Enabling Massive IoT Toward 6G: A Comprehensive Survey

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***Abstract*—Nowadays, many disruptive Internet-of-Things (IoT) applications emerge, such as augmented/virtual reality online games, autonomous driving, and smart everything, which are massive in number, data intensive, computation intensive, and delay sensitive. Due to the mismatch between the fifth generation (5G) and the requirements of such massive IoT-enabled applications, there is a need for technological advancements and evolutions for wireless communications and networking toward the sixth-generation (6G) networks. 6G is expected to deliver extended 5G capabilities at a very high level, such as Tbps data rate, sub-ms latency, cm-level localization, and so on, which will play a significant role in supporting massive IoT devices to operate seamlessly with highly diverse service requirements. Motivated by the aforementioned facts, in this article, we present a comprehensive survey on 6G-enabled massive IoT. First, we present the drivers and requirements by summarizing the emerging IoT-enabled applications and the corresponding requirements, along with the limitations of 5G. Second, visions of 6G are provided in terms of core technical requirements, use cases, and trends. Third, a new network architecture provided by 6G to enable massive IoT is introduced, i.e., space–air–ground–underwater/sea networks enhanced by edge computing. Fourth, some breakthrough technologies, such as machine learning and blockchain, in 6G are introduced, where the motivations, applications, and open issues of these technologies for massive IoT are summarized. Finally, a use case of fully autonomous driving is presented to show 6G supports massive IoT.**

***Index Terms*—6G, blockchain, Internet of Things (IoT), machine learning, space–air–ground–underwater networks.**

I. Introduction

INSTEAD of only exchanges of voice, image, or video in the fifth-generation (5G) mobile networks and the earlier generations, researchers are exploring new forms of interactions in the future, including holographic communications, five-sense communications, and wireless brain–computer interfaces (WBCI), which will lead to a true immersion into a distant environment. At the same time, advances in personal communications will promote the evolution of smart verticals in the fifth-generation networks (5G) to a higher level, including healthcare, remote education/training, industry Internet, fully autonomous driving, and super smart homes/cities. During this paradigm shift, the Internet of Things (IoT) plays a vital role in enabling these emerging applications by connecting the physical environment to the cyberspace of communication systems [1].

Although these IoT-enabled applications will bring convenience to human life, it is an extremely daunting task for 5G to support these applications. First, these IoT-enabled applications require superior performances in terms of data rate, latency, coverage, localization, and so on. Second, they are more data intensive and computation intensive, which far exceeds the range of ultrareliable low-latency communications (uRLLC) and massive machine-type communication (mMTC) of 5G [2]. Third, it is hard to efficiently manage massive IoT devices in this case. Fourth, with massive data generated, serious security issues are accompanying [3]. With IoT evolving, 5G will gradually reach its limitations and be unable to provide support to most of these advanced applications, which can be predicted from the history of previous generations. So there is a strong motivation for the sixth-generation networks (6G) to extend 5G capabilities to a higher level to enable massive IoT.

Motivated by the aforementioned facts, the visions of 6G in terms of requirements, use cases, and trends should be clearly investigated first, since 6G is not defined yet. Then, to have massive IoT deployed in 6G, the development with respect to architecture, breakthrough technologies, and their challenges should be known.

A. Visions of 6G

Inspired by the robust requirements of the future IoT-enabled applications and the limitations of 5G, 6G, as an evolutionary generation, will expand and upgrade based on 5G from every aspect, which revolutionizes not only human life but also society. First, network performance of 6G will upgrade to a superior level, e.g., higher data rate (up to Tbps), lower latency (sub-ms), 3-D (3-D)-ubiquitous coverage (into space, sea, and even the undersea), more accurate localization (up to cm-level), more stringent privacy and security, and so

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on. Second, use cases in 6G will be more multitudinous and complex, resulting in different and even conflicting requirements in different use cases. Third, several trends about 6G have started to emerge, which are summarized as follows.

1) More bits and spectrum, and denser networks.
2) Convergence of various communication systems.
3) Convergence of communication, caching, computing, control, sensing, and localization (4CSL).
4) From network softwarization to network intelligentization.
5) From centralization to distribution.

As a result, 6G maintains the ability to connect millions of devices and applications seamlessly with performance guaranteed. Thus, 6G plays a major role in supporting massive interconnectivity in IoT with highly diverse service requirements. To enable massive IoT, 6G will provide a new network architecture and breakthrough technologies to meet their demands.

B. New Network Architectures for Massive IoT

With human activities expanding to the extreme environment, e.g., higher altitudes, outer space, oceans, and deep under the sea, an ubiquitous (covering Earth, sea, sky, and space), everything-connected (IoE), omniscient (with various sensors), and omnipotent (4CSL) network should be built to truly realize the connection anytime and anywhere with diverse requirements. To achieve this goal, a four-tier network architecture enhanced by edge computing is provided by 6G, i.e., space–air–ground–underwater/sea networks.

The space tier contains various types of satellites, which aims to provide Internet connections for some extreme environment, e.g., rural areas, mountains, and so on. In this tier, the very low Earth orbit (VLEO) satellites are promising to provide high data rates, low round trip latency, and accurate localization with the lowest orbit [4], [5]. The air tier consists of UAVs, airships, and balloons, which are aerial mobile systems to complement the terrestrial networks with its flexibility. For example, UAVs could move closer proximity to the ground IoT devices to collect data or acting as a computing hub, achieving higher throughput rates and conserving the energy of less-capable IoT devices [6], [7]. As the main way to acquire services for most IoT-enabled applications, the ground tier refers to the legacy wireless networks, e.g., cellular networks, wireless local area networks, VLC, and so on, where terahertz communications are promising to achieve the ambitious goals of 6G [8]. In the underwater/sea tier, optical communications play a vital role in providing Internet services for distributed nodes over the broad or deep sea as the water exhibits different propagation characteristics from the land [9], [10].

For the IoT-enabled applications that require real-time operations and decentralized services, edge computing is regarded as a key enabler [11], [12]. From the perspective of users' level, edge computing directly helps IoT devices execute their tasks, e.g., rendering for VR, decision making for autonomous driving, and so on, which outperforms the centralized cloud computing technology due to its distributed nature and low latency. From the perspective of system, edge intelligence with machine learning is enabled by edge computing to manage IoT systems using an intelligent method.

C. Breakthrough Technologies

As an omnipotent network, 6G is enhanced by a number of breakthrough technologies, including machine learning and blockchain.

As one of the most powerful intelligence enabling technologies, machine learning has been widely used for different aspects of the IoT-enabled applications, ranging from the application layer and the network layer to the perception layer. In the application layer, machine learning is widely used for task offloading and resource allocation. In turn, edge computing in the application layer provides storage and computation capability to enable edge intelligence. In the network layer, network intelligentization and automation are the primary goals of the IoT systems in 6G. Machine learning is recently being adopted in wireless systems to address the related challenges and to pave the way for future massive IoT communications [13]–[15]. Toward the future IoT networking in 6G, machine learning algorithms are widely used for multiple resource allocation, power allocation, transmit scheduling, traffic offloading, and so on. In the perception layer, machine learning is used for autonomous control for different IoT scenarios, e.g., movement control for autonomous robots (e.g., tactile Internet, smart factory, and remote surgery), driving aid for autonomous driving, and intelligent management for smart grid [16].

In addition to intelligence, another stirring premise promised by 6G is distribution, which exactly hits the bullseye of the future massive IoT systems. The current centralized IoT network model, in which IoT devices use a single gateway to transfer data between them and connect through a cloud server, is no longer suitable for the future massive IoT devices and the volumes of data they share due to its shortcomings, i.e., high costs of centralized cloud maintenance and networking equipment, low interoperability due to restricted data exchange with other centralized infrastructures, and severe security issues due to the untrustworthy single gateway and centralized cloud server. Blockchain, a decentralized distributed ledger, is recently regarded as the key to solve many of the problems faced with the current model and improve security [17]–[19]. First, dynamic network management is enabled by blockchain with decentralization and low cost. Second, with a unified authentication system in blockchain, interoperability among different IoT systems is improved. Third, data stored on various nodes eliminate the single point of failure. Confidentiality, integrity, and authenticity of the data are protected by immutability, anonymity, and encryption of the blockchain [20], [21].

D. Review of Related Overview/Survey Articles

To the best of our knowledge, there is no detailed survey paper dedicated to massive IoT enabled by 6G. Chettri and Bera [22] presented a comprehensive survey on IoT toward 5G, while Akpakwu *et al.* [23] talked about 5G networks for

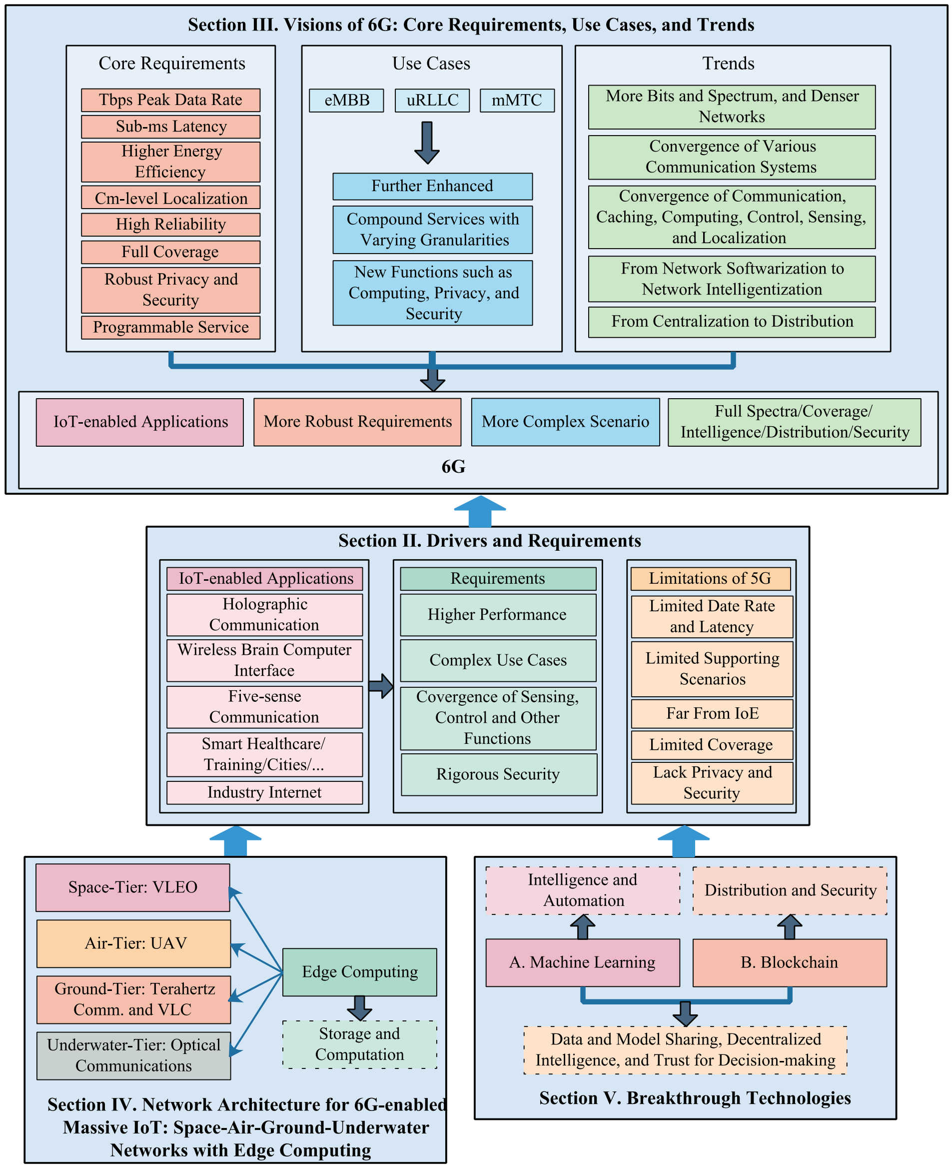

Fig. 1. Roadmap of this article.

IoT from the perspective of communication technologies and challenges. Huang *et al.* [24] presented an overview of wireless evolution toward green 6G networks, where new architectural changes related to 6G and related potential technologies are discussed. You *et al.* [25] discussed the visions and enabling technologies of 6G thoroughly, which provided an insightful picture of 6G. Focusing on breakthrough technologies for IoT, Sharma and Wang [16] discussed the current issues in ultradense cellular IoT networks and machine learning-assisted solutions. Hussain *et al.* [26] provided a survey on different aspects of resource management in cellular and IoT networks that leverage machine learning techniques. Several surveys [18], [19], [27] discussed blockchain for IoT from different aspects. Although these works have laid a solid foundation on 5G for IoT, 6G, and breakthrough technologies for IoT, the future massive IoT-enabled applications and the role of 6G for massive IoT have not been covered in the existing surveys. To fill this gap, we investigate the future IoT-enabled applications, visions of 6G, and the role of 6G for IoT in terms of network architecture and breakthrough technologies.

E. Contributions

In this article, we present a comprehensive survey of massive IoT enabled by 6G. We mainly identify four aspects, on which we focus drivers and requirements, visions of 6G, network architecture, and breakthrough technologies. The main contributions of this article are summarized as follows.

