Towards 6G: An Analysis of the Prospects for MAC Protocols

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Abstract— **Wireless networks are constantly evolving and sixth-generation networks are already being prepared for launch in 2030. The emergence of 6G will require networks to offer superior capabilities compared to 5G, particularly in the areas of physical (PHY) and Medium Access Control (MAC) layers, especially when considering applications such as massive Multiple-Input Multiple-Output (mMIMO), TeraHertz waves (THz), random access, energy efficiency, and radio access via Non-Terrestrial Network (NTN). This article aims to address proposals for improvement in the MAC layer for 6G networks. It covers topics related to the use of Artificial Intelligence (AI) for estimating the Channel State Information (CSI) report and reducing signaling overhead. Additionally, it discusses the main challenges and proposed solutions in using Dynamic Spectrum Sharing (DSS) and Multi-RAT spectrum sharing (MRSS) for smoothing transitions from 5G to 6G networks and solutions to optimize Adaptive Coding and Modulation (AMC) for millimeter waves (mmWaves) and TeraHertz (THz) networks.**

Keywords— **6G, MAC layer, CSI, AMC and DSS.**

I. Introduction

The growing number of users and the demand for ever higher and faster data transfer rates, even the applicability of technology to the sector, have promoted the progress of mobile communications networks over the last 10 years. The evolution from 5G to 6G marks a significant leap in wireless communication technology, promising to transform how people connect and interact with the digital world. While 5G has already revolutionized the telecommunications landscape with its high-speed data transfer, low latency, and enhanced connectivity, 6G aims to push these boundaries even further.

The deployment of 5G technology has enabled several transformed use cases, including Ultra Reliable Low Latency Communication (uRLLC), massive Machine Type Communication (mMTC), and Enhanced Mobile Broadband (eMBB) [1]. When considering the connections of a vast number of Internet of Things (IoT) devices, facilitating smart cities and industrial automation by allowing efficient communication between countless sensors and machines, mMTC ensures the necessary support to do this [2]. eMBB on the other hand, enhances user experiences in activities such as high-definition video streaming, even as virtual and augmented reality [3], [4].

As mentioned above, current 5G technology already brings about significant improvements and enables the implementation of various applications to meet the market's demands. However, the main drive behind the development of 6G is the necessity to support applications and use cases that require even more bandwidth and almost instantaneous response times. One clear use case to exemplify this is holographic communications, which allow the transmission of three-dimensional images in real-time and require extremely high data processing capacity and very low latency that only 6G networks can provide [5].

Currently, researchers and industries are working on developing standardization for 6th-generation networks. However, one of the main challenges in this effort is the need to develop new infrastructure that can support the demands of 6G. This involves the use of new antennas and networks in mmWaves and THz frequencies. While these frequencies offer increased bandwidth and consequently much higher transmission speeds, path loss issues, and channel sounding must be considered for the next generation of mobile networks [6].

Researchers are working together to develop the infrastructure required for 6th-generation networks, focusing on efficiency, performance, and reliability. Studies related to PHY and MAC layers are crucial, as they directly impact the quality of service and user experience in networks [5]. For 6G, the physical and MAC layer are expected to advance even further to meet new use cases and growing demands.

The authors present in [7] an analysis of several challenges that will be faced in terms of interoperability since 6th generation networks will have to interoperate with IoT. In addition, other features such as THz networks, mmWaves, sub-6GHz, and the inclusion of NTN are relevant for interoperability in 6G networks.

Standing out among the various studies on sixth-generation networks, and considering the still limited amount of work that highlights the transition of MAC layer features from 5G to 6G, this paper provides a bibliographical survey of the development of the MAC protocol throughout the advances in mobile communication technologies and offers a unique view of the main features in the MAC layers to fulfill the new requirements in the transition from 5G to 6G.

Finally, this paper is organized as follows. In Section II a literature search is carried out on what is being published related to the topic of 6G. Section III covers technologies that deal with aspects such as communication channel characterization, dynamic spectrum allocation, and adaptation of coding and modulation techniques to optimize data transmission performance. Lastly, in section, IV, the main conclusions of this study are presented.

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II. Research Overview

A significant increase in the production of articles related to 6G networks has been observed from 2013 to 2021, indicating a growing interest and research activity in this field. The main topics covered in the survey include architecture, structures, and requirements. Certain technologies and concepts such as *blockchain*, *mmWaves*, intelligent surfaces, edge computing, IoT, and AI were identified as key focus areas in 6G research, suggesting the direction of future studies in this domain [8], [9].

