Performance Analysis of MIMO using Machine Learning in 5G Networks

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***Abstract*— Massive Multiple-Input Multiple-output (MIMO) is a high-potential radio antenna technology for mobile wireless networks, such as 5th Generation (5G). The use of hybrid analog and digital precoding to minimize the energy consumption as well as the hardware complexity of mixed signal components is an essential strategy. Machine Learning (ML) could be able to boost 5G technologies due to the rising difficulty of configuring cellular networks. More than ever, an ML computational framework focused on successfully processing the expected huge data generated normally by 5G networks with high subscriber cell density, is required. In the Ultra-Dense Networks (UDNs) of 5G and beyond high demanding networks paired with beamforming and massive MIMO technologies, ML struggles to define network traffic aspects distinctively, especially when they are projected to be much more dynamic and complicated. This paper presents a state-of-the-art analysis of the combined and multiple uses of ML along with MIMO technology in 5G Networks.**

Keywords-MIMO; Machine Learning; 5G; Deep Learning; Internet of Things; Big Data.

I. INTRODUCTION

In recent decades, a rise in Internet traffic has been observed, which is projected to continue to grow exponentially in the near future. The reason for this is the widespread use of a wide range of User Equipment (UE), which includes everything from Internet of Vehicles (IoV) and Machine-to-Machine Communication (M2M) to Internet of Things (IoT), and so on. Network traffic management is expected to be a critical problem, especially in the 5th Generation (5G) and beyond cellular Ultra-Dense Networks (UDNs) and Heterogeneous Networks (HetNets), which are the main technologies that will host this traffic, reason being the significant congestion on wireless communication networks due to the amount of traffic generated from big data. The primary problem with the wireless network's ongoing growth is that to achieve the necessary area throughput, it must either increase bandwidth (spectrum) or densify the cells and increasing bandwidth or densifying the cells raises hardware costs and increases latency.

Because of its unique performance and freedom, Massive Multiple-Input Multiple-Output (MIMO) is a critical method for 5th Generation and future mobile wireless networks. Massive MIMO is a type of MIMO that requires connecting a base station with hundreds or even thousands of antennas to be able to boost spectral efficiency and throughput. Massive MIMO makes use of huge antenna arrays at base stations and Access Points (APs). When combined with millimeter-wave (mm-Wave) communications, which employ a bigger spectrum, this architecture enables for enhanced cellular communications with increased spectral density and reduced complexity. Massive MIMO can perceive data from several sensors in real time thanks to its high multiplexing gain and beamforming capabilities, resulting in decreased latency and larger data rates for sensors.

Artificial Intelligence (AI) has emerged as a cutting-edge method with the potential to make major advancements in a variety of telecommunications problems, thanks to the uses of Machine Learning (ML) and furthermore deep Learning, including network management, self-organization, self-healing, and Physical Layer (PHY) improvements (DL). The communication system will be taught how to recognize emergent channel models and how to react to changing channel conditions by utilizing deep learning techniques, all while delivering a cutting-edge tool for maximizing end-to-end efficiency. DL-based approaches are also perfect for operating on Graphics Processing Units (GPUs) to fully use parallel hardware because of the Deep Neural Network (DNN) framework with ways that can help manage big data and fast evolving scenes based on parallel processing architectures. The secure uses of AI can greatly optimize classical ways in most of the areas. To improve its performance, many machine learning methods have been applied to MIMO technology.

In [2], a methodology is presented for producing channel realizations that depict 5G scenarios with transceiver and artifact mobility. In [3], researchers investigate MT localization in Distributed Massive MIMO (DM-MIMO) systems using the Apache Spark big data computing

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framework and the RSS fingerprinting approach in conjunction with ML algorithms, with the goal of using it in microcells in metropolitan areas. The work in [1] explains how to utilize deep Long Short-Term Memory (LSTM) learning to produce localized traffic load estimates at the UDN base station, while [4] shows a Partial Learning (PL)-based detection technique and [5] gives a comprehensive review of 5G communications research utilizing DL. In [6], the authors undertake a review of the evolution of DL solutions for 5G communication before providing efficient strategies for DL-based 5G scenarios, whilst in [7], they provide a complete overview of the primary enabling technologies 5G and 6G networks, with a focus on massive MIMO systems. For successful hybrid precoding, [8] proposes a deep-learning-enabled mmWave massive MIMO architecture, in which each precoder selection for getting the best decoder is considered as a DNN mapping link. We will include a study of how MIMO technology can benefit from the modern application of ML in this paper.

