An AIFSN prediction scheme for multimedia wireless communications

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***Abstract*—The incessant development of High Quality (HQ) multimedia contents and the trend towards the use of wireless technologies have as a consequence the need for providing the users with an adequate level of Quality of Service (QoS) in IEEE 802.11 networks. The IEEE 802.11e amendment aims to overcome this situation by introducing the Enhanced Distributed Channel Access (EDCA) access method. This new method is characterised through a group of Medium Access Control (MAC) parameters, which are able to classify and prioritize the different types of traffic. In this regard, the most determining parameter is the Arbitration Inter-Frame Space Number (AIFSN). On this basis, we propose a new adaptation scheme that makes use of a *M5* regression model with the aim of improving the voice and video performance offered by EDCA. Our proposal is able to determine dynamically the optimum AIFSN values with regard to the network conditions, maintaining the backward compatibility with the stations that use the original IEEE 802.11 standard. The prediction algorithm is only queried by the Access Point (AP), without introducing additional control traffic into the network, making it possible to use it in real-time. With respect to the standard EDCA values, the results show an enhancement in the voice+video normalized throughput and a significant reduction in the number of the retransmission attempts.**

Keywords*—*QoS, 802.11e, EDCA, Artificial Intelligence

I. Introduction

Over the past few years, wireless technologies have become imperative in the context of networking and communications. Their simplicity of deployment, multimedia content support and lower cost are displacing the traditional wired networks. In order to define this networking model, the Institute of Electrical and Electronics Engineers (IEEE) developed the 802.11 standard [1], which introduces the set of media access and physical layers specifications for implementing Wireless Local Area Networks (WLAN). However, the use of the Internet and the consumption patterns are changing rapidly, especially those related to multimedia contents. The nature of such contents involves temporal restrictions that require Quality of Service (QoS) mechanisms to ensure an adequate level of satisfaction in the user perception. For this reason, the IEEE 802.11e amendment [2] was released with the aim of classifying and prioritizing the different types of traffic in wireless networks.

One of the main features introduced by the IEEE 802.11e amendment is the possibility of differentiating traffic flows and services. As a consequence, the QoS and the network performance are notably improved. For this purpose, this amendment defines a new contention-based channel access method called Enhanced Distributed Channel Access (EDCA), which allows for the prioritization of the different types of traffic, making use of a set of user priorities. Nevertheless, in some research it has been demonstrated that EDCA does not provide the required QoS for real-time applications. This situation worsens in the cases in which the network is partially or fully composed of stations that only support the IEEE 802.11 standard and the traffic load level increases.

The application of artificial intelligence and data mining techniques allows traffic patterns to be found in a network, making it possible to prioritize each traffic flow accordingly. As a result, a high level of QoS and a general improvement in the performance are achieved. In this paper we propose a prediction scheme for the Arbitration Inter-Frame Spacing Number (AIFSN) priority values based on network conditions, focusing on the temporal restrictions of the voice and video transmissions and maximizing their normalized throughput. This operation can be performed dynamically in the Access Point (AP) without altering the devices, therefore maintaining full compatibility. Furthermore, the adjustment of these parameters does not introduce additional control traffic into the network. In short, the main contribution of the proposed model is to address the existing limitations of the IEEE 802.11e amendment, providing QoS mechanisms for multimedia transmissions and maintaining the compatibility with existing devices.

The remainder of this paper is organized as follows. Section II reviews the IEEE 802.11e amendment and gives some background information on the points that aim to improve the QoS level offered by EDCA. In Section III the process of supervised learning of the chosen model is described. In Section IV, we present the proposed prediction scheme and the process followed throughout its design. The results of the performance evaluation and a comparison with the standard AIFSN values are described in Section V. Finally, Section VI provides some concluding remarks on our proposal.

II. QoS in IEEE 802.11 networks

Initially, the original IEEE 802.11 standard introduced two medium access functions: the Distributed Coordination Function (DCF) and the Point Coordination Function (PCF). However, these access functions are not able to differentiate the traffic flows and provide the required QoS. Therefore, the

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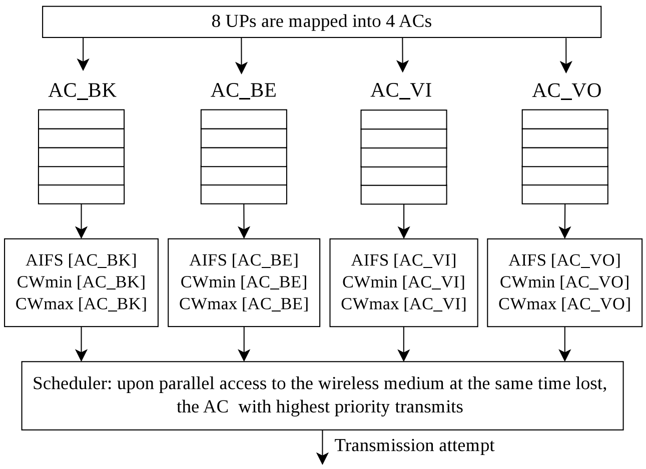

Fig. 1. EDCA Access Categories Mapping

IEEE formed a working group with the task of developing the IEEE 802.11e amendment that considered these aspects.

