput for station i , considering a renewal assumption, can be expressed as the ratio of the average amount of data transmitted by that station in one time interval over the average time interval $x_i = \frac{E[X_i]}{E[T]}$ [6, 3, 4]. If the individual transmission probabilities p_i and the aggregate transmission probability are very small, then the average throughput for station i is approximately [7]

$$x_i = \frac{p_i(1 - P_{-i})L}{\sum_k p_k(1 - P_{-k})T^{suc} + \sum_k p_k P_{-k}T^{col} + 1 - P}. \quad (2)$$

where L is the frame length, which for simplicity we assume to be the same for all stations, $P = \sum_j p_j$ is the aggregate transmission probability, and $P_{-k} = \sum_{j \neq k} p_j$.

In 802.11b with RTS/CTS, the transmission rate does not affect the collision interval, since the latter involves RTS frames which are always transmitted at the basic rate (1 or 2 Mbps). Hence, for 802.11b with RTS/CTS, the average throughput x_i is

$$x_i = \frac{p_i(1 - P_{-i})L}{\sum_k p_k(1 - P_{-k})T_k^{suc} + \sum_k p_k P_{-k}T^{col} + 1 - P}. \quad (3)$$

4 Resource control model

In this section, based on the throughput model for the EDCA mechanism, we present a congestion pricing framework for achieving efficient utilization of the shared wireless channel. For elastic traffic, users value the average throughput of data transfer. The utility for such a user i is $U_i(x_i)$, where x_i is the throughput for user i (for simplicity, we assume that one user corresponds to one wireless station, and we use the terms user and wireless station interchangeably), which depends on his transmission probability p_i and the transmission probabilities of the other stations.

The global problem of maximizing the aggregate utility (social welfare) in a network with a set of users N is

$$\begin{aligned} & \text{maximize} && \sum_i U_i(x_i) \\ & \text{over} && \{p_i \geq 0, i \in N\}. \end{aligned} \quad (4)$$

If $U_i(\cdot)$ is differentiable and strictly concave, then the necessary conditions for the maximization in (4) are

$$\frac{\partial \sum_i U_i(x_i)}{\partial p_i} = \frac{\partial U_i(x_i)}{\partial p_i} + \sum_{j \neq i} \frac{\partial U_j(x_j)}{\partial p_i} = 0, \quad (5)$$

for $i \in N$. The above conditions hold when the optimum is achieved for transmission probabilities in the interior of $[0, 1]$, which as our experiments show is indeed the case for utility functions we have considered and parameter values that correspond to IEEE 802.11.

4.1 Equal transmission rates

In this case the throughput for a wireless station is given by (2). Substituting this equation in (5) we find that the necessary conditions for the global optimum are

$$\frac{\partial U_i(x_i)}{\partial p_i} = L \frac{(1-P)^2 T^{suc} + P(2-P)T^{col}}{E[T]^2} \sum_j U'_j p_j, \quad (6)$$

for $i \in N$, where $P = \sum_j p_j$ and $U'_j = \frac{dU_j(x)}{dx}$; if $p_i \ll P$, which will hold when there is a large number of stations, we have $E[T] \approx P(1-P)T^{suc} + P^2 T^{col} + 1 - P$.

To solve the global optimization problem in a distributed manner, we define the following user problem

$$\begin{aligned} & \text{maximize} && U_i(x_i) - \lambda p_i \\ & \text{over} && p_i \geq 0, \end{aligned} \quad (7)$$

where λ is the congestion price. The necessary condition for the user optimum is $\frac{\partial U_i(x_i)}{\partial p_i} = \lambda$. From the last equation and (6), the user and global problems coincide if

$$\lambda = L \frac{(1-P)^2 T^{suc} + P(2-P)T^{col}}{E[T]^2} \sum_j U'_j p_j. \quad (8)$$

In (7) the congestion price is in terms of the transmission probability p_i . Application of the proposed model may require that the congestion price is defined in terms of the achieved throughput (e.g. see Section 5.2 on ECN marking). Substituting (2) in (7) and combining the result with (8), we have the following

$$\begin{aligned} & \text{maximize} && U_i(x_i) - \mu x_i \\ & \text{over} && p_i \geq 0, \end{aligned} \quad (9)$$

where, for the user and global problems to coincide, the congestion price μ is defined as

$$\mu = \frac{(1-P)^2 T^{suc} + P(2-P)T^{col}}{(1-P)E[T]} \sum_j U'_j p_j. \quad (10)$$

The above model differs from other models for wireless networks, such as CDMA networks [1, 2], in that there is no resource capacity constraint. The price is due solely to the congestion, in terms of the cost due to frame collisions.