It can be justified that the three themes mentioned above are on the rise in research related to 6th generation networks, due to being related to the standardization of this technology, raising ideas, and proposing solutions related to the physical part of the system (structures), main KPI's and use cases (requirements) and mode of operation and interoperability with existing systems (architecture). When considering the document types published the study highlighted the prevalence of open-access publishing in scientific journals for 6G research, indicating a trend towards open dissemination of knowledge in this field. Countries such as China, the United States, India, Germany, the United Kingdom, Australia, and Europe as actively involved in 6G research, collaboration, and publication activities. Compared with these countries, Brazil is among the 20 countries with the highest number of publications in the area, standing out as the South American country with the highest number of publications [9].

In the literature, as described briefly above, it is already possible to find various works developed with the aim of understanding and proposing new paradigms, applications, and standards that can be used with the arrival of the sixth generation of mobile networks. Among the various works found, one can be mentioned that developed in [10], in which the main features found in the MAC layer are presented systematically and in detail, including possible features that will be implemented with the arrival of 6G. Another point highlighted in this work was the potential of AI applied to the MAC layer since several previous studies have shown that the use of AI has significantly improved PHY layer applications. In the work carried out in [11], a new framework is proposed which, when applied, provides faster convergence in MAC protocol learning problems. The algorithm is multi-agent reinforcement learning (MARL) based. It should be noted that the simulations showed results of around 75% faster convergence compared to the best performance base.

Finally, the work presented in [12], in which the authors propose a new categorization of data-driven MAC protocols. This categorization is divided into three levels, called Level 1, Level 2, and Level 3. Level 1 MAC corresponds to task-oriented neural protocols created using deep reinforcement learning. Level 2 covers symbolic-oriented protocols for neural networks, which are developed by converting the outputs of the Level 1 MAC into explicit symbols. Lastly, Level 3 includes language-oriented semantic protocols that take advantage of large language models (LLMs) and generative models.

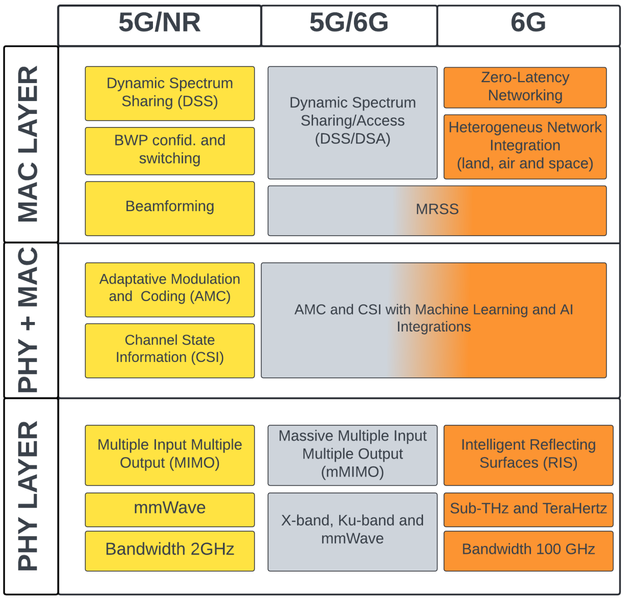

Fig. 1. Evolution of Key Features in the PHY and MAC Layers for 5G and 6G.

III. Improvements in MAC features for 6G

From the 3rd Generation Partnership Project (3GPP) onwards, the MAC's resources take place within the radio base. This protocol is allocated at the MAC layer and has several functions related to the user and control plane. One of its main functions is to map the logical channels in transport channels. Furthermore, the MAC protocol makes the multiplexing/demultiplexing of the transport blocks that are delivered to the physical layer through transport channels and also performs hybrid packet retransmission through the Hybrid Automatic Repeat Request (HARQ) method and makes scheduling data in both directions, downlink and uplink.

From the previous sections, it is possible to ensure that MAC layer protocols have a crucial role in optimizing wireless network performance. In the literature, there is a significant prospect of work that addresses MAC protocols in 6G focused on features such as CSI, DSS, MRSS, and AMC. Figure 1 presents key features for PHY and MAC layer and the transaction from 5G to 6G and new requirements expected for 6G.