A. *IEEE 802.11e*

The IEEE 802.11e amendment was developed with the aim of providing QoS support and meeting the voice and video streams requirements over IEEE 802.11 WLANs [2]. As backward compatibility must be kept, a distinction is drawn between the stations that support QoS (QSTAs) and the stations that do not offer such support (nQSTAs), only using DCF. For this purpose, the 802.11e amendment implements the Hybrid Coordination Function (HCF) and, thus, its two contention-based channel access methods: HCF Controlled Channel Access (HCCA) and EDCA. To this end, the HCF coordination function implementation is mandatory for all the QSTAs. Nevertheless, only EDCA is supported by the commercial network cards on current devices as a method for accessing the wireless medium.

The EDCA channel access method distinguishes between eight different User Priorities (UPs). Moreover, four Access Categories (ACs) are defined, which are derived from the UPs and are able to classify and prioritize the traffic streams. In this way, in order from highest to lowest priority, Voice (VO), Video (VI), Best Effort (BE) and Background (BK) access categories are considered, as shown in Figure 1. Each one of these ACs works on its own transmission queue and is characterised by an EDCA parameter set. This EDCA parameter set specifies a priority level by using an AIFSN value, a Transmission Opportunity interval (TXOP) and the duration of the Contention Window (CW). Thus, the AP sends this EDCA parameter set through beacon frames to the stations of a Basic Service Set (BSS). The IEEE 802.11e amendment allows the APs to modify the aforementioned values. However, no mechanism is considered in this amendment for carrying out this task and most commercial devices do not implement such a service.

The AIFSN determines the Arbitration Inter-Frame Spacing (AIFS), which is the period of time that a station has to wait until it is allowed to initiate a new transmission. The AIFS for each AC is shown in Equation 1, where the *SlotTime* denotes the duration of a slot according to the physical layer, and the Short Inter-frame Space (SIFS) refers to the amount of time used by high priority actions that require an immediate response.

TABLE I. DEFAULT EDCA PARAMETER SET

AC	CW_{min}	CW_{max}	AIFSN	TXOP
AC_BK	aCW_{min}	aCW_{max}	7	-
AC_BE	aCW_{min}	aCW_{max}	3	-
AC_VI	$(aCW_{min}+1)/2-1$	aCW_{min}	2	6.016 ms
AC_VO	$(aCW_{min}+1)/4-1$	$(aCW_{min}+1)/2-1$	2	3.264 ms

$$AIFS[AC] = AIFSN[AC] \cdot SlotTime + SIFS \tag{1}$$

Moreover, the stations are assigned an AIFSN value according to their priority, which must be higher than or equal to 2. In order to provide a fair transmission for the DCF stations, the IEEE 802.11e amendment defines a standard combination of AIFSN parameters, as shown in Table I. Meanwhile, the CW size determines the length of time that a station must wait until it is able to conclude the Backoff algorithm. In this way, the CW values are assigned in the inverse order to that of the priority of the corresponding AC. Similarly, the TXOP duration is longer for ACs with greater temporal restrictions.

With regard to these parameters, the AIFSN plays the most important role in order to ensure optimum traffic differentiation. In [3], J. Villalón et al. show several scenarios in which a set of values for the AIFSN and CW are taken into account. In this case, they prove that the AIFSN has a greater relevance when identifying priorities than the CW. This conclusion was also reached by J. Hui et al. in [4], who proved that both the collisions and access media delay decrease, allowing for an improvement in the network's global throughput.

B. *Dynamic adaptation in IEEE 802.11e*

Wireless network conditions, such as the network's load, can change over time. Consequently, several dynamic proposals that consider the aforementioned circumstances have emerged. Their main aim is to adapt the EDCA parameter set, i.e. to identify the optimal values for the AIFSN, CW_{max}, CW_{min} and TXOP parameters.

An approach with this same goal is presented in [5], where R. He et al. take into account three possible load levels, showing the behaviour of the proposed scheme under different network conditions. This proposal achieves a reduction in the number of retransmission attempts and an enhancement in the network performance. In spite of this, there is a drop in the amount of voice and video information transmitted, which impairs its temporal restrictions.

