Delay-Sensitive Wireless Content Delivery: An Interpretable Artificial Intelligence Approach

Estefanía Coronado*, Blas Gómez†, José Villalón†, Antonio Garrido†, Shuaib Siddiqui*, and Roberto Riggio‡
*i2CAT Foundation, Barcelona, Spain; Email: {estefania.coronado, shuaib.siddiqui}@i2cat.net
†Universidad de Castilla-La Mancha, Albacete, Spain; Email: {Blas.Gomez, JoseMiguel.Villalon, Antonio.Garrido}@uclm.es
‡Polytechnic University of Marche, Ancona, Italy; Email: r.riggio@univpm.it

***Abstract*—The COVID-19 emergency has made the consumption of multimedia content skyrocket in all contexts, including education. Many universities leverage hybrid learning models, in which students join a real-time video session via Wi-Fi from several classrooms to ensure safety and social distancing. This is creating a significant strain on the wireless access network, which is required to deliver an unusually high level of traffic. Artificial Intelligence (AI) and Machine Learning (ML) solutions have emerged as a way to make networks easier to control and to manage. However, their black box nature and in general their fire and forget approach has generated considerable skepticism over the entire value chain, from vendors to network administrators. This situation has led to a new interest in interpretable AI solutions, which aim at making the decisions taken by AI/ML models intelligible to a domain expert. In this article, we review the concept of interpretable AI and analyze the challenges, requirements, and benefits it can bring to delay-sensitive content delivery in 802.11 Wi-Fi networks. Furthermore, we apply these requirements to a use case in which we focus on advanced Quality of Service (QoS) provision, and we propose an interpretable and low-complexity ML model that addresses those requirements. The results demonstrate performance gains up to 60% in the sensitive traffic and up to 20% at network-wide level.**

***Index Terms*—802.11, ML, interpretable AI, QoS, delay-sensitive traffic.**

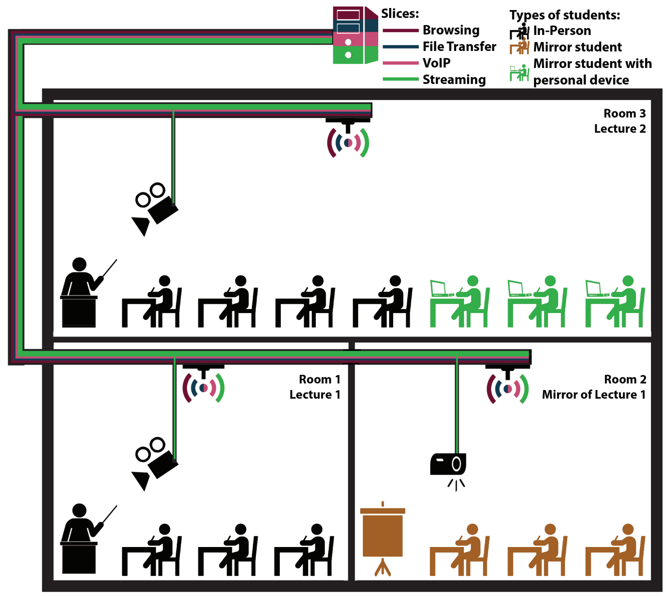


Fig. 1. Example of a hybrid learning environment supported by QoS optimization and network slicing over Wi-Fi.

I. Introduction

With the COVID-19 outbreak, network operators have witnessed a surge in traffic demands with peak utilization periods stretching across the whole day [1]. In some cases (e.g., campuses and hospitals), private 5G and Wi-Fi networks have positioned themselves as an attractive option to meet the high-bitrate and low-latency needs of a very diverse set of applications and services. The strain on the wireless communication infrastructure is particularly evident in the education system, with schools and universities offering various teaching options including in-person, hybrid, and distance learning. Some hybrid models are attracting greater attention through methods known as "mirror" lessons, in which the students are distributed over several classrooms and the teacher is present in only one of them. These measures respect social distancing, and ensure interaction and access to educational materials. However, the room size may hinder vision and make some students also use personal devices to follow the lesson over Wi-Fi, as shown in Fig. 1. The same applies to residences, where many students simultaneously join the same virtual classroom, having the access network (usually Wi-Fi) to sustain a significant number of connections.

