The Disruptions of 5G on Data-Driven Technologies and Applications

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Abstract—With 5G on the verge of being adopted as the next mobile network, there is a need to analyze its impact on the landscape of computing and data management. In this paper, we analyze the impact of 5G on both traditional and emerging technologies and project our view on future research challenges and opportunities. With a predicted increase of 10-100x in bandwidth and 5-10x decrease in latency, 5G is expected to be the main enabler for smart cities, smart IoT and efficient healthcare, where machine learning is conducted at the edge. In this context, we investigate how 5G can help the development of federated learning. Network slicing, another key feature of 5G, allows running multiple isolated networks on the same physical infrastructure. However, security remains the main concern in the context of virtualization, multi-tenancy and high device density. Formal verification of 5G networks can be applied to detect security issues in massive virtualized environments. In summary, 5G will make the world even more densely and closely connected. What we have experienced in 4G connectivity will pale in comparison to the vast amounts of possibilities engendered by 5G.

Index Terms—5G mobile communication, database systems, network slicing, Internet of Things, edge computing, federated learning, data privacy, security management

1 Introduction

Fifth Generation (5G) mobile communication technologies are on the way to be adopted all over the world. At the moment, 5G is being deployed in small areas in almost all the continents, with a higher number of available networks in Europe and the USA [76]. In future, 5G is predicted to account for at least 15 percent of the total mobile communications market by 2025 [108]. It is therefore timely to analyze the impact of 5G on key areas of research related to data management and processing, including databases, distributed systems, blockchain, and machine learning.

With its increased bandwidth of up to 20 Gigabits per second (Gbps), low latency of 1 millisecond (ms), high device density of one million devices per square kilometer, and virtualization technologies [73], 5G is generating new opportunities in computing. New use cases, such as remote healthcare based on virtual reality (VR) and augmented reality (AR), or ultra-high-definition (UHD) movie streaming can only be possible in 5G networks [3]. Other applications, such as machine-to-machine (M2M) communication in automotive and smart drones, and high-density Internet of Things (IoT) devices in smart cities can be handled by the current technologies, such as 4G, WiFi, and Bluetooth, but they can greatly benefit from the improvements of 5G [3].

In this paper, we provide performance measurements done in a real 5G network showing a maximum download bandwidth of 458 Megabits per second (Mbps) and minimum round-trip time (RTT) of 6 ms. While these numbers are still far from the 5G specifications [73], they represent current 5G networks running in Non-Standalone (NSA) mode and expose more than $5\times$ better performance, in terms of bandwidth and latency, compared to 4G networks. We plan to use these performance measurements to emulate 5G deployments where data management and processing systems can be evaluated.

Beyond the obvious impact of 5G in well-known areas, we examine the opportunities and challenges in computing areas related to distributed data management and processing. For example, 5G technology has the potential to bring forth the idea of millions of shared (micro-)databases which will impact data analytics, federated learning [118], and security at the edge. Nonetheless, the concept of millions of databases poses challenges in terms of privacy and security.

In this paper, we conduct a systematic survey of challenges and opportunities 5G is bringing to key areas in computing, such as edge computing and IoT (Section 3.1), networking (Section 3.2), data storage and processing (Section 3.3), blockchain (Section 3.4), artificial intelligence (Section 3.5), and

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Manuscript received 19 Sept. 2019; revised 12 Dec. 2019; accepted 11 Jan. 2020. Date of publication 17 Jan. 2020; date of current version 29 Apr. 2020. (Corresponding author: Dumitrel Loghin.)
Recommended for acceptance by Y. Zhang.
Digital Object Identifier no. 10.1109/TKDE.2020.2967670

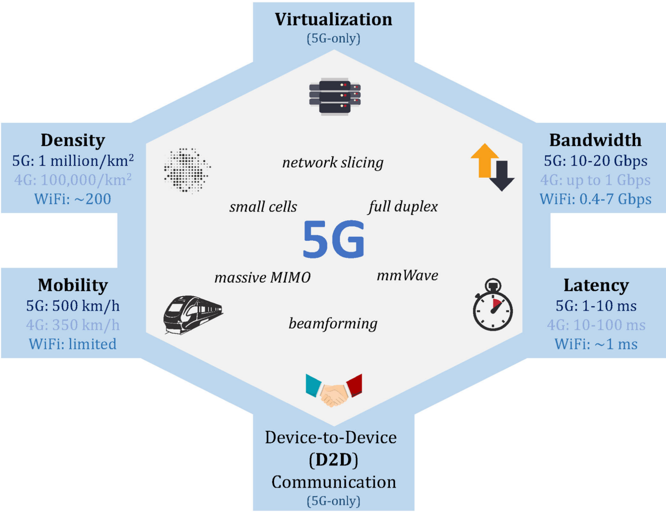


Fig. 1. 5G overview.

security and privacy (Section 3.6). We highlight security as a major challenge in 5G deployments, due to multiple factors. First, the high density and large number of IoT devices that can be connected to a 5G network will increase the risk of attacks, such as Distributed Denial-of-Service (DDoS). It is well-known that IoT devices are easier to break and that some of the largest-scale attacks were conducted using distributed IoT devices [47]. Second, the full virtualization in 5G networks is posing new challenges in security management. We analyze in this paper what are the risks of network slicing [31], the key technology in 5G virtualization.

Another key challenge is the current backhaul and cloud network infrastructure that is not able to cope with the increased traffic generated by the 5G mobile networks. Our measurements of inter-region cloud connections show that the throughput is almost always lower than 100 Mbps, while the latency exceeds 300 ms in some cases. These values are far behind the requirements of 5G. In a study by McKinsey, it is estimated that an operator needs to spend up to 300 percent more on infrastructure to cope with a 50 percent increase in data volume [34]. This, together with virtualization, introduces new challenges in the delivery and monetization of 5G services, while delaying the adoption of 5G.

The remainder of this paper is organized as follows. In Section 2, we review 5G specifications, evaluate current deployments with performance measurements and examine 5G network simulators. In Section 3, we analyze the impact of 5G on major computing areas that are related to data processing and management, such as edge computing and IoT, network verification, databases, blockchain, federated learning, security and privacy. We end Section 3 by discussing challenges and opportunities. In Section 4, we discuss how 5G is going to boost new use cases, such as telemedicine, AR/VR, e-commerce, fintech, smart cars, smart drones, and smart cities. We conclude the paper in Section 5.

2 5G Technologies

In this section, we review the properties of 5G, in comparison with the previous generations of mobile and wireless technologies. We provide a summary of current 5G deployments, with performance measurements done with two 5G smartphones, and explore solutions for simulating 5G networks.

TABLE 1
A Comparison of the Specifications of Mobile Communication Technologies

	5G	4G	WiFi (802.11ac)	Bluetooth 5
Bandwidth [Gbps]	10-20	1	0.4-7	2 Mbps
Latency [ms]	1	10-100	0.9/6.2	200
Mobility [km/h]	500	350	-	-
Frequency [GHz]	0.6-6, 28-95	0.7-2.6	5	2.4
Connected Devices	1,000,000/km^2	100,000/km^2	200/gateway	7/gateway
Year	2019	2009	2014	2016

2.1 An Overview of 5G

5G is the fifth generation of cellular network technologies specified by the 3rd Generation Partnership Project (3GPP). It proceeds 2G, 3G, and 4G and their associated technologies, while introducing significant performance improvements, as shown in Fig. 1 and Table 1. In this section, we briefly describe the technologies that enable the disruptive performance improvements of 5G.

Millimeter Wave Spectrum. In addition to the classical spectrum below 6 GHz used by the majority of wireless communication technologies, 5G will operate in a high-frequency spectrum, from 28 GHz up to 95 GHz [3], [10]. This range is known as the *millimeter wave (mmWave) spectrum*. Compared to previous cellular network technologies, 5G will use a larger band of frequencies, thus, avoiding congestion. In comparison, 4G operates typically in the range 700-2600 MHz [3], [115].

Massive MIMO and Beamforming. 5G uses the *massive multiple-input and multiple-output (MIMO)* technology [52]. This technology consists of large antenna formations in both the base station and the device to create multiple paths for data transmission. With massive MIMO technology, 5G can achieve high spectral efficiency [3] and better energy efficiency [52]. Beamforming[1] is a subset of massive MIMO [81]. Beamforming controls the direction of a wave-front by manipulating the phase and magnitude of the signals sent by a single antenna placed in a formation of multiple antennas. In this way, beamforming identifies the most efficient path to deliver the data to a receiver, while reducing the interference with nearby terminals. In addition, 5G uses a full-duplex technology which doubles the capacity of wireless links at the physical layer. With full-duplex, a device is able to transmit and receive data at the same time, using the same frequency [99]. Based on these new technologies, it is predicted that 5G has the potential to improve services at the edge, support more use cases, accelerate the development of smart cities, and enhance user experience [81].

Small Cells. In addition to a larger spectrum and massive MIMO, 5G will comprise densely distributed networks of base stations in *small cell* infrastructure. This enables enhanced mobile broadband (eMBB) and low latency [18], providing an ideal infrastructure for edge computing. While small cells are typically used to cover hot spots, in mmWave

1. The terms beamforming and massive MIMO are sometimes used interchangeably [82].

TABLE 2
Measurements on Current 5G Deployments

Location	Date	Operator	Device	Bandwidth (max) [Mbps]	Latency (min RTT) [ms]	Reference
Chicago, USA	19/5/2019	Verizon	Samsung Galaxy S10 5G	1,385	17	[102]
Chicago, USA	30/6/2019	Verizon	Samsung Galaxy S10 5G	1,070	-	[100]
New York, USA	30/6/2019	T-Mobile	Samsung Galaxy S10 5G	579	-	[100]
New York, USA	1/7/2019	T-Mobile	Samsung Galaxy S10 5G	529	53.5	[114]
Bucharest, Romania	19/7/2019	RCS/RDS	Xiaomi Mi Mix3 5G	458/20.6	12	this paper
Bucharest, Romania	6/9/2019	RCS/RDS	Huawei Mate 20 X 5G	458/8.5	6	this paper

5G, they become a necessity due to the high-frequency (above 28 GHz) radio waves that cannot cover the same area as the classical low frequencies (below 6 GHz) [18].