In [6] T. Nilsson et al. introduce an adaptation scheme by using the CW size, achieving better results than EDCA. However, compatibility with legacy DCF stations is not considered. A. Banchs et al. introduce in [7] a new way of offering backward compatibility with the DCF stations. This algorithm is able to prioritize the voice and video traffic streams over the others. As the priority of the DCF stations cannot be modified by updating the EDCA parameter set, the CW size is increased by retransmitting packets that are properly received by the DCF stations. In this way, the priority of the stations that use this medium access function decreases. Nevertheless, unnecessary traffic is introduced into the network.

The design of an analytical model to improve the network performance has also been taken into account. Nevertheless, most of these models make assumptions that may not be fulfilled in real transmissions. In [8] J.R. Gallardo et al. define a model by using Markov chains. However, they consider the same bit rate for all the stations. In a similar way, the mathematical model presented in [9] by A. Banchs et al. is only tested under network saturation conditions.

As can be seen, most of these approaches are not able to keep backward DCF compatibility and simultaneously provide a dynamic adaptation of the EDCA parameter set without introducing additional traffic.

III. Supervised learning with M5Rules

In supervised learning [10, 11], the information relative to objects or instances is represented by a set of n input features, $X = (X_1, \ldots, X_n)$, and an output variable, Y. The process consists of learning a model, $h_\Theta(x)$, from a training dataset, (X, Y), which contains the information relative to several objects whose current outputs are already known (that is why it is called *supervised*). The model is then used to predict the output value y for new cases when only the values of their input features (x) are known. In case of regression problems, $Y \in \mathbb{R}$, and therefore $h_\Theta(x) \in \mathbb{R}$. In classification, however, the goal is to determine the class of a certain instance. In such a case, $Y \in \{c_1, \ldots, c_K\}$.

In the context of this work, for instance, supervised learning is used for regression. X represents the configuration of the different parameters used for managing the multimedia traffic in a network, whereas the output Y represents the throughput achieved by the setting. Thus, $h_\Theta(x) \in \mathbb{R}$ returns the predicted throughput of the network, y, given the parameter configuration x.

There is a large number of supervised learning models for regression, such as Linear Regression [12], Neural Networks [13], Support Vector Machines [14], or Regression Trees [15]. The choice of a certain model depends on several factors. Thus, some are more powerful than others, i.e., achieve more precision and can detect more relevant patterns in data. However, the ease in which they can be interpreted can be an issue in some scenarios. Models such as Neural Networks are considered *Black Box* models, as the information related to underlying patterns in data can not be drawn from them. In contrast, regression trees are very easy to interpret, and provide useful information on the relation between input and output features. Another important issue concerns computational complexity. For instance, obtaining y from x with a Neural Network implies some matrix multiplications, and can be too slow in some settings. However, processing a regression tree might only require a few comparisons.

A. M5Rules

In the context of this work, it must be taken into account that the selected regression model must be used in real-time to determine which parameter setting produces a higher throughput. It is important then, that the output can be quickly obtained. It is also important that the obtained model can be interpreted, analysed, and even modified after having been learned.

```
Rule: 1
IF
VI_channel_occupancy <= 0.341
THEN

max_th[0] =
-0.0449 * global_channel_occupancy
+ 0.0701 * DCF_channel_occupancy
+ 0.1152 * BE_channel_occupancy
- 0.0392 * VI_channel_occupancy
- 0.279 * VO_channel_occupancy
+ 2.0059 [151/2.844\%]
```

Fig. 2. Example of rule induced by *M5Rules*

The *M5* algorithm [15] represents $h_\Theta(x) \in \mathbb{R}$ as a regression tree, and it is very similar to its counterpart, *c4.5* [16] which is used for classification problems.

A regression tree represents a partition of the input space. Each node contains a condition defined over some input attribute X_i. For instance, if a node of the tree is defined by the condition `[VI_channel_occupancy <= 0.341]`, it represents the one branch which would be used to process all objects so that their value for variable `VI_channel_occupancy` is smaller than 0.341, whereas the other branch would be used to process the rest of the cases. Each leaf represents an input subspace, and corresponds to all the cases which fit the conditions represented by the path from the root of the tree to the leaf.

In *M5*, there are two possibilities to obtain the output values for the cases falling into a leaf of the tree. The first one, namely *regression tree*, uses the mean output value of the training data falling into that leaf as default prediction. The second one, namely *model tree*, learns a multivariate linear regression equation from the training data corresponding to the leaf, and uses it to predict the output values.

