From 5G to 6G

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As the deployment of 5G mobile radio networks gains momentum across the globe, the wireless research community is already planning the successor of 5G.

Keywords: 3GPP ; 6G ; artificial intelligence ; beyond 5G ; edge computing ; next-gen ; THz

1. Introduction

The world's global communication network has come a long way since the second-generation (2G) mobile radio network systems were deployed in the early 1990s. The second-generation network, undoubtedly, has been internationally recognized as the start of a new era in digital communications. The aforesaid comes as no surprise based on the exploding rate of communication between users in the form of SMS texts and phone calls towards the end of the last century [1]. The world at that time experienced a paradigm shift on all levels, from individual users to large corporations, which created room for new business models. Since then, the focus has been concentrated on offering faster communication speeds and supporting more users. To alleviate the connectivity issues that occur when many users try to access the network at the same time and to offer a better experience, third-generation (3G) systems were introduced in the early 2000s with new innovations, the most notable being the Universal Mobile Telecommunications System (UMTS), which has wideband code division multiple access at its essence [2]. However, 3G was short-lived for a variety of reasons. Many analysts suggested that 3G faced regulatory and technical issues, leading to many operators phasing it out of their networks. Conversely, the global, widespread media praise of 3G's successor, i.e., 4G, introduced around 2010, demonstrated that it was so far the most successful generation since 2G. The fourth-generation network is based on orthogonal frequency division multiplexing (OFDM) and multiple-input, multiple-output (MIMO) systems [3], offering theoretical speeds of 1 Gb/s and beyond, which until very recently was considered sufficient for almost all existing network services and applications. **Figure 1** provides an overview of the timeline of the development of wireless networks.

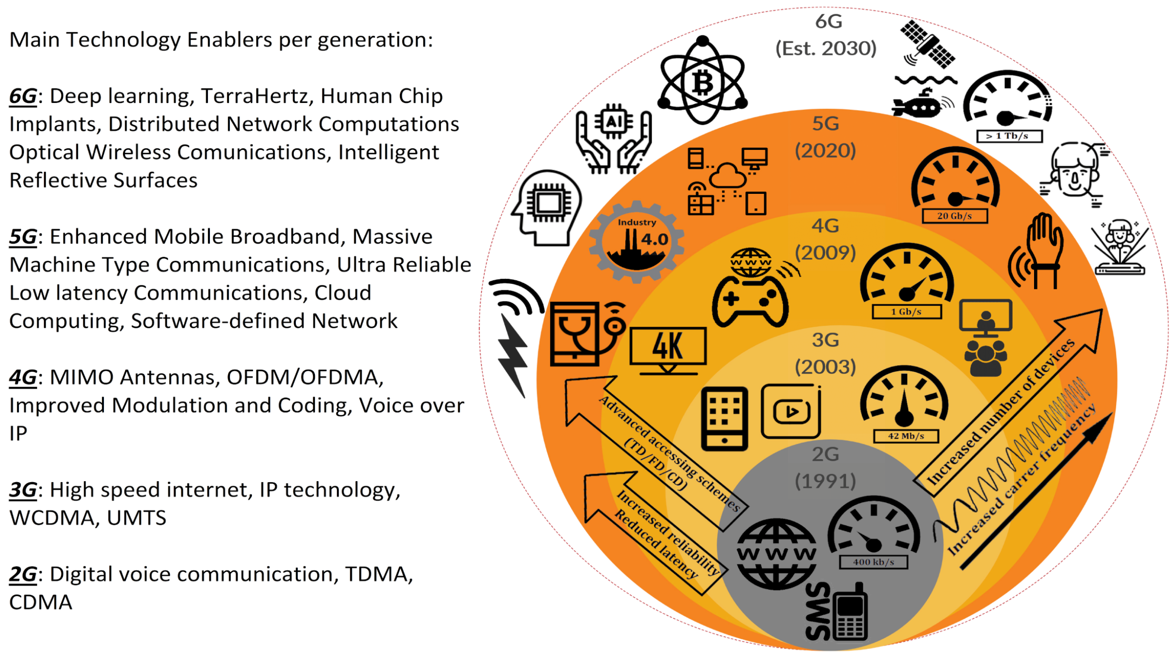

Figure 1. A brief overview of the history of wireless communication networks (TD: time division, FD: frequency division, CD: code division).

Currently, many emerging services and network needs require speeds and network infrastructures well beyond the capabilities of 4G. The recently inaugurated 5G system is often presented as an integrated system that fills the gap between 4G and the current network demands, such as ultra-high communication speeds and very-low-link latency [4]. Nonetheless, a new research direction has recently commenced, investigating alternatives to 5G and looking beyond it. The drivers for this new direction are explored in depth in the next section. In essence, 5G is expected to be inadequate for the future network requirements. Furthermore, some challenges remain unresolved or overlooked in current 5G standards, such as dealing with signal propagation loss, which will inevitably increase with the use of higher frequencies (beyond 20 GHz), or maintaining efficient network management under increasingly complicated networks [5][6].

2. Fifth-Generation Network's Shortcomings

This section looks at how well 5G is expected to perform as it is being rolled out in more and more global markets recently. It is appropriate first to examine the key technologies of 5G that are quickly becoming outdated. Network densification is a key player in 5G through the very wide deployment of small cells. However, the benefits of this deployment, i.e., enhanced coverage and higher data transfer rates, represent diminishing returns as more and more small cells are deployed due to the significant increase in infrastructure cost. Another technology is carrier aggregation, which allows users to be served by more than a single-component carrier to offer a higher bandwidth [7]. However, this has implications for hardware on the end users' side to support different frequency bands. It is worth looking at the cloud radio access network (C-RAN) as being a primary component of 5G to mitigate the hardware limitations of end devices. However, as networks grow exponentially in size, it becomes evident that the cloud alone is not enough, and fog and edge node computations are needed. Moreover, security in the main 5G technologies is not advanced enough to be deployed on very large scales, such as in software-defined networks (SDNs), where it lacks the mechanisms to verify trust between the management apps and the controller. Another example is network function virtualization (NFV), where attackers can target software-level components, such as the virtual infrastructure manager, and generate fake logs that hinder the operation of NFV [8]. Furthermore, 5G offers ultra-reliable and low-latency communication (URLLC) as one of its key drivers. However, it is limited to the edge of the network without real integration across the entire network (including the core) [9]. Moreover, the concept of heterogeneous networks (HetNets) is at the core of 5G technologies, but currently, such network integration is limited to terrestrial networks. This has to be further expanded to be three-dimensional by including aerial and space mesh networks in the main network. It is also important to note that 5G is not immune to denial of service (DoS) attacks or threats that compromise its availability [10]. It is crucial that this be improved in future networks to adjust for the size of ever-growing networks of billions of nodes.