1) Compared with the other survey papers related to this topic, we provide a comprehensive survey on massive IoT enabled by 6G, where the challenges of future massive IoT are reviewed and the roles of 6G for massive IoT are presented from the perspectives of network architecture and breakthrough technologies.
2) The visions of 6G are presented, including core technical requirements, use cases, and trends of 6G. The

technical requirements in terms of data rate, latency, etc., are summarized, along with use cases of 6G. Several trends associated with 6G are presented, encompassing more bits and spectrum, and denser networks, convergence of various communication systems, convergence of communication, caching, computing, control, sensing, and localization (4CSL), from network softwarization to network intelligentization, and from centralization to distribution.

3) A new four-tier network architecture enhanced by edge computing for massive IoT is reviewed. The promising technologies in each tier are presented, including VLEO satellites, UAVs, terahertz communications, VLC, and optical communications.

4) The breakthrough technologies in 6G for massive IoT are reviewed, e.g., machine learning and blockchain, which provide intelligence and distribution, respectively. The applications and open issues are also summarized.

F. Paper Organization

We structure this article in a manner shown in Fig. 1. We begin by summarizing the motivations behind 6G, where the IoT-enabled applications and corresponding requirements, limitations of 5G, and necessities to develop 6G are presented (Section II). It helps define the motivation and contributions of this article. Since 6G is not defined yet, we provide its visions in Section III, highlighting its technical requirements, use cases, and trends. To achieve 6G visions and enable massive IoT, modifications to existing network architecture and cloud computing technologies as well as the involvement of breakthrough technologies are essential. We discuss the supporting network architecture and breakthrough technologies, as well as open issues in Sections IV and V, respectively, aiming at helping researchers understand the roles of 6G. To show how 6G supports massive IoT, a use case of fully autonomous driving is presented in Section VI. Finally, this study is concluded in Section VII.

II. Drivers

Nowadays, many IoT-enabled applications emerge, such as holographic communications, five-sense communications, WBCI, and new verticals. The IoT system is evolving toward super massive in number and convergence of 4CSL, which needs higher key performance indicators (KPI) and more complex usage scenarios. As known, it is a rather daunting task for 5G to support this evolving IoT system due to its limitations. In this section, we try to summarize the main drivers behind 6G by introducing the evolution of IoT, limitations of 5G, and necessities to develop 6G.

A. Evolution of IoT

IoT in 5G is transforming and bringing industrial revolution 4.0 in every aspect of human life, including smart healthcare, smart education/training, industry Internet, autonomous driving, smart homes, and cities. At the same time, people are exploring new forms of IoT-enabled interactions in the future, including holographic, five-sense, and even brain-computer approaches, which will create new verticals in turn. All these evolving IoT-enabled applications will propose more robust requirements to the wireless communication networks. Next, we aim to present the evolution of IoT by summarizing emerging IoT-enabled applications and their requirements.

1) IoT-Enabled Applications and Corresponding Requirements: Instead of only exchanges of voice, image, or video in the earlier and current generations, people are exploring new forms of IoT-enabled interactions in the future, including holographic communications, five-sense communications, and WBCI, which can lead to a true immersion into a distant environment. Powered by near-real-time and true-immersive experiences in personal communication using holograms and five senses and autonomously operating machinery in the industry as new fundamental media-objects, new verticals emerge, including smart healthcare, smart education/training, industry Internet, fully autonomous driving, and super smart city/home.

Holographic Communications: The first new form of interactions refers to *holographic communications*, which is capable of projecting full-motion 3-D images in real time. This technology captures images of people and/or objects, presents in reality or at a remote location, and transmits these images and related sounds to the receiver. In this way, it makes objects or people along with the real-time audio information present at a different location and appear right in front of the users, resulting in a closer-to-reality experience than VR and AR. Holographic type communications will have a big part to play in the industry, agriculture, education, entertainment, and in many other fields. Due to rich details to transmit, the amount of data necessary to stream holographic media can be very large even after compression, which calls for very high throughput in the range of hundreds of gigabits per second or even terabits per second to support such capabilities. Besides, an additional ask from networks to provide reliability and timeliness is required to eliminate any jitter since that will immediately degrade interactive applications' behaviors. Concisely, the requirement of holographic communications is a synergistic mix of URLLC and eMBB to guarantee low latency and high data rates.

Five-Sense Communications: Despite tactile transmission and traditional human interaction in terms of the exchange of voice, images, and videos, researchers also state the trend of new forms of remote human interactions [13], the so-called immersive five-sense or five-dimension (5-D) communications. The five-sense media will integrate all human sense information, including sight, hearing, touch, smell, and taste. This technology detects sensations from the human body and the environment and integrates sensations by using the neurological process. Then, the information is transferred to the receiver at a remote location, leading to a truer immersion into a distant environment. Such multisensory applications (e.g., a remote surgery), combined with VR/AR or holographic communications, will constitute truly immersive services for 6G. It requires a joint design considering not only engineering (i.e., wireless, computing, and storage) requirements but also perceptual (e.g., human senses, cognition, and physiology) requirements, which jointly determine the service performance. In view of latency and data rate, the requirements of five-sense communications are a blend of traditional uRLLC and eMBB with accurate localization ability, as well as incorporated perceptual factors.

Wireless Brain–Computer Interfaces: Another potential form of interactions refers to WBCI, also known as wireless mind-machine interfaces (WMMI), which are interfaces that use human thoughts to interact with machines and/or the environments [28]. This technology first reads the neural signals generated in the human's mind with a certain number of electrodes and then translates these acquired signals into commands that a machine can understand [29], thus achieving control or other functions, e.g., turn on a light. WBCI is a communication pathway between the brain and the external peripheral devices, which is a promising approach to control the appliances that are used daily in smart cities, homes, and medical systems in a more simple and intelligent way. Beyond healthcare and smart cities/home scenarios, the recent advent of WBCI revolutionizes this field and introduces new use case scenarios, ranging from brain-controlled movies to fully fledged multibrain-controlled cinemas [30]. Coupled with tactile Internet or haptic communications and related ideas, in which the functions of emotion-driven devices can match the users' mood, WBCI will constitute important 6G use cases [31]. WBCI requires high data rates, ultralow latency, and high reliability, as well as powerful computation capability, which is similar to VR/AR but much more sensitive than VR/AR to physical perceptions and necessitates Quality-of-Services (QoS) and Quality-of-Experience (QoE) guarantees.

Smart Healthcare: 6G can help build smart healthcare systems, where a reliable remote monitoring system, remote diagnosis, remote guidance, and even remote surgery can be facilitated by 6G. 6G with high data rate, low latency, accurate localization, and ultra reliability will help to quickly and reliably transport huge volumes of medical five-sense data, which can improve both the access to care and the quality of care. Cooperated with artificial intelligence (AI), the data can be better analyzed by doctors to make accurate diagnoses. With blockchain, personal data can be privately and safely shared among the world to contribute to the development of medicine.

Smart Education/Training: Smart education/training will benefit from 6G wireless systems because innovations, e.g., holographic communications, five-sense communications, high-quality VR/AR, mobile-edge computing, and AI, will help build smart education/training systems. With the support of the above techniques, it allows students to view structures and models in 3-D form and even to be taught by a famous teacher at a remote location, thus achieving interactive and immersive online education. For training, by illustrating the processes (live) in holography and interacting with objects or other trainers, it helps learners retain more information, reduce high costs, and avoid being in dangerous environments than traditional training methods. 6G can also help build intelligent classes, in which data are collected by sensors, and sent to the clouds or edge clouds to be analyzed. Then, the results can be used to improve the quality of education to better interact with students.

Industry Internet: 6G will facilitate a variety of vertical industries, e.g., electricity, manufacturing, delivery, and ports. Based on AI, full automation will be provided by 6G with its ultramassive connectivity capability and ultra reliability, which means that automatic control of processes, devices, and systems is enabled by 6G. By transmitting data to clouds or edge clouds and analyzing the data, decisions are made intelligently to achieve automatic manufacturing. In this process, error-free data transfer is ensured by 6G. With the help of VR/AR/holographic communications, remote maintenance can be enabled by 6G, in which experts in remote locations and workers in present can work together timely to solve problems, resulting in higher efficiency and lower costs. Another service refers to remote control, which controls machines remotely to ensure the safety of workers and reduce costs. It requires rigorous low-latency, broadband, and reliable transmission of 6G.

Fully Autonomous Driving: Equipped with multiple high-definition cameras and high-precision radar sensors and supported by 6G, fully autonomous driving can be achieved, which means that the vehicle performs all driving tasks and there is not even a cockpit (opening up new mobility possibilities for people with disabilities, for example). The core functions of autonomous driving include perception, planning, and control [32]. The information (including the accurate vehicle location and target recognition) generated by various sensors, e.g., image sensors or cameras, millimeter-wave/terahertz radar, and light detection and ranging (LIDAR), is as the input of the perception layer, which can be regarded as the prerequisite to realize autonomous driving. The instructions of the planning layer include following, overtaking, and accelerating, which depend on the input information, i.e., the information from the perception layer and the feedback from the control layer. The control layer is in charge of implementing the specific control over the vehicles according to the instructions issued by the planning layer, including throttle, brake, and gear control. The key challenge to achieve fully autonomous driving is how to meet the stringent safety demands when faced with different driving conditions. With the help of AI, MEC, and reliable and low-latency transmission of 6G, the complex information can be handled in time by 6G. Besides, the information can be shared safely with blockchain to enhance the performance of autonomous driving.

Super Smart City/Home: The superior features of 6G will lead to significant improvement of life quality, intelligent monitoring, and automation to accelerate the building of super smart cities and homes. A city is considered to be smart when it can run intelligently and autonomously by collecting and analyzing mass quantities of data from a wide variety of industries, from urban planning to garbage collection, which can make better use of the public resources, increase the quality of the services offered to the citizens, as well as reduce the operational costs of the public administrations. The use of smart mobile devices, autonomous vehicles, and so on will make the cities smarter in 6G. A smart home is not only simply a residential or commercial building equipped with Internet-connected smart devices to help people manage and monitor a range of appliances and systems from mobile

TABLE I
COMPARISON OF APPLICATIONS IN 5G AND 6G

	5G	6G
Applications	VR/AR/4K/8K videos Tactile Internet Wearable Devices Vehicle to everything Smart verticals	Holographic communications Five-sense communications WBCI Fully autonomous driving Super smart verticals Space communications Deep-sea communications

phones but also an intelligent entity with instantaneous and distributive decision-making capabilities. Besides, people can control light, heat, or multimedia entertainment by voice or just mind (brain–computer interfaces, BCI) or leave them all to AI, which can analyze your behaviors to make people's lives safer and easier. 6G will make smart home a reality. To achieve smart city/home, it poses key challenges to the connectivity and coverage capability of 6G, since there are so many sensors and intelligent terminals.

2) Summary: 5G is the first generation that is specially designed for vertical IoT use cases, including VR/AR, tactile Internet, wearable devices, vehicle to everything, smart verticals, and so on. As shown in Table I, each application of 5G will evolve to be a part of 6G, which aims to boost every aspect of human life. For example, holographic communications and five-sense communications in 6G will bring a truer immersive experience when compared with VR/AR and tactile Internet in 5G. Instead of vehicle to everything, fully autonomous driving will bring more convenience to human life. Furthermore, 6G will explore communications in space and deep sea rather than focusing on the ground like 5G. Build upon the unique creation of new interactions, new verticals emerge and IoT in the future 6G will change a lot. The main differences of IoT in 5G and 6G are described as follows.

Super Massive in Number: Owing to the aforementioned applications, new device forms emerge. First, smartphones are likely to be replaced with lightweight extended reality devices (google glasses, for example) to deliver an unprecedented resolution, frame rates, and dynamic range. Second, wearable displays, mobile robots and drones, and specialized processors will be used for high-resolution imaging and sensing to make holographic experience or telepresence a reality. Third, with fully autonomous driving coming true in 6G, more vehicles will be connected to the Internet for ecologically sustainable transport and logistics. All these mobile devices embedded with various sensing abilities (called sensors) will contribute to the growth of IoT in volume. According to the new analysis from IHS Markit, the number of connected IoT devices will jump 12% on average annually and reach 125 billion in 2030 from 27 billion in 2017. With this trend continuing, it can be predicted that the number of IoT devices will be super massive in the future 6G, which will far exceed what 5G promises to support.

More Intensive and Sensitive: IoT in future 6G will be more data intensive, computation intensive, delay sensitive, and privacy/security sensitive. First, evolving from VR/AR, tactile Internet, and wearable devices to holographic communications, five-sense communications and WBCI brings a surge of big volume of IoT data, which is generated in a nearly real-time fashion. Second, in view of the quantum of IoT data, more computation power will be needed for data processing and analysis. Third, the aforementioned IoT-enabled applications in 6G usually need more stringent latency requirements compared with 5G. Fourth, with more data involved, the desire for data security/privacy protection will be more strong.

