electronics

Review

Machine Learning for Physical Layer in 5G and beyond Wireless Networks: A Survey

Jawad Tanveer [1], Amir Haider [2,*], Rashid Ali [2] and Ajung Kim [1,*]

[1] School of Optical Engineering, Sejong University, Seoul 05006, Korea; jawadtanveer@sju.ac.kr
[2] School of Intelligent Mechatronics Engineering, Sejong University, Seoul 05006, Korea; rashidali@sejong.ac.kr
* Correspondence: amirhaider@sejong.ac.kr (A.H.); akim@sejong.ac.kr (A.K.)

Abstract: Fifth-generation (5G) technology will play a vital role in future wireless networks. The breakthrough 5G technology will unleash a massive Internet of Everything (IoE), where billions of connected devices, people, and processes will be simultaneously served. The services provided by 5G include several use cases enabled by the enhanced mobile broadband, massive machine-type communications, and ultra-reliable low-latency communication. Fifth-generation networks potentially merge multiple networks on a single platform, providing a landscape for seamless connectivity, particularly for high-mobility devices. With their enhanced speed, 5G networks are prone to various research challenges. In this context, we provide a comprehensive survey on 5G technologies that emphasize machine learning-based solutions to cope with existing and future challenges. First, we discuss 5G network architecture and outline the key performance indicators compared to the previous and upcoming network generations. Second, we discuss next-generation wireless networks and their characteristics, applications, and use cases for fast connectivity to billions of devices. Then, we confer physical layer services, functions, and issues that decrease the signal quality. We also present studies on 5G network technologies, 5G propelling trends, and architectures that help to achieve the goals of 5G. Moreover, we discuss signaling techniques for 5G massive multiple-input and multiple-output and beam-forming techniques to enhance data rates with efficient spectrum sharing. Further, we review security and privacy concerns in 5G and standard bodies' actionable recommendations for policy makers. Finally, we also discuss emerging challenges and future directions.

Keywords: 5G; B5G; wireless networks; machine learning; MIMO; physical layer; IoT

Citation: Tanveer, J.; Haider, A.; Ali, R.; Kim, A. Machine Learning for Physical Layer in 5G and Beyond Wireless Networks: A Survey. *Electronics* **2022**, *11*, 121. https://doi.org/10.3390/electronics11010121

Academic Editor: Sotirios K. Goudos

Received: 16 November 2021
Accepted: 27 December 2021
Published: 30 December 2021

1. Introduction

Over recent years, the quantity of communicating devices and their consumers has been enormously growing, forcing cellular companies to expand their bandwidth to acquire higher data rates for wireless media [1]. In this regard, the advancement in mobile phone generations from 1G to 4G-LTE has brought about an improvement and numerous challenges [2]. Nowadays, internet speed is an eminent concern for both users and service providers; hence, cellular companies are in a battle for fifth-generation (5G) internet implementation so that they can provide a super fast and reliable connection to their users [3]. Fifth-generation networks are supposed to revamp the cellular industry from top to bottom by 2022, as their primitive focus is to enhance the transmission speed, capacity, and reliability of wireless channels. This task can be accomplished by using low power and low latency for the tactile internet, the Internet of Things (IoT), massive multiple-input and multiple-output (MIMO), robotics, autonomous vehicles, and industry [4]. Due to its super fast nature, it brings a latency rate of 1 ms, allowing problems to be solved instantaneously, which is essential for real-time applications and seamless connectivity [5].

5G technology has enabled multiple networks to interact with each other irrespective of their distinct characteristics to establish a heterogeneous wireless network (HetNet). Although this is a standard of 4G-LTE, the primary infrastructure does not support it [6].

Fifth-generation devices consume low power, and Tx/Rx transmits signals at a data rate of 10 Gbps (gigabits-per-second). This technology provides an environment for the connection of millions of IoT devices. The combination of 5G and IoT can be used to execute the smart city concept. Smart devices are capable of exchanging data over millions of devices at a high transmission rate with low latency and low cost [7]. Increased system capacity, high spectral efficiency (SE), and energy efficiency are other advantages that can improve user experience and satisfaction. The primary goal of 5G is to connect living beings and intelligent devices (machines, robotics) at any instant to provide complete services [8]. The roadmap of 5G provides boundless possibilities from economic and societal perspectives. The lower site density in the sub-6 GHz region is crucial for high-definition video streaming and massive machine-type communications (mMTC) applications with ultra-reliable low latency communication (uRLLC). Fifth-generation technologies will surely help to tackle applications that consume high data rates and require massive bandwidth and low latency [9,10].

In Figure 1, the heterogeneous network architecture of 5G new radio (NR) is presented, in which everything is connected with 5G internet. Artificial Intelligence (AI), machine learning (ML), and deep learning (DL) techniques are envisioned to be the best techniques to make the 5G vision a reality. Considering novel use cases such as critical delay-sensitive applications, drone mobility, autonomous vehicles, mixed reality, and industrial automation [11]. From virtual personal assistants to social media services, ML is expected to solve many challenges in numerous applications. The ML-based solutions are effective for intrusion detection and prevention, video surveillance, email spam, and predictions, while reducing online commuting. ML has become mature enough to enhance the performance of the network and its services by learning from the wireless network traffic behaviors [12]. ML-based 5G wireless communication is possible using various modern networking standards; i.e., big data analysis [13], mobile edge caching [14], mobile edge computing [15], and context-aware networking [16]. The existing heuristic radio resource management (RRM) algorithms cannot confront the fundamental demands of 5G due to their complex procedure [17]. However, ML works incredibly well for traditional approaches to complex problems that require a great deal of human intervention.

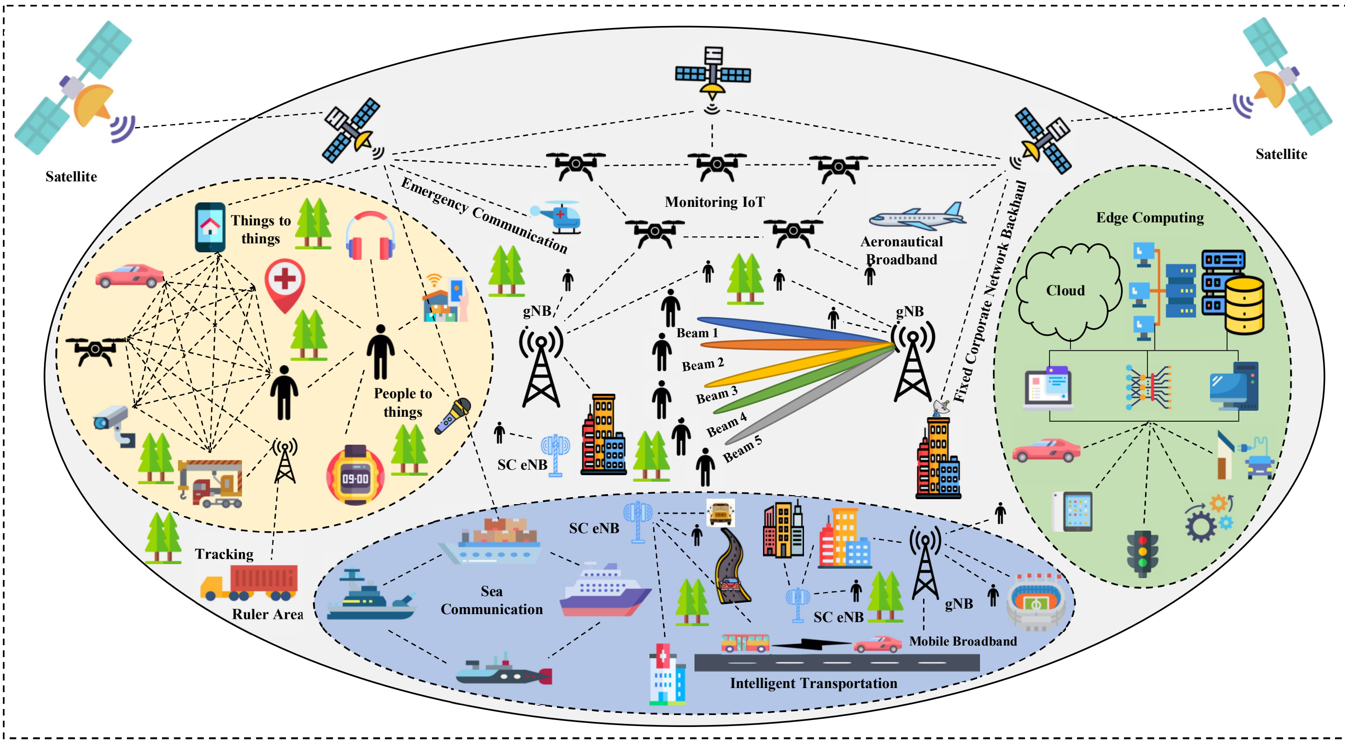

Figure 1. 5G network architecture.

In addition, ML-based algorithms learn from existing or run-time data, perform automatic feature extraction, and replace the stereotypically long instructions to tackle novel problems [18]. Substantially, an ML-based algorithm can help in the fields of education, patient sickness predictions, image recognition, self-driving cars, military surveillance, transportation, stock market, and recommendation engines. Complications in wireless networks are due to the exponential growth of heterogeneous networks, the immense numbers of end-user devices, and time-sensitive applications. For this reason, emerging use cases and services demand an automated network procedure [19]. However, the current state-of-the-art deployment of wireless networks has taken a sporadic approach based on the fix-and-patch mentality. ML principles are often drawn from established technologies of machine vision and robotics. Such borrowed regulations address the specific situation but negligently create new research challenges. These challenges include the inept usage of network resources, weak processing, memory sufficiency, and attack vectors [20]. Therefore, to enhance the wireless network capability, elementary units and all layers of a wireless system will integrate ML-based approaches [21]. In Table 1, we compare the capabilities of 5G in contrast with 4G and 6G technology.

Table 1. Comparison of 4G, 5G, and 6G communication systems.

Key Performance Indicator (KPIs)	**4G-LTE**	**5G**	**6G**
Deployment year	2000	2020	Yet to be implemented
Core architecture	Internet	Internet	Internet
Core networking	Internet	Internet	Internet
Multiplexing bandwidth	OFDMA/SC-FDMA (1.4 Mhz–20 Mhz)	BDMA/FBMC (60 GHz)	OMA/NOMA (up to 3 THz)
Per device peak data rate	1 Gbps	10 Gbps	1 Tbps
Switching	Packet switching	Packet switching	Packet switching
Forward error correction	Turbo codes	LDPC codes	LDPC codes
E2E latency	100 ms	10 ms	1 ms
Maximum spectral efficiency	15 bps/Hz	30 bps/Hz	100 bps/Hz
Mobility support	Up to 350 km/h	Up to 500 km/h	Up to 1000 km/h
Satellite integration	No	No	Fully supported
AI supported	No	Partially supported	Fully supported
Autonomous vehicle supported	No	Partially supported	Fully supported
XR supported	No	Partially supported	Fully supported
Haptic communication	No	Partially supported	Fully supported
Visible light communication (VLC)	No	No	Yes
Maximum frequency	6 GHz	90 GHz	10 THz
Architecture	MIMO	Massive MIMO	Intelligent surface
Service Level	Video	AR,VR	Tactile
Connectivity density	10^5 Devices/km^2	10^6 Devices/km^2	10^7 Devices/km^2
Area traffic capacity	0.1 Mb/s/m^2	10 Mb/s/m^2	1 Gb/s/m^2
Network energy efficiency	1$\times$	10–100$\times$ of 4G	10–100$\times$ of 5G
Spectrum efficiency	1$\times$	3$\times$ of 4G	5–10$\times$ of 5G
Reliability	99.99	99.999	99.99999

Contribution

This study presents a 5G network architecture and next-generation wireless networks (NGWN) communication architecture model. Besides this, we also present 3GPP-based physical layer services and functions, 5G massive MIMO and beam-forming techniques to enhance data rates with efficient spectrum sharing, 5G crosstalk issues and solutions, 5G-supporting signaling techniques, and security and privacy in 5G. This survey aims to understand and emphasize the emerging methods of ML for upcoming 5G use cases. In addition, the article discusses how forthcoming 5G technologies will meet their demanded goals using shared information and ML-based techniques and expected future challenges due to the combined architecture models. At the end, we also discuss emerging challenges and future directions.

2. 5G Technology

Wireless technology is frequently growing and expanding to entertain the higher state-of-the-art requirements of users with versatile applications. In the future, the above traits of 5G will assist in upcoming big data applications such as diagnosing critical-life situations in hospitals, fast money transfer in a stealthy way, handling inventory in warehouses, and much more [22]. Moreover, the latest applications that demand heavy traffic with quality of service (QoS) and quality of experience (QoE) cannot be maintained by 4G and its previous generations. Since 5G can offer 20 Gbps peak data rates, which are 100$\times$ faster than 4G, broadcasting rates are also in Gbps, and the average data rate is 100+ Megabits-per-second (Mbps) [23]. Therefore in upcoming years, we will be able to download videos and movies in a few seconds without waiting for streaming [24].

2.1. 5G Network Architecture

The architectural model of 5G has four layers: a network layer, controller layer, management and orchestration layer, and service layer. Radio link control (RLC) and packet data convergence protocol (PDCP) layers are the sub-layers of the 5G protocol stack. The network architecture of 5G contains adaptable, virtual, and flexible radio access networks (RAN) points instead of base stations (BS) and a complex distributed design. These virtual RANs include new interfaces, elements, and compositions to create numerous data access points [25]. In 5G architecture design, the RANs can support WiFi, WI-Max, CDMA-One, UMTS, LTE, LTE-adv, EV-DO, GSM, GPRS, IS-95, and different RANs connected through a single aggregate network using a software-defined network (SDN) controller to route the traffic to a gateway. The hyper-critical aspects of the IP-network, such as the cost of the entire architecture, are significantly cut down by reducing the network elements. The nano-core network (CN) is yet another essential component that has three further categories: (1) nanotechnology (nano-tech), which is essential for the protection of daily life devices; (2) cloud computing, which determines the availability of remote services over the internet; (3) the all IP network (AIPN), which is essential for cellular growth [26].

Third-generation partnership project (3GPP) enhancements also allow a more distributed architecture, which facilitates the usage of AI to assist network optimization through centralized data gathering and by processing the required intelligence. The current NR architecture has already introduced new functions in the core and the management domains—i.e., network data analytics function (NWDAF) and the management data analytics function (MDAF)—which can either run analytics on collected data or can enhance already supported network functions with statistics collection and prediction capabilities. This capability of 5G architecture either analyzes collected information or supports the existing procedure for analytics. ML will play a role in increasingly complex 5G networks; i.e., making adequately energy-efficient and economic policies for optimized network operations. Given the increased complexity of 5G networks, further leveraging 5G network data and ML will be necessary to derive optimum network-wide energy-efficient operation policies [27].

The core features of nanotechnology are a flexible structure, transparency, and environment sensor. Notably, molecular nanotechnology (MNT) uses the nanoscale range (0.1 to 100 nm) to control daily-life gadgets. This is essential for sensing, ensuring security, and cleaning the mobile phone from the unprotected environment. While the cloud computing layer is concerned with all internet services dealing with remote and real-time applications, the consumers can access their confidential data through private accounts. Flat AIPN is the advanced concept enabled by 3GPP to meet future demands of cellular technology. This eases the access of real-time applications by ensuring enhanced edge computing technology and provides features including a lower latency rate, seamless connectivity, system efficiency, and cost-effectiveness. The 5G NR improvement allows the aptitude of ML to endorse network optimization for an expanded distributed or centralized architecture [28]. In Table 2, we summarize the key attributes of 5G that allow the expected 5G performance to be achieved. AI, ML, and DL have been attracting increased attention in the past few years, and researchers are continuously developing applications using these techniques. These technologies deployed together improve QoE, reduce operational costs, and bring new paradigms for future needs. However, 4G did not take advantage of the potential of these approaches; therefore, 5G must involve AL, DL, and ML-based learning characteristics in its architecture.

Table 2. Summary of studies on 5G network technologies.

5G Network Technologies	Key Aspect	References
Centralized architecture C-RAN (Cloud-RAN)	1. RAN as a Service (RAAS) capabilities. 2. Boosts the network performance and highly favorable in low latency. 3. Offers to reuse infrastructure, pool resources, support multiple technologies, decrease energy usage, create a heterogeneous and self-organizing structure, and reduce the costs associated with CAPEX and OPEX. 4. Also allows other network operations in a data center environment.	[29–36],
Multi-access edge computing (MEC)	1. Support for ultra-low latency, interoperability, virtualization, high bandwidth, augmented reality, strengthens security and compliance. 2. Optimized local content distribution and data caching.	[37–45]
Network function virtualization (NFV)	1. Supports longer life cycles for network hardware. 2. Reduced space needed for network hardware, power consumption, maintenance, and hardware costs. 3. Ease in network upgrades.	[46–54]
Network Slicing (NS)	1. Improve performance. 2. Protecting sensitive data. 3. CAPEX and OPEX can also be reduced. 4. Offers various services based on the requirements. 5. Effective and efficient utilization of resources 6. Improves operational efficiency. 7. Overcomes all the drawbacks of DiffServ.	[55–61]
Beamforming (BF)	1. Improves the spectral efficiency. 2. Boosts cell range and capacity. 3. mmWave offers a large bandwidth. 4. Support for higher path loss and blockage scenarios.	[62–69]
Enhanced Common Public Radio Interface (eCPRI)	1. Supports carrier aggregation, downlink CoMP, MIMO, uplink L1 Comp. 2. Reduces jitter and latency for high priority traffic. 3. Ease in troubleshooting at the lower layers. 4. Reduced bandwidth is required. 5. Software upgradable interfaces. 6. Ethernet can carry eCPRI traffic. 7. Saves electricity.	[70–77]

Table 2. *Cont.*

5G Network Technologies	Key Aspect	References
5G Spectrum and Frequency	1. Multiple frequency ranges. 2. Supports higher frequencies, wide-area, outside-in coverage, deep indoor coverage, reliability, spectral efficiency, and the M2M type of communication. 3. Supports very high throughput services for eMBB, and industrial IoT. 4. Provides a balance between throughput, coverage, quality, and latency.	[78–85]

Traits such as the extreme complexity, enhanced problem-solving solutions, and the heterogeneous nature of 5G can only be achieved by using these approaches. In other words, the existence of these characteristics transforms the 6G infrastructure into an innovative and intelligent network [86–88]. Both AI and ML are somehow correlated with each other, where AI is the program of study that includes intelligent machines, such as robotics, along with the perception of human intelligence, and ML involves the study of creating computer programs [89]. It is stated that AL is generally about finding solutions, facts, logical reasons, and intellectual learning, but ML is about learning from existing experiments and examples. On the other side, DL, a part of the ML family, is based on ANNs and enables computing models to perceive, learn, and represent data by following human brain stimulation. The model has multiple processing layers and contains interconnected artificial neurons such as the human body's nervous system [90]. As 4G did not provide the required platform for all these learning methods and technologies, 5G must consider the importance of these categories and prepare its internal infrastructure for experiencing smart and intelligent designs. Real-time intelligent edge-distributed AI and intelligent radio must be a part of 5G design to acquire autonomous services, intelligent calculation, accurate decision planning, and a real-time approach [91]. According to [92], the 5G framework demands intelligent radio (IR) instead of deploying the PHY model as it has specific hardware and transceiver algorithm traits. In contrast, DAI outperforms other approaches with regard to the security and privacy of data.In Table 3, we discuss architectures that support 5G network technologies to deliver expected services.

Before moving forward, it is important to understand the trends and services of 5G. Some of the key trends provided by 5G are as follows:

1. Increased spectrum, bits, and reliability:
   For proper working and operation, the sub-6 GHz spectrum must deliver increased bits, a large spectrum, and increased reliability [93]. Fifth-generation networks are a standalone approach to provide services for the latest technological applications, such as wireless brain–computer interactions, abbreviated as BCI [94,95]; extended reality services, abbreviated as XR [96]; connected robotics and autonomous systems, abbreviated as CRAS [97]; distributed ledger technologies, abbreviated as DLT [98]; and much more. This is possible only by exploring more spectrum resources and achieving higher reliability ratios at high-frequency bands.
2. Using volumetric spectral efficiency and metamaterials:
   5G demands the use of volumetric spectrum efficiency and energy efficiency, abbreviated as SEE, with bps/Hz/m^3/Joules units. Along similar lines, 6G requires the support of XR, CRAS, DLT, BCI devices, and flying vehicles, which would not be possible without aerial bandwidths. Furthermore, the 3D evolutionary architecture of 6G requires active surfaces, smart, or intelligent coverings to transmit signals instead of deploying a conventional base system [99].
3. Moving from a centralized to distributed data approach:
   Due to the continuous transformation of data from large, big, and centralized to a small and distributed approach, 5G must furnish its infrastructure to provide services

for current centralized and future distributed data. This is one of the most crucial trends of 5G required for ML, and small data analytics [100].

4. Implementing wearable devices:
   5G creates a space for smart body implementation, wearable devices, and integrated handsets. All these devices operate through human sensory inputs [101].
5. Focusing self-sustaining networks:
   The technologies upheld by 5G and beyond demand intuitive networks instead of self-organizing networks, supported by previous cellular generations. These self-sustaining networks bring instantaneous sources, network operations, and optimization traits. Furthermore, the network can perform and explore dynamic environmental conditions, states, and key performance indicators [102]. Thus, beyond 5G networks (B5G) create artificial learning, quantum computing (QC), and quantum machine learning (QML) skill sets [103].
6. Enhancing communication premises:
   From 1G to 4G, the primary purpose of these generations is to serve wireless communication, but 5G has slightly different premises. 3CLS stands for communication, computing, control, localization, and sense, which is potentially given by 6G, allowing it to become a multi-purpose generation. The design of 5G must evolve in a way to achieve all the 3CLS services and bring something valuable for real-time applications [104].

Table 3. Summary of studies on 5G network architectures.

5G Network Architecture	Key Aspect	References
IIoT MEC based Architecture	1. Supports industrial IoT (IIoT), smart energy, wearables, environment monitoring, gaming, AR/VR, autonomous vehicles, healthcare and remote surgery, smart city/home.	[105–112]
TelcoFog Architecture	1. Providing unified cloud and fog resources for deploying NFV, MEC, and IoT services. 2. Distributed and programmable fog technologies. 3. Supports HVAC service. 4. Secure, highly distributed.	[113–120]
5G IoT Architecture	1. Supports nano-chip, millimeter wave, heterogeneous networks, device-to-device communication, 5G-IoT, machine-type communication, wireless network function virtualization, wireless software defined networks, advanced spectrum sharing and interference management, mobile edge computing, mobile cloud computing, data analytics and big data.	[121–128]
Blockchain-Based Architecture	1. Cost-effective, scalable, secure, and handles various vehicular network issues in a smart city. 2. Provides ledger and smart contract (chaincode) services to applications. 3. Provides a decentralized and distributed network. 4. Provides protection for the entire data life cycle. 5. Prevents internal and privacy attacks. 6. Distributed, reliable, and efficient authentication and traceability. 7. Empowered data-driven networks. 8. Supports several use cases; i.e., smart healthcare, smart city, smart transportation, smart grid, and UAVs.	[129–136]

The existing TCP/IP layered model cannot provide constraints for all futuristic applications, forcing researchers to build more powerful components in the stack architecture. The designer of the application recommends including meta-data and commands in the current model. They play the role of identifiers to make the communication process easy, analyze the application's essentials, and acquire information about flow states. After observing these benefits, in [137], the authors presented the concept of cross-layer, which can combine conventional network requirements with the transport layer to generate a combined layer. In addition to flow multiplexing capability, it efficiently reduces congestion and overall complexity and determines the network's requirements to boost state.

2.2. Next-Generation Wireless Networks (NGWN)

Regarding 5G and beyond, NGWN introduces various hypercritical challenges in the area of ultra-dense deployment heterogeneous networks (HetNets). Due to this factor, the upcoming wireless networks will be highly dynamic and complex [138]. Access points and low-cost end-user devices are growing drastically, and high mobility in this scenario results in a complicated and hectic communication process [139]. The propagation behavior of radio signals being broadcasted with exploded communication introduces spoofing and man-in-the-middle attacks. Nowadays, wireless data formation and utilization are progressively distributed, so the current paradigm is converging from people-centric to machine-oriented communications. To handle the future complex wireless operations, knowledge discovery, improved context-awareness, efficient data acquisition, and distributed computational resources using the adoption of AI principles and ML-based techniques are extremely important [140].

