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Review Article

Evolution of 6G Era: A Brief Survey of Massive MIMO, mm Wave, NOMA-based 5G and 6G Communication Protocols, Role of Deep Learning and Inherent Challenges

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Abstract *- People will be able to use the fifth generation (5G) mobile communication network in the upcoming years. With 5G technologies, anyone can have connectivity to other people all the time. Vehicle-to-vehicle networks Massive multiple-input multiple-output (MIMO) communications, high-speed train networks, and millimetre wave communications are some techniques that have been explored for 5G systems. Each of these innovations establishes new propagation characteristics and specifications for 5G channel modelling. Accurate and effective channel models that span diverse 5G technologies and situations are urgently required, as they are essential for system design and performance evaluation. This paper thoroughly assesses the currently used 5G communication techniques, including mmWave, NOMA, and Massive MIMO. Also, this paper gives an overview of 6G communication specifications and studies the challenges of 6G technologies. Moreover, this paper provides a conclusion and future research directions for mobile technologies.*

Keywords *- 6G, MIMO, mm Wave, NOMA, 5G.*

1. Introduction

Systems for wireless communications, particularly mobile communication systems, are expanding very quickly. Mobile communication technologies have to fulfil the demand of the growing number of customers, new applications, new traffic rates, and data amenities. For instance, node-to-node communications use concepts like the smart grid, smart cities and homes, and health care. These applications have a wide range of communication needs that must be met for a unified wireless technology to function properly. Rapid advancements in mobile communication technology can be linked to growing mobile usage and the scale of similar industries. As a result, wireless communication systems need to manage faster transmission speeds, larger capacity, and improved bandwidth utilization [1]. The system must increase its spectrum use due to a lack of spectrum resources. Utilizing constrained spectrum resources, conventional MIMO technology can meet users' performance requirements.

1.1. Brief discussion on MIMO

In wireless communication systems, MIMO technology uses numerous antennas to transmit many streams of data simultaneously. Multiuser MIMO term is used when MIMO is utilized to connect with many terminals simultaneously. In cellular networks, MU-MIMO leads to four improvements:

- Higher data rate since more antennas allow for the simultaneous service of more terminals and the sending of more independent data streams;
- Increased dependability because there are more separate paths that the radio signal can travel across with more antennas;
- Increased energy efficiency as a result of the base station's ability to direct its emitted energy in the directions in which it believes the terminals to be positioned; and
- Less interference since the base station (BS) can deliberately evade transmission in areas where it would be undesirable for interference to spread

However, a typical MIMO system performs less because it has fewer antennas. Future 5G networks will heavily rely on massive MIMO due to its potential to meet the needs of wireless business models, maximize spectrum efficiency, increase system capacity, and improve link and data transmission dependability.

1.2. Massive MIMO

A new technology called massive MIMO extends MIMO in terms of the number of users and resources. The massive MIMO is a system that employs antenna arrays with several antennas (approximately a hundred) and serves dozens of terminals concurrently using a similar time-frequency (T/F) spectrum. The fundamental idea of massive MIMO is to gain the maximum benefits of traditional MIMO on a larger scale. The Massive MIMO has a significant role in creating a forthcoming broadband (static or mobile) network that will be reliable, protected, and power-efficient while effectively utilizing the spectrum. As a result, it serves as a facilitator for the infrastructure of the imminent digital civilization that will link the Internet of People and the Internet of Things (IoT) to other technologies like cloud computing. Spatial multiplexing, a prerequisite for massive MIMO, requires that the base station have adequate uplink and downlink channel information. It is simple to achieve on the uplink by transmitting pilots through the terminals. Accordingly, the BS guesses the responses of the channel to every terminal. The process of linking links is extra complicated. In typical MIMO networks, such as the LTE paradigm, the BS transmits the pilot waveform that the terminals use to guess the responses of the channel. The terminals then quantize their estimations and transmit them back to the BS. Due to two factors, this won't be possible in M-MIMO systems, especially in a mobile environment. To achieve excellence, the antennas' downlink pilots must be orthogonal to each other. As a result, a massive MIMO network will need up to a hundred times more T/F spectrum than a traditional network. This is because the amount of T/F spectrum required for downlink pilots grows with the number of antennas. Second, the number of BS antennas is inversely related to the number of channel responses that each terminal must predict. Therefore, the base station would require up to a hundred times more uplink resources than traditional systems to receive information about the channel responses. Although FDD operation may be conceivable in some circumstances, the solution is to function in TDD mode and depend on the reciprocal between the uplink and downlink channels. [2]. The main benefits of massive MIMO systems can be briefed as follows:

- Enormous spectral efficiency;
- Communication consistency;
- High energy competence;
- Low complexity signal processing;
- Promising propagation;
- Channel hardening.

Massive MIMO's additional antennas will aid in concentrating energy into a more condensed space area, improving spectral efficiency and throughput. Fig. 1 depicts the uplink and downlinks of M-MIMO systems. In a massive MIMO network, as the number of antennas rises, the radiated beams narrow and spatially converge toward the user. Figure 10 displays the beam patterns for various antenna setups. These spatially fixed antenna beams upsurge the throughput and reduce intrusion among adjacent users [61]. Massive MIMO gives a huge benefit compared to a conventional MIMO system, as in table 1.

1.3. Progression of Communication Network

Since the beginning of the cellular communication period in the 1980s, it has grown significantly throughout the last few decades. The evaluation of cellular networks started with 1G and went beyond 5G. It is shown in Fig. 2. Generally, a BS, some mobile phones, and essential protocols constitute a cellular network.

Below is a brief description of numerous techniques. However, the key purpose of this work is to examine 5G and 6G networks, as well as their advantages and limits.

1.3.1. 1G Networks

The 1G mobile networks launched at the beginning of the 1980s used analog transmission for voice-only facilities. The data rates of 1G systems are up to 2.4 kbps, and these systems use Frequency Division Multiple Access (FDMA). They had a low-quality voice because of considerable interference. There are various types of 1G systems, such as NMTS, AMPS, and TACS [4].

1.3.2. 2G (second-generation) Networks

Launched in the early 1990s, the 2G systems were viewed as digital upgrades to first-generation (1G) networks. They offered primitive email services, Short Message Service (SMS) and voice services. These networks use CDMA and TDMA technologies with data rates of 14.5 kbps to 64 kbps. The GSM and IS-95 CDMA are some examples of popular 2G platforms. 2G networks have poor hardware capabilities and portability [4].

