IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 19, 2021, accepted September 7, 2021, date of publication September 10, 2021, date of current version September 20, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3111783

Emerging Tools for Link Adaptation on 5G NR and Beyond: Challenges and Opportunities

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This work was supported in part by the European Fund for Regional Development (FEDER), Junta de Andalucía, and the University of Málaga under Project P18-RT-3175, Project P18-TP-3587, and Project UMA-CEIATECH-06; and in part by the Postdoctoral Grant DOC_00265 ("Selección de personal investigador doctor convocado mediante resolución de 21 de mayo de 2020," PAIDI 2020).

ABSTRACT With the speeding up of the fifth generation (5G) new radio (NR) worldwide commercialization, one of the paramount questions for operators and vendors is how to optimize the radio links, considering the widely diverse scenarios envisioned. One of the key pillars of 5G has been an unprecedented flexibility on the configuration of the radio access network (RAN) on scenarios that include cellular, vehicular, and industrial networks among others. This flexibility has its main exponent on link adaptation (LA), which has evolved into a *multi-domain* technique where a plethora of parameters, like numerology, bandwidth part, radio frequency beam, power, modulation and coding scheme (MCS) or multiple antenna precoding can be adapted to the instantaneous link conditions. Although such enhancements open the door to a significant performance improvement, they also pose many challenges to LA optimization. In this article, we first present the signaling aspects of NR technology for multi-domain LA and the challenges that need to be faced. Then, we explore the latest advances on LA for wireless networks. We envision a combination of machine learning (ML) tools with multi-domain LA as a key enabler for 5G and beyond networks. Finally, we investigate emerging ML approaches for LA and present a promising application of ML for LA that is assessed with simulations. With this scheme, the training is performed at the network side to relieve the user equipment (UE) to do such a complex task. It is shown with simulations that our ML approach outperforms the well-known outer loop link adaptation (OLLA) algorithm in terms of instantaneous block error rate (BLER), while reaching the same average spectral efficiency (SE). Interestingly, it is shown that the proposed scheme only requires 4 bits to represent the features used to train the model, which makes it suitable for implementation in real systems with limited feedback.

INDEX TERMS 5G networks, link adaptation, machine learning, supervised learning.

I. INTRODUCTION

The main driving factor behind the fifth generation (5G) new radio (NR) is to provide a single wireless technology for a fully connected society. To this end, three extreme service requirements were considered: enhanced mobile broadband (eMBB), with target peak rates of 20 Gbps; ultra-reliable low-latency communications (URLLC), with target block error rate (BLER) of 10^{-5} and very low latency requirements; and massive machine type communications (mMTC), catering to 1 million devices/km^2 [1]. Combinations of these aforementioned extreme requirements cover a plethora of use cases and types of wireless networks, including cellular, vehicular, non-terrestrial, smart cities and factories among others [2].

This diversity of services requires a physical (PHY) and medium access control (MAC) layers with unprecedented flexibility. The wide range of frequencies, including centimeter and millimeter waves (mmW), has required a redesign of transceivers using a hybrid beam forming (HBF) approach, where full-dimensional massive multiple input multiple output (MIMO) can be used while limiting the complexity [3], [4]. A flexible numerology design was also needed to combat the impact of impairments like phase noise or IQ imbalance and the non-linearity of high power amplifiers (HPAs), since

The associate editor coordinating the review of this manuscript and approving it for publication was Sotirios Goudos.

their impact is more noticeable at higher frequency bands [1]. It is especially relevant the case of uplink (UL) where two types of waveforms, cyclic prefix orthogonal frequency division multiplexing (CP-OFDM) or transform precoding, can be selected depending on the link conditions. To cope with wide bandwidths, the active bandwidth part (BWP) of the carrier bandwidth can be dynamically selected [5]. The modulation and coding scheme (MCS) selection also needed major changes to cope with different waveforms and performance targets, like maximum throughput or minimum BLER, thus leading to a number of MCS tables depending of the working conditions. Finally, power control on downlink (DL) and UL has been improved by adding more degrees of freedom with respect to previous standards [6].

The impact of these design decisions on link adaptation (LA) is notorious, leading to an evolution towards a *multi-domain* LA, where transmission configuration can be adapted to maximize binary rate (BR) while guaranteeing a target BLER. Hence, besides the traditional triplet of MCS, power control, and digital MIMO precoding of previous standards, 5G NR allows selecting the numerology, BWP, waveform, and RF beam to maximize the efficiency of radio links.

However, these new degrees of freedom increase the complexity on LA since more parameter sets must be jointly optimized. Additionally, propagation and channel conditions expected for 5G and beyond pose many challenges to LA. The channel at mmW band exhibits non-linear characteristics that complicate an accurate channel state indicator (CSI) acquisition [7]. The high mobility of some scenarios like V2X (Vehicular to Everything) and railway communications or the long delays expected on non-terrestrial networks (NTNs), leads to outdated CSI that severely degrades LA performance. The dynamics of interference are extremely complicated due to the diverse nature of interfering nodes and transmission schemes. There is inter-numerology interference due to the use of mixed numerologies at the same time [1]. Furthermore, dynamic time division duplexing (TDD), which adds the concept of *flexible* slots, makes interference dynamics more intricate by adding cross-link interference [8]. The complexity is exacerbated with the existence of tropospheric ducting that augment the distance between interfering and victim nodes. In addition, the support of URLLC services involves that non latency critical transmission can be punctured by latency critical services which worsen LA. Due to all these reasons, conventional mechanisms for LA might be no longer adequate on 5G and beyond networks.

One of the most promising approaches to overcome the aforementioned challenges is to apply artificial intelligence (AI), as it can solve the intractable problems involving large amounts of data of this multi-domain LA [9]. On the one hand, machine learning (ML) algorithms might allow to model the highly non-linear nature of mmW channels, RF components, and the complex dynamics of the interference to estimate sub-optimal parameter sets for LA. On the other hand, ML might discover behavioral patterns to react against rapid network condition changes.

This article describes the multi-domain LA approach, the signaling aspects, and available measurements of the 3GPP 5G NR standard. Then, the main challenges that need to be faced are presented. Finally, a brief survey on ML approaches for LA is discussed, and a promising application of ML to LA is presented. The benefits of such a proposal are illustrated with simulations.

II. OVERVIEW OF LINK ADAPTATION IN 5G NR

A. MULTI-DOMAIN LA IN 5G NR

Due to its unquestionable benefits to make efficient use of the radio links, LA was considered for 5G since the early discussions. LA aims at maximizing or minimizing a given metric subject to a maximum BLER. Typically, the problem has been formulated as the maximization of the binary rate (BR), e.g., for eMBB services. Still, LA might also be posed as the minimization of the transmitted power in other applications, e.g., mMTC.

Previous standards (like Long Term Evolution (LTE)) mainly rely on adaptive modulation and coding (AMC), closed loop MIMO precoding and power control for LA. However, 5G NR adds some innovative concepts as HBF [10], scalable numerology, BWPs or waveform selection, leading to a *multi-domain* LA approach with an unprecedented flexibility. These domains are explained as follows.