2.1. A. Communication Speed and Scalability

It is projected that by 2030, global mobile traffic will be 670-times what it was in 2010, mainly due to machine-to-machine (M2M) communications [11]. This is an unprecedented exponential growth that motivates researchers worldwide to achieve technological breakthroughs in many network aspects, especially in spectral and energy efficiency techniques. The fifth-generation network is portrayed to bring to the network enhanced mobile broadband (eMBB), i.e., offer speeds up to 20 Gbps [12], and massive machine-type communication (mMTC) support, as shown in **Figure 2**. However, this will not be able to keep up with the near future demands, as it is expected by 2030 that 5G will reach it is limits [13]. The demand-driven nature of communication speeds dictates that in less that 10 years from now, the data transfer rates will have to experience substantial improvements to be well beyond 1 Tbps (up to 10 Tbps) [14]. Thus, looking beyond 5G incorporates researching techniques that can offer such speeds. Moreover, 5G is designed to utilize the millimeter wave range of 20–100 GHz [15]. However, it is not possible in this range to achieve such high speeds due to current transceiver designs and digital modulation techniques' limitations, such as non-linear power amplifiers, phase noise, and poor analog-to-digital converter (ADC) resolution [16]. Consequently, the next leap in communication will consider looking at frequencies beyond 100 GHz, possibly up to a few THz [17], as this spectrum is available in abundance to achieve high data rates. It was shown in a comparison [18] that beyond 100 Gbps speeds can be achieved in the 300 GHz range compared to 4 Gbps in the 60 GHz range.

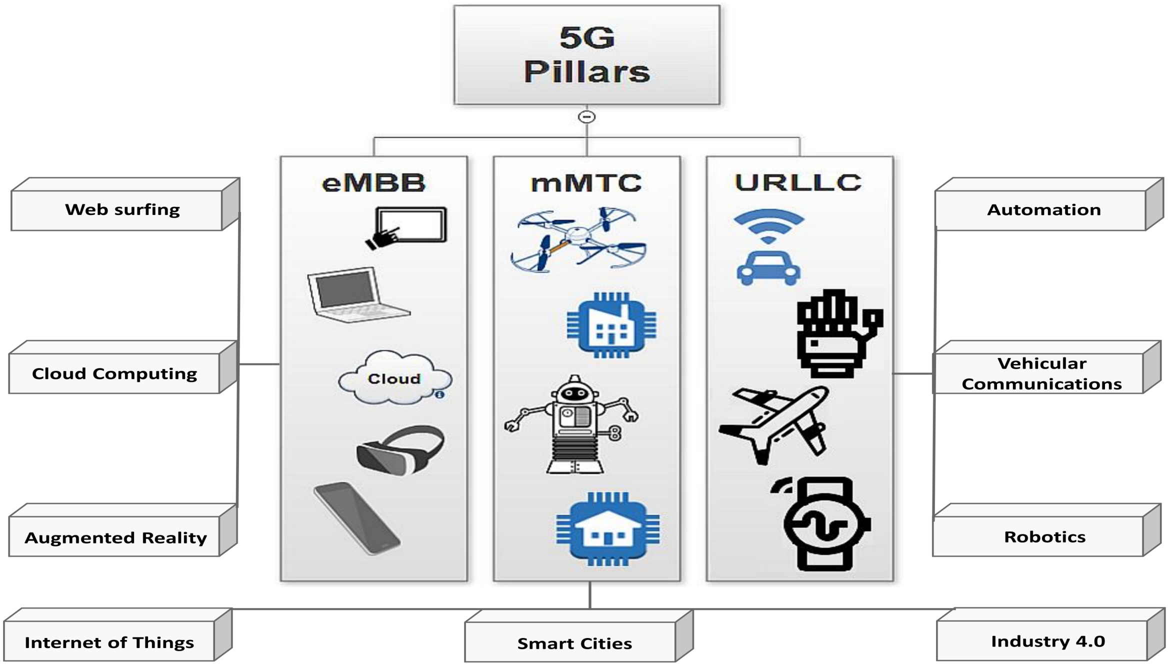

Figure 2. The fifth-generation network's pillars with examples of each of them.

The extremely high data rates are justified by the kind of services that are emerging or expected to be widely adopted in the near future. Services such as *augmented reality* (AR), human nano-chip implants, connected robotics, autonomous systems, and tele-medicine [19] are currently being under development and enhancement to be deployed on a wide scale in the near future. Additionally, with the envisioned growth in M2M communications, it is expected that there will be hundreds of billions of devices connected to the Internet [20]. However, 5G is expected to offer the best performance tradeoffs only up to the scale of a billion devices [21]. Therefore, the next major mobile network upgrade will be scaled to accommodate such a huge number of device connections and a more-than-ever condensed network.

2.2. B. Link Latency

Currently, many real-time services have emerged to be an integrated part of the network for many years to come. The services can range from helping in the creation of smart cities, such as autonomous vehicles and factories, to identifying new ways to interact with the environment, such as *virtual reality* (VR) and exoskeletons or prosthetic limbs [22]. Most real-time services are time sensitive and have stringent latency requirements (10 ms and below) in order to ensure an effective operation mode. Moreover, some technology-related factors can cause latency degradation, such as the length of the cyclic prefix (CP) in OFDM systems or using dedicated channels for machine communications, which require constant dynamic scheduling due to their sporadic nature of transmission [23].

In the latest industrial revolution, *Industry 4.0*, many applications require simultaneous support for URLLC (**Figure 2**) to achieve fully autonomous operation without human supervision or intervention. This has been considered in the latest release of the 5G standards; however, this support is limited for basic motion control at 1 ms latency at best [24]. In many applications, such as aircraft or vehicle control and intra-vehicle communication for suspension and engine control, the required latency is sub-ms (0.1–1 ms) [25].

Many of the previous applications have multiple rigorous requirements simultaneously for optimal operation. An example of this can be found in autonomous systems, where simultaneous support for super-URLLC is needed combined with high data rates for some scenarios. For instance, this can be translated to latencies down to a 250 μs (some papers even suggest 100 μs) round-trip time combined with a link reliability of 10−9 at 10 Gbps for applications such as operating factories using virtual presence [26][27]. This requires 10-fold and 50-fold improvements in latency and reliability, respectively, over current 5G standards [25]. Furthermore, 5G promises to offer low latency for short packets only. Customizing the data rate, latency, and link reliability for the different applications is not fully considered in 5G and has not yet been achieved efficiently. Thus, it is debatable if 5G holds the full prerequisites to construct smart cities with the support of the different machine communication requirements [19]. This leaves room for improvements in the next generation, such as securing better random access (RA) methods for machine communications, efficiently managing the more sophisticated industrial control schemes, and achieving sub-ms link latency.