A. Channel State Information (CSI) report

The estimation of radio links between the User Equipment (UE) and the Base Station (BS) is obtained through the CSI, which mainly contains Channel Quality Information (CQI), Precoding Matrix Index (PMI), Layer indicator (LI), and Rank index (RI) information. Accurate information on the CSI is relevant for more efficient throughput and Multiple-Input Multiple-Output (MIMO) and mMIMO systems. However, given the mobility of users, multipath channels, and the higher order of PMI, the quality of CSI related to delay and the amount of information in PMI and CQI, and the signaling overhead become a challenge for future 3GPP releases. To mitigate these problems, several authors use AI to improve the estimation of CSI reports and reduce signaling overhead focused on mMIMO and satellite and 6G communication. Table I shows the summary of references to the CSI report in section III-A, your contribution to topics, and the methodology used to mitigate the issues.

When considering CSI in mMIMO systems, challenges become even more evident due to the dynamic nature of the wireless channel and the need for accurate CSI for efficient system operation. The key challenges associated with CSI aging in mMIMO systems include Dynamic Channel Conditions, User Mobility, and Processing and Feedback Delays. To address these challenges, the authors in [13] present innovative DL solutions using 3D Complex Convolutional Neural Networks (CNNs) to improve CSI prediction performance. The authors achieve significant channel prediction results through the leveraging of temporal and spatial correlations in the channel through the angle delay decomposition of previously observed CSI. The solutions incorporate methods to enhance robustness to noise and time-frequency offsets, ensuring reliable CSI prediction even in the presence of interference and synchronization errors.

In [14] the author proposes a deep CNN with an entropy coding block and quantization based on a state matrix compression scheme, called DeepCMC. While other CSI compression approaches use autoencoders to extract features with an output of a complex 32-bit vector, uses entropy and quantization, obtaining better results for the Normalized Mean Square Error (NMSE) metrics. The CSINet [13] was used as a reference and for comparison. The results presented for DeepCMC achieve a reconstruction of the channel gain matrix with NMSE of $-13dB$ and p equal to 0.98 at a bit rate of less than 0.16 bits per channel dimension. On the other hand, CSINet achieves reconstruction of the channel gain matrix with NMSE of -5 dB at a bit rate between 0.08 and 0.12 bits.

On the other hand, Nokia [15] has proposed a transformer-based auto-encoder methodology that replaces the PMI and BTS encoder with bi-LSTM networks. For the proposed solution, Nokia has developed a specific training system for generating the CSI in the mobile device and another for the decoder in the base station (BS). This approach provides flexibility related to the local configuration of the cell and the configuration of the scenario.

For comparison purposes, the study carried out comparisons of transformers-based CSI feedback with 3GPP Rel-16 eType II codebook, obtaining the following results: for full buffer traffic with rank of 1, obtained 6.5% in mean and 2.5% in cell edge user throughput. For full buffer traffic with the rank of 2, got 8.5% in mean and 3.5% in cell edge user throughput, in bursty traffic (80% RU) with the rank of 1 has 4.5% in cell and 10.0% in cell edge user throughput, and in bursty traffic (80% RU) with rank of 2, got 13.0% in the mean and 22.5% in cell edge user throughput.

Other studies were conducted to assess mobility and positioning in indoor environments, even to enhance the estimation of CSI for NTN. In [16] the authors address the challenge of dynamic channel conditions and user mobility and explore new CNN structures to enhance indoor positioning accuracy using MIMO-based channel state information.

TABLE I

SUMMARY OF RECENTLY PRESENTED ARTICLES TO CSI REPORT FOCUSED ON 6G NETWORKS.

MAC FEATURE	MAIN TOPIC	METHOD APPLIED	RELATED WORKS
CSI	Prediction mMIMO	DL,CNN	[13], [16],[14]
CSI	Prediction BS and UE	Transformer Auto-encoder	[15]
CSI	NTN	RNN	[17]

CSI prediction is aimed at satellite communication, given that NTN communication must be integrated with Terrestrial Networks (TNs) for the 6G context. CSI prediction for NTN communication is relevant due to the aging of the communication channel, affecting traffic demands and frequency reuse. In [17], the author proposes an AI-based model for CSI prediction through temporal statistics of channel prediction using the correlation between Line-of-Sight (LoS) and shadowing. The model applies corrections to the CSI data received, minimizing the error in estimating the channel at the time it was collected. For the results, a Cell Free (CF- MIMO) system for Low Earth Orbit (LEO) was considered, obtaining an improvement of 15% per user.