1) BWP AND NUMEROLOGY

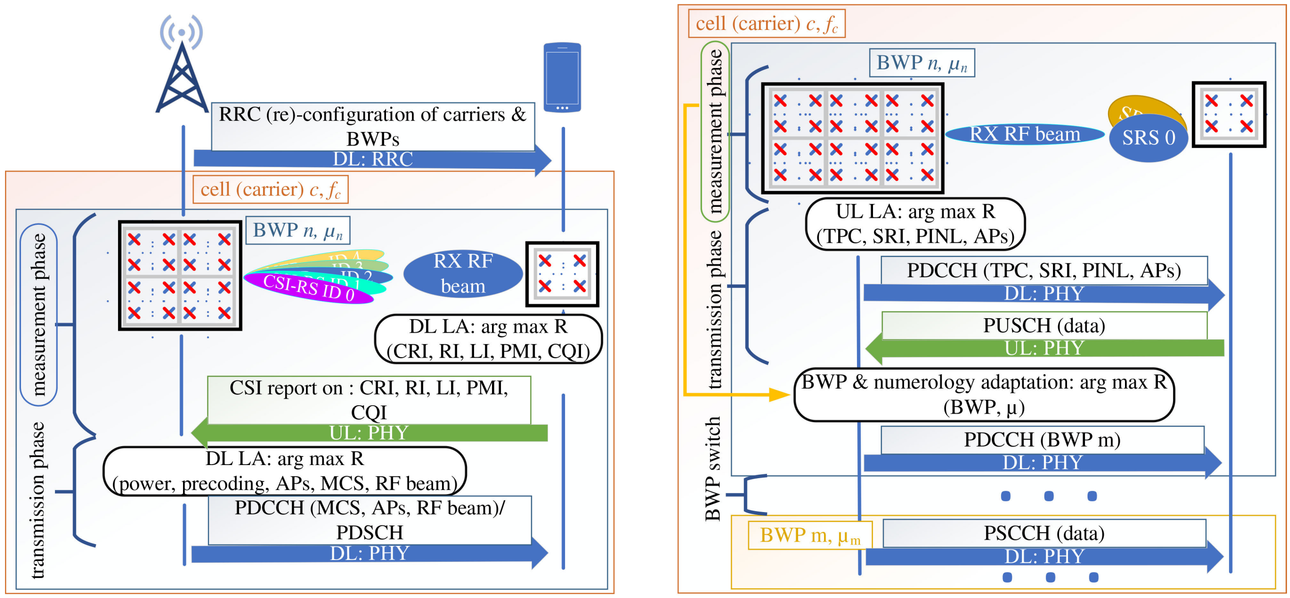
The BWP defines a portion of the bandwidth of each carrier. Up to four BWPs can be defined per carrier and link direction, but just one can be active at a time. BWPs aim at adapting the bandwidth size to the traffic demands to save energy. In addition, each BWP defines its own numerology (i.e., the sub-carrier spacing (SCS)) [6], so a BWP switch is needed to change the current numerology. This means that selecting the active BWP allows adaptation to the RF and channel conditions by selecting the most appropriate numerology. As the carrier frequency increases, RF impairments like phase noise or non-linear behavior of HPAs are exacerbated. To combat these effects, a higher SCS is needed [1]. However, a higher SCS implies that the OFDM symbol duration is reduced, which might lead to inter-symbol interference (ISI) if the delay spread of the channel is longer than the CP length.

2) WAVEFORM

While the DL waveform is fixed to CP-OFDM, the UL may use CP-OFDM or transform precoding [5], which is the name that 5G gives to discrete fourier transform spread OFDM (DFT-s-OFDM). CP-OFDM leads to higher spectral efficiency and better performance of MIMO techniques. Nevertheless, the peak to average power ratio (PAPR) of transform precoding is significantly smaller; this means that transmitted signals are less degraded by non-linear HPAs, thus leading to a lower BLER and smaller out-of-band emissions (OBE) [1].

TABLE 1. Summary of domains in 5G LA, potential benefits and trade-offs.

Domain	Benefits and trade-offs
BWP and numerology	◇ BWPs aim at adapting the bandwidth size to the traffic demands to save energy. A higher bandwidth size leads to a higher throughput, but at the expense of a higher energy consumption. ◇ It allows adaptation to channel conditions by selecting the most appropriate numerology. A higher numerology brings robustness against phase noise and Doppler spread, but it shortens symbol duration and might provoke ISI.
Waveform	◇ CP-OFDM or transform precoding can be used in the UL to mitigate the impact of non-linear HPAs. CP-OFDM exhibits a greater spectral efficiency (SE) and better MIMO performance, but transform precoding is associated with an smaller PAPR and OBE.
RF beam	◇ The principal RF beam is determined through initial access using a beam sweep based on the SSBs. ◇ Beam refinement aims at selecting the best beam after initial access, whereas beam tracking adapts to channel variations. ◇ Narrower beams lead to higher beamforming gain, but they are more sensitive to beam misalignment.
Power	◇ The BS decides the most suitable transmit power to be used in the UL and DL link directions. ◇ Increasing the transmit power provides coverage gain and increases the received signal power; but it increases the energy consumption and interference level towards neighboring cells.
Rank and MIMO precoding	◇ Rank adaptation allows selecting the best number of independent streams to be transmitted. ◇ A higher rank increases the throughput, whereas a smaller rank improves the beamforming gain.
MCS	◇ AMC selects the MCS that maximizes the throughput while ensuring a target BLER. ◇ A higher MCS leads to a higher SE but at the expense of a higher BLER.



(a) DL (b) UL

FIGURE 1. Multi-domain link adaptation on DL (a) and UL (b) of 5G NR.

3) RF BEAM

The principal RF beam is determined through initial access using a *beam sweep* based on the synchronization signal blocks (SSBs). This involves that the base station (BS) transmits a different SSB in a different access beam [11]. user equipments (UEs) search the best beam in terms of received power and transmit the preamble for initial access on a preamble occasion associated with that beam [12]. The mapping that exists between preamble occasions and DL RF beams allows the BS to identify the best initial beam for each UE after preamble reception [5], [6]. Afterwards, RF beam adaptation is carried out through *beam refinement* and *beam tracking* procedures [10]. Beam refinement aims at improving the link performance by selecting a narrower beam than the initial beam, whereas beam tracking aims at adapting to channel variations. Thus, beam tracking selects beams with a different steering angle that follows the UE movement to minimize the beam misalignment. There is a trafe-off between both procedures since narrower beams have a higher beamforming gain, but they exhibit a higher sensitivity to beam misalignment [13], [14]. Both procedures rely on CSI-RS that are transmitted on different RF beams. The UE measures the received power related to each channel state information reference signal (CSI-RS) and then informs about the set of K best beams using a physical layer reference signal received power (RSRP) report [12]. In addition, the best beam can be reported with the CSI-RS resource indicator (CRI) linked to a CSI report. In this case, the CSI is an index to the CSI-RS related to the best beam [5].

4) POWER

In the UL, a closed loop power control is applied. It means that the UE estimates an open loop transmit power to achieve a target nominal received power at the BS, P_0, scaled by a factor, $\alpha \in [0, 1]$, assuming the path loss estimated based on DL reference signal (RS). This DL path loss is used to compute an initial transmit power on the UL. Then, an offset, δ, is added to compensate for the differences between DL and UL paths. The BS transmits a transmit power control (TPC) command (with each UL grant) to increase or reduce such an offset, δ. Regarding the power used at DL, it is selected by the BS based on CSI reports. Each CSI report associated with a given UE assumes a physical downlink shared channel (PDSCH) power level that is signaled by higher layer configuration (i.e., radio resource configuration (RRC)) [6]. Using CSI reports linked to different PDSCH power levels, the BS can decide the most suitable transmit power for each UE. There is an interplay between transmitted power, coverage enhancement, and interference that must be considered by the power control algorithms in the UL and DL directions. On the one hand, increasing the transmit power increases the received power and thus extends the coverage of a given user. Nevertheless, this also increases the interference level in neighboring cells. Besides, increasing the transmit power might distort the transmitted signal and provoke OBE if the power level approaches the saturation point of the power amplifier.

5) RANK AND MIMO PRECODING

The rank, i.e., the number of layers, and the precoding matrix is adapted to the small scale variations of the equivalent MIMO channel. Rank adaptation is based on the actual rank of the channel matrix which determines the maximum number of independent streams that can be transmitted. The BS decides the transmission rank based on link conditions, selecting between spatial multiplexing or digital beamforming. With the selected rank and estimated channel matrix, the optimal precoding matrix is determined [10]. If channel reciprocity can be assumed in TDD mode, the rank and precoding matrix on the DL is based on the UL sounding reference signal (SRS). Otherwise, the UE selects the precoding matrix from the codebook and reports the related rank indicator (RI), precoding matrix indicator (PMI) and layer indicator (LI) metrics. This latter metric indicates the strongest layer.