1.3.3. 2.5G and 2.75G

As 2G innovation evolves to offer greater data rates and facilities, one can use internet service of a data rate higher than 384 kbps using 2.5G networks. CDMA2000, EDGE and GPRS are some instances of 2.5G systems [4].

1.3.4. 3G Networks

The GSM and CDMA-based 3G cellular networks were first presented at the beginning of the year 2000. These systems combined voice, MMS (Multimedia Message Support), and SMS services with mobile web browsing. The UMTS (Universal Mobile Telecommunication Systems) and WCDMA are two examples of 3G systems. In the middle of the 2000s, smartphones gained popularity. Although 3G networks could deliver data speeds of up to 384 Kbps, they needed a lot of bandwidth and complicated hardware.

1.3.5. 3.5G

The HSDPA (High-Speed Downlink Packet Access), HSUPA (High-Speed Uplink Packet Access), and HSPA+ (High-Speed Packet Access) were launched with 3G systems to enhance data speed in response to the ongoing need for faster data rates. These networks offered up to 2 Mbps data speed and were known as 3.5G networks.

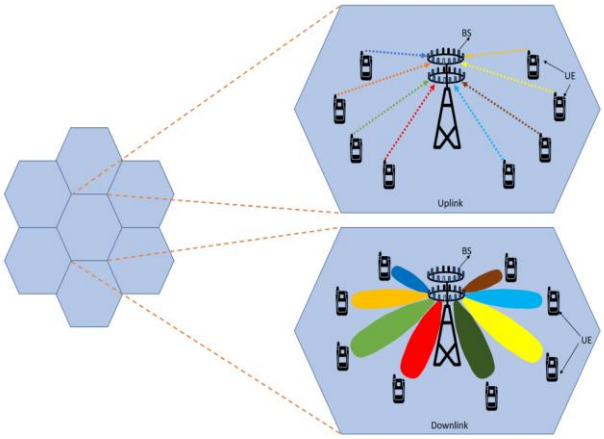

Fig. 1 Massive MIMO uplink and downlink

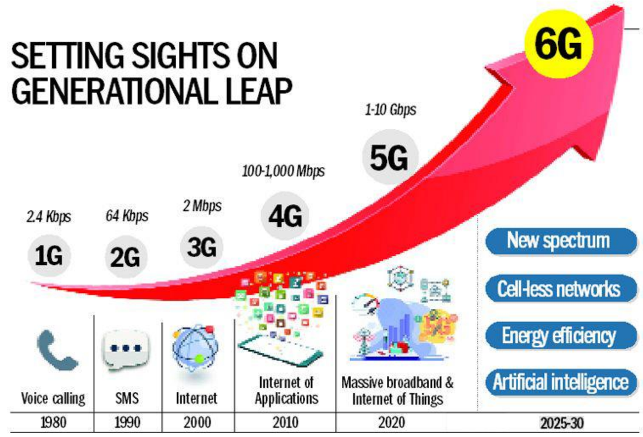

Fig. 2 Evolution of 1G to 6G communication model

Table 1. Below provides a summary of information on several communication methods.

Generation	Access Technique	Transmission Technique	Error Correction Method	Data Rate	Frequency Band	Bandwidth	Application	Description
1G	AMPS, FDMA	Circuit switching (CS)	NA	2.4 kbps	0.8 GHz	Analog	Voice	Chat with each other.
2G	CDMA, GSM, TDMA	CS	NA	10 kbps	0.8 GHz 0.9 GHz, 1.8 GHz, 1.9 GHz	25MHz	Data and Voice	Message and talk while traveling
3G	WCDA, CDMA 2000, UMTS, HSDPA	CS and packet switching (PS)	Turbo codes (TC)	384 to 5Mbps	800 MHz, 850 MHz, 900 MHz, 1800MHz, 1900MHz, 2100 MHz	25 MHz	video calling and Voice, Data	Internet surfing and mobile applications
4G	LTEA , OFDMA, SC-FDMA, WiMAX	PS	TC	100 to 200 Mbps	2.3 GHz, 2.5 GHz, 3.5 GHz	100 MHz	Video Calling, Voice, Data, HD TV & online games	Share Data & Voice over broadband
5G	FBMC BDMA, NOMA,	PS	LDPC	10 -50 Gbps	1.8 GHz 2.6 GHz, 30-300 GHz	30-300 GHz	virtual reality, HD, Voice, Data, Video Calling,	With IoT and V2X, broadband wireless services go beyond mobile broadband.

Although 3.5G offered a faster data throughput, the technology and implementation were expensive, and interoperability with 2G was complicated [4].

1.3.6. 4G

In the early 2010s, 4G mobile networks were launched. 4G networks can manage more data traffic while maintaining a higher level of service and provide data speeds of more than 90 Mbps. With the help of 4G networks, one can join a meeting with video conferencing, play online games, and watch smart TV. LTE, WiMAX, and LTE-A are among the 4G systems, and they are potentially compatible with networks from earlier generations [9]. 4G networks can only be used with high-end 4G-equipped cell phones because the frequency bands are quite expensive [9].

1.3.7. 5G Networks

The 5G mobile systems [59] now being developed are intended to be 100 times quicker than the 4G systems already in use. 5G technology can provide a data speed of around 10 Gbps, low latency, and superior consistency. A person can download an HD movie in a few seconds using a 5G network. As seen in Figure 3, this technology is compatible with a wide range of IoT-enabled gadgets and smart automobiles.

In order to meet the continuous demands posed by 5G, an effective wireless access technique is needed that can boost network efficiency without expanding network capacity or increasing the density of the cell. The key benefits of 5G technology are as follows:

- Data rate: A 5G technology can have a data speed of around 10 Gbps, much higher than 4G technology.
- Latency: Contrary to 4G networks' 10 ms latency, 5G networks offer a very low latency (around 1 ms).
- Efficient signalling: Effective signalling for IoT interoperability and M2M connectivity is provided by 5G networks.
- User experience: Different types of reality systems (like Augmented and virtual reality) and artificial intelligence (AI) systems are improved by 5G networks.
- Spectral proficiency: spectral and network efficiency of 5G systems is much higher than 4G systems.
- Power proficiency: Contrary to 4G systems, 5G systems offer effective power utilization in the network.
- Ubiquitous Connection: In comparison to 4G networks, 5G networks may sustain more than 65,000 connections and offer enormous broadcasting data.
- Life of Battery: 5G offers a battery life of almost ten years for low-powered Internet of Things gadgets.