When all users have the same utility function, then from (9) we have $U' = \mu$, which together with (10) gives the following condition for optimality

$$P = \frac{(1-P)E[T]}{(1-P)^2 T^{suc} + P(2-P)T^{col}}, \quad (11)$$

whose solution is

$$P = \frac{\sqrt{T^{col}} - 1}{T^{col} - 1}. \quad (12)$$

The last equation indicates that for a large number of stations with the same utility, if the aggregate transmission probability is much smaller than one, then the optimum aggregate transmission probability that maximizes the channel efficiency is independent of the specific utility function and the successful transmission interval, and depends only on the collision interval normalized to the idle time slot.

4.2 Different transmission rates: T^{suc} depends on and T^{col} is independent of transmission rate

The throughput for station i is now given by (3). Substituting (3) in (5), we find that the necessary conditions for the global optimum are

$$\frac{\partial U_i(x_i)}{\partial p_i} = L \frac{(1-P)^2 T_i^{suc} + P(2-P)T^{col}}{E[T]^2} \sum_j U'_j p_j, \quad (13)$$

for $i \in N$, where $P = \sum_j p_j$. When $p_i \ll P$, then we have $E[T] \approx (1-P) \sum_j p_j T_j^{suc} + P^2 T^{col} + 1 - P$.

As in the previous subsection, in order to solve the global optimization problem in a distributed manner, we can define the following user problem

$$\begin{aligned} & \text{maximize} && U_i(x_i) - (\mu_1 T_i^{suc} + \mu_2) x_i \\ & \text{over} && p_i \geq 0, \end{aligned} \quad (14)$$

where, for the user and global problems to coincide, μ_1, μ_2 are defined as

$$\mu_1 = \frac{(1-P)}{E[T]} \sum_j U'_j p_j, \quad \mu_2 = \frac{P(2-P)T^{col}}{(1-P)E[T]} \sum_j U'_j p_j. \quad (15)$$

The congestion price in (14), has two components: The first component $\mu_1 T_i^{suc}$ contains factor μ_1 , which depends on the level of congestion and the successful transmission interval T_i^{suc} . The second component μ_2 is related only to the level of congestion. The interpretation of the above is that the congestion cost for a wireless station depends, in addition to its throughput, also on the duration of the successful transmission interval, which in turn depends on the station's transmission rate. For stations with the same throughput, the station with the lower transmission rate, which will have a longer transmission interval, will induce a higher congestion cost since the channel is occupied for a longer time at each frame transmission. The contribution of the successful transmission interval, hence the transmission rate, to congestion is determined by the ratio μ_1/μ_2 .

The case where the transmission rate influences both T^{suc} and T^{col} is discussed in [7].

5 Application

5.1 Class-based proportional sharing

For proportionally fair sharing, the utility for user i is $U_i(x_i) = w_i \log x_i$ [8]. In this case, one can show that

$$\mu_1 = \frac{\sum_j w_j}{L}, \quad \mu_2 = \frac{P(2-P)T^{col}}{(1-P)^2} \frac{\sum_j w_j}{L}. \quad (16)$$

From the above and the conditions for optimality of the user problem, the optimum transmission probability is

$$p_i = \frac{w_i}{\sum_j w_j} \frac{(1-P)E[T]}{(1-P)^2 T_i^{suc} + P(2-P)T^{col}}. \quad (17)$$

$CW_{min,i}$ can then be computed from (1). This computation can be performed at the access point which, as indicated in

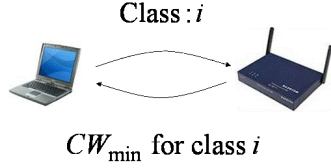


Figure 1. Class-based differentiation.

the 802.11e standard, periodically communicates the minimum contention window values to the wireless stations using beacon frames, Figure 1.