The most significant challenge in this scenario is the huge increase in delay-sensitive traffic that must be delivered while respecting other concurrent services. This also involves tackling issues related to the highly dynamic channel quality and the unpredictable traffic peaks. Although the current pandemic has aggravated these problems, the IEEE 802.11e amendment [2] already aimed to improve the delivery of real-time multimedia flows in Wi-Fi networks. Moreover, existing research proposes several approaches to this problem, such as analytical models for Quality of Service (QoS) differentiation [3], load balancing algorithms [4], and Software-Defined Networking (SDN) principles [5]. However, due to a greater diversity in the services to be supported and to an increasing number of parameters characterizing current networks, such approaches are not sufficient anymore. Consequently, Artificial Intelligence (AI) and Machine Learning (ML)-based solutions have started to be used to approximate complex network optimization functions [6]. Many of them leverage deep learning models which, despite their high accuracy, are black boxes providing limited insights on how decisions are taken. Understanding such decisions contributes to data discovery, reveals diagnostics insights, and allows expert input (especially correction and supervision). Therefore, the demand for interpretable AI is increasing. Albeit resent research has aimed to explain black box models via surrogate post-hoc models, the results can still be misleading and unreliable [7].

In this context, the contribution of this work is twofold.

- We identify the requirements in terms of interpretable AI more relevant in wireless networks for the delivery of delay-sensitive content and analyze how different learning models compare w.r.t these needs.
- We introduce an interpretable AI solution looking to meet the previous requirements in Wi-Fi networks with a particular focus on channel access optimization. Our approach is based on inherently interpretable models, namely decision trees and rule-based models, which are known for their off-the-shelf transparency and interpretability by non ML experts. Moreover, these models are lightweight and computationally efficient, which makes them excellent candidates for running on commodity hardware in real-time. The results prove the high effectiveness of our solution by outperforming the standard function in terms of delivery ratio and retransmissions.

The rest of the paper is structured as follows. Sec. II discusses the motivation and requirements for an effective interpretable AI solution. The IEEE 802.11 QoS channel access capabilities and the related work are surveyed in Sec. III. Sec. IV introduces the proposed AI-enabled QoS-oriented channel access scheme, while Sec. V discusses the performance evaluation. Finally, Sec. VI concludes the paper.

II. Motivation and Requirements

A. Interpretable and Explainable Artificial Intelligence

The development of wireless networks, and in general computer networks, has so far mostly leveraged analytical or numerical models from, for example, information and stochastic theory. Such approaches start to show their limitations when the number of knobs, i.e., the network parameters that can be optimized, increase or when the deployments become too complex. In this sense, the research on AI/ML will greatly affect the way communication systems are designed and operated.

Unfortunately, the AI techniques that currently perform best, i.e., deep learning, essentially behave as black boxes, preventing the user from understanding why a certain output was produced. Consequently, the research community (beyond just the telecommunications domain) is currently questioning the extent to which we should rely on such inscrutable AI models in mission-critical systems. Thus, the first question arising is clearly: *is it not enough to simply obtain a correct prediction?* In this section, we answer this question while identifying the main requirements and challenges in the field of interpretable and Explainable AI (XAI). Firstly, the concepts of interpretable and explainable AI must be defined. Unfortunately, there is no agreed definition for either term and both are often used interchangeably. In this work, we follow the same approach and define an interpretable AI model as one that produces outputs that are intelligible to a human domain expert. This essentially means that a human expert is able to comprehend the output of the model and trace back the steps that led it to produce that particular output.

B. Requirements

Given the above considerations, we define the following requirements for the interpretable solution to be used in this work for the wireless delivery of delay-sensitive content.