6) MCS

AMC is the main feature of LA and it aims at selecting the highest MCS that fulfills a target BLER. On the UL, the MCS selection can be made based on the estimated effective signal to interference and noise ratio (SINR). The MCS selection for the DL is based on the channel quality indicator (CQI), which quantifies the effective SINR after MIMO detection and it is fed back from the UE to the BS. 5G NR specifications define 3 MCS tables listing all available MCSs for DL and UL without transform precoding and 2 tables for the UL with transform precoding. These tables differ on the maximum modulation order (i.e., 64-QAM or 256-QAM) and target BLER (i.e., 10^{-1} or 10^{-5}).

A summary of the multi-domain LA in 5G that illustrates the potential benefits and trade-offs is shown in Table 1.

B. SIGNALING ASPECTS OF LA IN 5G NR

The signaling procedures involved in this multi-domain LA are illustrated in the examples of Fig. 1 (a) and (b), for DL and UL, respectively. As it can be observed from Fig. 1 (a), there is a slow adaptation to radio conditions and quality of service (QoS) requirements that is achieved using RRC (re-)configuration of radio bearers. This RRC configuration sets the BWP parameters, which consists on BWP start and size on the resource grid, numerology, power control, beam management, CSI reports and CSI-RS related parameters among others.

Once the configuration is established, measurements are needed to perform LA for data transmission. Hence, different CSI-RSs are transmitted on different RF beams. Based on these CSI-RSs, the UE computes the best RF beam, and then it calculates the triplet of metrics related to rank and MIMO precoding adaptation (RI, PMI and LI) [5]. Finally, the UE performs AMC to select the highest MCS that fulfills a target BLER. All these metrics compose the CSI report. Afterwards, on the transmission phase, the BS uses this CSI report to complete LA and selects the RF beam, transmit power, precoding matrix, antenna ports (APs) used for transmission and MCS. The transmit power and precoding matrix do not need to be signaled; however, the rest of the parameters are signaled on the physical downlink control channel (PDCCH) [5].

The LA procedure for UL is illustrated on Fig. 1 (b). This procedure is initiated with the transmission of SRS on different beams. SRSs are linked to a particular usage, which can be either beam management or codebook selection. First, SRSs for beam management determine the set of K best beams on the UL. Then, a pair of SRSs are used for codebook selection. These SRSs allow determining the best RF beam among the 2 best beams, and the rank and MIMO precoding, which is identified by the related transmit precoding matrix indication (TPMI). On the UL grant, the BS signals the best beam with the PDCCH field SRS resource indicator (SRI), which identifies the best beam among 2 RF beams; the rank and TPMI are signaled with the precoding information and number of layers (PINL) field, the antenna ports with APs field, and the power control with the TPC field [5].

Finally, the BS can decide to switch the active BWP to change the numerology or waveform in order to react against radio propagation changes. Nevertheless, the BWP switch has a cost since there is a guard period during which no transmission is allowed. This period is needed to prepare receptions for the next BWP [5].

III. CHALLENGES AND OPPORTUNITIES FOR LA ON 5G AND BEYOND

A. CHANNEL ESTIMATION

Channel estimation is of paramount importance for LA, since accurate and updated CSI information is needed to adapt the transmission parameters to the instantaneous link conditions. The wide range of frequencies supported by 5G implies that the propagation mechanism and underlying channel model greatly differ from high and low frequency bands. For high frequency bands, channel estimation is especially challenging due to the non-linear nature of the channel [7]. In addition, the adoption of HBF, where the number RF chains is much smaller than the number of antennas, greatly increases the channel dimension, which complicates channel estimation [15]. To overcome such complexity and provide accurate CSI, the hybrid approach and spatial structure of antenna array must be considered. On [16], channel estimation for uniform multi-panel antenna array is considered. This work considers the fact that mmW channels have a sparsity feature in the beamspace domain to propose an orthogonal projection method. It is used to detect the support of the channel response vector. Then, least squares estimation is performed. The authors of [15] show that the beamspace channel elements can be modeled according to a Gaussian mixture distribution. They use this model to derive a new shrinking function for an approximated message passing algorithm implemented with a deep neural network (DNN). The case of multi-user MIMO with HBF is considered in [17]. The authors propose a deep learning compressed sensing method for channel estimation, which is trained offline using simulation results to predict the beamspace channel amplitude. Then the channel is reconstructed based on the obtained indices of dominant beamspace channel entries.

B. RF IMPAIRMENTS

The use of mmW front-ends leads to significant hardware non-idealities that compromise the transmitted signal quality. The main RF impairments in 5G NR are herein described.

1) NON-LINEARITY OF HPAs

Due to the inherent high PAPR of OFDM, HPAs at the transmitter work in its nonlinear region, leading to distortion and undesired out-of-band emission (OBE). Therefore, alternative waveforms based on single-carrier with low PAPR (like DFT-s-OFDM) has been typically used in the UL to enhance the coverage probability. In the mmW band, HPA efficiency is expected to be degraded, and hence, transform precoding must be considered for coverage enhancement purposes [1]. In addition, windowing and filtering can be used to improve spectral confinement, thus reducing OBE.

2) PHASE NOISE

Phase noise of local oscillators increases for higher carrier frequencies, hence becoming a challenge for mmW bands as it produces common phase error (CPE) and inter-carrier interference (ICI). 5G NR has introduced phase tracking reference signals (PTRS) to estimate and compensate the CPE. However, this procedure is not enough to compensate ICI, especially when the phase variation error is faster concerning the OFDM symbol duration. In this case, ICI may be minimized by selecting higher SCS (e.g., 120 or 240 kHz) [1].

3) IQ IMBALANCE

The effect of IQ imbalance is more severe in the mmW band than in the sub-6 GHz band, thus causing a significant degradation in the SINR. Note that IQ imbalance is frequency selective and the sources of IQ imbalance are located both in the transmitter and receiver. Therefore, a good approach to cope with IQ imbalance must consider frequency-dependent estimation and compensation at both communication ends.

Due to the non-idealities previously described and inherent variability in link conditions, LA mechanism requires a closed loop to keep the target BLER. The well-known outer loop link adaptation (OLLA) technique is able to minimize previous impairments by adapting the AMC switching thresholds instantaneously based on the reported ACK/NACK [18].

C. COMPLEX INTERFERENCE DYNAMICS

The dynamics of the interference significantly degrade LA performance, since they affect the estimation of the effective SINR, which is used for MCS selection. The main challenges related to interference dynamics in 5G NR are described next.

1) INTER-NUMEROLOGY INTERFERENCE (INI)

Frequency domain multiplexing of different OFDM numerologies leads to INI since only sub-carriers within a numerology are orthogonal to each other. INI may be reduced by inserting an additional guard band between numerologies and/or by applying spectral emission confinement techniques that limit the energy leaked towards other numerologies. Additionally, the receiver may also include filtering/windowing techniques so that the received INI is minimized.

2) CROSS-LINK INTERFERENCE (CLI)

Spectrum utility in 5G NR can be increased through dynamic TDD. However, this flexibility for selecting the transmission direction makes interference dynamics more intricate by adding cross-link interference, i.e. BS-to-BS interference and UE-to-UE interference. As the DL generally has much higher transmit power than the UL, the impact of BS-to-BS interference is usually more adverse. Current research to mitigate CLI is extensive, covering clustering schemes, scheduling, and resource allocation techniques, advanced power control, MIMO beamforming techniques or coordinated UL/DL configuration, among others [8].