5G technology is considered evolutionary, service-oriented, or revolutionary. As mentioned, the systems of 5G will be designed so that they can bear the worldwide wireless web (WWWW), commonly known as real-world wireless. This will provide seamless broadband connectivity and permit the support of flexible ad-hoc networks—i.e., dynamic ad hoc wireless networks (DAWN)—which would be a rich ecosystem of mobile applications and cloud-based services [141]. Fifth-generation networks use enhanced modulation schemes (OFDM uplink and downlink) for higher SE, and the subcarrier modulation may vary from QPSK, 16QAM, and 64QAM to 256QAM, while the subcarrier spacing also varies from 15 kHz, 30 kHz, 60 kHz, 120 kHz, and 240 kHz to 480 kHz; that is, depending upon 5 g numerology (μ 0–4), carriers vary up to 3300. The massive intuitive antennas are critical factors in producing a high data rate and are committed to boosting 5G's capability for the new world [142]. Moreover, OFDM and its variants (COFDM, Flash OFDM, OFDMA, VOFDM, Vector OFDM, WOFDM), MC-CDMA, LAS-CDMA, Network-LMDS, UWB, and IPv6 play a significant role in supporting 5G networks [143].

Currently, 5G is providing advanced services and intelligent technologies such as AI, virtual reality (VR), augmented reality (AR), mixed reality (MR), and cloud computing which are being used to cater to the IoE behavior of the network. The 5G revolutionary view indicates that the existing infrastructure of previous generations (2G/3G/4G) is not suitable for advanced applications and services. Table 4 shows a comparison of 4G, 5G, and 6G with respect to network characteristics, applications, and use cases. To achieve the expected 5G vision, embedded architecture and intelligent designs are required in addition to emerging technologies; i.e., SDN, network slicing, and NFV located above the physical layer to support multiple services. NR wireless communication architecture is excellent for achieving ultra-reliable low latency communication, whereas other benefits from, i.e., eMBB and mMTC are also considered [144]. Low-density parity-check (LDP) codes and polar codes (PC) are regarded as the top-tier spectrum coding schemes for higher data rate networks such as 5G-NR [145]. The international telecommunication union (ITU) standardization group (ITU-T SG-12) endorsed new updating and defining recommendations to achieve QoS and QoE in the NGWN [146]. The ITU-T group has already been settled and named as a focus group on ML for future networks including 5G to mitigate and overcome the latest challenges of NGWN and to manage its operations [147].

In Figure 2, NGWN is presented under the consideration of the heterogeneous network architecture of 5G.

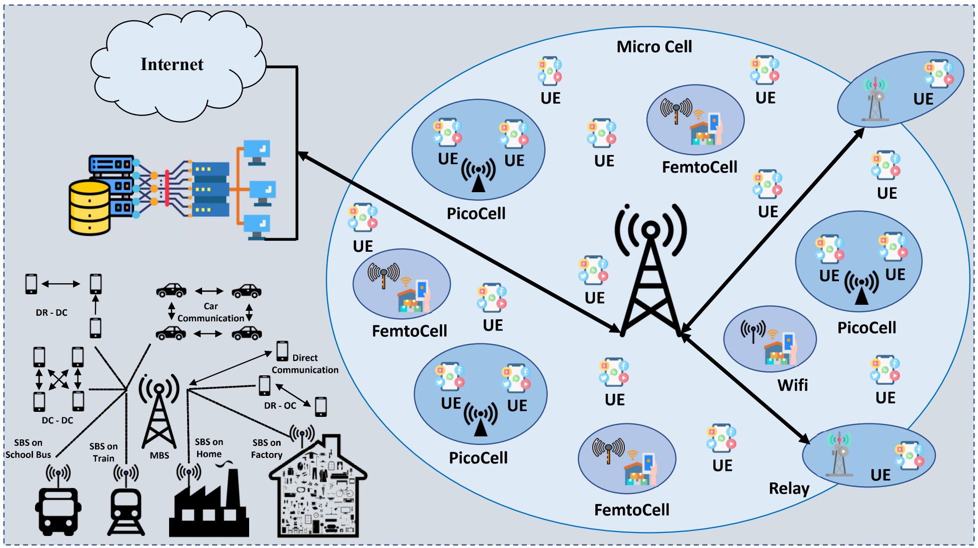

Figure 2. 5G wireless communication architecture.

Table 4. 4G, 5G, and 6G characteristics, application, and use cases.

	4G-LTE	5G	6G
Use cases	MBB	eMBB,URLLC,mMTC	FeMBB, ERLLC, umMTC, LDHMC, ELPC
Applications	Mobile TV/Pay, high-definition video, voice, mobile internet	Telemedicine VR/AR/360° video, IoT, V2X, UHD videos, wearable devices, smart-city	Autonomous vehicles, tactile/haptic internet, space travel, holography, Internet of Bio-Nano-Things
Network characteristics	Flat and all-IP	Slicing, cloud, software, virtual	Virtual, software, intelligent, cloud, slicing

Nonetheless, new methodologies are still required for the deployment of QoS management models using ML-based algorithms to identify optimal key performance indicators (KPIs) and key quality indicators (KQIs) to make efficient and optimized QoS frameworks. Conventional networking approaches are not competent and have limited capability (space and time) to assist persuasively future complex networks in terms of procedure and optimization costs [148]. A proactive, predictive, optimized, cost-effective, self-adaptive, and self-aware networking paradigm using ML is required to overcome these incompetencies and mitigate the complexity of future network operations. ML systematically exploits the big data of networks and provides an innovative and intelligent system with cost-effective and optimized operation. Next-generation wireless networks are anticipated in which AI, ML, and advanced data analytics tools will be the main drivers [149,150].

3. Physical Layer in 5G

The physical layer, the bottom layer of 5G, is the only layer that provides a direction to the top layers. The physical layer's primary functions include encoding/decoding, error detection, modulation/demodulation, digital and analog beam-formation, RF processing, and MIMO handling. These functions are carried out through a wireless environment surrounded by an electromagnetic field, RF, signal transmission, waves, and antenna propagation [151]. The major role of 5G is to boost the SE. Still, as soon as the bandwidth increases, the signal suffers from electromagnetic interference, pulses, and radiation, which decreases the quality of the signal. These unwanted endowments affect the signal's attributes and create unnecessary noise (i.e., additive, multiplicative, Poisson, transient, and phase noise) [152]. Additive noise is further divided into nine categories: white, additive white Gaussian, black, Gaussian, pink/flicker, Brownian, contaminated Gaussian, power-law, and Cauchy noise). Consider a simple example of a current flowing from the standard circuit to understand this concept. The circuit's elements (wire, resistor, battery) are designed to receive zero EM radiations for the current to flow without any disturbance. However, if the circuit does not follow standard regulations, unlimited reflections will be received, and the current will not flow easily. On similar lines, the circuit becomes a mono-pole antenna if the standards are not maintained in the transmission and receiving process of the wireless medium [153]. Likewise, by enhancing SE, distortion will be generated, and the signal will suffer a significant number of reflections, interrupted noises, and reflections in its path. Still, this can be overcome through massive MIMO technology, as discussed in [154]. Table 5 shows a summary of studies on physical layer functions in 5G wireless networks. Technically, electromagnetic interference is originated either from radiated or conducted sources. In the electromagnetic field and wireless communication networks, the communicating path directly links with electromagnetic propagation. Radiated interference transfers the source signal's reflection, crosstalk, and disruptive noises using inductive and capacitive coupling devices.

The above description proves that at high frequency or a low wavelength, unwanted radiations and interference originate from both internal and external means in 5G architecture. According to Faraday's law, these radiations may vary in electric and magnetic fields in both time and space along with alternating flux density. Contrary to this, conductive interference occurs due to impedance mismatching and the coupling of neighboring resistive elements (inductors, capacitors, and resistors), and this whole process reduces the voltage standing wave ratio [155]. Consequently, massive MIMO in the 5G architecture endures multiple Tx/Rx radiations at high SE by achieving high data rates and ensuring throughput, reliability, and bandwidth performance to tackle these limitations [156].

Table 5. Summary of the related work on the physical layer in 5G wireless networks.

Domain	Key Aspect	Related Work
mmWave channel characterization	1. Power delay profile. 2. Doppler effect. 3. Multi-path and propagation. 4. LOS and N-LOS communication.	[157–164]
Adaptive beamforming.	1. Angle of arrival. 2. Antenna training. 3. Adaptive beamforming.	[165–171]
Switched Beam	1. Overlapping sector. 2. Cost effective. 3. Sectorized antenna model.	[172–179]
Massive MIMO systems	1. MIMO small cell combination. 2. Inexpensive low-power component. 3. High number of antennas per BS. 4. Coherent superposition of waveforms.	[180–186]
Full duplex radio technology	1. Active and passive SI cancellation. 2. Improved spectral efficiency. 3. Decreased self interference (SI) and pathloss. 4. Decreased crosstalk between Tx and Rx. 5. Improved feedback and latency	[187–194]

In the recent past, the physical layer became an eye-catching topic for time-sensitive services due to its potential to provide more effective approaches for 5G and beyond networks [195]. ML-based techniques enhance the properties of the physical layer and make the process efficient and optimized. For instance, in [196], the authors proposed a CNN-based solution for intelligent communication in different situations, and [197] discussed channel estimation and detection using DNN, outperforming the minimum MSE-based joint approach in OFDM systems. In [198], the authors proposed an ML-based antenna design method to ensure the security of the IoT communication system, and [199] proposed a CNN-based technique to classify several key CSI parameters to adjust the physical layer parameters in noisy environment. In addition, ref. [200] proposed a DL model (CNN-DMA) to detect malware attacks based on a classifier—the Convolution Neural Network (CNN)—and [201] proposed a multi-scale convolutional neural network framework for wireless technique classification to improve the classification accuracy and obtain a higher convergence speed. Furthermore, in [202], the authors proposed a CNN-based equivalent channel hybrid precoding approach in mmWave massive MIMO systems to reduce complexity and improve performance, and [203] proposed a CNN-based multi-user authentication system to distinguish spoofers/attackers using CSIs and improve the authentication accuracy of MIMO-OFDM systems. ML-based algorithms can be used to estimate and predict channel behavior, the outcome of the encoding and decoding process, and suitable coding schemes accordingly. Based on these features and classifications, ML-based algorithms, ranging from simple to complex, can obtain the desired output and estimate the required performance. These efficient techniques can optimize the channel conditions and system loads, scheduling, transmitting, signal-to-noise ratio, and sub-code lengths [204].

3.1. Signaling Techniques for 5G

Initially, 5G works in conjunction with 4G infrastructure based on release-15 non-standalone (NSA) standards. The NSA standard proposes a 5G base station (gNB) that replaces the LTE infrastructure eNB and an evolved packet core. The network hierarchy is executed with eNB as the master and gNB as the secondary working node. In a dual connectivity structure, the user can access both 5G and 4G-LTE [205]. Telecommunication operators introduce many options, but the main options for 5G execution are 2, 3, 4, 5, and 7. Currently, option 2 (stand alone-SA) and option 3 (non-standalone-NSA) are standardized, in which the 5G architecture provides 5G services using LTE architecture [206]. Following the guidelines in [207], Figure 3 shows 5G deployment options with frequency division and the supported existing architecture. Signaling techniques are capable of transmitting lower to higher data rates while considering several issues; i.e., slow beam-forming, lethargic synchronization consisting of large gaps in time slots, and pitiable channel efficiency as compared to existing techniques and conventional OFDM [208]. Generalized frequency division multiplexing (GFDM) improves the SE and weak out-of-band emission compared to the 4G network. Orthogonal time-frequency-spread (OTFS) is essential in 5G mmWave to provide less BER, high reliability, and flexibility for pilot design in a noisy environment. OTFS transforms the fading medium and time-varying characteristics of the wireless channel into nonfading and time-dependent wireless channels [209,210].

In 5G mmWave, factors affecting the signal's quality are meteorological conditions, environmental surface, operational frequency, fading effect, the distance between the antenna and user, and baseband signals attacked by the signal's impairments. The presence of linear and nonlinear compression brings abrupt changes in signal originality. In-phase and quadrature-phase (IQ) impairments, frequency errors, and phase noise are significant physical layer challenges that are mandatory to maintain signal quality. The fundamental reasons are high range frequencies and the wide range of bandwidth usage, the hardware execution of modulated transmitters, and the fact that receivers turn into the non-ideal state [211]. Sampling circuit operations near sampling velocity create irregular noises, distortion, and nonlinear performance. Similarly, amplifiers, converters, and switches also distort the signal between the transmitter and receiver [212].

In a wireless medium, the error vector magnitude (EVM) is usually required to measure the RF signal's performance, and it determines waveform distortion, deformation errors, linear and nonlinear compression [213]. AI, ML, and DL-based techniques are anticipated to meet the 5G vision in the real world. The viability of ML-based 5G wireless communications has already been ensured using mobile edge computing [214,215], mobile edge caching [216], big data analysis [217], and context-aware networking [218] standards. Current radio resource management (RRM) algorithms cannot stand up to the primary expectations of 5G due to obscurity [219]. In this regard, ML-based solutions enable reliable communication and automated, efficient, and accurate decisions for analyzing and prediction, and 5G security is only as strong as its weakest links. Various techniques enhance the physical layer performance of 5G; for example, ref. [220] proposed a loss function to increase the performance of neural networks in a communication system, and [221] proposed a multi-antenna and multi-subcarrier channel state information (CSI)-based novel channel sounder architecture to achieve an accuracy better than 75 cm for line of sight (LoS) for indoor user positioning in three dimensions.

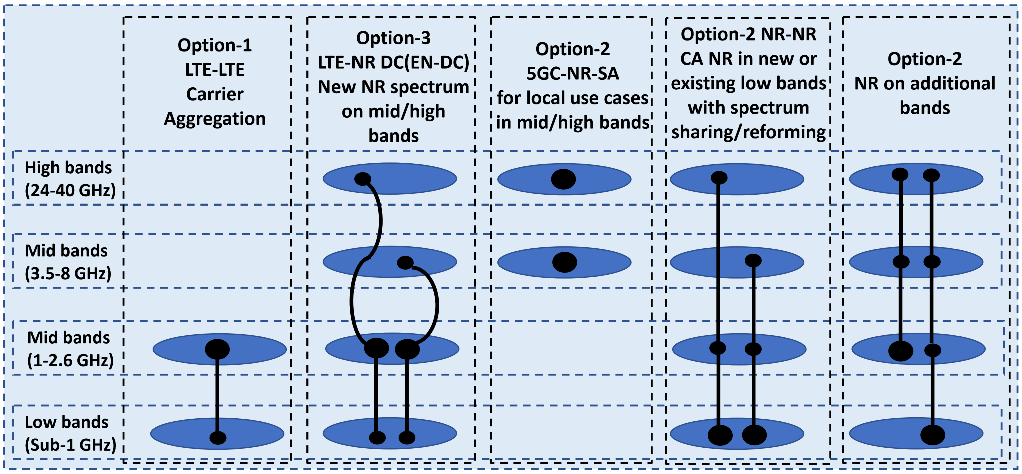

Figure 3. 5G NR-LTE options.

In [222], the author proposed an ANN-based novel Adaptive Modulation and Coding (AMC) scheme to estimate the signal-to-noise power ratio (SNR) to determine the optimal MCS with a low calculation complexity, and [223] proposed ML-based peak-to-average power ratio (PAPR) reduction using the optimal hyperparameter function and efficient approximation for the downlink channel of mMIMO with an OFDM signal. In addition, ref. [224] proposed a DRL-based channel and latency aware radio resource allocation scheme to optimize the uplink scheduling for service-oriented multi-user millimeter wave (mmWave) radio access networks (RAN). Furthermore, ref. [225] proposed a DRL-based channel prediction approach to reduce the signaling overhead when reporting full downlink (DL) channel state information (CSI) back to the base station. Orthogonal frequency division multiplexing (OFDM) is a mature technique in wired and wireless communication systems. In OFDM, high-order modulation schemes boost the SE of a signal and the power level for each subcarrier, enhancing the transmission performance, while digital signal processing complexity is another factor in contrast to single-carrier systems. Table 6 explains the 5G numerology from 0 to 4 and their corresponding attributes. Fifth-generation networks offer five options for different scenarios depending on the communication requirements. A high peak-to-average power (PAPR) offers vulnerability to fiber nonlinear effects, and ML-based techniques can play the best role here to control the PARP level and optimize the values for upcoming intervals [226].

Table 6. 5G numerology.

μ	$N\frac{Slots}{Subframes}$	$N\frac{Symbols}{Slot}$	SCS $\Delta f = 2^{\mu} \times$ 15 kHz	Supported Data (PDSCH, (PUSCH)	Supported Sync Blocks (PSS, PBCH)	Cyclic Prefix Type	Cyclic Prefix Length (µs)	OFDM and Useful Symbol Length (µs)
0	14	1	15	Yes	Yes	Normal	4.69	71.35/66.67
1	14	2	30	Yes	Yes	Normal	2.34	35.68/33.33
2	14	4	60	Yes	No	Normal/Extd	1.17	17.84/16.67
3	14	8	120	Yes	Yes	Normal	0.57	8.92/8.33
4	14	16	240	No	Yes	Normal	0.29	4.46/4.17

The existence of a high carrier frequency in the mmWave band generates non-ideal characteristics in the signal and extends the free space loss propagation. Researchers have also discussed the performance of radio channels by varying the RF and by analyzing the impact of propagation factors on 5G architecture, and the results show that if the wavelength is small, it is easy to build the entire structure on a single IC, but it is hard to cope with environmental factors. At low wavelengths, the chances of attenuation, shadowing objects, scattering, reflection, diffraction, and constructive and destructive interference are high because of delay, path loss, and unnecessary noises [227]. At the same time, multi-path propagation creates indirect rays to carry various duplicates of transmission side signals to receiving side signals. The authors first analyzed the performance of the signal at 28 GHz and then at 38 GHz, proving that, when using high range frequencies the radio channel behaves differently if the objects surround the environment. In addition, if the user/object is moving, the amplitude and phase of the traveling signal must be altered, and ultimately the receiver cannot decode the transmitted signal [228]. Similar efforts were performed by an authors in [229] to demonstrate the concept of vehicular positioning for 5G mmWave.

Following the guidelines in [150], Figure 4 illustrates the physical layer services of 5G and functions defined by 3GPP. Multi-path propagation and the simultaneous localization and mapping (SLAM) technique are used to determine the position of reflectors and users, respectively. Though multi-path propagation blocks GPS signals, it helps the reflectors to measure the transmitter signal scattered from objects.

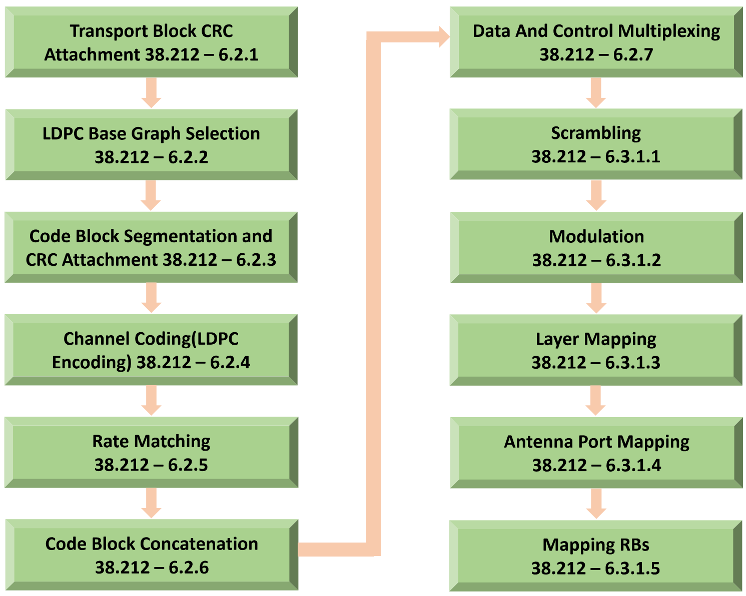

Figure 4. 5G physical layer functioning.

Furthermore, the instantaneous localization and mapping algorithm determines the user's position and constructs an atmosphere map. The author proposed a joint estimation scheme that depicts an automobile's location and resolves multi-path propagation projections while calculating their delays and angle deviations [230]. In [231], the author uses a single-cell multi-user millimeter wave system to achieve SE. The uniform rectangular array situated at the base station region is used for single consumers, who are present in large quantities. The authors achieved favorable results, where SE gave a logarithmic relation depending on the number of antennas using the azimuth and elevation degree for 3D model design and considered single-path propagation. Results showed that SE increased by increasing the number of antennas. Moreover, the SE is improved through the scheduling scheme of users, relying on the response obtained from the users. Table 7 shows the strengths and weaknesses of 5G waveform candidates.

Table 7. Comparison between 5G waveform candidates.

Waveform	Filter Granularity	Time Orthogonality	Frequency Orthogonality	Spectral Efficiency	uRLLC	PAPR	Reference
UFMC	Subband	Orthogonal	Quasi-orthogonal	High	Better	High	[232]
OFDM	Whole Band	Orthogonal	Orthogonal	Medium	Better	High	[233]
F-OFDM	Subband	Non-orthogonal	Quasi-orthogonal	Medium	Better	Medium	[234]
GFDM	Subcarrier	Non-orthogonal	Non-orthogonal	Medium	Better	Low	[235]
FBMC	Subcarrier	Orthogonal	Orthogonal	High	Bad	Medium	[236]

In [237], the authors made several efforts to boost the SE of the hybrid architectures by using discrete Fourier transform (DFT) signal processing and compared them with digital architecture. Zero-forcing pre-coding is used to perform baseband signaling, while BS contains the ideal state information. The viable SE for a hybrid architecture can be enhanced by upgrading SNR and RF chains such as the SE and DFT, which are independent of the number of antennas used at the BS. Moreover, in multi-core fiber (MCF), two or more signals carrying the same or partially the same frequency can be transmitted by using the available number of cores in the same fiber. We can experience more than one dimension of the fiber core through the MCF environment, but the transmission performance of the network is reduced [238]. So far, we have discussed crosstalk issues generated by mmWave frequencies and massive MIMO in 5G. It is essential to overcome these limitations to deploy 5G infrastructure successfully in upcoming years. Although the researchers have already suggested various proposals to overcome these issues, there are still several open research challenges [239].

Various efforts have already been shown in this regard; for example, ref. [240] proposed a DL-based hybrid precoding scheme to increase spectral efficiency in MIMO systems. In addition, ref. [241] proposed a DL-based spectrum situation prediction using RF traces collected from nine different coexistence scenarios for efficient spectrum prediction. Moreover, ref. [242] proposed an NN-based technique for detecting and decoding the SCMA codewords to optimize the Euclidean distance between constellation points and to increase spectral efficiency in enhanced mobile broadband (eMBB) use cases. The combination of 5G with the latest technologies (AI, ML, SDN, NFV, network slicing, edge computing, massive MIMO, mmWave, IoE, VR, AR, MR) will transform the data-centric future. These technologies present numerous opportunities for distributing intelligence from both life and business perspectives. In other words, 5G acts as a revolutionary tool for these technologies. The primary goal of these technologies is to connect machines and computers intuitively. These intelligent approaches provide digital assistance, hazardous investigation, 24/7 availability, reliability, minimum error, and high customer experience [243].

Moreover, with ML and DL-based approaches, we can optimize the performance of real-time applications and handle repetitive jobs adequately. Therefore, it is necessary to optimize the existing solutions and reduce the challenges of 5G to reap the benefits of these technologies [244]. Recent studies have mentioned the requirement of high data rate (in Gbps) links for the eMBB, uRLLC, and mMTC use cases and service implementation, since 4G LTE-A sub-6GHz bands will be highly overcrowded [245]. The mmWave bands (10–300 GHz) will lead to obstructions in the form of high path loss and penetration loss. At the same time, the beamforming, directed transmission, and higher distribution deployment density of base stations are the best countermeasures to tackle these problems. These state-of-the-art solutions allow mmWave to work with the modernized wireless technologies and architecture [246].

Nevertheless, this revamp also introduces many new challenges in the system design, such as accurate beam alignment between the base station and the users, while signals are prone to blockages (i.e., buildings). Hence, the performance of mmWave may be critically retarded by selecting an inaccurate beam. ML-based methodologies are well capable of tackling the dynamic traffic patterns and blockage issues perfectly [247]. After autonomous exploration and learning the environmental behavior, the ML-based techniques will help existing solutions to select the beam efficiently while providing a reliable connection so that performance degradation issues can be handled [248].