Device-to-Device Communication. Similar to Bluetooth and WiFi (i.e. WiFi-Direct), 5G allows devices to communicate with each other directly, with minimal help from the infrastructure [9]. This *device-to-device* (D2D) communication is a key feature of 5G that has the potential to accelerate the development of edge-centric applications. For example, in automotive applications, vehicles will be able to talk directly to each other, thus, reducing latency and avoiding the failure of the connection to the base station. Other use cases of D2D 5G communication are federated learning, where edge devices could share data among them, and blockchain where devices need to establish peer-to-peer (P2P) connections.

Virtualization. In addition to the improvements in the physical layer, 5G networks are going to be highly virtualized. Among the virtualization technologies used by 5G, we distinguish software-defined networking (SDN), network function virtualization (NFV), and network slicing. SDN is an approach that separates networking data plane (i.e., data forwarding process) from the control plane (i.e., the routing process). This separation leads to easier configuration and management, and higher flexibility and elasticity [48]. Complementary to SDN, NFV [35] uses commodity hardware systems to run networking services that are traditionally implemented in hardware, such as routers and firewalls. With NFV, network flexibility is greatly improved, and the time-to-market is reduced, at the cost of lower efficiency compared to dedicated hardware.

Network Slicing. Based on SDN and NFV, 5G networks will employ *network slicing* to multiplex virtualized end-to-end networks on top of a single physical infrastructure. By separating infrastructure operators and service providers, 5G will better utilize hardware resources while providing a diversified range of services to both businesses and end-users [31]. However, all these virtualization technologies pose new challenges in terms of security management and monetization, as we shall analyze in this paper.

Perfomance Improvements. Compared to 3G and 4G, 5G has a lower latency of approximately 1 ms, increased energy efficiency, and a peak throughput of 10-20 Gbps [3], [73]. The increase in bandwidth will not only support better user experience, but also allow for more connected devices, such as drones, vehicles, and AR goggles, among others. While a 4G base station can only support around 100,000 devices, 5G can support up to a million devices per square kilometer [73]. A 5G network is designed to be flexible and suited for edge deployment, which further improves the end-to-end latency and overall user experience.

In the context of IoT devices and their use cases, we compare the specifications of major wireless communication technologies in Table 1. 5G has almost always the best characteristics, except for latency, where newer generations of WiFi have similar specifications. However, median WiFi latency on an 802.11n router is 0.9 ms and 6.22 ms, when 5 GHz and 2.4 GHz frequencies are used for measurements [33], respectively. The 99th percentile goes up to 7.9 ms and 58.9 ms for the two frequencies [33], respectively. In practice, current 5G deployments exhibit latencies in the range of 6-40 ms, with jitter than goes up to 145 ms, as shown in Appendix A.1, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TKDE.2020.2967670.

2.2 Current 5G Deployments

In August 2019, some countries and operators were offering commercial 5G networks, with limited deployment. According to a map published by Ookla[2] [76], only the USA and Uruguay have 5G networks in the Americas. Besides Uruguay, only South Africa and Australia have 5G in the southern hemisphere. In Asia, 5G is available in some countries in the Middle East, such as Saudi Arabia, Qatar, Kuwait, and the United Arab Emirates, as well as in South Korea. In Europe, 5G is available in the UK, Spain, Germany, Switzerland, Italy, Romania, and Finland.

Table 2 summarizes existing speed tests on 5G networks around the world. All these tests are conducted using Ookla's Speedtest Android application. At the bottom of this table, we present our tests done in Bucharest, Romania where there is a 5G network provided by the local operator RCS/RDS using base stations produced by Ericsson [27]. These tests were done with two smartphones equipped with 5G modems, (i) a Xiaomi Mi Mix3 5G (*Mix3*) [117] and (ii) a Huawei Mate 20 X 5G (*MateX*) [41]. The former device has a Qualcomm X50 5G modem, while the latter is equipped with Huawei's own 5G modem.

We analyze the best results in this section, and present the details in Appendix A.1, available in the online supplemental material. Both smartphones exhibit a maximum

2. Ookla developed speedtest.net, a widely-used tool to measure the speed of Internet connections in terms of download and upload throughput, and ping latency. In this paper, we use Ookla's Speedtest Android application for measurements.

download throughput of 458 Mbps on 5G, compared to a maximum of 86.3 Mbps on 4G. But the upload throughput of 5G is similar or even lower compared to 4G. For example, the maximum upload throughput on 5G is 20.6 and 8.5 Mbps with Mix3 and MateX, respectively. On 4G, the maximum measured upload throughput is 23.9 and 29.6 Mbps with Mix3 and MateX, respectively. The latency is measured in terms of round-trip time, similar to the results reported by the *ping* Linux tool. RTT is accompanied by jitter, representing the deviation from the average latency. The minimum RTT measured on 5G with Mix3 and MateX is 12 and 6 ms, respectively. These RTTs have corresponding jitters of 4 and 1 ms on Mix3 and MateX, respectively. The RTT on 4G is much higher, with a maximum of 48 and 54 ms on Mix3 and MateX, respectively. On average, the download throughput of 5G across different test servers and measured in different locations is above 300 Mbps, while the upload speed is always less than 30 Mbps.

While the download speed[3] is significantly higher compared to 4G, both the upload speed and latency are surprisingly low, compared to the specifications [73]. This is caused by two main factors. First, the speed test consists of sending requests to servers that are not very close to the base station. Hence, the latency and throughput are influenced by both (i) the 5G wireless link to the base station and (ii) the wired, optic, wireless or mixed path from the base station to the server. Second, current 5G setups are using the Not-Stand-Alone mode [28]. Only the Stand-Alone (SA) 5G mode is supposed to achieve an ultra-low latency of 1 ms [28]. In terms of upload throughput, network operators tend to limit it because typical users are affected more by the download speed.

We note that our measurements are influenced by the connection between the base station and the test server. In our case, the number of hops between the device and the test server is in the range 9-13. While the number of hops is relatively high, the backhaul links connecting the base stations to the Internet are of high capacity. These links are usually based on fiber or microwave technology with capacities of up to 20 Gbps [119]. On the other hand, these measurements expose pertinent download and upload throughput as experienced by the end-user.

2.3 5G Simulators

With the limited amount of both 5G deployments and 5G-ready terminals, it is mandatory to explore simulation and emulation solutions for 5G in an effort to develop and analyze applications targeting this new technology. Since our focus is on the impact of 5G on data-driven software platforms, the simulator should be able to reproduce networking behavior at a high level, in terms of throughput, latency, jitter, and packet loss.

Many 5G simulators, such as MATLAB 5G Toolbox [68], NYUSIM [101], NetTest 5G Network Emulators,[4] ns-3,[5] [83], focus on the physical layer (i.e., radio access network - RAN). Such a detailed simulation at the physical level could offer useful insights to network engineers and mobile operators, but it is time-consuming and resource-intensive.

3. We use the terms bandwidth and speed interchangeably.
4. http://www.polarisnetworks.net/5g-network-emulators.html
5. https://www.nsnam.org/

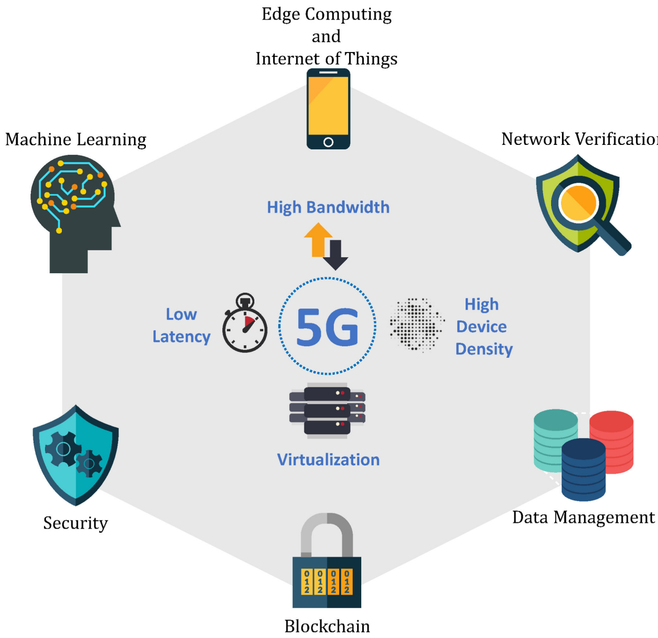


Fig. 2. Areas impacted by 5G.

Instead, simpler solutions could be used to emulate a 5G environment. For example, the *tc* Linux tool[6] is able to introduce delays with different patterns to emulate higher latency with custom jitter distributions. Moreover, *tc* can limit the bandwidth of a given interface. One can use *tc* in a cluster with Gigabit Ethernet or higher bandwidth links to emulate 5G networking conditions. However, it remains to be investigated how to emulate both D2D and device-to-base station communications on top of an Ethernet network.

In conjunction with network virtualization, which is a key feature of 5G, existing solutions for quick prototyping with SDN can be used, such as Mininet [51] and its fork, Mininet-WiFi [24]. Some researchers explored the idea of using Mininet as a platform to emulate 4G and 5G on top of wired or wireless networks [86], [92], [94]. However, some of the results reported by these projects are far from both the specifications of 5G and our preliminary measurements. For example, the throughput reported in [92] is below 100 Mbps. Hence, special care needs to be adopted when using these prototyping platforms to conduct performance measurements for data management and processing frameworks.

3 Areas of Impact

5G and its revolutionary features are going to impact multiple computer science domains and create new use cases, as highlighted in Fig. 2. In this section, we present our view on the domains impacted by 5G, such as edge computing, database systems, artificial intelligence, security, among others. In the next section, we present some use cases where 5G and related technologies will have a significant impact.