We will present how the components of a single 5G network that uses this combination work, what has been researched so far, and how it might be enhanced in the future. The rest of this work is organized as follows: In the following section, we showcase the literature review of the most state-of-the-art combinations of MIMO and ML. In Section III, we evaluate the use of ML and MIMO in 5G networks and Section IV includes our conclusions and future applications.

II. RELATED WORK

A. MIMO

We can think of communicating in a MIMO system as sending a matrix rather than a single vector. As a result, we can deliver a data stream in parallel to numerous recipients. The data to be delivered is encoded by the system, and the stream is sent via transmitters. MIMO is using multiple antennas to send data to a large number of wireless endpoints simultaneously. MIMO is a technique for doubling the capacity of a radio link by taking advantage of multipath propagation by using multiple transmission and receiving antennas. MIMO, being a radio antenna technology, uses many antennas at the transmitter and receiver to offer several signal channels for data transmission, effectively. Each antenna is associated with a distinct signal path, allowing for the usage of several signal paths. Massive MIMO is a new technology that scales up MIMO and provides significant energy economy, spectrum efficiency, resilience, and dependability benefits.

To highlight the importance of massive MIMO, we look at the work that has been done in [9]-[11]. In [10], Massive MIMO as an enabling technology for future generation of networks, is being showcased as a novel technology that scales up MIMO and offers considerable benefits. It enables both the base station and the mobile unit to use low-cost hardware. Expensive and powerful but inefficient equipment is replaced at the base station with many low-cost, low-power components that work together. The term "massive" refers to the utilization of the multiple antenna arrays to support a plethora of terminals at the same time-frequency resource. Comprehensively describing massive MIMO systems from several different perspectives in [11], the authors point out that, by expanding the capacity of Radio Frequency (RF) networks, MIMO provides a more reliable connection and reduces congestion. A base station's spectrum and energy efficiency can be considerably optimized by providing it with hundreds or even thousands antennas.

MIMO can enhance data carrying capacity without requiring more bandwidth due to spatial multiplexing, however, when compared to the classic single antenna antenna-based system, the resource requirements and hardware complexity are higher. Investigating the performance constraints of developing "wireless-powered" communication networks using opportunistic energy harvesting from ambient radio signals or specialized wireless power transfer, the authors conclude at [9] that when developing MIMO systems, compromises must be made in order to make simultaneous information and energy transmission as efficient as possible. When allocating resources in terms of communication to provide optimal solutions for network interference levels for maximum information vs. energy transfer, there are a few nontrivial considerations to keep in mind.

B. Machine and Deep Learning

Machine learning is a subfield of AI that refers to when computers are using data for learning techniques. It's the intersection of computer science and statistics when algorithms are used to carry out a procedure without being specifically written. The learning process for these algorithms falls into two categories based on the variety of data hat are given as an input: supervised or unsupervised. DL algorithms are a mathematically more complex and advanced evolution of machine learning techniques. DL is a subset of machine learning that deals with algorithms that analyze data in a way similar to the human brain.

The work that has been done in [3], [4] and [8] best describes the role of ML and DL in enhancing MIMO. The Partial Learning (PL)-based detection scheme that is proposed in [4] can achieve low Bit Error Rate (BER) with low computational complexity. They use non-linear techniques to have a more efficient BER while relying on linear methods to reduce computing complexity, which can be even more optimized by using neural network for linear detection. Because neural networks ensure that the signals are appropriately recognized at the start, this technique can achieve lower BER than standard techniques. The results of the evaluation of thirteen machine learning methods that is performed comparatively, in conjunction with fingerprint-based MT localization for dispersed Massive MIMO topologies [3], reveals that a subset of the assessed ML systems may accurately anticipate the position of an MT. Finally, the K-Nearest Neighbor (KNN) has been proven to appear the best ML algorithm performance, second being the

Kernel Ridge Regression (KRR) and Random Forest (RF) in all scenarios evaluated.

The deep-learning-enabled mmWave massive MIMO framework proposed in [8] presents a solution to the difficulty that already implemented hybrid precoding schemes have, which is that they are computationally complex and do not fully leverage geographical information. This method achieves successful hybrid precoding by treating each precoder choice as a associating relation in the DNN in order to achieve the best decoder, which is chosen by DNN training for optimization of the mmWave massive MIMO precoding process. The system model is a typical mmWave massive MIMO system with one BS and a modern DNN utilized to create a unique precoding framework. The suggested approach which has DL in it's core is viewed as a operation that is performing the mapping, and a training mechanism to acquire the mmWave-based model's structural statistics. With the data fed dynamically changing in accordance with the channel circumstances, the DNN is trained. The computational complexity of this unsupervised learning training strategy is reduced as well.