If all stations have the same transmission rate, then (17) reduces to (11), hence the optimum aggregate transmission probability P should satisfy (12). Note that this is true even when different stations have different weights, provided the utility is logarithmic. In this case the transmission probability for a station i is given by

$$p_i = \frac{w_i}{\sum_j w_j} P. \quad (18)$$

The above model for the case of identical transmission rates is similar to the one presented in [9]; the two approaches will be compared in Section 6.2.

The incentive compatibility of the above scheme, i.e. the fact that a station obtains a higher net benefit by declaring its true value of w_i , is shown in [7].

5.2 ECN marking

Next we assume that stations receive congestion feedback according to (10) or (15), and respond by selecting the optimum transmission probability, hence minimum contention window, according to (9) or (14). Equations (10) and (15) require estimating the aggregate transmission probability P . Recall from (2) that the throughput is proportional to the transmission probability. Moreover, the access point competes with the end stations for accessing the wireless channel. Hence, the aggregate transmission probability P can be estimated from $P = \frac{X \cdot p_{AP}}{X_{AP}}$, where X is the aggregate throughput, i.e. the sum of the throughput in the uplink and the downlink, X_{AP} is the transmission throughput from the access point to the wireless stations and p_{AP} is the transmission probability at the access point.

The congestion price given by (10) or (15) can be communicated to the stations either explicitly, by piggy-backing it on beacon frames periodically sent by the access point, or using ECN (explicit congestion notification) marking, Figure 2. When transmission rates differ, from (14) and (15) the marking probability \mathcal{P}_i for station i should satisfy $\mathcal{P}_i = \frac{\mu_1 T_i^{suc} + \mu_2}{p_{mrk}}$. The value of p_{mrk} (price-per-mark) should be such that for the range of user demands expected, the marking probability \mathcal{P}_i for all stations i is in $[0, 1]$.

5.3 TCP over EDCA with ECN marking

In this section we assume that the ECN marking scheme described above is applied, and investigate the performance

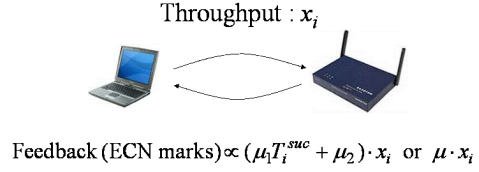


Figure 2. ECN feedback.

of the model presented in Section 4 when users respond in a manner similar to TCP's congestion control algorithm. Indeed, TCP congestion control can be viewed as having the following implicit utility $U_{TCP}(x) = -\frac{2}{RTT^2 x}$ [10], where RTT is the round trip time. If we assume that all TCP flows have the same RTT , then substituting the above utility in (13) and (15), we obtain

$$p_i = \sqrt{\frac{(1-P)E[T]}{(1-P)^2 T_i^{suc} + P(2-P)T^{col}}} \frac{1}{\sum_j \frac{1}{p_j}}. \quad (19)$$

If all stations have the same transmission rate, then the last equation reduces to (11), which also holds for proportional sharing. Indeed, as discussed in Section 4.1, when all stations have the same utility and transmission rate, then the optimum aggregate transmission probability is independent of the utility, and is given by (12).

If TCP flows have a different round trip time, with RTT_i the round trip time for flow i , and each station has one flow, then (19) becomes

$$p_i = \frac{1}{RTT_i} \sqrt{\frac{(1-P)E[T]}{(1-P)^2 T_i^{suc} + P(2-P)T^{col}}} \frac{1}{\sum_j \frac{1}{RTT_j^2 p_j}}.$$

If all stations have the same transmission rate, then from the last equation we see that the optimum transmission probability is inversely proportional to the RTT .

6 Experiments

In this section we present experimental results that demonstrate and evaluate the models presented in the previous two sections, and in particular

- we investigate how factors such as the CSMA/CA and RTS/CTS procedures and the network load affects the level of congestion,
- we compare simulation and analytical results for estimating the aggregate throughput and the optimum minimum contention window,
- we investigate a simple model capturing the closed-loop interaction between the access point and the wireless stations, when the latter select their transmission probability (equivalently, the minimum contention window).