2.3. C. Link Reliability

It is equally important to talk about the connection's reliability, which is usually measured by the bit error rate (BER) or by the frame error rate. Many mission-critical applications are in need of ultra-reliable connections to ensure low incident rates in places such as factory automation, vehicle-to-everything (V2X) communication, or railway system control. Specifically, for *Industry 4.0*, it is stated that some applications can require a link reliability of up to 10^{-9} in terms of the frame error rate; however, 5G only promises to support up to 10^{-5} [28]. Thus, to fully implement the concept of smart cities and fully dependable machine operations, such as remote surgery, the connection's reliability has to be improved by several orders of magnitude. Offering higher reliability at different levels in B5G systems will be needed for efficient resource allocation. Synonymous with link reliability, link availability in 5G networks is expected to be five-nines or 99.999% of the time; however, in a given factory setup, control and automation will require service availability to be six-nines or 99.9999% [29]. Moreover, some works went to the extreme by indicating that 6G networks will require service availability to be seven-nines or 99.99999% [19].

3. Sixth-Generation Network's Aspects

The future generation of wireless systems, i.e., 6G, is anticipated to possess multiple new specifications, requirements, and potential uses. The researchers looked at 6G from multiple angles based on the following hierarchy: the highest level includes a general discussion of the aspects of communications, from the social, technical, and economic points of view. The medium level presents the main points about the network requirements, such as services, technologies, and research problems. Lastly, the researcherstake a look at the network's technical operational improvements, such as modified radio frame structures and altered RA methods, at the lowest level of the approach. This approach the researchers took to describe 6G is further clarified in **Figure 3**.

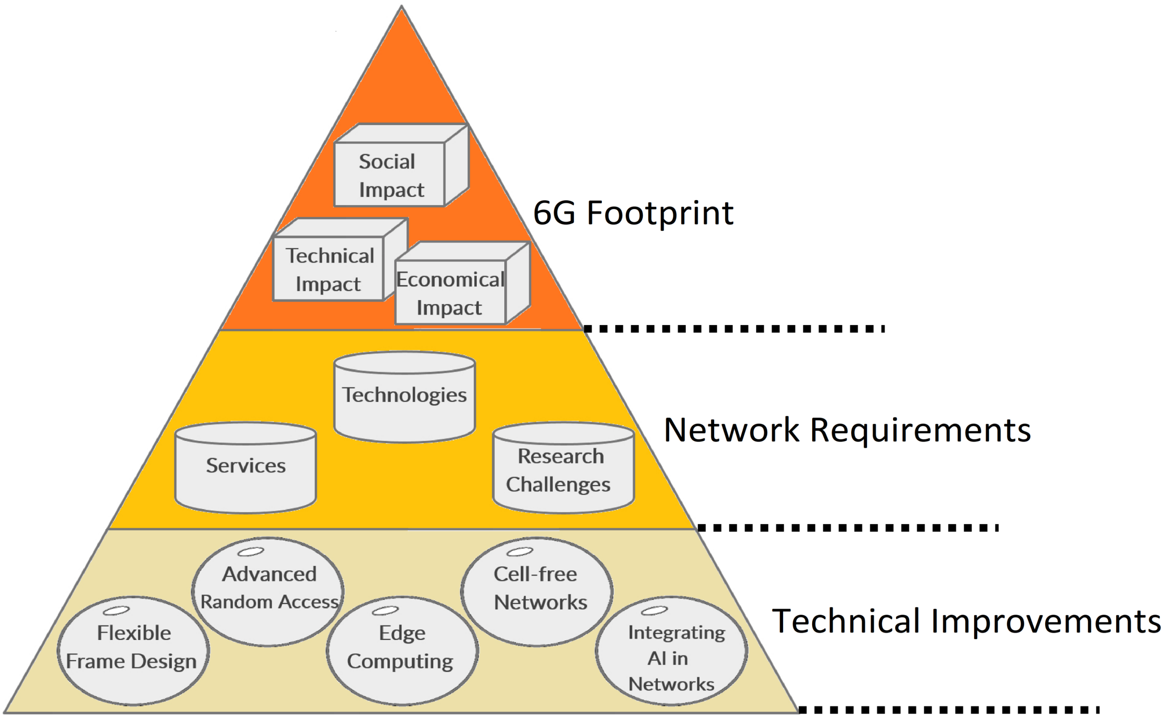

Figure 3. A hierarchical approach for the discussion of 6G's aspects.

3.1. Sixth-Generation Network's Footprint

3.1.1. Social Impact

Currently, there are multiple subjects receiving little attention when it comes to communication networks. Some of these topics include: users' personal data accessing rights, operators' subscription plans, and social awareness about sharing data between users on the community and individual level. These points hold important social value as they can heavily influence the public's opinion about sensitive topics. One famous example of such an issue was the case of *Cambridge Analytica*, the infamous British political consulting firm, which was able to access users' data through the Facebook Open API and link them to other available data, such as other social media platforms and online purchases, to collect over 5000 data points on 230 million U.S. citizens [30]. The data were claimed to have been used to impact the U.S.'s presidential race. Another example is with respect to the conventional spectrum allocation scheme, where regulators auction off the license to use certain frequency bands to the highest payer. This has negative consequences such as hiking up the data plan and telecommunication service prices for the end users, as well as the device costs. Therefore, it is important to propose novel spectrum regulation policies and reconsider the available data accessing options. Furthermore, as reported in the Digital 2020 July Global Statshot Report [31], 4.57 billion people are connected to the Internet; this is only a little over half the planet's population. This raises another challenge for 6G networks, i.e., bringing the world together and focusing on installing network infrastructure in third-world countries that have the least Internet access. This became clearer than ever before in 2020, as COVID-19 forced the entire world to almost operate entirely digitally. More importantly, the expansion of the Internet should consider the living inequalities among people worldwide by offering substantially less-expensive Internet access options to realize the aspiration of considering connectivity as a basic human right. This is achievable by offering near-free data plans and popularizing device leasing options. Due to the global language and cultural barriers, the emerging Internet services should consider the differences between people and work to integrate them under one umbrella. In other words, the offered network services should be tweaked to suit the demographics of the geographical area in which they are being provided. One famous example of this can be found with Google Maps, where disputed territories are displayed as belonging to different countries based on the geographical location of the map viewer.