From Communication, Caching, and Computing (3C) to 4CSL: For IoT, it is important to collect, store, query, understand, and utilize the raw sensor data. In 5G, a number of works studied the convergence of communication, caching, and computing in the case of edge computing [33], which can be used for data transmission, storage, and processing. However, it is not sufficient for IoT in 6G. For example, fully autonomous driving, which is context aware, needs to exploit the localization and sensing information to construct the environment accurately. Simultaneous localization and mapping methods are required to enable holographic communications or enhance the navigation of autonomous vehicles and drones. Remote control with ultrareliability is the key for industrial Internet and five-sense communications. Hence, the convergence of 4CSL is necessary for IoT in 6G.

B. Limitations of 5G

The limitations of 5G come from not only its architecture but also its technologies, both resulting in a mismatch between its capabilities and the requirements of all aforementioned IoT-enabled applications. The limitations of 5G will be described in detail as follows.

1) The first limitation lies in the best performance that 5G could provide in terms of data rate and latency. From the perspective of data rate, a peak data rate of 20 Gb/s and an experienced data rate of 100 Mb/s are touted, which indeed sounds fantastic. But this projection overlooks the critical fact that the capacity must be shared among multiple users and assumes unrealistic conditions that result in a condition that actual throughput capacity for wireless users is often only 15% of the peak data connection rate. In addition, the required data rate of an ideal VR user could reach several Gb/s and even Tb/s, and it is far away from meeting the requirement of high-quality VR for 5G. From the perspective of latency, a latency of 1 ms is promised by 5G. However, latency of less than 1 ms is needed for many IoT-enabled applications, e.g., fully autonomous driving, tactile Internet, and remote control.
2) The second limitation comes from the supporting service classes of 5G, i.e., eMBB, mMTC, and uRLLC. mMTC and uRLLC are designed for IoT. uRLLC supports low-latency transmissions with very high reliability for small payloads from a limited amount of user devices, which are active according to patterns typically triggered by outside events (e.g., alarms). While mMTC aims to connect a massive number of IoT devices, which are with small data payloads and only sporadically active. However, most of the future IoT-enabled applications are data intensive, computation intensive, and delay sensitive, e.g., augmented/virtual reality (AR/VR) online

games, which exceed the range of any of these three typical scenarios. Obviously, 5G will not be able to support such scenarios that combine any two classes or a synergistic mix of all three classes. For example, the requirements of five-sense communications are a blend of traditional uRLLC and eMBB.

3) The third limitation of 5G refers to its connection capability, which aims to connect everything (i.e., the Internet of everything, IoE). With technologies developing, humans are exploring mountains, seas, and even space, where communications should follow. Besides communications for human, IoT devices will vastly expand the geographic space for communication access, including deploying unmanned detectors deep into the Earth, sea, and space, UAVs at median altitude, autonomous robots that penetrate into harsh environments, and smart machines that are controlled remotely. However, 5G, including the earlier generations, focuses on communications over the surface, which ignore the activities in these extreme environments. So 5G is far away from connecting everything and ubiquitous connectivity is desired with time going on.
4) The fourth limitation of 5G is related to its coverage in rural areas. People in rural areas are by far the most underserved population when it comes to broadband access. Let alone for IoT. In 2018, the federal communications commission (FCC) found that 98% of Americans in urban areas had access to a broadband connection, yet only 69% of rural Americans do [34], which is nowhere near fast enough to be useful for most modern applications. In 5G, rural areas will not be left out, but it will be different there. The multi-Gb/s speeds and massive capacity of 5G is an urban phenomenon to a great extent, achieved by the huge bandwidths of mmWave spectrum, which does not travel very far, resulting in ultradense small cells. Considering the profitability, rural areas will get a form of 5G called "low-band" or "sub-6" 5G, which will have less capacity. Thus, how to provide IoT-enabled services for the last 4 billion people with broadband services in rural areas still remains unsolved in 5G, which is what rural residents probably most want and are most frustrated.
5) The fifth limitation is the new KPI arising from emerging applications, including privacy and security. With the capabilities promised by 5G, nearly all aspects of human life will be connected to communication networks, but it also provides a fertile hunting ground for criminals who are able to access the communication between a device and a network in order to intercept conversations or steal data [35]. The need for robust security mechanisms is underscored across all network segments of 5G. However, the research from the University of Dundee and so on found that while data protection in 5G has improved on that offered in the 3G and 4G versions, critical security gaps still exist [36]. For 6G, this problem will keep exacerbating, since so many sensors, which are used in IoT-enabled applications, such as healthcare, remote education, smart homes, and autonomous driving, will be involved in 6G. Hence, how to ensure privacy and security is a key challenge in the future.

C. Necessities to Start the Study on 6G

Besides the above drivers, we provide the following necessities of 6G.

Ten-Year Rule: A new mobile generation has appeared approximately every 10 years since the first 1G system was introduced since 1982 and it needs at least ten years from definition to commercial deployment, which means that when the previous generation enters the commercial phase, the concept and technology research of the next generation begins. Assuming that this trend continues, 6G will be a reality around 2030. With 5G rolling out across the world, it is the perfect time to start to study 6G.

Catfish Effect: Unlike previous generations of mobile communication systems, 5G is also targeted at IoT/vertical industry application scenarios. With 5G networks scaling, especially in the middle and late stages of 5G, more vertical industry members will surely participate in the 5G ecosystem. Compared with the current conditions that are dominated by traditional operators, the in-depth participation of emerging enterprises (especially Internet companies with innovative thinking) in the future will have a huge impact on the traditional communications industry, which is even revolutionary.

Exploding Potentials of Emerging Applications: Just as the emergence of smartphones that stimulates the development of 3G and triggers the demand to deploy 4G, it is believed that IoT business will also stimulate 5G at some point in the 5G era [15], and then further stimulate the demand for future 6G networks. To have enough imagination, it needs us to prepare for possible future networks and lay the technical foundation in advance.

III. Visions of 6G: Core Requirements, Use Cases, and Trends

6G envisions a data-driven society, which is enabled by near instant and unlimited connectivity to anything, ranging from tiny static sensors to autonomous objects, from anywhere, including the rural areas, mountains, and seas, and anytime. With 6G not defined, this section introduces the core technical requirements along with the use cases of 6G, followed by the arising trends of 6G.

A. Core Requirements and 6G Scenarios

With technologies developing and time going on, the current support scenarios will not be able to support the applications in the future, as stated in the limitations of 5G. Hence, new technical requirements will be imposed and new service classes should be supported in the future. In this section, core technical requirements will be introduced and new service classes will be defined.

1) Core Technical Requirements:

1) *Peak Data Rate:* Peak data rate is one of the key technical indicators that has been pursued since 1G. Without a doubt, 6G will further enhance the achieved peak data rate, which is expected to reach up to Tb/s [15], [31].

First, it can be predicted from the history of peak data rate improvement from 1G to 5G. Second, the demands of big data transmission for intelligence and emerging applications (e.g., high-quality VR/AR and holographic communications) will far exceed the current wireless applications.

2) *Sub-ms end-to-end Latency:* Low latency is pivotal to many wireless applications. For example, it makes the users feel dizzy with a latency of more than 20 ms for VR/AR users. 20 us $\sim$ 10 ms is required for machine-to-machine communications (M2M). For remote surgery or other remote control in most of the industrial use cases (e.g., industrial IoT and IIoT), a higher requirement in terms of latency is proposed [37], e.g., one submillisecond.
3) *Higher Energy Efficiency:* The energy consumption of mobile networks has become an ignorable problem around the world [38], which will not only generate a huge amount of carbon emissions that is harmful to the environment but also accounts for a considerable part of the operating expenses. First, with ultralarge throughput, ultrabroad bandwidth, and ultramassive ubiquitous wireless access points (APs), 6G will bring unprecedented huge challenges to energy consumption. Second, various sensors will be ubiquitous in human's life, which need bulky energy to operate and manage these sensor networks. Hence, green communication is particularly urgent for 6G, e.g., energy efficiency of 10–100 times (in J/bit) [39].
4) *Accurate Localization:* First, to determine the location of the mobile terminals in a cellular system is mainly in the case of an emergency call, which is also the demand of governmental institutions. Second, the location of the mobile device can be exploited for commercial services to obtain revenue, e.g., the so-called location-based services. Examples of such services include navigation, mapping, asset tracking, geo-marketing and advertising, social networking, location-sensitive billing, AR, etc. Third, the location information can be also used for network optimization to improve network efficiency and communication capacity. Examples are network management, resource management for device to device (D2D) communications, intelligent transportation systems, radio reconfigurable spectrum, vehicular *ad hoc* networks, etc., [40]. Fourth, new applications, e.g., autonomous driving, autonomous factory, and remote surgery, which involve complicated operations, pose a stringent localization requirement to 6G to ensure the safety of users and protect the values and people, both indoors and outdoors, which can reach up to the level of several centimeters for indoor localization and 1 m for outdoor localization. Hence, more accurate localization capability is required in 6G.
5) *High Reliability:* Many applications with remote control functions are emerging, such as autonomous driving, autonomous factory, and tactile Internet, which all require high reliability to ensure safety. The reliability requirements of different 6G applications are predicted to be dependent, the most extreme case of which can be one billion bits transmission with only one-bit error and a delay of 0.1 ms.
6) *Full Coverage:* With the advancement of science and technology, human activities are further expanded to the extreme environment, e.g., higher altitudes, outer space, oceans, and deep under the sea. Communication nodes, especially the IoT devices, will spread over a wider area, which is inseparable from human social activities. As a result, an ubiquitous (covering Earth, sea, sky, and space), everything-connected (IoE), omniscient (with various sensors), and omnipotent (based on big data and deep learning) network should be built to truly realize the connection anytime and anywhere. The ultimate goal of mobile communications is the provision of ubiquitous super connectivity on the global scale [41], i.e., anywhere on Earth, outside or inside buildings, prosperous cities, or remote rural areas. Hence, full coverage should be provided by 6G.
7) *Privacy and Security:* Individuals should have the rights to choose under what conditions his/her personal information can be accessible by others. However, privacy violations occur sometimes, e.g., unapproved auxiliary utilization and unauthorized gathering of individual data and unauthorized access of securely stored individual data. With new applications emerging (e.g., autonomous driving, healthcare) and technologies maturing (e.g., cloud and MEC), there will involve more personal information in the future wireless networks, which must be protected. Therefore, an extra level of privacy and security should be provided by 6G networks compared to the current 5G and the earlier generation of networks.
8) *Programmable Service to Deal With Different Requirements:* With the breakthrough and development of new technologies, new business and scenarios are spawned and users' demands will tend to be more diversified and personalized. Hence, on-demand services should be provided by future 6G networks, which are designed to meet the individual needs of users and provide users with extreme experiences. Dynamic and extremely fine-grained services should be enabled, which enable users with different service types, service levels, and free combinations of different services according to their demands. Considering this, to provide the end-users with tools allowing the individuals to configure/program personal services is a promising solution.

B. 6G Use Cases

Beyond imposing new performance metrics (e.g., technical requirements), the new technological trends will introduce new use cases, i.e., service classes, to redefine the application types by morphing classical eMBB, uRLLC, and mMTC, which depend on only one single constraint. Though different researchers have different opinions on classification, what is commonly agreed with is that the classification should be based on the requirements of different applications. Following this common rule, several novel forward-looking scenarios, i.e., service classes, are defined in [31], [39], and [42].

Saad *et al.* [31] defined four service classes: 1) mobile broadband reliable low latency communication (MBRLLC); 2) massive URLLC (mURLLC); 3) human-centric service (HCS); and 4) multipurpose communications, computing, control, localization, and sensing (3CLS) and energy service (MPS). MBRLLC provides services that require any performance within the rate-reliability-latency space, which merges eMBB and uRLLC. Examples of applications are AR/VR and WBCI. mURLLC scales classical uRLLC across the device dimension that generalizes 5G uRLLC with legacy mMTC, which brings forth a tradeoff among reliability, latency, and scalability. Examples of mURLLC are classical IoT, blockchain, and autonomous robots. HCS is tightly coupled with humans, the performance of which depends largely on the physiology of the human users and their actions rather than raw rate-reliability-latency metrics. Typical application refers to WBCI. MPS aims to provide 3CLS services including their derivatives, and can also offer energy to tiny devices via wireless energy transfer, which is important to the applications, such as telemedicine, special cases of AR/VR, and connected robotics and autonomous systems.

Zhang *et al.* [39] introduced five service classes, including further eMBB (FeMBB) to provide higher data rate, extremely URLLC (eURLLC) to meet the demand of lower latency, ultra mMTC (umMTC) to further scales the device amount, long-distance and high-mobility communications (LDHMC) to support deep-sea sightseeing and space travel, and extremely low-power communications (ELPC) to enable e-health and nanorobots.

In the opinions of Zong *et al.* [42], revolved core requirements for 6G will lead to ubiquitous mobile ultrabroadband (uMUB), ultrahigh data density (uHDD), and ultrahigh-speed-with-low-latency communications (uHSLLC). uMUB aims to provide ultrahigh data rate and ultralow latency ubiquitously by integrating space and terrestrial networks. uHDD requires huge wireless capacity and high reliability, while uHSLLC aims at ultrahigh rates and ultralow latency.