Due to space limitations, we include here a subset of the experiments that we have performed; additional experimental results appear in [7]. The simulation results were obtained

Table 1. Parameters for the experiments

Parameter	Value (in μs)	
	802.11b	802.11a
Slot Time	20	9
T_{DIFS}, T_{SIFS}	50, 10	34, 16
T_{PHY}	192	20
$T_{ACK} = T_{CTS}, T_{RTS}$	112, 160	

using the ns-2 simulator, with the module¹ documented in [11] for implementing the EDCA mechanism. The simulation experiments considered UDP traffic with packet size 1044 bytes, which includes the UDP/IP headers, and the results are the average of 12 runs, each for 300 seconds. The parameters used in the experiments are shown in Table 1.

6.1 Impact of various factors on congestion

We first consider the model of Section 4.2, focusing solely on how various factors affect congestion, when all users have the same utility and transmission rate; we do not consider the closed-loop interaction between the network and the users, which we investigate in Section 6.3. Figure 3 shows the two congestion price components $\mu_1 T^{suc}$ and μ_2 in (14), as a function of CW_{min} , when users have a logarithmic utility, in which case μ_1, μ_2 are given by (16). Observe that the first component $\mu_1 T^{suc}$ does not depend on CW_{min} ; this is due to the logarithmic utility, and is not the case for a TCP-like utility [7]. On the other hand, μ_2 increases as CW_{min} decreases, i.e. as the level of contention increases. Also observe in Figure 3 that $\mu_1 T^{suc}$ is larger for RTS/CTS, whereas μ_2 is smaller; both behaviors are because when the RTS/CTS mechanism is used, T^{suc} is larger (because a successful transmission now includes the transmission of an RTS and CTS) and T^{col} is smaller (because collisions involve an RTS message, which is typically smaller than a data frame).

Figure 4 shows that both $\mu_1 T^{suc}$ and μ_2 increase with the number of stations, for constant CW_{min} . Moreover, the increase of μ_2 is higher than that of $\mu_1 T^{suc}$, hence the ratio $\mu_1 T^{suc} / \mu_2$ decreases with the number of stations.

6.2 Comparison of simulation and analysis

Figure 5 compares the aggregate throughput estimated using the p-persistent model with the throughput found using simulation for 802.11b² (11 Mbps) with CSMA/CA, when all stations have the same transmission rate. Observe that the analytical results follow the simulation results very well. Similar results were obtained for 802.11a.

Figure 5 shows that the analytical model underestimates the throughput for small values of CW_{min} . This is be-

¹An IEEE 802.11e EDCF and CFB simulation model for ns-2", <http://www.tkn.tu-berlin.de/research/802.11e.ns2/>

²For the analytical results in Figure 5 we have considered 28 bytes MAC overhead, since the 6-byte address field in the MAC header is usually not considered; this is also the case with ns-2.

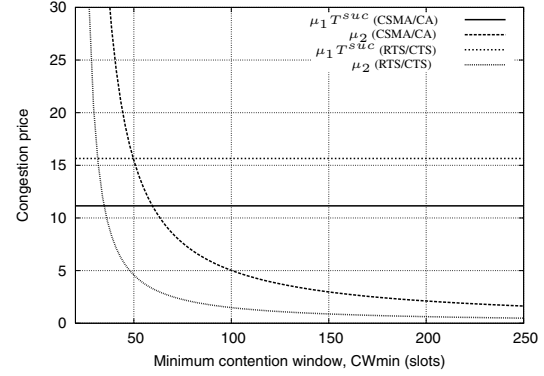


Figure 3. Effect of CSMA/CA and RTS/CTS on congestion for logarithmic utility. $C = 11$ Mbps, $N = 10$