Despite its many benefits, 5G technology has certain drawbacks. The 5 D technology has the following drawbacks:

- Frequency bands: The 5G networks use 300 GHz frequency bands. It will be very expensive for wireless operators to achieve this high-frequency band.
- Coverage: Since the wavelength of high-frequency waves is smaller, it cannot go beyond large distances. Due to this problem, more base stations should be placed in a small space to provide all users with a dependable link. The added BS doubles the network's overall expenses and intricacy.
- Cost: Since 5G involves more than adding a layer to the 4G network, it would be prohibitively expensive to design the system from the beginning.
- Device Support: It will be difficult for mobile companies to provide cheap phones that can sustain 5G infrastructure because the current phones can not operate 5G technology.
- Safety and Confidentiality: Even though 5G employs the AKA (Authentication and Key Agreement) process, it is still impervious to attacks like middleman attacks, position monitoring, and eavesdropping.
- Availability: Network overload and congestion will become significant issues with the launch of IoT and M2M. It will be challenging to make the network accessible to everyone due to the issues associated with radio access networks.
- Cybercrime: Data cybercrime would significantly rise at a fast speed. Consequently, strict cyber laws would be required to stop these attacks.

1.3.8. 6G Networks

The 6G cellular systems are limitless, full-featured wireless networks. It is in the process of being developed and will offer extraordinary transmission speeds in the terabit range. A smart antenna, a lot of memory in mobile phones, and massive optical networks would be necessary for this technology. Wireless networks could use artificial intelligence due to the absence of cells in 6G networks. Although the frequency range of 6G networks is unknown, it is evident that a significantly higher frequency band will be necessary to support the increased data throughput of 6G systems. While 6G is associated with significantly higher frequency in THz bands, 5G is expected to utilize up to 300 GHz frequency bands. It is anticipated that 6G will employ the THz band in the upcoming years. Certain applications of 6G networks are interconnected robotics and automated vehicles, wireless brain-computer interfacing, blockchain technologies, multi-sensor augmented realities, deep-sea exploration, haptic internet, and industrial IoT. It is expected that the 6G networks will be available in 2030. The benefits of 6G networks are listed below:

- Data rate: Higher data speed than 5G networks, approximately 10 Tbps.
- Latency: Compared to 5G networks, the latency of a 6G network is 0.1 ms.
- Efficient signaling: To support widespread IoT connection and M2M connectivity, 6G networks offer effective signaling.
- User experience: 6G improves artificial intelligence systems and different types of reality-based systems.
- Spectral performance: The spectral and network performance of 5G networks is much less than 6G networks.
- Energy proficiency: Contrary to 5G systems, 6G systems have less power consumption.
- Ubiquitous Connection: Huge broadcasting data will be provided by 6G, which may accommodate nearly 1 million users—much higher than 5G networks.

1.4. Article Organization

The following sections comprise the remaining text in the article: The literature overview is presented in part II. Topics covered include precoding, resource allocation, security, 5G massive MIMO, NOMA, machine learning, and deep learning solutions. Section III includes a brief review of 6G communication standards, Section IV includes problems and difficulties with 6G networks, and Section V includes closing remarks.

2. Literature Survey

For wireless systems, MIMO technology is essential. Multiple signals can be sent and received concurrently over a single radio channel. MIMO is a crucial technology in Wi-Fi, 3G, 4G, and 4G LTE-A networks. MIMO is primarily utilized to attain high energy and spectral efficiency, but it falls short because it offers poor throughput and incredibly unreliable communication. Numerous MIMO technologies were employed to address the issue, such as single-user MIMO, multiuser MIMO, and network MIMO.

Table 2. Below displays a feature evaluation of 4G, 5G, and 6G technologies.

Performance Index	4G	5G	6G
Peak Data Rate	100 Mbps	10 Gbps	Up to 10Tbps
Latency	10 ms	1 ms	Up to 0.1 ms
Connectivity density	1 Lakh gadgets /km^2	1 Lakh gadgets /km^2	100 Lakh gadgets /km^2
Power Efficiency	1x	100x4G	100x5G
Spectral efficiency	1x	100x4G	100x5G
Available spectrum	Up to 6GHz	Up to 300GHz	Up to 3THz
Mobility	200 m/h	300 m/h	600 h

Table 3. Comparative analysis of various 5G massive MIMO techniques

Ref	Objective	Method	Problem	Performance	Observation
Chen et al. [1]	Improving the resources' time, frequency, and spatial resources	Pattern division multiple access	It is a study about PDMA and its applications in 5G	BLER, Spectrum efficiency gain and spectral efficiency	PDMA uses SIC's joint transmission and reception design to optimize the multiuser communication system.
Yu et al. [2]	Predistortion for mm Wave and massive MIMO	Full-Angle Digital pre-distortion with power amplifiers (PAs)	To deal with beamforming-related issues		The full-digital beamforming (DBF) transmitter is developed
Liu et al. [4]	Hybrid beamforming for MIMO	beam-oriented digital pre-distortion	Inappropriate configuration of digital chain and Power amplifiers	Power spectral density, spectrum, phase offset	Low complex power scalable PA
Wu et al. [13]	Performance improvement for downlink MIMO	Precoding	Sum rate maximization for massive MIMO	Sum rate for varied SNR, total BS antennas	It is discovered that HBF with the fewest RF chains outperforms even for a very high number of antennas.
Yang et al. [14]	64-channel massive MIMO with digital beamforming	new sectorial transceiver array design with a bent substrate-integrated waveguide	heat dissipation, energy efficiency	achieves a downlink peak data rate of 50.73 Gb/s with spectral efficiency of 101.5 b/s/Hz.	Observed that beam-tracking and two data streams, the DBFbased millimeter-wave MIMO system can achieve steady 5.3-Gb/s throughput

These new MIMO technologies, though, again fell short of what end consumers wanted. Massive MIMO is a development of the MIMO system utilized in the 5G technology. Base stations are connected to hundreds of thousands or even millions of antennas to boost throughput and spectral efficiency. Massive MIMO employs several broadcasts and receives antennas to boost spectral efficiency and transmission rate. Massive MIMO can operate at a higher capacity when several UEs simultaneously produce downlink traffic. Massive MIMO enables spectral efficiency and throughput by employing additional antennas to channel energy into smaller space areas. In order to improve the performance of 5G communication standards. The most recent methods in this area of 5G communication are described in this section.