Motivating Use Case. Before diving deeper into each area impacted by 5G, we motivate our analysis with a use case that covers all the areas mentioned and shows the relationship among them. Representing the growing market of healthcare (Section 4.1), this use case assumes that patients

6. https://linux.die.net/man/8/tc

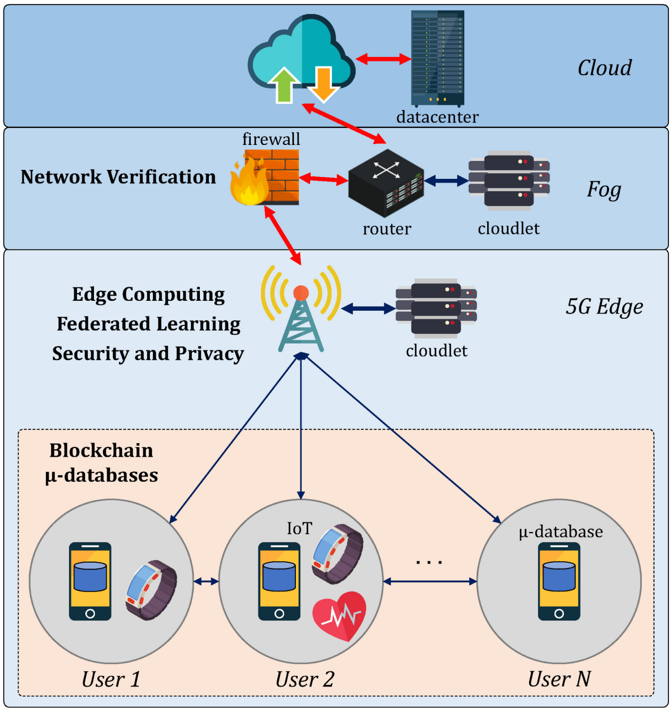


Fig. 3. Motivating use case.

(end-users) take ownership of their medical data, also known as electronic health records (EHR) or electronic medical records (EMR). This represents a global trend that tries to put the patient at the center of the healthcare system. For example, Apple allows users to download and keep their medical records on the iPhone [7].

By storing medical records locally, the user's smartphone becomes a small database that we refer to as μ*-database* (Section 3.3), as shown in Fig. 3. In addition to medical records downloaded from clinics and hospitals, this μ-database stores data collected by a variety of IoT devices, such as a smart watch and mobile electrocardiogram. Within a 5G network, these μ-databases could be interconnected either through the base station or directly, using the D2D feature of 5G. Furthermore, the emerging blockchain technology can be used to improve the security of these μ-databases in a hostile environment.

These data could be used to train medical deep learning models, such as disease progression models [127], which are then distributed to the devices to analyze new data and to send alerts to doctors. To make the training more efficient, federated learning (Section 3.5) is used to distribute the work among multiple devices with the help of a coordinator. With the emergence of edge computing (Section 3.1), the coordinator could be placed at the edge, in a virtualized micro-datacenter or cloudlet [95].

Nevertheless, the biggest concern in modern healthcare is the security and privacy of the patients' data. Recent data breaches [30], [105] motivate the research of new security techniques. With the adoption of 5G, its virtualization feature could help in isolating the healthcare use case from other verticals. However, virtualization does not always ensure privacy (Section 3.6). In addition, security management is problematic in the presence of network slicing, and both the physical infrastructure and SDN configurations need to be verified to ensure a secure environment (Section 3.2).

Another method to increase the security and privacy of distributed μ-databases is the use of blockchain technology (Section 3.4). For example, some startups, such as MediLOT [71] and Medicalchain [70], propose patient-centric healthcare based on blockchain. However, the scalability of blockchain [21] remains an open problem in the context of 5G networks.

3.1 Edge Computing and the Internet of Things

3.1.1 Overview

Edge computing is a relatively new paradigm that proposes to move cloud services closer to the users and to the devices that produce data, at the edge of the network [96]. With a growing number of devices connected to the Internet [64], the pressure on the backbone links of the Internet is increasing. Edge computing alleviates this issue by performing some or all computations closer to the devices that produce data. Depending on the location of these computations, we distinguish between edge and fog computing. In edge computing, the processing is done on the device or one hop away from the device, for example in a mini-datacenter connected to the 5G base station [103], as shown in Fig. 3. On the other hand, in fog computing, introduced by Cisco in 2015 [16], the computation could be done anywhere between the edge and the cloud, in switches, routers, base stations or other networking devices.

Edge computing has multiple flavors, among which we distinguish (i) the fog, (ii) Multi-access Edge Computing (MEC), and (iii) cloudlets [96], [103]. The fog is an extension of the edge, where the processing can be done on the way to the cloud, in the backbone's switches and routers. MEC is a set of standards addressing the diversity of protocols, applications, services, and providers of edge computing. At its core, MEC is based on virtualization to provide cloud-like services at the edge, within the range of RAN [39]. A cloudlet [95] is a small datacenter connected to a networking access point. Typically connected to a base station, one hop away from the devices, a cloudlet can also be placed in the fog, as shown in Fig. 3. A cloudlet is using virtualization to provide computing and storage services. Thus, cloudlet technology can be viewed as part of MEC. With 5G being a heavily virtualized technology, we are expecting an accelerated deployment of MEC and cloudlets.

With the adoption of 5G, which enables higher bandwidth and more connected devices compared to 4G, edge computing becomes a necessity because current cloud interconnections are not able to sustain the traffic. Our measurements on Google Cloud Platform (GCP) and Amazon Elastic Compute Cloud (EC2) show that bandwidths between different cloud datacenters (regions) can hardly hit 100 Mbps, while the majority of our measurements are below 10 Mbps. Only closely located regions, such as those in Western Europe, exhibit bandwidths of up to 92.8 and 126 Mbps, for GCP and EC2, respectively. These bandwidths are far from being able to sustain the demands of 5G edge devices, where a single device could upload data with a throughput of up to 1 Gbps [73].

The pressure on the backbone and cloud inter-region links is going to increase as 5G is considered to be the network for IoT [3]. In current deployments, IoT devices typically connect to a gateway or the Internet through WiFi, Bluetooth, Long

Range (LoRA), Zigbee, among others [72]. These protocols are suitable for short-range communications with low mobility, used in applications such as smart homes and smart offices. However, they may not be suitable for larger deployments, such as smart cities and smart farms, and high-mobility applications such as automotive. Next, we identify a series of devices that can benefit from 5G features, as listed below.

- *Surveillance systems*. These systems allow users to remotely scan the area inside or around their homes from the comfort of a smartphone. They can see who is snooping around while overseas, and alert the authorities if needed. For such a service, there is a need for good video quality and high frame rate. 5G has enough bandwidth to deliver high-quality UHD video with low delay while allowing flexible reconfiguration which is not possible when using wired connections. On the other hand, edge computing helps in pre-processing the image stream in a cloudlet and sending only the alerts to the cloud.
- *Autonomous cars*. Undoubtedly, smart cars need fast response times. The theoretical latency improvement from 50 ms in 4G to 1 ms in 5G may be enough to avoid accidents. Moreover, the D2D communications in 5G will have a positive impact on Vehicle-to-Vehicle (V2V) messaging, further reducing the latency compared to going through a base station. Using D2D, automotive communications can avoid the problem of a single point of failure represented by a faulty base station. As such, we predict that smart cars will adopt 5G to deliver large volumes of data with high speed to avoid accidents.
- *Drones*. In emergencies and dangerous situations, such as search-and-rescue, firefighting, surveying, delivery services, having high network bandwidth allows the drones to send high-quality sound and video back to the command center, at the edge. The low latency of 5G allows better control over the drone compared to 4g or WiFi. Similar to autonomous cars, smart drones could benefit from D2D communications, especially in remote areas with no access to a base station. Using D2D communications, a group of closely located smart drones can form a swarm to work towards a common objective [97].
- *Healthcare devices*. With a high bandwidth and low latency, 5G would improve the monitoring of patients with chronic diseases. Vital signs can be sent to the doctor or hospital with high frequency, while alerts can be triggered as soon as the edge device detects something wrong.

Some of the features of 5G address the challenges faced by the IoT domain. First, the increasing number of IoT devices could be handled by the superior device densities supported by 5G. According to a survey by IoT Analytics Research, there were 7 billion IoT devices in 2018 [64]. This number will triple by 2025 [64]. This increase in the number of IoT devices raises concerns about connectivity and security, among others. According to an online survey of IoT development conducted by the Eclipse Foundation in 2019 with 1717 participants [106], the top three concerns are security (38 percent), connectivity (21 percent), and data collection and analytics (19 percent).

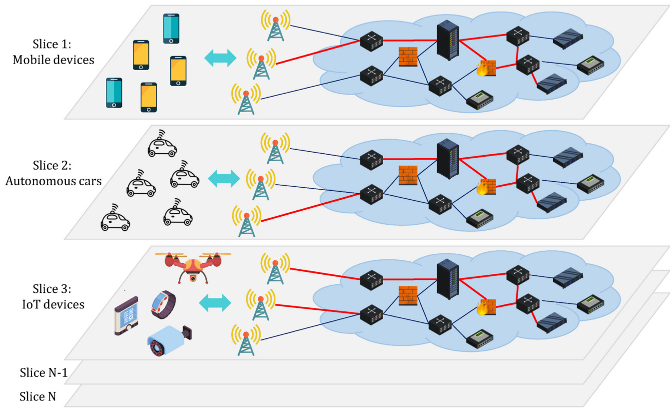


Fig. 4. 5G network slices.

3.1.2 Challenges and Opportunities in Edge Computing

Nonetheless, some challenges need to be considered and analyzed carefully before the successful adoption of 5G in edge computing. First, there is a high diversity of edge hardware, communication protocols, service providers and processing frameworks. To overcome this, the European Telecommunications Standards Institute created a special group of interest to propose standards for MEC [103]. 5G could address this issue using virtualization, where hardware functions and software protocols can be virtualized on commodity infrastructure, thus, decreasing the prototyping and deployment time.

