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Review

A Study on Multi-Antenna and Pertinent Technologies with AI/ML Approaches for B5G/6G Networks

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Abstract: The quantum leap in mobile data traffic and high density of wireless electronic devices, coupled with the advancements in industrial radio monitoring and autonomous systems, have created great challenges for smooth wireless network operations. The fifth-generation and beyond (B5G) (also being referred to as sixth-generation (6G)) wireless communication technologies, due to their compatibility with the previous generations, are expected to overcome these unparalleled challenges. Accompanied by traditional and new techniques, the massive multiple input multiple output (mMIMO) approach is one of the evolving technologies for B5G/6G systems used to control the ever-increasing user stipulations and the emergence of new cases efficiently. However, the major challenges in deploying mMIMO systems are their high computational intricacy and high computing time latencies, as well as difficulties in fully exploiting the multi-antenna multi-frequency channels. Therefore, to optimize the current and B5G/6G wireless network elements proficiently, the use of the mMIMO approach in a HetNet structure with artificial intelligence (AI) techniques, e.g., machine learning (ML), distributed learning, federated learning, deep learning, and neural networks, has been considered as the prospective efficient solution. This work analyzes the observed problems and their AI/ML-enabled mitigation techniques in different mMIMO deployment scenarios for 5G/B5G networks. To provide a complete insight into the mMIMO systems with emerging antenna and propagation precoding techniques, we address and identify various relevant topics in each section that may help to make the future wireless systems robust. Overall, this work is designed to guide all B5G/6G stakeholders, including researchers and operators, aiming to understand the functional behavior and associated techniques to make such systems more agile for future communication purposes.

Keywords: 5G and beyond (B5G); artificial intelligence (AI); 6G; massive MIMO (mMIMO); wireless networks; machine learning (ML)

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1. Introduction

The modern digital era has involved the proliferation of intelligent appliances and smart special-purpose computers by technological information organizations, industrial corporations, and individuals [1]. Wireless smart products generate enormous amounts of data through sensors and metal detector nodes in the process of mobilizing users' everyday routines [2]. The global amount of mobile data was calculated at 7.462 EB/month in 2010, and the estimators hypothetically believe it could reach 5016 EB/month by 2030 [3]. The current 5G mobile networks are densely heterogeneous in nature, with multiple modes and variously sized wireless devices linked via one unified air interface tailored for user-centric services [4]. The unprecedented and radical changes in the requests for wireless user data services and the involvement of low-to-high-scale intelligent devices have tremendously increased the current network load and management challenges. Modern wireless networks require new technologies that can handle the current network load, interact with the environment proficiently, deliver instantaneous responses within very short intervals, and avoid frequent network failures.

Before the emergence of the 5G era, the research was mainly focused on the successful transmission of packets with satisfactory data rates under negligible interference scenarios [5]. While mobility management congestion and power dissipation issues were never the non-trial features of mobile services [6], in B5G cellular systems, digital smart technologies, software-defined networking (SDN), and automated real-time activities have gained immense attention in wireless networks due to their interactions with the environment. These emerging joint networking and communication technologies have generated several challenges related to the bandwidth, latency, jitters, and security requirements [7]. The use of dynamic new features, e.g., network virtualization, mobile ad hoc networks (MANETs) [8], network routing [9], software-based systems, air interfaces [10], and the Internet of things (IoT) [11,12], inserts more complications into the network design [13], mobility protocols, and network operations [14]. Thus, the control, monitoring, and maintenance of different sizes of multi-tier HetNet cellular networks become more complicated with the escalating desire for wireless user facilities [15]. Although technological services such as augmented reality [16], 3D video [17], virtual reality [18], self-driving cars, drones [19], robotics, factory automation, wireless fronthaul–backhaul communication, and smart transportation would enrich the ultimate user experience and generate tremendous traffic on a daily basis, it is very hard to efficiently manage the continuously growing data requirements of such diversified services with the available technologies in the current networks [20].

Lately, 5G/B5G technologies with AI protocols have captured the attention of academic researchers and radio communication standardization groups [21]. Studies have firmly shown that AI-learning-based approaches are indispensable in managing the daily consumption of multiple gigabytes (GBs) of data by users, devices, and machines. The driving factors behind this AI drive are the challenges related to the administration, management, and security of the emerging massive bandwidths in mobile communication systems and the generation of unprecedented 'big data' [22]. It is expected that to resolve these uncoordinated, unstructured, and ungovernable challenges involved in the forthcoming cellular networks, where M-MIMO has the potential to embed the ML/DL technologies in not only the physical layer but also to augment the massive bandwidth in the higher layers [23], the emerging AI-based M-MIMO generic architecture will include a chain of processing layers starting from the users to the channel estimation layer. It will involves complex RF processing challenges as well as baseband processing-level challenges. This scenario will be unmanageable using conventional statistical and probabilistic approaches. It will require automation and massive data handling in real time using AI/ML-based approaches, as shown in Figure 1.

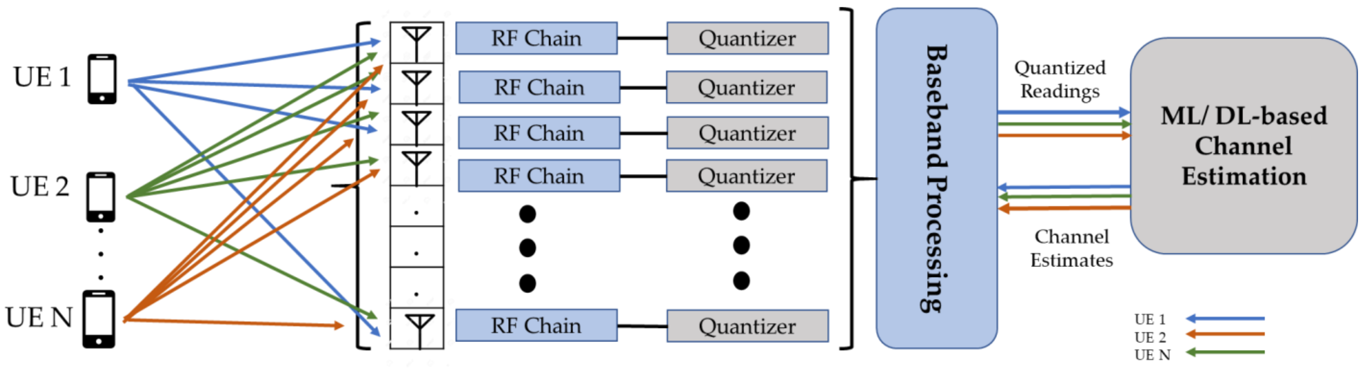

Figure 1. DL/ML-based M-MIMO system.

AI-learning-based approaches have been developed within a universal computing framework for diversified services, and have made significant progress in becoming state-of-the-art in various technological fields. AI technologies are considered to be sufficient to bear the costs of higher throughput, radio resource management, network adaptability, and ultra-enhanced coverage extension rates [24]. Telecommunication authorities, research communities, network specialists, material engineers, wireless accessory designers, and government institutions are continuously involved in the design process and have been delivering robust solutions for issues in the current 5G networks and those expected in the upcoming B5G radio communication networks [25]. The objective is to define a new paradigm for the rapid increase in wireless data traffic and the Internet of Everything (IoE), and to seek out more advanced ultra-reliable approaches for operational network setups [13]. This radical change in network traffic has driven these explorers to identify and offer new alternatives for network robustness and to diminish the traditional cellular architectural bottleneck to cope with the increasing challenges, administer network resources for advanced technology deployments, and controlling costs. This can be achieved through manipulating the channel bandwidth (BW) distribution and reductions in human efforts, complex networking activities, and serviceable errors [26]. The focus is now on transforming future wireless communication completely into functional distribution, autonomous design, relaxed computation, and edge-intelligence-driven networks.

Furthermore, multi-antenna technology (i.e., MIMO) is another promising mechanism for B5G communication. Such systems involve many closely packed small-aperture active antennae and can achieve significant spatial diversity and multiplexing gain performance. This technology has attracted global attention in wireless communication services because it greatly enhances the user experience and system capacity without adding extra power [27,28]. Due to the constant increase in the number of disparate wireless gadgets and industrial appliances, the next-generation cellular communication networks will require improvements to the existing MIMO systems [29]. Concerning this, a more sophisticated antenna technology with linear signal processing has been proposed and is referred to as massive MIMO (mMIMO). The theoretical analysis validated that the BS can adjust hundreds of antennae and can simultaneously serve each user with multiple streams. However, most of the use cases for B5G and 6G communication will gradually develop from the 5G network-based applications based on QoE and functional behaviors [30]. Then, soon after the 6G enablers become an active part of commercial cellular services, the applications will follow through with new use cases and contribute to further performance enhancements. In this regard, more agile approaches for antenna precoding and estimation with intelligence and learning-based processes must be critically explored. Table 1 below presents a comparative view to delineate the 6G network characteristics beyond the capabilities of 5G networks in several emerging domains, including their concepts and requirements [31].