3.2. Massive MIMO and Beamforming

MIMO refers to the fact that multiple spatially separated users are handled by the antenna array simultaneously and frequently in terms of resources. This is different from the conventional MIMO system that uses the assumed propagation abilities of the array antenna at the same time and frequency for multiple spatially scattered wireless connections. Massive MIMO requires numerous antennas at the BS to blow up the available bandwidth within a given spectrum using diversification, enabling spatial channelization. The intensive amplification of bandwidth depends on three techniques: beam steering, increased data capacity, and diversity. When the number of antennas is great, it becomes easy to select the most favorable or constructive propagation path for performing signal processing at uplink and downlink [249]. Practically, various factors draw the reader's attention to achieving high SE while having a small amount of radiated power. The 5G network provides a high quality of services by reducing radiation in contrast to 4G through massive MIMO technology, but hardware implementations have different aspects. Factors such as network design signal processing techniques, signal modeling, and EMF analysis constitute a significant obstacle to achieving high efficiency [250].

The quality of transmitted signals can be enhanced by the presence of many antennas in free spaces. The combined effect of many antennas caters to path loss, fading, and scattering issues that are different from the individual performance of single-input and single-output (SISO) and MIMO approaches. MIMO increases the linearity and precision performance of each amplifier, thus improving the robustness and prevention of system failure [251]. The jamming problem can be overcome by using a massive MIMO approach; for example, MIMO networks exploit joint path estimation and decoding to obtain channel estimation, which creates signal cancellation from intended jammers. Moreover, with MIMO, BS derives less power, which means it will receive low electromagnetic exposure [252].

Following the guidelines in [253], Figure 5 shows a massive MIMO (low complex linear processing) system for the 5G ultra-dense scenario that enhances spectral and energy efficiency, reduces power consumption, lessens fading, reduces latency, robustness, and reliability, and aids in enhanced security. Multiple-user MIMO (MU-MIMO) increases SE and overcomes the flaws of single-user MIMO. In MU-MIMO, numerous BSs interact to become an effective antenna. The primary advantage of this process is to carry out received interference and generate a quality signal from it. This process is known as a coordinated multi-point (CoMP), which is thoroughly studied by the authors in [254] to improve network performance through diversity and interference suppression at high frequencies. The CoMP provides optimized performance in dealing with blockages present in mmWave. The amalgamation of micro diversity and CoMP techniques is considered as one of the potential solutions to reduce bottlenecks. Scientists have derived a physically reliable explanation for MIMO transmission using linear processing and the collective integration of data symbols to generate a transmitted waveform to provide broadband services to multiple users, such as audio and video. Hence, by ignoring the rank constraints and through convex optimization, the capacity of MIMO can be increased. This entire process creates decoding complexity on the receiving side. The dirty paper coding (DPC) technique results in significantly improved performance in terms of understanding the capacity boundary of MU-MIMO, but there are complex problems encountered and operational issues at TX/RX [255].

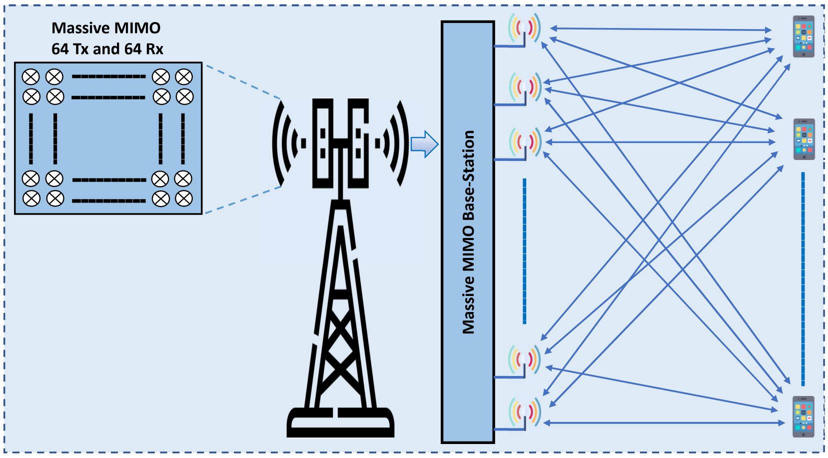

Figure 5. 5G massive MIMO system.

Beam-forming technology is used to boost and amplify the SE of wireless media intensively. This technology deals with the concentration of wireless signals for fast and reliable communication against particular devices, rather than spreading a signal in a broadcast manner [256]. Beamforming techniques could be conventional methods: fixed (switched beamformer) and phased array (adaptive beamformer) [257]. In a phased array, there are two modes: (1) maximization mode (desired signal) and (2) minimization mode (interference signal). In analog beamforming, the first step is the conversion of the signal from digital to analog, with the implication of pre-coding to an analog signal, and then signal transmission over the air. Contrary to this, the implication of pre-coding to a digital signal, digital to analog conversion, and RF conversion is performed in series, and then the signal is transmitted over the air. In contrast, in hybrid beamforming, the pre-coding step is adapted in both domains (analog and digital) at both frequencies (radio and baseband), respectively, and so hybrid beamforming can benefit from the advantages of both analog and digital beamforming. Beam-forming technology enhances and boosts the SE by delivering an improved signal-to-noise ratio (SNR) [258].

A combination of other 5G antenna technologies—i.e., massive MIMO with beamforming—increases the coverage area, boosts the power of beams in the desired direction, and reduces the power of the beam for nearby subscribers to mitigate the interference issues. Besides this, it increases the carrier-to-noise ratio of the signal, helping in a noisy and attenuating channel environment and increasing the overall bandwidth capacity. Hence, the users can be served with higher quality and stronger signals [259]. On the other hand, hardware complexity (due to a large number of antennas), high processing in terms of digital signal processing chips and the design of mathematical algorithms, hardware costs, and increased power are required due to increased resource consumption. Scientists also present different Tx analyses to perform the multi-casting of the physical layer in the MISO downlink channel [260]. In Table 8, we summarize the related work for massive MIMO. Stochastic beamforming and the grouping of transmit beamforming with space-time diversity—i.e., Alamoudi space-time coding—create a rank two software-defined radio (SDR) beamforming scheme.

According to the simulation results, the SNR of the SDR-based Alamouti scheme gives more effective results than conventional SDR (semidefinite relaxation) beamforming. Thus, a combination with the Alamouti scheme can improve the scale of the multicast rate in MISO [261]. In [262], researchers achieved full diversity through optimized quantizers that are capable of beamforming in a multiple inputs, single output multicast medium. The considered quantizers for a two RX system, which can approach outage probability, lies under the complete channel state information. However as the number of receivers increases, it becomes difficult to achieve the same output and optimized beamforming. In another research work [263], the authors discussed the issues related to multicast beamforming in impaired channel state information (CSI) and their limited feedback results. The amount of feedback of CSI significantly increased from the receiver to transmitter in these networks. The authors suggested that lowering the number of cooperative aerials at the transmission side can improve the outcome through simulations. The authors also proposed a solution using principal component analysis (PCA), which acts as a reducing scheme that can compress the dimension matrix of CSI and reduce the amount of feedback. Furthermore, it is also capable of eradicating the complexity of the codebook search and achieving a tradeoff between structure performance and feedback overhead [264].

Table 8. Summary of studies on massive MIMO.

Approach	Methodology	Advantages	Future Work	Related Work
Decreasing bit error rate	Approximate message passing algorithm for uplink detection	Efficient uplink detection and trade-off between complexity and performance	Large mMIMO	[265]
	Training-based blind channel estimation	BER count	Complex algorithm	[266]
Spectrum sensing	Direct localization algorithm based on source and location	Minimizes execution time and enhances spectrum accuracy	Higher computational complexity	[267]
	Match filter pre-coding techniques for performance analysis of SE and BS antennas	Improves throughput and spectral efficiency	Enhanced channel information is required for the pilot signal	[268]
Receiver design	Multi-user MIMO pre-coding schemes	Flexibility in system design	Limited to LOS environment only	[269]
	TDD realization based on zero forcing and max ratio combining schemes for uplink M-MIMO system	Spectral efficiency improvement and design condition depends upon number of antennas and pilot reuse factor	Limited for small number of antennas	[270]
	Virtual uniform linear array and uniform cylindrical array	Better performance close to that in i.i.d. fading rayleigh channels	Propagation delay should be included	[271]
Channel modeling	Gauss–Markov Rayleigh fading channel model in time-selective channels	Aggregate-rate achieved optimum results	Interference effect is not considered	[272]
	Designed mMIMO correlated channel using MATLAB for pilot contamination	Achieves better performance by increasing more antennas at BS	Correlated channels reduce the overall performance	[273]
	Scheduling algorithm based on the downlink mMIMO system along with zero forcing (ZF) beamforming approach	Better results in terms of error performance, sum rate, throughput, and fairness	Need to test on more realistic model and for multi-antenna users	[274]

Several efforts have been devoted to reducing the self-interference (SI) in the massive MU-MIMO system [275]. Zero-forcing (ZF) is assumed at the base station (BS), and maximum-ratio transmission (MRT) and maximum ratio combining (MRT/MRC) schemes are used to perform linear processing techniques. The authors proposed a pre-coded self-interference method by deploying orthogonal sequences and downlink pre-coding. This helps to convert the SI channel into the signal channel while having lower dimensions. Furthermore, by knowing the channel estimation, the SI suppression occurs through the combination of SI removal and the large-scale antenna linear processing (LALP) technique [276]. In [277], the authors performed pre-coding methods at a remote radio unit (RRU) to reduce the frequency hopping (FH) capacity. The spatial traffic and queuing model was used to achieve a relaxation in FH capacity through user traffic and statistical analysis. A double-layer decoding technique is used in [278] to remove inter-cell coherence and interference in massive MIMO systems. The algorithm determined the potential of large-scale fading to reduce the inter-cell interference in MIMO networks over a spatially correlated Rayleigh fading. Numerous SE expressions are derived from understanding the effective use of power resources and large-scale fading decoding (LSFD) vectors. Results show that LSFD can reduce pilot contamination while exploiting less computational complexity and an improved sum of SE vectors for all cells. Two-layer decoding provides better results than one-layer decoding [279].

The 5G NR specification also decreases the energy loss and greenhouse radiation of next-generation wireless networks in such a way that it contributes to the envisioned direction of information and communication technology sustainability. Besides other features, massive MIMO presents an exceptional obstacle in the ultra-dense scenario and introduces crucial challenges [280]. Defined CSI is a prerequisite to exploiting the MIMO system. After training the model for ML-based channel estimation and prediction, the complexity is extremely low compared to other models (Wiener filtering model/Kalman filtering-assuming model). Without previous information, ML-based techniques can find out the implicit characteristics from channel data throughout the training phase [281]. Moreover, a trained ML model predicts the performance and complexity while having user mobility information that identifies channel fluctuations (fast/low) in information between the user and gNB. More complex ML-based algorithms require more data to make decisions precisely in wireless communications.

Following the guidelines in [282], Figure 6 shows resource blocks and resource elements in OFDM symbol time versus the subcarrier domain. Index modulation (IM) is also a noteworthy approach for enhancing energy and spectral efficiency. Limited power consumption and transmitter complexities can be achieved in MIMO-OFDM through IM. Generally, index modulation exploits subcarriers to deliver the available data to a receiver, whereas in OFDM-MIMO, IM performs a similar function in a perpendicular multiplexing system [283]. Thus, it acts as an additional resource of information. Nevertheless, the addition of IM brings detector complexity and an inflated system overhead. In [284], the authors proposed the concept of non-iterative detector design by using DL knowledge to tackle these challenges and exploit IM for 5G architecture. In contrast to traditional MIMO-OFDM, simulations proved that the addition of IM in MIMO-OFDM improves the BER performance, limits the inter-channel problems, and decreases the prerequisites for inter-antenna synchronization [285].

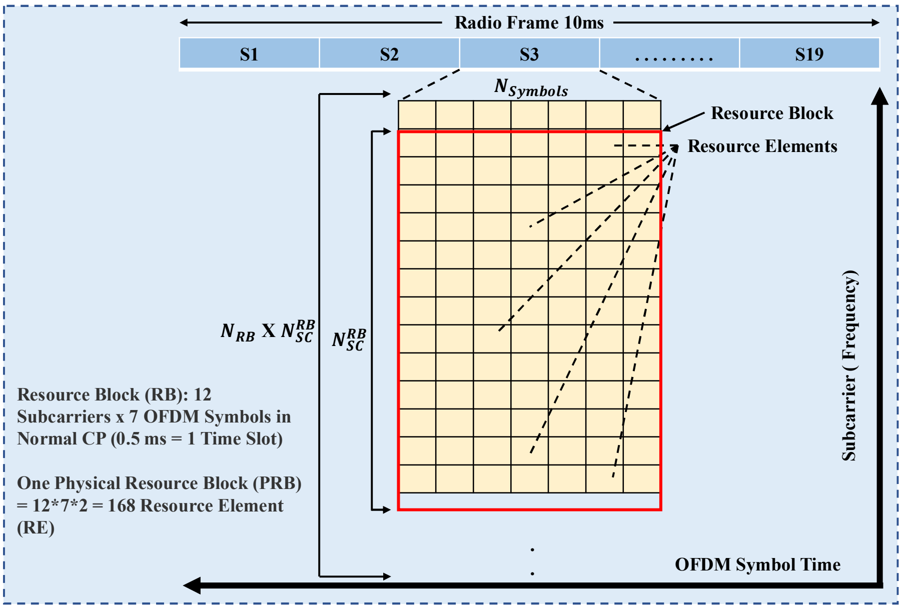

Figure 6. 5G radio resource allocation.

3.3. Physical Layer Issues

Mobile fronthaul indicates the connection of links using a centralized radio access network (C-RAN) architecture in cellular networks. It acts as a transmission medium between the remote radio unit (RRU) and baseband unit (BBU) via an optical cable. Still, it also brings research challenges, including low latency, jitter, transmission rate, and synchronization. These challenges are severe, particularly in the case of massive MIMO, where transmission faces inevitable consequences [286]. Distortion occurs due to amplitude interference, resulting in the transmission of unwanted signals between the channels, called crosstalk. The transmitted waveform produces interference or a coupling region in the neighboring signals, affecting the original signal by uncorrelated data patterns [287]. Electronic circuit elements (capacitors, inductors, and resistors) are the major sources of this coupling effect. These sources generate undesirable coupling results in the neighboring circuits. Crosstalk has two different forms:

- Near end crosstalk (NEXT):
  In NEXT, the aggressor signal performs couples with the victim signal in the opposite direction.
- Far end crosstalk (FEXT):
  In FEXT, both the victim and aggressor signal travel in the same direction [288].

At high speed, the crosstalk issue also reduces signal quality, and the entire system is affected by its associated impairments. To overcome the crosstalk challenge, it is essential to modify the impedance separation between the victim and the aggressor signal. The trace impedance has a direct relation with the crosstalk; i.e., by lowering the trace impedance in which we can decrease the crosstalk effect, as indicated in [289]. Increasing the guard band size between frame slots and the cyclic prefix (CP) can help to reduce the crosstalk noise in the communication link. Following the guidelines in [290], Figure 7 shows the frame, subframe, and subcarrier spacing standards of 5G NR and the numerology effect on a single frame. In 5G CN, an indirect relation exists between crosstalk noise and the distance between communication links, and the crosstalk factor reduces while the distance increases [291]. On the other hand, the presence of a shield among these lines reduces the undesirable coupling effects generated by crosstalk [292]. An improved version of crosstalk cancellation digital pre-distortion (CTC-DPD) is presented in [293], exploiting a novel estimating scheme and introducing a decoupling technique. This is used to compensate for crosstalk, possible delay, the non-linearity of power amplifiers (PA), and the inconsistency of transmitting channels in the MIMO system. The author suggested that the design estimates the coupling coefficient and the delay at the baseband signal through shared feedback and extracts this information to improve the digital pre-distortion. Simulation graphs showed high accuracy and an improvement in crosstalk cancellation compared to previous CTC-DPC models. Before cancellation, the coupled power is simulated at −20 dB, whereas the coupled power becomes −50 dB after performing crosstalk cancellation.

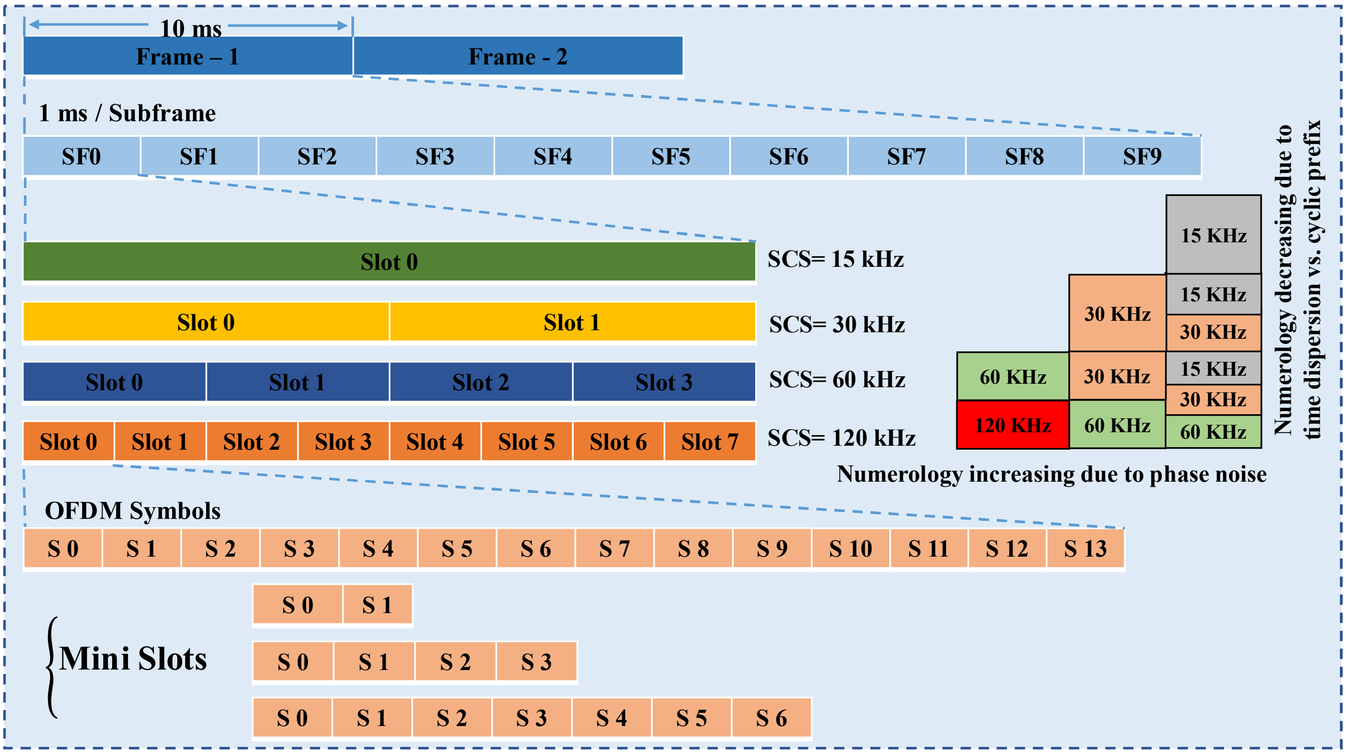

Figure 7. Fifth-generation frame, subframe, and subcarrier spacing.

In 5G, millimeter wavelengths (mmWave 30 GHz to 300 GHz) are used to increase the wireless capacity and achieve a higher data rate speed, as frequency has an inverse relationship with wavelength, and at low wavelengths, the user may suffer attenuation, reflection, and scattering. Precise system models and architecture designs are essential for air interfaces. Fifth-generation network applications such as the tactile internet, tele-hospitals, M2M communication, and vehicle to everything (V2X) communication require an exceptionally low latency rate, which cannot be achieved easily due to the presence of this propagation challenges [294]. In [295], the authors analyzed the receiver sensitivity prerequisites in a wireless 5G NR environment related to the single-to-noise ratio (SNR) constraints at BS to achieve maximum results for throughput. NR primarily has two frequency ranges: (1) 450–6000 MHz is defined for FR1, and (2) 24,250–52,600 MHz is defined for FR2. Physical impairments have bad effects on signal propagation. To implement the solution, an estimation of transmission quality for the light path is required. Trained ML and DL play a vital role in optimizing the existing algorithms for the estimation process. ML and DL-based algorithms constantly rely on input features that link occupation, length of the path, modulation format, source and destination nodes, etc. More features assist in precise estimation, while the bit error rate of a light path remains under the quality of transmission. Hence, the signal propagation remains less affected [296].

The traffic metrics and light-path requests are used to predict the future demand, and the selected path will be cost-efficient. Furthermore, the estimation can cause errors; for example, the light path may be impractical if the bit error rate (BER) does not go beyond the threshold, and its complexity will be increased by increasing the size of networks.

The increasing space dimension in resources enhances the crosstalk factor and affects service transmission quality (QoS). During the interval, multi-dimensional resource utilization declines, and the complexity of resource fragmentation increases, so the link quality may degrade [297]. Delay-sensitive applications may suffer from service provisioning where at first crosstalk is calculated, and then resource fragmentation is estimated. The whole process introduces more time; therefore, the delay in connection establishment increases, and the quality of service decreases [298]. Some other hybrid solutions involve saving the shortest paths throughout the routing process while considering the number of hops in the path and modulation format. ML-based approaches optimize transmission quality, and resource allocation has been implemented in [299]. Several ML-based algorithms can learn the distribution of input samples, which depends upon data types and availability, and classify the topology of the input vector.

4. Security and Privacy in 5G

In 5G, multi-user and broadband services are provided by the service providers lying above the physical layer. The 3GPP standardized cellular network is pervasive and capable of handling big data such that all critical and delay-sensitive applications require a latency of less than 1 ms. To provide different types of services—i.e., eMBBS, uRLLC, mMTC 5G—particular technologies will be used to cope with the user requirements [300]. Nonetheless, NGWN security and privacy will be the primary concerns in the future. For instance, a simple distributed denial of service (DDoS) attack may halt the services for a time and could result in disaster, particularly in delay-sensitive use cases; i.e., tele-hospital [301]. The cryptographic technique is a conventional technique for providing security for 5G and beyond networks [302]. A secret key is distributed between two parties in this scheme and acts as an essential primitive. However, due to high complexity in these heterogeneous networks, this technique becomes inefficient and creates bottlenecks in the IoT approach [303]. Cryptography is one of the encryption techniques used by these providers to grant security. Still, it has several loopholes: RSA, one cryptographic type, cannot fight insider attacks. An eavesdropper can break the cryptography technique with enough time and computational power. In distributed and ad-hoc networks, it is not easy to exchange the private keys, which are the base of the RSA algorithm [304]. These constraints indicate that security in the physical layer is a significant concern in 5G networks. Though these conventional cryptographic techniques provide reliable security methods for existing wireless systems, they could not facilitate an optimized IoT scenario platform due to the existence of point-to-point transmission, low latency rate, and heterogeneous infrastructure. Table 9 shows the standard bodies working in the security and privacy domain.

In [305], the authors described channel reciprocity-based key generation (CRKG), which overcomes the limitation of the cryptographic technique. It shows potential in the wireless domain to establish secure keys among devices. The authors investigated the technique by deploying 5G with three transmission modes: duplex modes, mmWave transmission, and MIMO systems. The key generation scheme includes four important steps: channel probing is the first step, quantization is the second, information reconciliation is the third, and privacy amplification is the last and final step. When two parties alternately probe in the wireless medium, they acquire correlated measurements that produce channel randomness. Preprocessing techniques are added between the channel sounding and quantization to reduce correlation and boost the reciprocal channel features (time, frequency, or spatial domains). In the third stage of this process, error detection codes and protocols are implemented to share the same keys between two ends. Lastly, privacy amplification evades eavesdropping activities. Due to independent quantization keys for every party, CRKG represents a promising solution for limiting holistic security measures. In [306], OFDM basics are used to generate secret keys to enhance security between two parties. In [307], the authors simplified the extraction procedure by selecting one party to probe the channel and perform quantization measurement instead of choosing two parties. The preliminary key access through this scheme is further covered by the channel phase, followed by mapping, and before the equalization method key is distributed to the other party. The final version of the shared key is then used at the physical layer to perform authentication schemes. Both random signals and masked keys are exchanged between two parties at the physical layer. This approach is also invulnerable to passive and active attacks, in contrast to conventional authentication schemes. Following the guidelines in [308], Figure 8 explains the 5G security and privacy architecture system.