2.1. 5G massive MIMO

Massive MIMO, generally known as radio frequency (RF) chains, is a requirement in recent proposals for 5G systems [1]. Along with boosting the transmitter volume significantly, RF chain extension also results in larger nonlinear distortions. Also, the efficient power amplifier (PA) linearization method should be used in 5G systems. An essential PA linearization method is digital pre-distortion (DPD). DPD can anticipate PA's nonlinear distortions based on precise modelling and can get rid of them by adding the right corrective signal [2] [3] [4]. Crosstalk correction and architectural modification are the two critical research areas in the massive MIMO technology.

Alternatively, the intermodulation distortion in either linear or nonlinear systems between the transmit pathways of MIMO systems causes higher signal distortion effects [5], making the DPD method more difficult than in SISO systems. The high level of integration causes powerful crosstalk in large MIMO systems. Many DPD approaches for crosstalk compensation has been recommended to solve this problem. On the other hand, the MIMO system requires that a distinct digital chain be built for each antenna, so there are an equal number of digital chains and PAs. Due to hybrid beamforming technology, the number of digital chains in M-MIMO transmitters can be significantly lower than the number of PAs [6]. Consequently, In the area of 5G communication, beamforming is viewed as a potential technology. Liu et al. [4] suggested a beam-based (BO-DPD) method for PAs in fusion-based beamforming (MIMO) transmitters that can attain linearization of the transmitted signal in the central beam direction and solve the issues of DPD deployment. Since there are fewer digital chains than PAs in large MIMO beamforming transmitters, it is impracticable to use the standard DPD to linearize each PA.

Therefore, the BO-DPD can alleviate this problem by creating and linearizing the "virtual" main beam signal rather than individual PAs. Due to shadowing and free space path loss, the electromagnetic waves of millimetre-wave (MWave) frequency face substantial diminution [8]. Furthermore, the millimetre-wave signal's shorter wavelength makes it possible to increase antenna gain by utilizing an array of many different antenna components. It is reported that the current MWave point-to-point communication system may produce very high data speeds at a very large distance when equipped with an enormous antenna array. Moreover, the fixed narrow beam only geographically offers a small coverage area, making it unsuitable for mobile communication environments. Due to this, specific cutting-edge beam-steerable antenna array approaches [9-11] and the active phased array have recently been implemented to empower 5G Mwave mobile networks [12,16,40]. The active beamforming systems can offer better transmission power and better beamforming tractability than a passive multi-beam antenna array. Further, the efficiency of the active beamforming systems can be enhanced when combined with MIMO technologies.

Wu et al. [13] analyzed a single-cell downlink multiuser MIMO system operating in a general channel paradigm with a mix design that permits several streams per UE, presuming perfect channel state information is obtained. They want to identify an analog and digital combiner that increases the communication system's sum rate. Their suggested condition mutually develops 2 phases by attempting to prevent information loss at each level, in contrast to the conventional 2 phase design standard, which individually plans the analog and digital phases. They present an optimum solution in a massive MIMO network where twice the least number of radio frequency chains are accessible.

Yang et al. [14] recommended a massive (MIMO) transceiver(64-channel) with an utterly DBF design for 5G millimetre-wave transmissions. The DBF-based large MIMO transmitter/receiver works in the TDD (time division duplex) form at a frequency of 28000 MHz with a 0.5 GHz signal bandwidth. The transceivers are set up as a 2-Dimensional array for improved beamforming in the horizontal plane with sixteen columns (horizontal orientation) and four rows (vertical orientation). Using a bent substrate-integrated waveguide, a novel sectorial transceiver array strategy is suggested to attain a half-wavelength element design in the horizontal orientation.

Due to the scattered architecture of the system, the channel gain from the APs (Access Points) to a user fluctuates significantly in cell-free massive (MIMO). Data decoding techniques with deterministic channels perform poorly due to these variations. Designing a precoding method that balances the efficient channel gain perceived by the consumers is a method of lessening the channel variations. Conjugate beamforming (CB) cannot efficiently harden the consumers' channel.

Table 4. Beamforming and precoding techniques

Attributes	Analog beamforming	Digital precoding	Mix precoding
Number of streams	Single stream	Multi-stream	Multi-stream
Number of consumers	single-user	Multiuser	Multiuser
Signal control capability	Phase control only	Phase and amplitude control	Phase and amplitude control
Hardware necessity	At least one RF chain	RF chains that have the maximum and an equivalent total transmit antennas	Intermediate; the number of RF chains less than the number of transmitter antennas
Cost	Slightest	Maximum	Intermediate
Energy consumption	Slightest	Maximum	Intermediate
Performance	Slightest	Optimal	Approximately-optimal
suitable for large MIMO at mmWave	Inappropriate, no amplitude control, no multiuser	High energy utilization, higher costs, and impracticality	Real and useful

Interdonato et al. [15] suggested a CB (ECB) method. Here, the precoding vector conjugates the channel estimation standardized by its squared norm. By assuming separate Rayleigh fading channels, allowing for channel estimate errors, pilot reusing, and the user's paucity of CSI, they construct an accurate closed-form equation for a feasible downlink spectral efficiency (SE) for this system. Table 4, given below, shows a comparative analysis of different beamforming techniques.

Zhou et al. [64] developed the optimal beamforming (OB) method for downlinking cell-free massive MIMO systems with TDD. In TDD systems, the access points estimate the uplink channel state information using pilots from the users and then apply channel mutuality to get the downlink CSI. In order to attain stability between the required signal and manage multiuser interference, the OB beamformer is centrally established at the CU based on the collaboration of all access points. The OB model is a max-min challenge that seeks to maximize the minimal prompt signal-to-interference-plus-noise ratio across all users to understand the highest possibility of massive cell-free MIMO while maintaining user equity.

By dynamically assigning the numbers of uplink and downlink RAUs (remote antenna units), network-assisted full-duplex distributed (NAFD) massive (MIMO) systems facilitate concurrent uplink and downlink communications, potentially increasing the spectral utilization in wireless transmission. In these systems, CSI is crucial for downlink transmission, uplink reception, and the cancellation of cross-link interference brought on from downlink RAUs to uplink RAUs. Furthermore, downlink terminals must estimate CSI to accurately decode the received signals due to the diminished channel hardening effect. In general, it is impossible to measure CSI due to substantial training overhead correctly. Li et al. [17] suggested an efficient CSI based on a beamforming training method. With this method, they can construct closed-form formulas for feasible downlink and uplink rates using various receivers and beamforming. From a multi-objective optimization standpoint, they suggest a practical power allocation approach that relies only on slowly fluctuating large-scale fading.