3.1.2. Technical Impact

The future of the digital world looks brighter than ever, thanks to the technical advancements that have increased exponentially over the last 30 years and are not showing any signs of slowing down. The sixth-generation network is expected to offer the most sophisticated technologies up to date. The researchers highlight the most prominent emerging technologies in the subsequent parts of the entry. However, the researchers demonstrate here a few examples of fundamental changes in the digital world. The introduction of the first binary-based computer in 1938 [32] started a line of technology that continues to this day with integrated circuits (ICs) able to perform billions of tasks in less than a second. In the near future, a new concept of computer computations will emerge, i.e., the Q-bit, based on quantum mechanics. In very simple terms, this concept suggests looking into the electron's state in wires to determine the encoded data by the transmitter [33]. This type of computation is expected to revolutionize the digital world and open the door to achieving unprecedented performance metrics, which can enable new services on the network. Another example worth looking at is integrating AI into the global network. AI is changing how end devices perceive communication networks by introducing many concepts, such as network self-sustainability/management and autonomous systems in factories, vehicles, and many other setups. AI is expected to be at the heart of many 6G services and technologies, which are expected to be so advanced that humans will not have to intervene with the work of the network at all. AI, at the highest levels, will be able to analyze human sentiments for various purposes, such as better selection of online content and advertisements to be delivered to the individual users based on their facial feedback [34] and offer a better user experience during human–bot chats, which are becoming more common. Similar to the impact of AI on future networks, VR is the cornerstone of many current and future network services that is foreseen to change in principle how humans perceive their surroundings and interact with each other. For instance, VR has been used in medical staff training and treatment of patients remotely during the COVID-19 pandemic, such as by performing VR-based physical or cognitive rehabilitation and telehealth services [35][36].

3.1.3. Economic and Environmental Impact

The economic and environmental impact of communication systems is usually overlooked, especially the toxic waste from electronics. Batteries for instance contain hazardous chemicals that are not eco-friendly if left in nature to decompose. Thus, one of the expected innovations with the arrival of 6G is a wider adoption of energy harvesting via radio waves or laser beams to realize battery-free devices [12]. Moreover, the exponential increase of devices connected to the Internet is partially responsible for the annual electronic waste increase. For instance, it has been reported that the yearly global amount of electronic waste reached a record high of 65.4 million tons in 2017, rising from 14 and 42 million, in 2005 and 2014, respectively [37][38][39]. To give some perspective on these figures, the amount of electronic waste generated in the year 2017 was roughly 11-times heavier than the Great Pyramid of Giza [40] or enough to stack a pile that can reach the Moon and back seven times. These numbers are constantly increasing, which is an alarming indicator for the health of the environment, especially as handheld devices and laptops contain toxic materials such as mercury, arsenic, and chromium [39]. Therefore, it is important to emphasize electronics' recycling in the international communication standards of 6G, improve the efficiency and performance of the disposal process, and spread awareness among consumers to participate in the recycling process. A possible direction for reducing electronic waste is fabricating chips using green biological materials, such as microbes [41], allowing for the recycling process to take place with less-toxic materials. Another potential benefit of considering green biological materials could be the reduction of energy consumption during the fabrication process.

Moreover, with the trend of using higher and higher carrier frequencies, little attention is being paid with respect to the health implications. This was demonstrated in [42], where millimeter waves were said to produce heat as a side effect of radiation, resulting in thermal hazards to the human body, such as eye and skin damage. Moving from the millimeter waves' range to the near−THz range (100–900 GHz) raises even more questions about health concerns and the safe limits of radiation exposure. For example, the work in [43] examined in depth the health implications of terahertz frequencies on human tissues and cells and tried to answer the question about the safe limits of exposure to terahertz frequencies. Another example was given in [44], where the researchers studied the effect of high-intensity terahertz radiation on human skin fibroblasts and its long-term effects. Moreover, the work in [45] characterized the effects of terahertz irradiation on human morphology and macromolecules and conducted experiments with different terahertz sources of varying intensities. The work in [46] provided a comprehensive survey of the relationship between terahertz radiation and the effects on human skin and the potential use of terahertz radiation as a therapeutic tool in skin tissue. More research should be invested in this area to create acceptable standards and rigorous regulations for communication device manufacturers. The health implications do not stop here: although the advancement in network connectivity has come a long way in bringing individuals closer than ever before, this has also left many feeling isolated and depressed [47]. The sixth-generation network promises extended immersion experiences by new means such as nano-chip implants, and this calls for the need for thorough research to analyze the severity of the resulting social disorders.

The communication range of terahertz frequencies should also be discussed, as the use of extremely high frequencies leads to low coverage [48]. This has the implication of limiting the use of terahertz frequencies to indoor communications only. Furthermore, terahertz frequencies are vulnerable to blockages from small-sized objects, such as home furniture or moving humans [49], which further reduces their applicability and usage. However, this is not the case for all terahertz frequencies; for example, the work in [50] demonstrated that the spectral windows at 1.0 THz, 4.5 THz, and 9.1 THz are able to minimize this effect and enhance the coverage, especially when terahertz frequencies are combined with ultra-dense base stations, beamforming antennas with a small beamwidth, and a low density of omnidirectional nanosensors.

3.2. Network Requirements

It should be noted that a few of the mentioned network requirements below are simultaneously under the scope of research on 5G and beyond 5G, such as network slicing [51] and edge computing [52]. However, research on these network features is still in its primitive state, and there is much work to do. Consequently, it is highly likely that proper, efficient, and wide-scale network utilization of these network features will only be available by the time beyond 5G networks are in use.

3.2.1. Services

It is envisioned that many services will emerge in the near future to meet the demands of the 21st Century. The researchers mention here a few of the most famous services on the rise. *Mixed reality* (XR) is foreseen to be a new way of interacting with the environment around us. Both of its forms, AR and VR, are very promising for many applications such as filtering the view ahead of the driver with warning signs and important instructions to help while driving. Another application of XR is to provide new ways of controlling our surrounding environments such as smart houses and work offices. *Holographic communication* is expected to reinforce the immersive experience and offer new ways of interaction with the environment. For instance, *holographic communication* can be used to add more authenticity to a conversation between humans, and this is manifested in scenarios related to telepresence or translating spoken words into descriptive virtual objects [53]. Collectively, XR and *holographic communication* are anticipated to have a powerful impact on the future of education, and this is exemplified by establishing educational institutions that are entirely based on virtual real-time remote learning. In **Figure 4**, the researchers display some of the 6G system's applications.