Edge services could be driven by the 5G end-to-end network virtualization. For example, network slicing would allow different application planes to run in isolation on the same infrastructure, as shown in Fig. 4. With network slicing, cloud-like services at the edge, the broadband connectivity plane, and smart city applications could all run in isolation. Nevertheless, the security of such a setup is challenging, as we shall see in the next sections.

A second factor that hinders 5G edge adoption is the high cost of installing, protecting and maintaining edge devices in remote areas [90]. 5G is able to address these issues partially by employing its high bandwidth and low latency features. The former implies that advanced, high-definition security monitoring solutions can be deployed together with the edge hardware. The latter helps in detecting and acting on problems faster, from a centralized command facility.

A third factor that needs to be considered in 5G edge computing is energy efficiency. Remote edge devices may face energy constraints due to the lack of connections to the power grid. Operating on alternative sources of energy, such as solar panels or batteries, imposes constraints on both computation and communication. While communication is often more energy-expensive compared to computation, it is a challenge to decide when to process the data at the edge and when to offload it to a cloudlet [96]. With its superior energy efficiency, 5G could help in improving the overall efficiency of edge computing.

3.1.3 Challenges and Opportunities in IoT

One of the biggest challenges IoT development has to encounter in a 5G environment is the new wave of security threats. Since the number of connected IoT devices continues to rise, there is a higher risk that systems will be attacked by malware and ransomware to steal sensitive data or to perform DDoS attacks [47]. This problem is more stringent with the IoT devices being used in automation and security systems at home or in vehicles. These systems may be compromised, leading to more serious threats, such as home intrusion or remote vehicle hijack. A piece of common advice to ensure the security of IoT devices is to keep their firmware and security patch up-to-date to avoid any vulnerabilities exploitable by attackers. Also, users need to change their default account and password periodically on the IoT devices to prevent unauthorized access by brute-force attacks. Finally, data transmission and communication between devices or from the devices to the 5G network need to be encrypted to prevent any leak of confidential data.

The second challenge that needs to be considered is how to guarantee data privacy when IoT devices have access to private data such as surveillance videos, daily habits, and health data. Although users can review the coarse-grained access control of these devices to sensitive information [90], they generally cannot supervise how these data are collected and utilized. For example, if users let IoT applications access their data, they will not know when the devices send the data to developers, advertisers, or any other third parties. To ensure the privacy of data, multiple solutions need to be considered. For example, it is important to set dedicated policies, regulations, rules, or laws to ensure that IoT service providers and developers take necessary actions to protect users' sensitive data. Besides, strong security solutions also need to be set up in IoT devices, to prevent any breach or exploitation of sensitive data.

The third challenge is that most IoT devices might not be tested sufficiently during their production and might not receive enough firmware updates after deployment. This might be due to the fierce competition in the IoT industry where manufacturers often focus on quickly producing and selling devices and do not pay enough attention to security issues. For example, many manufacturers only offer firmware updates for new devices, while stopping the update of old-generation devices when they start working on the new generation. This bad practice might leave IoT devices vulnerable to potential attacks due to the outdated firmware. To overcome this problem, manufacturers are encouraged to test their products properly and update firmware regularly. Furthermore, they should use safe programming languages and automatic program testing and verification techniques to avoid potential bugs during product development.

A fourth factor is the cost of a 5G subscription per IoT device. Given the large count of IoT devices, a linear pricing scheme is not going to incentivize the adoption of 5G in IoT. To leverage this, hybrid deployment could be used, where multiple IoT devices connect to a 5G gateway using traditional protocols, such as WiFi or LoRA.

3.2 Network Testing and Verification

3.2.1 Overview

Ensuring that modern networks, including 5G, operate properly as designed is crucially important to telcos, banks, content providers and other businesses. The failure of these networks might lead to severe consequences. For example, according to a report of IHS Inc. in 2016 [67], network failure caused the loss of billions of US dollars annually in North American businesses. The failure of a network can occur statically due to its misconfiguration or dynamically at runtime [122]. The misconfiguration errors are often introduced by human mistakes, and they can lead to problems such as unreachable servers, or security holes. On the other hand, runtime errors are due to failures in network links and hardware, or bugs in network software.

Huge efforts have been spent by researchers to develop testing and verification techniques to find network errors [56]. However, this task is known to be very complex since modern networks include a large number (thousands) of not only servers, routers, and end-user devices, but also many middleboxes such as firewalls, load balancers, transcoders, proxies, and intrusion detection systems [80]. Furthermore, the software controlling these devices is very complicated: it contains millions of lines of code and runs in a highly distributed environment. For 5G, this testing and verification task will be more challenging, due to the network's growth in complexity and flexibility. In particular, a 5G network can support a massive number (up to millions) of connected devices. It is also equipped with a novel network slicing feature which allows a slice (or virtual network) to be dynamically created, used, and deleted. In the following, we will discuss more about such difficulties and challenges.

3.2.2 Network Testing

Up to date, testing is the main method that has been used to discover errors in modern networks [32]. Network engineers often find bugs by using a wide range of tools, from the rudimentary `ping` and `traceroute`, to advanced tools like `nmap`, `tcpdump`, `netcat`, `acunetix`, `ip scanner`. They mostly conduct ad-hoc validations of existing networks (3G, 4G, or enterprise networks) via active monitoring to detect potential problems. For example, a network often needs to be validated after a configuration change, such as when new remote sites are installed, routing policies are changed, or firewall rules are updated.

However, the existing network testing solutions might need to evolve to cope well with the scale of 5G. Unlike 3G and 4G networks, which are limited only to the telecom industry, a 5G network will comprise millions of connected devices from many industry verticals [31] grouped in network slices, as shown in Fig. 4. Therefore, various ad-hoc cases of the network need to be considered for validation. Also, monitoring the network will be more challenging since network slices can be flexibly created, used, and deleted, based on user requirements [31]. Hence, it is difficult for network engineers to manually design testing strategies that thoroughly cover all behaviors of the network.

In order to make 5G network testing more effective and efficient, the tasks need to be automated as much as possible. First, there is a need to design tools that can automatically analyze the network configuration and generate tests to cover all ad hoc cases. Second, these test cases need to be run automatically and periodically on candidate networks to discover any possible errors. Although automatic testing is new in the context of network testing, this idea has been well-studied by the software engineering community. Recently, several efforts have been made to automate network testing.

For example, Zeng *et al.* [121] have proposed a technique to automatically generate test packages for testing the forwarding behavior of simple networks. However, the size and dynamicity of 5G will be much more complicated than existing networks. Hence, there are many challenges and opportunities to develop automatic testing tools for 5G networks.

3.2.3 Network Verification

Although testing is commonly used to detect network errors, this method has two limitations. First, it is often used to check the behaviors of a production network but not to examine the network's configuration. Second, this approach cannot guarantee that a network is implemented correctly according to its design since it is impossible to generate test cases that cover all the possible behaviors of the network. In reality, it is often desired that a network's configuration can be examined before being deployed to prevent any possible errors in the future.

Inspired by recent advances in software verification, researchers have proposed to treat networks like programs so that they can apply similar techniques to formally verify the forwarding behavior of networks [80], [111]. In essence, a network consists of two planes, namely, a *data plane* and a *control plane* [50]. The data plane decides how a network packet is handled locally by a router: when the packet arrives at one of the router's input links, it will determine which output link to forward it to. The control plane determines how a packet is routed among routers along a path from the source node to the destination node. In traditional networks, both these planes are implemented in routers. However, in modern networks, the control plane can be implemented as a separate service in centralized servers.

Recent works have focused on verifying simple networks, which are configured by static and immutable forwarding rules [44], or small-scale networks with a limited number (hundreds or thousands) of devices [8], [23], [46]. In reality, modern networks often contain various middleboxes, whose states are mutable and can be updated in response to received packets. Hence, the behaviors of routers and middleboxes in these networks are affected by not only their configurations but also by the incoming packets. Further, 5G networks will be even more complex since they allow a massive number (millions) of connected devices. These two challenges, namely, complexity and mutable states, will be the key factors that need to be considered when verifying the forwarding behavior of 5G networks.

As previously mentioned, 5G supports network slicing, where a network slice is a software-based, logical network that can span across multiple layers of the network and could be deployed across multiple operators. Furthermore, the isolation of slices can be flexibly configured at different levels to satisfy the customers' needs [31]. For example, some users may not mind sharing network resources with others but would require isolation for the computing resources. Therefore, it will be challenging to formally verify if the isolation property of network slices in a deployed network satisfies its design.

3.3 Data Management and Processing

3.3.1 Overview

5G could be the P2P network layer in a system comprising millions of interconnected μ-databases. A μ-*database* stores a subset of the data corresponding to a certain application. For example, a medical μ-database stores a part of the patient's medical records, where the entire dataset is represented by all the records of all the patients using the same medical application or going to the same group of hospitals. With a projected density of one million devices per square kilometer [73], 5G is able to connect a few million devices in a smart city, where each device stores a μ-database. This either gives rise to (i) a network of interconnected μ-databases or (ii) millions of independent μ-databases owned by individuals.

The realization of the first scenario in a traditional datacenter equipped with high-performance server systems is problematic due to networking and power constraints. First, the connectivity in a datacenter's cluster is done through switches or routers that become either bottlenecks or sources of network failure. Second, a typical server uses more than 50 W of power, while often reaching 100 W [63]. With one million servers, the power requirement of such a datacenter reaches 100 MW, $10\times$ more than the fastest supercomputer in Top500 [109].

On the other hand, low-power systems based on ARM CPU, such as smartphones and IoT devices, typically use less than 10 W when active [62], [63]. Besides, 5G is predicted to be more energy-efficient [3], hence, it will further reduce the power usage of the node. Previous research projects connecting low-power nodes in distributed data management and processing systems [2], [6], [61], [63] show that these devices can significantly reduce energy usage, while trading-off performance in terms of response time and throughput. Indeed, there is a high possibility that a distributed network of more than one million low-power 5G devices will exist in the near future.