Table 9. Standard bodies working in the security and privacy domain.

Standard Body	Work Groups	Focused Area	Breakthrough
3GPP	TSG SA WG3	Security architecture, security aspects, fraud information gathering system, cryptographic algorithm requirements, lawful interception requirements, security assurance specification, generic authentication architecture, network domain security.	TS 33.102,TR 33.899, TS 22.031,TS 23.031, TS 33.105,TR 33.901, TS 33.106, TS 33.126, TS 33.511,TS 33.326, TS 33.220,TR 33.918, TS 33.210,TR 33.810.
5GPPP	Security WG	Security requirements and risks, security architecture and enablers, access control, slicing and MEC security, privacy and trust in 5G, security architecture and solutions, policy management and orchestration.	Report 1.4,Report 1.5, Report 2.1,Report 2.3, Report 3.1,Report 3.2, Report 5.2,Report 5.3, Report 6.2,Report 6.3, Report 6.4.
IETF	i2nsf ipsecme sacm secdispatch secevent tls opsec	Network security function, IPsec, automation and continuous monitoring, security dispatch, security events, transport layer security, operational security.	RFC8192,RFC8329, RFC9061,RFC8983, RFC8598,RFC8784, RFC7632,RFC8248,RFC8412, RFC8936,RFC8935,RFC8417, RFC8996,RFC8744,RFC8773, RFC9099,RFC8704,RFC7707.
NGMN	NGMN alliances NGMN 5G security group	Security consideration for 5G, sustainable trust, 5G end-to-end architecture framework, 5G security recommendations, 5G security network slicing.	White paper V-1.0, White paper V-1.0, White paper V-4.31, White paper V-1.0, White paper V-1.0.
ETSI	Cyber security	Authentication mechanisms, quantum cryptography, Internet of Things, security threats analysis, access control, infrastructure cybersecurity.	ETSI TR 103 692, ETSI TR 103 823, ETSI TS 103 701, ETSI TR 103 743, ETSI TS 103 532, ETSI TR 103 741.
ITU	SG-17	Security assurance, security threats, security framework and requirements, secure protection guidelines, risk identification, guidelines for security services.	Recommendation X.1404, Recommendation X.1408. Recommendation X.1145, Recommendation X.1146, Recommendation X.1451, Recommendation X.1452.

In [309], the authors also followed the same approach in which a low pass filter (LPF) achieved high authentication, improved channel reciprocity, suppressed channel fluctuations, and reduced fundamental disagreement in the OFDM subcarrier's channel. The authors conducted another work to enhance channel reciprocity and CSI [310]. In this paper, the authors first demonstrated the interference and vulnerable noises present in the systems due to channel variations, synchronization offset, fingerprint issues, and nonreciprocity in frequency division duplex systems. Then, they adopted the loopback approach by exploiting frequency bands in different time slots known as LB-TDD. Through theoretical analyses, this scheme outperformed other approaches and brought tremendous results in terms of eradicating both eavesdropping (passive attack) and man in the middle (active attack) attacks compared to the classical TDD scheme while considering the key generation rate and disagreement rate factors. Furthermore, the authors designed a secret key generation protocol and proved it to be viable for mitigating interference in TDD systems through experimental and simulation results. In [311], the authors generated the secret key in an in-band full-duplex communication system (IBFD); both half-duplex and full-duplex modes were simulated. A simple framework model for generating the secret key in full-duplex mode is presented by considering the nonreciprocity embedded in the channel dimension. The simulation results illustrated that the key rate following the full-duplex approach was higher than the half-duplex approach while considering different correlation coefficients. Several efforts have been performed for reducing channel correlation, and preprocessing techniques are implemented to achieve the desired results.

Wireless technologies such as full-duplex communication that provide enhanced spectral efficiency can be utilized for 5G infrastructure because they have the potential to increase efficiency up to n-squared times, especially when a structure has a point-to-point link [312]. If deployed correctly, FD can also be used to reduce crosstalk and interference issues. On the other hand, it can become a factor in reducing potential gains in case of poor deployment. Thus, to reap the benefits of FD, it is essential to limit the crosstalk issue that lies between the receiver and transmitter. Furthermore, improved designs of TX and RX are significant to fully utilize the FD stack [313]. In [314], the authors tried to achieve high agreement uncorrelated keys by following preprocessing component analysis. To obtain this, they studied signal processing algorithms with an independent eavesdropper. In the beginning, they performed principal component analysis (PCA) and then a discrete cosines transform (DCT), and at the end, wavelet transforms (WT) were used. Among theses, principal component analysis outperformed the other approaches regarding overall key considerations, mathematical expenses, security leakage, and key conformity. The numerical results proved that the presence of PCA with a common eigenvector algorithm among two legal communicators creates an optimized secret key and has a limited key error rate and high key generation rate while reducing computational cost and information leakage in contrast to PCA with a private eigenvector algorithm. Physical layer security offers confidentiality and authentication by benefiting from the channel randomness of the wireless medium. It is a secure way to develop protected transmission compared to the conventional cryptographic method because it does not require any extra security controls, complex algorithms, and schemes to perform security functions on the high layers. Table 10 shows the security and privacy threats related to 5G technologies.

Table 10. Summary of studies on 5G security and privacy threats.

Security Threat/Attacks	Targeted Network Elements	SDN	NFV	Cloud	Links	Privacy	References
Boundary attacks	Subscriber location	✗	✗	✗	✗	✓	[315]
Configuration attacks	Virtual switches and routers	✓	✓	✗	✗	✗	[316]
DoS attack	Centralized elements	✓	✓	✓	✗	✗	[317]
Hijacking attacks	SDN controller and hypervisor	✓	✓	✗	✗	✗	[318]
IMSI catching attacks	Subscriber Identity	✗	✗	✗	✓	✓	[319]
MITM attack	SDN communication	✓	✗	✗	✓	✓	[320]
Penetration attacks	Virtual resources and clouds	✓	✗	✓	✗	✗	[321]
IP spoofing	Control channels	✗	✗	✗	✓	✗	[322]
Resource attacks	Shared cloud resources	✗	✓	✓	✗	✗	[323]
Saturation attacks	SDN controller and switches	✓	✗	✗	✗	✗	[324]
Scanning attacks	Open air interfaces	✗	✗	✗	✓	✓	[325]
Encryption keys attack	Unencrypted channels	✗	✗	✗	✓	✗	[326]
Semantic-info attacks	Subscriber location	✗	✗	✗	✓	✓	[327]
Signaling storms attack	5G core network elements	✗	✗	✓	✓	✗	[328]
TCP level attacks	SDN communication	✓	✗	✗	✓	✗	[329]
Timing attacks	Subscriber location	✗	✗	✓	✗	✓	[330]
User identity attack	User information databases	✗	✗	✓	✗	✓	[331]

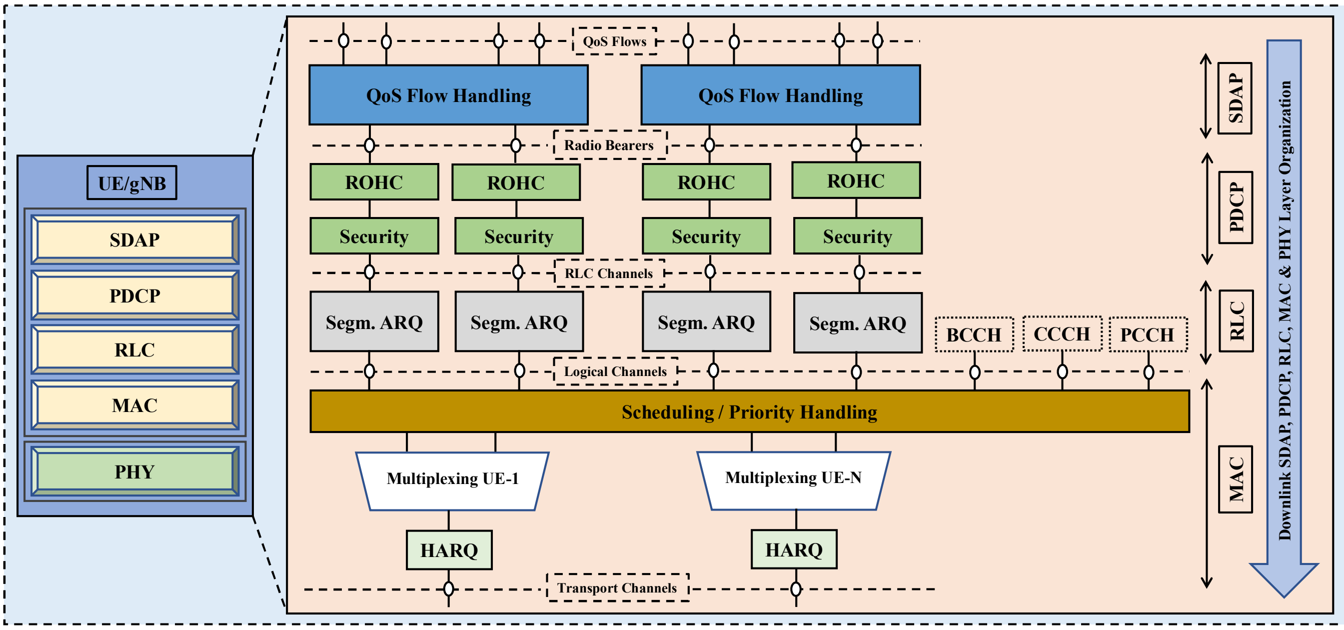

Figure 8. Fifth-generation network security architecture system.

A survey given in [332] mentioned that physical layer security carries multiple ways to enrich the security of wireless transmission media via the properties of wireless channels such as fading, reflection, noise, and interference. Multiple antennas were used in this paper to amplify the quality of the received signal and its power with legitimate transmission and an eavesdropper concurrently. Multiple antenna techniques were analyzed for the multi-user, dual-hop, heterogeneous, and point-to-point schemes. A physical layer authentication method is presented in [333] which calculates the distance of surrounding noise sources with the communicating parties. The author considers a maximum likelihood approach to compute the associated positions of these sources by adopting received signal strength (RSS) and angle of arrival (AOA) methods. Simulation results are obtained by considering both active and passive attacks. Results showed that the proposed design is suitable for dynamic conditions. The above existing papers highlight the importance of physical layer security but could not illustrate the case of multi-casting and broadcasting services. For this purpose, the concept of physical layer service integration was proposed [334]. Physical layer service integration (PHY-SI) provides two types of services: confidential services and public services. As the name indicates, confidential services are paid, whereas public services are free to support broadcast applications. Depending on their preferences, multiple users subscribe to these services and use them according to their demands. The public information is distributed to all users, and private data are kept confidential so that only limited users can access them. This shows that PHY-SI has a more secure and encrypted transmission than the physical layer. Both have their characteristics and points of divergence [335], as listed below.

- Shared information:
  For each message in the physical layer, security has a confidential shield—unauthorized users cannot share and access information. However, in the case of PHY-SI, the medium is served to transfer both public and private information at once. Public and confidential information waveforms are superimposed at the transmitting antenna and follow the channel path.
- Secrecy rate:
  In physical-layer security, only a single secrecy rate is used to perform the protection of signals, and the design of the system is maintained to maximize this rate. However, in PHY-SI, a Pareto transmit scheme is used to optimize the capacity of the secrecy rate, and each service has a different transmitting rate. These transmitting rates then combine to form a secrecy platform.
- Security issues:
  PHY-SI suffers more interference as compared to physical layer security. Any unauthorized users can view public messages, and it is easy for them to create security breaches. Therefore, both confidential and public messages are accessed by insiders. To avoid such issues, encoding techniques should be restructured and modified. In this way, the superimposition of both messages results in their transmission without facing any interference issue.
- Coding schemes:
  PHY-SI performs a superposition coding technique at the transmission side; on the other end, the receiving side performs interference cancellation to obtain desired outcomes. Depending on the service type, PHY-SI uses different codebook formats for transmitting waveforms.

Different PHY-SI models are presented in [336] to attain a high capacity region. Artificial noise (AN) and eigen transmission were also discussed to reduce the interference in the MIMO system. In the AN scheme, simulated noise is sent by the transmitter to create interference for the eavesdropper. Thus, this helps to protect the entire network from unauthorized access, crosstalk, noise, reflections, and jitter responses. Besides calculating the number and availability of eavesdroppers, it is also located after statistical analysis, and it optimizes the channel by transmitting AN noise through it. It generates a balance between the intervention provided to both authorized and unauthorized customers [337]. The authors analyzed a multi-core fiber (MCF) in the paper to investigate the impairments and detriments of inter-core crosstalk. The attack-aware routing and core assignments are taken into consideration to evade vulnerable threats to the bottom layer, and efforts were devoted to overcoming these effects. The integer linear programming model (ILP) increases the channel efficiency and simultaneously reduces inter-core crosstalk levels. For static network planning, a heuristic algorithm is proposed to analyze the issue and improve network efficiency in terms of time.

Similarly, for dynamic provision networks, the same algorithm was proposed to adjust the tradeoff between blocking probability and the impact of crosstalk [338]. Another paper [339] discussed the vulnerabilities caused by crosstalk in elastic optical networks (EON). The author proposed differentiating RSA schemes for inter and intra-domain requests while considering security measures. The author viewed the vulnerabilities created by both trusted and untrusted sources to achieve differentiation. Different RSA schemes were examined according to various physical layer attacks. The ILP model resolved the crosstalk issue, and simulation analyses were performed to determine the benefits of the heuristic algorithm. Crosstalk issues for EON (elastic optical networks) were discussed, and corresponding solutions were proposed in [340]. The crosstalk-aware routing spectrum and core assignment (CA-RSCA) algorithms for space-division multiplexing (SDM-EONs) were presented in [341].

The author investigated the RSCA issue and evaluated the band status in these networks by designing the CA spectrum compactness metric. First-fit (FF) and random-fit (RF), which are the two essential classifications of crosstalk-aware spectrum defragmentation (CASD) algorithms, were proposed to obtain high performance in contrast to baseline algorithms while considering PB (blocking probability) and frequency utilization [342]. In [343], the author determined the performance of the CASD algorithm with multiple spectrum compactness (SC) thresholds, and the improved results were generated at the SC threshold. By following the same approach, researchers investigated RSCA issues in SDM-EON from the network point of view. The number of cores present in the multi-core fiber (MCF) is larger than in the single-core fiber (SCF), but the presence of additional modes also increases the cost of MCF [344]. Currently, 5G and Beyond-5G (B5G) wireless network architectures have been revolutionized due to IoT applications, and the number of user devices and amount of data created by these devices is increasing exponentially [345,346]. This wireless interconnection model of numerous devices is observed and controlled using the internet. Besides other constraints, security and privacy are critical, considering data access controls at different levels in diverse applications [347].

Furthermore, devices and applications have very hypersensitive information for which security and privacy assurance are of absolute importance [348]. In such an environment, AI/ML/DL is a successful solution to recognize patterns, explore, analyze, handle, and provide intelligent and optimized real-time decision making. ML-based techniques that rely on a centralized framework may also lead to security breaches; e.g., data tempering and reliability, false authentication, a loophole in the algorithm, and privacy preservation. Existing centralized ML-based models are subordinate to trusted third parties (e.g., cloud service provider—TTP), raising privacy concerns [349]. In addition, an ML-based decentralized framework is required to deal with preceding and upcoming challenges. The integration of ML and 5G may be within the realm of possibility and lead to security threats. High-rated weaknesses could be larger attack surfaces, the authentication of many devices, insufficient perimeter defenses, automated network changes, dynamic network scaling, and multi-access edge computing, and many threats are still unknown. Combining the behavior of the latest technologies will also introduce missing characteristics of these technologies and applications of 5G networks [350].

5. Challenges and Future Directions

Fifth-generation networks require robust architectures and ML-based solutions on account of the heterogenous behavior of communication networks [351]. Hence, we mention the crucial security and privacy challenges and their potential solutions for 5G networks. Possible technologies—i.e., mmWave and terahertz band, RAN, NFV, network slicing, wireless SDN, MEC, and fog/cloud computing—are paving the way to revamp the upcoming 5G network architecture [352]. Besides this revolution, various challenges to complete 5G implementation lie ahead. In the following, we discuss the leading challenges and future research directions enabled by emerging technologies that demand to be addressed for the success of 5G.

1. Business model and economic challenges for 5G network:
   Before 5G technology, telecommunication operators were providing services using integrated services (IntServ) and differentiated services (DiffServ) models, while 5G technology introduces eMBB, URLLC, and mMTC. Therefore, 5G is expected to meet the requirements (bandwidth and latency) of various vertical applications and services

accordingly. Hence, the future network should be capable of new business models based on heterogeneously oriented services and provide the services in all use case scenarios. Business models for the network could be business to business (B2B), business to consumers (B2C), and business to business to consumer (B2B2C) [353]. Furthermore, we need to conduct detailed and comprehensive research to find out the real-time problems for all 5G use cases and embedded ML-based optimized solutions for the upcoming era.

2. Collaboration of OTT and ISP for 5G service management:
The quality of experience in vertical heterogeneous networks is one of the significant challenges. This can be achieved using QoE monitoring and QoE management theories. A collaboration between over-the-top providers (OTT) and internet service providers (ISP) needs to be established for QoE/QoS monitoring and measurement factors. Researchers have already proposed monitoring probes (passive) with OTT applications at UE to exchange information for desired QoS [354]. We need to find ML-based standardized interfaces, ML-based optimized level frequency, and ML-based tradeoffs between QoE and latency in network operations. This will have a high impact, and optimized ML-based algorithms can enhance network performance. Besides these issues, the scalability and effectiveness of QoE also need to be addressed.
3. RAN virtualization in 5G network:
RAN slicing, an integral part of virtualized 5G systems, is yet to be addressed because it is in the nascent phase. Docker and VM-based solutions do not address radio resource problems to an acceptable degree in terms of shared and multiple RATs in 5G networks. Hence, another challenge for RAN virtualization is RAN as a service (RaaS), where beyond physical infrastructure, radio resource sharing is crucial [355]. Furthermore, ML-based solutions are greatly needed for mobility management and the scheduling of radio resources as virtualized control functions to be implemented. The optimized RaaS will improve network performance and cost-effectiveness for the complex environment. At the same time, ML is needed to address system integration, achieving widespread adoption, technology support difficulties, and security risks.
4. End-to-end slice orchestration and management:
With the introduction of SDN and NFV in 5G networks, it is necessary to change the deployment, operation, and management of networks and find intelligent methods for how resources are to be orchestrated [356]. Recently, many projects have shown promise in this context; i.e., AT&T's ECOMP project, OSM project, ETSI MANO framework, and ONAP project implementation. However, several challenges remain with these advancements, such as moving towards a concrete network slice from a high-level service description. Scalability and resilience are core services supporting multi-vendor case scenarios and entertaining upcoming 5G network elements. We need to find a way to manage all underlying slices and the E2E orchestration of all available resources while keeping the fact in view that all network slices must meet their service; e.g., services and experience level agreements (ELAs/SLAs).
5. Mobility management in 5G networks:
Fifth-generation networks will face mobility management issues due to the numbers of smart devices increasing exponentially, heterogeneous networks, ultra-dense small cell networks, fast-moving vehicles, and concerns about the truthfulness of information in vehicle-to-vehicle communications [357]. While due to the fixed position of devices in an industrial area, there is no need for mobility management, as they do not need to relocate, a number of researchers have proposed frameworks/solutions to handle mobility management in 5G networks. Automated driving services have different criteria than mobile broadband management; i.e., high-speed trains (e.g., 600 km/h) may trigger multiple handovers for railway communication [358]. Maintaining high priority for real-time services and seamless mobility support is crucial, so the requirements for automated driving services are different. Therefore, ML-based optimized and efficient methodologies are required that depend upon use cases, main-

tain service-aware QoE/QoS control in 5G systems, and enable users to maneuver between all SDN controllers in a 5G heterogeneous environment.

6. Network sharing and slicing in 5G:
   Software-based platforms have the potential to make support for multi-tenancy more accessible using SDN/NFV based infrastructure in 5G systems. Therefore, multiple services and applications may be entertained successfully. This network sharing paradigm allows many virtual network functions to be set up on a similar 5G NFV platform and introduces various management challenges [359]. Vast amounts of research are required correlated to the isolation between slices, inter-domain services slicing, network functions placement within a slice, dynamic slice creation, and understanding the slicing concept's performance in 5G networks. Besides other issues, QoS/QoE performance must also be ensured on every slice, neglecting network congestion and other slices' performance levels.
7. Security and privacy challenges in 5G networks:
   Providing various services, multiple network slices, and resource sharing for different verticals can introduce different levels of security concerns and privacy policy requirements in 5G networks [360]. Hence, complicated research challenges are raised and addressed considering the impact of one slice on another, efficient coordination mechanisms, and the impact of entire network systems, particularly in multi-domain infrastructures. Intelligent ML-based algorithms can meet these challenges and ensure network performance.
8. Network reconstruction:
   Fifth-generation technology is envisioned to increase capacity, the density of connections, and energy efficiency with reliability while decreasing latency. At the network edge, 5G can also transmit touch-perception-type real-time communication; i.e., robotics and haptics equipment. In this respect, wide-ranging changes are required in network architecture, including the core and radio access network (RAN). Fifth-generation heterogeneous wireless networks are required to reconstruct RAN and CN architecture to support E2E to achieve an end-to-end latency of 1 ms in network slicing with the help of optimized ML-based methodologies. The cooperation of multiple RATs and macrocells with ultra-dense small cells in complex heterogeneous networks may confront these slicing demands [361].
9. Fifth-generation technologies collaboration:
   Future 5G architecture demands the coexistence and cooperation of all conventional and recent technologies—i.e., broadband transmission, LTE/LTE-A systems, C-RAN, mmWave, massive MIMO, SDN, NFV, network slicing, and mobile cloud engineering (MCE)—to support all use cases of 5G [362]. On the other hand, ML will participate alone with one on one technology or manage the whole system intelligently. Besides combining the benefits of emerging technologies, there are still many crucial challenges to achieving the desired collaborative performance. Low-cost internet and the maximum digital transmission capacity of a channel are concerns for broadband transmission. Virtualization, BBU cooperation and clustering, and high fronthaul capacities are needed in C-RAN. In mmWave, the higher path loss due to higher carrier frequency and mMIMO, reciprocity error, signal-to-interference ratio (SIR), and channel coherence time requires an optimized solution. With ML, it is also necessary to choose the SDN solution; inter-operability, budget constraints, and security are primary concerns. The key challenges that need to be addressed using advanced ML-based algorithms are orchestration and integration in hybrid networks, slice isolation mechanism, security, and privacy.
10. Backhaul 5G wireless network architecture design:
    It is a pivotal challenge to deploy a new backhaul network architecture design and security-aware protocols for heterogeneous ultra-dense small cell network use cases. The massive wireless network traffic caused congestion and later collapsed the backhaul network [363]. Motivations behind the backhaul wireless network architecture

design are ML-based mobility within small cell networks and the optimization of the cell load distribution. Besides this, ML-based admission and congestion control algorithms are also required for quality of service and experience, mainly focused on the backhaul network.