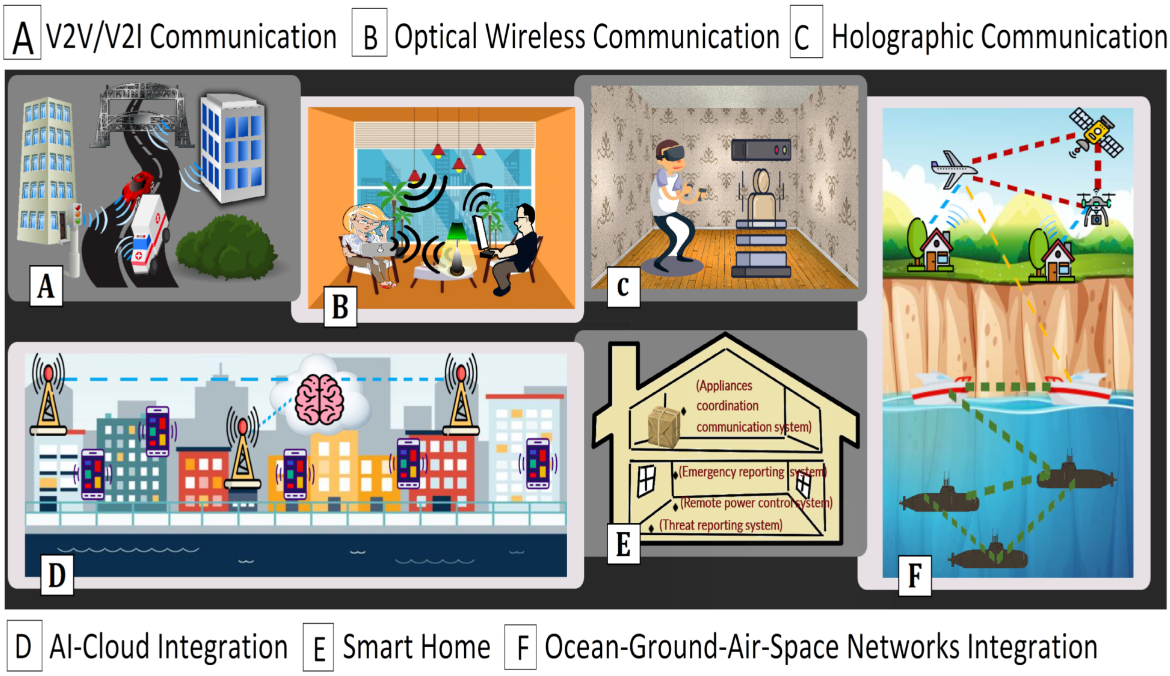

Figure 4. Some of the 6G system's applications.

Another technology worth looking at is human chip implants. It is projected that micro-chips will enable a whole new class of immersive experiences such as remote healthcare and monitoring and sharing human sensory data to allow for more personalized network experiences. Moreover, autonomous robots and systems are expected to play a huge role in the near future, some of which involve building smart cities, which will be tightly related to factory automation and self-sustaining networks. One of the challenges that is expected to be faced in the near future for communication between brain implants and the global Internet is establishing secure communication channels against eavesdropping and hacker attacks [54]. All of these services are expected to be deployed on a large scale, therefore under massive network deployments, such as 3D heterogeneous networks, multi-tier base stations, and *cyber–physical systems* (CPS), and there will be the need for high-precision communication to offer seamless and integrated connectivity.

3.2.2. Technologies

New, unprecedented, high data rates, low latencies, and high reliability metrics are expected to be achieved to enable many of the previously stated services. It is anticipated that optical wireless communication (OWC) will be a key component of 6G networks. OWC is projected to offer extremely high data rates at short ranges in indoor environments due to the massive availability of the unlicensed spectrum. Furthermore, OWC has a few benefits over regular RF communication, such as zero electromagnetic interference and a high frequency-reuse factor, due to the confinement of light within a room or a closed space [28]. Stepping beyond the millimeter waves' range to a new smaller wavelength range is also expected to unlock a new tier of data rates crossing the 1 Tbps mark, namely the *terahertz*-frequency range, as described earlier in the entry. However, this is expected to come at a price. Mainly, atmospheric absorption increases at higher frequencies due to the shorter wavelengths of the transmitted signals [17]. This raises concerns about how wireless channels should be modeled for tasks such as synchronization and channel estimation, especially when the atmospheric conditions are unstable and variable. Moreover, by looking at extreme link reliability as a key 6G requirement, OWC use will be limited to indoor environments due to its vulnerability in outdoor scenarios, especially in dynamic scenarios. Additionally, the use of extremely high frequencies and massive MIMO constellations complicates the beam management task, which is essential for many network operations, such as mobile user handover, not to mention the difficulty of designing transceivers able to operate at very high frequencies up to a few THz to offer ultra-high data rates, which are required at the network backbone to process the massive amounts of data generated by the end devices [55].

Another key technology that is expected to be deeply integrated into 6G systems is *intelligent reflective surfaces* (IRSs). The incentive behind using IRSs is that the wireless channel is de facto the least-controllable part in a given network; thus, it is a priority in next-gen systems to find a means of enhancing the overall performance of wireless systems by working on the channel part. The researchers can look at IRSs as passive signal-scattering elements that are installed between the communicating nodes in a network. There exist variants of this technology such as the ones that are software-defined and coupled with AI to conform with the network requirements, as well as the active surfaces that consume power and perform signal reflections based on a pre-determined angle to enhance the overall received signal strength. IRSs possess multiple benefits for different use scenarios; for instance, they can be considered as a complimentary element for ultra-massive MIMO. Moreover, IRSs can be installed in walls to create smart indoor radio propagation environments that perform frequency-selective signal energy penetration insulation [56] or implement passive beamforming, which can significantly enhance the efficiency of wireless power transfer [57]. However, there are multiple points that need to be addressed under IRSs' implementation such as accurate channel estimation for interference cancellation and alignment with the line-of-sight (LoS) path for optimal system performance. Moreover, how very large numbers of IRSs can work together, especially in heterogeneous and highly dynamic networks such as smart manufacturing plants and V2V/V2X networks, needs to be investigated. This also opens the front for research on the optimal number of IRSs to deploy in each scenario in beyond 5G or 6G networks.