3) REMOTE INTERFERENCE

To protect the UL from DL CLI in dynamic TDD systems, a guard period is typically used when switching from DL to UL. However, during certain atmospheric conditions, tropospheric ducting may transport the radio signals along hundreds of kilometers with low propagation losses, causing significant interference to remote cells. For this reason, remote interference management (RIM) mechanisms have been standardized in Release 16 to mitigate such interference.

4) IMPACT OF INTERFERENCE ON URLLC SERVICES

Fast varying CLI and switching time of configurations in dynamic TDD systems may lead to additional HARQ retransmissions that complicate to satisfy the URLLC target. This problem is more involved when multiplexing different types of traffic with different priorities and transmission directions. This challenge may be partially addressed by configuring hybrid (static and dynamic) radio slot sets.

IV. ML-ENABLED LA FOR 5G AND BEYOND

A. CLASSIFICATION OF ML TECHNIQUES

ML is a key enabler for 5G and beyond networks since it allows solving complex problems without explicit programming and provide fast adaptation to dynamic environments [7]. ML techniques can be classified according to how training data is used as: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning aims to infer a function using inputs with its desired labeled output. Depending on the output type, supervised learning can be divided as classification (discrete output) or regression (continuous output). K-nearest neighbors (KNN), support vector machines (SVM) and logistic regression (LR) are three of the most extended algorithms for supervised learning [19]. In unsupervised learning, no labeled data is provided and the aim of the learning agent is to find hidden features or structure of the data. Examples of this type include clustering analysis and dimensional analytic reduction. With reinforcement learning, a learning agent tries to maximize the cumulative weighted reward obtained from interactions with the environment. This reward depends on the action made by the agent and the state of the environment. In addition, the environment evolves to a new state based on the current state and the action made by the agent [20].

Deep learning is a subset of ML algorithms, where a multi-layer network uses inter-connected nodes for feature extraction and transformation. The output of a given layer is used by the following layer as input. According to the manner in which the training data is used, deep learning algorithms can be classified also as supervised, unsupervised or reinforcement deep learning [9].

Finally, according to the number of nodes involved in the learning process, ML techniques can be classified as centralized, where a single node trains the model, or decentralized, where several nodes participate in the learning process. Federated is one of the most promising decentralized approaches since it leads to high privacy, it requires limited communication bandwidth between nodes, and it has smaller latency than other decentralized approaches [21]. With federated learning, a specific ML model is trained collaboratively by several nodes, called *clients*, over many iterations. At one iteration, each client computes a local model update, using its local data, that is shared with a *server* that performs global model update based on the local updates of all the clients. Since the raw data is not exchanged between nodes, the privacy is high whereas the communication requirement and latency are limited.

B. EMERGING APPLICATIONS OF ML TO LA AND MAIN CHALLENGES

The introduction of new extreme services like URLLC or eMBB with different quality requirements together with the use of disrupting features like HBF or scalable numerology have made conventional LA techniques to be outdated. On the one hand, traditional LA based on rank adaptation and MCS selection according to SINR thresholds does not capture the complex nature of the channel nor interference. It leads to either not fulfilling the target BLER or to a throughput reduction [22]. For these reasons, recent works present different LA enhancements relying on different ML frameworks.

In [22], a multi-user HBF link adaptation method based on supervised ML is proposed. The method first computes the number of RF chains required for each user based on its distance towards the serving BS. Then, a two-stage link adaptation is performed. In a first stage, digital precoding is switched off if there is a single dominant path. In a second stage, the transmission scheme is selected, i.e., multiplexing or diversity transmission mode and the MCS to fulfill a target BLER while maximizing the throughput. This latter stage is implemented via supervised learning invoking KNN classification technique.

A deep learning framework based on convolutional neural networks (CNN) for AMC on a MIMO-OFDM system with spatial multiplexing is presented on [23]. AMC is treated here as a multi-class classification problem where each class represents a specific MCS and the number of spatial streams. The use of CNN allows using the estimated channel matrix and the noise as features for this multi-class classification. This avoids the need for preprocessing to reduce the dimension of the features, which might lead to performance degradation.

In [24], two ML frameworks are proposed for link adaptation with spatial modulation. Firstly, the problems of transmit antenna selection and power allocations are treated from a learning data driven perspective. Then, two frameworks, one based on supervised learning with KNN and SVM, and another based on DNN, are proposed using the modulus and correlation of the channel matrix coefficients.

In [25], a learning algorithm using back propagation artificial neural network is proposed for AMC. In this latter case the estimated channel, interference and noise are used as features for the learning process. It is shown that the proposal outperforms classical AMC in terms of throughput while fulfilling a target BLER.

A recent approach is the application of reinforcement learning for LA. This approach has been rigorously modeled as a multi-armed bandit (MAB) problem in [26], where each candidate MCS is encoded as a discrete arm of a multi-armed bandit. The MAB model is optimized using an statistical technique named upper confidence bound (UCB). With this scheme, the modeling complexity scales linearly with the number of candidate MCSs. As a result, the model is resource-intensive and inefficient to train in real time.

A novel work in this area is presented in [27], where the reinforcement learning algorithm for LA is based in latent Thompson sampling to overcome the limitations of [26]. The proposed algorithm adopts a probabilistic model of the channel SINR whose parameters are learned from the ACK/NACK feedback related to previous transmissions. Thanks to the use of latent Thompson sampling the algorithm is able to quickly estimate the channel state from only a few ACK/NACKs.

Nevertheless, the reinforcement learning approaches for LA that are proposed in [26] and [27] do not consider a target BLER. Instead, they maximize the SE of correctly transmitted bits per second and hertz. This is in sharp contrast with 4G and 5G cellular networks where a maximum permissible (i.e., target) BLER of the first transmission attempt is defined. This is of paramount importance because the target BLER is a key metric that has to be guaranteed by PHY and MAC layers for different services, e.g., eMMB services require a target BLER of 10^{-1} whereas URLLC require 10^{-5}. In addition, the BLER has a strong impact on the delay, since a higher BLER involves a higher delay due to the additional transmission attempts carried out by HARQ protocol until successful transmission.

Despite of the potential of ML techniques to improve the performance of LA in 5G and beyond networks, there are a number of challenges and open issues that need to be addressed. The main challenges are summarized as follows:

Black box nature: A major drawback of some ML algorithms, e.g., DNN, is their black box nature. This means that the ML algorithm is treated as a black box that is trained using a data set, and provide some desired outputs based on the inputs. Nevertheless, we do not have a deep comprehension about the behavior of the trained model, since we do not know the reasons behind the decisions taken by the algorithm. This makes difficult to tackle failures of the algorithm or to predict the impact of changes on the environment in terms of performance. Since LA on 5G aims at supporting a plethora of different scenarios on different kind of networks, this issue represents an on-going research challenge that needs to be solved [28].

Availability of training data: Standardized and labeled data sets for testing, validation and comparison of developed ML algorithms are extensively used in fields such as speech processing, computer vision or health-care applications. Nevertheless, there are not standardized data sets for wireless applications and operators and vendors have preferred traditionally to keep their data sets confidentially [29]. It is expected that this situation will change in the future as ML techniques gain relevance for future wireless communication networks. Since the performance of LA highly depends on the UE receiver capabilities and impairments, the required standardized date set would be huge, covering different UE implementations, interference patterns and channel scenarios.

Limited computational and memory resources: The great performance improvements that offer data-driven ML techniques require powerful computing capabilities and huge storage capabilities that are not possible with UE devices limited by computation, memory, and energy resources [28]. To overcome these limitations, cloud or edge processing is proposed as a promising solution where all the data collected by the devices is transferred to central unit to be processed. Nevertheless, this approach uses the wireless communication medium, which is always an scarce resource, and thus the data should be transmitted through a limited feedback channel. This is a paramount issue since the overhead needed to perform the training should be kept as small as possible, otherwise, the performance improvement of ML techniques might be counteracted by the additional data exchange. The fact that LA on 5G is a closed loop scheme where the BSs already acquire CSI information from the CSI reports for the DL and from the reference signals, e.g., SRS, for the UL, makes it suitable for a data-driven training at the edge. This is because the training can be based on the existing data exchange that is part of the LA scheme on 5G.