Challenges in 5G with regard to next-generation mobile networks (NGMN) are discussed and highlighted as follows [364]:

11. Flash network traffic:
    The potential of large-scale events causing significant changes in network traffic patterns, either accidentally or maliciously, increases as the network capacity and the number of UEs grows. While maintaining an acceptable level of performance, the 5G system must prevent significant fluctuations in traffic utilization and be adaptable to them when they do occur. ML-based algorithms are capable of learning the environments and suggesting optimized outputs in these situations.
12. Security of radio interfaces:
    In existing internet generations, keys for radio interface encryption are obtained in the home core network and then sent to the visiting radio network using signaling channels such as SS7 or Diameter. When sent between network nodes, the exposed cipher key is an example of a GSM network. The connection between operators' signaling systems should be adequately secured using ML so that the radio interface session keys can be transferred via SS7 and Diameter, and such exposure is prevented.
13. User plane integrity:
    There was no explicit user data plane or cryptographic integrity protection until the second-generation internet; in addition, the third and fourth generation have protection, but still not for user plane data. The transport layer, application layer, or bearer layer integrity with encryption is used if data integrity is required. There is also a risk of a man-in-the-middle attack, and session hijacking is also possible. In addition, the 5G network will not add integrity protection to user plane data but at the transport or application layer with the help of ML-based algorithms.
14. Mandated security in the network:
    There are service-driven restrictions in the security architecture, and generally, there are measures in place to minimize the effects of these restrictions, and these measures are often not mandatory in current cellular specifications. Reducing the security dependency on the access network and on the security provided on intranet interfaces is possible, but this dependency is unlikely to be eliminated entirely. The security measures using ML must be embedded in architectural design, and otherwise, the system will not work at all—this approach is the best solution to implement mandatory security.
15. Roaming security:
    While roaming from one network to another, updates on the security parameters of the user are greatly required, particularly in the 5G densification scenario. Ingress/egress firewall security policies, subscriber-level security, and personal firewalls are used to protect from security and privacy attacks, but the challenge is to provide these services to different subscribers in multiple locations. Hence, ML also provides an intelligent information-sharing mechanism for roaming security using network slices to address these challenges.
16. Signaling storms:
    Low-cost M2M devices have several limitations such as computational capabilities, energy support, and memory capabilities. At the same time, these low-cost devices can be compromised and allow DoS and DDoS attacks against the radio access network. Unexpected non-malicious events may also cause the devices to behave abnormally and produce "flash crowd" situations, leading to the exhaustion of radio resources. Hence, ML is required to provide an overload control (currently relying on MME) mechanism to prevent all devices from attempting to access the network, as well as to initiate the "START" and "STOP" and select UEs to target the overload procedures.

17. DoS and DDoS attacks:
Fifth-generation networks are expected to support a number of network devices, while DOS and DDOS attacks will become a real threat designed to exhaust the physical and logical resources of the target. In this regard, network infrastructure and devices DOS attacks are common categories. Using these attacks, the attackers drain the network, logical, and physical resources of 5G users and devices accordingly. These challenges can be minimized by introducing ML-based approaches. Intelligent ML-based approaches can predict an attack using ongoing traffic and offer optimized network management. Network control elements can be hidden and revamp the unencrypted control channels.

6. Conclusions

Nowadays, 5G is a leading sophisticated technology for cellular connectivity. This superfast generation brings flexible, reliable, and unsurpassed control for smartphones, machines, and vehicles. It represents a new path to improving lifestyle through low latency, fast access, and instant communication. However, at high frequency, 5G networks introduce several challenges; i.e., distortion and multi-path propagation, air-interfaces such as crosstalk, reflection, fading, EVM, cell-interference, jamming, etc. This paper discussed these challenges, their existing solutions, and the required machine learning techniques. To augment the spectral efficiency of the channel, multiple novel technologies were introduced. Benefits of CRKG techniques, the IPL model, the heuristic algorithm, PCA, and CASC schemes were discussed to reduce crosstalk issues in the physical layer. We also explained PHY-SI and the several potentials of PHY-SI to avoid unauthorized access and protect the channel from an eavesdropper. This study also drew the reader's attention to challenges related to eMBB, uRLLC, and mMTC use cases and 5G supporting technologies that leverage AI, machine, and deep-learning tools.

Author Contributions: Conceptualization, J.T. and A.K.; methodology, J.T. and A.H.; validation, J.T. and A.H.; formal analysis, J.T., R.A. and A.H.; investigation, J.T. and A.H.; resources, A.K. and A.H.; data curation, J.T. and R.A.; writing—original draft preparation, J.T.; writing—review and editing, J.T., A.H. and A.K.; visualization, J.T. and R.A.; supervision, A.H. and A.K.; project administration, A.H. and A.K.; funding acquisition, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by National Research Foundation of Korea (NRF) grant funded by Korean government (MSIT) (IITP-2021-0-01816) and Strengthening R&D Capability Program of Sejong University.

Conflicts of Interest: The authors declare that they have no conflict of interest regarding the present study.

Abbreviations

The following abbreviations are used in this manuscript:

5G	Fifth-generation
AIPN	All IP network
AI	Artificial intelligence
BBU	Base band unit
BS	Base stations
CN	Core network
CoMP	Coordinated multipoint
CRKG	Channel reciprocity-based key generation
CSI	Channel state information
DDoS	Distributed denial of service
DPC	Dirty paper coding
E-HARQ	Early hybrid automatic repeat request

ELAs/SLAs	Services and experience level agreements
EON	Elastic optical networks
GFDM	Generalized frequency division multiplexing
HetNet	Heterogeneous network
IntServ	Integrated services
IoT	Internet of Things
ISP	Internet service providers
KPIs	Key performance indicators
KQIs	Key quality indicators
LALP	Large-scale antenna linear processing
LDP	Low-density parity-check codes
LPF	Low pass filter
LSFD	Large-scale fading decoding
MCF	Multi-core fiber
MDAF	Management data analytic function
MIMO	Multiple-input and multiple-output
ML	Machine learning
MMTC	Machine-type communications
MRT	Maximum-ratio transmission
MRC	Maximum-ratio combining
NGMN	Next-generation mobile networks
NR	New radio
NSA	Non-standalone
NWDAF	Network data analytics function
OTFS	Orthogonal time–frequency spread
OTT	Over-the-top providers
PAPR	Peak-to-average power
PC	Polar codes
PCA	Principal component analysis
PHY-SI	Physical layer service integration
QoE	Quality of experience
QoS	Quality of service
RaaS	RAN as a service
RAN	Radio access networks
RLC	Radio link control
RRM	Radio resource management
RRU	Remote radio unit
RSS	Received signal strength
SDR	Software-defined radio
SE	Spectral efficiency
SNR	Signal-to-noise ratio
uRLLC	Ultra-reliable low latency communication
V2X	Vehicle to everything
WWWW	Worldwide Wireless Web

References

1. Al-samman, A.M.; Azmi, M.H.; Abd Rahman, T. A survey of millimeter wave (mm-Wave) communications for 5G: Channel measurement below and above 6 GHz. In Proceedings of the International Conference of Reliable Information and Communication Technology, Kuala Lumpur, Malaysia, 23–24 June 2018; pp. 451–463.
2. Da Silva, M.M.; Guerreiro, J. On the 5G and Beyond. *Appl. Sci.* **2020**, *10*, 7091. [CrossRef]
3. Patra, S.K.; Sundaray, B.K.; Mahapatra, D.M. Are university teachers ready to use and adopt e-learning system? An empirical substantiation during COVID–19 pandemic. In *Quality Assurance in Education*; Emerald Publishing Limited: Bentley, UK, 2021.
4. Awwad, A. The impact of Over The Top service providers on the Global Mobile Telecom Industry: A quantified analysis and recommendations for recovery. *arXiv* **2021**, arXiv:2105.10265.
5. Gökarslan, K.; Sandal, Y.S.; Tugcu, T. Towards a URLLC-Aware Programmable Data Path with P4 for Industrial 5G Networks. In Proceedings of the 2021 IEEE International Conference on Communications Workshops (ICC Workshops), Montreal, QC, Canada, 14–23 June 2021; pp. 1–6.

6. Lehr, W.; Queder, F.; Haucap, J. 5G: A new future for Mobile Network Operators, or not? *Telecommun. Policy* **2021**, *45*, 102086. [CrossRef]
7. Rahman, M.T.; Bakibillah, A.S.M.; Parthiban, R.; Bakaul, M. Review of advanced techniques for multi-gigabit visible light communication. *IET Optoelectron.* **2020**, *14*, 359–373. [CrossRef]
8. Guevara, L.; Auat Cheein, F. The role of 5G technologies: Challenges in smart cities and intelligent transportation systems. *Sustainability* **2020**, *12*, 6469. [CrossRef]
9. Amin, R. Introduction of 5G as a Next-generation Mobile Network. *ABC Res. Alert* **2020**, *8*, 129–138. [CrossRef]
10. Al-Absi, M.A.; Al-Absi, A.A.; Sain, M.; Lee, H.J. A State of the Art: Future Possibility of 5G with IoT and Other Challenges. *Smart Healthcare Analytics in IoT Enabled Environment*; Pattnaik, P., Mohanty, S., Mohanty, S., Eds.; Springer, Cham: Switzerland, 2020; pp. 35–65.
11. Jagannath, J.; Polosky, N.; Jagannath, A.; Restuccia, F.; Melodia, T. Machine learning for wireless communications in the Internet of Things: A comprehensive survey. *Ad Hoc Netw.* **2019**, *93*, 101913. [CrossRef]
12. Zikria, Y.B.; Afzal, M.K.; Kim, S.W.; Marin, A.; Guizani, M. Deep learning for intelligent IoT: Opportunities, challenges and solutions. *Comput. Commun.* **2020**, *164*, 50–53. [CrossRef]
13. Qiu, J.; Wu, Q.; Ding, G.; Xu, Y.; Feng, S. A survey of machine learning for big data processing. *EURASIP J. Adv. Signal Process.* **2016**, *2016*, 1–16.
14. Hou, T.; Feng, G.; Qin, S.; Jiang, W. Proactive content caching by exploiting transfer learning for mobile edge computing. *Int. J. Commun. Syst.* **2018**, *31*, e3706. [CrossRef]
15. Wang, S.; Chen, M.; Liu, X.; Yin, C.; Cui, S.; Poor, H.V. A Machine Learning Approach for Task and Resource Allocation in Mobile-Edge Computing-Based Networks. *IEEE Internet Things J.* **2020**, *8*, 1358–1372. [CrossRef]
16. Qin, M.; Yang, Q.; Cheng, N.; Zhou, H.; Rao, R.R.; Shen, X. Machine learning aided context-aware self-healing management for ultra dense networks with QoS provisions. *IEEE Trans. Veh. Technol.* **2018**, *67*, 12339–12351. [CrossRef]
17. Akhtar, T.; Tselios, C.; Politis, I. Radio resource management: Approaches and implementations from 4G to 5G and beyond. *Wirel. Netw.* **2021**, *27*, 693–734. [CrossRef]
18. Du, Z.; Deng, Y.; Guo, W.; Nallanathan, A.; Wu, Q. Green Deep Reinforcement Learning for Radio Resource Management: Architecture, Algorithm Compression, and Challenges. *IEEE Veh. Technol. Mag.* **2020**, *16*, 29–39. [CrossRef]
19. Elsayed, M. Machine Learning-Enabled Radio Resource Management for Next-Generation Wireless Networks. Ph.D. Thesis, Université d'Ottawa/University of Ottawa, Ottawa, ON, Canada, 2021.
20. Fourati, H.; Maaloul, R.; Chaari, L. A survey of 5G network systems: Challenges and machine learning approaches. *Int. J. Mach. Learn. Cybern.* **2021**, *12*, 385–431. [CrossRef]
21. Ari, A.A.A.; Gueroui, A.; Titouna, C.; Thiare, O.; Aliouat, Z. Resource allocation scheme for 5G C-RAN: A Swarm Intelligence based approach. *Comput. Netw.* **2019**, *165*, 106957. [CrossRef]
22. Valanarasu, M.R.; Christy, A. Comprehensive survey of wireless cognitive and 5G networks. *J. Ubiquitous Comput. Commun. Technol. (UCCT)* **2019**, *1*, 23–32.
23. Amjad, M.; Musavian, L.; Rehmani, M.H. Effective capacity in wireless networks: A comprehensive survey. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 3007–3038. [CrossRef]
24. Shaik, N.; Malik, P.K. A comprehensive survey 5G wireless communication systems: Open issues, research challenges, channel estimation, multi carrier modulation and 5G applications. *Multimed. Tools Appl.* **2021**, *80*, 28789–28827. [CrossRef]
25. Lin, X.; Lee, N. *5G and Beyond: Fundamentals and Standards*; Springer Nature: Cham, Switzerland, 2021.
26. Lei, W.; Soong, A.C.; Jianghua, L.; Yong, W.; Classon, B.; Xiao, W.; Mazzarese, D.; Yang, Z.; Saboorian, T. 5G system architecture. In *5G System Design*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 297–339.
27. Penttinen, J.T. *5G Second Phase Explained: The 3GPP Release 16 Enhancements*; John Wiley & Sons: Hoboken, NJ, USA, 2021.
28. Pedersen, K.; Kolding, T. Overview of 3GPP New Radio Industrial IoT Solutions. In *Wireless Networks and Industrial IoT*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 3–20.
29. Lassoued, N.; Boujnah, N.; Bouallegue, R. Reducing Power Consumption in C-RAN Using Switch On/Off of MC-RRH Sectors and Small Cells. *IEEE Access* **2021**, *9*, 75668–75682. [CrossRef]
30. Nakayama, Y.; Hisano, D.; Maruta, K. Adaptive C-RAN Architecture with Moving Nodes Toward Beyond the 5G Era. *IEEE Netw.* **2020**, *34*, 249–255. [CrossRef]
31. Askri, A.; Zhang, C.; Othman, G.R.B. Distributed Learning Assisted Fronthaul Compression for Multi-Antenna C-RAN. *IEEE Access* **2021**, *9*, 113997–114007. [CrossRef]
32. Wey, J.S.; Luo, Y.; Pfeiffer, T. 5G wireless transport in a PON context: An overview. *IEEE Commun. Stand. Mag.* **2020**, *4*, 50–56. [CrossRef]
33. Thangappan, T.; Therese, B. Overview of Fronthaul Technologies and the DBA Algorithms in XGPON-Based FH Technology in CRAN Architecture in 5G Network. In *Futuristic Communication and Network Technologies*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 271–280.
34. Borges, R.M.; de Souza Lopes, C.H.; Lima, E.S.; de Oliveira, M.A.; Cunha, M.S.B.; Alexandre, L.C.; da Silva, L.G.; Pereira, L.A.M.; Spadoti, D.H.; Romero, M.A.; et al. Integrating Optical and Wireless Techniques towards Novel Fronthaul and Access Architectures in a 5G NR Framework. *Appl. Sci.* **2021**, *11*, 5048. [CrossRef]

35. Iovanna, P.; Cavaliere, F.; Stracca, S.; Giorgi, L.; Ubaldi, F. 5G Xhaul and service convergence: Transmission, switching and automation enabling technologies. *J. Light. Technol.* **2020**, *38*, 2799–2806. [CrossRef]
36. Pateromichelakis, E.; Gebert, J.; Mach, T.; Belschner, J.; Guo, W.; Kuruvatti, N.P.; Venkatasubramanian, V.; Kilinc, C. Service-tailored user-plane design framework and architecture considerations in 5G radio access networks. *IEEE Access* **2017**, *5*, 17089–17105. [CrossRef]
37. Filali, A.; Abouaomar, A.; Cherkaoui, S.; Kobbane, A.; Guizani, M. Multi-access edge computing: A survey. *IEEE Access* **2020**, *8*, 197017–197046. [CrossRef]
38. Taleb, T.; Samdanis, K.; Mada, B.; Flinck, H.; Dutta, S.; Sabella, D. On multi-access edge computing: A survey of the emerging 5G network edge cloud architecture and orchestration. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 1657–1681. [CrossRef]
39. Pham, Q.V.; Fang, F.; Ha, V.N.; Piran, M.J.; Le, M.; Le, L.B.; Hwang, W.J.; Ding, Z. A survey of multi-access edge computing in 5G and beyond: Fundamentals, technology integration, and state-of-the-art. *IEEE Access* **2020**, *8*, 116974–117017. [CrossRef]
40. Liu, Y.; Peng, M.; Shou, G.; Chen, Y.; Chen, S. Toward edge intelligence: Multiaccess edge computing for 5G and Internet of Things. *IEEE Internet Things J.* **2020**, *7*, 6722–6747. [CrossRef]
41. Singh, S.P.; Nayyar, A.; Kumar, R.; Sharma, A. Fog computing: From architecture to edge computing and big data processing. *J. Supercomput.* **2019**, *75*, 2070–2105. [CrossRef]
42. Tufail, A.; Namoun, A.; Alrehaili, A.; Ali, A. A Survey on 5G Enabled Multi-Access Edge Computing for Smart Cities: Issues and Future Prospects. *Int. J. Comput. Sci. Netw. Secur.* **2021**, *21*, 107–118.
43. Hsieh, H.C.; Chen, J.L.; Benslimane, A. 5G virtualized multi-access edge computing platform for IoT applications. *J. Netw. Comput. Appl.* **2018**, *115*, 94–102. [CrossRef]
44. Khan, W.Z.; Ahmed, E.; Hakak, S.; Yaqoob, I.; Ahmed, A. Edge computing: A survey. *Future Gener. Comput. Syst.* **2019**, *97*, 219–235. [CrossRef]
45. Ryu, J.W.; Pham, Q.V.; Luan, H.N.; Hwang, W.J.; Kim, J.D.; Lee, J.T. Multi-access edge computing empowered heterogeneous networks: A novel architecture and potential works. *Symmetry* **2019**, *11*, 842. [CrossRef]
46. Kumar, M.S. Analysis of network function virtualization and software defined virtualization. *JOIV Int. J. Informatics Vis.* **2017**, *1*, 122–126. [CrossRef]
47. Alam, I.; Sharif, K.; Li, F.; Latif, Z.; Karim, M.M.; Biswas, S.; Nour, B.; Wang, Y. A survey of network virtualization techniques for Internet of Things using SDN and NFV. *ACM Comput. Surv. (CSUR)* **2020**, *53*, 1–40. [CrossRef]
48. Cheng, X.; Wu, Y.; Min, G.; Zomaya, A.Y. Network function virtualization in dynamic networks: A stochastic perspective. *IEEE J. Sel. Areas Commun.* **2018**, *36*, 2218–2232. [CrossRef]
49. Qi, D.; Shen, S.; Wang, G. Towards an efficient VNF placement in network function virtualization. *Comput. Commun.* **2019**, *138*, 81–89. [CrossRef]
50. Yi, B.; Wang, X.; Li, K.; Huang, M. A comprehensive survey of network function virtualization. *Comput. Netw.* **2018**, *133*, 212–262. [CrossRef]
51. Mirjalily, G.; Luo, Z. Optimal network function virtualization and service function chaining: A survey. *Chin. J. Electron.* **2018**, *27*, 704–717. [CrossRef]
52. Veeraraghavan, M.; Sato, T.; Buchanan, M.; Rahimi, R.; Okamoto, S.; Yamanaka, N. Network function virtualization: A survey. *IEICE Trans. Commun.* **2017**, 2016NNI0001. [CrossRef]
53. Yang, S.; Li, F.; Trajanovski, S.; Yahyapour, R.; Fu, X. Recent advances of resource allocation in network function virtualization. *IEEE Trans. Parallel Distrib. Syst.* **2020**, *32*, 295–314. [CrossRef]
54. Shiomoto, K. Research challenges for network function virtualization-re-architecting middlebox for high performance and efficient, elastic and resilient platform to create new services. *IEICE Trans. Commun.* **2018**, *101*, 96–122. [CrossRef]
55. Barakabitze, A.A.; Ahmad, A.; Mijumbi, R.; Hines, A. 5G network slicing using SDN and NFV: A survey of taxonomy, architectures and future challenges. *Comput. Netw.* **2020**, *167*, 106984. [CrossRef]
56. Shah, S.D.A.; Gregory, M.A.; Li, S. Cloud-native network slicing using software defined networking based multi-access edge computing: A survey. *IEEE Access* **2021**, *9*, 10903–10924. [CrossRef]
57. Chahbar, M.; Diaz, G.; Dandoush, A.; Cérin, C.; Ghoumid, K. A comprehensive survey on the e2e 5g network slicing model. *IEEE Trans. Netw. Serv. Manag.* **2020**, *18*, 49–62. [CrossRef]
58. Afolabi, I.; Taleb, T.; Samdanis, K.; Ksentini, A.; Flinck, H. Network slicing and softwarization: A survey on principles, enabling technologies, and solutions. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 2429–2453. [CrossRef]
59. Zhang, S. An overview of network slicing for 5G. *IEEE Wirel. Commun.* **2019**, *26*, 111–117. [CrossRef]
60. Kazmi, S.A.; Khan, L.U.; Tran, N.H.; Hong, C.S. *Network Slicing for 5G and beyond Networks*; Springer: Berlin/Heidelberg, Germany, 2019; Volume 1.
61. Ben Azzouz, L.; Jamai, I. SDN, slicing, and NFV paradigms for a smart home: A comprehensive survey. *Trans. Emerg. Telecommun. Technol.* **2019**, *30*, e3744. [CrossRef]
62. Rumyancev, I.A.; Korotkov, A.S. Survey on beamforming techniques and integrated circuits for 5G systems. In Proceedings of the 2019 IEEE International Conference on Electrical Engineering and Photonics (EExPolytech), St. Petersburg, Russia, 17–18 October 2019; pp. 76–80.
63. Alsaba, Y.; Rahim, S.K.A.; Leow, C.Y. Beamforming in wireless energy harvesting communications systems: A survey. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 1329–1360. [CrossRef]

64. Ahmed, I.; Khammari, H.; Shahid, A.; Musa, A.; Kim, K.S.; De Poorter, E.; Moerman, I. A survey on hybrid beamforming techniques in 5G: Architecture and system model perspectives. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 3060–3097. [CrossRef]
65. Sheeba, J.M.; Deepa, S. Beamforming Techniques for Millimeter Wave Communications-A Survey. In Proceedings of the International Conference on Emerging Current Trends in Computing and Expert Technology, Chennai, India, 22–23 March 2019; pp. 1563–1573.
66. Hwang, D.; Nam, S.S.; Yang, J. Multi-antenna beamforming techniques in full-duplex and self-energy recycling systems: Opportunities and challenges. *IEEE Commun. Mag.* **2017**, *55*, 160–167. [CrossRef]
67. Rezaei, F.; Tadaion, A. Multi-layer beamforming in uplink/downlink massive MIMO systems with multi-antenna users. *Signal Process.* **2019**, *164*, 58–66. [CrossRef]
68. Vaigandla, K.K.; Venu, D.N. A Survey on Future Generation Wireless Communications-5G: Multiple Access Techniques, Physical Layer Security, Beamforming Approach. *J. Inf. Comput. Sci.* **2021**, *11*, 449–474.
69. Caroline, B.E.; Xavier, S.C.; Kabilan, A.P.; William, J. Performance analysis and comparison of optical signal processing beamforming networks: A survey. *Photonic Netw. Commun.* **2019**, *37*, 38–52. [CrossRef]
70. Usama, M.; Erol-Kantarci, M. A survey on recent trends and open issues in energy efficiency of 5G. *Sensors* **2019**, *19*, 3126. [CrossRef] [PubMed]
71. Li, Y.; Martensson, J.; Skubic, B.; Zhao, Y.; Zhang, J.; Wosinska, L.; Monti, P. Flexible RAN: Combining dynamic baseband split selection and reconfigurable optical transport to optimize RAN performance. *IEEE Netw.* **2020**, *34*, 180–187. [CrossRef]
72. Morais, F.Z.; da Costa, C.A.; Alberti, A.M.; Both, C.B.; da Rosa Righi, R. When SDN meets C-RAN: A survey exploring multi-point coordination, interference, and performance. *J. Netw. Comput. Appl.* **2020**, *162*, 102655. [CrossRef]
73. Kiet, D.T.; Hieu, T.M.; Hung, N.Q.; Van Cuong, N.; Van, V.T.; Cuong, P.N. Research and Implementation of eCPRI Processing Module for Fronthaul Network on FPGA in 5G–NR gNodeB Base Station. In Proceedings of the 2020 4th International Conference on Recent Advances in Signal Processing, Telecommunications & Computing (SigTelCom), Hanoi, Vietnam, 28–29 August 2020; pp. 1–5.
74. Pérez, G.O.; López, D.L.; Hernández, J.A. 5G new radio fronthaul network design for eCPRI-IEEE 802.1 CM and extreme latency percentiles. *IEEE Access* **2019**, *7*, 82218–82230. [CrossRef]
75. Rabia, T.; Braham, O. A new SDN-based next generation fronthaul interface for a partially centralized C-RAN. In Proceedings of the 2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA), Krakow, Poland, 16–18 May 2018; pp. 393–398.
76. Liu, X.; Deng, N. Emerging optical communication technologies for 5G. In *Optical Fiber Telecommunications VII*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 751–783.
77. Saliou, F.; Chanclou, P.; Neto, L.A.; Simon, G.; Potet, J.; Gay, M.; Bramerie, L.; Debregeas, H. Optical access network interfaces for 5G and beyond. *J. Opt. Commun. Netw.* **2021**, *13*, D32–D42. [CrossRef]
78. Morgado, A.; Huq, K.M.S.; Mumtaz, S.; Rodriguez, J. A survey of 5G technologies: Regulatory, standardization and industrial perspectives. *Digit. Commun. Netw.* **2018**, *4*, 87–97. [CrossRef]
79. Huq, K.M.S.; Busari, S.A.; Rodriguez, J.; Frascolla, V.; Bazzi, W.; Sicker, D.C. Terahertz-enabled wireless system for beyond-5G ultra-fast networks: A brief survey. *IEEE Netw.* **2019**, *33*, 89–95. [CrossRef]
80. Zhang, L.; Zhao, H.; Hou, S.; Zhao, Z.; Xu, H.; Wu, X.; Wu, Q.; Zhang, R. A survey on 5G millimeter wave communications for UAV-assisted wireless networks. *IEEE Access* **2019**, *7*, 117460–117504. [CrossRef]
81. Rinaldi, F.; Raschella, A.; Pizzi, S. 5G NR system design: A concise survey of key features and capabilities. *Wirel. Netw.* **2021**, *27*, 5173–5188. [CrossRef]
82. Uwaechia, A.N.; Mahyuddin, N.M. A comprehensive survey on millimeter wave communications for fifth-generation wireless networks: Feasibility and challenges. *IEEE Access* **2020**, *8*, 62367–62414. [CrossRef]
83. Hu, F.; Chen, B.; Zhu, K. Full spectrum sharing in cognitive radio networks toward 5G: A survey. *IEEE Access* **2018**, *6*, 15754–15776. [CrossRef]
84. Al-Falahy, N.; Alani, O.Y. Millimetre wave frequency band as a candidate spectrum for 5G network architecture: A survey. *Phys. Commun.* **2019**, *32*, 120–144. [CrossRef]
85. Huo, Y.; Dong, X.; Xu, W.; Yuen, M. Enabling multi-functional 5G and beyond user equipment: A survey and tutorial. *IEEE Access* **2019**, *7*, 116975–117008. [CrossRef]
86. Kersting, K. Machine learning and artificial intelligence: Two fellow travelers on the quest for intelligent behavior in machines. *Front. Big Data* **2018**, *1*, 6. [CrossRef]
87. Voulodimos, A.; Doulamis, N.; Doulamis, A.; Protopapadakis, E. Deep learning for computer vision: A brief review. *Comput. Intell. Neurosci.* **2018**, *2018*, 706834 . [CrossRef] [PubMed]
88. Buczak, A.L.; Guven, E. A survey of data mining and machine learning methods for cyber security intrusion detection. *IEEE Commun. Surv. Tutor.* **2015**, *18*, 1153–1176. [CrossRef]
89. Kuleto, V.; Ilić, M.; Dumangiu, M.; Ranković, M.; Martins, O.; Păun, D.; Mihoreanu, L. Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability* **2021**, *13*, 10424. [CrossRef]
90. Chen, M.Y.; Fan, M.H.; Huang, L.X. AI-based vehicular network toward 6G and IoT: Deep learning approaches. *ACM Trans. Manag. Inf. Syst. (TMIS)* **2021**, *13*, 1–12. [CrossRef]