Table 1. A comparative analysis of the critical features of 5G and 6G networks.

Key Elements	5G	6G
Hardware Complications	Moderate	Very Low
Operational Error Margin	Low	Very low
Centre of gravity	User-centric	Service-centric
Reliability	High	Extremely high
Mission-critical real-time response	Fast	Very Fast
AI/ML	Partially	Completely
Functional Complexity	Moderate	Low
Computation Time	Low	Very Low
Satellite support	No	Yes
VR/AR	Partially	Comprehensively
Energy Efficiency	100× of 4G	100× of 5G
Spectrum Resources	Sub-6 GHz to 300 GHz	Sub-mmWave to 3 THz
Autonomous system	Partially	Completely
Latency	<1 ms	Up to 0.1 ms

1.1. Motivation

The prominent cellular protocol design institutions such as the International Telecommunication Union (ITU), European Telecommunications Standards Institute (ETSI), and Federal Communication Commission (FCC) are largely concentrating on virtual plus dynamic cellular communication systems [32]. The regulatory authorities are imposing new laws and standards and a multi-tier technology division for modern wireless network infrastructures. Large-scale multi-antenna systems have become a widely recognized hot research area in academia and technological society. Likewise, AI and ML approaches are widely recognized as enablers for 5G and future wireless networks [33]. In this context, since the advent of mMIMO technology, substantial survey articles [34,35] have been published in the literature focusing on the variety of optimization parameters, even under the supervision of AI/ML techniques. However, the challenges and limitations in the adaption of intelligent mMIMO systems for B5G/6G require a detailed survey and critical analysis to identify definite future research directions.

1.2. Contribution

We provide a deep insight into mMIMO systems with emerging antenna and propagation precoding techniques. We critically analyze and highlight various relevant topics in each section that may help to make future wireless systems robust. The main contributions of this survey are as follows:

- This survey article is designed to highlight the latest trends in the research on intelligent-learning-based mechanisms for multi-antenna signal processing;
- Similarly, the article discusses the current solutions, limitations, and challenges in the AI/ML designs and the requirements for more agile approaches;
- We critically analyze the current issues and highlight future research directions for emerging intelligent mMIMO-based B5G/6G mobile communication systems, including conventional AI/ML, distributed learning and FL, antenna selection, reconfigurable intelligent surfaces (RIS), energy-harvesting approaches, and intelligent fuzzy logic approaches;
- In addition, we briefly discuss the overall impact and potential of the joint use of both AI/ML and mMIMO along with a discussion on a few of the research challenges involved in the full exploitation of intelligent mMIMO characteristics.

1.3. Organization

This paper is organized as follows. Section 2 comprehensively discusses the evolution of mMIMO technology with different modes of operation, i.e., single-user and multi-user, favorable duplexing technique, and beamforming with high-frequency communication. Subsequently, Section 3 describes the new antenna deployment strategy, i.e., a cell-free mMIMO system for B5G/6G networks. Section 4 presents recent studies involving conventional AI/ML techniques on the performance enhancement of different mMIMO parameters for 5G/B5G mobile networks. Lastly, the limitations of the conventional learning-based schemes, the significance of edge node learning techniques, and the importance of intelligent reflective surfaces in the context of a multi-antenna system are discussed. Additionally, guidance is provided for the future research directions for ultra-mMIMO enhancements with fully enabled learning-based mechanisms for 6G cellular carriers in Section 5. This study is then concluded in Section 6. Figure 2 depicts the paper's overall structure and organization.

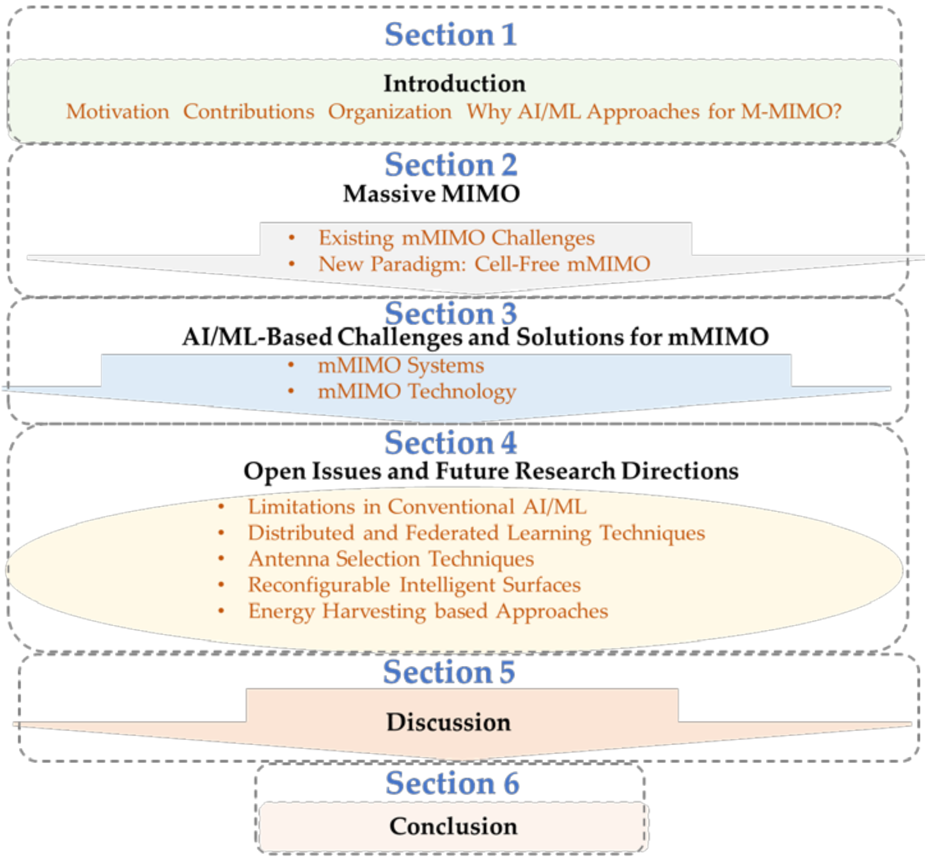

Figure 2. The paper's structure and organization.

1.4. Why AI/ML Approaches for Massive MIMO?

The intelligent AI/ML methods use advanced learning tools and are proficient in developing universal and easily assignable classifiers and general functions [36]. These notions have been widely investigated in diversified arenas such as device and network security, network operations, and mobility support.

In modern wireless communication, multi-antenna arrays require very complicated signal processing and conventional algorithms, such as game theory-based and stochastic geometry techniques, which can perform extremely sophisticated signal manipulation tasks [37]. The heuristic algorithms that can sufficiently handle the pilot assignment, signal detection, precoding, and antenna selection processes in conventional MIMO systems are not capable of tackling the large-scale mMIMO antenna selection and assessment processes robustly [38]. Additionally, the antenna's algorithmic complexities, processing time, and computation power are also significant challenges in optimizing B5G/6G mobile communications.

In light of this, the learning-based solutions are instrumental for these types of intricate analyses and have the potential to overcome high algorithmic and computing power issues. The online learning approaches are also useful in delivering instantaneous responses during mMIMO beamforming (BF), channel estimation, and load balancing tasks and in the efficient utilization of available space [39]. A prominent aspect of ML classification is the ability to learn from the real environment, analyze the received data, and deliver rewards based on the attained value functions. Therefore, after a certain number of iterations, the learning algorithm identifies the optimal value and performs further actions autonomously based on the achieved knowledge. This new paradigm has the potential to manage the mobile broadband and low-symbol URLLC cases in different 5G/B5G wireless communication systems [40].

2. Massive MIMO

Large-scale smart antenna arrays equipped with many Tx and Rx wireless sensing nodes are known as M-MIMO arrays. Since the traditional MIMO technology commonly consists of 2 × 2 or 4 × 4 antennae, M-MIMO wireless nodes are capable of accommodating hundreds or even thousand (theoretically) of antennae at the BS. This concept provides precise beamforming and tracking capabilities in 3D scenarios, including for the Internet of Flying Things (IoFTs), drones, mobile services, vehicular networks, and critical Internet of Medical Things (IoMT)-based availability applications, as shown in Figure 3 [41]. The distinctive feature of M-MIMO from the previous MIMO technology is the quantity of RF nodes at the BS. This idea leads to the basic assumption in M-MIMO operability, i.e., each piece of user equipment (UE) is equipped with a single antenna and the total number of wireless nodes is larger than the number of UE pieces served in a cell area. This is the multiuser transmission solution used to simultaneously serve a large number of users with flexible time–frequency resources [42]. Therefore, the classical M-MIMO technology has been adopted for 5G cellular communication networks due to its physical advantages, such as its increased multiplexing gain level, high SINR level, better coverage, and better capacity, as well as its reduction in latency. Nonetheless, it encounters many practical challenges, such as for high-dimensional CSI, the resource scheduling of substantial access nodes, sophisticated channel modeling, and lower numbers of RF chains, when trying to work at full capacity [43]. Focusing on all channel-demeaning issues, channel estimation and acquisition are the prime concerns when embracing the practical gains promised by M-MIMO in B5G networks. Hence, to cultivate the maximum potential gain in large-scale antenna elements, it is crucial to understand the number of inherent challenges during the CSI estimation, as is discussed below [44].