Privacy and security: The exchange of information that is needed for cloud or edge processing or even for decentralized training poses important issues with respect to privacy and security. This transfer of information increases the risk of launching inference attacks that aim to infer sensitive information from the users' training data. ML approaches should ensure that this sensitive information is safe and confidential. Federated learning might be a potential solution for this issue since the training is done locally at each node, and then it is combined at the cloud. This involves that no raw data is exchanged, which increases privacy and security.

Standardization and interoperability: A key factor in the commercial success of wireless communications is the interoperability between modules of different vendors, since this increases the competition and thus reduces the cost. This interoperability is especially relevant and challenging when ML techniques are applied to wireless networks. Here, any inconsistency between ML learning modules of different vendors can severely degrade the network performance [30]. Standardizing the interfaces between different modules is a key enabler for the application of ML techniques to wireless communications since it guarantees interoperability [20]. In this context, there is an initiative named open radio access network (O-RAN), that aims at standardizing most of the interfaces that have been kept as internal (i.e., vendor specific) in current 5G standard. O-RAN defines a RAN intelligent controller (RIC) for both real-time and non-real-time protocol stacks to ease interoperability between ML modules of different vendors [30].

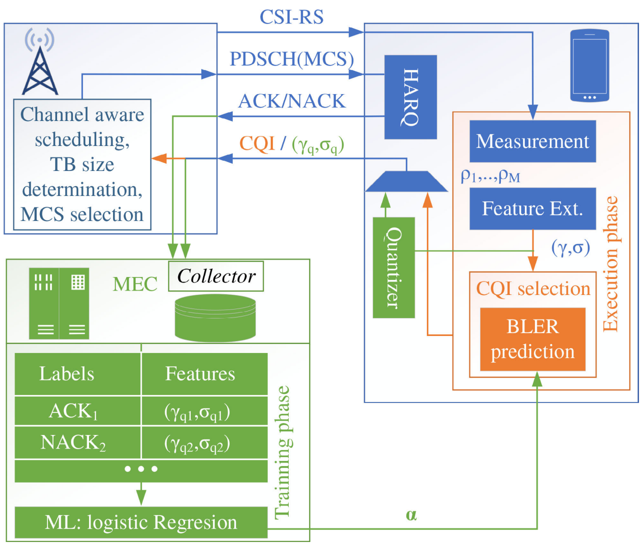


FIGURE 2. Block diagram of AMC based on logistic regression ML.

C. SUPERVISED LEARNING BASED ON LOGISTIC REGRESSION FOR AMC

As pointed out in our previous work [31], OLLA may not work properly in 5G scenarios when considering scalable numerology or distinct BLER targets per service, besides non-convergence for optimum fading region design. In fact, we showed that OLLA converges in average to a sub-optimal solution, concluding that novel flexible link adaptation implementation techniques for 5G based on machine learning are required.

In this section, a supervised learning framework based on LR for AMC is presented and compared with OLLA. We have focused on AMC to show the potential of the application of ML techniques to LA, since the MCS is one of the domains with higher impact on the BLER and throughput, which are key metric in wireless communications. For this reason AMC has received much attention in academia and industry to perform LA. Nevertheless, a real LA implementation for 5G must consider the other domains, and here ML techniques can be of great help, as justified in previous sections. We have selected supervised learning because AMC in 5G offers labeled data automatically that can be efficiently used to train the model. The BLER for a given MCS and transport block (TB) size depends on the UE implementation and on the channel state, which can be understood as the SINR per sub-carrier and symbol. The ACK/NACK feedback that the UE sends after PDSCH reception represents the labels of the data, which are the used MCS, TB size and channel state. The used MCS and TB size are known by the UE and the network, whereas the channel state is estimated on the UE side, and later processed and sent via a limited feedback channel to the BS in the form of a CSI/CQI report.

Our AMC scheme is illustrated in Fig. 2, where two different phases are described. Those blocks and metrics related to the *training phase* are drawn in green whereas the elements associated with the *execution phase* are marked in orange. Blue color is reserved to those elements related to both phases.

First, a vector of SINRs per resource block group in the frequency domain is measured by a given user. Extending our previous conference work [32], we have selected as features: the average SINR, γ, the variance, σ, the MCS index and the number of physical resource blocks (PRBs) related to a TB transmission. We keep as low as possible the number of features since an extensive dimension of the feature space leads to a much higher number of training samples for correct decision-making [22]. Additionally, it requires more information exchange. We estimate the SINR from realistic measurements since the performance of the LA considerably decreases when more realistic scenarios are considered [33], [34]. The mismatch between the actual (i.e., perfect) SINR, and the estimated SINR causes a degradation in terms of performance since the decision about the selected MCS is contaminated by the estimation error. Moreover, contrary to [32], we present results after training and execution of algorithms carried out with limited information. The impact of quantifying the information used for training is a key issue to perform an accurate evaluation of the framework, taking into account that the training can be carried out on the network side.

In this respect, machine training can be carried out on a real *live underlay network* or over a *sandbox* so that their effects on the network can be evaluated but preventing that the ML application affects the network [35]. The sandbox might be a real network but also emulated with the help of testing tools or simulated by software. We have considered that the model training is always carried out on the network side (mobile edge computing (MEC) or cloud) to relieve the UE to do such a complex task, although other possibilities, such as federated learning might be also considered.

The CQI selection looks for the higher MCS that leads to a BLER below the target. It is achieved using the BLER prediction based on LR. There are other approaches (like SVM) that might have followed, although we have chosen an LR model as it has reduced complexity [36], [37] and it is well known to work correctly for any physical scenario it was trained [38]. Besides of this, LR performs regression of the data to a sigmoid function, which is especially appealing to model S-shaped functions such as the BLER versus SINR curve associated to wireless communications systems [38]. In the present work, the model uses the mean and variance of the SINR, the index of the MCS and the number of PRBs. Hence, the BLER predicted at the UE side requires the following computation

$$\mathrm{i}\hat{\mathrm{BLER}}(\Psi) = \frac{1}{1+\exp\left(-\sum_{k=1}^{n_f}\alpha_k\Psi_k\right)} \tag{1}$$

where $\mathrm{i}\hat{\mathrm{BLER}}$ represents the predicted instantaneous BLER according to a feature vector $\Psi = [\gamma, \sigma, \mathrm{i}_{\mathrm{MCS}}, n_{\mathrm{PRB}}]$, with $n_f = 4$ and being Ψ_k its k-th element. Here, $\mathrm{i}_{\mathrm{MCS}}$ represents the MCS index, whereas n_{PRB} represents the number of

PRBs. The vector $\alpha = [\alpha_1, \ldots \alpha_{n_f}]$ represents the parameters of the model that are obtained as a result of the training performed at the MEC. Once these parameters are computed, they are transmitted to the intended UEs to be used in BLER prediction. It should be noticed that it is being used full precision for the mean and variance of the SINR in prediction. This is due to the fact that the prediction is made at the UE side as it is a non-complex task. The training, however, is computationally more complex and thus the features are quantized and sent through a limited feedback channel to perform the learning process at the MEC.

According to the above formula, the computational complexity is limited since it involves 4 summations, 4 multiplications, one inversion and one exponential. To select a given MSC to perform LA, the UE checks the higher MCS index whose predicted BLER is smaller than the target BLER of 10^{-1}. Since there are 28 MCS indexes, in the worst case, the BLER prediction given by the above expression is preformed 28 times for a given CQI report. The overall overhead in terms of the information exchange needed to perform the training at the MEC is 5 bits per data sample: 4 bits are required for the quantized mean and variance; and 1 for the ACK/NACK that represents the label of the data.