Smart cities and self-sustaining networks are closely related to AI; therefore, AI has to undergo heavy developments and enhancements for 6G networks [14]. In particular, the network resources are limited; thus, it is vital to integrate AI within the network to boost the performance while maintaining high network efficiency and capacity levels. This means much of the future network is going to be underpinned by AI and deep learning (DL) algorithms to bring balance and stability among all network nodes. In other words, AI will be integrated in the underlying fabric of networks and will act as an anchor for designing, deploying, and optimizing networks. For instance, the chip manufacturer, Nvidia, very recently announced a cloud-AI video streaming platform called Maxine [58] to reduce the bandwidth needed for video calls to one-tenth without any reduction in quality. Moreover, Nvidia's latest graphical processing unit (GPU) lineup, the 3000 series, features enhanced AI for constructing a higher number of frames per second with enhanced details for video games, and this will directly enhance the virtual reality experience, which will be featured heavily in 6G. Another significant use for AI in networks can be found in integrating convolutional neural networks for autonomous modulation classification [59]. This gains its importance from the varying end user requirements and applications while maintaining a high spectrum efficiency. However, there are a few challenges to address such as implementing secure distributed AI models with reasonable network complexity for autonomous systems. Network complexity will keep increasing exponentially with time, and this is arguably the result of many activities such as network densification, multi-tier heterogeneous base stations' deployment, AI integration, and softwarization. One way to deal with high network complexity, especially in smart facilities such as smart factories [60], is by apportioning a section of the network to Internet of Things (IoT) devices' communication for coordination, self-organization, and optimization of their operational methods in, for example, conveyor systems.

The researchers are also interested here in examining a number of DL techniques, as they will be the power house for a magnitude of services in 6G networks. Two of the main candidates are supervised DL based on deep neural networks and deep reinforcement learning (DRL), which can combine theoretical models and real-world data on latency and reliability to fulfill the stringent network requirements. In detail, they can approximate the optimal resource allocation policy and predict traffic and mobility using state–decision pairs acquired from optimization algorithms or recorded data [61]. Additionally, beam selection is an important measure when operating under high frequencies, such as the ones required by 6G networks. Thus, deep neural networks can also be used for beam selection with the incorporation of the power delay profile of the channel into the model [62]. Another pivotal DL technique in 6G networks can be pinpointed, which is the deep Q-network based on reinforcement learning (RL). It can be used to optimize multi-layer radio resources in challenging scenarios, such as unmanned aerial vehicles' (UAVs) deployment [63]. The discussion can be expanded further to include the long short-term memory DL method, which can be utilized in integrated networks (refer to F in **Figure 4**). This method can be used in predicting energy harvesting in the network. The importance of this stems from energy harvesting's role in reducing the economic and environmental footprint of 6G communication systems, as discussed earlier [64]. The researchers list a summary of potential promising DL techniques to be used in 6G networks in **Table 1**.

Another concept on the rise as a promising key technology in 6G is hybrid networking. Hybrid layering refers to de-constructing the structure of the conventional network communication protocols and layers to be more modular and versatile based on the service the network needs to provide [65]. For example, the work in [66] proposed dividing the physical layer and creating new logical layers to enhance the user experience in massive multi-player online gaming sessions by enhancing the connection between the server and the client. The work in [67] proposed creating new hybrid protocols based on combining the long-range (LoRa) and IEEE 802.11s protocols for the purpose of enhancing data exchange in UAV groups.

It is also worth discussing an interesting new technology that is expected to play a main role in 6G networks, i.e., digital twins [68]. These work by creating an identical version of a physical system with all the real-life constraints, parameters, variables, objects, conditions, etc., in such a way that the digital version behaves identically to the physical version. This concept can be applied in multiple scenarios, such as healthcare systems, manufacturing plants, and smart cities. Through digital twins, the researchers will be able to enhance the user experience by gathering all the possible data of a system that otherwise would be extremely difficult or impossible to collect in real life, as well as allow upgrading physical systems with minimal cost and the greatest efficiency by first implementing the upgrade on the digital twin. The researchers will also be able to create a digital biological version of all humans on Earth for Metaverse application [69].

Table 1. An overview of promising deep learning methods in 6G networks.

DL Method	Potential Use
MD-IMA [70]	Focuses on designing an intelligent situation-aware resource allocation technique for multi-dimensional intelligent multiple access (MD-IMA). The deep learning (DL) framework is based on long short-term memory (LSTM) and deep reinforcement learning (DRL).
AOW-DQN [71]	Building a machine learning (ML)-based architecture for the 6G Industrial Internet of Things (IoT) and improved learning efficiency by modifying the observation window size to respond to the industrial environment's dynamics via an novel adaptive observation window for deep Q-network.
Micro-Safe [72]	Maintaining customized safety services to the end users in 6G intelligent transportation systems to minimize the rate of accidents via developing algorithms based on a deep neural network (DNN) that would enhance the accuracy of the decisions to be presented to the end users.
DDPG [73]	In the 6G RAN, a slicing control strategy is performed though the DRL framework based on the twin-timescale Markov decision. The developed algorithm is based on the convergence of the double deep-Q-network (Double-DQN) and the deep deterministic policy gradient (DDPG).
FAT-DL [74]	Developed for massive device detection in 6G networks by using a feature-aided adaptive-tuning deep learning (FAT-DL) network. It is based on a layer-by-layer training design that uses the trained data to decide the distribution parameters of the devices in the network.
DL [75]	Developed for connected autonomous vehicles in 6G networks, DL combined with stochastic network calculus is used to train on the data for the fast calculation of the delay limits in real-time operations, which helps in cooperative driving.
DRLR [76]	In 6G IoT networks, unmanned aerial vehicles (UAVs) can be used to collect data from sensors. UAV route planning algorithms can be developed using the DRL recruitment (DRLR) scheme. The data collection process is improved by reducing the cost and enhancing the coverage area.
IScaler [77]	In 6G Internet of Everything (IoE) systems, IScaler, a technique based on DRL, is utilized for resource scaling and service placement, especially for mobile edge computing. It offers improved scaling and placement decisions and overcomes the dynamic environment challenges.
DRL [78]	In 6G optical wireless communication (OWC) systems, the handover problem can be resolved efficiently using a DRL-based framework for smooth and uninterrupted access point switching for end users. DRL utilizes the Q-target and the Q-evaluation to train and update the neutral network.
H-DAC-RL [79]	In massive 6G space–terrestrial integrated IoT systems, network control and resource allocation can be performed through hierarchical deep actor–critic RL (H-DAC-RL), where the policy function is considered as the "actor" and the value function is named the "critic".