1) Low-complexity: The envisioned models must be deployed on a wide range of devices, ranging from low-cost Wi-Fi APs to smart TVs. Thus, it is imperative that their computational complexity is low enough to be run on devices with limited resources in terms of CPU, memory, and storage.

2) Privacy preserving: Traffic patterns and users behavior change over time, forcing the models to be retrained. Unfortunately, a single deployment does not provide the level of diversity required for models to be able to generalize their results. It is thus important to allow the various devices to combine, in a privacy preserving way, models trained in different settings to build a more general model that can be deployed on a wider scale.

3) Consistency: The ML models must be consistent in the way outputs are produced in the sense that small perturbations in the input should also produce small perturbations in the output. This allows easier troubleshooting and, in general, greater intelligibility of the models. However, it is not an all-purpose requirement. Depending on the context, there could be situations in which non-linear behavior is expected. Typical examples are found in models dealing with the volatile nature of the wireless medium that often display non-linear behaviors.

4) Transparency: This term refers to a ML model that is by itself understandable to a domain expert. For example, regression models are transparent since the law mapping input to output is in the form of mathematical functions. Likewise, random forests and decision trees are also transparent (at least until their size makes it difficult to have a complete picture of the reasoning behind a certain output). Conversely, models based on deep learning are not transparent.

5) Capable of being simulated/emulated: Before reaching real-world test and validation stages, an AI solution for the wireless delivery of delay-sensitive content must be validated in a controlled environment, e.g., on a small-scale testbed, and via numerical or event-based simulations. Therefore, it is important that the models can be fully executed and validated in such environments. Considering that in simulations it might be necessary to test particular subsystems of an ML model, this requirement could also be formulated as the ability to decompose and interpret each part of the model.

6) Post-hoc analysis: This refers to the possibility of providing some form of explanation for AI/ML models that are not easily readable by design (e.g., deep learning models). One common way of doing this is by studying the relevance of a certain feature for the model's precision. This allows the quantification of the sensitivity of a model to a certain feature and its importance in the inner machinery of a model. Another

TABLE I
AI INTERPRETABILITY AND COMPLEXITY ANALYSIS: LOW [$O(n)$], MEDIUM [$O(n \cdot log(n))$], HIGH [$O(n^2)$, $O(n^3)$], VERY HIGH [$O(2^n)$, $O(n!)$].

	Execution Complexity	**Privacy Preserving**	**Consistency**	**Transparency**	**Simulatability**	**Post-hoc analysis**
Regression	low	✓	✓	✓(with mathematical tools)	✓	✗
Decision Tree	low	✓	✓	✓	✓	✗
Naive Bayes	low	✓	✓	✓(with mathematical tools)	✓	✗
Random Forest	high	✓	✓	✗	✗	✗
SVM	high	✓	✓	✗	✗	✓
Rule-based	low	✓	✓	✓(with mathematical tools)	✓	✗
Neural Networks (NNs)	very high	✓	✗	✗	✗	✓

post-hoc analysis consists in extracting some sample input/output to gain insights into the model's operation. Models that are transparent by design do not require post-hoc analysis to be interpretable and are thus preferred for this work.

III. AI-ENABLED QOS-ORIENTED CHANNEL ACCESS

A. QoS Capabilities in the IEEE 802.11 Standard

The 802.11 access link represents a clear bottleneck in the delivery of delay-sensitive content due to its contention-based operation and stochastic nature. This is acknowledged by IEEE 802.11e [2], which enables differentiated channel access schemes for various traffic types through the Enhanced Distributed Channel Access (EDCA) function. EDCA defines a set of parameters for the various traffic types: Arbitration Interframe Spaces (AIFSs), Contention Window (CW) and Transmission Opportunities (TXOP). However, IEEE 802.11e also pursues interoperability between stations with (QSTAs) and without QoS support (nQSTAs). Thus, very small values for AIFS and CW were fixed, causing high collision rates between voice and video services. Many studies have proven that such values perform poorly under heavy traffic loads. Adapting them (mainly AIFS and CW) to the channel status can boost system performance [8]. Although the modification of these values is allowed, this is left to the vendor's choice.