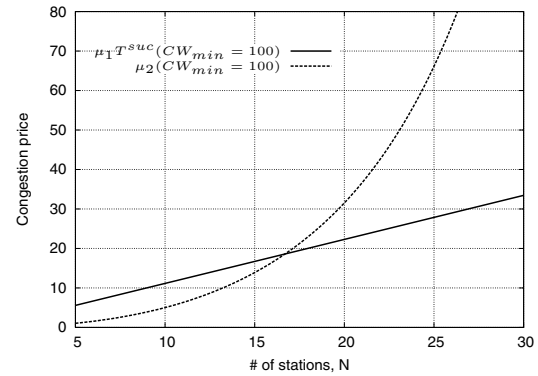


Figure 4. Effect of number of stations on congestion for logarithmic utility. $C = 11$ Mbps, $CW_{min} = 100$

cause the p-persistent model does not capture the exponential backoff procedure of 802.11; the backoff procedure can improve the throughput in the case of high contention, which occurs for small values of CW_{min} . Nevertheless, what is important for the work in this paper is that there is good agreement in the region of the optimum CW_{min} . Table 2 compares the simulation with the analytical approach based on (2) for estimating the optimum CW_{min} , when the latter obtains discrete values³ that are powers of 2. Observe that the optimal selection of CW_{min} based on the simple analytical model agrees with the selection based on simulation for $C = 11$ Mbps, but is overestimated for $C = 24$ Mbps. However, note that using the values indicated by analysis for $C = 24$ Mbps results in an aggregate throughput reduced by less than 2.7%.

It is important to note here that using a minimum contention window smaller than the optimum does not only have an impact on the aggregate throughput, which Fig-

³This is motivated by the fact that all current implementations of 802.11e specify CW_{min} in powers of 2.

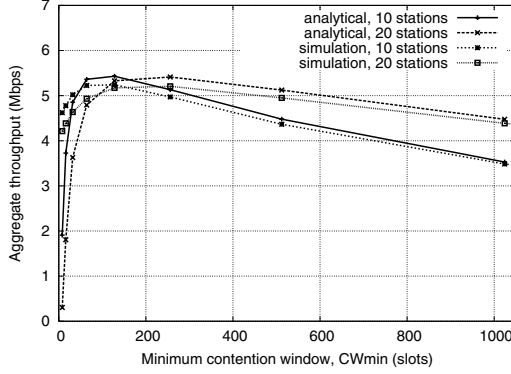


Figure 5. Simulation and analytical results for 11 Mbps. The 95% confidence interval is within $\pm 4\%$ and $\pm 3\%$ of the values shown, for 10 and 20 stations, respectively.

Table 2. Optimum CW_{min} (discrete values, powers of 2) based on analysis and simulation, for IEEE 802.11b (11 Mbps) and 802.11a (24 Mbps)

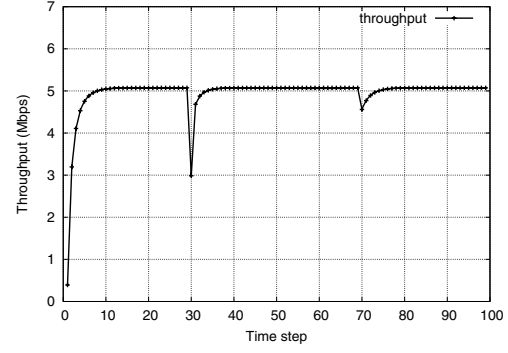
C	N	analysis	simulation
11	10	128	128
11	20	256	256
24	10	128	64
24	30	512	256

ure 5 shows to be a reduction of up to about 15%. Indeed, a smaller CW_{min} , especially when there is a large number of stations, results in higher channel contention, which can lead to short-term unfairness and higher channel access delays [12]; this occurs because after a collision, the station that has successfully transmitted a frame has a higher probability of transmitting subsequent frames, since it would have decreased its contention window to the minimum value (this is referred to as the *channel capture effect*).

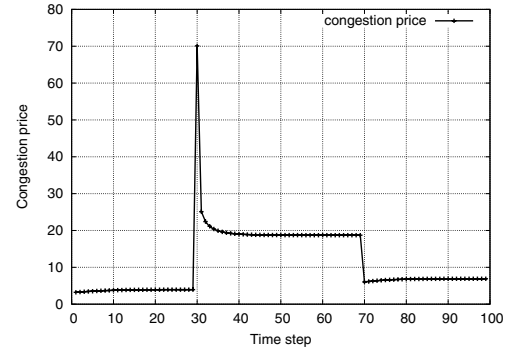
Table 3 compares, when all stations have the same transmission probability, the analytical expression for estimating the transmission probabilities in (12) and (18), with the approach in [9]. These results show that the optimum CW_{min} estimated using the two approaches are very close.