The algorithm used in this work, namely *M5Rules*, is included in the *weka* package for machine learning [17]. It first learns a regression (or model) tree from training data by means of the implementation of *M5* included in this package, namely *M5P*; and then extracts a set of rules. Figure 2 shows an example of the obtained rules. So that the value of all objects for variable `[VI_channel_occupancy <= 0.341]`, the output value is obtained as a linear expression from the rest (5) of the variables. The information `[151/2.844\%]` indicates that 151 objects of the training dataset fall into that leaf, and that the relative error obtained with the linear expression for those objects is 2.844%.

IV. AIFSN tuning scheme

A. Proposal Description

Recently, the consumption of multimedia contents through wireless networks has shown a considerable increase. In this regard, the research on QoS has become especially relevant since the IEEE 802.11e amendment was published. However, there has been a recurring problem in such research due to the existence of stations that only support the original IEEE 802.11 standard. Most of these efforts are focused on improving the features of the EDCA channel access method. However, even though the different EDCA parameters can be adapted to network conditions, no changes can be made in the case of DCF stations.

In IEEE 802.11e, EDCA allows it to adapt the access channel parameters over time in a dynamic way. Nevertheless, this feature is not used in commercial APs due to the complexity involved in determining the network conditions. Furthermore, the process in charge of carrying out this task should be as simple as possible due to the fact that the updating of the network information must be carried out in real-time. For this reason, the standard values of the EDCA parameter set specified in the aforementioned amendment are usually considered by the stations that use EDCA, regardless of the network saturation level.

The main goal of our proposal is to enhance the offered QoS level and maximize the performance of the voice and video traffic. To achieve this goal, our scheme aims to identify the optimal AIFSN values and adapt them to the network conditions in order to enhance the performance offered by the standard EDCA parameter set. At the same time, it seeks to ensure backward compatibility between the stations that use EDCA and DCF in the BSS. Our main aim is to enhance the audio and video performance by decreasing the collisions between these application types. Accordingly, a reduction in the global retransmission attempts and an increase in the network's overall performance are achieved.

When a transmission takes place, there is a large number of variable parameters that may determine the channel conditions. Accordingly, deploying an adaptive scheme for the priority setting through the AIFSN values is not a simple task. The main conditioning factors are described below.

- *Number of active applications of each type of traffic*. This is a parameter that can be identified in a simple way by the AP. However, this value at a particular moment in time is insufficient. That is because it cannot provide further information about the current conditions of the network, i.e., the scheme will not be allowed to obtain real information about the current occupancy of the wireless channel.
- *Applications bit rate*. Linked to the previous one, this factor provides more detailed information about the state of the wireless medium. Unfortunately, it is difficult to calculate in real-time. To identify these values it is necessary to introduce periodical control traffic in the network. Nevertheless, this feature is not typically used in IEEE 802.11e.
- *Transmission rate*. Every single station may carry out its transmissions by using a different transmission rate. Therefore, the specific period of time that each of them keeps the channel busy is different. This parameter would be a good way of estimating the network conditions. Nonetheless, this value needs to be used jointly with the above factors.
- *Presence or absence of DCF legacy stations*. The existence of DCF applications restricts the use of priority parameters in EDCA due to the fact that these values cannot be duly adjusted for these stations.

TABLE II. PROPOSED SET OF AIFSN VALUES

	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9
BK	7	8	9	8	9	12	10	12	14	14
BE	3	4	5	4	5	6	6	8	10	12
VI	2	2	2	3	3	3	4	5	6	7
VO	2	2	2	2	2	2	2	2	2	2

Due to the inherent variability of the aspects that are part of a wireless network transmission, we must consider a scheme with low computational complexity and capacity to adapt itself to changes over time. On the basis of these requirements, artificial intelligence techniques are used in order to identify and interpret traffic patterns. Furthermore, such techniques are capable of making decisions based both on their previous decision and the behaviour of the network.

In order to address such a problem, we have considered the design of a *M5* regression model. Before deciding on the use of this classifier, many others, such as the Naive Bayes classifier, have been taken into account. However, the main features of this classifier are its low computational complexity, its self-explanatory capacity and its high degree of adaptability to the problem as is described in Section III. In [3] and [4] it is concluded that the AIFSN is the most important factor in the EDCA parameter set. As a consequence, the main function of the designed *M5* regression model is to identify the AIFSN combination that achieves the highest voice+video normalized throughput in every single moment regardless of network saturation.

In this context, 9 sets of AIFSN values are selected as candidates to be considered by the model. These values can be seen in Table II. These values have been chosen by gradually increasing the difference in slots of time between the different ACs. For that reason, the AIFSN value related to each AC is suitably separated from each other. However, in those cases in which the AIFSN for video traffic is higher than 2, its priority to access the wireless channel is reduced with regard to the legacy stations. These combinations aim to outperform the results offered by EDCA, enhancing the voice+video normalized throughput and the overall network performance, mainly by reducing the collisions between the different types of traffic.