It is worth noting that the above definitions are quite different and not considerate, since the affiliation of one application may be confusing based on the above definitions. In summary, novel service classes aim to provide compound services, which depend on more than one single constraint and, more importantly, are with varying granularities [43], as well as to support new functions, such as localization, mapping, computing, privacy, and so on. What is concrete is that 6G will provide more complex and heterogeneous services than ever before.

C. Trends of 6G

The applications above, limitations of 5G, and the development of new technologies will lead to new system-wide trends, which will be discussed in the following.

More Bits and Spectrum, and Denser Networks: Fig. 2 presents the evolution of wireless technologies. From the history of mobile communications from 1G to 5G, it shows the trend of pursuing higher data rates. This trend will continue in 6G. As discussed above, most of the driving applications of 6G

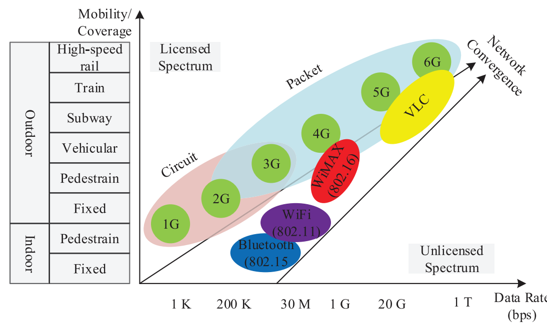

Fig. 2. Evolution of wireless technologies.

require much higher data rates than 5G, and a $1000\times$ increase in data rate should be delivered by 6G to cater to these applications, such as holographic communications and WBCI [31]. To support these extremely high data rate requirements in 6G, new spectral bands will be explored [44]. In this context, the terahertz spectrum (0.1–10 THz) has been envisioned as a key technology to fulfill this requirement [45], [46], as well as the visible light spectrum (430–790 THz) and unlicensed spectrum (e.g., 2.4 GHz/5–7 GHz/57–71 GHz). It is worth noted that the handsets will combine more modes of operation from multiple frequencies in addition to cellular, WiFi, and Bluetooth [47]. Providing a massive amount of available bandwidth up to several THz (three orders of magnitude higher than unregulated regions at mmWave frequencies), terahertz spectrum has the potential to provide several Tbps data rates. By using the terahertz spectrum, the communication range of which is limited to 50 m [48], an unprecedented level of network densification, and base stations (BSs) miniaturized and embedded all around us will be needed [49]. At the same time, hundreds of simultaneous beams will be a part of 6G, which helps yield much higher data rates. In addition, the licensed spectrum, unlicensed spectrum, and VLC will play crucial roles in achieving the ultrahigh data rate.

Convergence of Various Communication Systems: In the earlier generations of mobile communications, researchers have tried to integrate the satellite networks with the terrestrial wireless networks [50], as well as in 5G [51], though it was never integrated into cellular handsets [47] due to a series of complications in terms of technical and political challenges. In 6G, this trend will continue, which will extend to a convergence of various communication systems, focusing not only on terrestrial wireless networks but also on airborne communication networks [52]. Airborne communication networks are engineered to utilize various aircraft, including satellites, airships, and balloons on high-altitude platforms, and UAVs on low-altitude platforms [52], while a terrestrial wireless network is a typical heterogeneous wireless network comprised of macrocells, microcells, picocells, or femtocells, WiFi, VLC APs, and even D2D devices. In this converged system, each communication technology maintains its advantages and disadvantages, which could compensate each other to improve the system performance, e.g., coverage.

Convergence of Communications, Caching, Computing, Control, Sensing, and Localization (4CSL): As stated by Saad *et al.* [31], the past four generations of cellular systems maintained one exclusive function: wireless communications. When it comes to 5G, more functions are involved, e.g., caching and computing. It is believed that 6G will completely disrupt this premise through a convergence of diverse functions, including communications, caching, computing, sensing, control, and localization. The drivers behind this convergence mainly refer to the inherent features, e.g., tracking, control, localization, and computing, of applications, such as AR, autonomous driving, and smart homes. Hence, 6G is envisioned to be a multipurpose system that could deliver multiple 4CSL services and functions. Especially, sensing and localization services will enable 6G systems to provide users with a 3-D mapping of the radio and physical environments. Hence, to tightly integrate and manage 4CSL functions is vital to 6G, and it will be enabled by the evolutions pertaining to previous trends.

From Network Softwarization to Network Intelligentization: It is envisioned that 6G will take network softwarization toward network intelligentization, i.e., a new level of softwarization [53]. In 5G, two key technologies, SDN and NFV, have shifted modern communication networks to software-based virtual networks, which is enabled by network slicing to create multiple virtual networks atop a shared physical infrastructure to meet the diverse and heterogeneous requirements. In 6G, diverse capabilities, such as communication, caching, computing, and even energy harvesting, should be supported by the network entities to support the AI-based applications. More advent IoT functionalities, including sensing, control, localization, data collection and analytics, caching, and computing, should be supported by 6G. Furthermore, intelligent surfaces and terahertz communications will be embraced in 6G. All these contribute to a more complex and heterogeneous future network, which calls for a flexible, adaptive, and more importantly, intelligent architecture. As a result, softwarization is not going to be sufficient for 6G, which needs to be further improved to meet these challenges. Recent successes have motivated AI to form part of 5G. However, the combination of AI and 5G only scratch the surface and is only expected to be operated in isolated areas, which involve powerful computing facility and massive training data. It is envisioned that a part of 5G will realize some form of AI and AI will become one of the core components in 6G [54], from the application layer to the physical layer, i.e., ubiquitous intelligence.

From Centralization to Distribution: A trend from centralization to distribution has arisen in 6G, from the architecture to technologies. In 5G, the weakness of the centralized architecture and management mechanisms has been initially revealed, an example of which is the proposal of distributed SDN, MEC, and edge caching to meet the increasing complexity. Besides the complexity, the drivers behind the distribution of 6G are omnifarious, including the development of IoT applications, the increasing amount of users, and the introduction of AI and blockchain. In 6G, various functionalities, e.g., communication, caching, computing, sensing, localization, and so on, are integrated, and the networks tend to be more complex and heterogeneous, especially with the increase of mobile users. To operate and manage huge networks with stringent requirements and limited resources, fully distributed management mechanisms are desired. With emerging IoT applications containing personal information and the popularity of cloud services, future wireless networks are generating and carrying massive data. In view of privacy, the data are usually stored on mobile devices, which needs distributed training when applying AI [55], i.e., distributed computing and intelligence. A new mechanism is needed to enable the sharing of a large amount of information without jeopardizing users' privacy, which is also required to be distributed due to the complexity. A promising solution refers to blockchain, which could enable safe data sharing with its nature of distribution and immutability. In addition, FCC states that blockchain can help remake spectrum access, which reboots the old binary system of licensed or unlicensed airwaves [49], thus improving spectral efficiency. Besides spectrum, blockchain can be also used for resource management in terms of computing, caching, and so on.

D. Full Picture of 6G

A schematic diagram of future 6G wireless systems is shown in Fig. 3, which includes applications, services, architecture, and management. As shown in this figure, the applications and services encompass every aspect of human life and society, which are both human centric and machine centric. It provides more ways, such as through gestures, voices, and minds, for communicating and interacting with mobile users and intelligent devices [39], and the interaction forms are diverse, such as hologram videos and five senses. As a result, immersive experiences and super smart verticals based on IoT will be supported by 6G. For the network architecture, 6G is envisioned to incorporate multiple innovative technologies, such as space–air–ground-underwater/sea networks and cloud technologies. First, the integration of space, air, ground, and underwater/sea networks will constitute a large-dimensional 6G network, which will provide ubiquitous and unlimited connectivity. By adding terahertz spectrum, visible light spectrum, and unlicensed one, full spectra will be featured by this network architecture. To make full use of full spectra, massive MIMO, full duplex, and beamforming are necessary to achieve high network capacity and data rates, which need to be adjusted and upgraded of course. Especially, the usage of terahertz spectrum will lead 6G to be even denser. For network management, facing with more types of terminals and network devices, more complex and diverse business types, and more complex and huge networks, intelligence and distribution are needed by incorporating machine learning, blockchain, and SDN/NFV.

6G vision can be summarized into immersive connectivity, ubiquitous connectivity, intelligent connectivity, and distributed connectivity, which constitute the overall vision of 6G, "Wherever you think, everything follows your heart" [15]. In summary, 6G will be the first generation that fully achieves the digital transformation of societies by providing ubiquitous, near-instant, ultrareliable, and secure wireless connectivity for both humans and machines. The incorporation of innovative technologies, such as space–air–ground–underwater/sea networks, machine learning, blockchain, and so on, will make it multidimensional, human intelligent, and fully distributed.

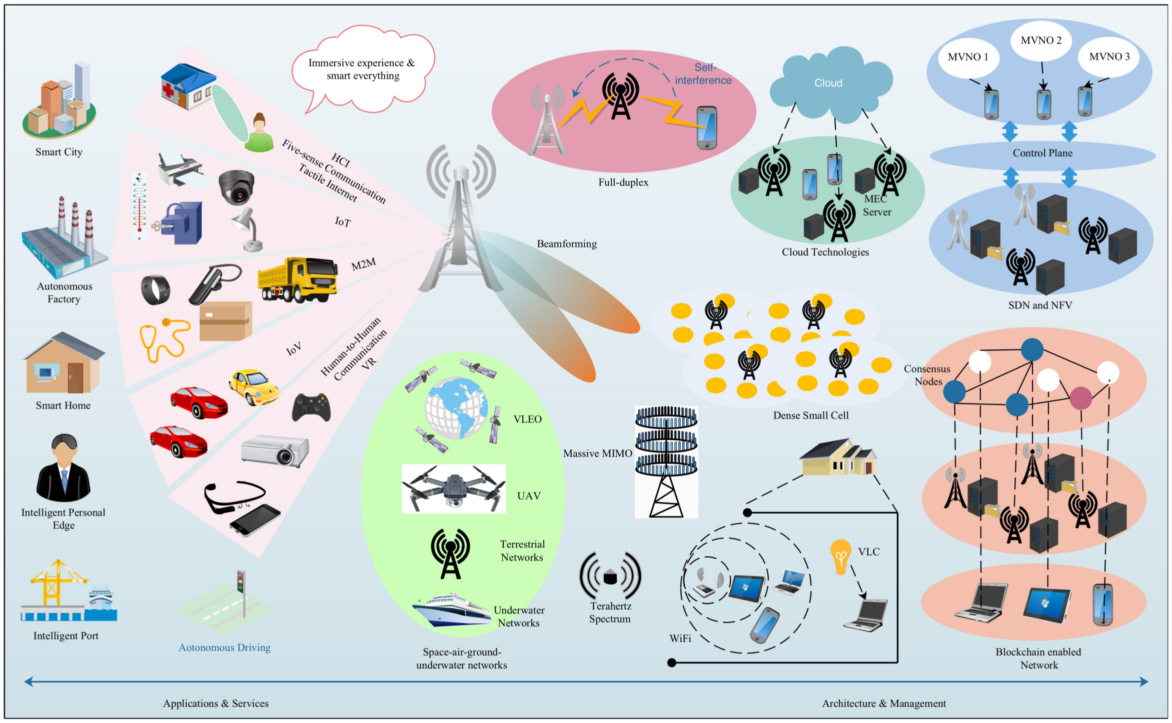

Fig. 3. Schematic diagram of future 6G wireless systems.

IV. Network Architecture for 6G-Enabled Massive IoT: Space–Air–Ground–Underwater Network With Edge Computing

In this section, we first introduce the space–air–ground–underwater/sea network and edge computing. Then, the overall network architecture is described by explaining how this network architecture can support the massive IoT in 6G. Finally, we discuss some open issues faced by the system design.

A. Space–Air–Ground–Underwater/Sea Networks

A space–air–ground–underwater/sea network is a large-dimensional network, which consists of four tiers, i.e., a space-network tier formed by various satellites, an air-network tier constituted by various flying BSs (e.g., high-altitude platforms, mobile airborne cells, UAVs, and so on), a terrestrial-network tier consisting of all kinds of legacy BSs, and an underwater-network tier, including underwater hubs, ships, and so on.

1) Space Tier-Massive VLEO Satellites: The space tier is composed of all kinds of satellites, constellations, and their corresponding terrestrial infrastructures (e.g., ground stations). These satellites are deployed at different orbits and maintain different characteristics, which can be classified into four categories based on the altitude, i.e., geostationary Earth orbit (GEO), medium Earth orbit (MEO), low Earth orbit (LEO), and VLEO satellites [56]. Among these four kinds of satellites, VLEO satellites are promising to provide high-rate data services and accurate localization due to the lowest orbit.

Considering the outstanding performance in terms of extremely low round trip latency and low cost of VLEO satellites, this technology attracts the attention of academia and industry in the future wireless communications [57], [58]. The ongoing VLEO constellation projects, e.g., SpaceX [58] and OneWeb [59], plan to launch over thousands of VLEO satellites over the Earth, aiming to construct a massive VLEO constellation and cooperate with the traditional terrestrial operators to support seamless and high-capacity communication services. In the future 6G, *massive VLEO satellites* will be deployed in the sky to provide both diverse geographic coverage and enough capacity to support a wide range of broadband communication services for residential, commercial, institutional, governmental, and professional clients globally [60].