Table 3. Optimum transmission probability p and CW_{min} for IEEE 802.11b (11 Mbps) and 802.11a (24 Mbps).

C	N	Access	Eq. (12)		Approach in [9]	
			p	CW_{min}	p	CW_{min}
11	10	CSMA/CA	0.0123	162	0.0130	153
11	10	RTS/CTS	0.0182	109	0.0194	102
11	20	CSMA/CA	0.0061	325	0.0063	316
11	20	RTS/CTS	0.0091	218	0.0094	212
24	10	CSMA/CA	0.0128	155	0.0136	153
24	30	CSMA/CA	0.0043	467	0.0044	458



(a) Throughput



(b) Congestion price

Figure 6. Throughput and price as a function of time. Initially $N_{hi} = N_{low} = 5$, at time $t = 30$, $N_{hi} = 30$, and at time $t = 70$, $N_{hi} = 10$. $w_{hi} = 3$, $w_{low} = 1$, $C = 11$ Mbps, CSMA/CA

6.3 Closed-loop interaction between access point and wireless stations

In this subsection we investigate the closed-loop interaction between the access point and wireless stations, when prices are explicitly signalled to the stations. We assume that one user corresponds to each station, and has a logarithmic utility. The access point estimates the congestion price from (8) and communicates it to the end users, which select their transmission probabilities to maximize their net benefit (7). We assume that the access point can accurately estimate the aggregate transmission probability used in (8). Consideration of more complex scenarios, which include asynchronous operation of wireless stations, propagation delays, and measurement errors, is left for future work.

We consider two types of users, with weights $w_{hi} = 3$ and $w_{low} = 1$. Initially, there are 5 users of each type. Time is assumed to be discrete. At time $t_1 = 30$, we assume that 25 more users of type “hi” enter the network, hence giving a total of 30 users of type “hi”. Then, at time $t_2 = 70$, 20 users of type “hi” depart the system, leaving 10 users of type “hi”, and 5 users of type “low”. Figure 6(a) shows the aggregate throughput, computed using (2), as a function

of time. Observe that the system reacts to changes of the number of users, quickly reaching the equilibrium, where the aggregate throughput achieves its maximum value. Figure 6(b) shows the behavior of the congestion price with time. As expected, the congestion price is higher when there are more users in the network.

7 Related work

The work of [4, 9] proposes an approach for achieving weighted fairness in IEEE 802.11e. The throughput model considered is similar to the model considered in our work. Moreover, the weighted fairness model is similar to the proportional sharing model presented in Section 5.1, albeit considering different approximations. The model presented in our work is more general in that it considers multi-rate 802.11 networks, and the general case where user requirements are encoded through utility functions. The problem of service differentiation is also investigated in a number of papers, e.g. [13, 14] and the references therein. These works do not quantify the degree of differentiation, nor do they investigate the aggregate efficiency of the network.

The work of [15] investigates the problem of fairness and weighted resource sharing in wireless networks using models based on utility functions, and proposes rate control schemes applied at the end systems to achieve the specific resource sharing model. Although some general characteristics of the wireless channel are taken into account, such as location-dependent contention and inaccurate channel state information, the specific characteristics of the 802.11 MAC operation are not considered. Also, the utility for each user is taken to be a function of the rate of transmission attempts, rather than the actual throughput that is achieved, as we consider. Our work also differs from [16] which also considers maximizing the aggregate utility, but focuses on single rate 802.11 networks, and develops a distributed scheme for obtaining the optimum contention window. Finally, the work of [17] applies game theory to investigate the Nash equilibrium in CSMA/CA networks, whereas our work focusing on maximizing the efficiency of such systems through maximization of the aggregate utility.

8 Conclusions

We presented a congestion pricing framework for efficient resource control of elastic traffic in IEEE 802.11e's EDCA mechanism that captures how various factors, such as the minimum contention window, the CSMA/CA or the RTS/CTS procedure, and the physical layer transmission rate, affect congestion. The framework can be applied for achieving class-based proportional throughput differentiation, for performing ECN marking based on the level of congestion in the wireless channel, and for modelling the performance of TCP over EDCA with ECN marking.