91. Shafin, R.; Liu, L.; Chandrasekhar, V.; Chen, H.; Reed, J.; Zhang, J.C. Artificial intelligence-enabled cellular networks: A critical path to beyond-5G and 6G. *IEEE Wirel. Commun.* **2020**, *27*, 212–217. [CrossRef]
92. Huang, T.; Yang, W.; Wu, J.; Ma, J.; Zhang, X.; Zhang, D. A survey on green 6G network: Architecture and technologies. *IEEE Access* **2019**, *7*, 175758–175768. [CrossRef]
93. Saad, W.; Bennis, M.; Chen, M. A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. *IEEE Netw.* **2019**, *34*, 134–142. [CrossRef]
94. Mezgár, I. Collaborative Networks and ICT Trends for Future CPPS and Beyond. In Proceedings of the Working Conference on Virtual Enterprises, Turin, Italy, 23–25 September 2019; pp. 21–28.
95. Zioga, P.; Pollick, F.; Ma, M.; Chapman, P.; Stefanov, K. "Enheduanna—A Manifesto of Falling" Live Brain-Computer Cinema Performance: Performer and Audience Participation, Cognition and Emotional Engagement Using Multi-Brain BCI Interaction. *Front. Neurosci.* **2018**, *12*, 191. [CrossRef]
96. Braud, T.; Bijarbooneh, F.H.; Chatzopoulos, D.; Hui, P. Future networking challenges: The case of mobile augmented reality. In Proceedings of the 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), Atlanta, GA, USA, 5–8 June 2017; pp. 1796–1807.
97. Piran, M.J.; Suh, D.Y. Learning-driven wireless communications, towards 6G. In Proceedings of the 2019 International Conference on Computing, Electronics & Communications Engineering (iCCECE), London, UK, 22–23 August 2019; pp. 219–224.
98. Yrjölä, S. Decentralized 6G business models. In Proceedings of the 6G Wirel. Summit, Levi, Finland, 24–26 March 2019; pp. 5–7.
99. Mahmoud, H.H.H.; Amer, A.A.; Ismail, T. 6G: A comprehensive survey on technologies, applications, challenges, and research problems. *Trans. Emerg. Telecommun. Technol.* **2021**, *32*, e4233. [CrossRef]
100. Giordani, M.; Polese, M.; Mezzavilla, M.; Rangan, S.; Zorzi, M. Toward 6G networks: Use cases and technologies. *IEEE Commun. Mag.* **2020**, *58*, 55–61. [CrossRef]
101. Mucchi, L.; Jayousi, S.; Caputo, S.; Paoletti, E.; Zoppi, P.; Geli, S.; Dioniso, P. How 6G technology can change the future wireless healthcare. In Proceedings of the 2020 2nd 6G Wireless Summit (6G SUMMIT), Levi, Finland , 17–20 March 2020; pp. 1–6.
102. Saxena, N.; Rastogi, E.; Rastogi, A. 6G Use Cases, Requirements, and Metrics. In *6G Mobile Wireless Networks*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 7–24.
103. Nawaz, S.J.; Sharma, S.K.; Wyne, S.; Patwary, M.N.; Asaduzzaman, M. Quantum machine learning for 6G communication networks: State-of-the-art and vision for the future. *IEEE Access* **2019**, *7*, 46317–46350. [CrossRef]
104. Sharma, T.; Chehri, A.; Fortier, P. Review of optical and wireless backhaul networks and emerging trends of next generation 5G and 6G technologies. *Trans. Emerg. Telecommun. Technol.* **2021**, *32*, 1–16. [CrossRef]
105. Hou, X.; Ren, Z.; Yang, K.; Chen, C.; Zhang, H.; Xiao, Y. IIoT-MEC: A novel mobile edge computing framework for 5G-enabled IIoT. In Proceedings of the 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, 15–18 April 2019; pp. 1–7.
106. Xia, W.; Zhang, J.; Quek, T.Q.; Jin, S.; Zhu, H. Mobile edge cloud-based industrial internet of things: Improving edge intelligence with hierarchical SDN controllers. *IEEE Veh. Technol. Mag.* **2020**, *15*, 36–45. [CrossRef]
107. Liao, Y.; Shou, L.; Yu, Q.; Ai, Q.; Liu, Q. An intelligent computation demand response framework for iiot-mec interactive networks. *IEEE Netw. Lett.* **2020**, *2*, 154–158. [CrossRef]
108. Spinelli, F.; Mancuso, V. Toward Enabled Industrial Verticals in 5G: A Survey on MEC-Based Approaches to Provisioning and Flexibility. *IEEE Commun. Surv. Tutor.* **2020**, *23*, 596–630. [CrossRef]
109. Bebortta, S.; Senapati, D.; Panigrahi, C.R.; Pati, B. An adaptive performance modeling framework for QoS-aware offloading in MEC-based IIoT systems. *IEEE Internet Things J.* **2021**, 1, doi: 10.1109/JIOT.2021.3123554. [CrossRef]
110. Yang, B.; Cao, X.; Li, X.; Zhang, Q.; Qian, L. Mobile-edge-computing-based hierarchical machine learning tasks distribution for IIoT. *IEEE Internet Things J.* **2019**, *7*, 2169–2180. [CrossRef]
111. Qiu, T.; Chi, J.; Zhou, X.; Ning, Z.; Atiquzzaman, M.; Wu, D.O. Edge computing in industrial internet of things: Architecture, advances and challenges. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 2462–2488. [CrossRef]
112. Okwuibe, J.; Haavisto, J.; Harjula, E.; Ahmad, I.; Ylianttila, M. SDN Enhanced Resource Orchestration of Containerized Edge Applications for Industrial IoT. *IEEE Access* **2020**, *8*, 229117–229131. [CrossRef]
113. Vilalta, R.; López, V.; Giorgetti, A.; Peng, S.; Orsini, V.; Velasco, L.; Serral-Gracia, R.; Morris, D.; De Fina, S.; Cugini, F.; et al. TelcoFog: A unified flexible fog and cloud computing architecture for 5G networks. *IEEE Commun. Mag.* **2017**, *55*, 36–43. [CrossRef]
114. Velasco, L.; Ruiz, M. Flexible fog computing and telecom architecture for 5G networks. In Proceedings of the 2018 20th International Conference on Transparent Optical Networks (ICTON), Bucharest, Romania, 1–5 July 2018; pp. 1–4.
115. Ray, P.P.; Kumar, N. SDN/NFV architectures for edge-cloud oriented IoT: A systematic review. *Comput. Commun.* **2021**, *169*, 129–153. [CrossRef]
116. Yousefpour, A.; Fung, C.; Nguyen, T.; Kadiyala, K.; Jalali, F.; Niakanlahiji, A.; Kong, J.; Jue, J.P. All one needs to know about fog computing and related edge computing paradigms. *J. Syst. Archit.* **2018**, *98*, 289–330. [CrossRef]
117. Sivasangari, A.; Lakshmanan, L.; Ajitha, P.; Deepa, D.; Jabez, J. Big Data Analytics for 5G-Enabled IoT Healthcare. In *Blockchain for 5G-Enabled IoT*; Springer: Cham, Switzerland, 2021; pp. 261–275.
118. Arivazhagan, C.; Natarajan, V. A Survey on Fog computing paradigms, Challenges and Opportunities in IoT. In Proceedings of the 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 28–30 July 2020; pp. 385–389.

119. Cheng, B.; Fuerst, J.; Solmaz, G.; Sanada, T. Fog function: Serverless fog computing for data intensive iot services. In Proceedings of the 2019 IEEE International Conference on Services Computing (SCC), Milan, Italy, 8–13 July 2019; pp. 28–35.
120. Giannelli, C.; Poltronieri, F.; Stefanelli, C.; Tortonesi, M. Supporting the development of next-generation fog services. In Proceedings of the 2018 IEEE 23rd International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD), Barcelona, Spain, 17–19 September 2018; pp. 1–6.
121. Rahimi, H.; Zibaeenejad, A.; Safavi, A.A. A novel IoT architecture based on 5G-IoT and next generation technologies. In Proceedings of the 2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), Vancouver, BC, Canada, 1–3 November 2018; pp. 81–88.
122. Sarrigiannis, I.; Ramantas, K.; Kartsakli, E.; Mekikis, P.V.; Antonopoulos, A.; Verikoukis, C. Online VNF lifecycle management in an MEC-enabled 5G IoT architecture. *IEEE Internet Things J.* **2019**, *7*, 4183–4194. [CrossRef]
123. Huang, M.; Liu, A.; Xiong, N.N.; Wang, T.; Vasilakos, A.V. An effective service-oriented networking management architecture for 5G-enabled internet of things. *Comput. Netw.* **2020**, *173*, 107208. [CrossRef]
124. Li, S.; Da Xu, L.; Zhao, S. 5G Internet of Things: A survey. *J. Ind. Inf. Integr.* **2018**, *10*, 1–9. [CrossRef]
125. Chettri, L.; Bera, R. A comprehensive survey on Internet of Things (IoT) toward 5G wireless systems. *IEEE Internet Things J.* **2019**, *7*, 16–32. [CrossRef]
126. Gupta, N.; Sharma, S.; Juneja, P.K.; Garg, U. SDNFV 5G-IoT: A framework for the next generation 5G enabled IoT. In Proceedings of the 2020 International Conference on Advances in Computing, Communication & Materials (ICACCM), Dehradun, India, 21–22 August 2020; pp. 289–294.
127. Rahimi, H.; Zibaeenejad, A.; Rajabzadeh, P.; Safavi, A.A. On the security of the 5g-IoT architecture. In Proceedings of the International Conference on Smart Cities and Internet of Things, Mashhad, Iran, 26–27 September 2018; pp. 1–8.
128. Mudigonda, P.; Abburi, S.K. A Survey: 5G in IoT is a Boon for Big Data Communication and Its Security. In *ICDSMLA 2019*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 318–327.
129. Nguyen, D.C.; Pathirana, P.N.; Ding, M.; Seneviratne, A. Blockchain for 5G and beyond networks: A state of the art survey. *J. Netw. Comput. Appl.* **2020**, *166*, 102693. [CrossRef]
130. Mistry, I.; Tanwar, S.; Tyagi, S.; Kumar, N. Blockchain for 5G-enabled IoT for industrial automation: A systematic review, solutions, and challenges. *Mech. Syst. Signal Process.* **2020**, *135*, 106382. [CrossRef]
131. Arshad, U.; Shah, M.A.; Javaid, N. Futuristic blockchain based scalable and cost-effective 5G vehicular network architecture. *Veh. Commun.* **2021**, *31*, 100386. [CrossRef]
132. Gupta, R.; Tanwar, S.; Kumar, N. Blockchain and 5G integrated softwarized UAV network management: Architecture, solutions, and challenges. *Phys. Commun.* **2021**, *47*, 101355. [CrossRef]
133. Kiyomoto, S.; Basu, A.; Rahman, M.S.; Ruj, S. On blockchain-based authorization architecture for beyond-5G mobile services. In Proceedings of the 2017 12th International Conference for Internet Technology and Secured Transactions (ICITST), Cambridge, UK, 11–14 December 2017; pp. 136–141.
134. Khujamatov, K.; Reypnazarov, E.; Akhmedov, N.; Khasanov, D. Blockchain for 5G Healthcare architecture. In Proceedings of the 2020 International Conference on Information Science and Communications Technologies (ICISCT), Tashkent, Uzbekistan, 4–6 November 2020; pp. 1–5.
135. Honar Pajooh, H.; Rashid, M.; Alam, F.; Demidenko, S. Multi-layer blockchain-based security architecture for internet of things. *Sensors* **2021**, *21*, 772. [CrossRef]
136. Hakiri, A.; Dezfouli, B. Towards a Blockchain-SDN Architecture for Secure and Trustworthy 5G Massive IoT Networks. In Proceedings of the 2021 ACM International Workshop on Software Defined Networks & Network Function Virtualization Security, Virtual Event, 28 April 2021; pp. 11–18.
137. Zhani, M.F.; ElBakoury, H. FlexNGIA: A flexible Internet architecture for the next-generation tactile Internet. *J. Netw. Syst. Manag.* **2020**, *28*, 751–795. [CrossRef]
138. Tariq, F.; Khandaker, M.R.; Wong, K.K.; Imran, M.A.; Bennis, M.; Debbah, M. A speculative study on 6G. *IEEE Wirel. Commun.* **2020**, *27*, 118–125. [CrossRef]
139. Agiwal, M.; Roy, A.; Saxena, N. Next generation 5G wireless networks: A comprehensive survey. *IEEE Commun. Surv. Tutor.* **2016**, *18*, 1617–1655. [CrossRef]
140. Morocho-Cayamcela, M.E.; Lee, H.; Lim, W. Machine learning for 5G/B5G mobile and wireless communications: Potential, limitations, and future directions. *IEEE Access* **2019**, *7*, 137184–137206. [CrossRef]
141. Sanchez, J.M. Mobile revolution: From 2G to 5G. In Proceedings of the 2021 IEEE Colombian Conference on Communications and Computing (COLCOM), Cali, Colombia, 26–28 May 2021; pp. 1–6.
142. Hussain, M.; Amin, Y.; Lee, K.G. A Compact and Flexible UHF RFID Tag Antenna for Massive IoT Devices in 5G System. *Sensors* **2020**, *20*, 5713. [CrossRef] [PubMed]
143. Dilli, R. Analysis of 5G wireless systems in FR1 and FR2 frequency bands. In Proceedings of the 2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bangalore, India, 5–7 March 2020; pp. 767–772.
144. Samdanis, K.; Taleb, T. The road beyond 5G: A vision and insight of the key technologies. *IEEE Netw.* **2020**, *34*, 135–141. [CrossRef]
145. Patil, M.V.; Pawar, S.; Saquib, Z. Coding techniques for 5G networks: A review. In Proceedings of the 2020 3rd International Conference on Communication System, Computing and IT Applications (CSCITA), Mumbai, India, 3–4 April 2020; pp. 208–213.

146. Henry, S.; Alsohaily, A.; Sousa, E.S. 5G is real: Evaluating the compliance of the 3GPP 5G new radio system with the ITU IMT-2020 requirements. *IEEE Access* **2020**, *8*, 42828–42840. [CrossRef]
147. Dandekar, A. Towards autonomic orchestration of machine learning pipelines in future networks. *arXiv* **2021**, arXiv:2107.08194.
148. Sridharan, S. Machine Learning (ML) In a 5G Standalone (SA) Self Organizing Network (SON). *arXiv* **2020**, arXiv:2011.12288.
149. Abdellah, A.; Koucheryavy, A. Survey on artificial intelligence techniques in 5G networks. *J. Inf. Technol. Telecommun. SPbSUT Russ.* **2020**, *8*, 1–10. [CrossRef]
150. Lin, X.; Li, J.; Baldemair, R.; Cheng, J.F.T.; Parkvall, S.; Larsson, D.C.; Koorapaty, H.; Frenne, M.; Falahati, S.; Grovlen, A.; et al. 5G new radio: Unveiling the essentials of the next generation wireless access technology. *IEEE Commun. Stand. Mag.* **2019**, *3*, 30–37. [CrossRef]
151. Bizaki, H.K. *Towards 5G Wireless Networks: A Physical Layer Perspective*; BoD–Books on Demand; InTechOpen: London, UK, 2016.
152. Abubakar, I.; Din, J.; Alhilali, M.; Lam, H.Y. Interference and Electromagnetic Compatibility Challenges in 5G Wireless Network Deployments. *Indones. J. Electr. Eng. Comput. Sci.* **2017**, *5*, 612–621. [CrossRef]
153. Kongara, G.; He, C.; Yang, L.; Armstrong, J. A comparison of CP-OFDM, PCC-OFDM and UFMC for 5G uplink communications. *IEEE Access* **2019**, *7*, 157574–157594. [CrossRef]
154. Peccarelli, N.; James, B.; Irazoqui, R.; Metcalf, J.; Fulton, C.; Yeary, M. Survey: Characterization and mitigation of spatial/spectral interferers and transceiver nonlinearities for 5G MIMO systems. *IEEE Trans. Microw. Theory Tech.* **2019**, *67*, 2829–2846. [CrossRef]
155. Dion, T.; Torres, P. Electromagnetic Interference Analysis of Industrial IoT Networks: From Legacy Systems to 5G. In Proceedings of the 2020 IEEE Microwave Theory and Techniques in Wireless Communications (MTTW), Riga, Latvia, 1–2 October 2020; Volume 1, pp. 41–46.
156. Taheribakhsh, M.; Jafari, A.; Peiro, M.M.; Kazemifard, N. 5g implementation: Major issues and challenges. In Proceedings of the 2020 25th International Computer Conference, Computer Society of Iran (CSICC), Tehran, Iran, 1–2 January 2020; pp. 1–5.
157. He, R.; Schneider, C.; Ai, B.; Wang, G.; Zhong, Z.; Dupleich, D.A.; Thomae, R.S.; Boban, M.; Luo, J.; Zhang, Y. Propagation channels of 5G millimeter-wave vehicle-to-vehicle communications: Recent advances and future challenges. *IEEE Veh. Technol. Mag.* **2019**, *15*, 16–26. [CrossRef]
158. Shafi, M.; Zhang, J.; Tataria, H.; Molisch, A.F.; Sun, S.; Rappaport, T.S.; Tufvesson, F.; Wu, S.; Kitao, K. Microwave vs. millimeter-wave propagation channels: Key differences and impact on 5G cellular systems. *IEEE Commun. Mag.* **2018**, *56*, 14–20. [CrossRef]
159. Kumari, M.S.; Kumar, N. Channel model for simultaneous backhaul and access for mmWave 5G outdoor street canyon channel. *Wirel. Networks* **2020**, *26*, 5997–6013. [CrossRef]
160. Azpilicueta Fernández de las Heras, L.; López Iturri, P.; Zuñiga Mejia, J.; Aguirre Gallego, E.; Falcone Lanas, F.J. Fifth-generation (5G) mmwave spatial channel characterization for urban environments' system analysis. *Sensors* **2020**, *20*, 5360. [CrossRef]
161. Sánchez, J.D.V.; Urquiza-Aguiar, L.; Paredes Paredes, M.C. Fading channel models for mm-wave communications. *Electronics* **2021**, *10*, 798. [CrossRef]
162. Segura, D.; Khatib, E.J.; Munilla, J.; Barco, R. 5G Numerologies Assessment for URLLC in Industrial Communications. *Sensors* **2021**, *21*, 2489. [CrossRef]
163. Khan, I.; Zafar, M.H.; Jan, M.T.; Lloret, J.; Basheri, M.; Singh, D. Spectral and energy efficient low-overhead uplink and downlink channel estimation for 5G massive MIMO systems. *Entropy* **2018**, *20*, 92. [CrossRef]
164. Al-Samman, A.M.; Azmi, M.H.; Al-Gumaei, Y.A.; Al-Hadhrami, T.; Fazea, Y.; Al-Mqdashi, A. Millimeter wave propagation measurements and characteristics for 5G system. *Appl. Sci.* **2020**, *10*, 335. [CrossRef]
165. Chen, K.T.; Ma, W.H.; Hwang, Y.T.; Chang, K.Y. A Low Complexity, High Throughput DoA Estimation Chip Design for Adaptive Beamforming. *Electronics* **2020**, *9*, 641. [CrossRef]
166. Shevada, L.; Raut, H.D.; Malekar, R.; Kumar, S. Comparative Study of different beamforming techniques for 5G: A Review. In *Inventive Communication and Computational Technologies*; Springer: Singapore, 2021; pp. 589–595.
167. Ali, E.; Ismail, M.; Nordin, R.; Abdulah, N.F. Beamforming techniques for massive MIMO systems in 5G: Overview, classification, and trends for future research. *Front. Inf. Technol. Electron. Eng.* **2017**, *18*, 753–772. [CrossRef]
168. Reddy, K.S. 5G VANETs: A Details Performance Analysis of Fusion Beam Forming Techniques for Vehicular Environment. *Turk. J. Comput. Math. Educ. (TURCOMAT)* **2021**, *12*, 5518–5533.
169. Noh, S.; Zoltowski, M.D.; Love, D.J. Multi-resolution codebook and adaptive beamforming sequence design for millimeter wave beam alignment. *IEEE Trans. Wirel. Commun.* **2017**, *16*, 5689–5701. [CrossRef]
170. Zhao, Y.; Ai, B.; Liu, Y. A Novel Adaptive Beamforming with Combinational Algorithm in Wireless Communications. In Proceedings of the International Conference on Intelligent Computing, Liverpool, UK, 7–10 August 2017; pp. 637–646.
171. Zhang, Q.; Zhao, J.; Chen, A.; Wang, C. Adaptive Beamforming and Power Allocation for mmWave Communication in High-Speed Railway. *Radio Sci.* **2021**, *56*, e2020RS007073. [CrossRef]
172. Yashchyshyn, Y.; Derzakowski, K.; Bogdan, G.; Godziszewski, K.; Nyzovets, D.; Kim, C.H.; Park, B. 28 GHz switched-beam antenna based on S-PIN diodes for 5G mobile communications. *IEEE Antennas Wirel. Propag. Lett.* **2017**, *17*, 225–228. [CrossRef]
173. Ikram, M.; Sharawi, M.; Klionovski, K.; Shamim, A. A switched-beam millimeter-wave array with MIMO configuration for 5G applications. *Microw. Opt. Technol. Lett.* **2018**, *60*, 915–920. [CrossRef]
174. Zhang, W.; Wei, Y.; Wu, S.; Meng, W.; Xiang, W. Joint beam and resource allocation in 5G mmWave small cell systems. *IEEE Trans. Veh. Technol.* **2019**, *68*, 10272–10277. [CrossRef]