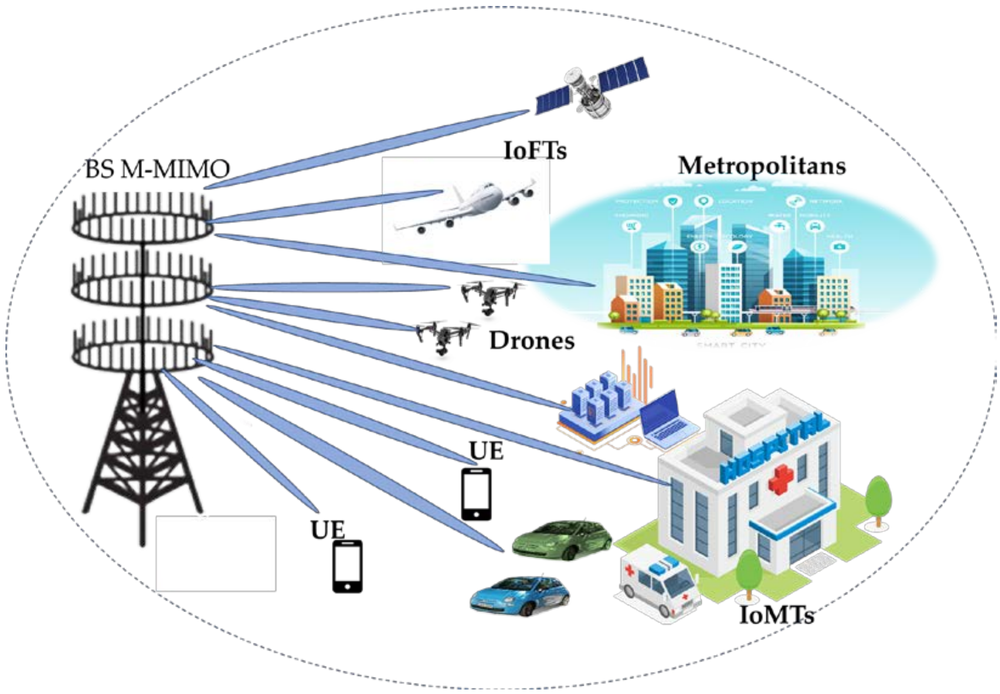

Figure 3. The use of M-MIMO in the HetNet system.

2.1. Existing mMIMO Challenges

The active M-MIMO antenna nodes provide excellent performance in real practical environments for different scenarios. A few persistent challenges still demand a sharp and vigorous approach to reduce the related issues.

2.1.1. Pilot Contamination

The radio spectrum efficiency is a non-trivial feature and a hot research topic in wireless communication. It demands suitable time–frequency or pilot training reuse factors to achieve maximum system throughput [45]. In the context of the conventional orthogonal pilot training process for CSI, the length and required number of orthogonal training sequences should be equal to or greater than the quantity of transmitting antennae [46]. If the network observes an unexpected rise in the number of UEs, there may not be adequate orthogonal training sequences available to separate the UL CSI from the different UEs. Consequently, the same training or non-orthogonal training sets are adopted during the CSI stage and give rise to inter-cell interference, which is coined as pilot contamination.

2.1.2. Overhead DL Training and Feedback

Similar to UL scenarios, the number of training sequences for DL must be equal to or larger than the number of antennae at the BS, whereas the BS may not have an appropriate quantity of training sequences to isolate the DL channels [47]. However, if the number of pilot sequences justifies the argument, still the traditional DL training technique could be vulnerable to interference problems due to the very limited coherence time. Meanwhile, to control the quantization error, the number of antennae must be scaled with the amount of CSI feedback from the users to the BS, as it is a non-trivial feature in practice [48].

2.1.3. Bulky Computational Complications

In channel estimation, a channel matrix operation involves inversion, multiplication, eigenvalue decomposition, and singular value decomposition [49]. In practical circumstances, as soon the magnitude of channel matrices increases, it proliferates the computational complexities that need to be minimized at ground level.

2.1.4. CSI in FDD and TDD Modes

The fundamental criteria in M-MIMO operation are the channel estimation information and data that must be acquired correctly for uninterrupted and ultra-reliable channel transmission. To estimate the CSI, the pilot data are exchanged between the BS and the smart node for proper radio link connectivity [50]. The process is further divided into two categories according to the time and frequency division of resources. FDD is a time-continuous phenomenon, while TDD involves discontinuous slots of transmissions, as shown in Figure 4.

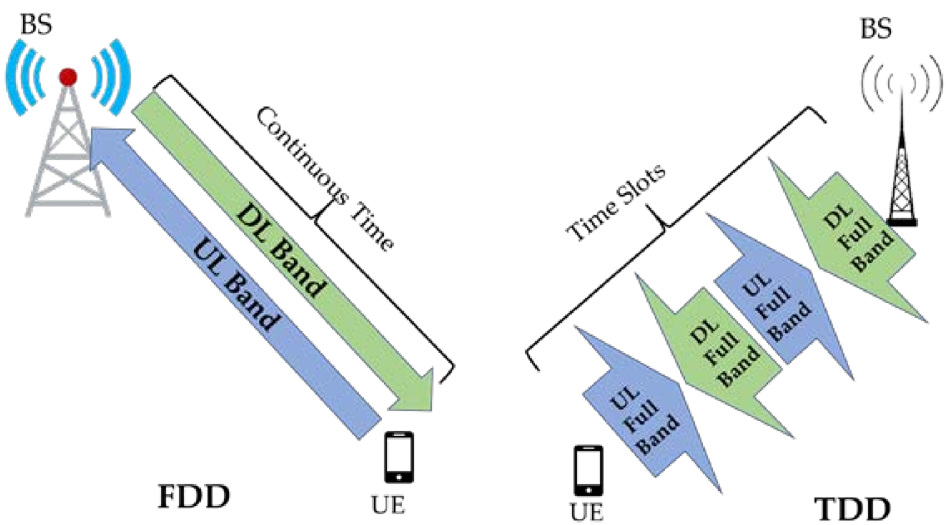

Figure 4. The FDD and TDD modes.

2.2. New Paradigm: Cell-Free mMIMO

In cell-free (CF) mMIMO networks, a substantial number of individually controllable Tx_s and Rx_s antennae are distributed over a wide terrestrial area for parallel transmission to all UEs. The new physically dispersed autonomous antenna system delivers the same quality of experience (QoE) to all users and much better network services with low complexity during signal processing [51]. Particularly, it contributes to the channel propagation characteristics and channel hardening more vibrantly. In contrast to the mMIMO cell-based concept, cell boundary limitations disappear and smart devices are linked simultaneously with multiple antenna lobes. In comparison to cellular-connected mMIMO systems, it shows much better propagation attributes and various other benefits [52], as follows: (i) due to its distributive in nature, it reduces the distance between users and APs; (ii) it spatially covers the maximum coverage area and can provide ubiquitous connectivity, especially in the non-line of sight (NLOS) space; (iii) it enhances the user's capacity and reduces costs, as well as providing flexibility in AP deployments; (iv) it also capitalizes on the EE and SE. These significant traits of CF mMIMO systems make them viable and prudent options for cellular and IoT services in the NR 5G and future 6G mobile communication era [53].

A large array of distributed multi-antenna access points (Aps) simultaneously serves all mobile devices via the accurate characterization of the local CSI. The CF mMIMO infrastructure is comprehensively delineated in [54] and is a highly desirable candidate for cellular user data facilities for forthcoming wireless mMIMO networks. Many multi-antenna elements are geographically distributed and jointly deliver the data requisite to a small group of smart devices via TDD operation. They serve each terminal with the aid of computational measures and fronthaul access network operations with the same time–frequency resources. The TDD protocol is highly recommended for CF mMIMO architectures because it exploits the channel reciprocity. Precisely, in TDD mode, each UE sends a UL pilot to assist each AP to estimate the UL channel, and if the channel reciprocity holds true, then the UL estimation is valid for the DL channels. Therefore, no UL feedback information is required and the pilot resources are independent of the AP antenna elements [55]. Nonetheless, two possible TDD frame structures, i.e., with and without DL pilot signals, are shown below.

Figure 5 depicts the two TDD transmission cases in which the TDD frame without the pilot DL signals is used in the network-based mMIMO system. When no pilot is used for the DL path, the UEs either depend on channel hardening or blindly predict the DL channel from the data. However, both options are available for the CF mMIMO deployment scenario.

Figure 5. With and without pilot-based DL training.