Related work is investigating the extension of the proposed framework when both the contention-based EDCA

and the polling-based HCCA (HCF Controlled Channel Access) mechanisms coexist, consideration of control variables other than the minimum contention window, e.g. see [18], and the extension to multihop wireless networks.

References

- [1] J. W. Lee, R. R. Mazumdar, and N. B. Shroff, "Downlink power allocation for multi-class CDMA wireless networks," in *Proc. of IEEE INFOCOM'02*, June 2002.
- [2] V. A. Siris, "Resource control for elastic traffic in CDMA networks," in *Proc. of ACM MOBICOM'02*.
- [3] F. Cali, M. Conti, and E. Gregori, "Dynamic tuning of the IEEE 802.11 protocol to achieve a theoretical throughput limit," *IEEE/ACM Trans. on Networking*, vol. 8, no. 6, pp. 785–799, 2000.
- [4] D. Qiao and K. G. Shin, "Achieving efficient channel utilization and weighted fairness for data communications in IEEE 802.11 WLAN under DCF," in *Proc. of IEEE/IFIP International Conference of Quality of Service (IWQoS'02)*, May 2002.
- [5] A. Kumar, E. Altman, D. Miorandi, and M. Goyal, "New Insights from a Fixed Point Analysis of Single Cell IEEE 802.11 WLANs," in *Proc. of IEEE INFOCOM'05*.
- [6] G. Bianchi, "Performance analysis of the IEEE 802.11 distributed coordination function," *IEEE J. Select. Areas Commun.*, vol. 18, no. 3, pp. 535–547, March 2000.
- [7] V. A. Siris and C. Courcoubetis, "Resource Control for the Enhanced Distributed Channel Access (EDCA) Mechanism in IEEE 802.11e," FORTH-ICS, Tech. Rep. No. 352, March 2005.
- [8] F. P. Kelly, "Charging and rate control for elastic traffic," *European Transactions on Telecommunications*, vol. 8, pp. 33–37, January 1997.
- [9] A. Banchs, X. Perez-Costa, and D. Qiao, "Providing throughput guarantees in IEEE 802.11e wireless LANs," in *Proc. of the 18th International Teletraffic Congress (ITC - 18)*, 2003.
- [10] F. P. Kelly, "Mathematical modelling of the Internet," in *Mathematics Unlimited - 2001 and Beyond*, B. Engquist and W. Schmid, Eds. Springer-Verlag, 2000.
- [11] S. Wietholter and C. Hoene, "Design and Verification of an IEEE 802.11e EDCF Simulation Model in ns-2.26," Technical University of Berlin, Tech. Rep. TKN-03-019, November 2003.
- [12] G. Berger-Sabbatel, A. Duda, O. Gaudoin, M. Heusse, and F. Rousseau, "Fairness and its Impact on Delay in 802.11 Networks," in *Proc. of IEEE GLOBECOM'04*.
- [13] I. Aad and C. Castelluccia, "Differentiation mechanisms for IEEE 802.11," in *Proc. of IEEE INFOCOM'01*.
- [14] A. Lindgren, A. Almquist, and O. Schelen, "Quality of Service Schemes for IEEE 802.11 Wireless LANs - An Evaluation," *Mobile Networks and Applications (MONET)*, vol. 8, no. 3, pp. 223–235, June 2003.
- [15] T. Nandagopal, T.-E. Kim, X. Gao, and V. Bharghavan, "Achieving MAC layer fairness in wireless packet networks," in *Proc. of MOBICOM'00*.
- [16] Y. Yang, J. Wang, and R. Kravets, "Distributed Optimal Contention Window Control for Elastic Traffic in Wireless LANs," in *Proc. of IEEE INFOCOM'05*.
- [17] M. Galaj, S. Ganeriwal, I. Aad, and J.-P. Hubaux, "On Selfish Behavior in CSMA/CA Networks," in *Proc. of IEEE INFOCOM'05*.
- [18] V. A. Siris and C. Courcoubetis, "Resource Control for the EDCA and HCCA Mechanisms in IEEE 802.11e Networks," in *Proc. of 4th Int'l Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt)*, 2006.