Analog beamforming design, hybrid beamforming design, and fully (DBF) design are only a few of the various active beamforming designs that have been suggested and examined in the literature so far [11]–[15]. The practical hardware implementation of the millimetre-wave MIMO beamforming system still faces significant obstacles. The primary hardware limitations result from the high signal bandwidth, circuit technology, connectivity approaches, energy consumption, and size of the transceiver components, among other factors.

2.2. 5G NOMA

Nonorthogonal multiple access (NOMA) is a significant 5G mobile technology technique. NOMA can increase spectral performance and enable vast connections with low transmission delay and signalling cost through nonorthogonal resource allocation. Power NOMA can create a new power dimension to accomplish multiplexing in the present access domain, which can be viewed as superposing multiple signals into one orthogonal resource. Consequently, successive interference cancellation (SIC), in which duplicate signals are removed based on related CSI, is a vital method for extracting the information from these superposed signals.

Using CR-NOMA, Budhiraja et al. [18] suggested a simultaneous channel allocation and power control technique for femtocell users (FUs). The key goal is to exploit the sum rate of the femtocell users for the assured quality of service (QoS). The Femto base station (FBS) employs CR-NOMA to provide guaranteed QoS for FUs. Next, they proposed a method for coupling strong and weak users through channel gain variation. By coupling, the NOMA intrusion between users lessens, leading to better channel utilization. Also, In a femtocell, they distinguish between an even and an odd number of FUs to offer a quality of service for weak users. In order to do this, a greedy channel allocation technique called NOMA is used.

Kazemian [19] stated that due to several users being superimposed on the same frequency subchannel, the standard FFT-NOMA model exhibits inter-user intrusion and PAP Ratio. The enhanced-NOMA (ENOMA) method, which uses a new, less complex improved version of the CSLM cascaded, is suggested to lessen the PAP Ratio, inter-user intrusion, and bit error rate(BER) in an FFT-NOMA model.

Riaz et al. [20] stated that to overcome the issues of 5G networks, (NOMA) is a practical substitute for the most advanced orthogonal multiple access (OMA) approaches now available. Additionally, it is possible to integrate a power control method to lessen the impact of user disturbance in the network. This work goes through the fundamental ideas, distinguishing characteristics, and advantages and disadvantages of the numerous power domain NOMA designs. Furthermore, they suggest an uplink PC strategy for power domain NOMA network users. The EGT framework is used in the given technique to alter the transmission energy level of the user, reducing user interference. A (SIC) receiver is used at a base station to disperse the user signals.

Gandotra et al. [21] used NOMA-based device-to-device communication 5G systems for performing sectorization. The suggested NOMA-based methodology brings the theory of multiple interference annulment, which activates the event of revocation of intrusion levels in the network and involves optimum resource distribution.

Table 5. comparative analysis of various 5G NOMA-based communication techniques.

Ref	Objective	Method	Problem	Performance	Observation
[18]	joint channel allocation and power control algorithm for CR-NOMA, maximize the sum rate of the FUs	Interference reduction by pairing the strong and weak users	Power management, QoS	Sum rate	Greedy channel allocation, along with successive convex approximation for low complexity (SCALE) with KKT
[19]	Low complex NOMA to reduce the PAPR, BER, interference	Used of modified mapping (CSLM) cascaded with the Walsh–Hadamard transform	Distortions, spectrum efficiency, BER	PAPR= 4.3 BER= 9.5 Complexity = reduced to 56%	Reduced complexity is beneficial for 5G and beyond networks that require low energy consumption, maximum capacity
[20]	Power control for uplink 5G networks	Evolutionary game theory helps to adjust the power levels	congestion, cooperation, and competition users	Spectral efficiency, network efficiency	Automated power level selection according to the requirement
[21]	Interference cancellation and resource allocation for NOMA	Interference reduction using multiple interference cancellation	Traditional methods work on omni-directional antennas at the BS, but this model considers D2D-NOMA	Suma rate, Energy efficiency, Fairness Factor, Complexity	Interference cancellation is obtained by optimal signal detection
[22]	Cooperative NOMA broadcasting for 5G cellular V2X	Half and full duplex assisted NOMA for V2X communication	Power allocation problem, computational complexity	Achievable rate	Quasi –concave problem is formulated and solved by transforming them into convex feasibility problems
[24]	Power and SCMA-based downlink NOMA	A method obtained by combining message-passing and successive-interference-cancellation algorithm	Connectivity issue	Symbol error rate	Achieves better performance despite being overloaded

Since the current LTE networks are built on the OMA method, the few spectrum resources have not been entirely and effectively exploited, making dense networks susceptible to acute data congestion and poor access proficiency [6]. Hence, we need more efficient radio access technology. As a viable solution for 5G systems, the NOMA can completely exploit its capacity, attaining better transmission rates, lesser system latency, better consistency, and cheap service requisites than the OMA system. It is made possible by power domain multiplexing [7] at the transmitter and SIC [8] at the receivers [9], [10]. NOMA offers a new 5G vehicle-to-vehicle services paradigm to prevent resource conflict, enhancing spectrum efficiency and decreasing latency. It has the potential to achieve high-capacity transmission over constrained resources [11]. Numerous academic bodies have expressed interest in these vehicular networking issues and potential. Numerous academics are working to incorporate NOMA into various scenarios to improve efficiency and meet the LLHR standards of vehicular networks. In [12], [13], the central SPS at the base station and the dispersed power control of the vehicles are combined in the authors' novel NOMA-related mix centralized and distributed strategy for the V2X (vehicle-to-everything) broadcasting system.

It has been demonstrated that NOMA can decrease access latency and increase reliability in a crowded network. Liu et al. [22] recommended 2 relay-based NOMA transmission methods for 5G vehicle-to-vehicle transmissions, i.e., HDR-NOMA broadcasting/multicasting and FDRNOMA broadcasting/multicasting. They studied the optimal power distribution challenges for them. Power distribution issues are designed to optimize the least feasible rate for all users to ensure fairness and enhance the QoS for customers using channels with a poor environment. It is demonstrated that the problems are quasi-concave even if neither of the problems expressed is concave nor convex. Consequently, a bisection-related power distribution technique is suggested to find the problems' optimized solution.