In order to design an accurate classifier, a large amount of information must be provided during its construction. The information must contain a wide range of different network conditions in order to acquire enough knowledge. For this reason, previous to the learning process, a huge set of tests is carried out by considering several factors that may compromise the network performance and that are described in Subsection IV-B. As part of these tests, the aforementioned 9 sets of AIFSN values are considered with the aim of finding an alternative value to the standard one in order to enhance the performance of the network.

Once the results of the aforementioned tests have been obtained, they must undergone a significant pre-processing. Initial tests included several outcomes, such as the number of applications of every type of traffic or the percentage of

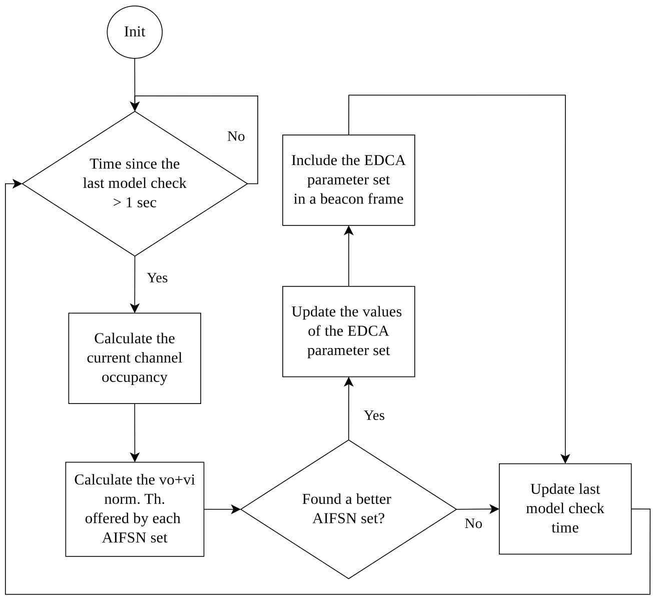

Fig. 3. Proposal Description

occupancy of the wireless medium. Nevertheless, this fact is unacceptable since part of our main aim is to develop a regression model as simple as possible. Due to the wide variety of resulting parameters, it was necessary to perform a variable selection to discard those that were unrelated. After carrying out this supervised variable selection, only the global occupancy level of the wireless channel and the particular level of each type of traffic are considered by the model. The purpose of this regression model is to maximize the sum of voice and video normalized throughput by using a group of regression functions. For this reason, this last value is added as a parameter to the model due to the fact that this is the factor that the regression model must maximize. Furthermore, the final model is made up of ten groups of sub-models, i.e. it contains one group of rules per AIFSN tested combination, which attempt to achieve the highest voice+video performance. These few factors are able to provide a good approximation of the network conditions while allowing the construction of a simple and accurate regression model.

The described parameters are used as an entry point for the *M5* regression model and must be calculated periodically. In our case, they will be calculated once per second. After this period of time, the classifier checks whether the previously selected AIFSN values are already the most favourable combination or whether they need to be modified. Once the optimal AIFSN set has been calculated by the AP, it is responsible for distributing these values embedded in an EDCA parameter set. Distribution is handled through the beacon frames and, therefore, no additional control traffic is introduced into the network. This behaviour is shown in Figure 3.

Thus, the proposed scheme has low complexity due to the fact that the AP only has to perform simple operation checks by using the described model, and there is no need to transmit additional control traffic. Furthermore, this scheme only requires making a few minor adjustments to the APs and no changes are made to the commercial network cards. Therefore, total compatibility with existing devices is maintained at the same time an enhancement in network performance is made possible, especially for voice and video traffic.

TABLE III. TRAFFIC PARAMETERS USED FOR CLASSIFIER CONSTRUCTION

	Packet size	Data rate
DCF	552 bytes	512 Kbps
BK	552 bytes	512 Kbps
BE	552 bytes	512 Kbps
VI	1064 bytes	800 Kbps
VO	104 bytes	20 Kbps

B. *M5 Regression Model Design*

The design and construction of the *M5* regression model need to have a considerable amount of proper information that must be acquired during the training period. In our case, this information is obtained from the results of a set of tests that is previously performed, aiming to cover a wide range of possible scenarios with different network conditions. This process makes the construction of the most accurate model possible. In this regard, a group of 18 scenarios has been designed and tested by using Riverbed Modeler 18.0.0 [18]. These scenarios take into account applications that utilize EDCA and those that only make use of DCF as a channel access method. In this way, our proposal can guarantee full compatibility with those stations that only support the original IEEE 802.11 standard.