Furthermore, the novel CF mMIMO schemes provide better multi-user interference suppression and higher macro-diversity coverage expansion as compared to the state-of-the-art models. Since the distributed architecture enables each UE to connect simultaneously with multiple APs, the multi-point connection contributes to achieving strong link reliability [56]. All UEs in a physical location would be able to receive a higher symbol rate at all times with negligible interference. The potential applications of CF mMIMO systems that are eminently appropriate for current and next-generation networks are hot-spot and indoor coverage spaces [57]; for example, train stations, shopping malls, stadiums, subways, public arenas, smart factories, and community centers.

In the context of a higher frequency spectrum, the CF mMIMO system facilitates more timely data delivery, mitigates path loss issues, and supports a better SINR level. It also provides macro-diversity gains by reducing the detrimental shadowing, scattering, and low-to-high fading effects. Another important feature of using large distributed APs is that short-dimension antenna array can exploit the mmWave with minimum hardware and algorithmic complexities [58]. Table 2 below delineates the differences between centralized and CF-mMIMO systems.

Table 2. A comparison of centralized mMIMO and CF-mMIMO networks.

Configuration	Centralized	CF
Number of Antennae	Large	Large
Channel Estimation	Global	Local
Energy Efficiency	High	Very High
Coverage Uniformity	Bad	Excellent
Macro Diversity	Small	Large
Deployment Cost	High	Low
Fronthaul Resource	Less	Moderate

The geographically distributed large-scale antennae jointly serve a small group of randomly dispersed UEs without cell boundaries. All of the APs are directly linked to the processing unit and connect each user via low-power transmission to the CF mMIMO network, with centralized connectivity for all of the APs, as shown in Figure 6.

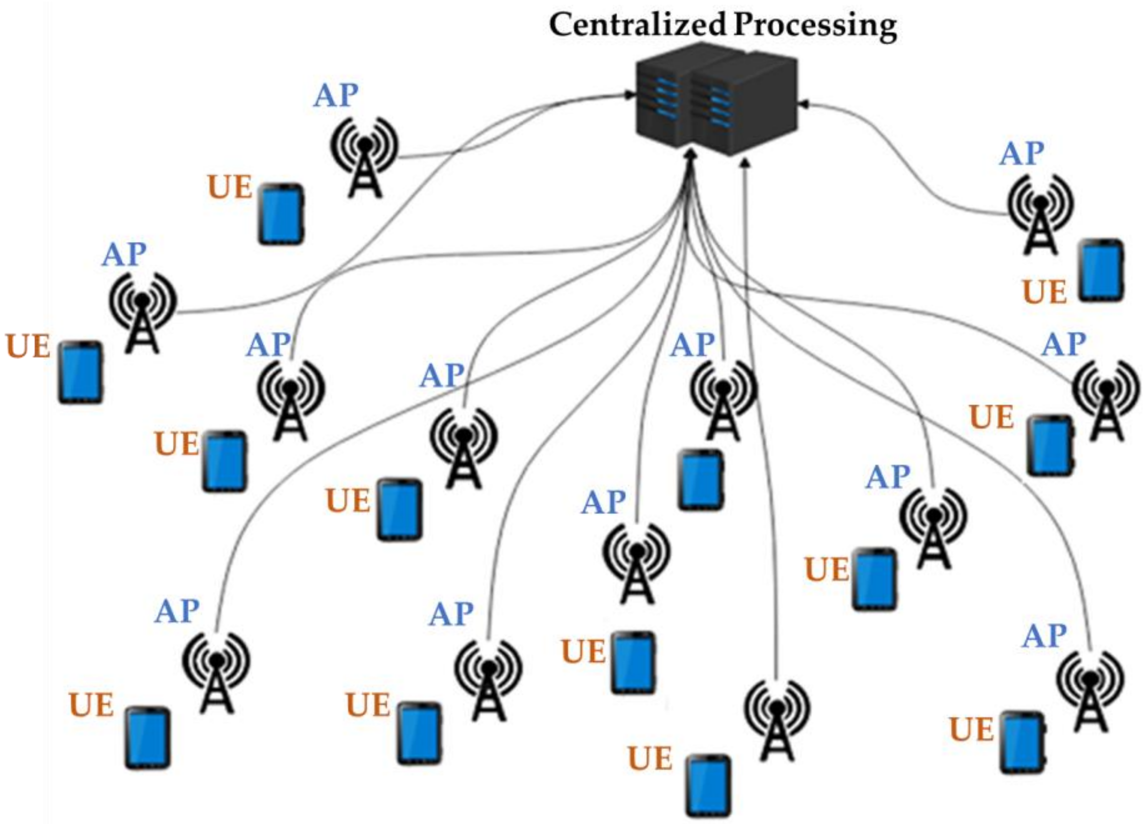

Figure 6. The CF mMIMO architectural system.

3. AI/ML-Based Challenges and Solutions for mMIMO Systems

In the current cellular networks, centralized AI/ML processes are partially involved in the different domains of the 5G services and perform several operations satisfactorily. For the optimization of B5G and upcoming 6G wireless networks, learning-based mechanisms are pivotal to governing various networking processes [59]. The use of mMIMO systems requires very complex mathematical formulations, while the conventional frameworks, such as stochastic geometry and game theory frameworks, are very sophisticated and consume enormous amounts of computational power. The dynamic and active behavior of ML algorithms could be instrumental for these complicated empirical analyses and could be helpful in saving excessive computing power. In this regard, for current 5G networks, centralized AI/ML-based strategies are considered reliable for different mMIMO operations and avoid several limiting factors, including computing latencies [60]. Some of the studies that have been performed on different constraints in mMIMO operations are discussed below.

3.1. mMIMO Systems

Previously, many studies have been developed using heuristic algorithms and complicated mathematical models for the optimization of MU-mMIMO networks. Those algorithms and designs have achieved satisfactory results in real-world scenarios with high computing times and latencies. Algorithmic intricacies and delay sensitivity represent serious challenges, especially for time-sensitive services and immersive media applications in B5G cellular networks. To overcome these obstacles, recent studies exploiting learning-based algorithms on the cooperative work of distributed MU-mMIMO systems for different wireless applications have received enormous attention. In these research studies, the authors have attempted to decrease the mean square error (MSE) of the channel estimation and interference issues while improving the precoding designs and resource allocation schemes [61].

The modern CF mMIMO systems involve a deployment strategy that transforms the cell-centric architecture into a user-centric one. Remarkably, CF mMIMO schemes are 95% more likely to use SE than conventional cellular designs under different circumstances [62]. The FD-TDD mode is considered a more reliable and efficient approach due to the lower feedback overhead in CF mMIMO networks. The use of downlink pilot sequences will result in additional signal overheads that may rely on the number of distributed units. Another impactful feature in achieving overall greater network performance for CF mMIMO networks is optimizing the resource allocation strategies [63]. The distribution of resources following the user-centric scheme is a major challenge in the current 5G HetNet architecture.

3.1.1. Design Constraints

A multi-layer deep neural network (DNN) was devised to efficiently distribute the power allocation to each pilot sequence and to reduce the sum of the MSEs [64]. The authors stated that the proposed solution helped them to attain reliable sum MSE performance as well as less computing complications in comparison to the baseline schemes. In [65], dual ML-based detectors, i.e., semi-supervised learning and online learning algorithms, were proposed for the UL MU-MIMO system. In this context, the authors advised that semi-supervised learning would help to address the drawbacks of the current SL detector, while the online learning (OL) detector can been used to provide robustness to the implemented SSL algorithm. Consequently, the simulation tests proved that the SSL algorithm outperformed the traditional SL detector and the OL detector achieved HQ performance for time-varying channels.

To reduce the hardware control complexities and systematically utilize the power resources of mMIMO systems, hybrid precoding has attracted a lot of attention and allows many valuable solutions for future tangible communication. Most of the preceding work for hybrid precoding was based on exhaustive search mechanisms, resulting in high mathematical calculation intricacies. A hybrid precoding network (HPNet) based on a deep learning approach has been proposed for mmWave MU-MIMO networks [66]. The suggested algorithm validity proved by the experimental test and the outcome of the practical examination showed that the HPNet outperforms the latest schemes with fewer operational difficulties.

3.1.2. Interference and SNR Level

In [67], an extreme learning machine (ELM)-based receiver for MU-mMIMO networks was considered. The authors showed that the ELM attains a greater SE and a low bit error rate (BER) with a minimum MSE (MMSE) level via the efficient setting of several hidden neurons. Since 5G cellular services are already functional and performing satisfactorily in different parts of the world, researchers are focusing on the optimization of 6G cellular communication networks, which will be denser than the NR 5G services. Thus, observing the future requirements, more advanced and active approaches that can respond instantaneously to different cases are much needed. As such, a convolutional neural-network-based likelihood ascent search (CNNLAS) detection scheme was designed for the UL high-order QAM MU-mMIMO model to exploit the interference issues [68]. The algorithm showed strong resistance against the high BER and channel estimation errors and required low average received signal-to-noise (SNR) ratios to achieve the theoretical SE. In [69], the authors discussed the interference issue in MU-MIMO IoT-enabled 5G/B5G systems and devised a learning detection scheme, namely a deep convolutional neural network (DCNN). The proposed design significantly overcomes the influence of interference and computational adversities.