175. Lee, S.; Lee, Y.; Shin, H. A 28-GHz Switched-Beam Antenna with Integrated Butler Matrix and Switch for 5G Applications. *Sensors* **2021**, *21*, 5128. [CrossRef]
176. Moubadir, M.; Mchbal, A.; Touhami, N.A.; Aghoutane, M. A Switched Beamforming Network for 5G Modern Wireless Communications Applications. *Procedia Manuf.* **2019**, *32*, 753–761. [CrossRef]
177. Al-Tarifi, M.A.; Sharawi, M.S.; Shamim, A. Massive MIMO antenna system for 5G base stations with directive ports and switched beamsteering capabilities. *IET Microwaves Antennas Propag.* **2018**, *12*, 1709–1718. [CrossRef]
178. Orakwue, S.; Ngah, R. Switched-beam array antenna at 28 GHz for 5G wireless system based on butler matrix beamforming network. *Niger. J. Technol.* **2019**, *38*, 484–489. [CrossRef]
179. Vilas Boas, E.C.; Filgueiras, H.R.D.; Feliciano da Costa, I.; Ribeiro, J.A.J.; Sodre, A.C., Jr. Dual-band switched-beam antenna array for MIMO systems. *IET Microwaves Antennas Propag.* **2020**, *14*, 82–87. [CrossRef]
180. Ge, L.; Zhang, Y.; Chen, G.; Tong, J. Compression-based LMMSE channel estimation with adaptive sparsity for massive MIMO in 5G systems. *IEEE Syst. J.* **2019**, *13*, 3847–3857. [CrossRef]
181. Wu, W.; Liu, D.; Hou, X.; Liu, M. Low-complexity beam training for 5G millimeter-wave massive MIMO systems. *IEEE Trans. Veh. Technol.* **2019**, *69*, 361–376. [CrossRef]
182. Wu, X.; Beaulieu, N.C.; Liu, D. On favorable propagation in massive MIMO systems and different antenna configurations. *IEEE Access* **2017**, *5*, 5578–5593. [CrossRef]
183. Shinjo, S.; Nakatani, K.; Tsutsumi, K.; Nakamizo, H. Integrating the front end: A highly integrated RF front end for high-SHF wide-band massive MIMO in 5G. *IEEE Microw. Mag.* **2017**, *18*, 31–40. [CrossRef]
184. Kammoun, A.; Debbah, M.; Alouini, M.S. Design of 5G full dimension massive MIMO systems. *IEEE Trans. Commun.* **2017**, *66*, 726–740.
185. Dicandia, F.A.; Genovesi, S. Exploitation of triangular lattice arrays for improved spectral efficiency in massive MIMO 5G systems. *IEEE Access* **2021**, *9*, 17530–17543. [CrossRef]
186. Huang, J.; Wang, C.X.; Feng, R.; Sun, J.; Zhang, W.; Yang, Y. Multi-frequency mmWave massive MIMO channel measurements and characterization for 5G wireless communication systems. *IEEE J. Sel. Areas Commun.* **2017**, *35*, 1591–1605. [CrossRef]
187. Suk, G.Y.; Kim, S.M.; Kwak, J.; Hur, S.; Kim, E.; Chae, C.B. Full duplex integrated access and backhaul for 5G NR: Analyses and prototype measurements. *arXiv* **2020**, arXiv:2007.03272.
188. Zhang, L.; Ansari, N. A framework for 5G networks with in-band full-duplex enabled drone-mounted base-stations. *IEEE Wirel. Commun.* **2019**, *26*, 121–127. [CrossRef]
189. de Melo Guimarães, L.; Luiz Bordim, J. A Full-duplex MAC tailored for 5G Wireless Networks. *Wirel. Commun. Mob. Comput.* **2018**, *2018*, 5408973. [CrossRef]
190. Yadav, A.; Dobre, O.A.; Ansari, N. Energy and traffic aware full-duplex communications for 5G systems. *IEEE Access* **2017**, *5*, 11278–11290. [CrossRef]
191. Kolodziej, K.E.; Perry, B.T.; Herd, J.S. In-band full-duplex technology: Techniques and systems survey. *IEEE Trans. Microw. Theory Tech.* **2019**, *67*, 3025–3041. [CrossRef]
192. Xia, X.; Xu, K.; Wang, Y.; Xu, Y. A 5G-enabling technology: Benefits, feasibility, and limitations of in-band full-duplex mMIMO. *IEEE Veh. Technol. Mag.* **2018**, *13*, 81–90. [CrossRef]
193. Biswas, S.; Bishnu, A.; Khan, F.A.; Ratnarajah, T. In-Band Full-Duplex Dynamic Spectrum Sharing in Beyond 5G Networks. *IEEE Commun. Mag.* **2021**, *59*, 54–60. [CrossRef]
194. Abbas, F.; Yuan, X.; Bute, M.S.; Fan, P. Performance Analysis Using Full Duplex Discovery Mechanism in 5G-V2X Communication Networks. *IEEE Trans. Intell. Transp. Syst.*; **2021**, 1–12. [CrossRef]
195. Matthaiou, M.; Yurduseven, O.; Ngo, H.Q.; Morales-Jimenez, D.; Cotton, S.L.; Fusco, V.F. The road to 6G: Ten physical layer challenges for communications engineers. *IEEE Commun. Mag.* **2021**, *59*, 64–69. [CrossRef]
196. Wu, N.; Wang, X.; Lin, B.; Zhang, K. A CNN-based end-to-end learning framework toward intelligent communication systems. *IEEE Access* **2019**, *7*, 110197–110204. [CrossRef]
197. Qin, Z.; Ye, H.; Li, G.Y.; Juang, B.H.F. Deep learning in physical layer communications. *IEEE Wirel. Commun.* **2019**, *26*, 93–99. [CrossRef]
198. Hong, T.; Liu, C.; Kadoch, M. Machine learning based antenna design for physical layer security in ambient backscatter communications. *Wirel. Commun. Mob. Comput.* **2019**, *2019*. [CrossRef]
199. Vora, A.; Thomas, P.X.; Chen, R.; Kang, K.D. CSI classification for 5G via deep learning. In Proceedings of the 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall), Honolulu, HI, USA, 22–25 September 2019; pp. 1–5.
200. Anand, A.; Rani, S.; Anand, D.; Aljahdali, H.M.; Kerr, D. An Efficient CNN-Based Deep Learning Model to Detect Malware Attacks (CNN-DMA) in 5G-IoT Healthcare Applications. *Sensors* **2021**, *21*, 6346. [CrossRef]
201. Yuan, L.; Zhang, H.; Xu, M.; Zhou, F.; Wu, Q. A Multi-Scale CNN Framework for Wireless Technique Classification in Internet of Things. *IEEE Internet Things J.* **2021**, *1*. [CrossRef]
202. Bao, X.; Feng, W.; Zheng, J.; Li, J. Deep CNN and equivalent channel based hybrid precoding for mmWave massive MIMO systems. *IEEE Access* **2020**, *8*, 19327–19335. [CrossRef]
203. Liao, R.; Wen, H.; Pan, F.; Song, H.; Xu, A.; Jiang, Y. A Novel Physical Layer Authentication Method with Convolutional Neural Network. In Proceedings of the 2019 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, 29–31 March 2019; pp. 231–235.

204. Strodthoff, N.; Göktepe, B.; Schierl, T.; Hellge, C.; Samek, W. Enhanced machine learning techniques for early HARQ feedback prediction in 5G. *IEEE J. Sel. Areas Commun.* **2019**, *37*, 2573–2587. [CrossRef]
205. Storck, C.R.; Duarte-Figueiredo, F. A survey of 5G technology evolution, standards, and infrastructure associated with vehicle-to-everything communications by internet of vehicles. *IEEE Access* **2020**, *8*, 117593–117614. [CrossRef]
206. Agiwal, M.; Kwon, H.; Park, S.; Jin, H. A Survey on 4G-5G Dual Connectivity: Road to 5G Implementation. *IEEE Access* **2021**, *9*, 16193–16210. [CrossRef]
207. El Rhayour, A.; Mazri, T. 5G Architecture: Deployment scenarios and options. In Proceedings of the 2019 International Symposium on Advanced Electrical and Communication Technologies (ISAECT), Rome, Italy, 27–29 November 2019; pp. 1–6.
208. Kim, H.; Kim, J.; Hong, D. Dynamic TDD systems for 5G and beyond: A survey of cross-link interference mitigation. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 2315–2348. [CrossRef]
209. Khan, M.S.; Kim, Y.J.; Sultan, Q.; Joung, J.; Cho, Y.S. Downlink Synchronization for OTFS-Based Cellular Systems in High Doppler Environments. *IEEE Access* **2021**, *9*, 73575–73589. [CrossRef]
210. Kishore, G.S.; Rallapalli, H. Towards 5G: A Survey on Waveform Contenders. In *Advances in Decision Sciences, Image Processing, Security and Computer Vision*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 243–250.
211. Alammouri, A.; Mo, J.; Ng, B.L.; Zhang, J.C.; Andrews, J.G. Hand grip impact on 5G mmWave mobile devices. *IEEE Access* **2019**, *7*, 60532–60544. [CrossRef]
212. Yang, X.; Matthaiou, M.; Yang, J.; Wen, C.K.; Gao, F.; Jin, S. Hardware-constrained millimeter-wave systems for 5G: Challenges, opportunities, and solutions. *IEEE Commun. Mag.* **2019**, *57*, 44–50. [CrossRef]
213. Su, Y.; LiWang, M.; Huang, L.; Du, X.; Guizani, N. Green Communications for Future Vehicular Networks: Data Compression Approaches, Opportunities, and Challenges. *IEEE Netw.* **2020**, *34*, 184–190. [CrossRef]
214. Lai, S.; Zhao, R.; Tang, S.; Xia, J.; Zhou, F.; Fan, L. Intelligent secure mobile edge computing for beyond 5G wireless networks. *Phys. Commun.* **2021**, *45*, 101283. [CrossRef]
215. Shakarami, A.; Shahidinejad, A.; Ghobaei-Arani, M. An autonomous computation offloading strategy in Mobile Edge Computing: A deep learning-based hybrid approach. *J. Netw. Comput. Appl.* **2021**, *178*, 102974. [CrossRef]
216. Xu, S.; Liu, X.; Guo, S.; Qiu, X.; Meng, L. MECC: A Mobile Edge Collaborative Caching Framework Empowered by Deep Reinforcement Learning. *IEEE Netw.* **2021**, *35*, 176–183. [CrossRef]
217. Omar, T.; Ketseoglou, T.; Naffaa, I. A novel self-healing model using precoding & big-data based approach for 5G networks. *Pervasive Mob. Comput.* **2021**, *73*, 101365.
218. Jin, Z.; Zhang, C.; Zhao, G.; Jin, Y.; Zhang, L. A Context-aware Task Offloading Scheme in Collaborative Vehicular Edge Computing Systems. *KSII Trans. Internet Inf. Syst.* **2021**, *15*, 383–403.
219. Xu, Y.; Gui, G.; Gacanin, H.; Adachi, F. A survey on resource allocation for 5G heterogeneous networks: Current research, future trends and challenges. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 668–695. [CrossRef]
220. Stainton, S.; Johnston, M.; Dlay, S.; Haigh, P.A. EVM Loss: A Loss Function for Training Neural Networks in Communication Systems. *Sensors* **2021**, *21*, 1094. [CrossRef] [PubMed]
221. Arnold, M.; Hoydis, J.; ten Brink, S. Novel massive MIMO channel sounding data applied to deep learning-based indoor positioning. In Proceedings of the 12th International ITG Conference on Systems, Communications and Coding (SCC 2019), Rostock, Germany, 11–14 February 2019; pp. 1–6.
222. Kojima, S.; Maruta, K.; Ahn, C.J. Adaptive modulation and coding using neural network based SNR estimation. *IEEE Access* **2019**, *7*, 183545–183553. [CrossRef]
223. Kalinov, A.; Bychkov, R.; Ivanov, A.; Osinsky, A.; Yarotsky, D. Machine Learning-Assisted PAPR Reduction in Massive MIMO. *IEEE Wirel. Commun. Lett.* **2020**, *10*, 537–541. [CrossRef]
224. Shen, S.; Zhang, T.; Mao, S.; Chang, G.K. DRL-Based Channel and Latency Aware Radio Resource Allocation for 5G Service-Oriented RoF-MmWave RAN. *J. Light. Technol.* **2021**, *39*, 5706–5714. [CrossRef]
225. Arnold, M.; Dörner, S.; Cammerer, S.; Yan, S.; Hoydis, J.; Brink, S.T. Enabling FDD massive MIMO through deep learning-based channel prediction. *arXiv* **2019**, arXiv:1901.03664.
226. Singh, K.K.; Katiyar, H. A Survey Paper on 5G Suitable Waveform Candidates. In *Advances in Intelligent Computing and Communication*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 717–724.
227. Jijo, B.T.; Zeebaree, S.R.; Zebari, R.R.; Sadeeq, M.A.; Sallow, A.B.; Mohsin, S.; Ageed, Z.S. A comprehensive survey of 5G mm-wave technology design challenges. *Asian J. Res. Comput. Sci.* **2021**, *8*, 1–20. [CrossRef]
228. Hamid, N. Evaluation of Power Receiving Signal of 5G Small Cells for Outdoor/Indoor Environment at Millimeterwave Bands. *Appl. Comput. Electromagn. Soc. J.* **2021**, *36*, 84–189. [CrossRef]
229. Lee, J.; Kim, H.; Wymeersch, H.; Kim, S. Dirichlet process approach for radio-based simultaneous localization and mapping. *arXiv* **2021**, arXiv:2107.00864.
230. Alsadik, B.; Karam, S. The Simultaneous Localization and Mapping (SLAM)-An Overview. *Surv. Geospat. Eng. J.* **2021**, *2*, 34–45. [CrossRef]
231. Dilli, R. Performance of Multi-User Massive Mimo in 5G NR networks AT 28 GHz band. *Telecommun. Radio Eng.* **2021**, *80*, 61–74. [CrossRef]
232. Sakkas, L.; Stergiou, E.; Tsoumanis, G.; Angelis, C.T. 5G UFMC Scheme Performance with Different Numerologies. *Electronics* **2021**, *10*, 1915. [CrossRef]

233. Mathur, H.; Deepa, T. A Survey on Advanced Multiple Access Techniques for 5G and Beyond Wireless Communications. *Wirel. Pers. Commun.* **2021**, *118*, 1775–1792. [CrossRef]
234. Ramadhan, A. Overview and implementation of the two most important candidate 5G waveforms. *J. Theor. Appl. Inf. Technol.* **2019**, *97*, 2551–2560.
235. de Almeida, I.B.F.; Mendes, L.L.; Rodrigues, J.J.; da Cruz, M.A. 5G waveforms for IoT applications. *IEEE Commun. Surv. Tutorials* **2019**, *21*, 2554–2567. [CrossRef]
236. Khudhair, S.A.; Singh, M.J. Review in FBMC to Enhance the Performance of 5G Networks. *J. Commun.* **2020**, *15*, 415–426. [CrossRef]
237. Zhang, J.; Rakhimov, D.; Haardt, M. Gridless Channel Estimation for Hybrid mmWave MIMO Systems via Tensor-ESPRIT Algorithms in DFT Beamspace. *IEEE J. Sel. Top. Signal Process.* **2021**, *15*, 816–831. [CrossRef]
238. Meshkov, I.K.; Gizatulin, A.R.; Vinogradova, I.L.; Meshkova, A.G.; Sultanov, A.K.; Bagmanov, V.K.; Bourdine, A.V. Usage of SDM technology in radio-over-fiber (RoF) transmission systems in high-speed scalable 6G wireless networks. In *Optical Technologies for Telecommunications 2020*; International Society for Optics and Photonics: Bellingham, WA, USA, 2021; Volume 11793, p. 117931G.
239. Gorre, P.; Vignesh, R.; Arya, R.; Kumar, S. A Review of mm-Wave Power Amplifiers for Next-Generation 5G Communication. In *Soft Computing: Theories and Applications*; Springer: Singapore, 2020; pp. 173–184.
240. Nalband, A.H.; Sarvagya, M.; Ahmed, M.R. Spectral Efficient Beamforming for mmWave MISO Systems using Deep Learning Techniques. *Arab. J. Sci. Eng.* **2021**, *46*, 9783–9795. [CrossRef]
241. Omotere, O.; Fuller, J.; Qian, L.; Han, Z. Spectrum occupancy prediction in coexisting wireless systems using deep learning. In Proceedings of the 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Chicago, IL, USA, 27–30 August 2018; pp. 1–7.
242. Vidal-Beltrán, S.; López-Bonilla, J.L. Improving Spectral Efficiency in the SCMA Uplink Channel. *Mathematics* **2021**, *9*, 651. [CrossRef]
243. Khan, R.; Kumar, P.; Jayakody, D.N.K.; Liyanage, M. A survey on security and privacy of 5G technologies: Potential solutions, recent advancements, and future directions. *IEEE Commun. Surv. Tutor.* **2019**, *22*, 196–248. [CrossRef]
244. Olfati, M.; Parmar, K. Deep Learning and AI for 5G Technology: Paradigms. In Proceedings of the IFIP International Conference on Artificial Intelligence Applications and Innovations, Hersonissos, Crete, Greece, 25-27 June 2021; pp. 398–407.
245. Alves, H.; Jo, G.D.; Shin, J.; Yeh, C.; Mahmood, N.H.; Lima, C.; Yoon, C.; Rahatheva, N.; Park, O.S.; Kim, S.; et al. Beyond 5G URLLC Evolution: New Service Modes and Practical Considerations. *arXiv* **2021**, arXiv:2106.11825.
246. Mchangama, A.; Ayadi, J.; Jiménez, V.P.G.; Consoli, A. MmWave massive MIMO small cells for 5G and beyond mobile networks: An overview. In Proceedings of the 2020 12th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP), Porto, Portugal, 20–22 July 2020; pp. 1–6.
247. Jia, C.; Gao, H.; Chen, N.; He, Y. Machine learning empowered beam management for intelligent reflecting surface assisted MmWave networks. *China Commun.* **2020**, *17*, 100–114. [CrossRef]
248. Khan, M.S.; Sultan, Q.; Cho, Y.S. Position and Machine Learning-Aided Beam Prediction and Selection Technique in Millimeter-Wave Cellular System. 2020 International Conference on Information and Communication Technology Convergence (ICTC), Jeju, Korea, 21–23 October 2020; pp. 603–605.
249. Mumtaz, S.; Rodriguez, J.; Dai, L. *MmWave Massive MIMO: A Paradigm for 5G*; Academic Press: Cambridge, MA, USA, 2016.
250. Wen, F.; Wymeersch, H.; Peng, B.; Tay, W.P.; So, H.C.; Yang, D. A survey on 5G massive MIMO localization. *Digit. Signal Process.* **2019**, *94*, 21–28. [CrossRef]
251. Khwandah, S.A.; Cosmas, J.P.; Lazaridis, P.I.; Zaharis, Z.D.; Chochliouros, I.P. Massive MIMO Systems for 5G Communications. *Wirel. Pers. Commun.* **2021**, *120*, 2101–2115. [CrossRef]
252. Arjoune, Y.; Faruque, S. Smart jamming attacks in 5G new radio: A review. In Proceedings of the 2020 10th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, 6–8 January 2020; pp. 1010–1015.
253. Zhang, Y.; Du, J.; Chen, Y.; Li, X.; Rabie, K.M.; Khkrel, R. Dual-iterative hybrid beamforming design for millimeter-wave massive multi-user MIMO systems with sub-connected structure. *IEEE Trans. Veh. Technol.* **2020**, *69*, 13482–13496. [CrossRef]
254. Papadopoulos, H.; Wang, C.; Bursalioglu, O.; Hou, X.; Kishiyama, Y. Massive MIMO technologies and challenges towards 5G. *IEICE Trans. Commun.* **2016**, *99*, 602–621. [CrossRef]
255. Cao, L.; Hu, X.; Zhang, M.; Wang, X.; Zhang, X. Interactive CoMP with user-centric clustering based on load balancing in 5G dense networks. In Proceedings of the 2018 IEEE International Conference on Communications Workshops (ICC Workshops), Kansas City, MO, USA, 20–24 May 2018; pp. 1–6.
256. Sultan, Q.; Khan, M.S.; Cho, Y.S. Fast 3D beamforming technique for millimeter-wave cellular systems with uniform planar arrays. *IEEE Access* **2020**, *8*, 123469–123482. [CrossRef]
257. Rao, L.; Pant, M.; Malviya, L.; Parmar, A.; Charhate, S.V. 5G beamforming techniques for the coverage of intended directions in modern wireless communication: In-depth review. *Int. J. Microw. Wirel. Technol.* **2020**, *13*, 1039–1062. [CrossRef]
258. Gao, L.; Rebeiz, G.M. A 22–44-GHz phased-array receive beamformer in 45-nm CMOS SOI for 5G applications with 3–3.6-dB NF. *IEEE Trans. Microw. Theory Tech.* **2020**, *68*, 4765–4774. [CrossRef]
259. Molisch, A.F.; Ratnam, V.V.; Han, S.; Li, Z.; Nguyen, S.L.H.; Li, L.; Haneda, K. Hybrid beamforming for massive MIMO: A survey. *IEEE Commun. Mag.* **2017**, *55*, 134–141. [CrossRef]
260. Chataut, R.; Akl, R. Massive MIMO systems for 5G and beyond networks—overview, recent trends, challenges, and future research direction. *Sensors* **2020**, *20*, 2753. [CrossRef]