The second scenario is that of a P2P database comprising millions of μ-databases, where each individual user owns their data, stores them on its own device, and decides how to share them. For example, a user can store her entire medical history on the smartphone, instead of keeping fragmented records in the databases of different hospitals. By storing the data locally, the user has better control on privacy and sharing. In addition to data, the user may choose to share resources, such as storage space or computing units. In this scenario of independent μ-databases, sharing requires a fine-grain access control mechanism to ensure security and privacy, especially in the context of strict data protection and privacy rules, such as the European Union's General Data Protection Regulation (GDPR) [29].

3.3.2 Challenges and Opportunities

With the ownership of the data being passed back to the users and with the implementation of strict data protection frameworks, such as GDPR, big data analytics has to be efficiently supported both on the cloud and at the edge. First, it is challenging to perform efficient batch or stream processing in the presence of a fine-grain access control mechanism. For example, users may choose to share only part of the data which could affect the final results of the analytics task. Second, the highly dispersed and volatile nature of distributed P2P μ-databases make fault-tolerance and task scheduling stringent issues in big data processing frameworks. It is well-known that strugglers affect the performance of data analytics [120], [123].

When large amounts of fragmented data are stored across a large number of devices, data have to be processed locally and/or transferred to the cloud for large scale analytics. For local data management and resource sharing over devices, efficient and light data management is required, possibly with some form of distributed shared memory [12].

The D2D and high density of connections in 5G will present a great opportunity for human-in-loop data processing. A complex high-level job may be partitioned into computer-based tasks and human-based tasks [57], which is in line with the exploitation of AI for tasks that machines can do best. Decomposition and classification of tasks need to be designed for specific application domains since domain knowledge and availability of experts are key to high accuracy. Fast response from a human is needed to improve the overall data quality and decision-making. However, all these must be examined to ensure that humans do not introduce noise into the system and cause further irregularity.

3.4 Blockchain

3.4.1 Overview

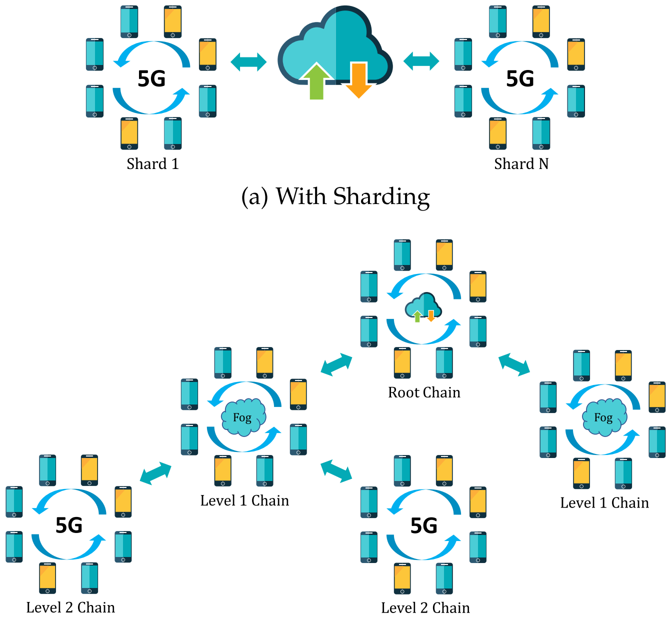
In the last decade, we have witnessed the rapid proliferation of blockchain platforms, both in public, permissionless networks and private, permissioned setups [21]. From the performance point of view, blockchains are known to exhibit low transaction processing throughput, high latency and significant energy usage [22], [60]. This low performance is, in part, due to the costly consensus protocol, either in the form of Proof-of-Work (PoW) or PBFT [13]. In the context of 5G adoption, it is useful to investigate how blockchain systems are going to be impacted.

From the applications point of view, blockchains could help in providing trusted services at the edge while connecting multiple mutually untrusted entities. For example, mobile number portability (MNP) is an application where different telecommunication companies (telcos) that do not trust each other need to work together to offer this service to their clients [49]. Using MNP, a client can keep her mobile number while switching the telecommunication provider. For this application, the blockchain could store a unified database to keep track of mobile numbers, client ids, and telecommunication providers.

3.4.2 Challenges and Opportunities

With the adoption of 5G, the number of devices that can potentially connect to a blockchain will increase significantly. Thus, traditional blockchains are expected to exhibit even lower performance. To improve the scalability of blockchain, researchers have looked into reorganizing the structure of the network. There are two key approaches to do this re-organization, as depicted in Fig. 5. These two approaches are (i) sharding where the network is split into smaller partitions [17], [65] and (ii) hierarchical chains where there is a main (root) network and many secondary networks [84], [85]. These approaches become more relevant in the era of 5G, edge computing, and network virtualization.

Both sharding and hierarchical networks could improve the performance of blockchains. Shards or secondary blockchains running at the edge, in close proximity to 5G base stations, are supposed to run much faster compared to global networks. For example, Hyperledger Fabric 0.6 with PBFT exhibits up to 5× higher throughput in a local cluster with Gigabit Ethernet networking compared to Google Cloud Platform distributed across 8 regions [17].



(a) With Sharding

(b) With Hierarchical Chains

Fig. 5. 5G in blockchain networks.

3.5 Artificial Intelligence and Federated Learning

3.5.1 Overview

With higher connection density and bandwidth, a few billion devices are expected to be connected to the 5G network, including mobile phones, tablets, wearables, automobiles, and drones. The increased number of interconnected devices and the accompanying sensors will generate a tremendous amount of data on a daily basis. At the same time, there is a surging demand for personalized services on mobile devices to enhance user experience. For example, companies may want to provide real-time personalized recommendations to users. The unprecedented amount of data residing in the edge devices is the key to build personalized machine/deep learning models for enhanced user experience. This trend presents new opportunities as well as challenges for machine learning (ML) and deep learning (DL).

Over the past few years, various hardware accelerators like AI processing unit (APU), neural processing unit (NPU) and vision processing unit (VPU), have been integrated to mobile chip platforms, including Qualcomm, HiSilicon, MediaTek, and Samsung chipsets, to support fast inference of ML and DL models in the edge devices. Corresponding software libraries are also developed, e.g., SNPE SDK, Huawei HiAI SDK, NeuroPilot SDK, Android NNAPI, and TensorFlow-Lite. On the other hand, the training is typically done on the cloud. The model is then converted into a certain format to be deployed in edge devices. Although 5G enables fast data transfer between mobile devices and base stations, the edge-cloud links have a limited capacity which may not scale with the number of connected 5G devices.

Consequently, some training tasks need to be shifted from the cloud to the edge to save the communication cost of data transfer. Meanwhile, training in edge devices resolves the data privacy issue as the data are not shared on the cloud.

Edge devices are expected to handle the training process in some specific scenarios. With datasets getting larger at the edge, the training has to be conducted locally or in the fog, rather than on the cloud, since edge-cloud links typically have limited capacity. In this case, each device or sensor is no longer merely a data carrier; it will also handle processing and data requests from servers or other devices. With faster data flow between mobile devices and 5G base stations, carriers can directly transfer the required data to the client via the edge, fog or D2D, without involving cloud servers. Even ML/DL models can be transferred directly between devices without a server.

3.5.2 Edge Data Properties

Data from mobile devices has some special properties that are different from the assumptions of traditionally centralized training. Therefore, training in edge devices requires substantial adaptations of model design, training, and deployment algorithms. The main properties of mobile datasets for learning in the 5G era can be summarized as:

- *Highly-distributed.* The data are distributed among end devices instead of being collected in a centralized server, where the number of end devices would easily surpass the number of training samples per client.
- *Unstructured.* The majority of samples in a local dataset are expected to be in unstructured and diversified formats since raw data are collected from various applications or sensors.
- *Non-IID.* The local dataset is gathered from a particular client, and thus, a great variance is expected among different local datasets. Hence, the local dataset is not independent, identically distributed (IID) sampled from the population distribution.
- *Unbalanced.* The amount of training samples varies in different clients. Moreover, sensors bias and the difference in user preferences lead to unbalanced local datasets.

These data properties pose challenges to the traditional ML/DL training which requires centralized structured training data [75]. First, providing real-time personalized services while reducing the server-side burden is highly demanded. Second, the large number of client-side *data islands* [118] and increased communication efficiency of 5G connections will undoubtedly require substantial adaptation of model design, training, and deployment. In response to these challenges, the research community has focused on techniques for edge device architecture engineering [42], [66], [93], model compression [20], [36], [37], and neural architecture search [11], [88], [128].

3.5.3 Model Training and Deployment

New opportunities for a wide range of research directions in AI are arising with the adoption of 5G. In terms of model design and deployment, more client-side models are anticipated. This is possible because (i) edge storage and compute resources are more powerful with various system-on-chip (SoC) technologies and (ii) there is a data-privacy practice to keep personal data locally. Further, due to its inherent capability of adaptive modeling and long-term planning, reinforcement learning presents potential in building interactive and personalized models, such as interactive recommendation systems [125], [126].

How to build the *correct* machine learning model on edge devices remains a challenging problem. Since the computational capabilities of edge devices are mostly limited by battery and storage space, several key factors should, therefore, be taken into consideration for better deployment of an ML/DL model: power consumption, storage space occupation, service latency, and model performance. In real-world applications, these end-user perceptible requirements and constraints should be considered in the model structure engineering and hyper-parameter configurations during the training procedure.

Mobile edge devices also vary greatly in hardware capacity [116]. These hardware differences require automation in the model building workflow to satisfy the model deployment in diversified environments. Automated machine learning and Neural Architecture Search (NAS) could provide technical clues to tackle the challenge [11], [104]. For example, the meta-information of datasets, local resource profiles, and service-time constraints can be gathered to model the automation procedure and recommend model configurations.