Finally, several researchers and companies focused on mobile devices and BS are trying to mitigate problems related to better estimating CSI for 6G communication and avoiding signaling overhead. These efforts are essential for future mobile networks (6G) and better data rates, greater efficiency of mMIMO systems, and lower consumption of mobile devices due to fewer reporting signals. To this end, the use of AI favors relevant gains for the MAC layer related to channel estimation, PMI, and MIMO from both the UE and BS perspectives.

B. Dynamic Spectrum Information (DSS)

Just like the MAC layer features mentioned previously, DSS enables efficient use of spectrum through frequency sharing to ensure high data transfer rates [18], [19]. About DSS, it is important to observe the relationship between DSS and MRSS and understand the effects and impacts of both features on the MAC layer for future mobile network generations. According to [10], MRSS allows different radio technologies to share the frequency spectrum in a dynamic and coordinated way. The spectrum is a limited resource and multiple network technologies can coexist, MRSS is convenient because it enables better spectral efficiency and Quality of Service (QoS) for users, making the transition from 5G to 6G smoother.

According to [20], DSS permits two RATs to share the same spectrum and radio unit and adapt allocations based on traffic conditions in near real-time. The two RATs share spectrum resources and use a common radio unit for transmission and reception. DSS brought the ability to distribute orthogonal resources between the two radio technologies based on near real-time traffic conditions. The 3GPP guidelines did not specify a specific method for deploying DSS, but instead developed a framework to support various options.

In the literature, it is common to see that the most recent DSS applications at the MAC layer for 6G propose the use of DSS-based blockchain. Blockchain opens up opportunities for DSS and is considered a promising solution because it has features such as decentralization, transparency, and traceability. The authors of [21] cite that with blockchain, a decentralized DSS framework is built to facilitate reliable spectrum sharing between spectrum providers and requesters without a third-party proxy, and the consensus mechanism provides a viable way to solve the channel contention problem where multiple users compete for unlicensed bands. Table II presents a summary of references related to DSS and MRSS, highlighting key topics and methodology used to mitigate the issues.

C. Adaptive Modulation and Coding (AMC)

The AMC is a technique used at the MAC layer. It is responsible for dynamically adjusting the modulation scheme and coding rate based on variations in communication channel conditions. With the 6G, new KPI demands such as ultra-high reliability and high data rates to enable ultra-fast downloads, and ultra-high resolution streams to facilitate the integration of emerging technologies. The introduction of a 6G communication ecosystem will use Unmanned Aerial Vehicles (UAV), Reconfigurable Intelligent Surfaces (RIS), Industrial Internet of Things (IIoT) and autonomous vehicles, and finally an air interface with frequencies between 7GHz -15GHz, mmWave and sub-THz. These issues point to AMC as an emerging and crucial technology for future telecommunications systems. Table III shows the summary of the main topics to AMC.

According to [10], the challenges of AMC in the context of 6G are exemplified by balancing transmission according to the BLER target. In cases where uRLLC is required to meet the needs of autonomous cars and remote surgeries, as mentioned in section 1 of this article, the AMC challenges are even greater. To overcome these challenges, new approaches are being proposed in the literature, including ML and DL to achieve satisfactory performance.

For studies focused on automatically adjusting modulation schemes for 6G systems, in [22] the authors propose approaches for Automatic Modulation Classification (AMC) in O-RAN cell-free network scenarios with multiple receivers and configuration distribution for each receiver. These approaches utilize the concepts of central, distributed, and hybrid models. The central model uses IQ data input from all Radio Units (RUs) to determine the output.

TABLE II

SUMMARY OF RECENTLY PRESENTED ARTICLES TO DSS/MRSS FOCUSED ON 6G NETWORKS.

MAC FEATURE	MAIN TOPIC	METHOD APPLIED	RELATED WORKS
DSS	Potential Research Fields	DL, RL,CNNs, TN and TL	[10],[18], [19]
DSS	DSS Framework	Blockchain	[21]

TABLE III

SUMMARY OF PRESENTED ARTICLES TO AMC FOCUSED ON 6G NETWORKS.