C. 5G Networks

After 1G, 2G, 3G, and 4G networks, 5G is a new global standard that is taking over wireless communications. 5G is intended to provide data speeds many times faster than the previous classic networks, latency that is being characterized as "ultra-low", enhanced dependability, massive network capacity, increased availability, larger bandwidth of up to 10 gigabits per second (Gbit/s) ensuring a more consistent user experience for a larger number of people. AI along with the infrastructure of Internet of Things (IoT) enable higher performance and efficiency. In 2019, cellular phone companies began installing 5G networks around the world, which are the projected successors to the 4G networks that connect the majority of today's handsets. In 5G, the service area is separated into cells, which are small geographical areas. All 5G wireless devices are connected to the Internet and to the telephone network via radio waves via a local antenna in the cell. Massive New antennas will be employed by MIMO for the several transmitters and receivers to be able to transfer a larger amount of data at the same time.

Observing [1], [2], [7] and [11], the authors take a close look at the fundamental technologies that will be critical for 5G and beyond networks, with a particular focus on massive MIMO systems. They discuss some of the many and most important challenges in a massive MIMO system, such as pilot contamination, channel estimation, precoding, user scheduling, energy efficiency, and signal identification, as well as some cutting-edge mitigation measures, as seen in [7]. For massive MIMO systems, they discuss contemporary advances, such as terahertz communication, Ultra-Massive MIMO (UM-MIMO), Visible Light Communication (VLC), ML, and DL. They believe that MIMO is the solution to the massive increase in wireless data traffic because to achieve excellent spectrum and energy efficiency with very simple processing, antennas are used in combination at both the transmitter and the receiver ends. In [11], the authors conclude that DL models, such as DNN and Convolutional Neural Networks (CNN), while optimizing channel estimations and feedback for large MIMO, will dramatically improve BER performance and system capacity. Massive MIMO and Non-Orthogonal Multiple Access (NOMA) will give improved performance and lower internal power usage, resulting in overall energy efficiency gains.

[1] describes the way to employ the deep LSTM learning method to produce traffic load based on location estimates at the base station of UDN, emphasizing how important it is for the 5G network operators to perform control on all the resources of the radio in an efficient manner. According to this study, traditional traffic control strategies are "reactive," meaning that if alike traffic circumstances arise, they are prone to congestion again. Predicting congestion incidents seeks to prevent them from happening in the first place. The study in [2] describes a system with a car traffic simulator along a raytracing simulator, in combination, to create channel realizations that reflect 5G scenarios and allow for the use of sophisticated traffic simulator features with mobility of transceivers as well as objects. The research then goes on to offer a dataset that may be used to investigate beam selection approaches for vehicle-to-infrastructure communication utilizing millimeter waves in mmWave MIMO.

III. MACHINE AND DEEP LEARNING ALGORITHMS COMPARISON

ML and DL methods' dynamic nature may be advantageous for analysis of complex tasks while also conserving a substantial amount of processing power. Massive MIMO beamforming, channel estimation, signal detection, load balancing, and spectrum optimization can all benefit from ML and DL technology, according to [7]. During channel estimation, data coming from the channel can be assumed to be big, and a variety of ML methods can be used to predict massive MIMO channels. Massive MIMO will see a significant increase in throughput thanks to ML-based channel prediction. In massive MIMO, ML was utilized in the past for effective beam alignment to track users, and numerous machine learning and DL approaches are also useful for uplink signal detection in massive MIMO. Despite its benefits, massive MIMO has many challenges, including pilot contamination, channel estimation, precoding, user scheduling, hardware impairments, energy efficiency, and signal detection, all of which need understanding and need to be applied in a real-world setting before their promised benefits can be realized.