The collector brings together data sets from different users as far as they can be considered as equivalent: the performance is highly dependent on the actual implementation (e.g., on the decoding algorithm), which is improved as manufacturers design new phones). Different BLER models can be developed per constellation, coding rate, TB size, etc., but we have obtained a single regression model by adding the MCS and number of allocated PRB as features. As MCS and number of PRBs are known at the network side, only mean and variance metrics are quantized (γ_q, σ_q) and sent to the BS via a limited feedback channel together with the related hybrid automatic repeat request (HARQ) report, i.e., ACK or NACK. Minor modifications on the 5G NR specs are required since sending these metrics with a related HARQ report is not allowed. Performing the training on the UE side would be compliant with the 5G NR specifications; nevertheless, this would involve higher computational capabilities at the terminal side.

Once the model is trained, the network *machine learning function orchestrator (MLFO)* is in charge of selecting which *ML intent* to apply and placing and chaining the nodes to form the ML pipeline. For example, our BLER prediction model might be instantiated at the UE but also at MEC, which brings the high computational capabilities of the cloud, without increasing the latency nor network traffic. In the last case, feature values should be quantized in order to be sent to the MEC by the UE, while full precision values of γ and σ might be used if the prediction is carried out at the device. The prediction of the model is distributed to those nodes for which it is of interest. In our example, the CQI function selects the highest MCS that fulfills the target BLER for the grant allocation.

In the training phase, the transmitted TBs might carry real data; yet fulfilling the target BLER is not guaranteed at this stage because the model is not trained. Nevertheless, once the execution phase starts the target BLER is guaranteed and the throughput is maximized. During this phase LA behaves as a real-time function of the PHY & MAC protocol stack.

The proposed scheme of Fig. 2 has been simulated based on the 5G NR standard under realistic channel conditions. To this end, an ad-hoc simulator has been developed by the authors. The simulator is written in MATLAB and uses the *5G* and the *Statistics and Machine Learning* toolboxes. The simulator implements the physical and transport channel processing of the PDSCH channel according to [39], [40] and [5]. This includes among other features the transport block size determination, rate matching, CRC attachment, low density parity check (LDPC) encoding and decoding, coded block segmentation and concatenation and the OFDM modulation and demodulation following the frame and grid structure of the 5G NR standard. The channel estimation is based on the demodulation reference signal (DMRS) and the channel estimates are used to perform minimum mean square error (MMSE) equalization. The implementation is limited to a single carrier with a single BWP. The PDCCH channel has not been implemented, and thus it is assumed that the UE is aware of the PDSCH resource allocations. A TDL-A channel model at 3.35 GHz has been considered, with a maximum Doppler frequency of 50 Hz. A SCS of 30 kHz is used and the channel estimation uses a DMRS configuration involving 3 single symbol DMRSs. The PDSCH allocations consist of 12 symbols with 6 PRBs. A maximum of 4 bits has been assumed to quantize γ and σ. We have considered two options to quantify the bits used for training: i) 3 bits for γ and 1 bit for σ; and ii) all 4 bits for γ (σ is not used).

CSI signals have not been implemented in this simulator, but the SINR values are obtained through a realistic estimation based on DMRS signals. Such an estimation undergoes estimation errors and impairments due to the time and frequency selectivity of the channel and the additive noise. The time selectivity might cause ICI whereas the frequency selectivity involves that the SINR is different for different sub-carriers. The estimation of the SINR is performed at two stages. Firstly, it is estimated the noise plus interference power, N_{eq}, as follows [32]

$$N_{\mathrm{eq}} = \frac{1}{N} \sum_{n=0}^{N-1} \left| y_n - \hat{h}_n x_n \right|^2 \tag{2}$$

where N is the number of sub-carriers with DMRS pilots within the PDSCH allocation in a given slot. y_n stands for the complex IQ received symbol after synchronization, cyclic prefix extraction and the fast Fourier transform (FFT) for the n-th sub-carrier. x_n represents the transmitted DMRS pilot (i.e., DMRS IQ complex symbol) at the n-th sub-carrier, whose power is $S = \mathbb{E}[|x_n|^2]$, and $\hat{h}_n$ is the estimated complex channel gain at the n-th sub-carrier, which is also subject to estimation errors. Afterwards, the SINR at sub-carrier n-th,

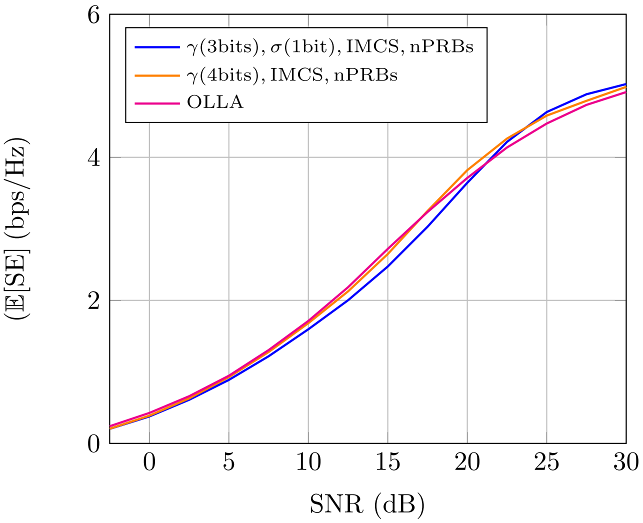


FIGURE 3. Average SE for OLLA and LR approaches with 4 available bits to feedback the features γ_q and σ_q.

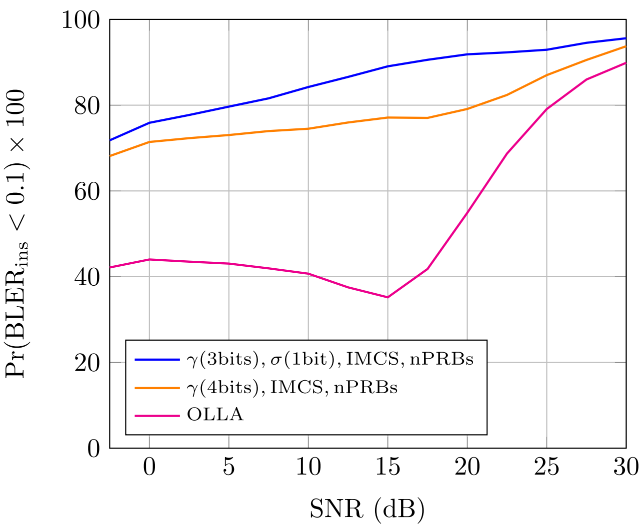


FIGURE 4. Percentage of time of having an instantaneous BLER smaller than the target BLER, 0.1, for OLLA and LR.

γ_n, is estimated as follows

$$\gamma_n = \frac{S}{N_{eq}} \left|\hat{h}_n\right|^2 \tag{3}$$

The vector of estimated SINR values for the N sub-carriers with DMRS pilots in the whole PDSCH allocation is used to compute the mean and variance of the SINR, which are the main features

$$\gamma = \frac{1}{N} \sum_{n=1}^{N} \gamma_n; \quad \sigma^2 = \frac{1}{N} \sum_{n=1}^{N} (\gamma_n - \gamma)^2. \tag{4}$$

Nevertheless, as mentioned, due to the use of a limited feedback channel, those metrics are quantized to get the final features used for the training on the MEC (γ_q, σ_q).