MAC FEATURE	MAIN TOPIC	METHOD APPLIED	RELATED WORKS
AMC	Prediction to uRLLC	ML, DL and TDRNN	[10], [23]
AMC	6G Free-Cells	Distributed solutions for AMC	[22]

The distributed model employs a separate model for each IQ dataset of each RU and a voting model in the Distributed Unit (DU). The DU predicts modulation by concatenating decisions from each RU model. The hybrid model combines three sub-models, the DU model aggregates IQ data from all linked RUs using an untrained Equal Gain Combining (EGC) block, and the output results in a set of features extracted from the combination of all IQ samples, which is then forwarded to the voting model that receives data from different DUs. The presented results for the different approaches indicate that the hybrid model achieved a 2.5% improvement over the central and distributed models for various Signal-to-Noise Ratio (SNR) levels.

In conclusion, the author notes that the distributed model becomes impractical due to front-haul restrictions and privacy concerns when compared to the central model. Although the distributed model has similar complexity when using EGC, its computational demand is higher. Meanwhile, the hybrid model with EGC in the DU, strikes a balance between accuracy and complexity, offering greater efficiency in load distribution, surpassing the central model.

In [23] the authors propose an automatic modulation classification algorithm called Threshold Denoise Recurrent Neural Network (TDRNN) using the noise reduction method and recurrent neural networks for URLLC systems standardized for 6G networks. The proposed model obtained significant results for the inference time of 0.007 ms, exceeding the requirement of 0.01 ms. He presented the influence of Threshold Denois (TD) on the model, where the Recurrent Neural Network (RNN) was compared with and without TD, obtaining an accuracy of 93% with the use of TD and 82% without it, representing a gain of approximately 11%. Finally, a comparison between the proposed model and other recent models for estimating AMC is found in the literature. For SNR values between -8dB to 20dB, the algorithm proposed by the author obtained a maximum accuracy of 93.2%, while the other models obtained results between 90.4%, and up to 71.6%.

In traditional AMC technology, a query is made to the MCS to obtain information on the signal-to-noise ratio, under the condition that the BLER is less than a specific value for selecting the appropriate MCS for the next transmission time interval (TTI). However, the relationship between channel quality and system performance is not a simple matter and the effect of transmission is weak. Therefore, through AI, it is possible to increase the accuracy of the AMC. The operations of channel mapping and querying the MCS can be mapped using algorithms that increase the accuracy of the measurements. With machine learning, it is possible to recognize different modulation signals, thus reducing the signaling overload on the AMC [24].

From these and other points, it can be concluded that AI and machine learning can make AMC more dynamic and intelligent, but there are still many open research points due to the complexity of the parameters involved. In general, these are the major features and challenges that AMC will face in 6G due to the variable channel conditions.

IV. Conclusion

This article presented a synthesis of topics that have not yet been extensively explored in the literature, including an overview of the perspective of the MAC layer for the next generation of mobile networks and the mitigation of issues for CSI, DSS/MRSS, and AMC. Through this survey, it was possible to verify that new paradigms and standards can be created with 6G and improvements implemented in the MAC layer.

The CSI report is relevant to NTN, massive MIMO, and mobility networks. The main points that need to be addressed for 6G networks are signaling overhead, information delay for NTN and mMIMO networks, and PMI not being able to represent massive MIMO systems accurately. All of these points were addressed and mitigated through AI, presenting satisfactory results on UE and BS.

DSS and MRSS play a very relevant role in the smooth transition from 5G to 6G, as the DSS was relevant to the transition from 4G to 5G. Nokia [20] points to MRSS and DSS combined with FR1 and frequencies between 7 GHz to 15 GHz for the transition between 5G, 5G advanced, and 6G networks. Other points are the study related to DSS and a blockchain-based framework and tokenization to promote security in DSS systems.

The AMC is relevant because your application is related to dynamically adjusting the modulation scheme and coding rate based on CQI. Some articles using the AI and RNN for applications in uRLLC better estimate the AMC based on SNR than other abording, and these proposed methods are better than the requirements of 0,01ms for uRLLC.

Finally, these points are most relevant for next-generation mobile networks. The MAC layer always evolved with releases of 3GPP and works together with the evolution of the physical layer with increasingly higher frequencies, greater bandwidths, and system interoperability. Future works also aim to focus on the challenges of computational intelligence and hardware in the transition from 5G to 6G.

Acknowledgment

The authors would like to thank the Instituto de Pesquisas Eldorado from Brazil through the internal project called Study Group Architecture 6G.

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