Distributed network computations (DNCs) can satisfy the different end devices' requirements and applications. For instance, critical applications that are delay sensitive can be served via the geographically closest network component (such as an edge node) instead of the core network, or non-urgent data can be filtered out before network core processing; this is also known as *edge computing* [80]. Although most of the currently deployed AI models are based on a centralized computation approach, i.e., in the cloud or the core network, a distributed AI and edge computing structure looks promising for consideration in 6G wireless systems. Moreover, building networks that support AI workflows on multiple levels can accelerate the use of AI in many ways, such as providing new models and data, which can help in achieving faster convergence rates with lower errors or prioritize and manage the connected end devices based on the application and the available resources. It is worth noting some of the challenges that DNC's implementation may face, such as the heterogeneity of the global network, resulting in the problem of integrating multiple sub-systems to work together efficiently, especially in vertical industries. For example, the compatibility between the different road vehicles and smart objects along the road is important in order to fully realize vehicle-to-vehicle (V2V), V2X, and smart objects' communications. *Edge computing* is usually coupled with *network slicing*; the latter is considered to be crucial in 6G networks as different end devices require vastly different network metrics. Each set of nodes can be grouped into a network slice; for example, V2V/V2X communication requires extremely low-latency connections compared to smart homes; thus, each communication type will be grouped into different network slices with different qualities of service.

Communication links and transceivers are bounded by upper and lower transmission energy costs. These limits are directly related to the ICs' rated power, BER constraints, data rates, and channel interference [81][82]. Sixth-generation networks are expected to bring record energy cost efficiency. This can be achieved by utilizing AI in data bits' modulation and OWC, as mentioned earlier. This can translate into smaller communication nodes, a less expensive overall communication cost, and giant complex networks. Moreover, integrating pervasive AI models with 6G networks, especially at the edge networking components' and end devices' levels, can contribute heavily to achieving advanced personalized network security and better network key performance indicators [83]. However, security in 6G will still be one of the challenging areas due to increasing threats arising from using new technologies [84]. For example, quantum communication will require special mechanisms to protect quantum encryption keys, which are different from the conventional methods used currently in protecting encryption keys for RF communications. Another example is related to massive AI deployment in 6G networks, where unauthorized DL sessions can take place in the network by intruders or eavesdroppers. This calls for developing new methods of user identification and authorization in the network.

As networks evolved to become what they are today by offering a myriad of emerging services and applications, such as lightning-fast communication speeds for end users, support for Industry 4.0, VR/AR, and many more, space–air–ground integrated networks (SAGINs) have emerged as a focal research area recently. This sheds light on the idea of vertically unifying the different network components, which are heterogeneous by nature, to achieve unprecedented network coverage, enhancing the quality of service (QoS), and granting access to a ubiquitous spectrum of services and application [85]. For example, the work in [86] gave a comprehensive study and survey of SAGINs and their role in 6G. It laid out a technical insight into the architecture, requirements, and use cases of SAGINs in 6G. In parallel, researchers are exploring in depth the edge computing and AI fields to match the needs of the ever-expanding networks and their roles in SAGINs [87]. Edge nodes can be incorporated into SAGINs as heterogeneous network controllers to handle network information collection, monitoring, and control, mobility and radio resources' management, and content caching. For example, parts of the aerial network can be transferred to edge servers; for example, a group of UAVs can be deployed for distributed computing, when resources are limited in ground terminals, or to mitigate backhaul transmission congestion. Edge computing UAVs can also support pioneering services, such as vehicular VR/AR gaming or road sign recognition. It is also possible to deploy satellites as edge nodes; this is helpful in many scenarios, such as in Earth observation, where image processing can take place on board for critical real-time applications. Some of these applications are space junk capturing, infrastructure monitoring, and disaster relief, leading to a reduction in time and savings on bandwidth. Moving on to AI's role in SAGINs, it is safe to say that native edge AI is forecasted to play a major part in SAGINs. One of the main points that involves edge AI is facilitating learning the network characteristics for traffic pattern and vehicle movement prediction and efficient packet routing, and this is of great interest, as many of SAGINs' components are dynamic by nature, such as UAVs and satellites. Moreover, edge AI plays a crucial role in content caching by optimizing content placement and delivery parameters on the different network nodes and links. Additionally, due to the heterogeneity of SAGINs and the contrasting QoS requirements, it becomes a hard task to perform resource allocation in the conventional way; thus, edge AI can assist by performing service load prediction and network slicing optimization based on the QoS requirements. Edge AI can also help satellites in object recognition tasks, whether space debris or structures on Earth's surface. However, there remain some challenges in the context of this discussion, such as that edge AI requests a considerable amount of data, which can be arduous to store and access in SAGINs on demand, as well as being costly to implement. The training of AI models can also incur a noticeable latency or delay that might not be tolerable in some applications, such as satellites performing real-time space junk avoidance.

Recent advances in information and communication technology (ICT) and AI have been stimulating the deployment of more and more devices at the edge of networks. It is expected that there will be over 75 billion sensors and edge devices by 2025 [88]. Besides, this has motivated the appearance of new applications, which request instant decision-making with minimal transmission delay. Examples of such applications include autonomous driving, XR for the Metaverse, facial recognition and sentiment analysis for digital twin profile construction, sensors' communication in factories and plants for a fully automated production process, and UAVs to facilitate SAGINs. To address these emergent challenges for next-generation networks, edge-native AI, a novel technology that intrinsically combines edge computing and AI, has been widely regarded as a predominant research area to provide on-the-spot processing and analysis of data generated at the edge of the network [89][90]. Its importance stems from the following facts: (i) future networks will be human-centric, that is to say they will rely heavily on shared human sensory data to offer personalized services; (ii) due to the immense amount of data generated at the edge of networks by the new generation of devices and latency-sensitive applications, the advent of new techniques will improve the efficiency of the networks at the edge; (iii) shifting data traffic and its processing from the cloud to the edge of the network reduces the load on backhaul links and potential decision latency; (iv) edge-native AI is expected to offer unprecedented intelligence in resource sharing by deploying real-time predictive algorithms. Therefore, it is envisioned that future networks (e.g., 6G) will consolidate edge-native AI within their core, thereby playing an essential role in optimizing key performance indicators (KPIs) in terms of energy and spectral efficiency, throughput, and communication latency and reliability.

Edge-native AI introduces distributed learning at edge nodes, which has been demonstrated to be capable of offering faster and more reliable decision-making than traditional centralized learning [91][92]. However, two implied challenges, the cooperation among network elements and the time cost of training, prevent the deployment of distributed intelligence and must be well addressed. Edge-native AI promotes human-centric networks by encouraging the participation of edge nodes in data sharing, data processing, and even network management. However, by considering the potential selfishness of edge nodes, they may not be willing to perform these tasks, as they may need to consume extra resources, experience possible service quality degradation, and/or face inconvenience, by changing the living habits and behaviors of their users; this also has to be addressed through the introduction of incentives with the aid of well-designed mechanisms to encourage all edge devices' participation. Security and user privacy comprise another important aspect. The focus is on designing efficient, secure, and robust data integrity and privacy protection mechanisms and developing edge-based threat intelligence frameworks. Integrating federated learning and blockchain technologies is a promising solution. However, the tradeoff between protection effectiveness and network resource (both communication and computation) efficiency must be well discussed.