B. AI-based Approaches for Improved Channel Access

AI has recently being adopted in all areas of wireless network management [9]–[11]. In [9] the authors first survey AI-based resources allocation schemes. Then, they propose an AI-enabled wireless network architecture and use it together with deep Q-network techniques to address the challenges of complex and high-dimensional resource allocation problems. A general framework for AI-based network slice management is introduced in [10]. The benefits delivered by AI are then evaluated for different case studies with improvements ranging from 20 to 80 percent. The classical Wi-Fi Access Points (APs) deployment problem is addressed in [11] using AI. The authors compare their solution against conventional coverage maximization approaches under practical uncoordinated scenarios. The results show that the AI-based approach can outperform the state-of-the-art in terms of both throughput and fairness. However, none of these works focuses specifically on optimizing the channel access of delay-sensitive content.

A number of works exist in the domain of adaptive methods for channel access [3], [12]–[18]. The authors of [3] analytically study how dynamically tuning some EDCA parameters can successfully prioritize voice and video transmissions over data in 802.11 networks. A novel contention window adaptation algorithm is introduced in [12] with the goal of reducing the collision probability and maximizing the energy efficiency of the network. A performance analysis via simulation shows that the proposed algorithm outperforms other techniques in terms of collision level and energy consumption. In [13] the authors propose an adaptive single stage CW control scheme, whose validation shows higher throughput and short-term fairness than the standard channel access scheme. Typical 802.11-based Wireless LANs (WLANs) are characterized by a significant heterogeneity in terms of traffic load, transmission rate, and packet size. This scenario is captured in [14], which proposes a novel CW control scheme based on a new theoretical model. The validation via simulation and over a testbed demonstrates a significant throughput improvement compared to the existing schemes that do not consider node heterogeneity. In [15], the authors propose an adaptive mechanism that adjusts the backoff time according to the number of active stations. The results prove that this approach outperforms EDCA in terms of throughput and delay in different scenarios. A similar approach, based on channel load, is also used in [16], [17]. A cognitive backoff mechanism that adapts the CW of an 802.11ax network is proposed in [18]. A simulation-based analysis shows that this solution can achieve higher throughput and lower delay than the one defined in the standard. All the aforementioned works are not based on AI solutions, which are instead the focus of our paper, due to their ability to adapt to complex and multi-service situations.

Several works leveraging non-interpretable and non-explainable AI for channel access optimization can be found in the literature [19]–[22]. A neural networks-based approach to tune channel-access opportunities is presented in [19]. Simulations results demonstrate the effectiveness of this method to maximize the system throughput in different environments. In [20] the authors introduce a Q-learning-based channel access scheme for Wi-Fi that adjusts the CW size according to the network density, proving its performance via simulation especially in dense network conditions. Another Q-learning-based scheme, in this case applied to the problem of coexistence between Wi-Fi and LTE in unlicensed bands, is presented in [21]. The proposed approach tunes the transmission opportunity and the muting period of an LTE device to provide fair coexistence with Wi-Fi networks. In [22] an ML-based approach to adjust the contention window of 802.11-based networks according to the current and past conditions is proposed. The authors demonstrate how their approach outperforms both the standard channel access scheme and other state-of-the-art techniques that only consider the last two transmissions. Albeit based on AI techniques, the works above leverage black-box models. Conversely, in this work we aim to focus on interpretable AI techniques for channel access optimization.

Similar to our work is [23], which uses a random forest model to adjust the CW parameters according to the network conditions. The authors define a large number of scenarios for training the model, including cases with misbehaving nodes. The results show that, in the case of a network with misbehaving nodes, the proposed approach can provide improvements in terms of throughput higher than 150%. Our paper follows a similar approach based on interpretable AI solutions but, as opposed to the previous work, we focus on supporting latency-critical services over 802.11-based WLANs.