The properties of edge data require model training on highly biased and unbalanced personalized data. Under such circumstances, Transfer Learning and Meta-Learning [79] are two promising approaches to facilitate edge training via warm start. A pre-trained global model can be either optimized on a large public dataset or initialized via meta-learning with meta-features collected, which is subsequently broadcasted and adapted to the local data. Further, few-shot learning [98], [113] also supports effective training with a minimum amount of edge data. Knowledge distillation [38], [43] is another promising technique that benefits training on edge via mutual learning, which transfers representation learned from a high-performing teacher model to student models that are typically smaller and more efficient for deployment. The teacher model can also be a pre-trained global model [124]. With these cutting-edge deep learning techniques, training on edge devices can be more effective and efficient.

Other techniques, such as model compression and quantization, may benefit the model deployment on edge devices. For instance, model compression techniques reduce the model complexity in various ways with controlled accuracy degradation. The quantization techniques can reduce the power consumption and storage space cost by taking advantage of the emerging edge-optimized hardware such as neural processing units.

3.5.4 Federated Learning

Increasingly, smartphones and other mobile devices become the primary computing devices for many people. The

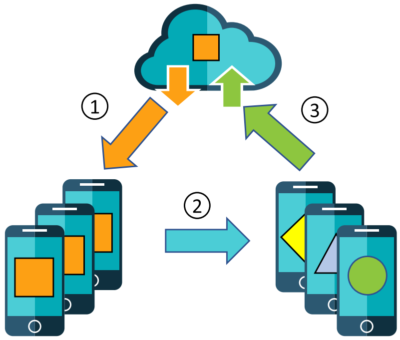


Fig. 6. Federated learning.

various embedded sensors are used by popular applications to collect an unprecedented amount of data on a daily basis. 5G technology will undoubtedly accelerate this trend. While these data could be used for AI model training and inference, the privacy issue should be taken into consideration more seriously when using personal data. Moreover, directives like GDPR [29] push for strict personal data processing, and require individuals or organizations to handle data in an appropriate manner.

To preserve data privacy, Federated Learning (FL) [69] has been proposed as a collaborative training technique that keeps the personal data residing in edge devices and constructs a shared model by aggregating updates that are trained locally, as illustrated in Fig. 6. In federated learning, data are only accessible to the data owner and the training process runs locally, on the mobile device. The centralized server can only receive intermediate results such as model updates from clients. Consequently, FL helps preserve privacy and reduce the communication costs of dataset transfer.

Federated learning is a feasible and ideal solution for the data privacy concern in the 5G era, where 5G and federated learning will complement each other. In recent years, most research projects on federated learning focus on communication efficiency and preserving privacy. The high-bandwidth and low-latency property of 5G will improve the communication efficiency of federated learning and compensate for the communication overhead caused by privacy-preserving protocols. In addition, the more stable connections brought by 5G can mitigate the dropout issues of clients during the federated learning training. Therefore, federated learning provides a privacy-preserving solution for learning in the 5G era, while 5G makes federated learning more practical and robust.

Further, vertical federated learning [118] is proposed to tackle the data islands problem. Succinctly, vertical federated learning is a collaborative privacy-preserving learning approach to handle scenarios where multiple parties separately hold datasets with different attributes. For example, when a bank and an e-commerce company decide to collaboratively train a model without disclosing sensitive data, the datasets involved are divided into multiple data islands and vertical federated learning comes to rescue. In addition, smart cities are applications of great potential in the 5G era, and different parties or platforms in a smart city will benefit from resolving the issues related to data islands. With the 5G technology and vertical federated learning, the world of Internet of Everything (IoE) is to be anticipated.

Many companies have been working on federated AI research. Google has released TFF[7] (TensorFlow Federated), which is an open-source framework based on TensorFlow for machine learning and computations on decentralized data. Meanwhile, WeBank initiated an open-source project called FATE[8] (Federated AI Technology Enabler). FATE provides a secure computing framework and a series of toolkits for the federated learning ecosystem. To preserve privacy, FATE implements secure computation protocols using homomorphic encryption and secure multi-party computation (SMPC). However, these frameworks are still targeting desktops, laptops, and datacenters. They have not been deployed on edge devices mainly due to the constraints of bandwidth and computing power. But with the adoption of 5G and the performance improvement in edge devices, we anticipate the proliferation of federated learning platforms.

3.6 Security and Privacy

3.6.1 Overview

One distinguishing feature of 5G is network slicing, which enables applications with distinct requirements to share the same network. A generalization of virtualization, network slicing works across all layers of the application stack, as shown in Fig. 7. The radio network layer is multiplexed through spectrum sharing. The networking layer is multiplexed at the telco providers via SDN and NFV. Cloud resources, especially the ones near the edge, are multiplexed via virtual machines. While virtualization has obvious advantages in terms of better exploiting the physical infrastructure and reducing the time to market, it poses security and privacy challenges, as we shall further discuss.

The other features of 5G, such as improved bandwidth and latency, higher device density and D2D communication may impact the security as well. As previously discussed, higher device density and increased bandwidth make it easier to conduct large scale DDoS attacks, especially using IoT devices. On the other hand, D2D communication requires isolation and well-implemented access control mechanisms such that data privacy is not compromised.

3.6.2 Challenges and Opportunities

The fact that one 5G network slice comprises multiple virtualized resources managed by multiple providers makes it difficult to ensure isolation. In particular, it is possible to achieve virtual machine isolation with the secure design of hardware virtualization, but does this still hold when, for example, slices at NFV layers are compromised? To ensure slice isolation, it seems necessary for the layers to coordinate and agree on a cross-layer protocol. Fig. 7 illustrates an example where a slice consists of several sub-slices at

7. https://www.tensorflow.org/federated
8. https://www.fedai.org

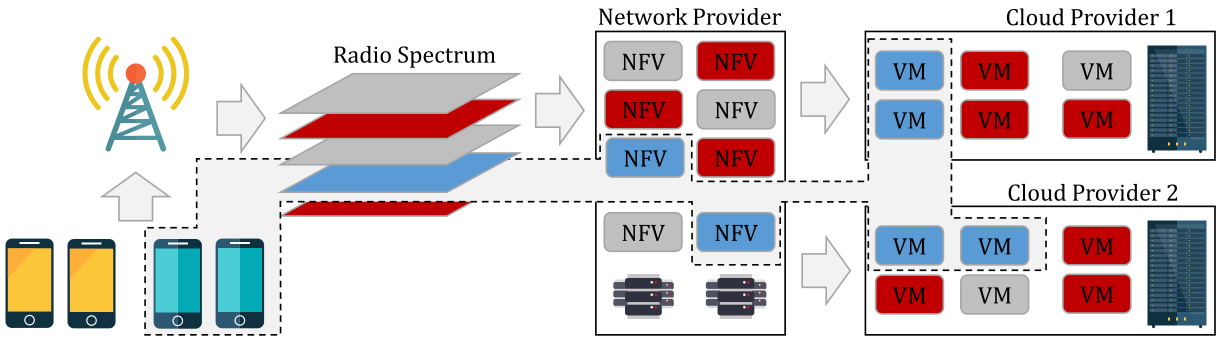


Fig. 7. Network slices operating at different layers need to be isolated. Red-color sub-slices are controlled by attackers trying to learn or tamper with data of the blue-color, honest sub-slices.

different layers. At each layer, the slice needs to be isolated to ensure security and privacy.

5G is a key enabler for machine-to-machine communication. Applications based on device location, for instance, may see new devices moving in and out of range at high velocity. This type of ad-hoc communication with a high churn rate poses a new challenge for device authentication. In particular, devices must establish identities of each other before communicating, for example, by knowing the mapping of devices to their public keys. The scale of 5G requires an identity system that supports a large number of users and avoids a single point of trust. Existing public key infrastructures (PKIs) are too heavyweight because they are designed for enterprise identities. Large-scale consumer systems such as those used for end-to-end encryption, for example, iMessage and WhatsApp, meet the performance and scalability requirements, but they still rely on a centralized party. To decentralize the existing identity systems, we envision a blockchain-based solution which maintains a highly available and tamper-evident ledger storing identity information. However, existing blockchains are severely limited in their throughput and latency. Therefore, novel blockchain systems are needed to meet the performance requirement of future 5G applications.

Current practices in enterprise security rely on collecting and analyzing data both at endpoints and within the network to detect and isolate attacks. 5G brings more endpoints and vastly faster networks. More endpoints mean a larger attack surface, raising the probability of the network being attacked to near certainty. Faster networks impact data collection, as it becomes unfeasible to store, and later analyze, highly granular data over long periods of time. Therefore, 5G demands a fundamentally new security analytics platform. We note that existing solutions, for example Splunk[9] and LogRythm,[10] are inadequate for the 5G scale since they stitch together general-purpose data analytics platforms. The desired solution should not have been designed to target general data management workloads, but specifically optimized for 5G workloads.

Apart from the security aspects, 5G also presents new challenges and opportunities in terms of privacy, as the improved bandwidth and reduced latency of 5G open up the possibility of transforming mobile devices into private databases that could be queried in real-time. For example, consider an online shopping service that provides recommendations to users based on their shopping histories. With current technologies, performing such recommendations requires the service provider to store users' shopping histories at the server-side, which has implications for privacy. In contrast, with the help of 5G, we may keep each user's shopping history in her local device, and let the service provider join hands with the users to perform recommendations in a privacy-preserving manner, e.g., by offloading to the users the part of the recommendation task that requires access to private data.