3.1.3. Beam and Resource Allocation

A new beam allocation issue was exploited by using a DNN in the mMIMO system [70]. The brute force and suboptimal search algorithms were used and achieved beam accuracy rates of 91.6% to 97.7%, respectively, at the Rx. Lately, beam allocation and training experience approaches have been exploited to reduce the training time [71]. A QoS-constrained (QC) beam allocation technique was presented and it significantly improved the SE. Likewise, a location-aided and ML-based beam allocation algorithm (LMLBAA) was designed for 3D mMIMO networks [72]. The simulation test demonstrated that the increase in the SNR level also increases the average available sum rate. In another study [73], the authors developed a joint ML-based radio resource management (RRM) and hybrid BF design for the mmWave DL MU-mMIMO system. The simulation test showed that for $K = 4$, the proposed algorithm is trained after 228 iterations with 28.72 less execution delays.

3.1.4. Power Allocation

Power allocation to individual antennae is one critical challenge in CF mMIMO networks when trying to achieve the maximization (max) of the minimum (min) capacity of each smart node. An algorithm based on deep learning for the upstream power distribution of a CF mMIMO network was presented in [74]. The task was conducted to increase the sum-rate value and max–min power adjustment by avoiding pilot contamination. The numerical assessment showed the existence of the pilot interferences but it did not deteriorate the performance metrics. Additionally, a DNN technique was tested for a max–min power policy for better QoS for all users [75]. Compared to other heuristic approaches, the proposed algorithm provided acceptable results and low time complexity for non-deterministic polynomial hard problems.

In [76], the EE was discussed in the context of substantial IoT terminals. Previously, a wireless power transmission (WPT) technique was utilized to rectify the sensor node's energy dissipation issues. The authors in [77] suggested a restart artificial bee colony (RABC) method to asymptotically converge to the optimal solution for energy-efficient data transfer in the wireless charging of a sensor network. Numerical simulations showed that the energy consumption in the studied network scenario can be minimized using the proposed method with good, robust properties. Unfortunately, the current WPT solutions are no longer supportive of long-range and multi-target transmission. An mMIMO cellular system has been implemented for IoT applications [78], however the presence of thousands of smart devices wirelessly connected via the Internet and communicating within a close proximity will cause inter-cell interference (ICI), which may cause severe degradation of the network quality, which will severely effect the modern requirements for high-definition (HD) video and data services, VR systems, and augmented reality applications [79]. Therefore, the power allocation solution for CF mMIMO IoT scenarios was fine-tuned and a memetic AdaBoost neighborhood field optimization (ABNFO) scheme was designed to tackle the obstacle [80]. Simulation tests were performed to analyze the total EE of the system based on the transmission power, circuit power, noise power effects, and system density to guarantee the sustainability of the CF IoT system. The results validated the high consistency of the CF mMIMO systems. In a recent paper [81], the authors tried to solve the max–min user fairness issue by considering the DNN learning algorithm. A simulation analysis confirmed that fewer computational issues occurred than when using GP-based optimization methods. Another system throughput maximization approach involving controlling the power levels in four possible modes using the DCNN technique was studied in [82]. By implementing the scheme, the simulation results proved the validity by raising the throughput exponentially.

3.1.5. Channel Estimation

Although the FDD mode delivers better system efficiency, the CSI feedback is always a problem. A denoise network based on deep learning was formulated to enhance the channel feedback performance [83]. Thus, the proposed method still delivers greater performance than existing algorithms at a low SNR level. Moreover, the use of narrow beams is considered a promising approach to attain higher throughput and dedicated paths for each user (especially for the distant terminal). A deep deterministic policy gradient (DDPG) algorithm has been presented with the combination of deep distributed deterministic policy gradients (D4PG). Both presented techniques were based on the deep reinforcement learning (DRL) algorithm [84]. Consequently, (i) the D4PG accomplished HQ performance, irrespective of the network size, (ii) while distributed BF model performed better than the DDPG and (iii) all DRL models showed shorter processing times than the conventional gradients. In another paper [85], a federated learning (FL) environment for CF mMIMO systems was used to enhance the FL framework performance. The numerical results showed that the proposed joint optimization design successfully decreased the training time of the FL algorithm over the baseline techniques. The CF mMIMO network also showed a low training time as compared to the CF-TDMA-mMIMO and collocated mMIMO networks. A next-generation paradigm for CF-mMIMO communication and operation with a more enhanced view was presented in [86]. The authors explored the potential solutions to the issues that persist with FDD CSI acquisition and feedback overheads in the network. A low-complexity multipath component estimation model with linear angle-of-arrival (AoA)-based BF schemes has been developed. The simulation test showed that in terms of the SE and EE, the FDD-based CF mMIMO system outperformed the cell-based wireless networks with an adequate count of antenna APs. An enhanced K-means clustering (E-KMC) algorithm for semi-blind channel estimation was investigated by the authors in [87]. The proposed E-KMC method performed much better than other semi-blind channel estimation schemes. Table 3 summarizes the current literature on AI/ML-based MU-mMIMO systems.

Table 3. A summary of the literature on AI/ML MU-mMIMO networks.

mMIMO System	Approach/Issue	Methodology	Advantages	Limitations	Ref.
Design Constraints	Sum MSE of channel estimation	Multi-layer (DNN)	Better sum MSE and low computational complexity	Pilot transmit power was considered as a predefined constant	[64]
	Designed a low-complexity detector	(i) SSL detector and (ii) OL detector algorithms	SSL reduced the pilot overhead and OL is robust to variations in the channel	Design is limited to a single antenna transmitting the binary signal to one BS only	[65]
	Reduced hardware complications, memory usage, and energy consumption	HPNet based on DL	Significantly decreased the complexities and enhances the EE/Extra operational work	The RF chains and streams antenna users are considered the same values	[66]
Interference and SNR Level	Effects of adjusting the number of neurons of the ELM scheme based on the BER and SE	ELM-based receiver	For BER 10^{-4} a difference of 2 dBs between MMSE and ELM; ELM required less training than the MMSE receiver	Perfect synchronization is needed between BS and UE	[67]
	Interference exploitation in the coming 6G networks and beyond	CNNLAS detection scheme	Supported theoretical SE/robust against channel estimation errors	A complex mathematical algorithm is required for higher interference mitigation	[68]
	Interference problem in 5G/B5G-enabled IoT system	Symbol-by-symbol detection and DCNN to suppress interference	Obtained ultra-reliable detection performance & reduced computation work	Limited to flat fading channel only	[69]
Beam and Resource Allocation	Evaluated the beam allocation in mMIMO	DNN with the assistance of the butler method	91.6 to 97.7% accuracy to predict and allot beams/multi-cell 3D BF and switching	It is required that the polar plots not exceed their respective radii	[70]
	Investigated the beam training & allocation	OP for beam training and QC-based beam allocation	QC beam allocation improved the SE/explore further critical metrics for beam allocation and training	The user suffers from channel power leakage due to beam conflict	[71]
	Beam allocation for 3D mMIMO systems	LMLBAA to optimize beam allotment in a short time	Tx SNR directly related to average sum rate	It can be replaced with other classification algorithms for further improvement	[72]
	Explored rank constraints in the mMIMO network	ML-based RRM algorithm	Supported a similar sum-rate given by CVX-based scheme but took 28.72 less seconds for execution time	Practical implementations require changes in analog and digital beamforming	[73]

Table 3. *Cont.*

mMIMO System	Approach/Issue	Methodology	Advantages	Limitations	Ref.
Power Allocation	Power allocation in UL CF mMIMO networks	DNN to learn the mapping between a set of input data and power allocation form	Achieved near-optimal performance	The presence of shadowing means the performance degraded	[74]
	Power allocation for QoS for all users	DNN algorithm	Achieved approximately similar results to other heuristic approaches with low complexity	This work is limited to sub-6 GHz applications and can expand to the mmWave model	[75]
	Power allocation in CF mMIMO IoT systems	A novel heuristic ABNFO scheme	Although the algorithm showed good convergence performance, a more robust algorithm still needed to reduce stagnation	Instructive comparison with various other ML processes	[80]
	Solved the user fairness problem in CF mMIMO	A DNN unsupervised learning-based approach	Constructed approach achieved a performance–complexity trade-off around 400 times faster than the optimization-based method	The design is only limited to the unsupervised learning approach	[81]
	Sum-rate maximization with ML-based power control	DCNN algorithm to determine mapping terms	UL sum-rate of the system increased by 3 times more than existing methods with less than 0.02% loss	The complexity increases with the larger network	[82]
Channel Estimation	Evaluated the CSI feedback in an FDD CF mMIMO network	Deep-learning-based denoise network (DDNet)	The algorithm showed better results than existing models (performance comparison conducted at SNR −5 dB to 40 dB)	A more advanced learning mechanism is used to achieve better denoise quality	[83]
	Distributed UL BF in CF mMIMO systems	DRL-based DDPG, D4PG, fully-distributed BF algorithms	All DRL schemes performed better than other methods (learning rate of gradient $\alpha = 0.1$, $K = {}^{M}/_{3}$, M = [15–150], K= user count)	The presented framework can be generalized to comply with different wireless network parameters	[84]
	Optimized the performance of any FL design	Designed FL algorithm with an optimization problem	Joint design minimized the training time by up to 55% over baseline models	Complex computational algorithm	[85]
	Analyzed the CSI acquisition and feedback overhead problem	Low-complexity estimation process with small overhead	SE and EE of the suggested power design outperformed cell-based networks	Cost increases with higher number of cellular users	[86]
	Investigated the semi-blind channel estimation at the CPU of a UL CF mMIMO	A low-complexity E-KMC algorithm	High BER performance, which was close to perfect CSI case/E-KMC, significantly reduced complexity, i.e., approximately 10^6-fold in a 6×64 QPSK system	Accurate CSI is required to achieve higher performance	[87]