The work in [8] indicates that using DL to solve the channel feedback problem could be a promising path for addressing concerns like codebook size and feedback overhead. The work in [6] states that improvement can be found if the data set acquisition and selection of the model issues are overcome, while the explainable development of DL methods is progressing, and we will have to establish the standard data sets that individuals in the industry support. The work in [1] discovers opportunities for improvement by taking a large number of traffic parameters and tensor-modeling them in order to create a learning framework that is even more robust and that can adapt and forecast with even more precision. The two challenges encountered in [3] are the effect of different locations and terrain on accuracy in terms of localization and the quantity of training datasets, as well as the effect of employing other DM-MIMO antenna array shapes and their effect on MT localization. Future work from [2] will entail simulating many sites and scenarios, as well as testing some of them with measurements, because it is crucial to decrease the computing cost in addition to precise modeling. DL in 5G can be examined utilizing a systematic and repeatable technique via experimentation.

All in all, finding effective techniques to decrease the pilot contamination effect is a crucial subject to research. A scheduling method that guarantees more efficiency and fairness that can deliver a higher rate of data while also ensuring fairness among users, to increase overall system performance is also an important topic of research, as is finding effective precoding techniques for massive MIMO. Finding a more effective and low-complexity uplink signal identification method is one of the most important topics of research. Designing a Massive MIMO that is able to work with today's 4G network is a fascinating topic to research (Figure 1). The following two algorithms show especially favorable results. [6] illustrates how DL models, like DNN and CNN for massive MIMO, may dramatically optimize the performance of BER and the capacity of the system while channel estimation and feedback are optimized. [4] proposes a neural network-based intelligent detection method to strike a balance between cheap computing complexity and low BER.

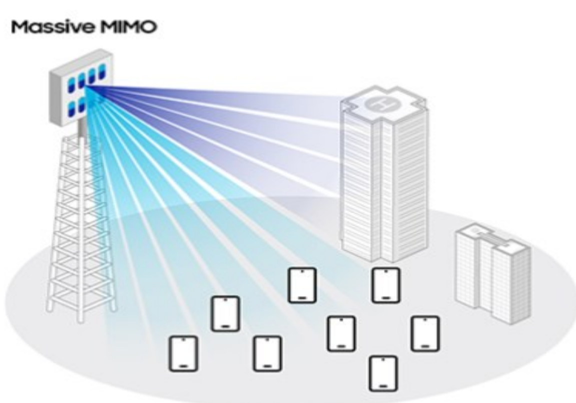

Figure 1. Massive MIMO

IV. PERFORMANCE EVALUATION

In this section, we discuss the performance evaluation of the works done in [1], [6] and [8]. We are observing interesting results in the use of ML and especially DL in combination with MIMO in 5G and beyond networks.

In general, in [6], a DL-based communication framework's performance has been demonstrated for channel estimation, encoding and decoding in massive MIMO, even though no theoretical work has been derived in this work to further verify and improve the framework's performance through understanding. Specifically, three deep learning-based frameworks, NOMA, massive MIMO, and mmWave hybrid precoding, are introduced and their performance evaluated with an emphasis on 5G. These models use extremely large parameters, a high level of memory and have increased time complexity. This suggests that we can create high-performance deep compression techniques and model compression strategies to increase the efficiency of the networks that utilize deep learning, making them simpler as well. As a result, in the future, the deep reinforcement learning-based wireless physical layer should be thoroughly researched in order to optimize critical resource management tasks and be capable of improving precoding performance, BER, SNR, and data rates by enhancing equipment performance, such as CSI, latency, and bandwidth management. Because the original input signals are frequently transformed into binary signals, one-hot vectors, modulated integers, and other styles of data representation for improving network performance in the DL area, it is unclear whether the most modern methods' performance is able to be achieved in DL-based wireless communication frameworks while the representation data is varying. In the field of DL-based wireless physical layer, the principles of learning schemes are still unclear, and a mechanism for picking training instances has not been created, which is one of the challenges that must be investigated further.

The authors in [8] compare the DNN-based scheme's BER performance to that of the SVD-based hybrid precoding scheme, fully digital SVD-based precoding method, fully GMD-based precoding method, and new GMD-based precoding scheme, demonstrating that the techniques with deep-learning at their core are more efficient than the traditional methods. In terms of BER, it is noticed that the deep-learning-based strategy's performance diminishes as batch size increases. In the DNN-based method, the performance of hybrid precoding is improved by using a lower rate of learning to guarantee a smaller validation error. The suggested hybrid precoding strategy surpasses prior strategies by achieving improved hybrid precoding performance thanks to DL's superior mapping and learning capabilities. The Mean Square Error (MSE) performance improves as the number of iterations increases, which is due to the fact that all of these algorithms approach conversion with more iterations. As a result, when compared to existing systems, the proposed DL-based methodology achieves improved performance in terms of hybrid precoding accuracy and conversion.