IV. Low-complexity AI-based Channel Access Optimization in IEEE 802.11

AI can be of great benefit in adapting the medium access parameters based on channel status information. However, given the computational limitations of the Wi-Fi APs and the need for running the ML models in real-time, low complexity is as important as accuracy. Conversely, due to possible failures, traceability and interpretability become essential. In this regard, Table I analyzes the capabilities of several ML models [6], [7] in relation to the requirements presented in Sec. II. Based on this, a decision tree and a rule-based model have been chosen for being the options that best suit the problem needs. The specific implementation of these models has been based on *J48* and *M5* algorithms, respectively.

The training phase of the ML-based model covers a wide variety of scenarios on a Wi-Fi network comprising a set of QSTAs and nQSTAs (ranging from 10 to 200), which deliver constant and intermittent traffic at different transmission rates to a single AP. Joint aggregated traffic from 1 to 30 Mbps has been considered. All traffic types defined in IEEE 802.11e (i.e., voice, video, best effort and background) have been used. From the dataset obtained, we have been able to identify the most significant features reflecting the network status, such as the number of transmissions of each traffic type, their bitrate and transmission rate, the presence of nQSTAs, and the channel utilization. From this dataset we have built a two-phase predictive scheme for the channel access function, which has been deployed at the AP and is executed every second.

Figure 2 showcases the flowchart of the two-phase ML model. The first phase computes the most appropriate AIFS combination from an alternative set of values that are proposed on the basis of the priorities defined by the standard and aimed at reducing their collision rate. The second phase uses

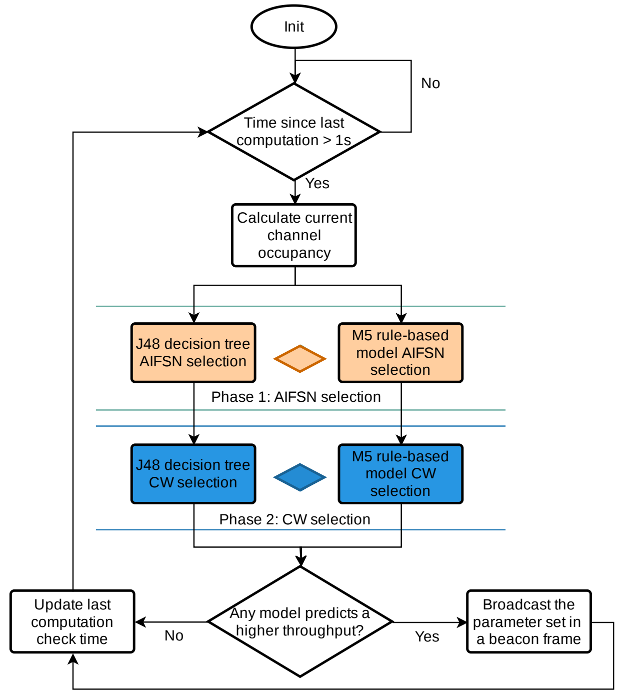


Fig. 2. Flowchart of the two-phase model for QoS-oriented channel access.