3.2. mMIMO Technology

The current mmWave and untouched sub-mmWave bands are the key enabling technologies for 5G cellular broadcasting and have been regarded as commendatory technologies for the forthcoming cellular carriers [88]. Since hybrid BF is an essential part of the existing wireless systems in the guidance of the best and fastest transmission route by generating continuous multiple ultra-high frequency lobes for short-distance measurements, the high-spectrum access with beam management is expected to deliver enhanced user and system data rates. This would raise the bar by almost 100 times more than the previous mobile generations with the help of mMIMO intelligent arrays [89]. However, the elemental limiting factor for the conventional hybrid precoding frameworks used in multi-antenna networks is the heavy computing complications, which severely affect the ability to optimize the spatial information gain.

Concerning the learning-based methods, the assistance of BF-mmWave and multi-antenna streams is considered an optimum remedy to maintain the current 5G wireless transmission activities. Some of the recently concluded studies presented in the literature focused on the optimization of different antenna challenges while exploiting AI/ML techniques are demonstrated below.

3.2.1. Hybrid Precoding Designs

A deep learning hybrid precoding method was designed to reduce the complexities and increase the system performance [90]. The analytical results validated the facilitation of hybrid precoding by reducing the BER level and increasing the SE. The super-fast data transferability rate of the mmWave spectrum makes it difficult to estimate channels based on the BS, especially pilot signals. The situation becomes worse for mobile users and smart moving platforms, which creates several challenging situations. The authors in [91] presented a deep learning compressed sensing (DLCS) channel estimation process and deep learning quantized phase (DLQP) hybrid precoder for low-resolution phase shifters. The results proved the high performance of both schemes in terms of the channel prediction and SE. Likewise, hybrid precoding was deemed a promising aspect to help provide high data rates for future IoT infrastructure. Nonetheless, the current literature does not contain discussions on the many soft solutions for high power consumption rates. To address this issue, CEO-based hybrid precoding with one-bit PSs for frequency-selective wideband mmWave mMIMO systems was investigated by the authors in [92]. The results validated the high EE and acceptable sum-rate performance of the previously developed schemes. Although various studies have been performed for hybrid precoding designs using OMP and AM techniques, in contrast few researchers have opted for different algorithms or constructed hybrid precoding solutions with low computational hardship. So far, all of these remedies are limited to narrowband mmWave channels, and wideband mmWave scenarios still need to be further explored. Therefore, a joint hybrid combiner and precoder technique for wideband mmWave mMIMO systems to acquire an achievable sum-rate was presented [93]. The empirical assessment highlighted the system's good performance in terms of computation time as compared to the existing solutions. The joint work of the Tx BF matrix at the BS and the phase shift matrix at the reconfigurable intelligent surface (RIS) using deep reinforcement learning (DRL) was considered for reliable system performance [94]. It was observed that the neural network parameter's appropriate settings significantly enhance the algorithm's convergence rate and overall performance. Table 4 summarizes the work conducted by the researchers recently using AI/ML algorithms for hybrid precoding designs.

Table 4. Summary of hybrid precoding designs in BF-mmWave-mMIMO systems with AI/ML.

Approach/Issue	Methodology	Advantages	Limitations	Ref.
High computational issues in hybrid precoding to reduce hardware complexities and energy consumption	Deep-learning-based hybrid precoding	DNN scheme facilitated the hybrid precoding because of mapping and recognition abilities; the simulation showed a reduction in BER and enhanced SE	Must apply a deep learning framework in the channel feedback problem to remove the codebook size and feedback overhead	[90]
Channel estimation with new precoding design	DLCS channel estimation and DLQP hybrid precoder	DLCS proved to be best channel estimation apporach rather than OMP and DGMP; the simulation results showed a fixed SNR = 15 dB for J = 6 DLCS provided 56.1% and 85.2% improvements; at J = 7, DLCS gave 56.0% and 84.3%	Ther is a need to develop channel estimation and hybrid precoding design for a wideband MU-mmWave mMIMO system with DL	[91]
Analyzed energy consumption, array gain loss, and sum-rate maximization problems	CEO-based hybrid precoding with one-bit PSs	The proposed CEO-based method at $N = 128$, $N_{RF} = 8$, and $M = 256$ achieved 80% of the sum rate and a higher EE, being comparatively better than other benchmark schemes	A higher antenna array is required for accurate results	[92]
Evaluated antenna gain and complexity costs	TS-based joint hybrid precoding and combination scheme	A higher sum rate achieved along with a low computing latency	Restricted to a limited number of use cases. There is a need to extend the strategy to multiple user cases	[93]
A large-dimension optimization problem	Joint design obtained via trial–error interactions using DRL	The proposed method gradually improved its behavior. The SNR affects the convergence rate and performance	The DRL is sensitive to low SNRs	[94]

3.2.2. Beam Management Techniques

The current 5G BSs have simultaneously served many users with multiple beams in MU-mmWave mMIMO networks. A hierarchical codebook-based beam training scheme is usually utilized in the beam selection and alignment process for different users. In [95], a new alignment method with partial beams using ML (AMPBML) was evaluated. The bench test verified the superiority of the algorithm in terms of the SE and total training time slots over conventional methods. Similarly, a combination of ML tools and a situational awareness model was demonstrated in a congested mobile vehicular environment [96]. The numerical analysis showed an improvement in prediction accuracy that contributed to the throughput with approximately zero overhead. In [97], the researchers fully capitalized on the AoA information to conduct beam selection in the UL direction. A mixture of analog BF with an adjustable beamwidth and zero-forcing (ZF) baseband processing block with two supervised ML approaches was established. As a result, the received accuracy and sum-rate values were close to the exhaustive search results. Moreover, the use of hybrid BF is a promising low-cost solution for wide-scale transceiver streams; however, the selection of codewords for analog BF is critical to efficiently maximize the UL sum rate [98]. A data-driven process based on ML is used to obtain the near-optimal proposition, and the analytical results proved the lower computational delay with a high-order magnitude. Two deep learning schemes, namely original DNN-based beam training (ODBT) and enhanced DNN-based beam training (EDBT), have been formulated. The analytical results proved the dominance of the process in reducing the beam training overheads as well as the RF signal coverage area. However, satisfactory behavior is yet to be shown in terms of the achievable success rate [99]. The 3D control of spectrum provisions involves combined implementations of various techniques. For example, the authors in [100] suggested the joint implementation of vertical space–time bell labs and spatial multiplexing to attain high transmission rates while maintaining the lowest number of RF chains at the transmitter. Similarly, hybrid beamforming is emerging as a vital concept in 6G physical layer intricacies for handling multi-GHz bandwidths [101]. The authors in [102] proposed a 3D hybrid beamforming approach for THz massive MIMO broadband communication. This is a low-cost scheme based on a two-tier true time delay for counting the beam squint effect in both the vertical and horizontal directions. Moreover, the authors in [103] suggested a deep-learning-based wideband hybrid precoding network for a THz-enabled massive MIMO system. The scheme preprocesses the CSI through the mean channel covariance matrix. The proposed scheme can handle the imperfect CSI due to having a higher sum rate than the full digital precoder. Table 5 summarize the work conducted recently using AI/ML algorithms for beam management techniques.

Table 5. A summary of the beam management techniques in BF-mmWave-mMIMO systems with AI/ML.