Ihsan et al. [23] stated that traffic proficiency, control, and consistency of transportation systems B5G have recently been shown to be much improved by incorporating (NOMA) in V2X transmissions. Because of the rapid mobility of vehicles and the associated increased channel estimation uncertainty, inspecting imperfect (CSI) is essential in V2X communications. In B5G cellular vehicle-to-everything networks, this research suggests a power-proficient distribution approach for the RSU-Supported NOMA multicasting. Specifically, the energy efficiency maximization challenge will study the outage probability of cars under faulty CSI, QoS, and power limitations. As the issue is non-convex and cannot be solved directly, they adopt a low-complexity GABS approach to approximate the outage probability constraints into non-probabilistic constraints before finding the effective power allocation at RSUs. Next, the power distribution problem of the automobiles connected to each RSU is transformed into a manageable CCFP problem using a sequential convex approximation (SCA) approach. Dinkelbach and the dual decomposition approach are used to obtain the best solution to the CCFP issue.

Sharma et al. [24] suggested a dual power and code domain-based NOMA method for the 5G and 6G wireless networks. They gave the concept of a downlink method where users encounter various channel settings. The transmitter uses a sparse code multiple access encoder and enables customers to receive a variety of power allocations. Integration of message-passing and consecutive interference-cancellation algorithms is the basis of the detection.

Liu et al. [25] suggested a NOMA-related CR which permits the SU to access multiple subchannels in the non-existence and existence of the PU. Correspondingly, the receiver decodes the NOMA signals using the PFDM and SFDM decoding. In the PFDM, the optimal SU throughput can be attained. However, the subchannel power has to be regulated to ensure the PU throughput. Owing to the interference that the PU causes in the SFDM, the SU throughput may be reduced. In order to increase the standardized throughput of the SU by mutually improving spectrum resources, such as the number of sub-channels and subchannel transmission energy, they have proposed two optimization problems focused on PFDM and SFDM, respectively. The suggested optimization issues are solved using a combined optimization approach. Next, the lower constraint of sensing time for energy recognition is determined to assure spectrum sensing performance, which includes false alarm possibility and detection possibility.

Saraereh et al. [62] stated that by assigning separate powers, NOMA could enable multiuser multipathing in the transmission power domain, which significantly boosts system capacity and spectral efficiency. This article suggests an improved radio resource distribution method for power distribution optimization and user grouping in (NOMA) based 5G systems, intending to reduce high computation intricacy and increase system bandwidth. Maximizing system capacity is the purpose of the optimization process. The non-convex optimization problem is divided into two smaller problems that must each be handled independently using the step-by-step optimization concept. Initially, all users are assembled using the greedy technique, and then the fixed group's sub-carriers are used for power allocation.

2.3. Machine Learning and Deep Learning Methods for 5G

2.3.1. Supervised Learning

Numerous deep learning (DL) techniques are based on supervised learning methods, which train the model using labelled datasets. From the perspective of resource distribution, supervised learning systems have been suggested in research articles [31]– [36]. Sun et al. [31]

suggested a DNN paradigm generalization that estimates the WMMSE intervention management technique with correct estimates and high computational performance compared to cutting-edge interference management techniques. Using the DL technique for dynamic channel assortment, carrier combination, and partial spectrum, the researchers [32] have suggested a resource distribution method for small cells. Zhou et al. [33] have presented an effective deep neural network for assigning resources in cognitive radio networks to maximise energy and spectrum efficiency. In order to forecast the bit and power distribution in a multiuser OFDM network, Li et al. [34] have devised a framework that uses a Hopfield neural network (NN). The researchers proposed a supervised DNN mode for subcarrier allocation in a NOMA-OFDMA downlink multimedia broadcasting network [35]. The suggested model offers a less complex performance that comes close to ideal. In [36], In "Learning to Optimize for Resource Management," the authors suggest a framework that achieves near-optimal efficiency with fewer data samples. A comparative analysis of these supervised and unsupervised is presented in table 6.

Table 6. Comparative analysis of supervised and unsupervised machine learning techniques

Ref	Objective	Method	Problem	Performance	Observation
[27]	Prediction of channel state by using machine learning	Identifying the features which affect the CSI and training CNN to learn the parameters	Complexity, the channel estimation error	Computing time, channel state information	The two-step training mechanism with CNN-LSTM improves learning and increases the accuracy
[28]	To develop an efficient network slicing approach and present a combined classification algorithm by using glowworm and deer hunting algorithm	A deep learning-based approach with an optimization function is developed. The optimization model uses	Network overload, huge training data	Accuracy, sensitivity, F1 score, false positive rate,	Network slices are classified as eMBB, mMTC, and URLLC by using deep learning classifier
[31]	A new machine learning method to reduce the complexity	Incorporating deep learning to train and improve the WMMSE	Computational complexity, implementation complexity	Mean square error, sum rate CPU time	Interference cancellation can be obtained by using deep neural networks; DNNs can reduce interference effectively
[32]	Resource management in unlicensed spectrum	Non-cooperative game theory and deep learning-based model	Resource allocation, multiple access, spectrum sharing	Traffic load, average airtime allocation	The game theory-based DL model achieves Nash equilibrium
[33]	Deep learning model for resource allocation	CNN-based deep learning model	Channel state information is required for resource allocation	Computational complexity, training duration	Deep learning improves the learning process resulting in better analysis of channel state information
[35]	Subcarrier, bit and power Allocation for multiuser OFDM	Use of fully connected hopified, i.e. recurrent neural network	Subcarrier allocation and channel state information	Sum power and energy function	Optimal subcarrier, bit and power allocation with the minimum transmit power

However, these studies fail to address the performance deterioration that develops over time in a dynamic atmosphere. Specifically, systems examined on lab-based databases ignore the realistic factor relating to the atmosphere's dynamic nature, which obscures the significance of retraining.

2.3.2. Unsupervised learning

Alternatively, unsupervised models train the model using several methods to avoid dependence on a labelling technique. In [37], the researchers suggest an unsupervised learning-based quick-beamforming formation technique for sum-rate maximization in the MIMO BS system. The suggested convolution model significantly increases computing speed with efficiency near the ideal WMMSE technique. It is best for real-time services. To improve performance, the authors change the suggested model's training procedure into two parts: supervised pre-training and unsupervised retraining [38]. In [39], the authors provide an unsupervised DNN model for multi-channel cognitive radio networks' best resource allocation and interference minimization. [61], the authors provide an ensemble model based on an unsupervised learning strategy that outperforms cutting-edge approaches for sum-rate expansion in a multiuser fading interference channel. In [41], the resource distribution policy is parameterized using a random edge graph NN that was trained by an unsupervised model-free learning technique. Generally, unsupervised methods degrade in performance over time, similarly to supervised models, because they converge to a local optimum.