2) Air Tier-UAVs: The air tier consists of UAVs, airships, and balloons, which is an aerial mobile system to complement the terrestrial networks by providing broadband wireless communications. Compared with terrestrial networks, it has the advantages of low cost, flexibility, easy deployment, large coverage, and no infrastructure required to offer wireless access services on a regional basis. Among these carriers, UAVs attract the focus of academic and industry due to its salient attributes of strong line-of-sight (LOS) connection links, and additional design degrees of freedom with the controlled mobility [61].

UAVs originated mostly in military applications. In recent years, the use of UAVs has quickly expanded into communication, commercial, scientific, recreational, agricultural, and other domains, the applications of which include acting as a relay, broadcasting, cargo transport, weather control, forest fire recognition, traffic detection, emergency search, and rescue. To deploy UAVs in wireless communication networks, it offers cost-effective services with no or limited infrastructure, which, as a relay, can extend the coverage of the traditional cellular networks. UAVs can be considered as a substitute to a wireless recovery network in cases of terrestrial disruption. Compared with satellite communications, UAV communications are more cost effective and provide lower latency and better signal-to-noise ratio [62]. In addition, the feature of UAVs, i.e., short-range LOS, provides better communication channels and mobility provides flexibility in deployment. Thanks to these advantages, many wireless applications for UAVs have been proposed, such as mobile relays, cache in the air, mobile computing cloudlets, and so on.

3) Ground Tier-Terahertz Communications and VLC: The ground tier refers to the legacy wireless networks, e.g., cellular networks, wireless local area networks, VLC, and so on, which is still the main way to acquire services for most IoT-enabled applications. 6G will be enhanced with higher spectrum bands (e.g., mmWave and terahertz bands), better modulation and channel coding, and new spectrum utilization (e.g., flexible spectrum sharing technology) to improve its system capacity.

Terahertz communications use the terahertz electromagnetic spectrum that lies in the boundary region between radio frequency (RF) and optical frequency, which is envisioned as a key technology to enable real-time applications for 6G by alleviating the spectrum scarcity and capacity limitations of current wireless systems [13], [45], [46]. Compared with mmWave communications, terahertz communication maintains a wider bandwidth, which induces various inspiring advantages. First, it has the potential to support unprecedented data rates from tens of Gb/s to several Tbps than mmWave communications, which can enable innovative applications for diverse scenarios. Second, it is easy to track beams for indoor wireless communications, which will enormously affect the mobility of the wireless communication systems. Third, the reflection paths can be utilized by terahertz communication systems to enhance link gains, especially for indoor applications. Fourth, thanks to the short transmission range of terahertz communications, interference in terahertz band-based networks can be substantially cut down with highly directional beams, resulting in terahertz band-based networks to be noise limited rather than interference limited, which further increases the performance. Fifth, extremely directional beams narrow beams can be used to partially secure the data at the physical layer in addition to extending the communication range [63]. As a result, more antenna elements (i.e., massive multiple-input and multiple-output, MIMO) can be packed at terahertz frequencies than at microwave (including mmWave), the formed beams of which can be narrower. It further facilitates the development of other applications, e.g., detection radars. Due to the short transmission range of terahertz communications, 6G envisions an ultradense network than ever before, which could further enhance the connectivity capacity and data rates of 6G. In summary, all these inspiring advantages make it ideal for transmission among IoT devices.

Another attractive technology for indoor IoT transmissions refers to VLC. VLC, a class of optical wireless communications, can be utilized as one of the promising alternative methods to the existing RF-based wireless communications, especially for indoor communications [64]. VLC can use the existing illuminating devices for communication purposes, which uses the visible light (430–790 THz) as a carrier for the data, and offers a 1000 times greater bandwidth compared to the RF communications [65]. The communication through visible light holds special advantages when compared to the other existing forms of wireless communications, such as several tens of Gb/s data rate [66], cost efficiency [67], security [65], and large geographical distribution [65]. The high data rates, ease of availability, and low cost of VLC make it a relevant wireless communication technology and a possible complementary technology that would cater to all kinds of future applications [68]. As a consequence, it has been widely considered as an enabling technology of 6G [13], [24], [39], which can be used for indoor positioning, human–computer interface (HCI), vehicular communications, and even underwater communications.

4) Underwater/Sea Tier-Optical Communications: The underwater tier aims to provide Internet services for distributed nodes over the broad or deep sea, including seabed sensors, relay buoys, autonomous underwater vehicles, and remotely operated underwater vehicles. All these nodes collaborate with each other to fulfill sensing, processing, and communication tasks for environmental monitoring, disaster precaution, offshore exploration, and military operations [9]. Compared with the acoustic and RF methods, optical communications, which employ optical waves as the transmission carrier, could provide the highest transmission data rate, lowest link delay, and lowest implementation costs for bidirectional underwater communications [10] due to water exhibiting different propagation characteristics from the land. Especially, VLC has been proven the possibility for underwater communications [69] by employing a single-photon avalanche diode for transmission in pure seawater, which maintains high data rate and low power consumption [70].

B. Edge Computing

As a dynamic global network infrastructure with self-configuring capabilities, IoT makes all things communicate with each other based on standard and interoperable communication protocols and realize information sharing and decision making [71], which involves data acquisition, exchange, and analysis. In addition to data analysis, edge computing plays a pivotal role in supporting massive computation-intensive IoT-enabled applications. First, these applications propose more robust requirements in terms of computation power, such as holographic communications, high-precision VR, autonomous driving, smart factory, and so on. Second, the caching power of edge computing could help further relieve the heavy burden caused by massive data uploaded to the cloud [72]. Third, edge intelligence can be enabled by edge computing, which is expected to provide intelligent services at the network edge, such as training machine learning models for decision making and analyzing big data generated by massive IoT devices at the network edge. In summary, the introduction of edge computing can significantly reduce the latency, save bandwidth resources, and protect privacy to some extent.

As noted, this section aims to introduce the network architecture for massive IoT provided by 6G. Since edge computing has been studied thoroughly, we only briefly introduce edge

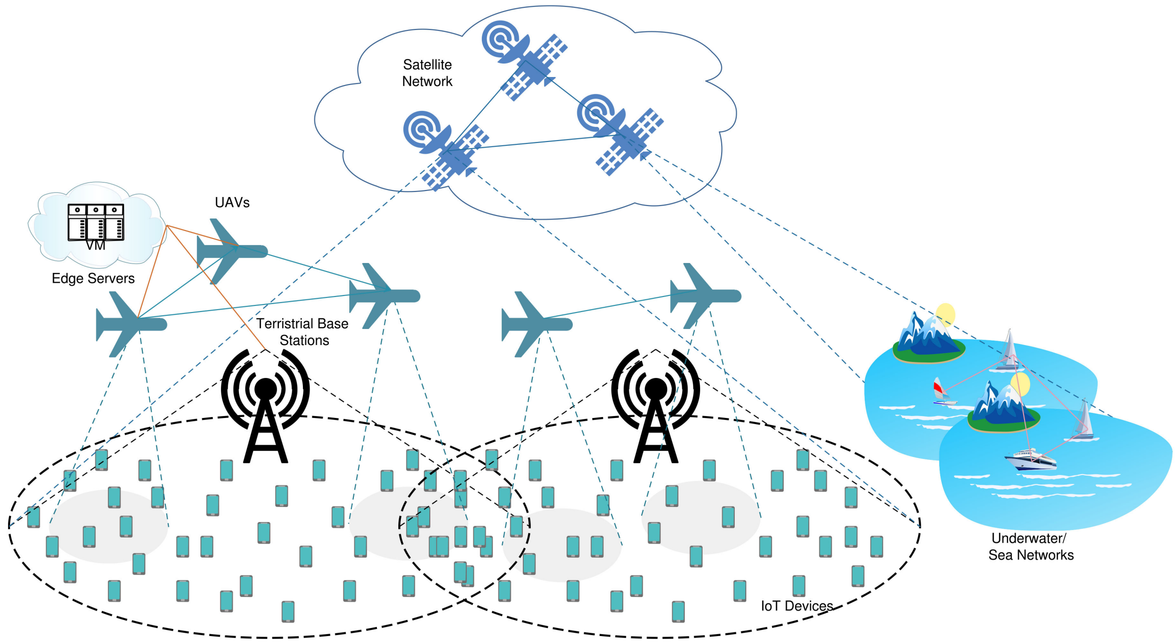

Fig. 4. Network architecture for 6G-enabled massive IoT: space–air–ground–underwater/sea networks with edge computing.

computing, focusing on its functions and advantages. For details on edge computing, we recommend the readers to refer to [72]–[76], and [77].

C. Overall Network Architecture

The overall network architecture for massive IoT in the upcoming 6G is shown in Fig. 4, which consists of space–air–ground–underwater/sea networks and edge computing. As described above, the space–air–ground–underwater/sea network extends the traditional cellular networks by integrating space, air, and underwater/sea networks, which cover all natural space, such as space, air, land, and ocean. It will lead to ubiquitous connectivity, that is, providing information assurance for any user who can access any subnetworks. With resorting to terahertz spectrum, visible light spectrum, and unlicensed spectrum (for both communication and sensing), this network can provide ultrahigh data rate and low latency for some data-intensive and mission-critical IoT applications. Edge computing endows tiny IoT devices with additional computational and caching capabilities through computation offloading. Rather than outsourcing storage and processing functionalities of IoT data to a third party with cloud computing, edge computing can realize edge storage and processing for the cumbersome traffic created by massive IoT and fill the gap between centralized clouds and distributed IoT, such as single point of failure, reachability, lack of location awareness, and latencies associated with core networks. As a result, the incorporating of edge computing can enable applications with the needs for mobility management, location awareness, geodistribution, scalability, and ultralow latency.

D. Open Issues

As discussed above, VLEO satellite, UAVs, terahertz, optical communications (especially VLC), and edge computing play important roles in supporting massive IoT. Though these technologies promise superior performances for IoT, there are some open issues needed to be addressed before fully achieving these visions.

1) VLEO Satellites Communications: Satellite communications are usually suffered from long latency, which consists of transmission time, propagation time, processing time, and queuing time. Though VLEO satellite communications maintain the lowest latency due to the lowest deployed altitude compared with GEO, MEO, and LEO satellites, it is far from enough to meet the demands of some time-sensitive applications. Hence, it is viable to integrate with other technologies, such as in-network caching. Not only technical challenges, e.g., long latency, are associated with VLEO satellite communications but also the ones related to standardization and political factors.

2) UAV Communications: There are different kinds of UAVs for different purposes. For example, consumer low-cost UAVs are with limited capabilities in terms of payload and flying time, which are suitable for photo/video shooting applications for entertainment. Commercial or military UAVs are capable of traveling long distances with heavy payloads carried, which are mainly for strategic operations, such as surveillance and wide-area communication coverage, involving high data throughput requirements, cargo delivery, and so on. How to achieve a balance among flying time, carried payload, and associated costs is essential where a joint optimization of these three important metrics is desirable in the future. Although some works have been done in this direction, several years are still needed to close this gap. Despite the technical aspects, regulations concerning privacy, data protection, and public safety should be also paid attention to.

3) Terahertz Communications: The research on terahertz communications needs further investigation, the achievement of which relies on various aspects.

Hardware Design: Transistor and hardware materials need to comply with excellent high-frequency characteristics, the potential materials of which is graphene. The researchers may also find more suitable materials. In addition, nanoantennas are desired to enable massive MIMO.

Channel Modeling: It is hard to establish the channel and noise modeling in terahertz bands. A mixture of models that consider path-loss mechanisms may be the solution to this problem.

Medium Access Control (MAC) Layer Design: In view of the relatively wide terahertz bands, the properties of different carrier frequency windows will be rather different. The MAC layer protocols and network deployment schemes need to be redesigned. To improve the coverage and support the seamless connection, new error control mechanisms and networking strategies should be developed, due to the high path loss.

Network Deployment Modeling: The future network will be multitier and heterogeneous. In 5G small cells, it tends to be user centric, which will be more emphatic in future 6G with even smaller cells. In addition, future networks will be deployed in 3-D. Thus, the current Poisson point process will not be applicable. A new network deployment model is required to consider the above facts.

4) VLC: As discussed in [70], LEDs in VLC have interesting properties to be used as sensors. The usage of VLC for sensing has attracted more focuses in recent years. In view of the complexity, it can be combined with WiFi or other techniques to improve accuracy.

Hybrid Systems: Adopted as a complementary technology to the current RF-based systems, new hybrid VLC systems are pointed out as a future trend. To enhance the quality of communications, VLC is expected to cooperate with wired-based-network devices, RF, and Ethernet networks.

Standardization: The research on VLC has conducted several years. However, actual solutions are not interoperated due to the different VLC hardware and testbeds. To better organize and optimize the research field, it calls for standardization.

5) Optical Communications: First, optical communications cannot perform well for scenarios with non-LOS (NLOS) links, while for LOS scenarios, precise pointing between the transceiver is essential. Second, the performance of optical communications for underwater scenarios can be severely degraded due to the absorption and scattering effects of seawater, misalignment errors, channel turbulence, and other impact factors, resulting in recurrent communication failures [10], [78]. To this point, how to ensure the reliability of optical communications for underwater networks should be further studied.