The aforementioned scenarios are made up of a variable number of stations, considering different percentages of uplink transmissions of every type of traffic (BK, BE, VI and VO). On this basis, the traffic load level is increased in every scenario in steps of 10 stations, causing the number of stations to range from 10 to 80. As a result, eight combinations of the same scenario with different traffic load levels are tested. In order to ensure that the proposed scheme is able to adapt itself to the network conditions independently of the transmission rate of the stations in the BSS, two different values for this factor have been considered to carry out the tests. In this way, all the applications share a transmission rate of 12 Mbps and 36 Mbps, regardless of the type of traffic that they transmit. In order to provide a further evaluation, all the tests have been carried out by using 60 different random seeds.

Each station of the BSS transmits a different type of traffic whose characteristics are shown in Table III. Furthermore, the bit rate of the different types of traffic is modelled by using a group of probability distributions. Table III shows that the stations that only support DCF and those that use EDCA to transmit BK and BE traffic use the same transmission source. This source is modelled by making use of a Pareto distribution with a location of 1.1 and a shape of 1.25. By contrast, voice traffic represents a Constant Bit Rate (CBR) service using the G728 codec [19], whereas video applications transmit H.264 [20] streams. In addition, multimedia applications have temporal restrictions that are important to be modelled in the scheme. For this purpose, deadline periods of 10 ms and 100 ms are considered for voice and video transmissions, respectively. In this way, when any packet remains in the transmission queue for longer than the indicated thresholds, it is discarded.

The different tests to analyse the model are performed by making use of the proposed AIFSN values that can be seen in Table II. Among the values that this table contains, the AIFSN combination proposed in IEEE 802.11e has also been considered due to the fact that it achieves the highest performance in certain cases. Therefore, it is a suitable combination to be chosen by the classifier. Furthermore, the results of this combination are compared with the ones achieved by our proposal. During the execution of each test scenario, the conditions of all the factors that determine it remain static. These values are modified according to a given order until all possible combinations of such parameters have been considered. In this way, the regression model is allowed to acquire real knowledge. If variable information were provided to the classifier during its development, the learning process would be unfeasible.

Moreover, both the data pre-processing and the design of the *M5* regression model are carried out using Weka 3.7.0 [21]. During the aforementioned design, a 10-fold cross validation process is performed in order to guarantee that both the training and the testing data sets are independent. This process achieves an average correlation coefficient of 0.8916 and a mean absolute error of 0.0554. The above values show the accuracy of the proposed model and the high relation between the parameters involved.

V. Performance Evaluation

In this section, we carry out a performance analysis in order to verify the proposed scheme via simulation, making use of Riverbed Modeler 18.0.0. In this regard, a set of 20 scenarios have been designed, covering a wide range of different network conditions. In this way, the main features of the evaluation and the results obtained during this process are shown below.

During the performance evaluation, both stations that use DCF and EDCA have been included. The first twelve scenarios take into account both types of stations while in the remaining eight only EDCA stations can be found. All these scenarios are made up of 100 stations, involving an equal proportion of applications of each type of traffic, i.e. 20 stations per type of traffic are included in the BSS. Despite this fact and with the aim of considering a wireless network as real as possible, all the stations are not active at the same time. Instead, a specific transmission probability has been assigned to every station according to its AC, as shown in Table IV. These probabilities and the variable number of active stations allow for the evaluation of our proposal under different network saturation conditions.

The scenarios have a duration of 300 seconds and are divided into two periods. During the first one, the stations that are not transmitting any information try to start a new transmission every 30 seconds with a probability associated with their AC (see Table IV). During the second one, the transmitting applications attempt to stop the transmission every 30 seconds with the same probability as that previously used. With this approach, many scenarios with a multitude of traffic loads are considered. Due to all scenarios being simulated by using 60 different random seeds and each of them being divided into 20 time intervals, in the end 24000 different intervals have been tested.

TABLE IV. Description of the Set of Test Scenarios

Scenario Number	Voice	Video	BE	BK	DCF
1	10%	1.5%	2%	2%	2%
2	10%	5%	2%	2%	2%
3	10%	7%	2%	2%	2%
4	8%	6%	3%	3%	7%
5	4%	2%	3%	3%	10%
6	3%	3%	4%	4%	8%
7	5%	3%	7%	7%	4%
8	6%	6%	10%	5%	5%
9	6%	9%	6%	6%	6%
10	8%	-	8%	8%	8%
11	-	6%	6%	6%	9%
12	6%	6%	6%	6%	6%
13	10%	8%	-	-	-
14	8%	4%	-	-	-
15	6%	10%	-	-	-
16	7%	7%	7%	7%	-
17	10%	-	8%	8%	-
18	-	8%	7%	7%	-
19	9%	8%	6%	6%	-
20	9%	7%	8%	-	-

The bit rate of all the applications used during the whole performance evaluation process is assigned according to their AC. These values are the same as the ones in Table III. Moreover, the stations are randomly distributed over the network coverage of the BSS. In addition, different transmissions rates have been taken into account for all the applications regardless of the type of traffic they transmit. In this way, and with the aim of modelling signal propagation through the wireless medium, the Ricean [22] model has been considered. This model is characterized by a factor, k, which determines the ratio between the power in the line-of-sight component and the power in the scattered paths. In our case, a k factor of 32 has been used. Furthermore, in all the analysis, IEEE 802.11g [23] defines the physical layer of the network.