2.3.3. Deep Learning Methods

For 5G technologies, Luo et al. [27] suggested an effective online CSI estimate technique, known as OCEAN, for envisaging CSI from historical data. Precisely, they first select several critical features that impact a radio link's CSI, then collect information about these qualities and the CSI in a sample of data. Next, they develop a learning framework that combines an LSTM (long short-term memory) network and a CNN (convolutional neural network). Additionally, they created a two-step offline-online training method, making the prediction outcomes more reliable when using the 5G wireless communication systems.

By dividing the physical network into many logical networks, network slicing is designed to support various developing applications with higher performance and flexibility demands. Thus, many mobile phones have generated a huge amount of data owing to these applications. This has created extraordinary hurdles and significantly affects the efficiency of network slicing. With the help of a hybrid learning algorithm, this research tries to build an effective network slicing. Consequently, Abidi et al. [28] suggested a system that has three basic stages: (a) Collection of Data, (b) OWFE, and (c) Slicing categorization. Initially, the variables connected with several network devices, like "user device type, period, packet loss ratio, packet delay budget, bandwidth, delay rate, speed, jitter, and modulation type," were collected in the 5G network slicing database. Then, they used the OWFE, which involves multiplying a weight function by the attribute values to produce a high-scale variance. The suggested model is known as glowworm swarm-based DHOA. They improved this weight function by fusing two meta-heuristic processes and named it GS-DHOA. They used a mixed classifier using deep belief and NN to categorize the precise network slices for each device according to the specified attributes, such as "eMBB, mMTC, and URLLC." The GS-DHOA optimizes the weight function of both networks.

Zhou et al. [29] stated that increased traffic demands, beamforming, and massive MIMO technologies, lead to more dynamic and complicated 5G networks. Thus, instead of using the straightforward standard F/TDD, 5G network operators must efficiently manage radio resource allocation. They explain how to overcome this issue using the deep LSTM learning method to produce localized predictions of the traffic load at the UDN base station. The suggested approach implements the suitable action strategy a priori to evade the congestion based on localized prediction.

He et al. [30] recommended an MU-MIMO sensor based on the DL method for the 5G and B5 G-based Internet of Things, where the network functions in intrusive atmospheres linked over the frequency domain or time. A traditional symbol-by-symbol sensor and a Deep CNN were used for this network in an iterative detection framework. The Deep CNN was used to suppress the competing signals by retaining the features via the DL method. The framework's standard sensor can be either MMSE-MLD or ZF (zero-forcing)-MLD, where the standard ZF or MMSE (minimum mean square error) is utilized before the maximum likelihood detection(MLD) is used to seek nearby signal possibilities. Therefore, the suggested MU-MIMO sensor may reduce the impact of interrelated intrusions with minimal computing effort, which ultimately increases the actual MU-MIMO networks' dependability in the context of interrelated intrusions. User scheduling is used to improve system detection performance, where numerous user selection standards are suggested to identify the best use from a group of users.

The mmWave represents the 30 GHz and 300 GHz wave spectra. It is a vital component of the 5G wireless systems. The coupling of a mmWave massive MIMO system with deep learning techniques was examined by Jin and Huang et al. [43] to simplify the hardware design, less power depletion, and precise estimation of CSI [42]. Huang et al., in contrast to Jin, concentrated on a massive mmWave MIMO model for successful hybrid precoding with a Deep neural network. In the DNN, a completely connected layer with 128 blocks following by 2 hidden layers, which are also completely connected but have more blocks than the previous layer. The next hidden layers, containing 128 and 64 blocks, are followed by an output layer. Next is the noise layer, which corrupts the signals with AWGN or other mixing errors. A ReLU activation function is present in each hidden and input layer [43]. With their mmWave massive MIMO system, both [42] and [43] achieved significant success. The adaptable denoising CNN is better than traditional estimating techniques and has a wider noise perception range than a traditional denoising CNN, as shown by the normalized mean square error (NMSE) results. The adaptable denoising CNN performs better than the denoising CNN in respect of NSME performance versus the number of iterations.

However, there is only a 1 dB difference between the two strategies until they converge after 150 cycles[42]. Due to deep learning exceptional mapping, structural information, and learning abilities, the deep learning-based hybrid precoding method outdoes other approaches in terms of spectrum efficiency. It suggests that the suggested mmWave massive MIMO method will be able to resolve the non-convex optimization in hybrid precoding [43].

In order to reduce the total MSE of the user's signals in MIMO-NOMA systems, the researchers suggested the deep learning system FNN with two hidden layers with 100 nodes. This approach produces a reduced MSE when learning the joint precoding and SIC decoding nonlinearly by tackling the problem of faulty SIC decoding compared to the present linear methods. Additionally, it delivers lower BERs, demonstrating the great reliability of NOMA systems [44].

To recuperate the initial channel state information for single-user and multiuser hoping, Liao et al. [45] deployed a Bi-LSTM and Bi-ConvLSTM system, which improves renewal eminence and response precision of the convolution neural network compressed organizational features of the massive MIMO channel. Feature vectors were recovered from the filtered data using the 2D and 3D CNN, and the data was then compressed using the 2D and 3D max-pooling networks, correspondingly. It reduces the data to 1/4 its original size and rearranges it into a 1D vector [45]. CNNs were used by Vieira et al. [46] to demonstrate how massive MIMO channel metrics may be used to accurately estimate user positions, fingerprints, and the sparse channel topology.

In order to regulate the best channel statistics while converting the power distribution problem into a basic program using a DCNN, authors in [47] addressed the non-convex sum rate maximization problem for massive MIMO systems. The sum spectral efficiency optimization problem in multi-cell massive MIMO systems was examined by authors in [48] using CNN. When comparing the training sets with the test sets, the deep convolutional neural network exhibits a loss of less than 0.02%. The DL models behave the same or better than training sets when these issues are solved using the fundamentals of optimization theory. Each study demonstrates the viability of applying deep learning to massive MIMO real-time power regulation. Table 7 demonstrates a comparative analysis of various deep learning-based schemes.