Fig. 3, 4 and 5 illustrate a comparison between our proposed AMC based on LR and OLLA algorithm in terms of spectral efficiency (SE) and BLER. The average spectral efficiency, $\mathbb{E}[\text{SE}]$, in Fig. 3 has been computed as the average

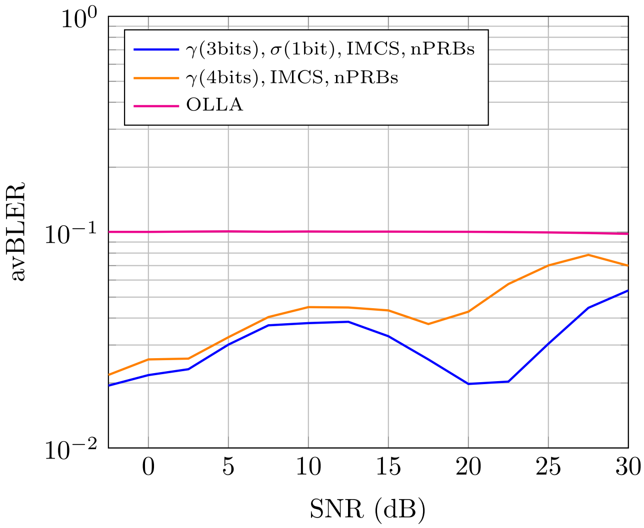


FIGURE 5. Average BLER for OLLA and LR schemes.

number of bits per second per hertz (bps/Hz) successfully transmitted according to the selected MCS. Such metric has been computed via Monte Carlo simulation, and it can be expressed as follows

$$\mathbb{E}[\text{SE}] = \frac{1}{n_{\text{slot}}} \sum_{i_{slot}=0}^{n_{slot}} \text{SE}_{i_{slot}} \cdot \text{ACK}_{i_{slot}} \tag{5}$$

where n_{slot} represents the number of slots to be simulated, $\text{SE}_{i_{slot}}$ represents the spectral efficiency associated with the MCS selected for the TB transmission in the i_{slot}-th slot. $\text{ACK}_{i_{slot}}$ is an indicator function that is equal to 1 if the TB transmitted in the i_{slot}-th slot is decoded correctly, whereas it is equal to 0 otherwise. The MCS values are according to table 5.1.3.1-1 of [5] and thus they range from MCS index 0, which has an SE of 0.2344 bps/Hz, up to MCS index 28, whose SE is 5.5547 bps/Hz. OLLA algorithm considers an SINR offset that is adjusted with each reception based on the decoding results, i.e., ACK or NACK. This offset is added to the estimated effective SINR. Hence, it aims at improving the stored SINR thresholds of conventional AMC to the current channel statistics and receiver impairments. Despite their differences, it can be argued that OLLA follows a similar approach to reinforcement learning in the sense that the state, i.e., the offset, is modified based on the rewards given by the environment, i.e., ACK or NACK. However, since the offset is adjusted based on TB reception, this algorithm is not suitable for low traffic demands or high user mobility since the convergence speed of the offset might not be fast enough to adapt to rapid channel fluctuations. In addition, URLLC services with target BLER of 10^{-5} are not appropriate for OLLA, which would need too long time to converge. The simulation considers full buffer traffic, which is the case where OLLA behaves better, since each time slot can be used to update the SINR offset. HARQ retransmissions are not considered and thus the BLER results represents the error rate of the first transmission attempt.

Fig. 3 shows that the proposed LR leads to a similar average SE to OLLA even with full buffer traffic. In addition, results show that the difference in terms of average SE between the two options to quantize the features for LR is negligible.

Nevertheless, as it is observed from Fig. 4, the percentage of time that the target BLER is fulfilled is superior in the case of LR. This means that LR predicts the BLER better than OLLA, thus providing a smaller instantaneous BLER while offering the same average SE. The instantaneous BLER represents the error rate that can be expected at a given time slot, and thus it is a time-varying metric. Hence, Fig. 4 represents the percentage of time that the instantaneous BLER is below the target BLER. In real systems, it is important keep the percentage of time that the target BLER is fulfilled as high as possible since the instantaneous BLER has a strong impact on the QoS experienced by the users. Even in a scenario where the target BLER is fulfilled in average terms, if the target BLER is not fulfilled at some time instants, the users will experience time periods with high packet losses. Besides, if the instantaneous BLER increases at some time instants, the packet delay will be also increased since a higher number of retransmissions will be required.

Among the two options considered for LR, the quantization scheme that includes the variance of the SINR, σ_q, with just 1 bit achieves a higher percentage of time fulfilling the target BLER that the other option with 4 bits for the mean. This justifies that the variance of the SINR has a valuable information for BLER prediction, and thus it is more beneficial to allocate 1 bit to include the variance, σ_q, rather than using that bit to increase the precision of the mean (without including the variance).

As it can be observed from Fig. 4, this target BLER is not fulfilled in all the transmissions because of the outdated CSI, since the prediction is made at some time slot, but used later. Yet, it is important to remark that the average BLER is smaller than the target BLER for the 3 considered approaches as shown in Fig. 5. As it can be observed, OLLA achieves an average BLER quite close to the target BLER of 0.1, which is expected since OLLA aims at fulfilling the target BLER in averaged terms. Nevertheless, as illustrated in Fig. 4 the percentage of time that OLLA fulfills the target BLER is quite small, which has implications on the QoS experienced by the users and others metrics like packet delay. The LR schemes on the other hand leads to a smaller average BLER than OLLA, and the scheme with 1 bit for the variance leads to a smaller average BLER than the scheme with 4 bits for the mean. Nevertheless, having a smaller average BLER than OLLA does not involve that the average SE of LR approaches is smaller than the one obtained with OLLA as it was confirmed with Fig. 3. This demonstrates that the proposed scheme brings benefits in terms of BLER without any penalty on the SE.

V. CONCLUSION

In this paper, the main aspects of the *multi-domain* link adaptation in 5G NR have been presented, emphasizing the signaling aspects and differences regarding previous standards. Then, the main challenges of this multi-domain LA on the diverse set of scenarios envisioned for 5G are presented. ML algorithms are introduced, followed by a small overview of latest advances on ML frameworks for link adaptation. Finally, a scheme of supervised learning based on logistic regression is presented. With this scheme, the training is performed at the network side to relieve the UE to do such a complex task. Numerical results show that our ML approach outperforms OLLA in terms of instantaneous BLER, while reaching the same average SE. Interestingly, it has been shown that the proposed scheme only requires 4 bits to represent the features used to train the model, which makes it suitable for implementation in real systems with limited feedback.

REFERENCES

[1] A. A. Zaidi, R. Baldemair, V. Moles-Cases, N. He, K. Werner, and A. Cedergren, "OFDM numerology design for 5G new radio to support IoT, eMBB, and MBSFN," *IEEE Commun. Standards Mag.*, vol. 2, no. 2, pp. 78–83, Jun. 2018.

[2] A. Ghosh, A. Maeder, M. Baker, and D. Chandramouli, "5G evolution: A view on 5G cellular technology beyond 3GPP release 15," *IEEE Access*, vol. 7, pp. 127639–127651, 2019.

[3] O. El Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, Jr., "Spatially sparse precoding in millimeter wave MIMO systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 3, pp. 1499–1513, Mar. 2014.

[4] J. Liu, K. Au, A. Maaref, J. Luo, H. Baligh, H. Tong, A. Chassaigne, and J. Lorca, "Initial access, mobility, and user-centric multi-beam operation in 5G new radio," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 35–41, Mar. 2018.

[5] *Technical Specification Group Radio Access Network; NR; Physical Layer Procedures for Data (Release 16)*, Standard TS 38.214, Rev. 16.4.0, 3GPP, 3rd Generation Partnership Project (3GPP), Jan. 2021.

[6] *Technical Specification Group Radio Access Network; NR; Radio Resource Control (RRC) Protocol Specification (Release 16)*, Standard TS 38.331, Rev. 16.3.1, 3rd Generation Partnership Project (3GPP), Jan. 2021.

[7] C.-X. Wang, M. D. Renzo, S. Stanczak, S. Wang, and E. G. Larsson, "Artificial intelligence enabled wireless networking for 5G and beyond: Recent advances and future challenges," *IEEE Wireless Commun.*, vol. 27, no. 1, pp. 16–23, Feb. 2020.