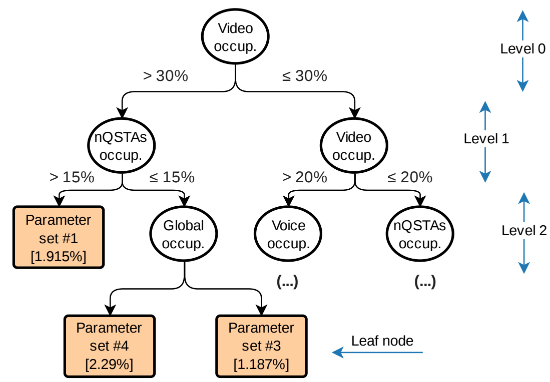
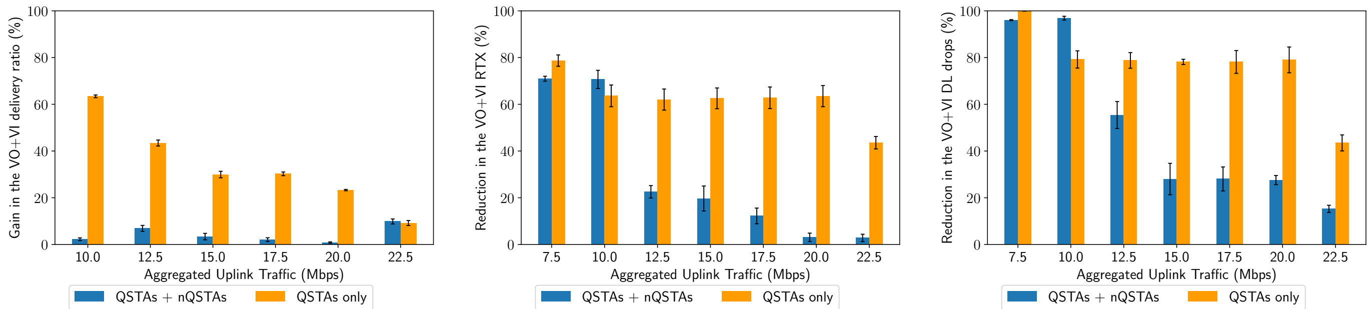


Fig. 3. Sample of the modeled J48 decision tree.

the selected AIFS, together with the channel status data, to select the CW size that delivers the highest voice and video performance while guaranteeing the aggregated network throughput. Both phases run in parallel for the *J48* and the *M5* models so that, for each execution, we select the output parameters of the model achieving the best trade-off between accuracy and throughput. Afterwards, the AP broadcasts the values via beacon frames to all the stations.

Note that a pruning technique is applied to reduce the size and complexity of the models, and that, in the case of the decision tree, the depth is limited to 3 levels to avoid over-fitting and provide greater transparency. A sample of this tree is depicted in Fig. 3, where the leaves show the set of values providing the highest throughput and the relative error in each case. In this way, networking experts can interpret a decision



(a) Improvement in the delivery ratio

(b) Decrease in the retransmission ratio

(c) Decrease in the traffic dropped for reaching the maximum queue deadline

Fig. 4. Comparison of results for voice a video traffic with respect to EDCA as the aggregated uplink traffic increases.

made by the model and understand whether the output makes sense. For example, *if the channel occupancy of video traffic is greater than 30%, and the nQSTAs channel occupancy is higher than 15%, then the parameter set #1 provides the highest throughput with a 1.915% relative error.* This output is reasonable since the suggested values identify the standard set, which is actually the most recommended option when the network has users without QoS support and users transmitting video services in order to avoid collisions between them. The same design principles apply to the M5 model.

V. Performance Evaluation

A. Methodology

The model has been evaluated using Riverbed Modeler 18.0.0. Using this simulator we have modeled a Wi-Fi network composed of 100 stations in which we have varied the aggregated traffic delivered to an AP from 10 to 22.5 Mbps in steps of 2.5 Mbps. The stations have been randomly distributed on the AP coverage, which was configured on channel 36 isolated from external noise. No other downlink or uplink traffic was present. The default rate control algorithm on the stations was responsible for selecting the appropriate transmission rate.