Such a computation paradigm, however, poses a number of challenges from a technical perspective. First, how should we manage each user's private data on her local device, so that different service providers could access data through a unified and efficient interface? Second, how could we enable users to make educated decisions regarding which service provider should be allowed to access what data item? In addition, given that each user may have a considerable amount of heterogeneous private data stored on her local device, how could we alleviate users' overhead in setting up access controls for a sizable number of service providers? Third, when a service provider and a user jointly compute the result of a certain task, the service provider may *infer* sensitive information from the computation result, even if she does not have direct access to a user's private data. For example, based on the result of the recommendation computed from a user's shopping history, the service provider may infer partial information about the items that the user purchased in the past. How should we prevent such inference attacks without degrading the accuracy of the result jointly computed by the user and the service provider? Addressing these issues could lead to the development of new techniques that advance the state of the art in privacy-preserving data analytics.

3.7 Challenges

We conclude this section by highlighting the key challenges that 5G is introducing in areas related to data management and processing, as depicted in Fig. 8.

Security and Privacy. Some of the key features of 5G have a significant impact on security and privacy. First, the support for a massive number of connections increases the area of attack and provides an ideal setup for large DDoS attacks. Second, network slicing and end-to-end virtualization are challenging in terms of security management in the presence of multiple service providers. Third, D2D communication

9. https://www.splunk.com
10. https://logrhythm.com

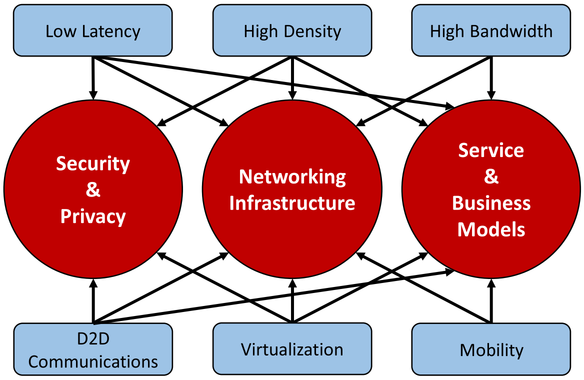


Fig. 8. Challenges (red) introduced by key 5G features (blue).

introduces security and privacy challenges in an era when people are more concern about their private data and when strict data protection frameworks, such as GDPR, are enforced. In this context, there is a need for security standards and ways to ensure consensus among entities participating in a 5G network.

Network Infrastructure. With its impressive bandwidth and high device densities, 5G allows more data to be downloaded or uploaded from and to the cloud. But this will exert a high pressure on both the (i) backhaul links from the base stations to the rest of the operator's network infrastructure and (ii) backbone of the Internet, including inter-cloud connections. Our networking performance measurements among different cloud regions show that current connections are not ready for the speeds of 5G. For example, inter-region connections can hardly reach 100 Mbps in throughput and 10 ms in delay, in the best case, while 5G specifications require at least 10 Gpbs and 1 ms throughput and latency, respectively (Section 2.1). We assert that there is a need for both (i) better backbone connectivity and (ii) smart edge-fog-cloud data offloading strategy to cope with the demands in services, data movement, and data processing.

Service and Business Models. With the explosion of the number of IoT and mobile devices connected to the Internet through 5G, there is a need for new service delivery and business models. 5G is considered the ideal network for connecting IoT devices, but creating a separate subscription for each device may be inconvenient for the user. On the other hand, operators will need to invest significantly to improve their network infrastructure [34] and to be able to deliver quality services at the edge. In addition to the pressure of high 5G bandwidth on the backhaul network, the high mobility specific to mobile devices introduces new challenges in service delivery and accountancy, in the context of virtualization and edge computing.

4 Use Cases and Challenges

While the previous section analyzed the impact of 5G on areas related to data management and processing, this section presents 5G use cases with a focus on analyzing challenges and identifying research opportunities.

4.1 Healthcare

The healthcare industry is rapidly expanding, mainly due to the advancements in machine learning which are applied to the medical domain [54]. In a recent study, Deloitte estimates that the healthcare market will grow to 10 trillion US dollars by 2022 [19]. With the adoption of 5G, new smart healthcare use cases are taking shape, such as telemedicine, telesurgery, and smart medical devices.

5G will be the foundation of telemedicine in countries where wired infrastructure is not well developed. 5G mobile services will enable more effective delivery of remote diagnosis and support for paramedics. This allows for a new and seamless way of delivering cost-effective and direct-to-consumer healthcare as it is no longer limited to traditional face-to-face consultations in healthcare facilities. In order to have connected care and telemedicine, 5G is needed to guarantee low latency and high-quality video streaming.

Telesurgery can also benefit from the low latency and high bandwidth of 5G. Telesurgery allows surgeons to execute real-time surgery, even when they are not physically in the same location, using a remote control to carry out the surgery. Although 4G is sufficient for real-time video transmission under ideal conditions, its relatively high latency renders it unusable for telesurgery. It remains to be studied if 5G, with its improved latency and increased bandwidth, is able to meet the requirements of telesurgery.

One of the main reasons patients with chronic diseases visit the hospital is the lack of medical equipment at home to measure and monitor vital body signs. 5G will alleviate the burden of hospital checks by transferring this functionality to the community (e.g., to local clinics and homes). Devices that are community-deployable should be equipped with vital signs sensing, biomarker sensing, video analytics, a chatbot and an AI-enabled intervention mechanism (e.g., a model that can predict disease progression [54], [127]). All these features are more feasible in the 5G era.

Massive Internet of Medical Things (IoMT) market is predicted to grow from 8 to 33 million shipments in the period 2016-2021 [55]. IoMTs are clinical wearables consisting of low-power medical monitoring devices that allow for tracking a patient's status. Such an integrative device receives information from various sensors and sends pre-processed data to healthcare providers who may adjust the medication doses or change the behavioral therapy.

We assert that the security and privacy challenges in the era of 5G pertain to the field of healthcare and IoMT, as well. With a series of recent security breaches in medical data management systems [30], [105], security and privacy are one of the biggest concerns in the digitalization of healthcare. Moreover, strict personal data processing directives, such as GDPR [29], require special attention. It remains to be studied if 5G virtualization could address these concerns.

4.2 Smart City

The key features of 5G, such as high speed, massive connections, and virtualization, will enable the development of smart cities. A *smart city* is a sustainable city that utilizes smart solutions to improve the infrastructure and provide better services to the community [4]. Among smart city solutions, we mention correlated traffic systems, public safety, security, and surveillance. A key objective of a smart city is to provide cohesion among the variety of deployed systems.

Below, we enumerate a few smart city applications that may be enhanced by 5G technologies. First, *smart homes* can be implemented with many interconnected devices and with fast Internet access which is needed for security monitoring. Second, *smart education* could be enabled by stable connectivity and high bandwidth. Students will be able to access a massive number of online courses and even participate remotely in real-time classes. Third, *smart safety and surveillance* could be enabled by reliable connections and the integration of real-time video observation from various locations. This allows real-time emergency response and surveillance of traffic conditions, accidents, banks and ATMs, stores, roads, among others. Lastly, *smart power* could be implemented using *smart grid* technology [26] consisting of smart meters, sensors, and data management systems. A smart power solution reduces energy and fuel consumption, while identifying power outages in real-time.

Currently, smart cities are not efficiently implemented due to a lack of powerful connectivity [87]. Low-latency, stable connectivity is required anywhere and anytime within a smart city. It is estimated that the reliability of the network in a smart city should be higher than 99.9999 percent [87]. Moreover, the network infrastructure of a smart city must be able to support an immense amount of IoT devices. 5G suits the requirements of smart city connectivity, with its low latency of 1 ms, and high device density of up to one million devices per square kilometer.

Another challenge in smart cities is ensuring the energy efficiency of monitoring solutions [25]. This is challenging in the context of maximizing the life of battery-operated sensors and requires a smart deployment of devices, as well as algorithms to compute an optimal communication-to-computation ratio per device. Nonetheless, the energy efficiency of 5G terminals could improve the battery life of remote monitoring devices.

While the benefits of 5G in smart cities are obvious, some challenges need to be addressed. First, with the interconnection of vital city infrastructure, there is a high security risk in case attackers manage to capture critical nodes. Network slicing is a partial solution to this, where different smart city applications are isolated. However, we discussed in Section 3.6 that 5G virtualization presents some security risks that need to be addressed. Second, the high volume of data from surveillance and monitoring systems will exert high pressure on the network infrastructure connecting 5G base stations with central facilities. A solution to this is the use of edge and fog computing where partial processing with the discarding of fruitless data can be done closer to the source of data.

4.3 Automotive

The automotive industry will be significantly impacted by 5G, as it opens up the potential for vehicles to be connected to roadside infrastructure, pedestrians, and other vehicles. Currently, autonomous vehicles are not fully supported by the IT infrastructure due to the lack of mobile antennas and sensors, which does not allow for efficient and stable communications [15].

4G technology is unable to reach the handling, processing, and analyzing standards needed by autonomous vehicles [15], [45], [59]. In order for autonomous cars, also known as smart cars or self-driving cars, to be well-implemented, the time to transmit and process sensor data needs to match at least the speed of human reflexes [91].

Existing 4G infrastructure, including the mobile antennas on buildings, is not sufficient for autonomous cars [91]. There is a need for significant amounts of antennas located a few hundred meters apart to enable stable car-to-car communications [91]. 5G, with its D2D technology, could help in alleviating this issue. In addition, D2D helps with sensor fusion such that cars can have a better view of the traffic and road condition beyond their line of sight.

Wireless communication enables vehicles to share, among them or with other participants, information about road and traffic conditions. For example, Cellular Vehicle-to-Everything (C-V2X) protocol comprises of multiple communication methods, such as Vehicle-to-Vehicle, Vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), and more [1]. 5G's low latency will allow for V2V and vehicle platooning, where vehicles communicate directly to share warnings and real-time road conditions. V2I enables communication between vehicles and roadside infrastructure components, such as traffic signs, traffic lights, and pedestrian crossings. The predicted reliability of 5G at 99.9999 percent will allow for V2N to run smoothly as it can share real-time traffic information with the wireless network infrastructure. These smart vehicle technologies can anticipate potential risks or help in planning an optimal route given real-time traffic conditions. Moreover, these technologies are predicted to improve safety and reduce deaths, since 90 percent of fatal car accidents are due to human error [14].