6) Integration: Despite the challenges associated with individual tier, the integration of the four tiers faces unprecedented challenges due to its specific characteristics of high heterogeneity, time variability, and self-organization. Since the space–air–ground–underwater networks are significantly affected by the limited, heterogeneous, and unbalanced resources in all four network segments, to obtain the best performance is difficult for traffic delivery. As known, existing works are mainly focusing on the space–air–ground-integrated architectures, performance analysis, and challenges in space-ground- or air-ground-integrated networks [79]. Few of them concerned the case of space–air–ground networks, let alone space–air–ground–underwater networks. As noted, the heterogeneity, time variability, and self-organization in space–air–ground–underwater networks bring new challenges, which will seriously affect the network performances, e.g., latency, throughput, and reliability for data transmission. That is, more research works are expected to concern such issues involving all four network tiers.

V. Breakthrough Technologies

Considering the increasing growth of IoT-enabled applications in terms of volume and requirements, it is essential to integrate breakthrough technologies to meet their demands, the most two promising of which refer to machine learning and blockchain. In this section, we mainly introduce the motivations, applications (or functions), and open issues when applying these two technologies to massive IoT.

A. Machine Learning

1) Motivation: The term "edge big data" results from the overwhelming volume of data, which is generated and collected by massive IoT devices at the network edge [80], [81]. As we know, machine learning is a data-driven technique, i.e., the machine learning models need to be trained and tested by using massive data. In this case, it just so happens that we cloud apply machine learning to massive IoT to fully unleash the potential of edge big data by data analytics, which in turn provides the opportunity to develop intelligent applications at the network edge.

From the perspective of communication networks, 6G will become more complex and heterogeneous, as more techniques are emerging, such as caching, edge computing, and terahertz communication networks, which provide more possibilities as well as pose more challenges for network organization, management, and optimization [82]. With computing and caching capabilities throughout the network, pervasive intelligence is expected to enable 6G, driving a fully autonomous future wireless system. With machine learning being such a craze, it has been considered as a key approach in [31], [39], and [53] to realize 6G from a user perspective. With intelligence introduced to 6G, machine learning enables wireless networks learning capabilities to autonomously make optimal decisions to adapt to the complex and varying environment, i.e., self-adaptive, self-upgrade, self-aware, and predictive ability.

In summary, for both IoT applications and communication networks, machine learning will play vital roles in building an intelligent IoT system to deliver smart services in the 6G massive IoT realm.

2) Roles of Machine Learning: In wireless communication networks, machine learning can be used for prediction, big data analysis, and decision making [15]. Considering its attractive advantages, machine learning has been proposed for 5G, the roles of which are summarized in Table II. As we can see, machine learning is proposed to be applied to the whole network, ranging from the physical layer to the application

TABLE II
ROLES OF MACHINE LEARNING IN 5G

Layer	Roles
Application Layer	Machine learning as a service
Network Layer	Handover optimization Mobility management Load management Routing management
MAC Layer	User selection Resource allocation Modulation and coding scheme selection Power control Handover control
Physical Layer	Channel coding Synchronization Positioning Channel estimations
Cross Layer	Cross-layer optimization Wireless security

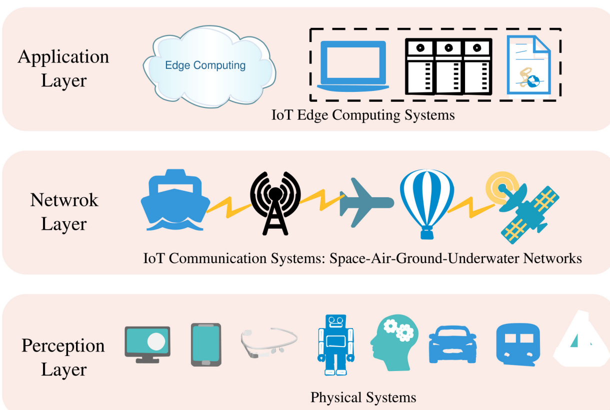

Fig. 5. Typical architecture of IoT systems.

TABLE III
SUMMARY OF EXISTING WORKS OF MACHINE LEARNING IN IoT

Learning Methods	Applications	Ref.
Logistic regression	Anomaly detection	[84]
Grey systems theory	Outlier detection	[85]
SVM	Fault detection	[86]
Support Tucker machine	Outlier detection	[87]
Q-learning	Relay selection Network association Autonomous overtaking	[88] [89] [90]
Deep learning	Resource scheduling	[91]
Deep Q learning	Relay selection Transmission scheduling	[92] [93]
RL	Task offloading Dynamic spectrum access Energy storage decision	[94] [95] [96]
DRL	Offloading decision Continuous resource allocation IoT connectivity Channel and power allocation Trajectory planning Path planning Autonomous lane changing	[97] [98] [99] [100] [101] [102] [103]
Federated learning		[104]
Meta learning	Sensing	[105]
Transfer learning	Compressed sensing	[106]
A3C	Multi-robot collaboration	[107]
Multi-agent RL	Driving coordination	[108]
Actor-critic learning	load scheduling	[109]

layer, which aims to provide automation for network management. Despite these roles in 5G, machine learning will play even more important roles in the future 6G. First, different from the global evolution in 5G, in which the system has to be rebuild when new waveforms, coding, and multiaccess protocols are applied, machine learning can enable local evolution to upgrade the local networks, which brings more flexibility. Second, different from 5G, which developed an intelligent physical layer paradigm relying on the algorithm-hardware coupled architecture, machine learning will enable intelligent radio based on the hardware-algorithm separation architecture [53], which can adapt the environment and hardware in an intelligent way by replacing the conventional modulation/coding modules with deep neural networks (DNNs). As 6G becoming concrete and machine learning developing, it is believed that machine learning will have more positions in 6G.

3) Applications of Machine Learning for Massive IoT in 6G: The future IoT-enabled applications encompass identification/authentication, sensing, communication, caching, computation, and localization services [83], which establish a more complex ecosystem than ever before. A typical architecture for these IoT-enabled applications is shown in Fig. 5, which consists of three typical layers, i.e., a perception layer, a network layer, and an application layer. The perception layer refers to the physical systems where IoT devices acquire data and exert control actions by interacting with the environment. The network layer corresponds to the communication networks for IoT, which encompasses wireless access networks and the Internet, aiming at discovering and connecting IoT devices to edge/cloud servers for data or control information transmission. The application layer refers to edge computing systems, which is in charge of data processing, storage, and decision making for control determination.

There have been many works focusing on the applications in the three layers of this IoT architecture, a brief summary of which is shown in Table III. As seen in Table III, deep reinforcement learning (DRL) has been attracted wide attentions from all areas.

Applications of Machine Learning in the Application Layer: With limited energy and computation capability in IoT devices, edge computing is essential for data analysis, prediction, decision making, (e.g., control instruction for IIoT and autonomous driving), and computation tasks execution (e.g., rendering for VR videos) [83]. IoT devices could offload such kinds of tasks to edge servers to save energy and reduce latency. To further improve the performance of IoT systems, the caching capability of edge computing can be utilized by some data-reusable applications, e.g., high-definition live streaming and VR/AR (i.e., rendering results [110]).

There have been numerous works dedicated to task offloading and resource allocation in edge computing for IoT systems. Different from task offloading and resource allocation in cellular networks with edge computing, some different aspects of IoT should be considered, e.g., ubiquitous coverage to suburban and rural areas and mobility in vehicular networks.

Space–air–ground networks are promising to provide ubiquitous services for remote IoT devices, which, however, leads to higher complexity for task offloading. Considering this fact, Cheng *et al.* [94] proposed a reinforcement learning (RL)-based algorithm for task offloading, which was proven to achieve a near-optimal solution with low complexity. However, the mobility of UAVs was ignored in this work, which introduces flexibility in terms of implementation and offloading choices as well as management complexity. Considering a hybrid edge computing platform with ground stations, ground vehicles, and UAVs, Jiang *et al.* [91] proposed a deep learning-based algorithm to solve the resource scheduling problem, where a large-scale path-loss fuzzy c-means algorithm was proposed to predict the optimal positions of ground vehicles and UAVs and a deep neural network was introduced for real-time decision making. It was proven that the proposed methods have better accuracy and could make real time and optimal design feasible in the proposed architecture.

In vehicle edge computing networks, vehicles act as mobile edge servers to provide offloading services for nearby users, which extends the range of computation services, as well as calls for intelligent networks. Constructing a three-layer offloading framework for the Internet of vehicles, Ning *et al.* [97] put forward a DRL algorithm to solve the flow redirection and offloading decision problem. However, this work only focused on services for vehicular entertainment. Focusing on time-critical services, such as safety warnings and navigation suggestions, Tan *et al.* [98] constructed a vehicular network with MEC in the finite block-length coding regime and proposed a deep deterministic policy gradient approach to solve the continuous resource allocation problem. However, the aforementioned works did not apply to large-scale problems. In this case, distributed machine learning provides a promising solution, e.g., multiagent RL [111] and federated learning [104], which needs further exploration.

Applications of Machine Learning in the Network Layer: Reliable and efficient wireless communication networks are essential for an IoT ecosystem, which range from short-range local area networks to long-range wide area networks. To transmit the tremendous amount of IoT data, efficient resource control mechanisms are desired to efficiently utilize the scarce radio, caching, and computing resources. First, the characteristics of IoT devices need to be considered, such as massive in number, limited energy, memory, and computation resources. Second, the diverse requirements of the IoT-enabled applications need to be taken into account, such as high data rate, low latency, high reliability, privacy, and so on. In addition, different applications may possess conflicting requirements. To counter these challenges, a promising solution is to deploy intelligence in the IoT ecosystem to enable IoT devices to operate autonomously, e.g., to use machine learning.

In a mesh topology, better network connectivity is essential for performance improvement, e.g., throughput, which could be achieved by deploying more relay nodes at the cost of larger energy consumption and higher complexity. Hence, it is important to achieve a tradeoff between node coverage and energy consumption and complexity. Kwon *et al.* [99] proposed a distributed intelligent IoT connectivity solution based on DRL that enables mobile IoT devices to strategically make decisions on whether to activate the transmission and the transmission power, which was proven to outperform the current state-of-the-art solutions only with a minimal amount of information from the IoT system. However, the cooperation between different agents was ignored in this work.

By using the licensed spectrum, narrowband IoT (NB-IoT) provides higher reliability and QoS. To enhance coverage, NB-IoT chooses to increase the number of retransmissions for data and control signals, which leads to throughput improvement, but in turn, lowers the spectral efficiency. Hence, it is important to extend coverage and reduce the number of retransmissions. Chafii *et al.* [95] proposed an RL-based dynamic spectrum access approach to increase the coverage. Based on the proposed approach, the IoT devices select the best channel considering both the criterion of availability and the best coverage condition. However, this work focused on a single-player scenario, which is not practical.

Cooperative communication has been regarded as a promising solution to enhance spectrum utilization, throughput, coverage, and so on. The cooperation among the relay nodes realizes the transmission sharing, thereby improves the system performance. In this case, it is important to select the best relay node. Jadoon and Kim [88] applied Q-learning to solve the relay selection problem for wireless cooperative networks. In this work, based on the state of previous system performance and the reward function about quality, the source node could determine the optimal relay with its learning capabilities. However, the proposed Q-learning-based algorithm cannot deal with large-scale problems. Considering this fact, Su *et al.* [92] proposed a deep Q network-based relay algorithm to rectify this problem, which selected the optimal relay from a plurality of relay nodes without any prior data or the need for a network model. However, this work did not consider the mobility of sensor nodes and assumed simple channel conditions.

To tackle the problem of the crowded spectrum to support the increasing amount of IoT applications, cognitive networks are regarded as one of the enablers in future IoT systems [112]. In this case, the IoT devices need to coordinate with the actions of the primary users with effective mechanisms in terms of spectrum access, transmission power control, transmission scheduling, and so on. Zhu *et al.* [93] proposed to utilize deep Q learning to solve the transmission scheduling problem in cognitive IoT networks. An appropriate strategy is found by the proposed mechanism to transmit packets with different buffers to maximize the system throughput. However, the authors only considered one relay in this work and the cooperation and competition between multiple relays were ignored.

In the resource-constrained IoT systems, an intelligent and efficient resource management scheme is pivotal to guarantee performance, since the future networks are more complex and heterogeneous. In a two-layer heterogeneous IIoT network, a distributed Q-learning-aided network association scheme was proposed [89]. However, the proposed algorithm cannot support a massive number of IoT connections. Considering the fact that the conventional RF networks may fail to support massive IoT connections as well as high data rate, a collaborative RF-VLC architecture was proposed for indoor communications [113], where RF networks offered long-distance transmissions with wide-range coverage, while VLC provided short-distance transmissions with high date rates. UAV plays an important role to collect information for IoT devices in remote or mountainous areas. Considering the high mobility of UAVs, which results in high dynamics for channel gain, it is impractical to obtain global information in the UAV-enabled IoT system. Hence, Cao *et al.* [100] proposed a DRL-based algorithm for channel and power allocation with only partial network information. However, the utilization of the proposed algorithm depended on the discretization of action space, which could not obtain the optimal solution.