All the mentioned technologies are expected to be implemented and ready for commercial use by the year 2030 [28]. This will give enough time to develop efficient proactive network management systems in parallel. A brief comparison between 5G and 6G regarding their specifications is displayed in **Figure 5**.

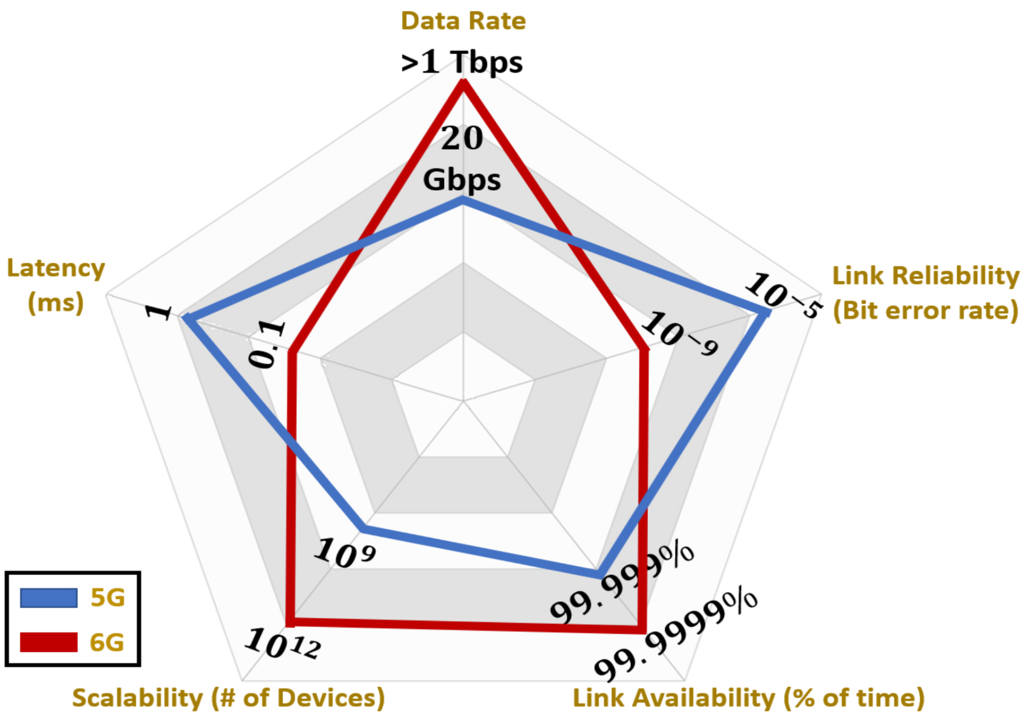

Figure 5. A comparison between 5G and 6G's theoretical achievable performances.

3.3. Technical Improvements

3.3.1. Frame Design

The diverse nature of future network requirements and applications stimulates the pace of innovating new solutions in networking. It is crucial to maintain high spectral and power efficiencies under massive network deployments. In [23], a new radio frame design was proposed to add flexibility to the system. The proposed design explores the idea of different waveforms co-existing in the same radio frame with different parameters, such as OFDM and filter bank multi-carrier (FBMC) modulation with different numbers of subcarriers and subcarrier spacing values, respectively. Furthermore, this flexibility can be taken one step further by giving freedom to adjusting the numerical aspectsof certain parts of the frame to suit a group of users. For instance, in OFDM, edge subcarriers can cause an out-of-band leakage, which can be mitigated by assigning a larger time window size to them compared to inner subcarriers (between consecutive OFDM symbols with shorter CPs). Moreover, this design is anticipated to offer reduced interference and enhanced non-orthogonal multiple access schemes (NOMAs).

3.3.2. Radio Access Schemes

One of the key enhancements needed for the network of the future is to develop ultrafast RA schemes. Their significance arises from the fact that a great part of the networks of the future will be based on IoE devices, which generate sporadic transmissions most of the time. Therefore, setting up conventional connections for IoE devices is highly inefficient in terms of spectrum utilization, which makes RA the most suitable method in this scenario. For example, the coded-ALOHA and successive interference cancellation (SIC) RA methods have been proposed in recent works [93][94]. However, for 6G, RA can be further optimized by integrating key design elements, such as MIMO and OFDM, into the RA algorithm [95]. RA methods require constant development, because with the increasing number of devices competing for a transmission slot, the latency and packet dropping rate will increase. This can lead to a significant drop in the overall network performance, which can have significant consequences in some scenarios such as V2V communication or remote healthcare.

3.3.3. Cell-Free Design

Radical network changes are expected to take place in 6G systems to move away from the conventional operation methods in favor of achieving better network performance. One possible direction is redefining the concept of network cells to create what is known as cell-free networks or distributed MIMO. Generally speaking, the architecture of such a network is made up of a number of access points (APs) equipped with a certain number of antennas evenly spaced in the coverage area. All the APs are connected to a centralized processing unit for the coordinated serving of users. This depiction of networks is believed to have multiple benefits. In its ideal form, it will be able to maintain a uniform level of the quality of service among all users in the network, especially under massive MIMO systems [96]. Another benefit is combating the unfavorable effects of signal propagation, such as signal fading and shadowing. In an attempt to elaborate this network architecture, the researchers explored the recent work of [97], where the scalability aspect of networks was under scrutiny. The foremost priority in that work was preserving a limited computational complexity under a huge number of users. In short, restraining each available pilot sequence to one user during the network's initial access procedure under *dynamic cooperation clusters'* (DCCs) deployment was proposed. This was performed to minimize the unwanted pilot contamination phenomenon and to fix the signal processing complexity. The backbone of the DCC's principle of operation is distributed MIMO systems. The objective of DCCs is to form a cluster of serving APs around each user with minimum signal interference from other users. An extension of this work under the name of the *radio stripe system* was described by [98]. Such a system considers integrating antennas and their own processing units inside active cables running on the edges of construction elements (such as fences, staircases, windows, etc). Some of the forecasted advantages of these systems are inexpensive and flexible cell-free MIMO network formation and enhanced system longevity.

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