The tests have been divided into two scenarios. On the one hand, the first scenario is composed of 80% of stations with QoS support and of 20% without such capability (i.e., QSTAs and nQSTAs, respectively). The QSTAs are split into four groups of equal dimension according to the type of traffic delivered (i.e., voice, video, best effort and background). On the other hand, the second scenario only comprises stations with QoS capabilities, which are also distributed in four groups, one per each traffic type. In the two scenarios the packet size is set to 552 bytes for best effort, background and nQoS traffic, to 1064 bytes for video traffic and to 104 bytes for voice traffic. The bitrate of each station has been configured according to the total aggregated uplink traffic in each experiment. Although delays can be experienced by all traffic types due to network's congestion, voice and video traffic are more sensitive to this issue. For this reason, we have set in both scenarios a maximum deadline up to which voice and video traffic can remain in the waiting queue for transmission before being discarded. This interval is set to 10 and 100 ms respectively for the voice and video applications.

We have evaluated the performance of our model with respect to the standard channel access function in terms of (network-wide and voice+video) delivery ratio and retransmission ratio, and in terms of improvement in the voice and video traffic dropped for reaching the maximum deadline. Each experiment has been repeated 30 times.

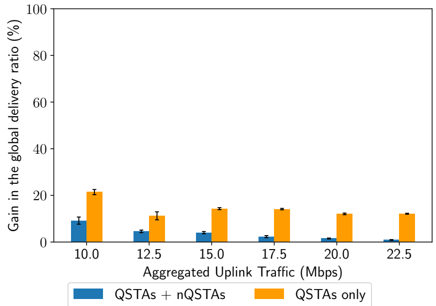
B. Results Discussion

Figure 4 depicts the results for voice and video traffic in both scenarios (i.e., QSTAs+nQSTAs and only QSTAs) w.r.t. the standard channel access function. In particular, Fig. 4a showcases the gains provided by our scheme in terms of delivery ratio, revealing that these are much larger when the network only comprises QSTAs, since the standard parameters seek to maintain compatibility between both types of stations. Although this gain decreases as the aggregated traffic grows, the predictive scheme provides up to a 60% enhancement. These results are partially due to the significant reduction in the voice and video retransmissions shown in Fig. 4b thanks to the decrease in the channel access collisions. More precisely, these retransmissions are lower than the standard by an average of 60% for only QSTAs and gradually decrease with the aggregated uplink traffic when both types of stations are present. Similarly, as displayed in Fig. 4c, our scheme demonstrates an improving trend about 50% and 75% on average in the amount of traffic discarded for exceeding the deadline for QSTAs+nQSTAs and only QSTAs, respectively.

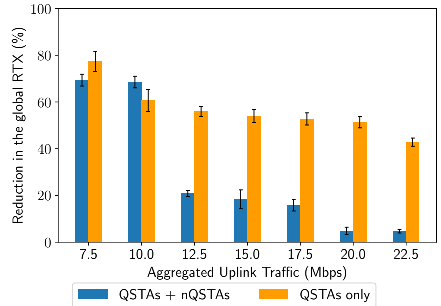
In Fig. 5 it can be seen that the enhancement in the delay-sensitive traffic not only does not impair the network-wide performance but that it contributes to its growth. More specifically, Fig. 5a indicates that the gains for QSTA differentiation are almost constant with the aggregated traffic at around 20%. By contrast, the improvement when also considering nQSTAs drops with network congestion. This improvement is due to the large decrease in the retransmission ratio shown in Fig. 5b.

VI. Conclusions

When complex systems, such as wireless networks, are managed by several ML models, interpretable AI is fundamental



(a) Improvement in the delivery ratio



(b) Decrease in the retransmission ratio

Fig. 5. Comparison of network-wide results for all traffic types with respect to EDCA as the aggregated uplink traffic increases.

in detecting component malfunctions, making informed decisions, and explaining the output to all the involved stakeholders. In this paper, we analyze the challenges and requirements that interpretable AI poses for delay-sensitive wireless content delivery in Wi-Fi networks, considering the traffic peaks and changes found in different settings, including education, and aggravated by the current pandemic. Within this field, we have proposed a predictive QoS-oriented channel access scheme for wireless networks using low-complexity explainable ML models. The results show the ability of our solution to adapt to traffic changes and to enhance the performance of delay-sensitive content provision by up to 60%.

Acknowledgments

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