Applications of Machine Learning in the Perception Layer: The applications of machine learning in the perception layer include sensing, control, and so on. Sensing refers to the procedure to collect the data generated by the IoT sensors. Control mainly refers to movement control for autonomous robots (e.g., tactile Internet, smart factory, and remote surgery), driving aid for autonomous driving, intelligent management for smart grid.

As the foundation of an IoT system, sensing is important for decision-making policies, where the reliability and accuracy of the sensed data need to be ensured. Since the IoT sensors are susceptible to malicious attacks, it is essential to detect outliers to ensure data quality. Recently, machine learning has been proven to be a powerful tool to detect outliers in sensor data [114], which can be classified into parametric methods, nonparametric methods, supervised learning, and unsupervised learning. Hasan *et al.* [84] used logistic regression to detect anomaly or outlier in sensed data. Though it is simple and learns fast from the data, it suffers from the drawback of assuming *a priori* of the data distribution. To this end, Nesa *et al.* [85] proposed an outlier detection approach based on the gray systems theory. Though it does not make an assumption about the data distribution, which makes it more pliable for any data, a lot of training data is needed to create a mapping function. Zidi *et al.* [86] used support vector machine (SVM) to detect faults in sensed data, where a cluster head made decisions on detection. However, this vector-based approach may destroy the original structure and correlation within large-scale sensed data, resulting in low detection accuracy. Thus, Deng *et al.* [87] proposed an intelligent outlier detection method with one-class support Tucker machine and genetic algorithm, which extended SVM to tensor space with retaining the structural information of data, resulting in improved accuracy and efficiency of anomaly detection.

Despite the outlier detection in sensor data, another problem in sensing is the increased communication overhead and data redundancy, which needs an efficient method to cut down the size of the data set and to reduce the communication cost. Traditional sensing algorithms are usually task specific and cannot be directly applied to other field sensing tasks, which is energy inefficient and time consuming. Considering this, Wu *et al.* [105] developed an efficient sensing algorithm with the help of RL and metalearning, which significantly reduced the communication head with integrated communication and computation. Compressed sensing is commonly used to downsize the transmitted data, and deep learning is proven to have better performance for data recovery. However, it does not apply to small data samples. To this end, Liang *et al.* [106] developed a convolution-based transfer compressed sensing model with the help of transfer learning, which could transfer a well-trained model to other related but insufficient data sets, resulting in better performance but less time cost.

Machine learning plays a pivotal role in enabling autonomous robots with or without intelligence, the research of which mainly focus on mobile behavior control, robotic manipulation, and multirobot collaboration. Referring to general movement control, DRL has been widely applied to existing research, e.g., trajectory planning for UAVs [101], [115] and path planning for navigation robots [102], [116]. Intelligent robots could perform some tasks in practice, where an appropriate control scheme tells the robot how to achieve a target. For example, Mnih *et al.* [117] utilized DRL to teach the machine itself to play Atari 2600 games from the Arcade Learning Environment, where it learned control policies from high-dimensional sensory input. For multirobot scenarios, collaboration among these robots is essential in order to achieve a common goal. In this case, a distributed machine learning algorithm may be more popular and appropriate, e.g., asynchronous actor–critic algorithms (A3C) [107].

Machine learning is considered as the key enabler of autonomous driving by the academia and industry, which is used to control the vehicles without the help of humans, e.g., following, overtaking, accelerating, and direction changing (i.e., remaining in the current direction, turn right or left, or lane changing). To study the autonomous lane changing problem for a single vehicle, Mirchevska *et al.* [103] proposed a DRL-based approach to learn high-level decision makings, where the relative distance between the considered vehicle and the neighboring six vehicles and the relative velocity of the neighboring vehicles were input as the state of the learning approach. Considering the overtaking problem, Li *et al.* [90] proposed a Q-learning-based approach to improve the overtaking policies to accord with the driving habits of humans. However, these works only consider a single vehicle, where the interactions among different vehicles are ignored. Motivated by this fact, cooperative adaptive cruise control [118], navigation coordination through intersections [119] through interactions, and cooperative lane changing on a freeway [120] have been studied using RL in multivehicle scenarios. However, these works only directly applied distributed RL, which ignored the coordination among vehicles in the process of learning. To solve this problem, Yu *et al.* [108] proposed a strategic distributed learning solution for coordinating multiple vehicles.

Smart grid has been the trend for future wireless networks and attracted the attention of the world [121], which aims to improve the electricity generation, consumption, transmission, and distribution. Due to its uncertainty, complexities, and high volume of data, machine learning has revealed its advantages in smart grid management, e.g., energy trading, energy storage management, and demand response [83]. The research and practice of deep learning and RL in smart grid were reviewed in [121]. Energy trading allows the users to switch their role between a consumer and provider depending on its relationship between its generated and demanded energy, where an autonomous control scheme is essential to ensure the supply/demand balance, especially for microgrid [122]. A promising solution is to integrate games with machine learning to achieve Nash equilibrium autonomously in a centralized or distributed way [123], [124]. To further consider prices, energy storage takes advantage of price fluctuations to buy or sell energy at a proper price in order to generate profit. Unlike previous works [125], with more practical assumptions, e.g., unknown electricity market prices, Cao *et al.* [96] adopted a model-free RL approach to learn an optimized control policy for storage charging/discharging. The demand response aims to control the customers' usage patterns in response to electricity tariffs or other incentives and reduce the demand during system contingencies or at peak time periods [126]. In view of the facts of the dynamic and unknown energy prices and the demand of the users' appliances, an online demand response scheme based on actor–critic learning was proposed in [109], where the long-term load scheduling problem was investigated with real-time prices. However, only one householder was considered and the competition among multiple multiple utility companies needs to be explored in the future.

4) Open Issues of Machine Learning for Massive IoT in 6G: Though there has been a flurry of research activities dedicated to machine learning, these works only scratch the surface, and the potential of machine learning to tackle problems for massive IoT in 6G remains largely unexplored [127]. Some challenges are summarized as follows.

Incomplete Data Set in Perception Layer: Most machine learning methods require data for training and testing, e.g., supervised, unsupervised learning, RL, and so on, which can be generated or collected with different approaches. For example, the more the data samples, the more accurately the machine learning algorithms can achieve. The more complete data samples are, the more accurately deep learning can learn its model. However, it is not easy to acquire the perfect data samples needed. First, the unpredictable link delays and radio interference may result in slow response and certain parameter miss or data errors. Second, some private data are usually possessed by different entities, which is to sell or for secrecy. Third, it is a privacy problem.

Long Time Cost: The long time cost may prevent the applications of machine learning, which includes training time and inference time. The former refers to the time to train the models to be accurate enough, while the latter refers to the time to output the results using the trained-well models. For some applications, such as autonomous driving and tactile Internet, it needs a near real-time response, e.g., usually a timescale of milliseconds. However, it is far more behind enough to train the machine learning algorithms in time, especially for large-dimensional IoT scenarios.

Computation and Storage Hungry: Most machine learning algorithms require powerful computation power and storage capacity. To implement machine learning on the clouds in core networks incurs long latency. To avoid transmission latency, machine learning can be implemented at the network edge, e.g., edge computing servers, which in turn may not meet the computation demands of machine learning algorithms.

Centralized or Distributed: Considering the high complexity, centralized machine learning methods are not practical, especially for large-scale IoT problems. To cater to the scalability problem, distributed machine learning plays an important role. However, it usually induces high overhead for information exchange and privacy problems. Also, it requires each node to be with powerful computation capability. Hence, a sophisticated choice between centralized and distributed machine learning-based schemes is crucial, which should be based on various factors about the addressed problem.

Optimization of Machine Learning: Due to the characteristics of IoT and 6G, the implementation of machine learning in 6G is not straightforward and some modifications need to be made. First, each machine learning model has its drawbacks, and it is essential to combine several machine learning techniques to provide better performance. Second, the capabilities of network entities may vary in hardware, connectivity, and energy. This heterogeneity is believed to bring flaws for machine learning models. Hence, machine learning should be optimized to fix this problem. In addition, model updates can be disclosed, and techniques, such as deep net pruning, differential privacy, and gradient compression are recommended to preserve privacy for machine learning. Third, distributed machine learning is considered to be more suitable for 6G and IoT, which, however, involves massive communication between different edge devices. Hence, distributed machine learning needs to be modified to cope with the wireless communication conditions.

B. Blockchain

This section mainly introduces motivations to apply blockchain to IoT, applications of blockchain for massive IoT in 6G, and some open issues. For a more explicit understanding of blockchain, refer to [18], [128], and [129].

1) Motivations of Blockchain for IoT in 6G-A Perfect Match: With the evolution of IoT, several challenges are arising, including high complexity in network management, poor interoperability, and privacy and security vulnerabilities, which are explained as follows.

First, IoT systems are becoming more complex and heterogeneous. In the perception layer, IoT devices are heterogeneous, which involves various sensors, machines, vehicles, robots, and so on. In addition, massive data are generated with different types, i.e., structured, semistructured, and nonstructured. In the network layer, the multidimensional space–air–ground–underwater networks incur extra management complexity with full spectra. In the application layer, multilevel caching and computing resources are presented from near to far from IoT devices. In summary, all these pose challenges to network management. For resource management, various resources are involved, i.e., communication, caching, and computing, the management of which should take sensing, control, and localization into considerations as well. For data management, massive data are difficult to manage with respect to elaboration, communication/transmission, and storage.

Second, interoperability for massive IoT in 6G becomes difficult in the presence of multiple protocol options and cross-platform architectures. To provide diverse services to IoT devices, multiple operational platforms, radio access service providers (SPs), edge cloud vendors, caching vendors, and so on coexist. It is essential to collaborate with different SPs and vendors and exchange data between different strategic centers, industrial sectors, and IoT systems, which is impractical in the current network architecture. First, a unified authentication and authorization mechanism is required to integrate individual systems of different operators. Second, diverse service provision and proper payment to different SPs and vendors need to be audited and ensured. For example, the computation offloading in the heterogeneous networks with MEC involves cellular networks and MEC providers. However, there is no trusted entity in this system to audit the computation offloading process or ensure the surefire payments to SPs and edge cloud vendors.

Third, it refers to privacy and security issues. Massive data are generated by massive IoT devices, which may contain confidential and private information. It is important to use IoT data with an appropriate approach so that there is no disclosure of user private information without users' consent. However, it is challenging to protect users' privacy in IoT due to the decentralization, heterogeneity, and complexity of IoT systems. In addition, a trend to integrate cloud technologies, i.e., fog/edge/cloud computing with IoT arises, which aims to empower IoT applications with extra computing and caching/storage capabilities. In this case, if clouds are attacked, a massive amount of data may be leaked, breaching users' privacy [130]. Due to the characteristics of IoT systems, i.e., decentralized, heterogeneous, and highly complex, it is also difficult to ensure the security of IoT. The current methods for providing privacy, security, and data handling rely heavily on the control of third-party entities, few of which can be fully trusted by end users.

With improved interoperability, reliability, privacy, security, and scalability, blockchain is perfect for massive IoT, which could exactly deal with these challenges. The combination of blockchain and IoT can bring the following merits.

1) *Decentralized Network Management:* It can be achieved by recording all network events as transactions of the blockchain. In this way, all events will be audited without a third party, which is more cost efficient.
2) *Interoperability Across IoT Devices, IoT Systems, Industrial Sectors, and SPs:* This can be achieved by building a blockchain-composite layer on the top of an overlay P2P network with uniform access to different systems by providing a unified authentication, authorization mechanism, and billing system.
3) *Traceability and Reliability of IoT Data:* A historic timestamp in each data block saved in a blockchain will consequently assure the data traceability. With inherent asymmetric encryption algorithms, digital signatures, and hash functions in blockchains, the integrity of IoT data is enforced. In this way, the security and privacy of massive IoT will be ensured.

In addition, as analyzed in Section III, a trend from centralization to distribution in 6G is arising, and the blockchain is regarded as a promising technology of 6G to provide a distributed network management platform, which can be used for resource management, data sharing, data storage, and so on. Hence, blockchain is a perfect match with IoT and 6G.

2) Applications of Blockchain for Massive IoT in 6G: With the inherent superior properties of blockchain, i.e., distributed nature, decentralized consensus, trust-less system, cryptographic security, and nonrepudiation guarantees, it is considered as the key enabler of massive IoT, as well as the next revolution of future mobile communication technology [24]. Generally, the use of blockchain can be categorized into three types: 1) recording as a distributed ledger; 2) decentralized storing; and 3) realizing automation with smart contracts [131]. The exact applications of blockchain for massive IoT are described as follows.