In order to evaluate the performed simulations, a large amount of statistical information has been obtained. However, some of them have been selected in order to consider only the factors that are able to summarize the main results. The metrics that have finally been considered include the voice+video normalized throughput, the number of retransmission attempts, the overall throughput of the network and the normalized throughput achieved by the stations that use DCF. As the main aim of our proposal is to enhance the performance of the voice and video applications, the first of these statistics refers to the sum of the normalized throughput of such applications.

In Table V, the voice+video normalized throughput results for the 24000 simulated intervals are shown. This table presents the percentage of 30 second transmission intervals during which our proposal has experienced losses or gains of voice+video normalized throughput with regard to the existence of DCF traffic. These values have been calculated in comparison with the results obtained from the standard AIFSN combination. Moreover, this table includes the cases in which the results are unaltered. We have considered as unaltered the results in which the gains or the losses are lower than 1%. Furthermore, those cases in which our proposal experiences a decrease in the level of performance higher than 1% have been designated as losses.

TABLE V. VOICE+VIDEO NORMALIZED THROUGHPUT IMPROVEMENTS IN 30S INTERVALS

	With DCF traffic	Without DCF traffic
Unaltered	52.11%	31.30%
Losses	5.48%	1.44%
Gain [1%-5%]	23.37%	17.35%
Gain [5%-10%]	12.78%	5.93%
Gain [10%-15%]	2.86%	6.89%
Gain [15%-20%]	1.52%	4.55%
Gain [up to 20%]	1.90%	32.55%

It can be observed in Table V that in a large number of cases, the results of our proposal remain unaltered. This situation is a consequence of taking into account low traffic load levels in a significant amount of the tested scenarios where all the AIFSN combinations achieve the highest performance. In particular, in presence of DCF traffic and depending on the network saturation, the percentage of unaltered scenarios is higher for the scenarios with DCF traffic than for those that only take into account EDCA stations (52.11% and 31.30%, respectively). Moreover, there is a small percentage of cases where our proposal experiences small losses in performance. These losses represent 5.48% of the cases in presence of DCF stations, while this value is lower when only stations that use EDCA are considered. This situation is due to a group of wrong decisions made during the test by the *M5* regression model. Furthermore, the usage of a single parameter allows it to have a good approximation of the network conditions, but it does not allow it to identify the network conditions completely. Nevertheless, the number of scenarios in which this situation occurs is much lower than those in which our proposal improves upon the performance offered by EDCA. In fact, the results show that the performance improvement is up to 20% in many cases. Finally, it can be clearly seen that the gains achieved by the proposed scheme are up to 20% in 32.55% of the scenarios in the absence of DCF traffic.

The scenarios shown in Figures 4, 6 and 7 are a representative subset of those where the traffic proportion is more problematic for EDCA usage. The first five scenarios take into account both DCF and EDCA stations. However, in the remaining three only EDCA stations are considered. In Figure 5 only scenarios with both types of stations are considered due to the fact that the DCF normalized throughput is evaluated.

During the simulations, twenty intervals with many different traffic load levels are taken into account. The first and the last five intervals have the lowest traffic load due to the fact that all the stations are starting or ending their transmissions. When the traffic load is low, all the tested AIFSN combinations offer the highest throughput. In this way, the results of both the standard AIFSN combination and those of the proposal are identical. For this reason, only the ten remaining intervals are shown in Figure 4, in which the standard values start to suffer traffic losses. In this figure, the voice+video normalized throughput is shown. It can be observed that in all cases the throughput achieved by our proposal is higher than when using the standard AIFSN values. Furthermore, it is shown that the difference is even greater in scenarios without DCF traffic. In these cases, an improvement of up to 35% can be obtained.