While 5G is seen as the natural choice for wireless communications in autonomous cars, there are some challenges that need to be addressed. First, critical decisions must be taken by the autonomous car based on its own processing, such that the reaction time is kept below 2 ms [91]. Even if 5G has a theoretical latency of 1 ms, this is the best-case latency to the base station. If multiple hops are needed to get the required data, the latency may increase above 2 ms. For example, our measurements on a real 5G network show an RTT of 6 ms to a sever that is a few hops away. Second, there is the challenge of trust and authenticity in the messages received by a vehicle from other entities. In the context of security issues in 5G environments, discussed in Section 3.6, there is an imperative need to evaluate their impact on critical systems, such as autonomous vehicles.

4.4 Smart Drones

The flexibility in the deployment of unmanned aerial vehicles (UAV), also known as drones, has enabled a series of use cases such as the spread of the Internet in remote areas, public safety communications, disaster recovery, flood area detection, and special deliveries. The use of multiple drones, or drone swarm, allows for the spread of the Internet to areas that lack reliable connectivity. In this use case, multiple drones fly autonomously in close proximity to build a wireless network with no gaps in signal distribution to the ground [89].

The deployment of UAV base stations (e.g., drone base stations) [5], can be accelerated by 5G, especially with the usage of the mmWave technology and a massive number of connections. Currently, the limited radio frequency spectrum below 6 GHz is not capable of supporting smart drones and UAVs. With the use of a larger spectrum, between 28 and 95 GHz (Section 2.1), 5G enables effective communication between drones and ground users. More specifically, 5G will enable wireless mobile broadband with low latency and high connection density.

Another feature of 5G, namely energy efficiency, could have an impact on UAV base stations. These UAVs are battery-operated and need to exhibit satisfactory operating time to enable reliable connectivity [89]. While alternative sources of energy, such as solar panels, can be used to enhance battery life, the energy efficiency of 5G is a complementary feature that can extend operating time.

5G-connected drones can aid in emergencies, where drones communicate and share real-time information with operators on the ground. This increases the success of the search and rescue missions and allows relief teams to dispatch rescue teams. For example, this use case can quickly estimate debris levels and distribute resources efficiently.

The adoption of smart drones and 5G will expose challenges related to security, privacy, and public safety [112]. In addition to DDoS cyber-attacks, such as those launched using IoT devices (Section 3.1), drones could be used to conduct physical attacks on the population of a smart city. In the context of UAV base stations, there needs to be a clear separation between the Internet providing service and the UAV control plane. Network slicing and virtualization could help in addressing some of the security challenges of smart drones.

4.5 Virtual and Augmented Reality

In a study by IBM's Institute for Business Value, prospective users of 5G are looking forward to entertainment applications based on VR and AR technologies [110]. The potential use cases of these interactive and immersive technologies are wide and varied, but the platform behind these revolutionary technologies is the same: a combination of cloud, edge, and 5G connectivity [58]. Currently, the challenges faced by VR, AR, and mixed reality are mainly related to the lack of mobility and bad user experience in terms of lag and low video quality. Under 5G, the distributed edge computing will be the main technology to tackle those issues. With the high bandwidth and low latency of 5G, cloud and edge computing can deliver the high-resolution content to the VR glasses, while enabling computation offloading from the VR glasses to the edge cloudlets or directly to the cloud. In this way, content delivery will be faster, enabling smooth VR/AR experiences.

As part of the AR/VR entertainment, users are interested in interactive gaming and immersive streaming of sports, e-sports, and reality shows [110]. With 5G, gaming experience improves due to low latency connections to gaming servers. At the same time, the high bandwidth of 5G allows graphics processing to happen on powerful servers on the cloud or at the edge, while the high definition video is transferred back to the gamer's device. A study by Intel and Ovum predicts that 5G will enable revenues of almost 50 billion US dollars by 2028 in the AR/VR gaming industry [77].

Beyond entertainment, 5G will connect the front-end and back-end workers in big organizations. Front-end workers are always the first to interact with a potential or existing customer or make a product demo for the company. It is often critical for big organizations to connect the customer, the front-end worker, and the leader, across geographic boundaries. With 5G, communication tools will support real-time feedback which allows distributed workers to overcome the communication delay and respond to customer needs timely. This is very useful, especially in a fast-paced environment.

Moreover, we envision that 5G will enable better experiences in working remotely. 5G latency is much lower compared to the refresh rate of ordinary displays, which is 60 Hz (or 17 ms). In such cases, the terminals connected to 5G do not need to be fat clients running an entire operating system: they can be low-power devices equipped with a simple browser. The high bandwidth of 5G allows UHD graphics streaming, where the 3D graphics engine runs on a remote server, for example in a cloudlet.

Huawei has started its cloud desktop service for both enterprise clients [40] and individual clients [78]. In a 5G environment, this cloud desktop service will support image quality of up to 4K. In this way, a mobile device connected to a 5G network can serve as a portable workstation or as a mobile game console. Nvidia introduced the RTX server for cloud-based GPU computing [74]. At the moment, these services do not deliver excellent user experience, especially for mobile users, because of high network latency. However, we expect an improvement with the adoption of 5G.

4.6 E-Commerce and Fintech

E-commerce, such as online shopping, will be further disrupted by the 5G technologies. High-quality video streaming and real-time information feed will not only provide an immersive shopping experience with fast and personalized recommendations but also enable dynamic mix-and-match choices [53]. For example, a piece of furniture may be viewed from the perspective of a real home environment. While 4G popularized online shopping, 5G is likely to take it a few steps further with augmented reality, fast fact-checking, recommendations, and overall experience.

5G, together with other technologies such as AI, IoT, and blockchain, will disrupt the e-commerce and financial industries in the near future. E-commerce and fintech companies will challenge traditional or legacy banks with their offer of better online customer experience through 5G and AI. The demand for seamless digital banking experience will transform banking services. Online transfers, payments, and purchasing of banking products will be the norm, and customer loyalty will become weak due to higher expectations and ease of moving the funds around.

5G, edge computing, and IoT are going to improve both the traditional and digital banking experiences. First, 5G with its low latency and network virtualization technology can enable safe yet flexible placement of automated teller machines (ATM) and point of sale (POS) in remote areas in smart cities or the countryside. Second, IoT devices, such as smart watches and smart wallets, will use 5G for faster and safer banking.

AI has been used to improve the profit in trading by examining historical records, relevant news and information, and model performance [107]. Trading bots are becoming more intelligent, being able to maximize profits and

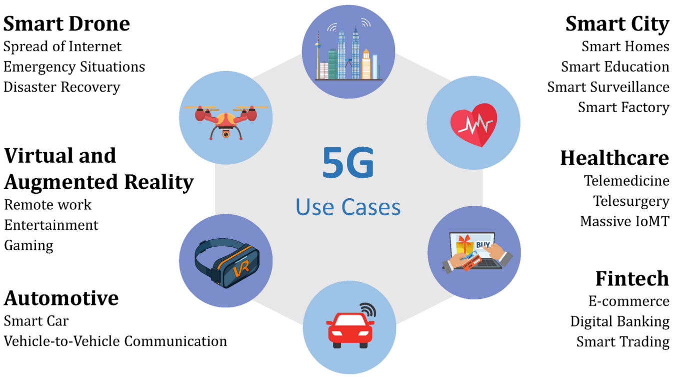


Fig. 9. 5G Use cases overview.

make smaller loses. While human traders are still dominant, AI algorithms are being increasingly deployed by trading companies. With 5G, real-time collaborative trading, either among humans or between humans and AI, becomes feasible due to low networking latencies.

4.7 Summary

Based on an extensive literature review, we have presented in this section some key use cases that are going to be enabled by 5G, as illustrated in Fig. 9. We summarize our presentation by highlighting the trends and challenges we foresee in the event of 5G adoption.

Efficient Healthcare. The healthcare sector has a huge market size which is going to increase with the population's aging all over the world. 5G, together with Machine Learning and IoMT, is going to enable more efficient and affordable healthcare, even in under-developed countries. However, the challenge in remote healthcare is represented by the security and privacy of patients' data.

Smart City. Smart cities, including smart cars, smart drones, and smart grids, are going to benefit from 5G, as it reduces latency, enables massive IoT, and offers highly-reliable connectivity. Again, the main challenge is represented by the security risks associated with the adoption of these technologies. It remains to be investigated if virtualization and network slicing in 5G are going to alleviate the security risks or introduce new issues.

Virtual and Augmented Reality. Virtual and augmented reality is a sector with huge business potential that spans both entertainment and work-related activities. With its increased bandwidth and low latency, 5G will create an immersive experience in movie and live streaming, gaming, reality shows, among others. On the other hand, 5G will increase the productivity of businesses that use remote desktop computing.

5 Conclusion

With 5G on the verge of being adopted as the next mobile network, it is necessary to analyze its impact on the landscape of computing and data management. In this paper, we have analyzed the broad impact of 5G on both traditional and emerging technologies and shared our view on future research challenges and opportunities. We hope this review serves as a basis for further study and development of relevant technologies. 5G will make the world even more densely and closely-connected, and will present us with vast amounts of possibilities and opportunities to overcome the challenges ahead of us.

Acknowledgments

We thank Dan Banica for helping us with 5G measurements in Bucharest. This research was supported by Singapore Ministry of Education Academic Research Fund Tier 3 under MOE's official Grant number MOE2017-T3-1-007. Tien Tuan Anh Dinh was supported by Singapore University of Technology and Design's startup grant SRG-ISTD-2019-144.

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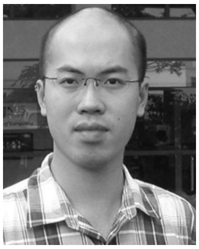

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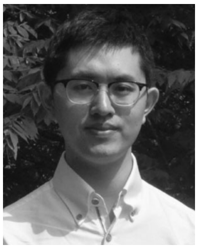

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