Recording as a Distributed Ledger: Blockchain is attracting the focus of 6G on the perspective of dynamic resource management, e.g., spectrum, computation, caching, network slicing, and so on, which could be used to record transactions of resource trading and audit the process of resource trading. Currently, spectrums are auctioned off one at a time in a process that is slow, complex to manage, and expensive. One option is to share the spectrum by using different bands at different levels of priority. Another option is to build a real-time spectrum market that would issue permissions dynamically using AI, which will bring new efficiencies and move the system from one of scarcity to one that can manage relative abundance. To achieve this goal, blockchain is one of the most promising solutions being looked at by the researchers. There have been some works dedicated to blockchain-based spectrum management. In [132]–[135], the spectrum sharing problem was investigated, where blockchain acted as a peer-to-peer decentralized ledger to record the spectrum trading efficiently. However, all these works ignored an important problem, i.e., the performance of blockchain itself. For example, the trading of the spectrum is obviously frequent, which is far larger than the throughput of the current blockchains. Also, blockchain itself is resource hungry in terms of computation and transmission. How to ensure the advantages of utilizing blockchain for spectrum sharing is essential. To create a new spectrum market is not easy, ranging from the framework design to the optimization of the system.

Decentralized Storage: In traditional cloud-based IoT systems, a centralized cloud server maintains and controls all the data, which poses some challenges: 1) high storage capacity required from the centralized server and 2) sensitive data easy to be leaked. To handle these issues, a decentralized structure may be more proper. Fortunately, decentralized storage is one of the most popular applications of blockchain in IoT systems [136]. In [137], a decentralized platform was studied, where blockchain was used to protect personal private data. Here, blockchain acts as a decentralized personal data management system to ensure users owning and controlling their data. In this work, the data were stored off blockchain, the security of which cannot be ensured. Li *et al.* [138] proposed to store the IoT data in distributed hash tables (DHTs) and the pointer to the DHT storage address in the blockchain. In this work, the authentication of the data requester is handled by the distributed blockchain nodes rather than a central server, which maintains the advantages of decentralized storage, without any intervention from a trusted server, traceability, and accountability. However, the authentication in this work was done by only verifying the identity of the data requester, which needs further improvement.

Realizing Automation With Smart Contracts: A smart contract is a computer program, which is self-executing, self-verifying, and tamper resistant. It takes the transactions as input and then executes the code. When some conditions are met, some events are triggered, in which way automation is achieved. In IoT systems, different nodes need to cooperate with each other to provide services, which necessities the need of managing the identity of nodes and realizing security authentication between nodes [139]. Some works have adopted smart contracts for access control in IoT systems [140], [141], where the main function of smart contracts is to manage the data records. Different from these works, Zhang *et al.* [142] proposed a smart contract-based access control framework, which consisted of multiple access control contracts to achieve distributed access control for untrustworthy IoT systems. Zhaofeng *et al.* [20] proposed a blockchain-based decentralized trust management and data usage scheme, where a smart contract was in charge of all data operation, i.e., data gathering, invoking, processing, transfer, and usage. In IoT networks, a blockchain-based identity management framework was proposed in [143], where a smart contract was utilized to govern the interactions between IoT devices by implementing the processes and rules. Apart from identity management, smart contract can be also used for autonomous energy trading [144], adaptive offloading [145], IoT device behavior regulation [146], and so on.

3) Open Issues of Blockchain for Massive IoT in 6G: Despite these potential visions of blockchain in massive IoT, multiple challenges need to be addressed before its widespread applications.

Performances of Blockchain-Based Systems: In blockchain-based systems, it performs as an overlaid layer to provide services to the underlaid layer, i.e., IoT systems. Hence, we need to guarantee the performances of both systems, which affect each other significantly.

Resource Hungry: Blockchain is inherently resource hungry in terms of both computation, caching, and transmission for block generation, verification, ledger storage, and the consensus among nodes. How to ensure the advantage of incorporating blockchain into IoT should be investigated.

New Security Threats: Outsourcing a large scale of services at the edge and self-organization to achieve automation both triggers new security problems, which need to be studied furthermore.

Resource Management: On one hand, the resources of the networks are limited, such as computation, caching, and wireless resources, especially at the network edge. On another hand, the blockchain system itself is resource hungry. Thus, the resources need to be allocated between the blockchain and wireless systems to make the best use of limited resources.

Optimization of Blockchain: To make full use of blockchain for IoT and 6G, it should be optimized in various ways. First, the services of IoT-enabled applications are highly heterogeneous in terms of different technical requirements. Some require ultralow latency, while some care only about privacy. Hence, blockchain needs to be modified with more powerful adaptivity to support a wide variety of services, where a generic blockchain platform for IoT and 6G is desired. Second, blockchain is limited by its own properties, i.e., scalability and delay (or time to finality), which is vital to apply it to massive IoT. Hence, a novel consensus protocol needs to be designed to improve the throughput, time to finality, security, and so on, which should meet the corresponding demands of IoT applications in 6G.

C. Combination of AI and Blockchain

As two of the most disruptive technologies, AI and blockchain have its own natural limitations, which restrict their applications to 6G. To fully unleash the potential of this two techniques and meet the future intelligent, distributed, and secure requirements, it is essential to combine these two megatrends, which will make mutual enhancement.

Blockchain for AI: To date, the majority of AI methods rely on a centralized model for training and inference by uploading data collected at edge devices to data centers. This centralized nature will lead to massive communication overhead and a possibility of data tampering. As a result, the decisions made by AI may be delayed and highly erroneous [147]. In this case, distributed AI is in dire need, where privacy preservation and network traffic congestion reduction are enabled by avoiding data uploading to a central server. However, distributed training and inference still require communications between different agents and a centralized server for data and model sharing. First, model updates can be disclosed. Second, it is hard to evaluate the contributions of each agent and lacks motivation for data and model sharing.

To deal with these problems, blockchain is considered as a promising solution. By replacing the centralized server in distributed AI with blockchain, in which models are stored in the form of transactions, model sharing is operated autonomously with smart contracts, and decisions are made on blockchain, multiple benefits are brought, which are illustrated in Fig. 6. First, it will provide rational motivations for data and model sharing. Second, security and privacy can be ensured with inherent asymmetric encryption algorithms, digital signatures, and hash functions in blockchain. Third, decisions made by distributed AI that utilize blockchain can be trusted. As a result, distributed intelligence will be enabled.

AI for Blockchain: The benefits brought by AI to blockchain are mainly twofold. First, AI can manage blockchains more efficiently. Nowadays, the operation of blockchain on computers requires a large amount of computer processing power, which is inefficient. Take the hashing algorithm as an example. A brute force approach is used by the Bitcoin blockchain to mine blocks, which tries every combination of characters until a transaction can be verified. Moving away from this brute force approach, a more intelligent and thoughtful manner to manage tasks is desired, e.g., a machine learning-powered mining algorithm. Despite mining, the other tasks can also

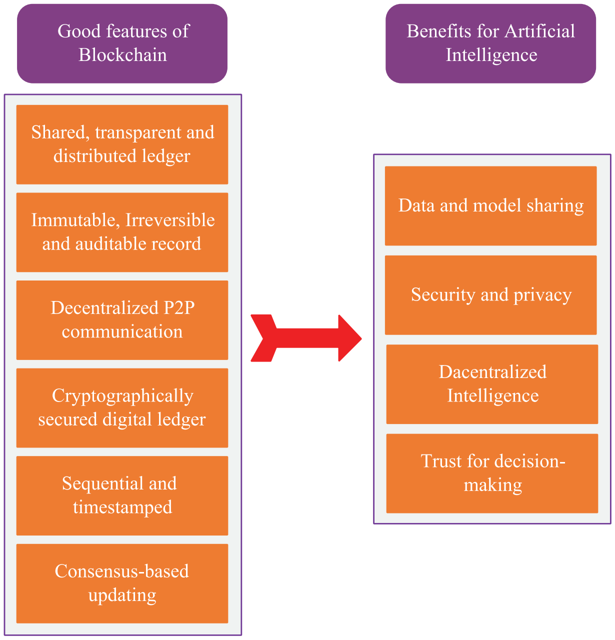

Fig. 6. Benefits of integrating blockchain to AI.

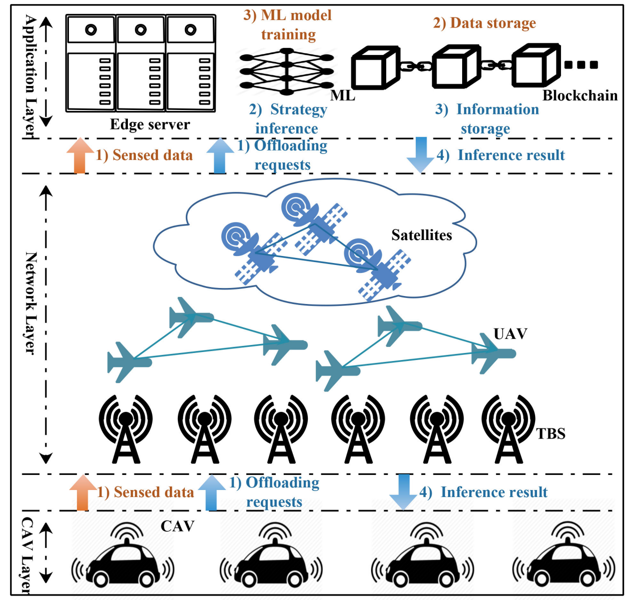

Fig. 7. Fully autonomous driving in 6G. CAV: connected autonomous vehicles. TBS: terrestrial base station. UAV: unmanned aerial vehicle. ML: machine learning.

be enhanced with AI, e.g., AI-powered smart contracts [148]. With AI embedded, blockchain will become more efficient, resulting in better performance. Second, AI could make full use of the blockchain encrypted data. Information is held on a blockchain database in an encrypted state, which provides high security for sensitive data, but in turn, proposes extra challenges for data usage. To make things safer, we should reduce such incidents in which unencrypted data are exposed in any part of data processing. Nowadays, a new field of AI is emerging, which aims at building algorithms capable of operating on encrypted data [149]. With AI working with encrypted data, it will further enhance data security and make full use of blockchain database.

VI. Case Study

To show how 6G can support IoT-enabled applications, we present a case study on fully autonomous driving in 6G, which is shown in Fig. 7. This system enables fully autonomous driving through offloading from connected autonomous vehicles (CAVs) to edge servers via the space–air–ground–underwater/sea networks, which includes three layers, CAV layer, network layer, and application layer. In the CAV layer, an autonomous vehicle is equipped with various sensors, including LIDAR, RADAR, cameras, GPS, ultrasonic sensors, and so on, which convert some events and physical environment into electrical signals for measurement, i.e., sensed data. The network layer refers to the space–air–ground–underwater/sea network, which aims to provide connectivity to CAVs. Especially, the ground tier is the main solution. The air tier provides flexible coverage for CAVs, which can also help sense the environment. The space tier can be used for localization and coverage for extreme areas. The application layer enables machine learning and blockchain by providing computing and storage capabilities. Here, machine learning deployed on edge servers could help solve tasks that CAVs could not deal with, which could also help enhance the performance of blockchain embedded on edge servers. Blockchain can help store important information for CAVs and model parameters for machine learning (in an encrypted state, of course), and audit the offloading process of CAVs, which ensures the security and privacy of this system.

As shown in Fig. 7, fully autonomous driving can be achieved in the following procedure.

1) The vehicles use terahertz spectrum or other unlicensed spectrum for sensing data, e.g., the location and velocity of the surrounding vehicles, the conditions of the road surface, and the traffic light. Then, the sensed data are transferred to the application layer through the network layer with the help of the space–air–ground–underwater networks, which provide high data rate, low latency, full coverage, and high reliability.
2) These data can be stored on blockchain, which preserves privacy for CAVs.
3) Machine learning models are trained with these sensed data on blockchain.
4) CAVs offload computation tasks to edge servers via the space–air–ground–underwater/sea networks.
5) The application layer uses trained machine learning models to make intelligent decisions for driving assistant, e.g., lane changing and overtaking (i.e., strategy inference).
6) Offloading processes are stored on blockchain, which provides audition and motivation for offloading services.
7) The inference results, e.g., the control information, are delivered to the vehicles through the network layer. In this way, fully autonomous driving is achieved. In addition, access control, data sharing between different cars

and edge servers, and resource sharing can be controlled by blockchain, which could further enhance the performance of this system.

VII. Conclusion

In this article, we did a comprehensive survey on massive IoT enabled by 6G. We provided an overview of the drivers and requirements, where the emerging applications and limitations of 5G were summarized. These applications include holographic communications, five-sense communications, WBCI, smart healthcare, smart education/training, industry Internet, fully autonomous driving, and super smart city/home. Then, a discussion on the visions of 6G in terms of core technical requirements, use cases, and trends is carried out. To meet the demand of the IoT-enabled applications, especially the full coverage requirement, 6G provides a four-tier network architecture enhanced by edge computing. As an omnipotent network, 6G also provides some breakthrough technologies, including machine learning and blockchain, to enable intelligence and distribution in future IoT systems, which play vital roles in the whole IoT architecture, from the perception layer and network layer to the application layer. Finally, we present a use case of fully autonomous driving to show how 6G supports massive IoT.

In summary, research on 6G and massive IoT is quite broad and a number of challenges lay ahead. Nevertheless, it is in favor of the wireless community to swiftly address the challenges and go forward. This article attempts to briefly explore the technologies related to 6G and IoT, and to discuss future research that may benefit the pursuit of this vision. We hope that our discussion and exploration here may open a new avenue for the development of 6G and IoT, and shed lights on effective and efficient designs therein.

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