Approach/Issue	Methodology	Advantages	Limitations	Ref.
Analyzed beam alignment for MU-mmWave mMIMO	Alignment method with partial beams using ML (AMPBML) algorithm	The output was achieved when SNR = 0 dB, NPS I, at U = 3 59.0%, 68.7%, and 257.0%, respectively, whereas at U = 7, AMPBML received 17.3%, 131.4%, and 376.5% improvements over the ACS, MDR, and HS schemes, respectively	NPS II still shows slightly better performance than NPS I	[95]
Capitalized on mmWave RF energy in a highly mobile vehicular scenario	Combinatorial of ML and situational awareness to learn beam characteristics	It helped to identify useable beams from the bad beams; the dataset's highest beam power was P_{max} = 44.23 dBm and the lowest P_{min} = −15.15 dBm	The given stats for the dataset's upper- and lower-bound power evaluation	[96]
Examined AoA information for beam selection	ML approaches: k-nearest neighbors, support vector classifiers, multi-layer perception	ML algorithms held about 90% of the sum rate with optimal beam prediction	Requires generalization in the context with multipath propagation	[97]
Investigated the selection of codewords for hybrid BF	Data-driven scheme based on ML with analog beam selection in the training of data constraints	Produced near-optimal sum-rate percentage and complexity was significantly reduced	The complexity of the BF algorithms is increased	[98]
Investigated beam training in an mmWave mMIMO system	Two DNN-based beam training schemes, i.e., ODBT and EDBT	Successfully reduced the beam training overhead and enlarged the signal coverage zone	Needs improvements to the DNN design and preprocessing format	[99]
3D control of the spectrum	Joint implementation of vertical space–time bell labs and spatial multiplexing	High transmission while maintaining the lowest number of RF chains at the transmitter	A complex mathematical algorithm is required for large-scale SMx-SM systems	[100]
3D hybrid beamforming	Two-tier true time delay	Counters the beam squint effect in both the vertical and horizontal directions	An additional phase shifter array is needed with the same number of antennae	[102]
Deep-learning-based precoding	Preprocesses CSI through mean channel covariance matrix	Handles the imperfect CSI due to having a higher sum rate than the full digital precoder	A uniform planar array (UPA) is utilized rather than a conventional uniform linear array (ULA)	[103]

4. Open Issues and Future Research Directions

4.1. Limitations of Conventional AI/ML Approaches

Regarding the current multi-tier 5G HetNet systems, researchers have developed several intelligent and learning-based methods for managing the real-time user's activities, the link budgeting, the data traffic load capacity, the network resources, and the scalability. In this context, centralized AI and ML algorithms are promising methods that can extract a substantial amount of data from electronic appliances and instruments without being extensively programmed [104–106]. The AI and ML techniques are partially involved in different domains of 5G mobile operations, allowing smooth network functionality, agility, and robust instantaneous performance for diversified broadband and delay-sensitive applications.

However, the continuous growth in data traffic from diversified mobile multimedia activities and the many upcoming high-BW plus delay-tolerant use cases, such as digital replica, extended immersive reality, and brain–computer wireless interaction applications, will require extreme reliability (up to 10^{-9} percentile), ultra-low latencies (up to 0.5 ms), and superior throughput rates (multiple Tbps) using B5G/6G networks [107]. The centralized learning approaches are not able to smoothly govern the challenges related to daily data consumption and the network load due to their cloud-centric architecture, whereby a large volume of data is centrally collected, processed, and stored. The unprecedented throughput and reliability–latency requirements have shifted the focus to intelligent federated and distributed learning approaches, where data can be processed and computing resources can be located at the edge nodes instead of routing across the network [108,109].

4.2. Distributed and Federated Learning Techniques

4.2.1. Distributed Learning

In the contemporary wireless communication ecosystem, the majority of the AI/ML approaches are based on a centralized architecture, wherein the collected data set has to be route through a central server location (or cloud). Subsequently, the cloud server is used for the analysis and processing of the data, which are then sent back to the sensors and actuators [110]. However, due to the paradigm shift regarding big data and the limited radio resources, not all smart devices should transmit all of their accumulated data to a cloud server that can further utilize a centralized learning approach for the analysis of data. Moreover, many emerging wireless services, e.g., D2D communication, aerial vehicles, and industrial robotics networks, are inherently distributed, and in view of the future applications, centralized learning techniques may not be appropriate for delay-sensitive and stringent data success probability services [111]. To overcome this unprecedented scalability challenge, as well as latency, privacy, BW efficiency, and ultra-reliability challenges, distributed learning frameworks (e.g., MapReduce) and autonomy of edge intelligence devices are much needed to compute, analyze, and process data in real-time at the edge of the cellular network for the swift training of ML models [112].

To attain very high accuracy levels and unmatchable QoS performance in assorted future extreme broadband and URLLC cases, the upcoming 6G networks will be adjoined in an integrated system of sensing, computing, communication, and control functions, while the new distributed learning-based algorithms will be precisely exploited to accelerate the training of ML models [113]. In regard to this, new refined frameworks and algorithms for integrated communication, sensing, and learning are indispensable.

A few of the widely discussed approaches for distributed learning design in wireless network environments are the (i) compression and sparsification, (ii) spatial resource management, and (iii) AirComp methods. Regarding the compression and sparsification methods, the compression methods utilize fewer bits to train the ML model parameters, while sparsification methods update the high-dimensional ML frameworks to their sparse symbols by trimming some of the relatively trivial elements [114]. Thus, both methods assist in reducing the magnitude of ML model parameters and ultimately achieve lower communication overhead costs.

In the context of spatial resource management, for the efficient utilization of limited resources, the time–frequency slots, transmit power, training sequences, computing times, and computational complications are being optimized with the support of distributed learning techniques. This is being done to escalate the process and enhance the functionalities of future wireless networks. AirComp provides scalability solutions for multi-access in the presence of substantial edge devices in a dense geographical area, and is critical for achieving good minimal learning performance [115]. Moving forward, an approach that must be considered is to construct a distributed training model that simultaneously considers the cellular network dynamics (e.g., channel characteristics), distributed learning parameters, and topologies of the wireless ecosystem (e.g., mobility patterns of smart nodes, locations) [116].

4.2.2. Federated Learning

The use of federated learning (FL) has also become popular in wireless communication activities due to its benefits over centralized systems. In the FL process, raw data are reserved at end-user nodes, which contribute to training the joint model [117]. At the central server end, locally computed updates are acknowledged and accumulated for an improved global model assisted by distributed learning. Thus, in this way, future wireless systems could not only maximize the rate–reliability–latency aspects but also escalate the training of the AI/ML models [118,119]. The current applications of FL frameworks are in Google prediction keyboards and many other diverse areas, including healthcare, smart transportation system, and industrial automation [119].

Lately, many studies have been conducted on different training aspects to allow personalization (i.e., multi-task learning), to train sets over dynamic topologies, and to guarantee agility in comparison with traditional centralized ML and data analysis approaches [120]. Nonetheless, a concern that limits the potential results of the FL model is its overhead communication cost, which is proportional to the number of model parameters, meaning the FL model has a deficiency in supporting deep NNs over capacity-limited cellular systems.

4.3. Antenna Selection Techniques

The use of a multi-antenna system is a beneficial approach to accommodating a massive number of intelligent electronic devices with uninterrupted data rates and reliability, whereby each antenna element requires a dedicated RF chain, which results in higher energy dissipation rates and hardware costs. The antenna selection method can alleviate the practical limiting aspects of mMIMO systems, whereby a group of antennae are connected to a small number of RF electronic chains by an RF switching network, which eventually achieves EE and lowers the hardware cost. Consequently, the authors in [121] proposed a matching pursuit approach with a generalized bit plane technique based on a greedy algorithm for antenna selection, while optimizing the MSE of the signal reception, minimizing the Tx power, and achieving reliable reception with low algorithmic complexity. Likewise, the concepts of submodularity and monotonicity are based on the greedy algorithm, maximizing the sum-rate capacity in the DL stream under the antenna selection trouble scenario proposed by the authors in [122]. The results showed that the suggested algorithm performed extremely well under restrictive switching feasibility and multi-subcarrier transmission conditions.

The antenna selection strategies were beneficial in terms of improving the performance of the wireless network and the SE while reducing power consumption issues. Nonetheless, the antenna selection process inherently leads to performance loss owing to the activity of a special group of antenna elements [123]. It is necessary to construct a new system architecture that alleviates the overall performance loss issues while benefitting from low power dissipation and hardware overheads.

4.4. Reconfigurable Intelligent Surfaces

The concept of reconfigurable intelligent surfaces (RIS) is closely related to the M-MIMO technology, and it has been validated that it will play a pivotal role in achieving the objectives of B5G/6G M-MIMO networks [124]. Principally, the RIS system involves a planar meta surface array comprised of several low-cost and passive electronic elements, whereby each unit can be independently regulated to a certain degree of the phase shift via a central RIS controller, ultimately causing changes to the incident signal [125,126]. The modification can be observed either in the form of the phase, amplitude, polarization, or frequency. Therefore, by approximately modifying the phase shift of each passive element, the incident signal reflected by the smart meta surface can be constructively converged at the position of interest [127]. The newly introduced RIS technology is a robust mechanism that can assist in maintaining the transmission rate under a poor channel state [128,129].

However, the analysis and design frameworks used in the RIS technology are still in their initial stages, while researchers and mobile communication authorities have firmly stated that it has the potential to meet future communication needs [130]. Thus, in the forthcoming years, substantial analytical, empirical, deployment, and elemental research studies on RIS will pave the way for enhanced QoS performance and user experiences in different B5G/6G wireless ecosystems [131,132].