The gradual separation of the AIFSN values assigned to the different ACs, especially in the cases in which the

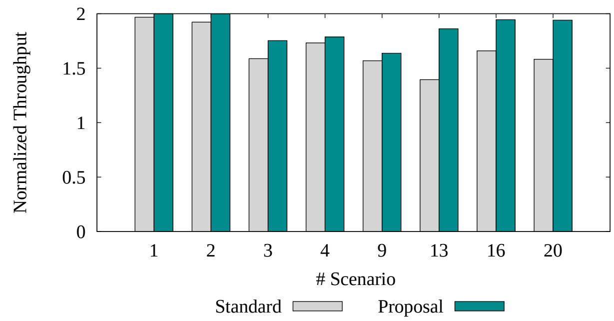

Fig. 4. Voice+Video Normalized Throughput

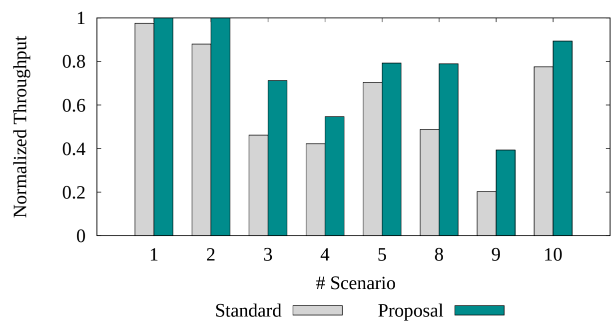

Fig. 5. DCF Traffic Throughput

AIFSN for video traffic is higher than 2, allows the stations that support the original IEEE 802.11 standard to be given a higher priority to access the wireless channel. Therefore, our scheme is not only able to maintain the compatibility with the aforementioned stations, but also to enhance their offered performance. In this way, the eight most representative scenarios in which DCF transmissions take place have been selected in order to show this improvement (see Figure 5). In spite of providing a higher priority to the legacy stations and improving their performance, our scheme does not only not penalize the voice and video applications, but also enhances the throughput offered as can be seen in Figure 4.

The improvement achieved by our proposal is a direct consequence of decreasing the amount of collisions in the network. Furthermore, the proposed scheme offers a reduction in the number of retransmission attempts as can be seen in Figure 6, whose average value is around 16%. These decreases have a direct impact on the improvement of the global throughput of the network, which is illustrated in Figure 7. Suitable selection of the AIFSN values contributes not only to enhancing the performance offered by the voice and video applications, but also to improving the remaining types of traffic performance and overall network quality.

VI. CONCLUSIONS

The demand for multimedia services is growing fast, especially in real-time applications which require an adequate level of QoS. On this basis, the use of artificial intelligence techniques contributes to find traffic patterns and enhance the network performance. In this paper, we have proposed a prediction scheme for improving the voice and video communica-

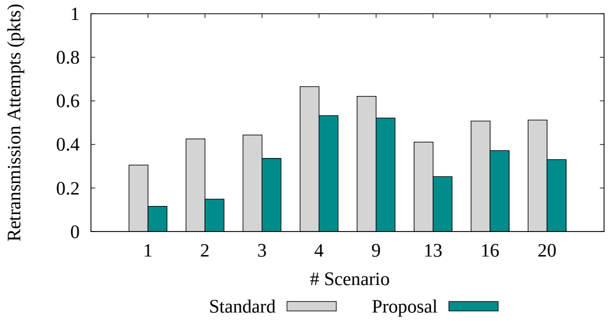

Fig. 6. Overall Retransmission Attempts

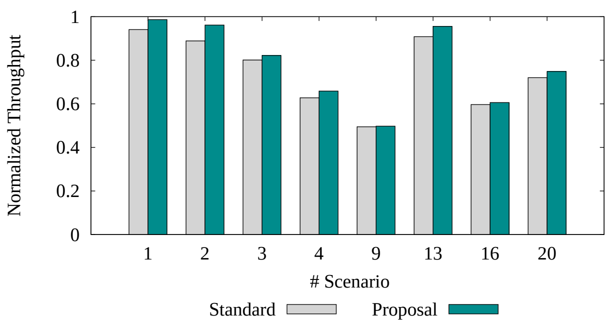

Fig. 7. Overall Throughput

tions over WLANs, making use of a previously designed *M5* regression model. With this aim, it is able to dynamically adapt the standard AIFSN combination defined in IEEE 802.11e while allowing for the compatibility with the stations that only support the original IEEE 802.11 standard. This regression model is only queried by the AP, transmitting the calculated values to all stations without introducing additional control traffic into the network.

The experimental results show that our proposal outperforms the voice+video normalized throughput of the standard AIFSN combination, achieving an improvement of up to 20%. It is also shown that a suitable separation of the AIFSN values from each other for each AC leads to a reduction in the amount of collisions between the traffic of different ACs. As a consequence, the global throughput of the network is also enhanced. Furthermore, and mainly due to its simplicity, the proposed scheme is able to be executed in real-time.

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