261. Wu, S.X.; Luo, Y.; Wang, H. Some New Results on Stochastic Beamforming Schemes. In Proceedings of the 2019 IEEE 19th International Conference on Communication Technology (ICCT), Xi'an, China, 16–19 October 2019; pp. 107–112.
262. Abdelkader, A.; Jorswieck, E. Robust adaptive distributed beamforming for energy-efficient network flooding. *EURASIP J. Wirel. Commun. Netw.* **2019**, *2019*, 1–15. [CrossRef]
263. Chen, D.; Kuehn, V. Robust resource allocation and clustering formulation for multicast C-RAN with impaired CSI. In Proceedings of the 2017 IEEE International Conference on Communications (ICC), Paris, France, 21–25 May 2017; pp. 1–6.
264. Liao, Y.; Yang, X.; Yao, H.; Chen, L.; Wan, S. Spatial correlation based channel compression feedback algorithm for massive MIMO systems. *Digit. Signal Process.* **2019**, *94*, 38–44. [CrossRef]
265. Chataut, R.; Akl, R. Efficient and low complex uplink detection for 5G massive MIMO systems. In Proceedings of the 2018 IEEE 19th Wireless and Microwave Technology Conference (WAMICON), Sand Key, FL, USA, 9–10 April 2018; pp. 1–6.
266. Pappa, M.; Ramesh, C.; Kumar, M.N. Performance comparison of massive MIMO and conventional MIMO using channel parameters. In Proceedings of the 2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, India, 22–24 March 2017; pp. 1808–1812.
267. Garcia, N.; Wymeersch, H.; Larsson, E.G.; Haimovich, A.M.; Coulon, M. Direct localization for massive MIMO. *IEEE Trans. Signal Process.* **2017**, *65*, 2475–2487. [CrossRef]
268. Rithe, J.P.; Khairnar, D.; Sharma, M. Performance of cooperative massive MIMO 5G cellular system. In Proceedings of the 2017 International Conference on Information, Communication, Instrumentation and Control (ICICIC), Indore, India, 17–19 August 2017; pp. 1–5.
269. Kashima, T.; Qiu, J.; Shen, H.; Tang, C.; Tian, T.; Wang, X.; Hou, X.; Jiang, H.; Benjebbour, A.; Saito, Y.; et al. Large scale massive MIMO field trial for 5G mobile communications system. In Proceedings of the 2016 International symposium on antennas and propagation (ISAP), Okinawa, Japan, 24–28 October 2016; pp. 602–603.
270. Dikmen, O.; Kulac, S. A New Method in Pilot Reuse Factor Selection in Spectrum Efficient Massive MIMO Systems. *Elektron. Ir Elektrotechnika* **2019**, *25*, 70–77. [CrossRef]
271. Gao, X.; Edfors, O.; Rusek, F.; Tufvesson, F. Massive MIMO performance evaluation based on measured propagation data. *IEEE Trans. Wirel. Commun.* **2015**, *14*, 3899–3911. [CrossRef]
272. Mahyiddin, W.A.; Martin, P.A.; Smith, P.J. Massive MIMO systems in time-selective channels. *IEEE Commun. Lett.* **2015**, *19*, 1973–1976. [CrossRef]
273. Fang, X.; Fang, S.; Ying, N.; Cao, H.; Liu, C. The performance of massive MIMO systems under correlated channel. In Proceedings of the 2013 19th IEEE international conference on networks (ICON), Singapore, 11–13 December 2013; pp. 1–4.
274. Chataut, R.; Akl, R. Channel Gain Based User Scheduling for 5G Massive MIMO Systems. In Proceedings of the 2019 IEEE 16th International Conference on Smart Cities: Improving Quality of Life Using ICT & IoT and AI (HONET-ICT), Charlotte, NC, USA, 6–9 October 2019; pp. 49–53.
275. Xing, P.; Liu, J.; Zhai, C.; Yu, Z. Self-interference suppression with imperfect channel estimation in a shared-antenna full-duplex massive MU-MIMO system. *EURASIP J. Wirel. Commun. Netw.* **2017**, *2017*, 1–13. [CrossRef]
276. Raza, Z.; Akhtar, Z.; Nawaz, N.; Hussain, G.; Nawaz, S. Single Cell Massive Mimo Downlink System: Energy Efficiency Solution. *Pak. J. Sci.* **2019**, *71*, 78.
277. Ha, T.N.; Nguyen, X.X.; Ha, H.K. Energy Efficiency Maximization for Full Duplex MIMO Cloud Radio Access Networks. *Sci. Technol. Dev. J.-Eng. Technol.* **2020**, *3*, 488–499. [CrossRef]
278. Gong, Z.; Li, C.; Jiang, F. Pilot contamination mitigation strategies in massive MIMO systems. *IET Commun.* **2017**, *11*, 2403–2409. [CrossRef]
279. Demir, Ö.T.; Björnson, E. Joint power control and LSFD for wireless-powered cell-free massive MIMO. *IEEE Trans. Wirel. Commun.* **2020**, *20*, 1756–1769. [CrossRef]
280. Zhao, K.; Zhang, S.; Ho, Z.; Zander, O.; Bolin, T.; Ying, Z.; Pedersen, G.F. Spherical coverage characterization of 5G millimeter wave user equipment with 3GPP specifications. *IEEE Access* **2018**, *7*, 4442–4452. [CrossRef]
281. Kim, H.; Kim, S.; Lee, H.; Jang, C.; Choi, Y.; Choi, J. Massive MIMO channel prediction: Kalman filtering vs. machine learning. *IEEE Trans. Commun.* **2020**, *69*, 518–528. [CrossRef]
282. Xia, N.; Chen, H.H.; Yang, C.S. Radio resource management in machine-to-machine communications—A survey. *IEEE Commun. Surv. Tutor.* **2017**, *20*, 791–828. [CrossRef]
283. Yesilkaya, A.; Basar, E.; Miramirkhani, F.; Panayirci, E.; Uysal, M.; Haas, H. Optical MIMO-OFDM with generalized LED index modulation. *IEEE Trans. Commun.* **2017**, *65*, 3429–3441. [CrossRef]
284. Liu, J.; Lu, H. IMNet: A Learning Based Detector for Index Modulation Aided MIMO-OFDM Systems. In Proceedings of the 2020 IEEE Wireless Communications and Networking Conference (WCNC), Seoul, Korea, 25–28 May 2020; pp. 1–6.
285. He, H.; Wen, C.K.; Jin, S.; Li, G.Y. Model-driven deep learning for MIMO detection. *IEEE Trans. Signal Process.* **2020**, *68*, 1702–1715. [CrossRef]
286. Trestian, R. *5G Radio Access Networks: Centralized RAN, Cloud-RAN, and Virtualization of Small Cells: Centralized RAN, Cloud-RAN and Virtualization of Small Cells*; CRC Press: Boca Raton, FL, USA, 2017.
287. Gomes, R.; Reis, J.; Al-Daher, Z.; Hammoudeh, A.; Caldeirinha, R.F. 5G: Performance and evaluation of FS-FBMC against OFDM for high data rate applications at 60 GHz. *IET Signal Process.* **2018**, *12*, 620–628. [CrossRef]

288. Katzis, K.; Ahmadi, H. Challenges implementing Internet of Things (IoT) using cognitive radio capabilities in 5G mobile networks. In *Internet of Things (IoT) in 5G Mobile Technologies*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 55–76.
289. Li, Y.; Guan, Z.; Luo, H.; Wang, X.; Wang, M.; Li, Y.; Wei, Y.; Ma, Y. Crosstalk and Equivalent Circuit Model of Segmented Coplanar Waveguide Transmission Line at 5G FR2 Band. In Proceedings of the 2021 13th Global Symposium on Millimeter-Waves & Terahertz (GSMM), Nanjing, China, 23–26 May 2021; pp. 1–3.
290. Lien, S.Y.; Shieh, S.L.; Huang, Y.; Su, B.; Hsu, Y.L.; Wei, H.Y. 5G new radio: Waveform, frame structure, multiple access, and initial access. *IEEE Commun. Mag.* **2017**, *55*, 64–71. [CrossRef]
291. Zaidi, A.A.; Baldemair, R.; Molés-Cases, V.; He, N.; Werner, K.; Cedergren, A. OFDM numerology design for 5G new radio to support IoT, eMBB, and MBSFN. *IEEE Commun. Stand. Mag.* **2018**, *2*, 78–83. [CrossRef]
292. Rebola, J.L.; Cartaxo, A.V.; Marques, A.S. 10 Gbps CPRI signals transmission impaired by intercore crosstalk in 5G network fronthauls with multicore fibers. *Photonic Netw. Commun.* **2019**, *37*, 409–420. [CrossRef]
293. Ackermann, T.; Potschka, J.; Maiwald, T.; Hagelauer, A.; Fischer, G.; Weigel, R. A Robust Digital Predistortion Algorithm for 5G MIMO: Modeling a MIMO Scenario With Two Nonlinear MIMO Transmitters Including a Cross-Coupling Effect. *IEEE Microw. Mag.* **2020**, *21*, 54–62. [CrossRef]
294. Ahamed, M.M.; Faruque, S. 5G backhaul: Requirements, challenges, and emerging technologies. In *Broadband Communications Networks: Recent Advances and Lessons from Practice*; BoD–Books on Demand: Norderstedt, Germany, 2018; Volume 43.
295. Peralta, E.; Levanen, T.; Ihalainen, T.; Nielsen, S.; Ng, M.H.; Renfors, M.; Valkama, M. 5G new radio base-station sensitivity and performance. In Proceedings of the 2018 15th International Symposium on Wireless Communication Systems (ISWCS), Lisbon, Portugal, 28–31 August 2018; pp. 1–6.
296. Bashir, A.K.; Arul, R.; Basheer, S.; Raja, G.; Jayaraman, R.; Qureshi, N.M.F. An optimal multitier resource allocation of cloud RAN in 5G using machine learning. *Trans. Emerg. Telecommun. Technol.* **2019**, *30*, e3627. [CrossRef]
297. Zhang, Y.; Xin, J.; Li, X.; Huang, S. Overview on routing and resource allocation based machine learning in optical networks. *Opt. Fiber Technol.* **2020**, *60*, 102355. [CrossRef]
298. Jere, S.; Fan, Q.; Shang, B.; Li, L.; Liu, L. Federated Learning in Mobile Edge Computing: An Edge-Learning Perspective for Beyond 5G. *arXiv* **2020**, arXiv:2007.08030.
299. Nama, M.; Nath, A.; Bechra, N.; Bhatia, J.; Tanwar, S.; Chaturvedi, M.; Sadoun, B. Machine learning-based traffic scheduling techniques for intelligent transportation system: Opportunities and challenges. *Int. J. Commun. Syst.* **2021**, *34*, e4814. [CrossRef]
300. Sengupta, R.; Sengupta, D.; Pandey, D.; Pandey, B.K.; Nassa, V.K.; Dadeech, P. A Systematic Review of 5G Opportunities, Architecture and Challenges. In *Future Trends in 5G and 6G: Challenges, Architecture, and Applications*; CRC Press: Boca Raton, 2021; p. 247.
301. Park, J.H.; Rathore, S.; Singh, S.K.; Salim, M.M.; Azzaoui, A.E.; Kim, T.W.; Pan, Y.; Park, J.H. A Comprehensive Survey on Core Technologies and Services for 5G Security: Taxonomies, Issues, and Solutions. *Hum.-Centric Comput. Inf. Sci.* **2021**, *11*. [CrossRef]
302. Ree, M.d.; Parsamehr, R.; Adat, V.; Mantas, G.; Politis, I.; Rodriguez, J.; Kotsopoulos, S.; Otung, I.E.; Martínez-Ortega, J.F.; Gil-Castiñeira, F. Security for UDNs: A Step Toward 6G. In *Enabling 6G Mobile Networks*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 167–201.
303. Ferrag, M.A.; Maglaras, L.; Argyriou, A.; Kosmanos, D.; Janicke, H. Security for 4G and 5G cellular networks: A survey of existing authentication and privacy-preserving schemes. *J. Netw. Comput. Appl.* **2018**, *101*, 55–82. [CrossRef]
304. Malhi, A.K.; Batra, S.; Pannu, H.S. Security of vehicular ad-hoc networks: A comprehensive survey. *Comput. Secur.* **2020**, *89*, 101664. [CrossRef]
305. Zoli, M.; Barreto, A.N.; Köpsell, S.; Sen, P.; Fettweis, G. Physical-Layer-Security Box: A concept for time-frequency channel-reciprocity key generation. *EURASIP J. Wirel. Commun. Netw.* **2020**, *2020*, 1–24. [CrossRef]
306. Melki, R.; Noura, H.N.; Mansour, M.M.; Chehab, A. An efficient OFDM-based encryption scheme using a dynamic key approach. *IEEE Internet Things J.* **2018**, *6*, 361–378. [CrossRef]
307. Melki, R.; Noura, H.N.; Mansour, M.M.; Chehab, A. A survey on OFDM physical layer security. *Phys. Commun.* **2019**, *32*, 1–30. [CrossRef]
308. Lisi, F.; Losquadro, G.; Tortorelli, A.; Ornatelli, A.; Donsante, M. Multi-Connectivity in 5G terrestrial-Satellite Networks: The 5G-ALLSTAR Solution. *arXiv* **2020**, arXiv:2004.00368.
309. Lee, J.; Han, S.; Lee, J.; Kang, B.; Bae, J.; Jang, J.; Oh, S.; Chang, J.S.; Kang, S.; Son, K.Y.; et al. A sub-6-GHz 5G new radio RF transceiver supporting EN-DC with 3.15-Gb/s DL and 1.27-Gb/s UL in 14-nm FinFET CMOS. *IEEE J. Solid-State Circuits* **2019**, *54*, 3541–3552. [CrossRef]
310. Linning, P.; Li, G.; Zhang, J.; Woods, R.; Liu, M.; Hu, A. An investigation of using loop-back mechanism for channel reciprocity enhancement in secret key generation. *IEEE Trans. Mob. Comput.* **2018**, *18*, 507–519.
311. Vogt, H.; Awan, Z.H.; Sezgin, A. Secret-key generation: Full-duplex versus half-duplex probing. *IEEE Trans. Commun.* **2018**, *67*, 639–652. [CrossRef]
312. Kalbande, D.; Haji, S.; Haji, R. 6G-Next Gen mobile wireless communication approach. In Proceedings of the 2019 3rd international conference on electronics, communication and aerospace technology (ICECA), Coimbatore, India, 12–14 June 2019; pp. 1–6.
313. Mistry, Z.; Kumar Yadav, A.; Kothari, M. A Review on 6th Generation Wireless Communication Networks Based on Artificial Intelligence. In *Innovations in Cyber Physical Systems*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 275–286.

314. Sánchez, J.D.V.; Urquiza-Aguiar, L.; Paredes, M.C.P. Physical layer security for 5G wireless networks: A comprehensive survey. In Proceedings of the 2019 3rd cyber security in networking conference (CSNet), Quito, Ecuador, 23–25 October 2019; pp. 122–129.
315. Ahmad, I.; Kumar, T.; Liyanage, M.; Okwuibe, J.; Ylianttila, M.; Gurtov, A. Overview of 5G security challenges and solutions. *IEEE Commun. Stand. Mag.* **2018**, *2*, 36–43. [CrossRef]
316. Suraci, C.; Araniti, G.; Abrardo, A.; Bianchi, G.; Iera, A. A stakeholder-oriented security analysis in virtualized 5G cellular networks. *Comput. Netw.* **2021**, *184*, 107604. [CrossRef]
317. Köksal, S.; Dalveren, Y.; Maiga, B.; Kara, A. Distributed denial-of-service attack mitigation in network functions virtualization-based 5G networks using management and orchestration. *Int. J. Commun. Syst.* **2021**, *34*, e4825. [CrossRef]
318. Prabakaran, D.; Nizar, S.M.; Kumar, K.S. Software-defined network (SDN) architecture and security considerations for 5G communications. In *Design Methodologies and Tools for 5G Network Development and Application*; IGI Global: Hershey, PA, USA, 2021; pp. 28–43.
319. Khan, H.; Martin, K.M. A survey of subscription privacy on the 5G radio interface-The past, present and future. *J. Inf. Secur. Appl.* **2020**, *53*, 102537. [CrossRef]
320. Zhang, S.; Wang, Y.; Zhou, W. Towards secure 5G networks: A Survey. *Comput. Netw.* **2019**, *162*, 106871. [CrossRef]
321. Prasad, V.K.; Tanwar, S.; Bhavsar, M.D. Advance Cloud Data Analytics for 5G Enabled IoT. In *Blockchain for 5G-Enabled IoT*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 159–180.
322. Zhang, R.; Zhou, W.; Hu, H. Towards 5G Security Analysis against Null Security Algorithms Used in Normal Communication. *Secur. Commun. Netw.* **2021**, *2021*, 4498324. [CrossRef]
323. Wijethilaka, S.; Liyanage, M. Survey on network slicing for Internet of Things realization in 5G networks. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 957–994. [CrossRef]
324. Madi, T.; Alameddine, H.A.; Pourzandi, M.; Boukhtouta, A. NFV security survey in 5G networks: A three-dimensional threat taxonomy. *Comput. Netw.* **2021**, *197*, 108288. [CrossRef]
325. Yurekten, O.; Demirci, M. SDN-based cyber defense: A survey. *Future Gener. Comput. Syst.* **2021**, *115*, 126–149. [CrossRef]
326. Yang, P.; Xiong, N.; Ren, J. Data security and privacy protection for cloud storage: A survey. *IEEE Access* **2020**, *8*, 131723–131740. [CrossRef]
327. Yue, K.; Zhang, Y.; Chen, Y.; Li, Y.; Zhao, L.; Rong, C.; Chen, L. A Survey of Decentralizing Applications via Blockchain: The 5G and Beyond Perspective. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 2191–2217. [CrossRef]
328. Ranaweera, P.; Jurcut, A.; Liyanage, M. Mec-enabled 5g use cases: A survey on security vulnerabilities and countermeasures. *ACM Comput. Surv. (CSUR)* **2021**, *54*, 1–37. [CrossRef]
329. Ubale, T.; Jain, A.K. Survey on DDoS attack techniques and solutions in software-defined network. In *Handbook of Computer Networks and Cyber Security*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 389–419.
330. Sharma, A.; Balasubramanian, V.; Jolfaei, A. Security Challenges and Solutions for 5G HetNet. In Proceedings of the 2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom), Guangzhou, China, 29 December–1 January 2021; pp. 1318–1323.
331. Mahdi, M.N.; Ahmad, A.R.; Qassim, Q.S.; Natiq, H.; Subhi, M.A.; Mahmoud, M. From 5G to 6G Technology: Meets Energy, Internet-of-Things and Machine Learning: A Survey. *Appl. Sci.* **2021**, *11*, 8117. [CrossRef]
332. Arfaoui, M.A.; Soltani, M.D.; Tavakkolnia, I.; Ghrayeb, A.; Safari, M.; Assi, C.M.; Haas, H. Physical layer security for visible light communication systems: A survey. *IEEE Commun. Surv. Tutorials* **2020**, *22*, 1887–1908. [CrossRef]
333. Sánchez, J.D.V.; Urquiza-Aguiar, L.; Paredes, M.C.P.; Osorio, D.P.M. Survey on physical layer security for 5G wireless networks. *Ann. Telecommun.* **2021**, *76*, 155–174. [CrossRef]
334. Ning, B.; Chen, Z.; Tian, Z.; Wang, X.; Pan, C.; Fang, J.; Li, S. Joint Power Allocation and Passive Beamforming Design for IRS-Assisted Physical-Layer Service Integration. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 7286–7301. [CrossRef]
335. Jayakody, D.N.K.; Srinivasan, K.; Sharma, V. *5G Enabled Secure Wireless Networks*; Springer: Berlin/Heidelberg, Germany, 2019.
336. Mei, W.; Chen, Z.; Fang, J.; Li, S. Physical layer service integration in 5G: Potentials and challenges. *IEEE Access* **2018**, *6*, 16563–16575. [CrossRef]
337. Ahmed, M.; Bai, L. Secrecy capacity of artificial noise aided secure communication in MIMO Rician channels. *IEEE Access* **2018**, *6*, 7921–7929. [CrossRef]
338. Rommel, S.; Grivas, E.; Cimoli, B.; Dodane, D.; Morales, A.; Pikasis, E.; Bourderionnet, J.; Feugnet, G.; Carvalho, J.B.; Katsikis, M.; et al. Real-time high-bandwidth mm-wave 5G NR signal transmission with analog radio-over-fiber fronthaul over multi-core fiber. *EURASIP J. Wirel. Commun. Netw.* **2021**, *2021*, 1–20. [CrossRef]
339. Yousefi, F.; Rahbar, A.G. Novel crosstalk, fragmentation-aware algorithms in space division multiplexed-Elastic Optical Networks (SDM-EON) with considering physical layer security. *Opt. Switch. Netw.* **2020**, *37*, 100566. [CrossRef]
340. Brasileiro, Í.; Costa, L.; Drummond, A. A survey on crosstalk and routing, modulation selection, core and spectrum allocation in elastic optical networks. *arXiv* **2019**, arXiv:1907.08538.
341. Cao, Y.; Zhao, Y.; Yu, X.; Ou, Q.; Liu, Z.; Liao, X.; Zhang, J. Mode conversion-based crosstalk-aware routing, spectrum and mode assignment in space-division multiplexing elastic optical networks. In Proceedings of the 2017 16th International Conference on Optical Communications and Networks (ICOCN), Wuzhen, China, 7–10 August 2017; pp. 1–3.
342. Zhu, J.; Zhu, Z. Physical-layer security in MCF-based SDM-EONs: Would crosstalk-aware service provisioning be good enough? *J. Light. Technol.* **2017**, *35*, 4826–4837. [CrossRef]

343. Zhao, Y.; Hu, L.; Zhu, R.; Yu, X.; Wang, X.; Zhang, J. Crosstalk-aware spectrum defragmentation based on spectrum compactness in space division multiplexing enabled elastic optical networks with multicore fiber. *IEEE Access* **2018**, *6*, 15346–15355. [CrossRef]
344. Yang, H.; Zhan, K.; Kadoch, M.; Liang, Y.; Cheriet, M. BLCS: Brain-like distributed control security in cyber physical systems. *IEEE Netw.* **2020**, *34*, 8–15. [CrossRef]
345. Nguyen, V.L.; Lin, P.C.; Cheng, B.C.; Hwang, R.H.; Lin, Y.D. Security and privacy for 6G: A survey on prospective technologies and challenges. *IEEE Commun. Surv. Tutorials* **2021**, *23*, 2384–2428. [CrossRef]
346. Ziegler, V.; Viswanathan, H.; Flinck, H.; Hoffmann, M.; Räisänen, V.; Hätönen, K. 6G architecture to connect the worlds. *IEEE Access* **2020**, *8*, 173508–173520. [CrossRef]
347. Zhang, Z.; Xiao, Y.; Ma, Z.; Xiao, M.; Ding, Z.; Lei, X.; Karagiannidis, G.K.; Fan, P. 6G wireless networks: Vision, requirements, architecture, and key technologies. *IEEE Veh. Technol. Mag.* **2019**, *14*, 28–41. [CrossRef]
348. Kakkar, A. A survey on secure communication techniques for 5G wireless heterogeneous networks. *Inf. Fusion* **2020**, *62*, 89–109. [CrossRef]
349. Suomalainen, J.; Juhola, A.; Shahabuddin, S.; Mämmelä, A.; Ahmad, I. Machine learning threatens 5G security. *IEEE Access* **2020**, *8*, 190822–190842. [CrossRef]
350. Haider, N.; Baig, M.Z.; Imran, M. Artificial Intelligence and Machine Learning in 5G Network Security: Opportunities, advantages, and future research trends. *arXiv* **2020**, arXiv:2007.04490.
351. Dogra, A.; Jha, R.K.; Jain, S. A survey on beyond 5G network with the advent of 6G: Architecture and emerging technologies. *IEEE Access* **2020**, *9*, 67512–67547. [CrossRef]
352. Jiang, W.; Han, B.; Habibi, M.A.; Schotten, H.D. The road towards 6G: A comprehensive survey. *IEEE Open J. Commun. Soc.* **2021**, *2*, 334–366. [CrossRef]
353. Yrjola, S. Technology antecedents of the platform-based ecosystemic business models beyond 5G. In Proceedings of the 2020 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), Seoul, Korea, 6–9 April 2020; pp. 1–8.
354. Boulogeorgos, A.A.A.; Alexiou, A.; Merkle, T.; Schubert, C.; Elschner, R.; Katsiotis, A.; Stavrianos, P.; Kritharidis, D.; Chartsias, P.K.; Kokkoniemi, J.; et al. Terahertz technologies to deliver optical network quality of experience in wireless systems beyond 5G. *IEEE Commun. Mag.* **2018**, *56*, 144–151. [CrossRef]
355. Basu, D.; Datta, R.; Ghosh, U. Softwarized Network Function Virtualization for 5G: Challenges and Opportunities. In *Internet of Things and Secure Smart Environments*; Chapman and Hall/CRC: Boca Raton, 2020; pp. 147–192.
356. Santos, J.F.; Liu, W.; Jiao, X.; Neto, N.V.; Pollin, S.; Marquez-Barja, J.M.; Moerman, I.; DaSilva, L.A. Breaking Down Network Slicing: Hierarchical Orchestration of End-to-End Networks. *IEEE Commun. Mag.* **2020**, *58*, 16–22. [CrossRef]
357. Nguyen, V.L.; Lin, P.C.; Hwang, R.H. Enhancing misbehavior detection in 5G vehicle-to-vehicle communications. *IEEE Trans. Veh. Technol.* **2020**, *69*, 9417–9430. [CrossRef]
358. Jain, A.; Lopez-Aguilera, E.; Demirkol, I. Are mobility management solutions ready for 5G and beyond? *Comput. Commun.* **2020**, *161*, 50–75. [CrossRef]
359. Alotaibi, D. Survey on Network Slice Isolation in 5G Networks: Fundamental Challenges. *Procedia Comput. Sci.* **2021**, *182*, 38–45. [CrossRef]
360. Ziani, A.; Medouri, A. A Survey of Security and Privacy for 5G Networks. In *Emerging Trends in ICT for Sustainable Development*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 201–208.
361. Kakkavas, G.; Stamou, A.; Karyotis, V.; Papavassiliou, S. Network Tomography for Efficient Monitoring in SDN-Enabled 5G Networks and Beyond: Challenges and Opportunities. *IEEE Commun. Mag.* **2021**, *59*, 70–76. [CrossRef]
362. Yuan, G. Key Technologies and Analysis of Computer-based 5G Mobile Communication Network. In *Journal of Physics: Conference Series*; IOP Publishing: Bristol, UK, 2021; Volume 1992, p. 042001.
363. Zhang, Y.; Kishk, M.A.; Alouini, M.S. A survey on integrated access and backhaul networks. *arXiv* **2021**, arXiv:2101.01286.
364. Döhler, A. Report from the Next Generation Mobile Networks Alliance. *IEEE Netw.* **2021**, *35*, 3. [CrossRef]