4.5. Energy-Harvesting-Based Approaches

4.5.1. Energy Harvesting via Conventional Approaches

The upcoming 6G networks are expected to be hyper ultra-dense networks that will enable data connectivity for a massive number of smart devices for a variety of services. The immediate concern is the energy usage, because the majority of the Internet-connected peripherals will be either powered by a battery charger or batteryless tools [133]. In practice, the use of battery pack backups with limited charging capabilities minimize the overall network's lifetime, eventually degrading the QoS. In this regard, frequent battery replacements are still advisable to offer flexibility, yet excessive labor, hardware, and material costs are a major stumbling block to the performance and optimization of a colossal smart device's wireless data connectivity [134]. Thus, different advanced AI/ML-based energy restoration solutions are urgently required to ameliorate the energy distribution challenges in future mobile networks. Therefore, 6G deployments have been trialed with several novel approaches, such as green and sustainable communication, energy harvesting, intelligent reflecting surface, and deep enforcement learning-based resource allocation approaches [135].

Wireless energy harvesting solutions have been studied to address various real-world scenarios where electric grid systems are not applicable; for example, aerial platforms and wireless sensor networks have been studied [136] with sensing elements in challenging environmental structures [137,138]. In theory, the RF energy radiated by the Tx can be cultivated at the Rx side, which can be modified into electrical energy for future use. Nonetheless, wireless energy transfer (WET) technologies encounter many technical hardships related to resource allocation, energy beam alignment, and frequent signal path loss attenuation. Thus, to completely unlatch the full potential of the WET technology, it needs to be collocated with other contemporary technologies and architectures to achieve the practical demonstration of IoE networks [139].

4.5.2. Energy Harvesting Using RIS-AIDED CF mMIMO Systems

CF mMIMO APs are inherently distributed and can conspicuously assist each user via multiple RF streams across a massive access network. In such a massive network architecture, a large amount of energy would be dissipated while significantly elevating the interference trouble imposed by the hyper ultra-dense APs. Hence, it is imperative to investigate innovative and robust SE and EE solutions for low-cost 6G wireless networks [140].

Recently, the RIS metasurface approach, which requires very low power consumption to process the RF incident signal, has shown good performed when deployed in communication networks and is able to support cellular services in dead zones; thus, it is considered an efficient solution to minimize the energy effects in wireless propagation environments [141]. Despite the commendable attributes of RIS-aided CF mMIMO systems, a few researchers have focused on optimizing the energy consumption performance. For instance, these authors have investigated the combined performance of BF and phase shifts and the energy credibility at the IRS for a fast-fading channel model as a non-convex optimization issue [142]. The proposed computationally efficient iterative scheme shows superior performance as compared to traditional MISO antenna systems without IRS arrays. The authors of [143] studied the overall network performance and sustainability of a single RIS-aided CF mMIMO system; however, the study was conducted under idealistic scenarios, investigating the Rayleigh fading channels and adequate energy storage capacity. Another study was performed on the precoding design for RIS-assisted CF mMIMO systems [144]. However, a comprehensive research analysis on the exposure of RIS with CF mMIMO antenna systems and WET technology is an open research area.

4.6. Fuzzy Neural Network (FNN) for MIMO

MIMO systems display high oscillations in time and signal amplitudes, making AI/ML-based learning a challenging task for conventional techniques. Therefore, the neuro-fuzzy approach is considered suitable for the collection of the timed automata-based dynamic behavior of the MIMO system [145]. Due to the non-linear analysis abilities of the ANN and fuzzy interference methods, fuzzy neural networks (FNNs) have been extensively researched for MIMO network designs. MIMO systems involve non-linear and uncertain functions with increased complexity, which can be approached effectively using fuzzy adaptive control methods [146].

Likewise, fuzzy rules can improve the detection and correlation criteria via iterative extension in clustering algorithms [147]. The handling of fault estimation and matching conditions in mode-dependent interval type-2 fuzzy systems can be sufficiently improved through the use of quantized signal output [148]. The authors of [149] suggested trajectory tracking for a class of Takagi–Sugeno fuzzy Markovian jump time-varying delay systems with unknown uncertainties and disturbances.

Adaptive interval type-2 (IT2) fuzzy slicing can be used to provide improved estimation performance for unknown dynamic behaviors in distributed MIMO systems. The authors of [150] suggested the Lyapunov stability approach for the driving adaptation law based on adaptive IT2 fuzzy slicing for the MIMO system. Similarly, the use of approaches such as fractional-order interval type-2 fuzzy systems can be researched for effective beam tracking in mMIMO systems [151].

5. Discussion

The complex heterogeneous network (HetNet) cellular architecture, the progression of information and communication technologies, and the extensive mobile Internet usage raise several unprecedented challenges in the successful utilization of network resources. In addition, HetNet systems will support the massive connectivity of mobile and portable appliances and allow relaxation in the functionality of networks, with rapidly increasing higher bandwidth applications for users over the next decade. The potential benefits of mMIMO systems are the underlying the timely acquisition of CSI, either in the form of long-term statistical or instantaneous data (for each antenna node) [152,153]. Since the overall latency is formed via the transmission, processing, signaling, and retransmission of data packets, the initial channel request, training signals, scheduling, and queuing latencies add enormous weight when establishing a link between the BS and smart node functions [154,155]. Herein, any sort of latency is susceptible to link-connectivity failure, and single-packet corruption in extreme, broadband, and scalable URLLC cases would be catastrophic. Robust techniques are needed for open loop or grant-free access communication with mMIMO systems for URLLC cases in 6G networks.

Although large-scale multi-antenna technologies offer multiple spatial degrees-of-freedom, such as greater SINR linking due to better array gain rates and channel hardening in quasi-immune to fast-fading links [156], the modern multi-antenna system sets new model and performance expectations regarding the physical layer aspect, which can complement the upper-layer mechanisms to meet the stringent requirements of B5G/6G use cases, especially for unprecedented time-sensitive applications [157].

- Similarly, various approaches have evolved for the optimized implementation of AI/ML approaches, in M-MIMO systems, such as fuzzy logic approaches. AI/ML algorithms can naturally handle the issues of large-scale complicated design formations and can be gradually increases for the applications and service requisites of 5G/B5G cellular networks [158]. The mMIMO systems with the partial assistance of AI/ML strategies have the potential to support current 5G mobile user services, and could be used to construct wireless systems that are more concrete and sharper. Contrarily, the complete involvement of AI/ML frameworks and higher-spectrum access upgrades in mMIMO systems is certainly desirable for 6G mobile communication networks and requires tremendous research work. Thus, a few of the research challenges on the full exploitation of mMIMO characteristics with fully enabled AI/ML techniques are discussed below.

- ML approaches face trouble regarding their successful implementation in mMIMO systems due to the use of large antenna elements, leading to complex dimensional search issues.
- In real-world mMIMO scenarios, convergence is a serious threat when training AI/ML models.
- It is crucial to construct a channel model that can allow the real-time adaption of the time-varying system.
- A robust distributed learning-based solution is needed for mmWave mMIMO systems to learn the beam combinations of transmitting and receiving signals in real time.
- The precoding technique in mMIMO systems enhances the throughput and reduces the interference; however, it increases the computational complexity. It is of the utmost importance to use low-complexity and efficient precoders in mMIMO networks.
- The future 6G networks will introduce more diverse use cases and allow the full connectivity of satellite and aerial vehicles. Comprehensive research on learning-based precoding and channel estimation schemes for ultra-mMIMO networks is critical.
- AI and ML algorithms can be used in THz ultra-mMIMO architectures to analyze statistical channel characteristics, user scheduling, signal detection, and pilot contamination issues.
- Although fuzzy approaches are considered empowering elements in AI/ML-based solutions for MIMO systems, the growing size of the fuzzy logic rule base can become a challenge in edge computing and low-resource scenarios such as IoT applications.
- Currently, smartphones are not fully capable of implementing mMIMO structures (more than or equal to 8×8 antennae) and face difficulties in UL acquisition. It is an essential and excellent area of study to design a smartphone equipped with an mMIMO system with an intelligent mechanism and low manufacturing costs. In addition, it should be compatible with all previous mobile technologies and services.
- Wireless fronthaul–backhaul communication with the assistance of higher spectrum access and the mMIMO system is a promising topic of study. Substantial research work is required to explore this theme; thus, a flexible and stringent transmission scheme with a learning-based active interference cancellation mechanism is needed.

6. Conclusions

The tremendous growth of mobile data traffic and the continuous increase in the number of smart wireless connected devices are inescapable challenges. The use of massive MIMO intelligent antenna sensing equipment is the answer to handle these global challenges. However, the escalation and complex architectures of the different technologies increase the computational time, latency, and algorithmic complexity when managing network operations. The use of AI and ML approaches and analytical measurements has resulted in sharp reductions in computing time and prominent increases in the robust operation performance of diversified technologies, including mMIMO antennae. This work has presented a critical and comprehensive overview of mMIMO networks with the key enabling techniques. Since the AI and mMIMO methods form a fundamental path to enable future cellular systems, they have also been fully discussed in relation to B5G and next-decade wireless networks. We believe that this work will help researchers to make the expected AI–mMIMO transition possible.

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