[8] H. Kim, J. Kim, and D. Hong, "Dynamic TDD systems for 5G and beyond: A survey of cross-link interference mitigation," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 4, pp. 2315–2348, 4th Quart., 2020.

[9] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, "Thirty years of machine learning: The road to Pareto-optimal wireless networks," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 3, pp. 1472–1514, 3rd Quart., 2020.

[10] E. Onggosanusi, M. S. Rahman, L. Guo, Y. Kwak, H. Noh, Y. Kim, S. Faxer, M. Harrison, M. Frenne, S. Grant, and R. Chen, "Modular and high-resolution channel state information and beam management for 5G new radio," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 48–55, Mar. 2018.

[11] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "Standalone and non-standalone beam management for 3GPP NR at mmWaves," *IEEE Commun. Mag.*, vol. 57, no. 4, pp. 123–129, Apr. 2019.

[12] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "A tutorial on beam management for 3GPP NR at mmWave frequencies," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 1, pp. 173–196, 1st Quart., 2018.

[13] J. Fan, L. Han, X. Luo, Y. Zhang, and J. Joung, "Beamwidth design for beam scanning in millimeter-wave cellular networks," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 1111–1116, Jan. 2020.

[14] V. Va, H. Vikalo, and R. W. Heath, "Beam tracking for mobile millimeter wave communication systems," in *Proc. IEEE Global Conf. Signal Inf. Process. (GlobalSIP)*, Dec. 2016, pp. 743–747.

[15] X. Wei, C. Hu, and L. Dai, "Deep learning for beamspace channel estimation in millimeter-wave massive MIMO systems," *IEEE Trans. Commun.*, vol. 69, no. 1, pp. 182–193, Jan. 2021.

[16] W. Wang and W. Zhang, "Orthogonal projection-based channel estimation for multi-panel millimeter wave MIMO," *IEEE Trans. Commun.*, vol. 68, no. 4, pp. 2173–2187, Apr. 2020.
[17] M. Wenyan, Q. Chenhao, Z. Zhang, and J. Cheng, "Sparse channel estimation and hybrid precoding using deep learning for millimeter wave massive MIMO," *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 2838–2849, Feb. 2020.
[18] F. Blanquez-Casado, G. Gomez, M. del Carmen Aguayo-Torres, and J. T. Entrambasaguas, "eOLLA: An enhanced outer loop link adaptation for cellular networks," *EURASIP J. Wireless Commun. Netw.*, vol. 2016, no. 1, p. 20, Jan. 2016.
[19] J. Kaur, M. A. Khan, M. Iftikhar, M. Imran, and Q. E. Ul Haq, "Machine learning techniques for 5G and beyond," *IEEE Access*, vol. 9, pp. 23472–23488, 2021.
[20] S. Han, T. Xie, C.-L. I, L. Chai, Z. Liu, Y. Yuan, and C. Cui, "Artificial-intelligence-enabled air interface for 6G: Solutions, challenges, and standardization impacts," *IEEE Commun. Mag.*, vol. 58, no. 10, pp. 73–79, Oct. 2020.
[21] O. A. Wahab, A. Mourad, H. Otrok, and T. Taleb, "Federated machine learning: Survey, multi-level classification, desirable criteria and future directions in communication and networking systems," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 2, pp. 1342–1397, 2nd Quart., 2021.
[22] K. Satyanarayana, M. El-Hajjar, A. A. M. Mourad, and L. Hanzo, "Multi-user hybrid beamforming relying on learning-aided link-adaptation for mmWave systems," *IEEE Access*, vol. 7, pp. 23197–23209, 2019.
[23] M. Elwekeil, S. Jiang, T. Wang, and S. Zhang, "Deep convolutional neural networks for link adaptations in MIMO-OFDM wireless systems," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 665–668, Jun. 2019.
[24] P. Yang, Y. Xiao, M. Xiao, Y. L. Guan, S. Li, and W. Xiang, "Adaptive spatial modulation MIMO based on machine learning," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 9, pp. 2117–2131, Sep. 2019.
[25] L.-S. Chen, W.-H. Chung, I.-Y. Chen, and S.-Y. Kuo, "AMC with a BP-ANN scheme for 5G enhanced mobile broadband," *IEEE Access*, early access, Sep. 18, 2020, doi: 10.1109/ACCESS.2020.3024726.
[26] R. Combes, J. Ok, A. Proutiere, D. Yun, and Y. Yi, "Optimal rate sampling in 802.11 systems: Theory, design, and implementation," *IEEE Trans. Mobile Comput.*, vol. 18, no. 5, pp. 1145–1158, May 2019.
[27] V. Saxena, H. Tullberg, and J. Jalden, "Reinforcement learning for efficient and tuning-free link adaptation," *IEEE Trans. Wireless Commun.*, early access, Jul. 28, 2021, doi: 10.1109/TWC.2021.3098972.
[28] D. Gunduz, P. de Kerret, N. Sidiroupoulos, D. Gesbert, C. Murthy, and M. van der Schaar, "Machine learning in the air," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2184–2199, Oct. 2019.
[29] Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of machine learning in wireless networks: Key techniques and open issues," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3072–3108, 4th Quart., 2019.
[30] R. Shafin, L. Liu, V. Chandrasekhar, H. Chen, J. Reed, and J. Zhang, "Artificial intelligence-enabled cellular networks: A critical path to beyond-5G and 6G," *IEEE Wireless Commun.*, vol. 27, no. 2, pp. 212–217, Apr. 2019.
[31] F. Blanquez-Casado, M. D. C. A. Torres, and G. Gomez, "Link adaptation mechanisms based on logistic regression modeling," *IEEE Commun. Lett.*, vol. 23, no. 5, pp. 942–945, May 2019.
[32] J. C. Ruiz-Sicilia and M. C. Aguayo-Torres, "Logistic regression for BLER prediction in 5G," in *Proc. Simposio Nacional de la Unión Científica Internacional de Radio (URSI)*, Málaga, Spain, Sep. 2020. [Online]. Available: https://hdl.handle.net/10630/19923
[33] X. Yu, S.-H. Leung, W. Ho Mow, and W.-K. Wong, "Performance of variable-power adaptive modulation with space–time coding and imperfect CSI in MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 58, no. 4, pp. 2115–2120, May 2009.
[34] Q. Kuang, S. H. Leung, and X. Yu, "Adaptive modulation and joint temporal spatial power allocation for OSTBC MIMO systems with imperfect CSI," *IEEE Trans. Commun.*, vol. 60, no. 7, pp. 1914–1924, Jul. 2012.
[35] *Architectural Framework for Machine Learning in Future Networks Including IMT-2020*, document ITU-T, Y.3172, Telecommunication Standardization Sector of International Telecommunication Union (ITU-T), Jun. 2019.
[36] A. Singh, N. Thakur, and A. Sharma, "A review of supervised machine learning algorithms," in *Proc. 3rd Int. Conf. Comput. Sustain. Global Develop. (INDIACom)*, Mar. 2016, pp. 1310–1315.
[37] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 3rd ed. Upper Saddle River, NJ, USA: Prentice-Hall, 2010.
[38] A. C. Mesa, M. C. Aguayo-Torres, F. J. Martin-Vega, G. Gómez, F. Blanquez-Casado, I. M. Delgado-Luque, and J. Entrambasaguas, "Link abstraction models for multicarrier systems: A logistic regression approach," *Int. J. Commun. Syst.*, vol. 31, no. 1, Jan. 2018, Art. no. e3436.
[39] *Technical Specification Group Radio Access Network; NR; Physical Channels and Modulation (Release 16)*, Standard TS 38.211, Rev. 16.4.0, 3GPP, Jan. 2021.
[40] *Technical Specification Group Radio Access Network; NR; Multiplexing and Channel Coding (Release 16)*, Standard TS 38.212, Rev. 16.4.0, 3GPP, 3rd Generation Partnership Project (3GPP), Jan. 2021.

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