Table 7. Comparative analysis of deep learning-based methods

Reference	Research	DL Method	Performance and observation
[42] [43]	• Estimation of CSI • mmWave band	• DNN • CNN	• FFDNet and DnCNN perform significantly better than traditional channel estimation techniques (LS and MMSE).
[44]	• Downlink of MIMO-NOMA • Precoding and SIC decoding	• FNN	• Attains lesser MSE and lesser BERs • Nonlinearly addressed the problems of faulty SIC decoding
[45]	• Estimating the channel and DOACSI feedback	• DNN • CNN • LSTM	• With bigger batch sizes, the MSE efficiency of the Computation is more stable. • When using longer training sequences, the channel estimation's performance is optimised. • Keeps strong system performance and gain at the BS even with various antenna arrangements.
[32] [46]	• Wi-Fi positioning • Improve localization	• CNN • MLP	• As the number of users rises, average precision declines. • Capability for positioning generalise effectively in line-of-sight or highly clustered propagation circumstances
[47]][48]	• Power control • Address a non-convex issue	• CNN	• As network size grows, the required number of cycles to attain the static point does not change noticeably. • Although the average gain is only 1%, the biggest relative improvement occurs when initialization is increased from 1 to 5. • A single neural network may accommodate various user counts per cell.

Table 8. Challenges in 5G deployment

Challenges	Description
Coexistence of 5G Radio with other networks	Several networks operate in the same frequency bands, which causes overlapping of frequencies. Therefore, frequency prioritizing plays an important role in smooth coexistence.
Signal distortion	The advancement in wireless communication schemes has led to the evolvement of modulation schemes. The higher modulation schemes cause signal distortion, which degrades the communication performance because of dense constellations
Propagation losses	These networks are operated in high-frequency domains such as mmWave, and terahertz frequencies which are associated with high propagation losses. Therefore, signal quality is degraded, and low SNR is obtained
Coexistence of uRLLC, mMTC, and eMBB	The existence and deployment of 5G in the same RAN significantly impact the working of 5G, and massive connectivity violates the uRLLC and increases delay.
Handover synchronization	The handover between high mobility radio access technologies consumes more time, resulting in increased delay and call drop.

3. The beginning of 6G

The commercialization of 5G networks, including all of their services and use cases, is in the primary stage of development. In order to be effectively implemented, these networks have to eliminate many obstacles (Table 1) effectively. The problems and technological shifts have led to the development of a 6G network. According to speculations, 6G networks will dominate the following ten years (2030–2055), ushering in the era of "everything connected." Many nations have already begun exploring 6G networks. Finland launched its flagship 6Genesis programme in 2018 to create an entire 6G ecosystem [49]. ITU has created a group named "Network 2030,". The purpose of this group is to explore new technologies for the networks beyond 2030.

For many applications, such as the transfer of sensations and emotions, next-generation networks are anticipated to be connected with high bandwidths, terahertz frequencies (up to 3THz), and high data speeds (up to 1Tb/s). According to authors in [63], from 1G to 5G, with an emphasis on 6G, the next generation of wireless networks has been addressed along with their innovations, services, and problems. The goal of 6G networks is to increase user happiness. It moves along the same path as networks from earlier generations.

4. Issues and challenges in 6G

The study of the 6G network is still in its beginnings. As a result, many problems and difficulties need to be solved. With various potential methodologies and use cases, 6G networks are thought to be intelligent and versatile. This section discusses a few topics of 6G communication networks:

- THz communication is quickly becoming a desirable technology for the 6G network, increasing system capacity by supplying more spectrum ranges. But, due to obstructions and high absorption losses, these frequencies may only be suitable for short-range transmission. Small-sized transceivers with low noise and lower inter-module intrusions are needed to enable such high-frequency sophisticated devices [58]. Thus, to get high-performance gain, researchers should examine how well the equipment can function at such high frequencies and adjust it appropriately.
- The current channel estimate models cannot accommodate higher frequencies' variability and uncertainty. Therefore, new channel and propagation models must be developed to estimate the performance of such intricate environments. 6G is expected to work in distinct types of networks. It is essential to design flexible systems and dynamic protocols that can react to the context in order to enable seamless connectivity and network interoperability.
- 6G will incorporate several networks, such as terrestrial and satellite networks, to achieve broad coverage and high mobility. Furthermore, because of the significant delay, apparent Doppler shift, and inter-satellite links, it is difficult to implement satellite communication with ground communication. These difficulties may impact synchronization, random access, signal recognition, reception efficiency, and other activities. So, to properly reap the benefits of an interconnected communication system, innovative approaches must be provided to reduce the associated difficulties.
- Edge computing or intelligence will significantly increase the network's computational capability. However, it is exceedingly challenging to run complicated AI-based systems that necessitate large data collection on edge nodes due to the limited supply of resources and storage. Therefore, researchers must create sophisticated and original AI algorithms for edge nodes. Additionally, efficient mobile edge scheduling and offloading mechanisms must be developed to improve the system's efficiency.
- AI will be the driving force behind 6G, which demands highly powerful Computation and extensive data manipulation. Therefore, the key components of the 6G network will be energy efficiency and power

optimization. It is necessary to develop power-efficient methods for next-generation systems.

- Wireless network security and privacy are the main concerns. The key 6G network technologies necessitate massive data transmission and collection. Numerous PHY security strategies and encryption systems must be developed to guarantee security and privacy. 6G networks are thought to offer protection from new threats. Future society and the economy will be entirely reliant on technology. Therefore, a trustworthy design with the necessary privacy and secrecy is needed.

5. Conclusion

MmWave massive MIMO technologies embody an effort to connect the significant prospects of the bandwidth available in the mmWave frequency band and the vast capacity gains of massive antenna array models. In this work, we have summarized the theories and methods given for mmWave massive MIMO technologies. Also, we outlined the differences between the features of the new network technology and the earlier systems from which it is deriving, as well as the main research difficulties and future objectives. It is essential to remember that 5G and B5G technologies are not solely driven by technological advancements and the ability to supply large bandwidth and rapid data rates for booming mobile data. This article discusses the current advancements in this area of massive MIMO, mmWave, and NOMA-based 5G and 6G communication protocols. Deep learning-based communication performance-improving methods are also examined. Moreover, there are a number of difficulties in the area of 5G communication standards. These difficulties must be overcome for the 5G network to transition to the 6G network.

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