By comparing the work in [1] to the conventional method, the technique showcased in [1] achieves a lower rate of packet loss than the conventional method. The resource allocation approach that is given clearly leads to increased throughput. This result demonstrates that, even with a huge number of UEs, the proposed strategy outperforms the standard way. The solution that is stated results in a much lower packet loss rate, because it may make a localized prediction of future crowding and attempt to alleviate or completely eschew it ahead of time. Unlike the traditional methodology, the proposed method may employ DL to generate a localized forecast of future bottleneck, which would then be utilized to adjust the UL/DL settings to reduce congestion. When compared to the old technique, the UDN that utilizes the proposed method can achieve significantly higher throughput and lower rates of packet loss. Furthermore, in comparison to the traditional method, the proposal results in a higher throughput while, in terms of network efficiency, surpasses traditional solutions.

To sum up, from DL-based communication frameworks to DL predictions, the DL is clearly the state-of-the-art technique that seems to have overtaken the way MIMO in 5G and beyond networks work.

V. CONCLUSIONS

All in all, we conclude that the use of ML and DL in combination with MIMO in 5G and beyond networks (Figure 2) has a lot of benefits and better performance in the variety of the aspects that are being showcased. Especially, the most promising state-of-the-art techniques consist of the various uses of DL. It is obvious that such techniques, as well as all the principles of learning schemes, still have some unclear areas that can be further explored. In the future, more analysis needs to be conducted on DL-based wireless physical layer mechanisms, congestion optimization techniques and precoding strategies, expanding the comparison presented in Table I. It is safe to assume that with exploration and exploitation of the aforementioned artificial intelligence combinations, various benefits can be derived in terms of BER, energy consumption, complexity, throughput, congestion and, in general, overall efficiency.

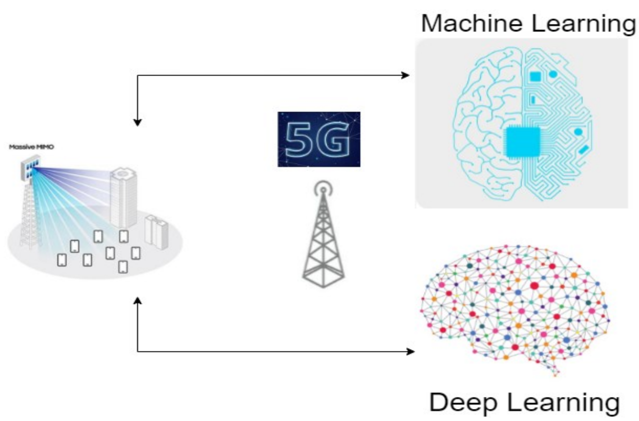

Figure 2. Machine/Deep Learning – 5G - MIMO

TABLE I. COMPARISON OF DL-BASED MECHANISMS, CONGESTION OPTIMIZATION TECHNIQUES AND PRECODING STRATEGIES

Work	***Strategy***	***Results***
[2]	In mmWave MIMO, a dataset is used to examine beam selection algorithms for vehicle-to-infrastructure interaction	Channel realizations that simulate 5G scenarios with transceivers and objects moving about.
[10]	Energy and spectrum efficiency, robustness, and reliability analyses	Massive MIMO description
[7]	Overview of core issues in massive MIMO system	MIMO as the solution to the massive increase in wireless data traffic
[8]	Deep-learning-enabled mmWave massive MIMO framework	Successful hybrid precoding
[6]	Overcoming the dataset acquisition and model selection issues	Better results with the progressing use of DL
[1]	Deep LSTM learning technique for localized traffic load predictions at the UDN base station	Learn and forecast with even greater precision
[4]	Partial Learning (PL)-based detection scheme	Low BER with low computational complexity
[3]	Comparative performance evaluation	KNN was the best ML algorithm performance that could effectively forecast the position of an MT.
[11]	Comprehensively describing massive MIMO systems from several different perspectives	Better BER performance and system capacity while optimizing channel estimates and feedback for massive MIMO and overall energy efficiency gains on NOMA
[5]	Overview of 5G communications research using DL	DNN and CNN can increase BER performance and system capacity while optimizing channel estimates and feedback for massive MIMO
[9]	Investigating the performance constraints of developing "wireless-powered" communication networks using opportunistic energy harvesting from ambient radio signals or specialized wireless power transfer	To maximize the efficiency of simultaneous information and energy transmission, fundamental compromises must be made when developing wireless MIMO systems.

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